Multimodal Learning from Videos: Exploring Models and Task Complexities

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To my parents, Dr. Sangeeta Palaskar and Dr. Jayant Palaskar, and my uncle, Shrikant Palaskar, for making me who I am today

Abstract

Human learning is inherently multimodal. We watch, listen, read, and communicate to learn from and understand our surroundings. There have been several advancements in machine learning fields related to these human activities such as speech recognition or computer vision that make computationally modeling this human-like inherent multimodal learning a possibility. Multimodal video understanding as a machine learning task is close to this form of learning.

This thesis proposes to break down this complex task of video understanding into a series of relatively simpler tasks with increasing complexity. We start with the monotonic task of speech recognition and introduce an end-to-end audio-visual speech recognition model. A more complex task is speech translation that tackles re-ordered output sequences in addition to speech recognition, which is the second task in this thesis. For speech translation, we introduce a multimodal fusion model that learns to leverage the multiple views multimodal data provides in a semi-supervised way. Further, we progress to the tasks of multimodal video summarization and question answering that tackle abstract-level understanding tasks further involving information compression and restructuring. Finally, we extend this work to multimodal self-rationalization that not only performs abstract-level learning, but also provides an explanation of the achieved video understanding. For the four main tasks, we present a series of multimodal fusion models based on the nature and complexity of the task, the modalities involved in each and compare and contrast the models on commonly used video and language understanding datasets.

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Contents

Abstract ii

Acknowledgements iii

List of Figures ix

List of Tables xii

1 Introduction 1

1.1 Thesis Overview 5

2 Learning Tasks 9

2.1 Dataset 9

2.1.1 How2 Dataset 11

2.1.2 Direction of Research 16

2.2 Terminology 17

2.3 Learning Tasks 18

2.4 Models and Modalities 19

3 Speech Recognition 21

3.1 Introduction 21

3.2 Audio-Visual Speech Recognition 24

3.2.1 Model 24

3.2.2 Experimental Setup 25

3.2.3 Results 26

3.3 Acoustic-to-Word Speech Recognition 28

3.3.1 Model 28

3.3.2 Experimental Setup 29

3.3.3 Results 29

3.3.4 Automatic Word Segmentation 31

3.4 Chapter Conclusion 36

4 Speech Translation **37**

4.1 Introduction 37

4.2 Contextual Acoustic Word Embeddings 40

4.2.1 Audio-to-Semantic Learning 40

4.2.2 Model 41

4.2.3 Experiments and Results 43

4.3 Multiview Learning for Multimodal Embeddings 47

4.3.1 Multiview Learning 47

4.3.2 Model 47

4.3.3 Experiments 50

4.3.4 Results 51

4.4 Chapter Conclusion 54

5 Summarization & QA **55**

5.1 Introduction 55

5.2 Summarization 58

5.2.1 Task Formulation 58

5.2.2 Models 58

5.2.3 Experimental Setup 61

5.2.4 Results 62

5.3 Question Answering 65

5.3.1 Task Description 65

5.3.2 Transfer Learning: Summarization to QA 66

5.3.3 Experimental Setup 67

5.3.4 Results 68

5.4 Chapter Conclusion 71

6 Rationalization **72**

6.1 Introduction 72

6.2 Rationales through Semantic Concepts 77

6.2.1 Defining Semantic Concepts 77

6.2.2 Learning Semantic Concepts 78

6.2.3 Task Setup 80

6.2.4 Models 82

6.2.5 Results 84

6.3 Self-Rationalization 89

6.3.1 Background 90
6.3.2 Tasks and Datasets 90
6.3.3 Automatic & Human Evaluation 91
6.3.4 Models 95
6.3.5 Results 99
6.4 Chapter Conclusion 106

7 Conclusions and Future Directions **107**
7.1 Summary of Contributions 107
7.2 Broader Impact and Limitations 110
7.3 Future Directions 112

Bibliography **113**

List of Figures

1.1 An example from the How2 dataset showing the different modalities that exist in this data. There are 4 time-synchronous modalities: the video signal, the audio/speech signal, corresponding English transcripts and the Portuguese transcripts. There is a human annotated textual summary for each video. Additionally, we also have access to relevant metadata such as the video title, topics, categories, view count, etc. 2

1.2 Overview of the Multimodal Video Understanding tasks in this thesis: Speech Recognition, Speech Translation, Summarization, and Rationalization. The tasks are ordered in increasing level of complexity from left to right. 3

2.1 How2contains a large variety of instructional videos with English transcriptions, Portuguese translations, and English video summaries. 11

2.2 Modalities and possible tasks around How2: EN and PT respectively stands for English and Portuguese. 12

2.3 LDA topic distributions for the *300h* subset of the How2 data. The labels are manually annotated based on frequency of topic words. The overall *2000h* corpus exhibits very similar characteristics. 14

2.4 Segment durations for the *300h* subset. The overall *2000h* corpus exhibits very similar characteristics. 14

2.5 Overview of the model complexities across four learning tasks: Input Fusion, Latent Representation Fusion, Hierarchical Latent Representation Fusion, and Hierarchical Interpretable Fusion. 20

3.1 Illustration of the Monotonic Input Fusion technique for multimodal adaptation. 22

3.2 Audio-Visual Sequence-to-Sequence ASR. 24

3.3 Length Distribution for the How2 and WSJ Train sets. 26

3.4 Length normalization by S2S for WSJ and How2 28

3.5 Attention visualization for a sample utterance from the validation set shows highly localized attention for a word-level S2S model 32

3.6 Encoder hidden state visualization for WSJ (acoustically clean data) and SWBD (acoustically noisier). Visualization shows encoder activations across input time frames. 34

4.1 We build on top of the existing Input Fusion model for semi-supervised Speech Translation. We present the Latent Representation Fusion model that learns a multimodal latent representation LY_1, and uses that via retrieval for downstream tasks. 39

4.2 A2W model with the CAWE representations obtained by combining the encoders representations and attention weights. 41

4.3 Learning from multiple modalities using Canonical Correlation Analysis (CCA) loss. 47
4.4 Extracting sequence embeddings from trained sequence to sequence models. . . 48

5.1 We build on top of the existing Input Fusion and Latent Representation Fusion models presented so far for Summarization and Question Answering. We present the Hierarchical Latent Representation Fusion model that not only learns a multimodal latent representation LY_1, but converts it into observable outputs Y_1 via hierarchical combination. 57
5.2 How2 dataset example with different modalities. "Cuban breakfast" and "free cooking video" is not mentioned in the transcript, and has to be derived from other sources. 59
5.3 Building blocks of the sequence-to-sequence models, gray numbers in brackets indicate which components are utilized in which experiments. 60
5.4 Word distribution in comparison with the human summaries for different unimodal and multimodal models. Density curves show the length distributions of human annotated and system produced summaries. 63
5.5 An example from the Charades dataset. For every video, there exists a video-dialog of 10 questions and answers each. The dataset additionally has the audio, summary and caption for each video. 65
5.6 Our best performing model use the weights of a trained summarization model on the How2 dataset (left) to initialize the training of our DTSC7 challenge model (right). 66

6.1 Examples demonstrating the rationalization task. The model is trained to generate the answers (or labels) as well as the commonsense rationales (or explanations) that justify the answers. Examples are ordered in increasing order of difficulty from three widely used multimodal datasets in this field: VQA-X (Park et al., 2019), E-SNLI-VE (Kayser et al., 2021), and VCR (Zellers et al., 2019). . 73
6.2 Demonstration of rationalization for existing multimodal generation tasks. Framework depicts three different multimodal generation tasks: captioning, summarization, and self-rationalization. For each, the auxiliary tasks are the entities, noun phrases, and answers respectively. 74
6.3 Expanding the fusion models to the fourth model: Hierarchical Interpretable Fusion model. 75
6.4 An example from the How2 dataset showing semantic concepts – specific concepts: granular, utterance-level, in blue, and abstract concepts: higher-level, video-level, in red. 77
6.5 Learning Semantic Concepts from existing data. Flowchart shows the data curation process, and its relation with the remaining task setup. 78
6.6 Hierarchical video understanding depiction: input is the video, outputs are a sequence of 3 levels of hierarchy: Specific concepts, Abstract concepts, and the Summary. Specific concepts are detailed, domain-specific. Abstract concepts provide a concise high-level overview. Summary is a textual overview of the video. 79
6.7 Hierarchical Interpretable Fusion through two phase training. Two phase cascaded model for multimodal summarization via semantic concept learning. . . 82
6.8 Screenshot of instructions to human evaluators for the VQA-X dataset. 93

6.9 Screenshot of an example HIT shown to human evaluators. This image, question, and answer are from the VQA-X dataset. Evaluators are asked to categorize the model generated explanation into four categories as shown. 94
6.10 Depiction of the Vision Adapted T5 (VA-T5) model. The encoders and decoders are first pre-trained on complex text. In the next stage, finetuned with visual features. This is the stage shown in this image. 95
6.11 Qualitative examples showing model generated answers and rationales for two sample images from the VCR dataset. 105

List of Tables

2.1 Statistics of How2 dataset. 13
2.2 Training set statistics for English and Portuguese: the number of unique words is computed after tokenization. 13
2.3 Task-specific multimodal views available for each task. 19

3.1 Results for Audio-only and Audio-Visual adaptation with the How2 data. . . . 27
3.2 TER of the S2S model on WSJ (eval92) and How2 (test set). 27
3.3 Typical transcription on How2 test set: S2S model keeps to the style of the reference which is an abstraction of the spoken content. Currently, there is little semantic difference between regular and adapted (AV) S2S output. 27
3.4 Average frame error mean and standard deviation (std dev.) between groundtruth forced-alignments and S2S word segment prediction 33

4.1 Comparing three methods to obtain acoustic word embeddings from an A2W model: unweighted average (U-AVG), weighted average (CAWE-W) and maximum attention (CAWE-M). 44
4.2 Sentence Evaluations on 16 benchmark datasets for Switchboard and How2 corpus. We compare the CAWE-M method with the word2vec embeddings trained with CBOW method and with CAWE-M + CBOW concatenated (Concat) embeddings. 45
4.3 Speech-based contextual word embeddings (CAWE-M and CAWE-W) match the performance of the text-based embeddings (CBOW) on the ATIS dataset with an RNN and GRU model 46
4.4 Recall@10 for retrieving reference modality given source modality ("source - reference"). Swapping source and reference change retrieval scores by less than 1% absolute. 51
4.5 Scoring top-1 retrieval result from DGCCA models with ASR, MT and ST metrics. Models used (from left to right) were trained using speech and text (en); text (en) and text (pt); speech, text (en), text (pt) and video. Source sentences for the retrieval are from the test set. 52
4.6 Recall@10 for retrieving column modality given source row modality, for a DGCCA model trained on 3 views. Results from the bottom left triangle can be compared to those in Table 4.4. 53
4.7 Recall@10 for retrieving column modality given source row modality, for a DGCCA model trained on 4 views. Results from the bottom left triangle can be compared to those in Table 4.4. 53

5.1 Most frequently occurring words in Transcript and Summaries. 61

5.2 ROUGE-L and Content F1 for different summarization models: random baseline (1), rule-based extracted summary (2a), nearest neighbor summary (2b), different text-only (3,4,5a), pointer-generator (5b), ASR output transcript (5c), video-only (6-7) and text-and-video model (8). 62
5.3 Human evaluation scores on 4 different measures of Informativeness (INF), Relevance (REL), Coherence (COH), Fluency (FLU). 64
5.4 Example outputs of ground-truth text-and-video with hierarchical attention (8), text-only with ground-truth (5a), text-only with ASR output (5c), action features with RNN (7) and action features only (6) models compared with the reference, the topic-based next neighbor (2b) and random baseline (1). Arranged in the order of best to worst summary in this table. 64
5.5 Dataset statistics for Charades and How2. The number of videos in the held_out test set of How2 is from the 300 hours subset of the data (*). 67
5.6 Automatic evaluation metrics on the test set provided by the organizers (groundtruth available). Models 1-6 are trained using the methods described in (Alamri et al., 2017) with different modalities. We treat them as our baselines. Models 7 and 8 are trained on text-only, models 9 an 10 on video-only and models 11-15 on text-and-video. Models 8, 10 and 15 are first trained on the How2 data and then fine-tuned `FT` on the Charades data. 69
5.7 **Automatic and Human evaluation** scores on the undisclosed evaluation test set prepared by DTSC7 organizers (we do not have access to groundtruth). Models 1 and 2 are the same baselines as in Table 5.6. Models 3 and 4 are trained on text-only. Models 5 and 6 are trained on text-and-video using Hierarchical attention. Models 4 and 6 are first trained on the How2 data and then fine-tuned `FT` on the Charades data. Systems marks with an asterisk (*) were the ones submitted to the challenge. Model 6 i.e. 'How2 `FT` Charades' was the best performing model. Note that the first column has a reference number to the model in Table 5.6. 70
5.8 Qualitative evaluation of different systems. % sentences (sent) changed are with respect to text-only Charades model. 71

6.1 Table shows dataset statistics, available modalities, vocabulary and average number (#) of concepts for Flickr8k, How2-300h, and How2-2000h datasets. This table introduces the proposed task from a dataset size and vocabulary perspective. Note the large target vocabulary space. 80
6.2 Concept extraction results as a classification (Clf) or generation (Gen) task on Flickr8k captions. 84
6.3 Specific concepts generation on the How2-300h-Utt data at utterance level. Train column indicates whether the model is trained for concept generation. I/P modalities shows the model-specific input modalities. OOD: out-of-domain. 85
6.4 Specific concepts generation results on the Flickr8k dataset. OOD: out-of-domain. 85
6.5 Abstract concepts generation on the How2-300h-Video and How2-2000h-Video data. Train column indicates whether the model is trained for concept generation on the given input modalities (I/P modalities). OOD: out-of-domain. 86
6.6 Summarization using Specific and Abstract concept generation models evaluated using METEOR (M) and ROUGE-L (RG). Concept model in cascade denotes the particular concept generation model used for summarization. 87
6.7 Example model outputs showing creative generation. OoD stands for out-of-domain ASR. 87

6.8 Specifications of the target datasets. VCR explanations and answers are notably more longer which makes them more challenging to generate automatically. Sources: VCR (Zellers et al., 2019), E-SNLI-VE (Kayser et al., 2021), VQA-X (Park et al., 2018). 90
6.9 Summary of benefits and downsides of training unified vision-language (VL) models (VLP or GPV) versus adapting pretrained language models (PLM) to visual features (VA-T5). Some models are combination of these two approaches (VL-T5, VL-BART). 96
6.10 Overview of text and image datasets used for pre-training by the different models. 96
6.11 Comparison of unified pre-training (VLP) and pre-trained language model adaptation methods (VL-BART, VL-T5, VA-T5) with baseline from (Dua et al., 2021) on VCR answer generation. VA-T5-Base significantly outperforms other models on this metric. 100
6.12 Comparison of unified pre-training (VLP) and pre-trained language model adaptation methods (VL-BART, VL-T5, VA-T5) on all three datasets VCR, E-SNLI-VE, and VQA-X. We report on proxy or task accuracy (Acc.), BERTscore for self-rationalization (BERT) and human evaluation of generated natural language rationales/explanations (Plausibility). 100
6.13 Different Plausibility computation methods to compare unified pre-training (VLP) and pre-trained language model adaptation methods (VL-BART, VL-T5, VA-T5) on all three datasets VCR, E-SNLI-VE, and VQA-X. We report average plausibility (Avg), aggregated plausibility (Agg), and majority vote plausibility (Vote). 101
6.14 Analysis of various visual features. We use the proposed VA-T5-BASE as the common model. None indicates no multimodal features; this is a text-only model. Caption indicates automatically generated natural language captions from a pre-trained image captioning model. As captions are natural language, this is a text-text adaptation model. Object features are extracted from an R-CNN object detector. CLIP features are extracted from a pre-trained CLIP model and are the latest off-the-shelf visual features. CLIP consistently outperform other features. 102
6.15 Analysis of various visual features evaluating using human plausibility. We use the proposed VA-T5-BASE as the common model. 102
6.16 Comparing model size for the VA-T5 model for all three datasets. Each model uses CLIP features for adaptation. Acc: Accuracy, BERT: BERTscore, Plau: Human evaluation of Plausibility. 102
6.17 LayerNorm analysis for the VA-T5-BASE model using CLIP-based adaptation on the E-SNLI-VE dataset. 103
6.18 Different modeling and model size comparison for all three datastes on a limited data setting. We train with only 30% randomly shuffled data. For E-SNLI-VE we sample evenly across Entailment, Neutral and Contradiction classes. Acc: Accuracy, BERT: BERTscore, Plau: Human evaluation of Plausibility. 104
6.19 Different modeling and model size comparison for all three datastes on a limited data setting. We train with only 20% randomly shuffled data. For E-SNLI-VE we sample evenly across Entailment, Neutral and Contradiction classes. Acc: Accuracy, BERT: BERTscore. 104

6.20 Different modeling and model size comparison for all three datastes on a limited data setting. We train with only 10% randomly shuffled data. For E-SNLI-VE we sample evenly across Entailment, Neutral and Contradiction classes. Acc: Accuracy, BERT: BERTscore. 104
6.21 Different modeling and model size comparison for all three datastes on a limited data setting. We train with only 5% randomly shuffled data. For E-SNLI-VE we sample evenly across Entailment, Neutral and Contradiction classes. Acc: Accuracy, BERT: BERTscore. 105

Chapter 1

Introduction

Videos are an inherent part of our day-to-day lives in the 21st Century. One of the goals of Artificial Intelligence (AI) research is to teach machines to perform certain tasks to off-load human labor, by modeling and simulating human intelligence. Videos closely capture our interactions in the world and often contain multiple modalities of information such as the audio, transcription, and the visuals itself.

Self-recorded instructional videos are a domain of videos that particularly focus on coaching a viewer on certain tasks, colloquially known as the How-To videos. These videos are informative, explanatory, and with visual and spoken demonstration, for example, making a Cuban breakfast omelet, or fixing a Polaris swimming pool cleaner (e.g. Figure 1.1). Such videos provide a readily available, well crafted source of instructional information that can be used to teach machines certain How-To tasks.

With this long-term view in mind, we approach this problem through the task of Multimodal Video Understanding. This task accounts for the various modalities available in a video, as well as performs downstream tasks that demonstrate "understanding". Video Understanding as a research problem is still in its nascent phase with various tasks falling under the umbrella term understanding ranging from video classification to video commonsense reasoning.

Video Understanding was initially approached as a video classification problem analogous to image classification with time-series input (Karpathy et al., 2014; Yue-Hei Ng et al., 2015; Szegedy et al., 2016; Abu-El-Haija et al., 2016). Research soon progressed towards human action recognition (Simonyan and Zisserman, 2014a; Caba Heilbron et al., 2015; Feichtenhofer et al., 2016; Carreira and Zisserman, 2017; Kay et al., 2017; Gu et al., 2018), scene understanding (Feichtenhofer et al., 2014; Tran et al., 2015; Ros et al., 2016; Cordts et al., 2016), text-to-video retrieval (Miech et al., 2019; Gabeur et al., 2020; Albanie et al., 2020), or video captioning (Yao et al., 2015; Yu et al., 2016; Krishna et al., 2017a; Zhou et al., 2018b) and description generation (Das et al., 2013; Regneri et al., 2013; Donahue et al., 2015). More complex language-based video understanding task formulations followed the success of easier tasks such

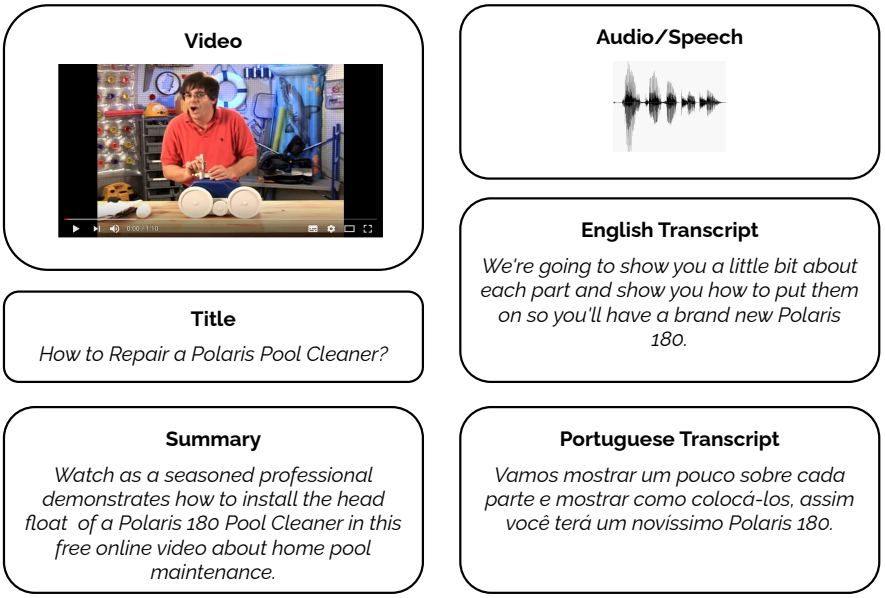


FIGURE 1.1: An example from the How2 dataset showing the different modalities that exist in this data. There are 4 time-synchronous modalities: the video signal, the audio/speech signal, corresponding English transcripts and the Portuguese transcripts. There is a human annotated textual summary for each video. Additionally, we also have access to relevant metadata such as the video title, topics, categories, view count, etc.

as video captioning or description generation. More recently, there is a huge push towards unsupervised, self-supervised, and semi-supervised approaches to representation learning that use existing annotations to train general purpose multimodal representations that can be later used in downstream tasks (Chen et al., 2019; Sun et al., 2019; Miech et al., 2020; Arnab et al., 2021).

Despite the tremendous progress in such tasks, the field of Video Understanding has not quite progressed towards *holistic* Video Understanding that studies the video signal in its natural form with audio, text, speech, metadata, and other available modalities. The Multimodal Video Understanding tasks involve at least one additional modality apart from the video signal used in tandem towards a downstream task. Often, there is a lack of annotated datasets that facilitate multimodal tasks which contain more than 3 parallel modalities. One of the first 5-way parallel multimodal videos dataset of instructional videos, the How2 dataset, was collected and released by Sanabria et al. (2018). Figure 1.1 shows a sample video along with its various modalities from the How2 dataset. Being the first-of-its-kind 5-way parallel dataset, it enabled the formulation of various video understanding tasks, with a special focus on language-based understanding such as summarization or translation. In this thesis, we present a series of tasks that can be performed unimodally and multimodally with this data, which together, constitute a step towards *holistic* Multimodal Video Understanding. Figure 1.2 gives an overview of the four major tasks detailed in this thesis.

The four main learning tasks for Multimodal Video Understanding covered in this thesis are Speech Recognition, Speech Translation, Summarization, and Rationalization. These tasks are ordered in terms of increasing task complexity and specific model architectures and constraints

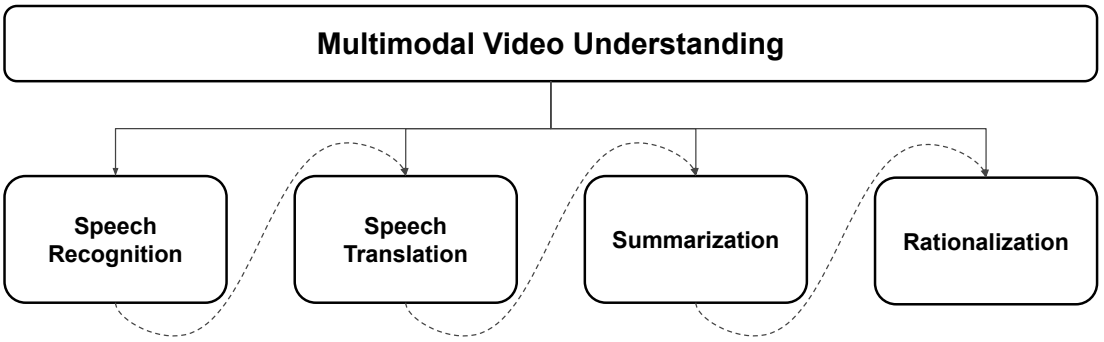


FIGURE 1.2: Overview of the Multimodal Video Understanding tasks in this thesis: Speech Recognition, Speech Translation, Summarization, and Rationalization. The tasks are ordered in increasing level of complexity from left to right.

are designed based on the task-specific complexities. Each of these tasks is performed unimodally as well as multimodally to investigate the influence of multimodal data for each task. Despite the wide array of understanding tasks, the tasks in this thesis are language generation-based, exploring video understanding from a speech-vision-language based generation perspective.

We start with a monotonically constrained audio-visual task, Video Speech Recognition (Palaskar and Metze, 2018; Palaskar et al., 2018; Caglayan et al., 2019). Input speech and corresponding transcription which is the output of speech recognition follow a strict monotonic constraint where the temporal order of the speech is maintained in the temporal order of the transcription. We refer to this task as the *Monotonic Learning* task.

Beyond *Monotonic Learning*, we can extend to a Speech Translation task, that maintains similar inputs as the Speech Recognition task, but handles a non-monotonic constraint in the output. The translation outputs can be re-ordered (not following the same temporal constraint as the input speech), and are language dependent. We refer to this type of learning as *Non-Monotonic*. The translation task in this thesis is on English and Portuguese (Palaskar et al., 2019b; Holzenberger et al., 2019).

Abstract Learning tasks are those that require abstraction of the inputs to generate the corresponding outputs, for example, generating natural language summaries for videos, or video question answering. Often, these tasks involve compression, restructuring, and rephrasing of input information to perform the necessary *abstraction*. These are comparatively complex tasks than Recognition or Translation and focus on video-level non-trivial understanding. Video Summarization (Palaskar et al., 2019a) and Video Question Answering (Sanabria et al., 2019; Palaskar et al., 2020b) are the abstract learning tasks here.

Finally, to extend beyond these tasks, we address an *Explanatory* task that provides human interpretable rationales for human actions in videos beyond summarizing or answering questions about them. Visual Commonsense Reasoning (Zellers et al., 2019) and Video Question Answering with Explanation (Li et al., 2018) tasks have been proposed in recent years but are often

modeled as a classification problem of choosing a correct option from four options. This formulation of the task has heavy annotation requirement and cannot be extended to open-vocabulary free-form generation. To extend this task beyond these constraints, we use existing datasets collected for classification in a free-form natural language rationale generation setting (Rationalization) as the final learning task in this thesis.

The collection and release of the How2 dataset enabled the design and execution of many of these tasks. It also led to the collection of a much larger scale dataset containing similar types of videos (Miech et al., 2019). Using the How2 dataset , a huge effort was led by Specia et al. (2020) in the Summer of 2018 at Johns Hopkins University, Baltimore, MD, to explore a *one-model-rules-all* type of model for this multimodal understanding task. A lot of interesting results emerged from this effort for each of the tasks above, one of it being that is it more effective to optimize towards each task individually than in a single large model (Specia et al., 2020) with current technology. Very recently, researchers are exploring large-scale pre-training using Transformer models (Vaswani et al., 2017) that try to build many-in-one latent representations by pre-training on auxiliary tasks such as classification (Chen et al., 2019; Lu et al., 2020; Nguyen and Okatani, 2019; Pramanik et al., 2019). Such models have not yet shown good performance on natural language generation based tasks covered in this thesis. With further developments in this direction, the *one-model-rules-all* approach might have success in the future.

Overall, with this breakdown of Multimodal Video Understanding into various smaller tasks, we aim to establish a structured pathway towards the bigger goal of *"Can machines learn multimodally from the world as humans naturally do?"*

1.1 Thesis Overview

Thesis Statement

Multimodal Video Understanding is a complex task, and various disconnected tasks have been proposed within this domain. This thesis ranks four such tasks according to the complexity and shows how increasingly expressive models are needed to perform well on them. Our ordering is intuitive to humans, and corresponds to the difficulty of human learning tasks.

Chapters & Contributions

I. Multimodal Learning Tasks. Multimodal Video Understanding is a complex task spanning numerous sub-tasks across the fields of Computer Vision, Natural Language, and Speech & Audio. To structure this learning problem in the context of this thesis, we identify four learning tasks, with gradually increasing complexities, and build multimodal fusion models based on the nature of the tasks and modalities involved. In this chapter, we define the four tasks, the models used for each, and the modalities involved that guide the model developed.

II. Speech Recognition. Automatic speech recognition simulates the human process of listening with a neural network. Similarly, audio-visual speech recognition emulates watching and listening synchronously. This is a strictly monotonic task. We propose a multimodal fusion model, Monotonic Input Fusion, based on the monotonicity and the time-scales of each three modalities: speech, video, and text.

Contributions

1. Audio-Visual Speech Recognition
   We build a *Monotonic Input Fusion* model for end-to-end audio-visual speech recognition that learn to use relevant information from each modality to improve speech recognition performance. Using the multimodal fusion model, we demonstrate a relative improvement of 9% in the word error rate over unimodal models. The related publication is: Palaskar et al. 2018 which was later extended by Caglayan et al. 2019.

2. Acoustic-to-Word Speech Recognition
   To fuse information in the semantic space, there is a difference of time-scale alignment of the speech signal (speech frames), video signal (latent representations for word-level labels) and the corresponding text sequence (characters). Towards bridging this gap, we build speech recognition models that operate directly at the word-level labels to match them with the visual representations. We build direct Acoustic-to-Word models that align speech frames with corresponding word labels and evaluate their performance against standard phoneme-based or character-based speech recognizers. The related publication is: Palaskar and Metze 2018.

III. Speech Translation. Speech Translation is a non-monotonic task that converts an ordered set of speech signals to a re-ordered set of Portuguese translations in words. The Acoustic-to-Word model from previous chapter is useful to bring the time-scales of speech and text to common word-level units here as well. Further, we also explore a semi-supervised learning model for this task called the *Latent Representation Fusion* model to utilize the inherent supervision provided by training across modalities. For translation, the Monotonic Input Fusion model can also be used if a supervised translation model is required.

Contributions

1. Contextual Acoustic Word Embeddings
   We begin by building appropriate word-level representations from speech inputs. We propose a Contextual Acoustic Word Embeddings (CAWE) model that uses the location-aware attention (Chan et al., 2016) mechanism to localize and contextualize across all speech frames of a word to a single representation. the corresponding acoustic word embedding. Upon evaluation of these embeddings with their textual counterparts on 13 standard semantic similarity and classification tasks, we find the acoustic embeddings perform equally or better than the textual word embeddings, showing the semantic strength of the learned embeddings. The corresponding publication for this is Palaskar et al. 2019b.

2. Multiview Learning for Multimodal Embeddings
   These acoustic word embeddings are used in a multi-view representation learning setup trained via Deep Canonical Correlation Analysis (Hotelling, 1992; Andrew et al., 2013) to perform semi-supervised speech recognition and speech translation. We evaluate these embeddings using a retrieval-based metric. Using the Latent Representation Fusion model, the semi-supervised model achieves within 3% WER of the fully supervised model for speech recognition, and within 7 BLEU points for speech translation. The corresponding publication for this is Holzenberger et al. 2019.

IV. Summarization & QA. Video Summarization is the task of generating a short informative textual summary highlighting the important contents of the video. For instructional videos, the video by itself is very detailed. A textual summary that attracts viewers based on its focus on the most differentiating factor is more relevant than summarizing the different instructions of the video – here the summary acting like a textual teaser of the video itself. In this chapter, we address this task of abstraction first. In the Video Question Answering task, we evaluate transfer learning capabilities of models trained on the How2 dataset (all tasks so far are on How2 dataset), on other open-domain datasets and tasks. One such dataset is the Audio-Visual Scene-aware Dialog dataset (Alamri et al., 2019) based on the Charades dataset (Sigurdsson et al., 2016) provides very similar types of modalities to the How2 dataset : speech, video, summary, and question answer pairs, enabling transfer learning.

Contributions

1. Video Summarization
   For the task of video summarization, our multimodal approach uses a *Hierarchical Latent Representation Fusion* model to fuse visual and textual data for summarization, leading to an absolute improvement 1.5 points in the content F1 score. We compare the proposed model and task with numerous strong multimodal and summarization models and find hierarchical model to perform best. Human evaluation on this novel task also measures the quality of generated summaries on coherency, fluency, informativeness, and relevance. Finally, we demonstrate the strong relevance of the visual signal for this abstractive generation task. The associated publication for this work is Palaskar et al. 2019a.

2. Video Question Answering
   We explore various unimodal and multimodal transfer learning approaches for cross-dataset learning between the `How2` dataset and the Audio-Visual Scene-aware Dialog dataset (Alamri et al., 2019) here. We cast the task as a multi-modal video summarization problem, in which the input is video features along with concatenated with the textual question, and the summary is the desired "answer". We observed significant consistent gains by transfer learning for all unimodal tasks (Sanabria et al., 2019; Palaskar et al., 2020b) through transfer learning but did not observe significant gain or drop in performance for the multimodal task. With our best multimodal transfer learning model for dialog question answering, we participated and ranked first in the 7^{th} Dialog State Tracking Challenge, Audio-Visual Scene-aware Dialog track (Yoshino et al., 2018) on both automatic and human evaluation metrics. The associated publications for this work are Sanabria et al. 2019 and Palaskar et al. 2020b.

V. Rationalization. Finally, we extend to a natural language rationale generation task, commonly known as commonsense reasoning. This is also a multimodal task with image or video for the visual modality. This is a relatively new area of work compared to other tasks covered in this thesis. The goal for this task is to extend question answering by providing supporting rationales for a given system-generated answer. This task differs from abstractive summarization as the information required for the rationale to be generated may not be present in the input at all. Rather, it is a commonsense deduction based on the provided context (for well-defined scope of the term "commonsense").

Contributions

1. Rationales through Semantic Concepts
   We present a method to rationalize for existing downstream tasks such as video summarization, captioning or question answering by generating interpretable semantic concepts as an auxiliary task. This approach does not require added annotation; the concepts can be curated through existing multiview annotations available for multimodal data. We present a two-phased training approach for a further adapted model architecture, *Hierarchical Interpretable Fusion* model, that is built to handle the increased complexity of this task. The associated publication for this work is Palaskar et al. 2020a.

2. Multimodal Self-Rationalization
   For the Visual Commonsense Reasoning dataset collected by Zellers et al. 2019, we design a generation-based task for rationalization. In this work, we study the efficacy of this generation task, and evaluate the dependency between the generated answer and generated rationale. Further, we specifically build joint models designed for computational control over the dependency between the generated answer and rationale for this task, called the *Hierarchical Interpretable Fusion* model.

Chapter 2

Learning Tasks

Video Understanding is a broad field in itself spanning multiple tasks. In addition to this, there is no standard theory to contain the term *understanding* across multiple research areas in Machine Learning. Computer Vision research has approached this problem from the vision-focused lens – action recognition, object detection, localization, etc. Language research has approached this problem from the language generation angle – textual video summarization, question answering, sparse and dense captioning, etc. Audio and Speech modalities are often used as supplementary information for cross-modal learning as they are often tightly coupled with the temporal visual stream in a video.

To contain this broad field into smaller components in this thesis, we provide a comprehensive study with 4 main tasks that handle each of these three main modalities – audio, video, and language. We pick these learning tasks based on the theory of multimodal learning in humans (Rentfrow et al., 2011; Hattie, 2012; Brame, 2016), map them to existing machine learning tasks, and order them in increasing order of complexity. This order spans surface-level tasks such as Speech Recognition or Translation and expands to interpretable and explanatory rationale-generation tasks.

We also propose relevant model architectures based on the nature of the task (Monotonic, Non-monotonic, Abstract, and Explanatory), complexity of the task (utterance-level, video-level), the modalities involved in each (audio, video, text), and the expected outputs (transcription, translation, summarization, rationalization). In this chapter, we describe a central dataset to this thesis, formally define the various terms used to construct this learning task structure, the four learning tasks, and the respective models and modalities for each.

2.1 Dataset

Grounding or fusion in Multimodal learning research refers to anchoring one modality into others for joint inference. It is the computational means towards the human quality of using

multiple senses at once, for example, watching, listening, and reading at once while watching a movie (Rentfrow et al., 2011).

Strongly coupled grounding exhibits in tasks where a question asked can only be answered through information contained in an image, e.g. Visual Question Answering (Antol et al., 2015). Various models have been proposed for such multimodal fusion and are often dataset and task based. Weakly coupled grounding refers to inherent inferences drawn via available data, for example, given an image of a person wearing a chef's hat and an apron, we can understand the potential genre of the video as cooking, baking, food, and scene as kitchen. Weak coupling is often achieved through semantic or representation learning while strong coupling is achieved through specifically designed modeling approaches such as bounding box grounding of an image with the corresponding referring expression.

Lack of One Dataset There has been considerable progress made across multimodal learning tasks, however, these tasks are often uncorrelated and modeled in isolation. Towards the human quality of using multiple senses at once, it might also help to model many of these tasks together, or in some form of order where the models build off of each other depending on the task at hand. There is a lack of a single dataset that has many of these modalities which could enable modeling various tasks together using a single dataset. The `How2` dataset was proposed by Sanabria et al. in 2018 which enabled, at the time, large-scale grounding for various language-oriented multimodal tasks with a 5-way parallel dataset. The following Section describes this dataset and contrasts it with some of the previously published datasets and multimodal tasks. More recently, Miech et al. collected a much larger version of a similar type of data that contain 100 Million videos.

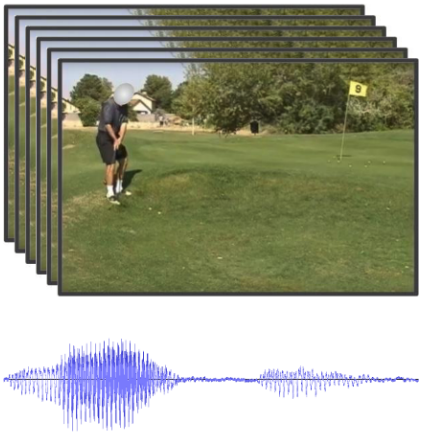


FIGURE 2.1: How2contains a large variety of instructional videos with English transcriptions, Portuguese translations, and English video summaries.

2.1.1 How2 Dataset

Multimodal sensory integration is an important aspect of human concept representation, language processing and reasoning (Barsalou et al., 2003). From a computational perspective, major breakthroughs in natural language processing (NLP), computer vision (CV), and automatic speech recognition (ASR) have resulted in improvements in a wide range of multimodal tasks, including visual question-answering (Antol et al., 2015), multimodal machine translation (Specia et al., 2016), visual dialogue (Das et al., 2017), and grounded ASR (Palaskar et al., 2018).

Despite these advances, state-of-the-art computational models are nowhere near integrating multiple modalities as effectively as humans. This can be partially attributed to a lack of resources that are *pervasively* multimodal: existing datasets are typically focused on a single task, *e.g.* images and text for image captioning (Chen et al., 2015), images and text for visual-question answering (Antol et al., 2015), or speech and text for ASR (Godfrey et al., 1992). These datasets play a crucial role in the development of their fields, but their single-task nature limits the collective ability to develop general purpose artificial intelligence.

Sanabria et al. introduce How2, a dataset of instructional videos paired with spoken utterances, English subtitles and their crowdsourced Portuguese translations, as well as English video summaries. The pervasive multimodality of How2 makes it an ideal resource for developing new

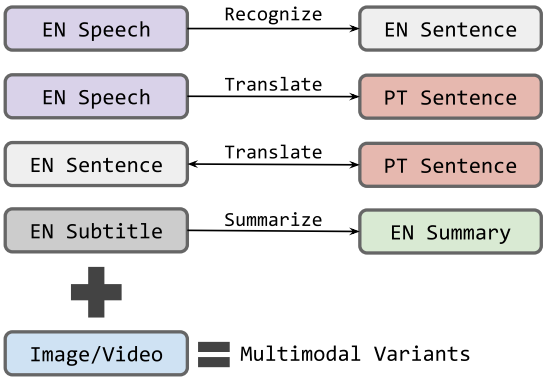


FIGURE 2.2: Modalities and possible tasks around How2: EN and PT respectively stands for English and Portuguese.

models for multimodal understanding (see Figure 2.2). In comparison to other multimodal resources, How2 is a naturally occurring dataset: neither the subtitles, nor the summaries have been crowdsourced. Furthermore, the visual content is inherently related to the spoken utterances – How2 is a dataset of people showing other people how to accomplish tasks.

Figure 2.1 shows an example from How2 in which the presenter is explaining how to play a golf shot. The English speech and subtitles are aligned with a Portuguese translation. If one only considers the text for this instance, it is unclear whether the "*green*" in the subtitles refers to the color green ("*verde*") or the golf playing surface ("*green*")[1], thus the textual context alone is not enough to disambiguate the meaning of the subtitles. However, given some additional visual context (green grass with a flag pole), or the audio context (outside with the sound of chipping a golf ball), or the sequential context of the video, multimodal models can integrate multiple inputs to understand this utterance.

The value of additional modalities can also be demonstrated in the context of ASR. Object and motion level visual cues can filter out systematic noise that co-occurs with activities. Scene information from an image can be used to learn a common auditory representational space through recordings with different environmental characteristics such as indoor vs outdoor settings (Miao and Metze, 2016a). It has also been shown that entities in an image can dynamically guide a speech recognition language model towards a more specific and relevant domain (Gupta et al., 2017a).

The How2 dataset consists of 79,114 English instructional videos from YouTube with English subtitles. The dataset consists of a total of 2,000 hours of video. Videos have an average length of 90 seconds (how, 2018) and manual Portuguese translations. This collection of videos and translations constitutes a large-scale resource for testing a substantial part of multimodal language processing methods in a real-world scenario.[2]

[1] At the time of writing, both Google Translate and Microsoft Translator incorrectly translate this sense of **green** as *verde*.

[2] The tools to download and construct the corpus are freely available at https://github.com/srvk/how2-dataset.

		Videos	Hours	Clips/Sentences
300h	train	13,168	298.2	184,949
	val	150	3.2	2,022
	test	175	3.7	2,305
	held-out	169	3.0	2,021
2000h	train	73,993	1,766.6	-
	val	2,965	71.3	-
	test	2,156	51.7	-

TABLE 2.1: Statistics of How2 dataset.

Statistic	**English**	**Portuguese**
Sentences	185K	
Words	3.50M	3.30M
Words per sentence	18.9	17.9
Unique words	57.5K	74.9K

TABLE 2.2: Training set statistics for English and Portuguese: the number of unique words is computed after tokenization.

An alignment process is needed to use the audio, the English subtitles, the Portuguese translations, and the video modality together. To this end, we first re-segment the English subtitles into sentences using NLTK (Loper and Bird, 2002). Then, we force-align the speech signal at the word level with an HMM-GMM pre-trained on the Wall Street Journal dataset. Finally, using the timings provided by the word alignment, we create video *clips* aligned to the initial segmented sentences. This process splits a video into a sequence of clips, aligned with the speech signal and the segmented sentences. Tables 2.1, 2.2 presents summary statistics of the *2000h* set and *300h* subset: the *val* and *test* sets can be used for early-stopping, model selection and evaluation; the *held* set is reserved for future evaluations or challenges. The total set (*i.e.* 2000h) contains around 22.5M words. The tokenized training set of *300h* subset contains around 3.8M (43K unique) and 3.6M (60K unique) words for English and Portuguese respectively. Videos are broken down into clips, as described above, with an average length of 5.8 seconds, or 20 words of spoken language.

Figures 2.3 show the LDA topic distribution and segment length analysis of the *300h* subset of the How2 dataset .

To estimate the topic diversity in How2 dataset, we ran a Latent Dirichlet Allocation (LDA) (Blei et al., 2003a) over the English subtitles. Then, we defined 22 clusters by analyzing empirical distances between videos and centroids. Finally, we applied a topic label to each cluster by analyzing the top words. Figure 2.3 shows the distribution of all videos according to each topic.

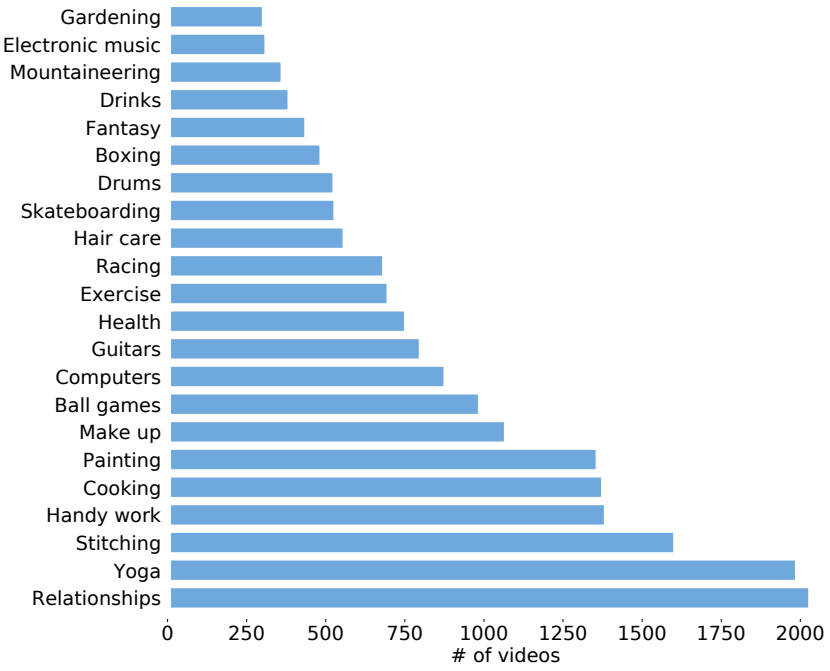


FIGURE 2.3: LDA topic distributions for the *300h* subset of the How2 data. The labels are manually annotated based on frequency of topic words. The overall *2000h* corpus exhibits very similar characteristics.

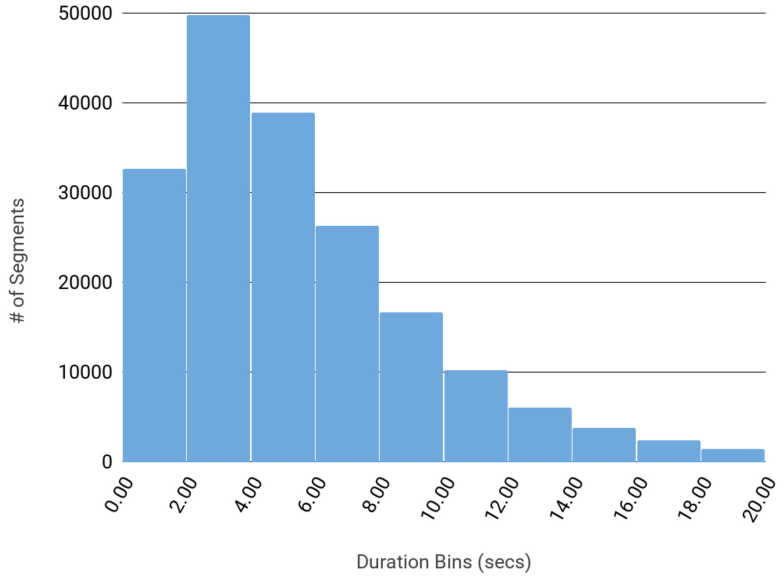


FIGURE 2.4: Segment durations for the *300h* subset. The overall *2000h* corpus exhibits very similar characteristics.

Features

The following features are extracted and used as representations of the various modalities of the `How2` dataset .

Speech Features For speech, we extract 40-dimensional filter bank features from *16kHz* raw speech signal using a time window of *25ms* and an overlap of *10ms*. 3-dimensional pitch features are then concatenated to form the final 43-dimensional feature vectors. The speech features of a given video are further normalized using the mean and variance statistics from that specific video.

Action Features (video-level) We extract action-level video features from a 3D ResNeXt-101 (Hara et al., 2018) pre-trained on the Kinetics action recognition dataset (Kay et al., 2017) which comprises 400 different actions.

Object Features (frame-level) A ResNet-152 (He et al., 2016a) trained on ImageNet (Deng et al., 2009b) which consists of 1000 categories ranging from animals, flowers to devices and foods and so on.

Scene Features (frame-level) A ResNet-50 trained on Places365 (Zhou et al., 2017) for scene recognition with 365 categories including, but not limited to: garden, valley, studio, theater and office.

Topic distribution There are gold-labels for category of each video in the content-provider metadata that narrowly categorizes each video into 8 different topics. The most frequently occurring category according to the metadata is *Howto & Style* (39.5%) but as we are already dealing with instructional How-To videos, we wanted to look for more insight by obtaining a finer grained topic distribution. For this purpose, we clustered the entire English subtitles of a video using Latent Dirichlet Allocation (LDA) (Blei et al., 2003b). Upon analyzing the clusters with top words in each topic, inter-topic and intra-topic distances, we found that a good representation for the *300h* subset consists of 22 different topics. We hand-labeled these topics based on top words in each cluster. The relative frequency of each topic is shown in Figure 2.3.

2.1.2 Direction of Research

Video understanding has been approached via various tasks, either unimodal or multimodal. Most often, these tasks are uncorrelated and modeled in isolation. We propose to bring some order to this task by exploring four tasks chosen based on the complexity. Across these tasks, we demonstrate how increasingly expressive models are required to address the increase in complexity and multimodal views depending on the task. Additionally, we focus on open-vocabulary language generation tasks for possible extensions to domain-agnostic and large-scale modeling.

Free-form language generation, especially for multimodal data, is a sequential generation task conditioned on the various inputs as well as the text generated so far. Often, the vocabulary of these tasks are sub-words or word units that have an unrestricted vocabulary or a large word vocabulary, facilitating open-ended generation. For language-oriented multimodal video understanding tasks, free-form generation tasks model open-vocabulary generation beyond a closed-set classification tasks.

Instead of approaching video understanding as a set of various uncorrelated tasks, we order the tasks in increasing order of complexity and develop model architectures accordingly. Based on the task, the modality views get progressively complex. With the ordering presented in this thesis, other video understanding tasks can be arranged based on the input modalities, or model specifications, or task complexities[3].

This thesis explores grounding and multimodal learning with an emphasis on speech, audio, language, and vision inputs, for downstream tasks ranging from simple monotonic speech recognition to commonsense rationalization. Below, we first define the four tasks with the terminology, the models used, and the modality views, followed by a chapter on each of the main tasks.

[3]Tasks presented here are not comprehensive but cover a broad range of generation-based problems.

2.2 Terminology

Monotonic Tasks A functional constraint where the input time-series sequence and output time-series sequence are dependent on each other. Between two ordered sets, a monotonic function preserves or reverses the order. For a given function, f such that $f : X \rightarrow Y$ is a set function from a collection of sets X to an ordered set Y, then f is said to be monotonic if whenever $A \subseteq B$ as elements of X, $f(A) \leqslant f(B)$.

Speech recognition is a speech-to-text task; given a window of speech frames (commonly used smallest divisible feature of speech representation) it is converted to its corresponding phonemes, characters, sub-words, words or word-pieces. These input speech frames are mapped to the corresponding textual units following a strictly monotonic constraint.

Non-monotonic Tasks For Translation tasks where the output sequence may not follow a strictly monotonic constraint. The output text can be ordered depending on the language being translated to. For speech recognition this is a strict condition across all languages, i.e. whatever is spoken is transcribed with preserved temporal order from left-to-right. For speech translation, this constraint is language-dependent. Many languages exhibit re-ordering in the translated text and the left-to-right order is not preserved.

Abstract Tasks To contrast with *Surface* tasks, we define *Abstract* tasks as those that operate at video-level time-scales rather than utterance-level. To perform *Abstract* tasks, access to video-level information across all modalities is necessary. This information is compressed, aggregated, restructured and rephrased as outputs in these tasks. Video summarization and question answering are the two *Abstract* tasks covered in this thesis.

Explanatory Tasks *Explanations or Rationales* can be useful method of evaluating *understanding* beyond abstraction tasks. They also provide further support for system-generated responses in video understanding tasks. *Explanatory* tasks refer to generation of interpretable rationales for *Abstract* tasks. An example of such tasks is the Visual Commonsense Reasoning (Zellers et al., 2019) or the Visual Question Answering with Explanations (Li et al., 2018). For *Abstract* and *Explanatory* tasks monotonicity is inherently not a constraint.

2.3 Learning Tasks

The four multimodal video understanding tasks covered in this thesis are:

I. **Speech Recognition**
Can we recognize what is being spoken? Does watching the video while listening help?

II. **Speech Translation**
Can we recognize and translate what is being spoken? Can we do it with lesser supervision?

III. **Summarization & QA**
If we have understood a video, can we summarize it? Can we answer questions?

IV. **Rationalization**
Can we provide reasoning for our answers?

These tasks are arranged in an increasing order of complexity. Speech Recognition is a monotonic task i.e. the input speech sequence and the output text sequence are bounded by a time-series monotonic constraint (left-to-right). Video speech recognition is a multimodal equivalent of this task where there is an added time-series video signal in the input. For Speech Translation, there is a monotonic constraint to some extent, but the outputs are re-ordered sequences of input speech where the extent of re-ordering depends on the output language being translated to. Speech Recognition and Translation can be thought of as *surface* tasks because of this monotonic constraint.

In contrast with Recognition and Translation, the next learning tasks covered are Summarization and Question Answering. In these tasks, video-level information needs to be compressed, aggregated, rephrased, and restructured to generate natural language summaries or answer questions based on the video. These tasks represent higher-level video understanding that abstracts information and outputs it in the form required without any monotonic constraint as in speech recognition or translation. Finally, we propose to cover the learning task of Rationalization that extends question answering to providing natural language reasoning for the generated answers. Rationalization can be considered an explanatory task that provides interpretable and observable rationales for a question answering task.

We design models for each of these tasks to satisfy these constraints and evolve the model as necessary based on the task complexities and modalities involved. These are discussed in the subsection below.

Task	Inputs	Outputs
Speech Recognition	Speech, Video	Transcripts
Speech Translation	Speech, Video, Transcripts	Portuguese Transcripts
Summarization & QA	Speech, Video, Transcripts, Questions	Summary, Answers
Rationalization	Video, Questions	Answers, Rationales

TABLE 2.3: Task-specific multimodal views available for each task.

2.4 Models and Modalities

Across the tasks, there are multiple views of the multimodal data available. In Table 2.3, we list the task-specific modalities (or views of a modality) available and note the ones used in the input vs. output in this work.

Based on the complexities of the four tasks and the modalities involved in each, we design specific multimodal fusion models. Across tasks, these models progressively get more complex to handle the idiosyncrasies of each. Figure 2.5 shows an overview of all four models. These models are explained in more detail in the respective Chapters.

I. **Input Fusion**
For the monotonic correlations between Speech and Text.

II. **Latent Representational Fusion**
For the non-monotonic, re-ordered sequences between Speech and Translations.

III. **Hierarchical Latent Representational Fusion**
For the video-level abstraction, compression, and re-phrasing of information as a Summary.

IV. **Hierarchical Interpretable Fusion**
For interpretable and explanatory Rationalization.

The Input Fusion model is used for video speech recognition type tasks that have a monotonic constraint. We fuse the modalities in the input (early fusion) to align video, speech, and text time-scales. But this is a restrictive model with limited modeling capacity for more complex tasks like translation where output is not strictly monotonic. For this reason, we extend the model to a Latent Representational Fusion model where the two input modalities are fused in the latent space instead of in the input. These fused multimodal representations are then used for translation.

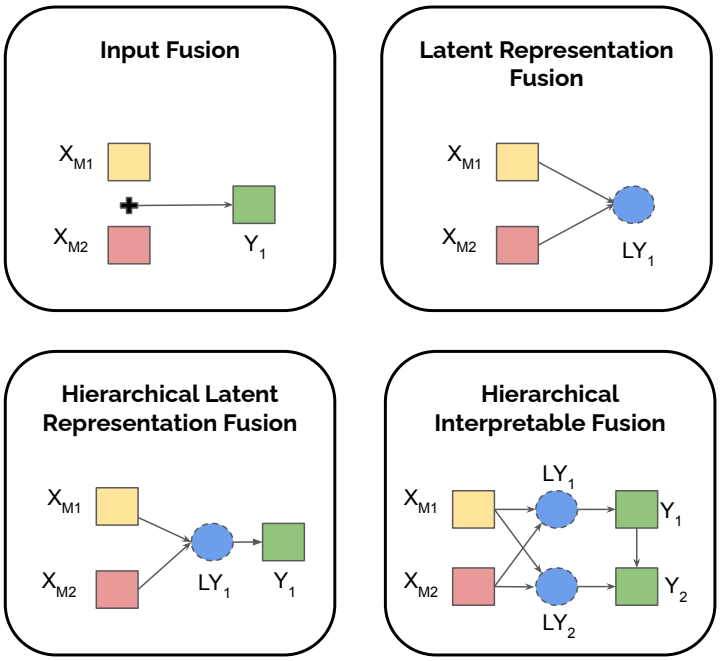


FIGURE 2.5: Overview of the model complexities across four learning tasks: Input Fusion, Latent Representation Fusion, Hierarchical Latent Representation Fusion, and Hierarchical Interpretable Fusion.

Both speech recognition and translation operate at a finer time-scale than summarization, question answering or rationalization which are the *abstract* learning tasks. These tasks need access to video-level information rather than utterance-level like *surface* tasks. We design a Hierarchical Latent Representation Fusion model for summarization and question answering that provides this video-level control for abstractive tasks. Finally, we propose a Hierarchical Interpretable Fusion model that extends the models so far to interpretable intermediate outputs for explanatory tasks. An example of utility of this model is for visual commonsense reasoning where for a given video and question, the model generates an answer as well as a rationale for why that answer is the correct answer.

Chapter 3

Speech Recognition

3.1 Introduction

Humans are capable of processing speech by making use of multiple sensory modalities. Lip reading is a common example of audio-visual speech recognition by humans in noisy or distant scenarios, with seamless adaptation and balance between lip-reading and hearing. Although, beyond lip reading, the environment of source speech is often rich with semantic and/or acoustic context that helps us resolve ambiguities or to recall relevant words. In this Chapter, we present a novel task of end-to-end audio-visual speech recognition, and follow it with large-vocabular Acoustic2Word models that can directly map input speech features to word-units.

For audio-visual speech recognition, we propose to use multi-modal video information slightly differently than to replicate lip-reading (Chung et al., 2017) within a neural network. We propose a multimodally adapted end-to-end speech recognizer to the visual semantic concepts extracted from a *correlated visual scene* that accompanies some speech, for example in a "How-To" instructional video. If we see a person standing in a kitchen, holding sliced bread, it is likely that the person is explaining how to make a sandwich, and the acoustic conditions will be comparably clean. If a person is standing in front of an airplane, it is likely an informative video of that plane, and happening outdoors, and hence with noisier acoustics. With such semantic adaptation, we do not need constant access to the visual stream as is the case for lip-reading, and visual cues from the recording environment (indoor vs. outdoor) or the interaction between salient objects (people, instruments, vehicles, tools and equipment) can be exploited by the recognizer in various ways. We use the `How2` dataset of open-domain instructional videos for this task that are recorded in a varied acoustic environments, both indoors and outdoors (Sanabria et al., 2018).

Transcription or sub-titling of open-domain videos is a challenging domain for Automatic Speech Recognition (ASR) due to the data's challenging acoustics, variable signal processing and the essentially unrestricted domain of the data. Previous work has shown the visual channel – specifically object and scene features – can help to adapt the acoustic model (AM) and language

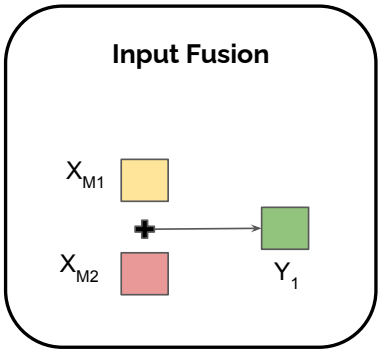


FIGURE 3.1: Illustration of the Monotonic Input Fusion technique for multimodal adaptation.

model (LM) of a speech recognizer (Miao and Metze, 2016b; Gupta et al., 2017b). Basing off of the same hypothesis, we expanding this work to an end-to-end model that no longer requires separate AM and LM adaptation, but can jointly adapt both within a single model.

Aligning speech to word-like units is a challenge (Kamper et al., 2016; Bengio and Heigold, 2014). As a first step towards this problem, we begin by training direct acoustic-to-word speech recognition models with the aim to achieve useful speech embeddings from these trained encoders. In addition to providing a means to learn speech embeddings, Acoustic-to-Word recognition provides a straightforward solution to end-to-end speech recognition without needing external decoding, language model re-scoring or a lexicon. While character-based models offer a natural solution to the out-of-vocabulary problem, word models can be simpler to decode and may also be able to directly recognize semantically meaningful units. We analyze the encoder hidden states and the attention behavior, and show that the monotonically constrained location-aware attention naturally represents words as a single speech-word-vector, despite spanning multiple frames in the input. We finally show that the Acoustic-to-Word model also learns to automatically segment speech into words, a task that previously required careful human annotation. This property of Acoustic2Word speech recognizers was necessary for our work on semi-supervised Speech Translation in the following Chapter 4.

Monotonic Input Fusion Model

For given input modalities X_{M1} and X_{M2}, under the assumption of monotonicity, we propose an Input Fusion model that maintains input time-scale alignment between the modalities. In the case of speech and vision as the input modalities, we condition every speech frame on the corresponding visual representation to maintain monotonicity. Input Fusion is similar to standard Early Fusion in multimodal research with the main difference of fusion happening within the model, hence model-dependent, instead of model agnostic as traditional Early Fusion. Following Input Fusion, any end-to-end model can be applied to convert given inputs to output Y_1. This model is output-unit independent and can be applied to character-level or word-level outputs.

Chapter Structure

We begin this chapter by describing an end-to-end audio-visual speech recognition model applied to the How2 dataset. At the time (2017), end-to-end approaches for speech recognition were fairly new. To demonstrate the quality of the trained models, we also evaluate them on standard speech corpora and compare against prior work. We analyze the model success and failure cases and highlight the differences in standard speech recognition corpora used to train unimodal speech recognizers with multimodal speech corpora, and its corresponding effects on recognition performance. In the following Section, we focus on building direct Acoustic-to-Word Speech Recognizers that map acoustic features directly to semantically meaningful output units. Word-level output units are a common target for text-based and vision-and-language based downstream tasks. As the tasks described in this thesis often use all video modalities at once, having a common target unit space is useful. Specifically, Acoustic2Word modeling provides the necessary groundwork to perform Audio-to-Semantic Learning and Multiview Learning used for Speech Translation in the following Chapter. In this Chapter, we describe the methods necessary for Acoustic2Word modeling, and evaluate the models utility towards learning speech embeddings. The work presented in this chapter has been published previously as conference papers in Palaskar et al. 2018 and Palaskar and Metze 2018.

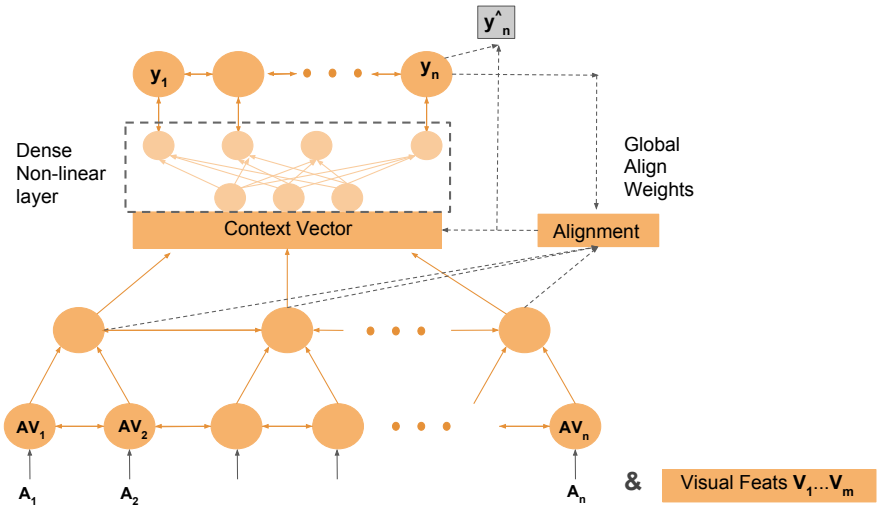


FIGURE 3.2: Audio-Visual Sequence-to-Sequence ASR.

3.2 Audio-Visual Speech Recognition

Following work builds on prior work on traditional models for audio-visual speech recognition (Miao and Metze, 2016b; Gupta et al., 2017b) and presents first results on multi-modal adaptation Sequence-to-Sequence models (Cho et al., 2014; Bahdanau et al., 2014a). We present a monotonic input fusion adaptation strategy first results with S2S model adaptation on audio-visual data. The ultimate goal of this work will be to view automatic speech recognition not primarily as the speech-to-text task, but as a process which sub-titles multi-media material removing repetitions, hesitations or corrections from spontaneous speech as required, much like "video captioning" (Vinyals et al., 2015b). We show that multi-modal adaptation helps by 2% absolute improvement in the token error rate.

While multi-modal adaptation improves recognition in such noisy datasets, we see that there is need for deeper insight into the S2S models for audio-visual speech recognition. These models behave very differently with clean, prepared datasets like WSJ than with spontaneous, noisy speech, How2. Ground truth references for the How2 data are less accurate than for WSJ; we see that this influences model training. We present insights into the differences in the output of these two approaches as these issues have not been addressed in prior work yet.

3.2.1 Model

We use the standard setup of an attention-based sequence-to-sequence (S2S) model (Chorowski et al., 2014; Bahdanau et al., 2014b) applied to audio-visual inputs. The encoder maps the input acoustic features vectors $\mathbf{x} = (\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_T)$ where $\mathbf{x}_i \in \mathcal{R}^d$ into a sequence of higher-level features $\mathbf{h} = (\mathbf{h}_1, \mathbf{h}_2, ..., \mathbf{h}_{T'})$. The encoder is a multi-layer bi-directional Long Short Term Memory (BLSTM) RNN that is structured as a pyramid by skipping every other frame between

certain encoder layers for efficient training. This reduces the length of the input from T to T'. This encoder network is analogous to the traditional acoustic model of an ASR. The decoder network is also an LSTM network that learns to model the output distribution over the next target conditioned on sequence of previous predictions i.e. $P(\mathbf{y}_l|y^*_{l-1}, y^*_{l-2}, ..., y^*_0, \mathbf{x})$ where $\mathbf{y}* = (y^*_0, y^*_1, ..., y^*_{L+1})$ is the ground-truth label sequence. This decoder network is similar to the language model in traditional ASR as it generates targets $\mathbf{y}$ from $\mathbf{h}$ using an attention mechanism. The attention model learns an alignment weight vector between the encoding $\mathbf{h}$ and the current output of decoder $\mathbf{y}_l$. At each time step, the attention module computes a context vector that is fed into the decoder together with the previous ground-truth label y^*_{l-1}.

We implement the Global Attention that learns a weighted context vector W_α calculated using the source hidden state h_s and the *current* target y_t (Luong et al., 2015). This context vector is global as it always attends to all source states s'. We compute a variable-length alignment vector α_t using: $exp(h^T_t.W_\alpha.h_s)$ and this is normalized over all input s' as $\sum_{s'} exp(h^T_t.W_\alpha.h_{s'})$. The model architecture with attention is shown in the Figure 3.2.

We use 3 layers of 512 bidirectional LSTM cells in the encoder. We use SGD with learning rate of 0.2 and decay of 0.9. We use curriculum learning (Bengio et al., 2009) for the first epoch to speed up convergence. We note that our training process is much simpler than (Chan et al., 2016; Chorowski and Jaitly, 2016; Bahdanau et al., 2016). The decoder is made of 2 layers of 512 bidirectional LSTM cells each. For decoding, we use a beam size of 5. We do not use any techniques for better decoding with WSJ as given in (Chorowski and Jaitly, 2016) but use a length normalization with How2 data (Sanabria et al., 2018), to address the length distributions variance shown in Figure 3.3. Training took 4 days with a TitanX GPU on the 90 h subset. Experiments were performed using the OpenNMT toolkit (Klein et al.).

Input Fusion The video adaptation technique we use with S2S is early fusion where 100 d visual features are concatenated with 120 d audio features giving 220 d vector for each frame. Our experiments with early fusion show that S2S benefits with this technique while CTC or DNN (Miao and Metze, 2015; Palaskar et al., 2018) does not. Caglayan et al. 2019 extend the experimentation of S2S adaptation to other fusion strategies and find that ensemble of various ASR models performs best.

3.2.2 Experimental Setup

We conduct our experiments on two data-sets, the Wall Street Journal (WSJ, SI-284, LDC93S6B and LDC94S13B), and the How2 audio-visual dataset (Sanabria et al., 2018). The How2 corpus consists of English language open-domain instructional videos that explain specific tasks like baking a cake, or nutrition habits, and have been recorded in various environments indoors and outdoors (like kitchen, or garden), usually with a portable video recorder. Ground truth

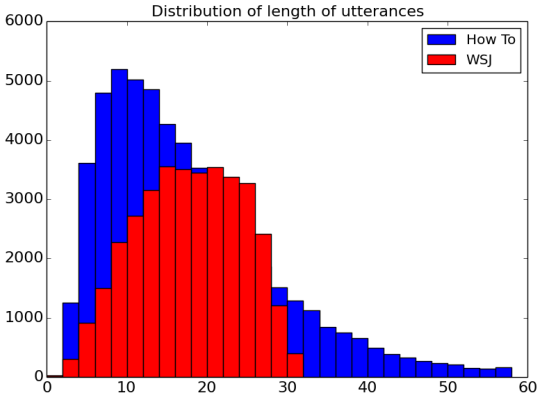


FIGURE 3.3: Length Distribution for the How2 and WSJ Train sets.

transcriptions of these videos have been created by re-aligning provided sub-titles, which sometimes are mis-matched because of missed phrases, word repetitions, hesitations, and other noise and punctuation that hasn't been transcribed.

We use the 90 and 480 hour subsets of the How2 data and 87 hours of WSJ, and extract 40-dimensional MEL filter banks, with a step size of 30 ms, 3-fold oversampling of the data at 0, 10, and 20 ms offsets, and stacking 3 neighboring frames together, resulting in a 120-dimensional input vector. The 90 h subset of How2 has been selected randomly. We have a separate 4 h test set. 5% of the training data is used as dev set [1]. For WSJ, we use the eval92 test set. Both models are character-based with 43 labels/tokens: 26 alphabets, 10 digits, and special symbols for {'.', '"', '-', '/'}, space, start and end of sentence.

Figure 3.3 shows the length distributions for the How2 and WSJ train sets. This shows that for "open-domain" speech data, the distribution is less normalized when compared with prepared datasets.

Visual Features The visual features used here are the same as those in prior work with this dataset (Gupta et al., 2017b). We extract object and place/scene features from pre-trained CNNs and perform dimensionality reduction to obtain 100 dimension features. As described above, the data contain indoor and outdoor recordings of instructional videos where object and place features are most relevant. We use these features to infer acoustic and language information from the scene where the utterance has been recorded.

3.2.3 Results

In Table 3.1, we present the effect of visual adaptation on the Token Error Rate (TER) for speech models. Adaptation with visual features helps improve the absolute TERs by 1.6% using the S2S model. Using length norm described below, TER further improves to 2%. This is a

[1] These are early subsets of the How2 datasets created and used in prior work (Miao and Metze, 2016b; Miao et al., 2014). The official release of the How2 dataset (how, 2018) processed these initial splits before release.

significant improvement for speech recognition with S2S models. The test set named 'dev' is a tougher set than the 'test' set in the How2 dataset. This work was extended by Caglayan et al. to other monotonic fusion approaches for S2S models, namely the Visual Adaptive Fusion method leading to an absolute improvement of 1.4% word error rate, which is a similar degree of improvement as with the Input Fusion model.

	TER dev	**TER test**
Audio-only	18.4	16.3
Audio-Visual	**16.8**	**15.7**

TABLE 3.1: Results for Audio-only and Audio-Visual adaptation with the How2 data.

	S2S Model
WSJ	7.9
How2	15.3

TABLE 3.2: TER of the S2S model on WSJ (eval92) and How2 (test set).

In Table 3.2, TER with S2S on WSJ is a strong baseline compared to prior work (Bahdanau et al., 2016; Kim et al., 2017). We see a huge disparity in ASR for clean prepared data (WSJ) and real application data (How2) as discussed with Figure 3.4.

Spoken	now it does only say for do- or doesn't even say for dogs or cats it's neither
Reference	now **doesn't even** say dogs or cats **it says** neither
Audio-only S2S	now it does**n't we** say for **a** do**g or that use a** dogs or cats **so is night or**
Audio-Visual S2S	now it does**n't leave safer** do**g or it does use a** dogs or cat **so in night or**

TABLE 3.3: Typical transcription on How2 test set: S2S model keeps to the style of the reference which is an abstraction of the spoken content. Currently, there is little semantic difference between regular and adapted (AV) S2S output.

Figure 3.4 compares reference length to hypothesis length for 40 short and long WSJ and How2 dataset test utterances. On WSJ, the range of lengths of short and long utterances are similar, and reference and hypothesis follow each other closely. On How2, hypothesis prediction is very unstable and the model makes a lot of mistakes, even breaks completely at times. Length of the hypothesis is greater than the length of reference for short utterances, while it is lesser for longer utterances. As seen from the example in Table 3.3, the output of the S2S model is much closer to the reference transcript. The model learns a form of length normalization over the entire dataset hence performs badly on short and long utterances. We use the length normalization factor during decoding to stabilize the output of the S2S model and get absolute improvements of 2% (dev) and 1% (test) for the non-adapted case, which is slightly better than the adapted case and shows that adaptation stabilizes model performance.

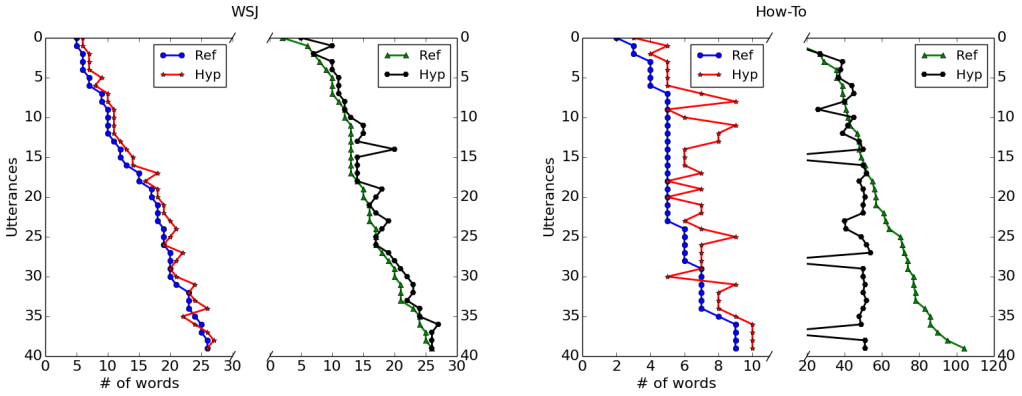


FIGURE 3.4: Length normalization by S2S for WSJ and How2

3.3 Acoustic-to-Word Speech Recognition

3.3.1 Model

Our S2S model is similar in structure to the Listen, Attend and Spell model (Chan et al., 2016) which consists of 3 components: the encoder network, a decoder network and an attention model. The difference between the S2S model used for audio-visual speech recognition described earlier is the type of attention mechanism used: location-aware attention. In this work, $y_i^* \in \mathcal{U}$ can be a token from a character, sub-word or word vocabulary.

Location-aware Attention We use a location-aware attention mechanism (Chorowski et al., 2015) that enforces monotonicity in the alignments, which may be beneficial for speech recognition. To do so, the location-aware attention applies a convolution across time to the attention of previous time step using trainable filters. This convolved attention feature is used for calculating the attention for the current time step. We apply a one-dimensional convolution $\mathcal{K}$ along the input feature axis t to get a set of T features $\{\mathbf{f}\}_{t=1}^{T}$ described as follows:

$$
\begin{aligned}
\{\mathbf{f}\}_{t=1}^{T} &= \mathcal{K} * \mathbf{a}_{l-1} \\
e_{lt} &= \mathbf{g}^{\mathrm{T}} \tanh\left(\mathrm{Lin}(\mathbf{y}_{l-1}) + \mathrm{Lin}(\mathbf{h}) + \mathrm{LinB}(\mathbf{f}_t)\right) \\
a_{lt} &= \mathrm{Softmax}(\{e_{lt}\}_{t=1}^{T})
\end{aligned}
$$

where $\mathbf{a}_{l-1} = [a_{l-1,1}, ..., a_{l-1,T}]^{\mathrm{T}}$, $\mathbf{g}$ is a learnable vector parameter, $\{e_{lt}\}_{t=1}^{T}$ is a T-dimensional vector, Lin() is a linear layer with learnable matrix parameters without bias vectors, LinB() is a linear layer with learnable matrix and bias parameters.

The S2S model is trained by optimizing the cross entropy loss function which maximizes the log-likelihood of the training data. We use beam search to perform inference. We also apply

unigram label smoothing that distributes the probability of most-probable token to prevent the over-confidence of the model (Pereyra et al., 2017; Chorowski and Jaitly, 2016).

3.3.2 Experimental Setup

We use the standard 300-hour Switchboard corpus (SW, LDC97S62) (Godfrey et al., 1992) which consists of 2,430 two-sided telephonic conversations between 500 different speakers and contains 3 million words of text. We evaluate on the HUB5 eval2000 (LDC2002S09, LDC2002T43) containing Switchboard subset similar to training data and CallHome (CH) subset that is a tougher set. There are 196,656 total utterances out of which we use the first 4,000 utterances as a validation set. Our input features are 80-dimensional log-mel filter banks normalized with per-speaker mean and variance. We also use 3-dimensional pitch features.

We present three different types of target units for speech recognition: characters, Byte-Pair Encoding units (BPE) (Gage, 1994; Sennrich et al., 2016) and words. BPE units are generally longer than characters and shorter than words. The character vocabulary is made of 46 units containing 26 letters, 10 digits, and other frequently occurring special symbols. We use 12k BPE operations to get comparable vocabulary with word level models. We finally present a large-vocabulary model made of all 29,874 unique words in the Switchboard set. The vocabularies also contain non-language special symbols that denote noise, vocalized-noise and laughter. We train character and word level RNN language models on the Switchboard + Fisher (LDC2004T19) (Cieri et al., 2004) transcripts as is the common practice for this data.

Our encoder consists of 6 layers each with 320 bi-directional LSTM cells (Hochreiter and Schmidhuber, 1997). The second and third layer skip every other frame to get a reduction of $T/4$ in input frames. We use the AdaDelta (Zeiler, 2012) optimizer. The location-aware attention convolution uses 10 filters with width 100. We use a projection layer of 320 dimensions after each layer of the encoder. Our decoder is a single layer LSTM containing 300 cells. We initialize all parameters uniformly within $[-0.1, 0.1]$ unless otherwise specified. We use unigram label smoothing with weight 0.05. The beam size used for all experiments is 10. We use the ESPnet toolkit (Kim et al., 2017; Watanabe et al., 2017) for our experiments.

3.3.3 Results

We first compare a character-level S2S model with previously published Connectionist Temporal Classification (CTC) (Graves et al., 2006) model, both of which were considered the state-of-the-art model approaches at that time. Character-level evaluation and comparison will provide a better perspective on S2S and CTC comparison, as well as the corresponding difference in performance when the vocabulary is changed to word-level. Note that character-level modeling was the widely-used vocabulary at the time of this publication.

Our models obtained the best Word Error Rate (WER) of that time in both SW (5% absolute improvement without LM) and CH test sets among the previous S2S models (Lu et al., 2016; Zenkel et al., 2017; Toshniwal et al., 2017). We also perform better than previous CTC models (Hannun et al., 2014; Zweig et al., 2017; Audhkhasi et al., 2017) in the SW test set and the difference in the CH set is minor. Furthermore, we observe a 13% relative improvement in our results on the SW subset by using an RNNLM with shallow fusion (Gulcehre et al., 2015) which is trained at the character and word level. The best absolute WER at character-level modeling is 15.6% on the SW test set and 31% on the CH test set. Following the publication of this work, most recently, the state-of-the-art on this dataset has been reduced further to 5% and 8% respectively (Chan et al., 2021) by training on more data and by using large-scale models with a variety of training tricks (Park et al., 2019; Baevski et al., 2020) developed over the last few years. This latest result uses more than 5000 hours of speech for training as compared with 300 hours used in this work.

Next, we compare the A2W models with prior work using BPE and word units. We start by restricting the vocabulary to words occurring at least 5 times *(Word >= 5)* in the training set before moving on to complete vocabulary A2W modeling. *Word >= 5* leads to a vocabulary of 11069 words with an OOV rate of 2.3% for the CH test set. This model leads to an absolute WER of 23% on SW and 37.2% on CH. To address this high OOV rate, we try to match the word vocabulary by an equivalent BPE vocabulary of 12k merge operations. This model performs better than the word model as expected: 21.3% and 35.7% respectively. We also experiment with initializing the word>=5 model with a pretrained character model (similar to Audhkhasi et al. 2017) for better convergence and observe slight improvements: 22.4% and 36.1%.

We proceed to the large vocabulary speech recognition model made of all the words in the training set. This model performs better than our previous word models which may be due to absence of the frequently occurring OOV token. We get an absolute improvement of 4% in SW and 11% in CH subsets over the previously published number on such large vocabulary recognition (Lu et al., 2016) with or without a language model. Similarly, Chen et al. also perform large vocabulary recognition and our model shows 9% and 4% absolute improvement on the two test sets respectively.

Ideally, S2S A2W model does not need a separate language model as it directly predicts a sequence of words using the decoder LSTM. But as the LM is trained on a larger text corpus, we integrate it to check its effect and do not observe improvements as large as the character model.

Our work is not directly comparable with other S2S or CTC models that use BPE units or a smaller vocabulary (Audhkhasi et al., 2017; Zeyer et al., 2018) as the goal here is whole-word recognition to predict semantically meaningful units. This work is necessary for the Audio-to-Semantic learning and consequently Speech Translation work described in the following Chapter 4. With these results, we demonstrate our character-level and word-level models performed well as compared to the prior work published at that time. Irrespective of that, absolute WER performance is not the focus of this work. In the sections below, we describe the benefits of an

A2W model for automatic speech segmentation and towards learning contextual acoustic word embedding.

3.3.4 Automatic Word Segmentation

In the following two sections we analyze the behavior of S2S models, specifically for the A2W recognition task. We analyze attention in the decoder and the hidden representations of the encoder.

Human Annotated Word Boundaries in SWBD. NXT Switchboard Annotations (LDC 2009T26) are a subset of the Switchboard corpus (LDC97S62) containing 1 million words that were annotated for syntactic structure and disfluencies as part of the Penn Treebank project. This subset contains human annotated word-level forced alignments that mark the beginning and end of each word in the utterance in time [2]. In the following sections, we analyze attention behavior of the A2W model and the speech-word-vectors obtained from it. To do this analysis, we need groundtruth word-level segmentations and this corpus is a good match.

From NXT Switchboard, we choose those utterances that are also present in the Treebank-3 (LDC99T42) corpus. The speech in this corpus is re-segmented to match the sentences in Treebank-3. We filter out utterances with less than 3 words resulting in 67,654 utterances in total. This is divided into 56,100 train, 5,829 validation and 5,725 test sets. We train a separate A2W model with this data using the same setup without using any explicit information about word-segments. We only train on this dataset to avoid introducing a more variability in our analysis, i.e. are the segmentations due to our model or due to training with a larger corpus (SW 300h)? In our setup, we split compound words into two words (eg. they‘re $\rightarrow$ they and ‘re).

Attention Behavior

In Figure 3.5 we plot the attention of a sample utterance from our validation set of the corpus. We notice that the attention is very peaky and focuses only on certain frames in the input although generally a word spans multiple input frames.

To understand this behavior of the model, let us revisit the location-aware attention. The location-aware attention is useful in speech to enforce a monotonic alignment between source and target. It does so by convolving the previous attention vector along input time-steps and feeding it as another input parameter while calculating attention of the current time step. This way, the model is informed where to pay attention “next” and would mostly look in the “future” to make a prediction.

As this model is trained towards word-units and the attention is focused only on certain frames, we speculate that the hidden states corresponding to those frames are the speech-word-vectors

[2] http://groups.inf.ed.ac.uk/switchboard/structure.html

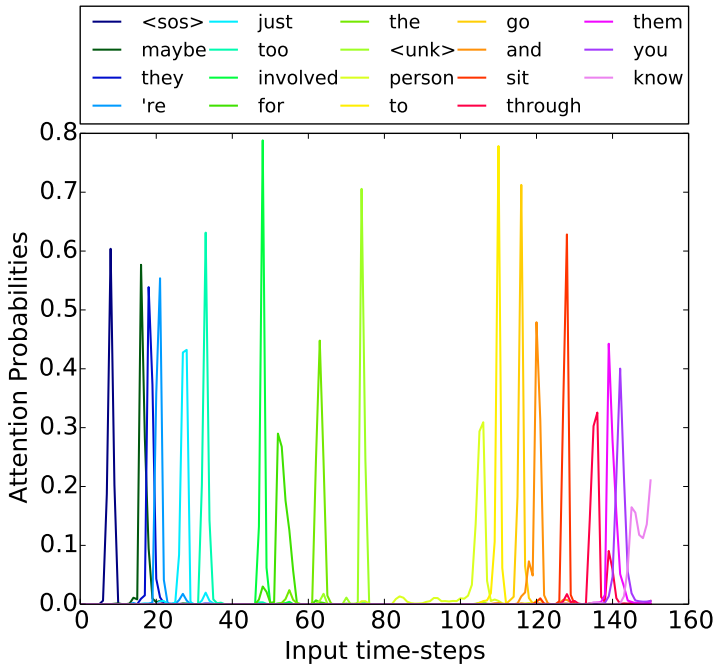


FIGURE 3.5: Attention visualization for a sample utterance from the validation set shows highly localized attention for a word-level S2S model

for those words. Here, we are able to extract speech-word-vectors from an end-to-end model trained for direct word recognition without the need of any predefined forced-alignments. The size of these embeddings is equal to the number of RNN cells in the last layer of the encoder.

Automatic Segmentation of Speech into Words

Given that the attention is highly localized, we attempt to quantify whether the attention weights corresponded to actual word boundaries. From the Switchboard NXT dataset, we chose all utterances (train, validation and test) for which we have 0% WER during testing. 39% of the total utterances have 0 WER. We perform decoding with beam size 1 here. We converted the human-annotated forced-alignments to their corresponding frame numbers using the 10ms frame rate of our model. The predicted frame number is calculated from the attention distribution shown in Figure 3.5 as follows. The input frame with the max attention probability is chosen as the predicted frame for the word. The frame error is calculated at each word level by taking an absolute difference between the predicted and grouthtruth frame number. A positive difference means the predicted frame was after the groundtruth alignment, and a negative difference means that it was before. We average this frame error for all words in all utterances (171073 words). An example of this computation is

	Avg. Frame Error		
	Train	**Val**	**Test**
W/o Last Word - Mean	0	-	-
		0.08	0.01
W/o Last Word - Std Dev	3.7	3.3	2.0
All Words - Mean	0.4	0.3	0.3
All Words - Std Dev	10.1	9.8	10.5

TABLE 3.4: Average frame error mean and standard deviation (std dev.) between groundtruth forced-alignments and S2S word segment prediction

$$\begin{aligned} \text{Predicted} &= [988, 1008, 1012, 1044, 1092] \\ \text{Groundtruth} &= [988, 1005, 1013, 1042, 1100] \\ \text{and Frame Error} &= [0, +3, -1, +2, -8] \end{aligned}$$

The attention weights for the last word predicted in the sequence is often most erroneous. As an example, in Figure 3.5 we see that "know", the last word, has a distributed attention weight, and has the least probability value (approximately 0.2) compared to other words. For better understanding, we also compute frame errors without considering the last word of every utterance.

We compute the mean and standard deviation of frame errors for all words. During training, we use a pyramidal encoder that reduces the input frame lengths by a factor of 4. Hence, while computing mean and standard deviation of frame errors, we scale them by 4 as well for fair comparison. The standard deviation of frame error without including last word is 3.6 frames after the groundtruth. For a word-based model, this is an encouraging result as usually a character unit spans 7 (or 1.75 frames after a pyramidal encoder) and a word would span many more.

Why does attention focus on the end of word? The optimization task in A2W recognition is to map a sequence of input frames (usually larger number of input frames than in character or BPE prediction models) to a sequence of target words. During training, the model learns where word boundaries occur by recognizing the attention distribution that leads to highest probability of generating the correct output. The bi-directional LSTM in the encoder has access to the past as well as future input. Therefore, the encoder learns to look into the future to recognize where a different word is beginning, and the BLSTM would hold richest embeddings in the unit corresponding to each of frame of the current word. We investigate the encoder embeddings in the next section in more detail. It is also important to note that the location-aware attention constrains the model to only look into the future, and not the past, which would push the boundaries towards word ends rather than beginnings. Hence, the attention mechanism learns to focus mostly on the word boundaries.

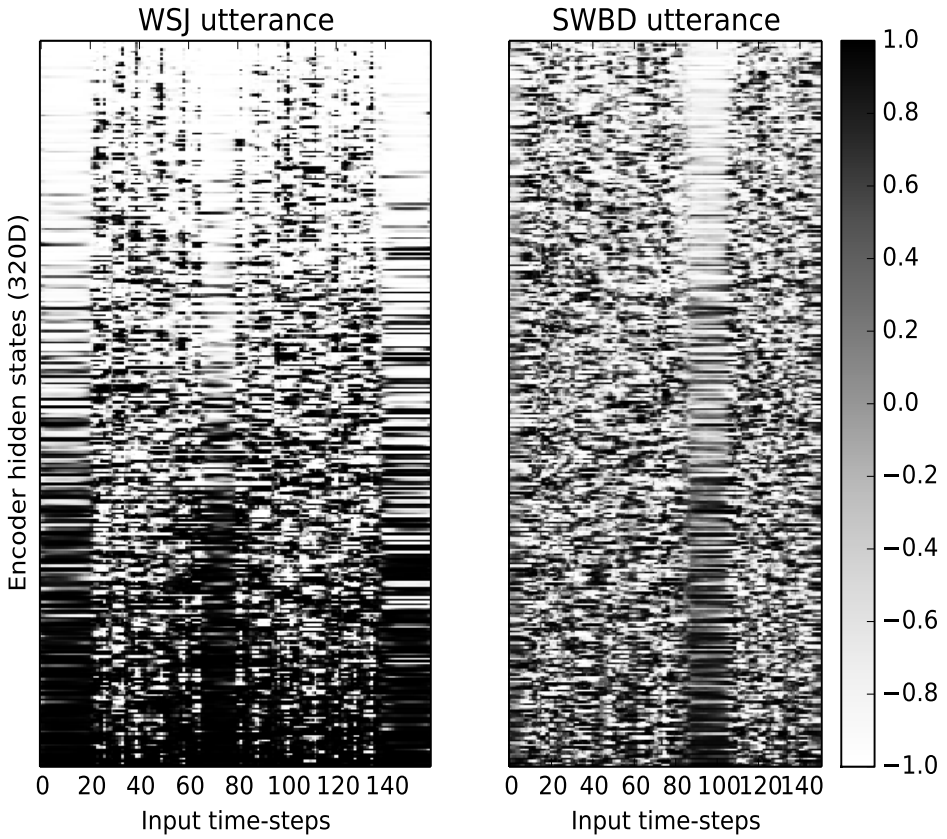


FIGURE 3.6: Encoder hidden state visualization for WSJ (acoustically clean data) and SWBD (acoustically noisier). Visualization shows encoder activations across input time frames.

We obtain a context vector from the attention mechanism that is a weighted sum of the encoder hidden states. Following this peaky nature of the attention mechanism, we expect to see certain patterns reflected in the encoder embeddings. This is explored in the following section.

Speech Embeddings

We train a similar A2W model on the Wall Street Journal corpus (WSJ, LDC93S6B and LDC 94S13B) which comprises about 90 hours of read speech in clean acoustic environments with a close-talk microphone. This dataset has about 300 different speakers in the train, validation (dev93) and test (eval92) sets. WSJ is sampled at 16kHz while SWBD is sampled at 8kHz and we upsample SWBD to 16kHz for implementation reasons. We bring the readers attention to these major differences in acoustic and speaker variability and domain of the data in WSJ and SWBD. In Figure 3.6 we visualize the encoder hidden states for sample utterances from the validation sets of WSJ (4k8c030h) and SWBD (same as in Figure 3.5). We train a WSJ model to compare hidden state activations of the noisier SWBD dataset with a clean WSJ dataset as we expect the activation patterns to be clearer and more interpretable in the cleaner dataset. The

hidden state dimension here is same as the number of BLSTM cells in the last encoder layer (320D). For this visualization, we sort the hidden states of the encoder in an ascending order of total activation over time. We use a tanh non-linearity hence all values range from -1 to +1. We note that there are three types of patterns to observe in these activations: 1) stable horizontal lines, 2) disruptions, and 3) vertical dashed-line pattern across encoder hidden states (Y-axis) within the disruptions. Pattern 3 is easier to notice in the WSJ activations.

Upon listening to these utterances, we found that stable horizontal lines (pattern 1) corresponds to silence in the utterance, while disruptions (pattern 2) corresponds to the speech. We observe similar patterns identifying speech and non-speech in both WSJ and SWBD. From this, we understand that the model has learned to detect and segment pauses in speech. As WSJ is the acoustically cleaner corpus with less variability, "silence" acoustics are stable and repetitive throughout, which is what we observe in the beginning, middle and end of the WSJ utterance– while the SWBD "silence" activations look different. In WSJ, we can further identify multiple vertical dashed-line patterns across all encoder hidden states (i.e. Y-axis; pattern 3). This pattern is formed by encoder units turning on and off (+1, -1) when a word boundary is reached. This particular WSJ utterance has 15 words and we observe 15 vertical dashed-line patterns in the activations. This further reinstates that we are able to represent multiple frames of speech using single 320D speech-word-vectors. Pattern 3 is tougher to spot in SWBD comparatively but still noticeable; it might need more training data or better regularization with this data to obtain similar properties as the WSJ model.

3.4 Chapter Conclusion

We present a monotonically motivated Input Fusion model for audio-visual end-to-end speech recognition. We establish the efficacy of this model on a standard speech recognition corpus, WSJ, and extend it to a new open-domain noisy multimodal speech recognition dataset, How2. We find significant gains of over 1.6% absolute improvement in the token error rates with the audio-visual model. We delve deeper into the modeling capabilities and limitations of this model by analysis of the How2 dataset in comparison with standard, clean, WSJ corpus. We extend this analyses to compare the failure cases of model generated hypotheses for the noisy How2corpus compared with the WSJ corpus.

To extend this model to end-to-end word-level speech recognition we build direct Acoustic2Word (A2W) models. The motivation for this word-level speech recognition is to perform direct audio-to-semantic tasks addressed in further chapters. We build strong A2W models, comparing on standard widely-used speech corpora. We further investigate the power of these direct A2W models by analyzing monotonic location-aware attention mechanism and find that the model learns to automatically segment speech frames into individual words, leading to clearly identifying acoustic word embeddings. In the next chapter, we make use of these inherently learnt speech embeddings for semi-supervised learning. Additionally, we introduce the Latent Representation Fusion model that handles non-monotonic constraints in modalities, building on top of the Input Fusion model presented in this chapter. Particularly, the Input Fusion model assumes strict monotonicity and multimodal fusion is built keeping that in mind. For tasks like Translation, while utterance-level dependence is involved, monotonicity is not. Hence, the Latent Representation Fusion model is required for this task and Input Fusion is no longer sufficient.

Chapter 4

Speech Translation

4.1 Introduction

In this Chapter, we present semi-supervised multimodal Speech Translation with the limited supervision obtained through multimodal inputs. Speech Translation is a language-dependent re-ordering task where the input time-series speech sequence is converted to the corresponding re-ordered text sequence. Speech Translation has been approached by a cascaded pipeline approach with speech-to-text followed by text-to-text translation (Pham et al., 2019; Wu et al., 2019b; Inaguma et al., 2020) or via end-to-end models (Inaguma et al., 2020; Guo et al., 2020), all in a fully supervised setting. Here, we utilize the inherent supervision available through multiple views of the same data to build semi-supervised speech translation systems that first learn multimodal representations, that are then used for a retrieval based speech translation task.

Semi-supervised learning is preferred over fully supervised learning in scenarios where data annotation is limited, expensive, or unavailable. In contrast, access to multiple views of the same data, or multimodal data, is more readily available. Specifically, data from instructional videos such as the How2 dataset is available in large quantities (Sanabria et al., 2018; Abu-El-Haija et al., 2016; Miech et al., 2019). As described earlier in Chapter **??**, video data often comes with multiple views of the same data point: the speech, audio, video itself, English transcription, metadata, and possibly, auto-generated transcriptions in other languages. Using well-established representation learning method for such multiview data, Cannonical Correlation Analysis (CCA) (Hotelling, 1992), we apply it to such noisy large-scale data and demonstrate its utility in downstream tasks. This method is universal and can be applied to multiple downstream tasks such as speech recognition, text translation, and speech translation.

Apart from the noisiness of the data, application of this technique to such open-domain data involves solving multiple challenges before it can be applied to Speech Translation. CCA requires initial independently learned representations for all modalities. For speech/audio, no such method exists to learn contextual acoustic embeddings at scale. Prior work required clean annotated word boundaries or word-level speech (He et al., 2016b; Kamper et al., 2016). Secondly,

the individual modality representations need to be aligned at the same time-scale, i.e. character embeddings, word embeddings, sentence embeddings, etc. Speech is often at phoneme or character-levels, text is at word-level, and vision can be at a word-level as well (annotated object/scene/action labels). To address both these issues, we develop a method to learn contextual acoustic word embeddings that bring speech/audio to the word-level embeddings.

Using the model described in Section 3.3, we build a Contextual Acoustic Word Embedding model that does not require manual alignment of word boundaries, but can instead recognize them on-the-fly (Palaskar and Metze, 2018). With this automatic segmentation, we can now extract the useful speech representations for each word (Palaskar et al., 2019b). With this technique, we bring the speech, text, and visual modality views to word-level latent alignment. These modality-specific representations are then used for further joint multi-view multimodal representation learning.

We explore an advanced, correlation-based representation learning method, Deep Generalized Canonical Correlation Analysis (DGCCA) (Arora and Livescu, 2013), on a 4-way parallel, multimodal dataset, and assess the quality of the learned representations on retrieval-based tasks. We show that the proposed approach produces rich representations that capture most of the information shared across views. Our best models for speech and textual modalities achieve retrieval rates from 70.7% to 96.9% on open-domain, user-generated instructional videos. This shows it is possible to learn reliable representations across disparate, unaligned and noisy modalities, and encourages using the proposed approach on larger datasets.

Latent Representation Fusion Model

The Input Fusion model provides an utterance-level monotonic adaptation with the input modalities X_{M1} and X_{M2}. We expand this model from strictly monotonic input fusion to a latent-space fusion, LY_1. The Latent Representation Fusion model relaxes the monotonic constraint allowing fusion for re-ordering tasks like speech translation. For speech translation, the monotonicity between input speech and output translations is language dependent, and enforcing strict monotonicity (for e.g. via input fusion) is not optimal. The Latent Representation Fusion model maintains the time-resolution of input speech (and video) at the utterance-level, and has the flexibility of output re-ordering in the latent space which was not possible in the Input Fusion model.

The Latent Representation Fusion model, is further expanded to perform semi-supervised modeling by leveraging information from the multiple multimodal views available. Using the DGCCA model for representation learning mentioned above, we train generalized multimodal representations that fuse the various input multimodal views into a single latent representation LY_1. We use retrieval-based evaluation for this model that also performs the downstream task; given the generalized multiview multimodal representation LY_1, we retrieve the corresponding translation representation $Y_1^{retrieval}$.

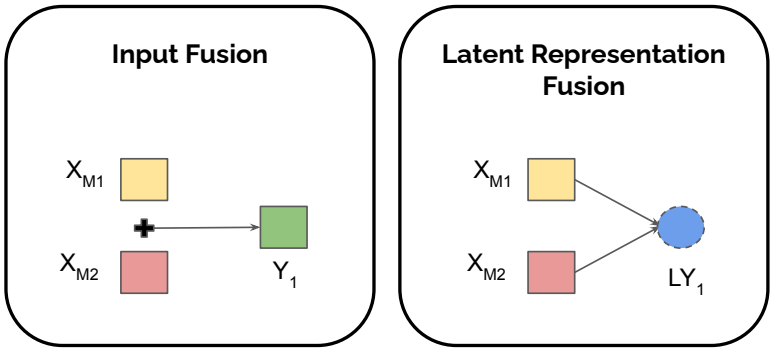


FIGURE 4.1: We build on top of the existing Input Fusion model for semi-supervised Speech Translation. We present the Latent Representation Fusion model that learns a multimodal latent representation LY_1, and uses that via retrieval for downstream tasks.

Chapter Structure

The work in this Chapter is structured in two main parts: (1) learning contextual acoustic word embeddings (a novel method to represent speech by word-level semantically meaningful embeddings), followed by (2) using these embeddings to perform semi-supervised multimodal Speech Translation. We begin by describing the approach for Audio-to-Semantic learning, the model used, and the evaluation of the quality of learned embeddings on 16 benchmark embedding evaluation tasks. In the following Section, we describe the multiview learning method for semi-supervised Speech Translation. This work presents one of the first applications of multiview learning to open-domain video data, the `How2` dataset. We first perform implicit evaluation of the effectiveness of the proposed approach on such data, followed by explicit evaluation on the Speech Translation downstream task. The work presented in this chapter was published in Palaskar et al. 2019b and Holzenberger et al. 2019.

4.2 Contextual Acoustic Word Embeddings

4.2.1 Audio-to-Semantic Learning

The task of learning fixed-size representations for variable length data like words or sentences, either text or speech-based, is an interesting problem and a focus of much current research. In the natural language processing community, methods like word2vec (Mikolov et al., 2013), GLoVE (Pennington et al., 2014), CoVe (McCann et al., 2017) and ELMo (Peters et al., 2018) have become increasingly popular, due to their utility in several natural language processing tasks. Similar research has progressed in the speech recognition community, where however the input is a sequence of short-term audio features, rather than words or characters. Therefore, the variability in speakers, acoustics or microphones for different occurrences of the same word or sentence adds to the challenge.

Prior work towards the problem of learning word representations from variable length acoustic frames involved either providing word boundaries to align speech and text (Chung and Glass, 2018), or chunking ("chopping" or "padding") input speech into fixed-length segments that usually span only one word (Kamper et al., 2016; Bengio and Heigold, 2014; Harwath and Glass, 2015a; He et al., 2016b). Since these techniques learn acoustic word embeddings from audio fragment and word pairs obtained via a given segmentation of the audio data, they ignore the specific audio context associated with a particular word. So the resulting word embeddings do not capture the contextual dependencies in speech. In contrast, our work constructs individual acoustic word embeddings grounded in utterance-level acoustics.

We present different methods of obtaining acoustic word embeddings from an attention-based sequence-to-sequence model (Sutskever et al., 2014a; Chan et al., 2016; Chorowski et al., 2015) trained for direct Acoustic-to-Word (A2W) speech recognition (Palaskar and Metze, 2018). Using this model, we jointly learn to automatically segment and classify input speech into individual words, hence getting rid of the problem of chunking or requiring pre-defined word boundaries. As our A2W model is trained at the utterance level, we show that we can not only learn acoustic word embeddings, but also learn them in the proper context of their containing sentence. We also evaluate our contextual acoustic word embeddings on a spoken language understanding task, demonstrating that they can be useful in non-transcription downstream tasks.

Our main contributions are the following: (1) We demonstrate the usability of attention not only for aligning words to acoustic frames without any forced alignment but also for constructing Contextual Acoustic Word Embeddings (CAWE). (2) We demonstrate that our methods to construct word representations (CAWE) directly from a speech recognition model are highly competitive with the text-based word2vec embeddings (Mikolov et al., 2013), as evaluated on 16 standard sentence evaluation benchmarks. (3) We demonstrate the utility of CAWE on a speech-based downstream task of Spoken Language Understanding showing that pretrained speech models could be used for transfer learning similar to VGG in vision (Simonyan and Zisserman, 2014b) or CoVe in natural language understanding (McCann et al., 2017).

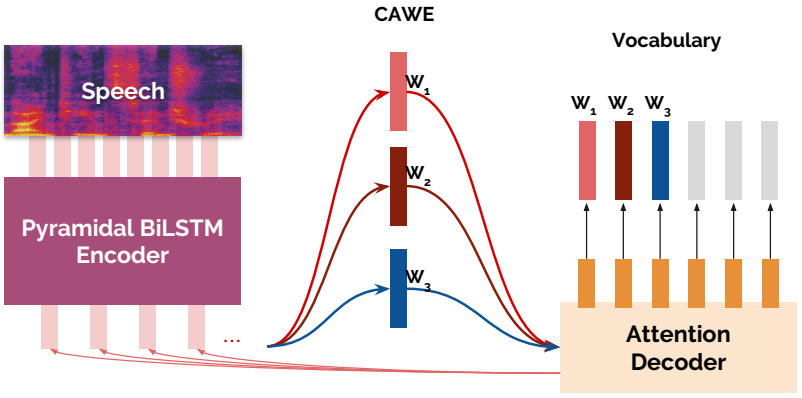


FIGURE 4.2: A2W model with the CAWE representations obtained by combining the encoders representations and attention weights.

4.2.2 Model

Our S2S model is similar in structure to the Listen, Attend and Spell model (Chan et al., 2016) which consists of 3 components: the encoder network, a decoder network and an attention model. The encoder maps the input acoustic features vectors $\mathbf{a} = (\mathbf{a}_1, \mathbf{a}_2, ..., \mathbf{a}_T)$ where $\mathbf{a}_i \in \mathcal{R}^d$, into a sequence of higher-level features $\mathbf{h} = (\mathbf{h}_1, \mathbf{h}_2, ..., \mathbf{h}_{T'})$. The encoder is a pyramidal (sub-sampling) multi-layer bi-directional Long Short Term Memory (BLSTM) network. The decoder network is also an LSTM network that learns to model the output distribution over the next target conditioned on sequence of previous predictions i.e. $P(\mathbf{y}_l|y^*_{l-1}, y^*_{l-2}, ..., y^*_0, \mathbf{x})$ where $\mathbf{y}* = (y^*_0, y^*_1, ..., y^*_{L+1})$ is the ground-truth label sequence. In this work, $y^*_i \in \mathcal{U}$ is from a word vocabulary. This decoder generates targets $\mathbf{y}$ from $\mathbf{h}$ using an attention mechanism.

We use the location-aware attention mechanism (Chorowski et al., 2015) that enforces monotonicity in the alignments by applying a convolution across time to the attention of previous time step. This convolved attention feature is used for calculating the attention for the current time step which leads to a peaky distribution (Chorowski et al., 2015; Palaskar and Metze, 2018). Our model follows the same experimental setup and model hyper-parameters as the word-based models described in our previous work (Palaskar and Metze, 2018) with the difference of learning 300 dimensional acoustic feature vectors instead of 320 dimensional.

We now describe our method to obtain the acoustic word embeddings from the end-to-end trained speech recognition system. The model is as shown in Figure 4.2 where the embeddings are constructed using the hidden representations obtained from the encoder and the attention weights from the decoder. Our method of constructing "contextual" acoustic word embeddings is similar to a method proposed for text embeddings, CoVe (McCann et al., 2017).

The main challenge that separates our method from CoVe (McCann et al., 2017) in learning embeddings from a supervised task, is the problem of alignment between input speech and output words. We use the location-aware attention mechanism that has the property to assign higher probability to certain frames leading to a peaky attention distribution. We exploit this

property of location-aware attention in an A2W model to automatically segment continuous speech into words as shown in our previous work (Palaskar and Metze, 2018), and then use this segmentation to obtain word embeddings. Below, we formalize this process of constructing contextual acoustic word embeddings.

Intuitively, attention weights on the acoustic frames hidden representations reflect their importance in classifying a particular word. They thereby provide a correspondence between the frame and the word within a given acoustic context. We can thus construct word representations by weighing the hidden representations of these acoustic frames in terms of their importance to the word i.e. the attention weight. We show this in the Figure 4.2 wherein the hidden representations and their attention weights are colored according to their correspondence with a particular word.

Given that a_j represents the acoustic frame j, let $encoder(a_j)$ represent the higher-level features obtained for the frame a_j (i.e. $encoder(a_j)$ = $\mathbf{h} = (\mathbf{h}_1, \mathbf{h}_2, ..., \mathbf{h}_{T'})$). Then, for the i^{th} word w_i our model first obtains the mappings of w_i to acoustic frames a_K where K is the set such that $\forall k \in K$

$$k = \arg\max_j(attention(a_j))$$

over all utterances U containing the word w_i in the training set.

Below we describe three different ways of using attention to obtain acoustic word embeddings for a word w_i (here, $n(K)$ represents the cardinality of the set K):

$$w_i = \frac{\sum_{k \in K} encoder(a_k)}{n(K)} \tag{4.1}$$

$$w_i = \frac{\sum_{k \in K} attention(a_k) \cdot encoder(a_k)}{n(K)} \tag{4.2}$$

$$w_i = encoder(a_k) \;\; where \;\; k = \arg\max_{k \in K} attention(a_k) \tag{4.3}$$

Therefore, unweighted Average (U-AVG, Equation 5.1) is just the unweighted combination of all the hidden representations of acoustic frames mapped to a particular word. Attention weighted Average (CAWE-W, Equation 5.2) is the weighted average of the hidden representations of all acoustic frames using the attention weights for a given word. Finally, maximum attention (CAWE-M, Equation 5.3) is the hidden representation of the acoustic frame with the highest attention score for a given word across all utterances in the training data. We call the attention-weighted average and the maximum attention based techniques as Contextual Acoustic Word Embeddings (CAWE) since they are contextual owing to the use of attention scores (over all acoustic frames for a given word).

4.2.3 Experiments and Results

We use a commonly used speech recognition setup, the 300 hour Switchboard corpus (LDC97S62) (Godfrey et al., 1992) which consists of 2,430 two-sided telephonic conversations between 500 different speakers and contains 3 million words of text. Our second dataset is a 300 hour subset of the `How2` dataset (Sanabria et al., 2018) of instructional videos, which contains planned, but free speech, often outdoor and recorded with distant microphones, as opposed to the indoor, telephony, conversational speech of Switchboard. There are 13,662 videos with a total of 3.5 million words in this corpus. The A2W obtains a word error rate of 22.2% on Switchboard and 36.6% on CallHome set from the Switchboard Eval2000 test set and 24.3% on dev5 test set of How2.

Comparing Methods for Constructing Embeddings

Datasets for Downstream Tasks We evaluate our embeddings by using them as features for 16 benchmark sentence evaluation tasks that cover Semantic Textual Similarity (STS 2012-2016 and STS B), classification: Movie Review (MR), product review (CJ), sentiment analysis (SST, SST-FG), question type (TREC), Subjectivity/Objectivity (SUBJ), and opinion polarity (MPQA), entailment and semantic relatedness using the SICK dataset for SICK-E (entailment) and SICK-R (relatedness) and paraphrase detection (MRPC). The STS and SICK-R tasks measure Spearman's coefficient of correlation between embedding based similarity and human scores, hence the scores range from $[-1, 1]$ where higher number denotes high correlation. All the remaining tasks are measured on test classification accuracies. We use the SentEval toolkit (Conneau and Kiela, 2018) to evaluate.

Training Details In all downstream evaluations involving classification tasks, we have used a simple logistic regression for classification since a better representation should lead to better scores without using complicated models (hence abstracting away model complexities from our evaluations). This also means that we can use the concatenation of CAWE and CBOW as features to the logistic regression model without adding tunable embedding parameters.

Discussion From the results in Table 4.1 we see that CAWE-M outperforms U-AVG by 34% and 13% and CAWE-W by 33.9% and 12% on Switchboard and How2 datasets respectively in terms of average performance on STS tasks and leads to better or slightly worse performance on the classification tasks. We observe that CAWE-W usually performs worse than CAWE-M which could be attributed to a noisy estimation of the word embeddings on the account of taking even the less confident attention scores while constructing the embedding. In contrast, CAWE-M is constructed using the most confident attention score obtained over all the occurrences of the acoustic frames corresponding to a particular word. We also observe that U-AVG performs worse than CAWE-W on STS and SICK-R tasks since it is constructed using an even noisier

	Switchboard			How2		
Dataset	**U-AVG**	**CAWE-W**	**CAWE-M**	**U-AVG**	**CAWE-W**	**CAWE-M**
STS 2012	0.3230	0.3281	**0.3561**	0.3255	0.3271	**0.3648**
STS 2013	0.1252	0.1344	**0.1969**	0.2070	0.2071	**0.2716**
STS 2014	0.3358	0.3389	**0.3888**	0.3375	0.3426	**0.3940**
STS 2015	0.3854	0.3881	**0.4275**	0.3852	0.3843	**0.4173**
STS 2016	0.2998	0.2974	**0.3833**	0.3248	**0.3271**	0.3159
STS B	0.3667	0.3510	**0.4010**	0.3343	0.3440	**0.4000**
SICK-R	0.5640	0.5800	**0.6006**	0.5800	0.6060	**0.6440**
MR	63.86	63.75	**64.69**	63.46	63.19	**63.64**
MRPC	**70.67**	69.45	69.80	68.29	67.83	**70.61**
CR	71.42	72.13	**72.93**	**74.12**	73.99	73.03
SUBJ	**82.45**	82.22	81.19	81.48	**81.88**	81.01
MPQA	**73.76**	73.28	73.75	**74.21**	74.18	73.53
SST	66.45	**66.61**	65.02	63.43	63.43	**65.13**
SST-FG	32.81	32.04	**33.53**	31.95	**32.35**	32.03
TREC	63.80	62.40	**67.60**	**66.60**	66.00	60.60
SICK-E	**74.20**	73.41	74.06	75.14	75.34	**75.97**

TABLE 4.1: Comparing three methods to obtain acoustic word embeddings from an A2W model: unweighted average (U-AVG), weighted average (CAWE-W) and maximum attention (CAWE-M).

process in which all encoder hidden representations are weighted equally irrespective of their attention scores.

Comparing with Text-based Embeddings

Datasets for Downstream Tasks The datasets are the same as described above in Section 4.2.3 (Comparing Methods for Constructing Embeddings).

Training Details In all the following comparisons, we compare embeddings obtained only from the training set of the speech recognition model, while the text-based word embeddings are obtained by training Continuous Bag-of-Words (CBOW) word2vec model on all the transcripts (train, validation and test). This was done to ensure a fair comparison between our supervised technique and the unsupervised word2vec method. This naturally leads to a smaller vocabulary for CAWE. Further, one of the drawbacks of A2W speech recognition model is that it fails to capture entire vocabulary, recognizing only 3044 words out of 29874 (out of which 18800 words occur less than 5 times) and 4287 out of 14242 total vocabulary for Switchboard and How2 respectively. Despite this fact, the performance of CAWE is very competitive with word2vec CBOW which does not suffer from reduced vocabulary problem.

	Switchboard			How2		
Dataset	**CAWE-M**	**CBOW**	**Concat**	**CAWE-M**	**CBOW**	**Concat**
STS 2012	0.3561	**0.3639**	0.3470	0.3648	0.3688	**0.3790**
STS 2013	0.1969	0.1960	**0.2010**	**0.2716**	0.2524	0.2675
STS 2014	**0.3888**	0.3745	0.3795	0.3940	**0.3973**	0.3971
STS 2015	0.4275	0.4459	**0.4481**	0.4173	**0.4781**	0.4710
STS 2016	**0.3833**	0.3471	0.3651	0.3159	**0.4023**	0.3388
STS B	0.401	**0.4100**	0.3995	0.4000	**0.4720**	0.4487
SICK-R	0.6006	0.6170	**0.6228**	0.6440	0.6550	**0.6945**
MR	64.69	66.24	**66.89**	63.64	66.03	**66.89**
MRPC	**69.80**	68.99	68.00	**70.61**	69.68	68.52
CR	72.93	74.49	**75.39**	73.03	**74.89**	74.84
SUBJ	81.19	**84.62**	84.59	81.01	84.75	**85.04**
MPQA	73.75	**76.44**	75.36	73.53	75.56	**75.60**
SST	65.02	68.37	**68.97**	65.13	67.66	**68.20**
SST-FG	33.53	34.71	**35.79**	32.08	33.62	**33.67**
TREC	67.60	69.80	**71.40**	60.60	**68.40**	67.40
SICK-E	74.06	75.02	**76.19**	75.97	76.29	**78.14**

TABLE 4.2: Sentence Evaluations on 16 benchmark datasets for Switchboard and How2 corpus. We compare the CAWE-M method with the word2vec embeddings trained with CBOW method and with CAWE-M + CBOW concatenated (Concat) embeddings.

Discussion In Table 4.2, we see that our embeddings perform as well as the text-embeddings. Evaluations using CAWE-M extracted from Switchboard based training show that the acoustic embeddings when concatenated with the text embeddings outperform the word2vec embeddings on 10 out of 16 tasks. This concatenated embedding shows that we add more information with CAWE-M that improves the CBOW embedding as well. The gains are more prominent in Switchboard as compared to the How2 dataset since How2 is planned instructional speech whereas Switchboard is spontaneous conversational speech (thereby making the How2 characteristics closer to text leading to a stronger CBOW model).

Evaluation on Spoken Language Understanding

Dataset In addition to generic sentence-level evaluations, we also evaluate CAWE on the widely used ATIS dataset (Price, 1990) for Spoken Language Understanding (SLU). ATIS dataset is comprised of spoken language queries for airline reservations that have intent and named entities. Hence, it is similar in domain to Switchboard, making it a useful test bed for evaluating CAWE on a speech-based downstream evaluation task.

Training Details For this task, our model is similar to the simple Recurrent Neural Network (RNN) based model architecture as investigated in (Mesnil et al., 2013). Our architecture is comprised of an embedding layer, a single layer RNN-variant (Simple RNN, Gated Recurrent

	CAWE-M	CAWE-W	CBOW
RNN	91.49	91.67	91.82
GRU	93.25	93.56	93.11

TABLE 4.3: Speech-based contextual word embeddings (CAWE-M and CAWE-W) match the performance of the text-based embeddings (CBOW) on the ATIS dataset with an RNN and GRU model

Unit (GRU)) along with a dense layer and softmax. In each instance, we train our model for 10 epochs with RMSProp (learning rate 0.001). We train each model 3 times with different seed values and report average performance.

Discussion (Mesnil et al., 2013) concluded that text-based word embeddings trained on large text corpora consistently lead to better performance on the ATIS dataset. We demonstrate that direct speech-based word embeddings could lead to matching performance when compared to text-based word embeddings in this speech-based downstream task, thus highlighting the utility of our speech based embeddings. Specifically, we compare the test scores obtained by initializing the model with CAWE-M, CAWE-W and CBOW embeddings and fine-tuning them based on the task.

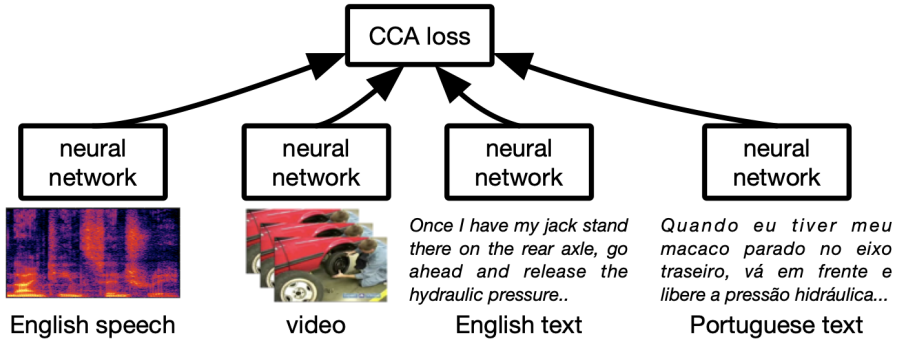


FIGURE 4.3: Learning from multiple modalities using Canonical Correlation Analysis (CCA) loss.

4.3 Multiview Learning for Multimodal Embeddings

4.3.1 Multiview Learning

Many large datasets include multiple modalities, leading to an exploration of methods that exploit the multimodal structure of the data. Further, collecting large datasets with multiple views is relatively easier than collecting large datasets with high quality annotations. Multiple views help learn better representations for each view separately (Ngiam et al., 2011), or a shared representation across multiple views (Arora and Livescu, 2013), and multiview learning has also been shown to be useful in low-resource settings (Socher and Fei-Fei, 2010). However, the fusion of information from disparate modalities remains a challenging problem (Baltrušaitis et al., 2019).

We build multiview models on the `How2` dataset (Sanabria et al., 2018), which at the time was the largest multi-view multimodal dataset. It contains various views of the *same* data point which is necessary for multi-view learning. While previous multiview models have exploited the natural alignment between views, such as speech and articulatory features (Wang et al., 2015), here we have to overcome challenges resulting from latently aligned views. For instance, there exists an alignment between words in an English sentence, and the words in its Portuguese translation. Figure 4.3 shows an overview of our learning algorithm with 4 different input views, described below.

Given these multiple parallel modalities, we address the following: how much information is shared across modalities? How can we learn a representation that captures information from all modalities? We measure this using intrinsic evaluations via retrieval for speech recognition and speech translation downstream tasks.

4.3.2 Model

In the following, we describe the sequence-to-sequence model-based encoders we used to extract features for speech, text and video data. We then describe the correlation-based methods we used

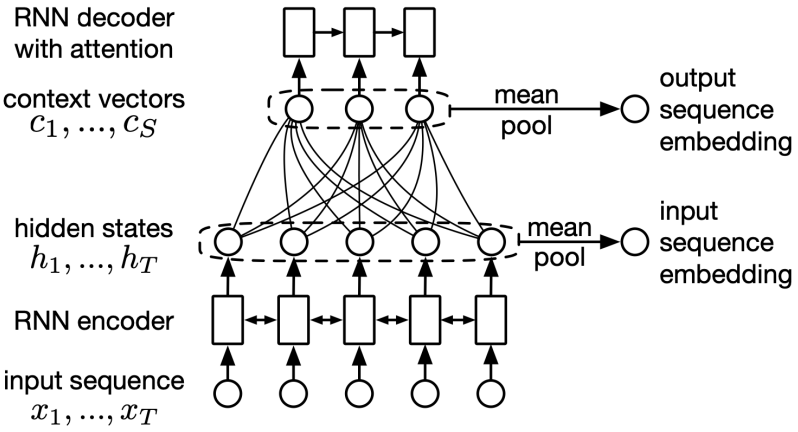


FIGURE 4.4: Extracting sequence embeddings from trained sequence to sequence models.

to learn representations.

Input Representations

We use word-level representations from Machine Translation (MT) and Automatic Speech Recognition (ASR) systems to build utterance-level representations. All the models we consider are attention-based, sequence-to-sequence models (Bahdanau et al., 2014b) that were trained in a supervised way on the How2 dataset. The encoder, a stacked bi-directional RNN, reads a sequence of feature vectors $x_1, \ldots, x_T$ and produces a sequence of hidden states $h_1, \ldots, h_{T'}$ ($T' <= T$ because of possible sub-sampling). The decoder, an RNN with attention mechanism, produces context vectors $c_1, \ldots, c_S$. We use the average of the h_i (resp. c_i) as the representation for the input sequence (resp. output sequence), as depicted in Figure 4.4. The RNNs for ASR are LSTMs (Hochreiter and Schmidhuber, 1997) and GRUs (Cho et al., 2014) for MT. For the acoustic representations to be at the same level of granularity as the word representations from MT, we use the Acoustic2Word model (Palaskar and Metze, 2018) as our ASR model, and obtain acoustic embeddings h_i at word-level.

For the video modality, we condense the information present in each utterance into a single vector as follows. We first use a ResNet (He et al., 2016a) to map each frame of the video to a multi-class posterior, based on the 1000 ImageNet classes. We then compute the average of those posteriors. As the video frames are sampled with a hard temporal threshold, it may contain noisy artifacts. We average over all the frames to capture the most persistent predictions and reduce the variability due to noise. We experimented with representations from action networks (Hara et al., 2018) trained on an action dataset (Kay et al., 2017), and obtained similar results as with ResNet features.

Linear CCA

To measure how much information is shared by pairs of representations, we use Canonical Correlation Analysis (CCA) (Hotelling, 1992). We assume that we are given two views of the same data point: for instance, for a given utterance, the audio recording and the transcription. These two views are represented by random variables X and Y (d_x - and d_y - dimensional respectively), and k is the dimensionality of the shared representation. Linear CCA seeks two linear transformations

$$U \in R^{d_x \times k} \quad \& \quad V \in R^{d_y \times k} \tag{4.4}$$

such that the components of $U^T X$ and $V^T Y$ are maximally correlated. Formally, we want to maximize

$$\mathbb{E}_{X,Y}[\mathrm{tr}(U^T X Y^T V)] \tag{4.5}$$

subject to

$$\mathbb{E}_X[U^T X X^T U] = E_Y[V^T Y Y^T V] = I_k. \tag{4.6}$$

For dataset $\{x_i, y_i\}_{i=1}^N$, we define C_{XY} the empirical cross-covariance matrix between X and Y , and C_{XX} and C_{YY} the empirical auto-covariance matrices of X and Y, respectively. U and V are given by the k left and right singular vectors of $C_{XX}^{-1/2}.C_{XY}.C_{YY}^{-1/2}$ with the largest singular values.

CCA is a better objective than predicting one view with the other when no single regression provides a fully adequate solution. For instance, it is very hard to generate speech from text. Instead, it is easier to predict the dependent variate which has the largest multiple correlation.

Deep CCA

Deep CCA (DCCA) (Andrew et al., 2013) is a natural extension of linear CCA, with the objective to maximally correlate $U^T\ f(X)$ and $V^T\ g(Y)$. f and g are non-linear feature extractors, which can be learned via gradient descent on the CCA objective. It is also natural to extend CCA to multiple views (Horst, 1961).

Instead of 2 views, we have J views $X_1, \ldots, X_J$ attached to each data point, stored in matrices $X_j \in R^{d_j \times N}$. Linear transformations $U_j \in R^{d_j \times k}{}_{j=1}^J$ are computed, that minimize the mutual reconstruction error under constraints, in a way equivalent to maximizing correlation. This framework can be extended to non-linear feature extractors (Arora and Livescu, 2013) with the objective:
minimize

$$\sum_{j=1}^{J} ||G - U_j^T f_j(X_j)||_2^2 \tag{4.7}$$

subject to

$$GG^T = I_k \tag{4.8}$$

with respect to parameters $\{G, \{f_j, U_j\}_j\}$. Here, $f_j(X_j) \in R^{h_j \times N}$ is the output of j-th feature extractor, and $G \in R^{k \times N}$ can be viewed as the learned representations for the given dataset. Effectively, each pair of feature extractor f_j and linear transformation U_j tries to reconstruct the learned representation G. The constraints on G prevent the feature extractors from collapsing the features. We refer to this method as Deep Generalized CCA (DGCCA). A linear variant of DGCCA where the f_j's are identity maps has been applied to acoustic feature learning (Arora and Livescu, 2013) and learning word embeddings (Rastogi et al., 2015).

4.3.3 Experiments

We applied the methods described above to the `How2` dataset and evaluated the learned representations using a retrieval task.

Dataset Setup

We apply the described methods to the `How2` dataset (Sanabria et al., 2018), which we use as a 4-way parallel corpus: video, speech, transcription in English, translation in Portuguese. The dataset contains 13,500 videos, or 300 hours of speech, and is split into 185,187 training, 2022 development (dev), and 2361 test utterances. It is yet unclear how much temporal coherence there is between the video modality and the language (text and speech) content, as objects mentioned early in the video may only appear much later on screen, or only for a very brief time.

Whenever we mention an MT task, it consists of translating English (en) text to Portuguese (pt) text; an ASR task consists of transcribing English speech to English text; a Speech Translation (ST) task consists of mapping English speech to Portuguese text.

Evaluations

To measure the richness of the learned representations, we use them in a retrieval task: given a source sequence in view 1, and a set of reference sequences in view 2, find the n sequences in the reference set that are closest to the source sequence. Since we have parallel corpora, we can check whether the correct sequence is present within those n sequences. We report this as Recall@10 (n = 10 throughout here), with scores ranging from 0 to 100. Finding the closest sequences consists of projecting the reference set as well as the source sequence into the shared space, then computing distances between source and references, and retrieving the closest points. The Recall@10 of picking at random from the reference set is 0.5% for the dev set and 0.4% for the test set.

	Linear CCA		Deep CCA		
	dev	**test**	**dev**	**test**	***k***
text (en) - text (pt)	82.5	81.4	95.1	94.6	400
speech - text (en)	98.3	96.9	92.1	90.1	160
video - text (en)	0.9	0.8	2.3	1.6	400
video - speech	0.8	0.6	1.9	1.8	160

TABLE 4.4: Recall@10 for retrieving reference modality given source modality ("source - reference"). Swapping source and reference change retrieval scores by less than 1% absolute.

4.3.4 Results

In the following, we will use k to indicate the dimensionality of the shared representation. Typically, k should be at most the smallest dimensionality of all views involved. We set k to half the smallest dimensionality as a balance between keeping as much information as possible while dropping uninformative components. Throughout all our experiments, we add the identity matrix scaled by 10^{-16} to the view-specific co-variance matrices.

In all experiments involving DCCA and DGCCA, we use 2-layer feedforward neural networks as feature extractors (f, g, f_j), the first layer with the same size as the input, and the second of size k. The training proceeds in epochs, which consist of a full pass over the training set with batch size 5500. After each epoch, we compute the retrieval scores between all possible pairs of different views on the dev set, and aggregate the scores by picking the highest of those scores. Our final model is the one with the highest aggregate score. For the experiments involving the video modality, we used a weight decay of 10^{-5}.

Bimodal Experiments

We start by applying linear CCA and deep CCA to pairs of views, at the utterance level. Text, speech and video sequences are represented with 800-, 320- and 1000-dimensional vectors respectively. As measured by the retrieval rates shown in Table 4.4, the representations learned for text (en and pt) and speech capture almost all of the information present in both views, in a space with half the dimensionality. The original text (en) and text (pt) representations having the same dimensionality, we scored the retrieval of a Portuguese sentence given an English sentence, which yielded a score of 0.38%. For other pairs of modalities, there is no obvious way of computing pairwise distances in the original space. The retrieval scores involving the video modality are very low (discussed below).

To tie the results in Table 4.4 to known metrics, we take the first retrieval result and score it as though it were the output of an ASR or MT system. Given a speech utterance from the test set that we want to transcribe, or a source sentence we wish to translate, we pick the closest sentence from a reference set using our learned DCCA model. We then score this pick using the relevant metric, WER for ASR and BLEU for MT. The score strongly depends on the contents of the reference set: if the reference set contains no appropriate sentence to transcribe (resp. translate)

Reference Set	WER	BLEU (MT)	BLEU (ST)
train	134%	5.2	0.2
train + test	27.4%	80.7	19.8
Baseline S2S	24.3%	57.3	27.9

TABLE 4.5: Scoring top-1 retrieval result from DGCCA models with ASR, MT and ST metrics. Models used (from left to right) were trained using speech and text (en); text (en) and text (pt); speech, text (en), text (pt) and video. Source sentences for the retrieval are from the test set.

the source, the WER (resp. BLEU) will be high (resp. low). We thus test on two reference sets: 1) the training set, 2) the union of the training and test set. In setting 1, the reference set does not contain the correct answers, whereas it does in setting 2. When using only the test set as a reference set, the score is almost perfect, and we only report the more challenging settings, in columns WER and BLEU (MT) of Table 4.5. The results on the train set are quite poor given that the train set may not contain appropriate sentences for the test set. We estimate this by finding, for each sentence in the test set, the closest sentence (in terms of edit distance) from the train set. This yields a BLEU of 10.6, and a WER of 63.0%. When using the union of test and train as a reference set, our model is still able to mostly pick out the correct sentences, achieving on par or better performance than a baseline sequence-to-sequence model. This is consistent with our retrieval scores, as the retrieval for text and text was slightly higher than speech and text.

n-modal experiments

In subsequent experiments, we used DGCCA to learn representations with more than 2 views. We learned representations with English text, speech and video, with k = 160, and report retrieval results in Table 4.6. As compared to Table 4.4, the retrieval scores between speech and text (en) decrease, as the model has to accommodate a third view. Keeping hyperparameters fixed and adding a fourth view, Portuguese text, we obtain the results in Table 4.7. Relative to Table 4.4, the text - text retrieval score increases, while the speech - text (en) score decreases, and the scores involving video decrease slightly. This could be explained by the fact that text - text retrieval is an easier task than those involving speech and video, so that the model trades off a higher loss in the video and speech domain for a lower loss in the text domain. To remedy this, one could add weights w_j to each reconstruction loss, or tune the architectures of the f_j. We again evaluate our speech - text (pt) retrieval with an ST task. The results are shown in column BLEU (ST) of Table 4.5, and are again consistent with the retrieval scores.

Discussion

As shown by our Recall@10 retrieval results, the CCA objective induces a shared space capturing most of the information shared across the original spaces. Scoring the top-1 retrieved data point with common MT, ASR and ST metrics is consistent with this finding. Moreover,

		Text (en)	**Speech**	**Video**
text (en)	dev	-	92.1	1.7
	test	-	89.8	1.8
speech	dev	92.1	-	1.9
	test	89.1	-	1.2
video	dev	1.4	1.9	-
	test	1.7	1.2	-

TABLE 4.6: Recall@10 for retrieving column modality given source row modality, for a DGCCA model trained on 3 views. Results from the bottom left triangle can be compared to those in Table 4.4.

		Text (pt)	**Text (en)**	**Speech**	**Video**
Text (pt)	dev	-	98.8	73.5	2.1
	test	-	98.3	71.0	1.1
Text (en)	dev	98.8	-	88.2	1.4
	test	98.4	-	85.4	0.9
Speech	dev	73.0	88.1	-	1.1
	test	70.7	85.4	-	1.0
Video	dev	2.1	1.1	1.0	-
	test	1.1	1.1	0.9	-

TABLE 4.7: Recall@10 for retrieving column modality given source row modality, for a DGCCA model trained on 4 views. Results from the bottom left triangle can be compared to those in Table 4.4.

this shared space is learned on top of high-level, unrelated representations: the training of the ASR and MT systems is entirely independent. Our results involving video are not in agreement with that hypothesis, and we see two possible explanations. First, there is a temporal mismatch between the video modality and the language content. Second, it is possible that the ResNet posteriors are either extremely noisy, or simply fail to identify certain relevant objects because of a domain mismatch. Previous work in the context of ASR shows that using the penultimate instead of the last layer of the ResNet makes little difference (Palaskar et al., 2018).

4.4 Chapter Conclusion

We propose a Contextual Acoustic Word Embedding (CAWE) model that is necessary to align the latent representations across the multiple modalities commonly available through video datasets for the semi-supervised learning approach we use (DGCCA). CAWE does not require word-boundary annotations within a spoken sentence as was necessary for previously developed acoustic word embedding methods. This method performs competitively on 16 standard word embedding evaluation benchmarks and are also useful for other acoustic downstream tasks such as spoken language understanding.

We use these word-level speech representations in an advanced, correlation-based representation learning method, Deep Generalized Canonical Correlation Analysis (DGCCA), which required latent space representation alignment across modalities. This method is a semi-supervised learning method that learns from the multiple multimodal views instead of fully supervised training. We use a real-world noisy dataset (the `How2` dataset) with this method for the first time; prior work had shown the utility of DGCCA either on synthetic datasets or on clean controlled-environment datasets. In addition to expanding this method to a real world dataset, we demonstrate its effectiveness on standard downstream tasks: speech translation, speech recognition, and text translation.

In the next chapter, we address video-level tasks such as summarization and question answering. For these tasks, there is no utterance-level information flow but rather video-level. To handle the complexity of video-level information control, we introduce the Hierarchical Latent Representation Fusion model that builds on top of the Latent Representation Fusion model presented in this chapter, which can now be used for longer context control of different input modalities. While the Latent Representation Fusion model was a semi-supervised learning problem, Hierarchical Latent Representation is designed for text generation that handles information selection, compression, and restructuring.

Chapter 5

Summarization & QA

5.1 Introduction

With Chapter 3 and Chapter 4, we focused on monotonic and re-ordering tasks that fuse multimodal information directly at the input or at a higher-level latent representation for Speech Recognition and Translation. Both of these tasks are conventionally modeled at a sentence-level with each sentence of a video considered an independent data point. While there could be necessary context across a video that improves these tasks with the entire video context instead of a single sentence, the memory and compute requirement make such modeling infeasible currently.

While sentence-level modeling is a solution to Speech Recognition and Translation, there are certain *abstraction* tasks such as Video Summarization or Question Answering that do not enjoy the same flexibility. For such abstraction tasks, entire video context is necessary to perform the information compression, re-phrasing, and re-structuring that is necessary to generate a natural language video summary or answer. In this Chapter, we extend the multimodal learning tasks to Video Summarization and Question Answering. We perform these tasks independently, as well as in conjunction using a transfer learning approach.

For video-level modeling and abstraction, there is a necessity for the multimodal fusion model to adapt to these task requirements as well. In this Chapter, we introduce the *Hierarchical Latent Representation Fusion* model that provides the necessary control for video-level abstraction. Figure 5.1 contrasts the Hierarchical Latent Representation Fusion model with the other fusion models used so far. Conceptually, the "hierarchical" design of this model allows for this video-level control to generate abstractive text accessing information from any of the input modalities: video or text transcript. Further discussion on this model is below.

Video summarization is a compression, rephrasing and restructuring task. Mulitmodal video summarization further combines information obtained from the visual modality. With these two input modalities, we address this by aiming to generate a short text summary of the video that describes the most salient content of the video. A video summary can aid the search and retrieval

of relevant videos without watching. it can also help in representing content of a video where other searchable metadata is unavailable (Song et al., 2011; Wang et al., 2012; Otani et al., 2016; Torabi et al., 2016). Video summaries benefit users through better contextual information and user experience, and helps video sharing platforms with increased user engagement and retention by retrieving or suggesting relevant videos.

We study multimodal summarization with various methods to summarize the intent of *open-domain instructional videos* stating the exclusive and unique features of the video, irrespective of modality. We study this task in detail using the How2 dataset (Sanabria et al., 2018) which contains human annotated video summaries for a varied range of topics. Our models generate natural language descriptions for video content using the transcriptions (both user-generated and output of automatic speech recognition systems) as well as visual features extracted from the video. We also introduce a new evaluation metric (Content F1) that suits this task and present detailed results to understand the task better.

In addition to summarization, we explore the video question answering task that generates natural language answers based on audio, video, textual questions, and textual video-summaries. In this task, we extend beyond the summarization task that involves compression of *all* input information into a shortened form, to now generating text based on specific questions by selecting appropriate portions of the inputs. In addition to compression and rephrasing required for summarization, question answering further requires information selection. For question answering, we design a transfer learning model that leverages the summarization model properties and adapts them to answer generation. We participated in the 7^{th} Dialog State Tracking Challenge (2019) with this transfer learning model. Our submissions ranked first in the automatic as well as human evaluation metrics of this challenge (Yoshino et al., 2018).

Hierarchical Latent Representation Fusion Model

The Input Fusion model provides a technique for monotonic adaptation of the various input modalities, here X_{M1} and X_{M2}, and is specifically designed for modalities that have a high granularity of monotonic constraint, for example, speech and transcription. The Latent Representation Fusion model provides a higher-level adaptation in the latent space, LY_1. This higher-level representation relaxes the strict monotonicity constraint allowing re-ordering tasks like translation.

For video summarization and question answering, there is no such monotonic constraint in the task. Instead, the is an abstraction constraint wherein the information across the entire video (not utterances) needs to be compressed and restructured to form natural language summaries or answers. This is often an open-vocabulary text generation problem. For such an abstraction constraint, we propose to extend the Latent Representation Fusion model to a *Hierarchical Latent Representation Fusion* model that can fuse input modalities, perform abstraction, as well as generate observable outputs Y_1. In our formulation, Y_1 is the output of a text generator.

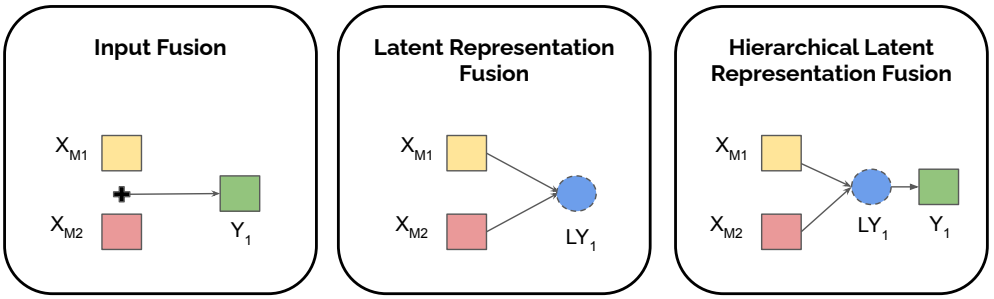


FIGURE 5.1: We build on top of the existing Input Fusion and Latent Representation Fusion models presented so far for Summarization and Question Answering. We present the Hierarchical Latent Representation Fusion model that not only learns a multimodal latent representation LY_1, but converts it into observable outputs Y_1 via hierarchical combination.

The output generator achieves explicit control over the input time-scales for both modalities X_{M1} and X_{M2} through LY_1. More specifically, to implement joint input fusion and abstraction, we use the Hierarchical Attention mechanism proposed by Libovický and Helcl within Latent Fusion (LY_1) step, and this modified LY_1 is used for text generation Y_1. The Hierarchical Attention mechanism was initially proposed for Machine Translation. In this work, we explore its applications for video-level abstraction tasks, Summarization and Question Answering. While the Hierarchical Latent Representation Fusion model can be used for Speech Recognition and Translation, the converse is not possible. For abstraction tasks, the hierarchical control over input modality time-scales provided by this model is essential. Through the experiments in this chapter, we show the need for such model evolution across learning tasks.

Chapter Structure

In this Chapter, we explore the two abstraction tasks in sequence, and in conjunction. We begin by describing the video summarization task formulation, followed by models used and the corresponding automatic and human evaluation results. The next Section describes the video question answering task, transfer learning from summarization to question answering to connect the two abstraction tasks, followed by the transfer learning results and the system description for our participation in the Dialog State Tracking Challenge with this transfer learning approach. The work presented in this chapter has been published in Palaskar et al. 2019a, Sanabria et al. 2019 and Palaskar et al. 2020b.

5.2 Summarization

5.2.1 Task Formulation

Summarization is a task of producing a shorter version of the content in the document while preserving its information and has been studied for both textual documents (automatic text summarization) and visual documents such as images and videos (video summarization). Automatic text summarization is a widely studied topic in natural language processing (Luhn, 1958; Kupiec et al., 1995; Mani, 1999); given a text document the task is to generate a textual summary for applications that can assist users to understand large documents. Most of the work on text summarization has focused on single-document summarization for domains such as news (Rush et al., 2015; Nallapati et al., 2016; See et al., 2017; Narayan et al., 2018) and some on multi-document summarization (Goldstein et al., 2000; Lin and Hovy, 2002; Woodsend and Lapata, 2012; Cao et al., 2015; Yasunaga et al., 2017).

Video summarization is the task of producing a compact version of the video (visual summary) by encapsulating the most informative parts (Money and Agius, 2008; Lu and Grauman, 2013; Gygli et al., 2014; Song et al., 2015; Sah et al., 2017). Multimodal summarization is the combination of textual and visual modalities by summarizing a video document with a text summary that summarizes the content of the video. Multimodal summarization is a more recent challenge with no benchmarking datasets yet. Li et al. (2017) collected a multimodal corpus of 500 English news videos and articles paired with manually annotated summaries. The dataset is small-scale and has news articles with audio, video, and text summaries, but there are no human annotated audio-transcripts.

Related tasks include image or video captioning and description generation, video story generation, procedure learning from instructional videos and title generation which focus on events or activities in the video and generating descriptions at various levels of granularity from single sentence to multiple sentences (Das et al., 2013; Regneri et al., 2013; Rohrbach et al., 2014; Zeng et al., 2016; Zhou et al., 2018a; Zhang et al., 2018; Gella et al., 2018). A closely related task to ours is video title generation where the task is to describe the most salient event in the video in a compact title that is aimed at capturing users attention (Zeng et al., 2016). Zhou et al. (2018a) present the YouCook II dataset containing instructional videos, specifically cooking recipes, with temporally localized annotations for the procedure which could be viewed as a summarization task as well although localized with time alignments between video segments and procedures.

5.2.2 Models

Text-based We study various summarization models. First, we use a Recurrent Neural Network (RNN) Sequence-to-Sequence (S2S) model (Sutskever et al., 2014b) consisting of an encoder RNN to encode (text or video features) with the attention mechanism (Bahdanau et al.,

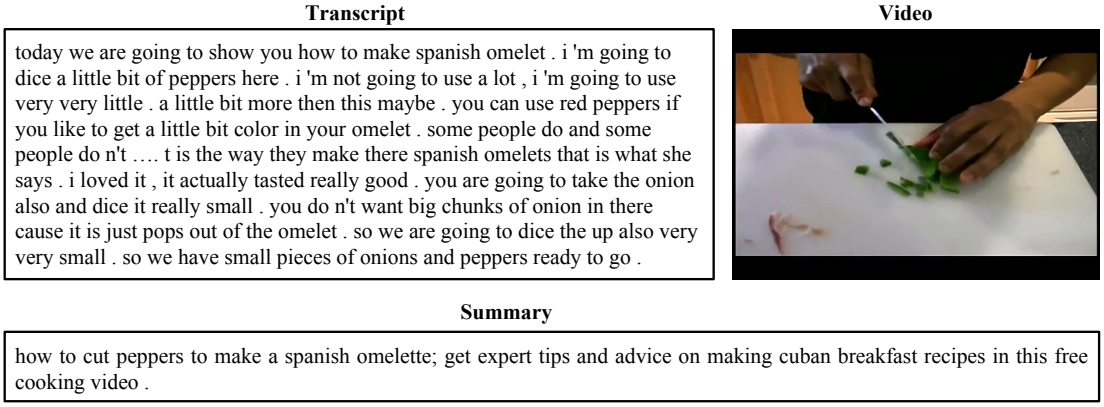


FIGURE 5.2: How2 dataset example with different modalities. "Cuban breakfast" and "free cooking video" is not mentioned in the transcript, and has to be derived from other sources.

2014b) and a decoder RNN to generate summaries. Our second model is a Pointer-Generator (PG) model (Vinyals et al., 2015a; Gülçehre et al., 2016) that has shown strong performance for abstractive summarization (Nallapati et al., 2016; See et al., 2017).

Video-based We represent videos by features extracted from a pre-trained action recognition model: a ResNeXt-101 3D Convolutional Neural Network (Hara et al., 2018) trained to recognize 400 different human actions in the Kinetics dataset (Kay et al., 2017). These features are 2048 dimensional, extracted for every 16 non-overlapping frames in the video. This results in a sequence of feature vectors per video rather than a single/global one. A single-layer RNN encoder is used to represent these sequence-based video features.

Text-and-Video-based As our third model, we use hierarchical attention approach of Libovický and Helcl 2017 originally proposed for multimodal machine translation to combine textual and visual modalities to generate text. The model first computes the context vector independently for each of the input modalities (text and video). In the next step, the context vectors are treated as states of another encoder, and a new vector is computed. In Figure 5.3 we present the building block of our models.

More specifically, the computation of the hierarchical attention model is divided in two steps as described in Libovický and Helcl 2017. Firstly, independent context computation, using the standard attention mechanism proposed by Bahdanau et al. (Bahdanau et al., 2014b). Equations 1-3 describe the standard attention mechanism that we will use further to build the hierarchical attention mechanism. e_{ij} is the representation of the attention energies, α_{ij} is the attention distribution, and c_i is the context vector in the i^{th} decoder step.

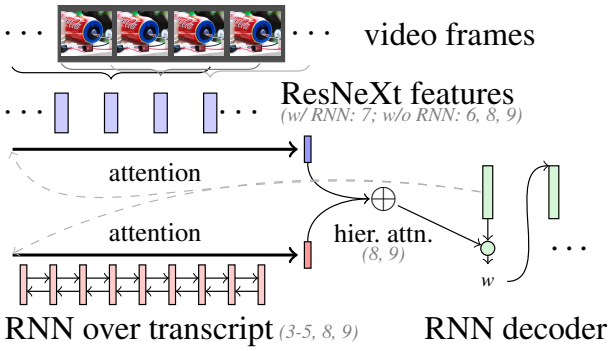


FIGURE 5.3: Building blocks of the sequence-to-sequence models, gray numbers in brackets indicate which components are utilized in which experiments.

$$e_{ij} = v_a^T tanh(W_a s_i + U_a h_j) \tag{5.1}$$

$$\alpha_{ij} = \frac{exp(e_{ij})}{\sum_{k=1}^{T_x} exp(e_{ik})} \tag{5.2}$$

$$c_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j \tag{5.3}$$

Equation 5.3 computes the context vector for each encoder state independently. The second step of hierarchical attention computation is as follows:

$$e_i^{(k)} = v_b^T tanh(W_b s_i + U_b^{(k)} c_i^{(k))} \tag{5.4}$$

$$\beta_i^{(k)} = \frac{exp(e_i^{(k)}}{\sum_{n=1}^{N} exp(e_i^{(n)})} \tag{5.5}$$

$$c_i = \sum_{k=1}^{N} \beta_i^{(k)} U_c^{(k)} c_i^{(k)} \tag{5.6}$$

The context vectors obtained via Equation 5.3 is projected onto a shared space (Equation 5.4) to compute another attention distribution over the projected context vectors (Equation 5.5), and their corresponding weighted average (Equation 5.6). $c_i^{(k)}$ is the context vector of the k-th encoder, additional trainable parameters v_b and W_b are shared for all encoders. $U_b^{(k)}$ and $U_c^{(k)}$ are encoder-specific projection matrices, that can be set equal and shared.

Set	Words
Transcript	the, to, and, you, a, it, that, of, is, i, going, we, in, your, this, 's, so, on
Summary	in, a, this, to, free, the, video, and, learn, from, on, with, how, tips, for, of, expert, an

TABLE 5.1: Most frequently occurring words in Transcript and Summaries.

5.2.3 Experimental Setup

Dataset The How2 dataset (Sanabria et al., 2018) contains about 2,000 hours of short instructional videos, spanning different domains such as cooking, sports, indoor/outdoor activities, music, etc. Each video is accompanied by a human-generated transcript and a 2 to 3 sentence summary is available for every video written to generate interest in a potential viewer. The example in Figure 5.2 shows the transcript describes instructions in detail, while the summary is a high-level overview of the entire video, mentioning that the peppers are being "cut", and that this is a "Cuban breakfast recipe", which is not mentioned in the transcript. We observe that text and vision modalities both contain complementary information, thereby when fused, helps in generating richer and more fluent summaries. Additionally, we can also leverage the speech modality by using the output of a speech recognizer as input to a summarization model instead of a human-annotated transcript. The How2 corpus contains 73,993 videos for training, 2,965 for validation and 2,156 for testing. The average length of transcripts is 291 words and of summaries is 33 words. A more general comparison of the How2 dataset for summarization as compared with certain common datasets is given in (Sanabria et al., 2018).

Table 5.1 shows the frequent words in transcripts (input) and summaries (output). The words in transcripts reflect conversational and spontaneous speech while words in the summary reflect their descriptive nature.

Evaluation We evaluate the summaries using the standard metric for abstractive summarization ROUGE-L (Lin and Och, 2004) that measures the longest common sequence between the reference and the generated summary. Additionally, we introduce the Content F1 metric that fits the template-like structure of the summaries. We analyze the most frequently occurring words in the transcription and summary. The words in transcript reflect the conversational and spontaneous speech while the words in the summaries reflect their descriptive nature. For examples, see Table 5.1.

The Content F1 metric is the F1 score of the content words in the summaries based over a monolingual alignment, similar to metrics used to evaluate quality of monolingual alignment (Sultan et al., 2014). We use the METEOR toolkit (Banerjee and Lavie, 2005; Denkowski and Lavie, 2014) to obtain the alignment. Then, we remove function words and task-specific stop words that appear in most of the summaries (see Table 5.1) from the reference and the hypothesis. The stop words are easy to predict and thus increase the ROUGE score. We treat remaining content

No.	Description	ROUGE-L	Content F1
1	Random Baseline using Language Model	27.5	8.3
2a	Rule-based Extractive summary	16.4	18.8
2b	Next-neighbor Summary	31.8	17.9
3	Using Extracted Sentence from 2a only (Text-only)	46.4	36.0
4	First 200 tokens (Text-only)	40.3	27.5
5a	S2S Complete Transcript (Text-only, 650 tokens)	**53.9**	**47.4**
5b	PG Complete Transcript (Text-only)	50.2	42.0
5c	ASR output Complete Transcript (Text-only)	46.1	34.7
6	Action Features only (Video)	38.5	24.8
7	Action Features + RNN (Video)	**46.3**	**34.9**
8	Ground-truth transcript + Action with Hierarchical Attn	**54.9**	**48.9**

TABLE 5.2: ROUGE-L and Content F1 for different summarization models: random baseline (1), rule-based extracted summary (2a), nearest neighbor summary (2b), different text-only (3,4,5a), pointer-generator (5b), ASR output transcript (5c), video-only (6-7) and text-and-video model (8).

words from the reference and the hypothesis as two bags of words and compute the F1 score over the alignment. Note that the score ignores the fluency of output.

In addition to automatic evaluation, we perform a human evaluation to understand the outputs of this task better. Following the abstractive summarization human annotation work of Grusky et al. (2018), we ask our annotators to label the generated output on a scale of $1-5$ on informativeness, relevance, coherence, and fluency. We perform this on randomly sampled 500 videos from the test set. We evaluate three models: two unimodal (text-only (5a), video-only (7)) and one multimodal (text-and-video (8)). Three workers annotated each video on Amazon Mechanical Turk. They compared outputs of unimodal and multimodal models with the ground-truth summary and assign a score between 1 (lowest) and 5 (highest). The annotators were shown the ground-truth summary and a candidate summary (without knowledge of the type of modality used to generate it). Annotation was restricted to English speaking countries. In total, 129 annotators participated in this task.

5.2.4 Results

As a baseline, we train an RNN language model (Sutskever et al., 2011) on all the summaries and randomly sample tokens from it. The output obtained is fluent in English leading to a high ROUGE score, but the content is unrelated which leads to a low Content F1 score in Table 5.2. As another baseline, we replace the target summary with a rule-based extracted summary from the transcription itself. We used the sentence containing words "how to" with predicates *learn*, *tell*, *show*, *discuss* or *explain*, usually the second sentence in the transcript. Our final baseline was a model trained with the summary of the nearest neighbor of each video in the Latent Dirichlet Allocation (LDA; Blei et al., 2003a) based topic space as a target. This model achieves

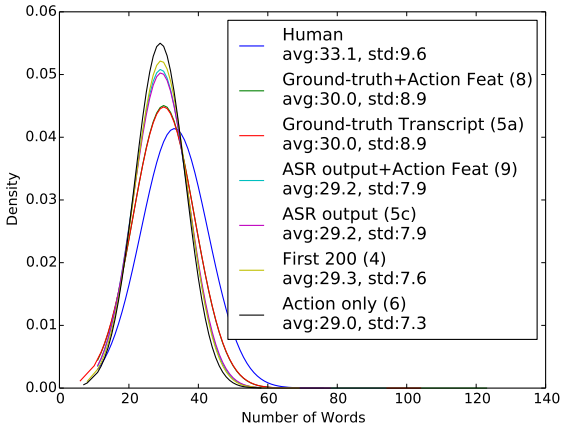


FIGURE 5.4: Word distribution in comparison with the human summaries for different unimodal and multimodal models. Density curves show the length distributions of human annotated and system produced summaries.

a similar Content F1 score as the rule-based model which shows the similarity of content and further demonstrates the utility of the Content F1 score.

We use the transcript (either ground-truth transcript or speech recognition output) and the video action features to train various models with different combinations of modalities. The text-only model performs best when using the complete transcript in the input (650 tokens). This is in contrast to prior work with news-domain summarization (Nallapati et al., 2016). We also observe that PG networks do not perform better than S2S models on this data which could be attributed to the abstractive nature of our summaries and also the lack of common n-gram overlap between input and output which is the important feature of PG networks. We also use the automatic transcriptions obtained from a pre-trained automatic speech recognizer as input to the summarization model. This model achieves competitive performance with the video-only models (described below) but degrades noticeably than ground-truth transcription summarization model. This is as expected due to the large margin of ASR errors in distant-microphone open-domain speech recognition.

We trained two video-only models: the first one uses a single mean-pooled feature vector representation for the entire video, while the second one applies a single layer RNN over the vectors in time. Note that using only the action features in input reaches almost competitive ROUGE and Content F1 scores compared to the text-only model showing the importance of both modalities in this task. Finally, the hierarchical attention model that combines both modalities obtains the highest score.

Human Evaluation In Table 5.3, we report human evaluation scores on our best text-only, video-only and multimodal models. In three evaluation measures, the multimodal models with the hierarchical attention reach the best scores.

In Figure 5.4, we analyze the word distributions of different system generated summaries with the human annotated reference. The density curves show that most model outputs are shorter

Model (No.)	INF	REL	COH	FLU
Text-only (5a)	3.86	**3.78**	3.78	3.92
Video-only (7)	3.58	3.30	3.71	3.80
Text-and-Video (8)	**3.89**	3.74	**3.85**	**3.94**

TABLE 5.3: Human evaluation scores on 4 different measures of Informativeness (INF), Relevance (REL), Coherence (COH), Fluency (FLU).

No.	Model	R-L	C-F1	Output
-	Reference	-	-	watch and learn how to tie thread to a hook to help with fly tying as explained by out expert in this free how - to video on fly tying tips and techniques .
8	Ground-truth text + Action Feat.	54.9	48.9	learn from our expert how to attach thread to fly fishing for fly fishing in this free how - to video on fly tying tips and techniques .
5a	Text-only (Ground-truth)	53.9	47.4	learn from our expert how to tie a thread for fly fishing in this free how - to video on fly tying tips and techniques .
5c	ASR output	46.1	34.7	learn tips and techniques for fly fishing in this free fishing video on techniques for and making fly fishing nymphs .
7	Action Features + RNN	46.3	34.9	learn about the equipment needed for fly tying , as well as other fly fishing tips from our expert in this free how - to video on fly tying tips and techniques .
6	Action Features only	38.5	24.8	learn from our expert how to do a double half hitch knot in this free video clip about how to use fly fishing .
2b	Next Neighbor	31.8	17.9	use a sheep shank knot to shorten a long piece of rope . learn how to tie sheep shank knots for shortening rope in this free knot tying video from an eagle scout .
1	Random Baseline	27.5	8.3	learn tips on how to play the bass drum beat variation on the guitar in this free video clip on music theory and guitar lesson .

TABLE 5.4: Example outputs of ground-truth text-and-video with hierarchical attention (8), text-only with ground-truth (5a), text-only with ASR output (5c), action features with RNN (7) and action features only (6) models compared with the reference, the topic-based next neighbor (2b) and random baseline (1). Arranged in the order of best to worst summary in this table.

than human annotations with the action-only model (6) being the shortest as expected. Interestingly, the two different uni-modal and multimodal systems with ground-truth text and ASR output text features are very similar in length showing that the improvements in Rouge-L and Content-F1 scores stem from the difference in content rather than length. Example presented in Table 5.4 shows how the outputs vary.

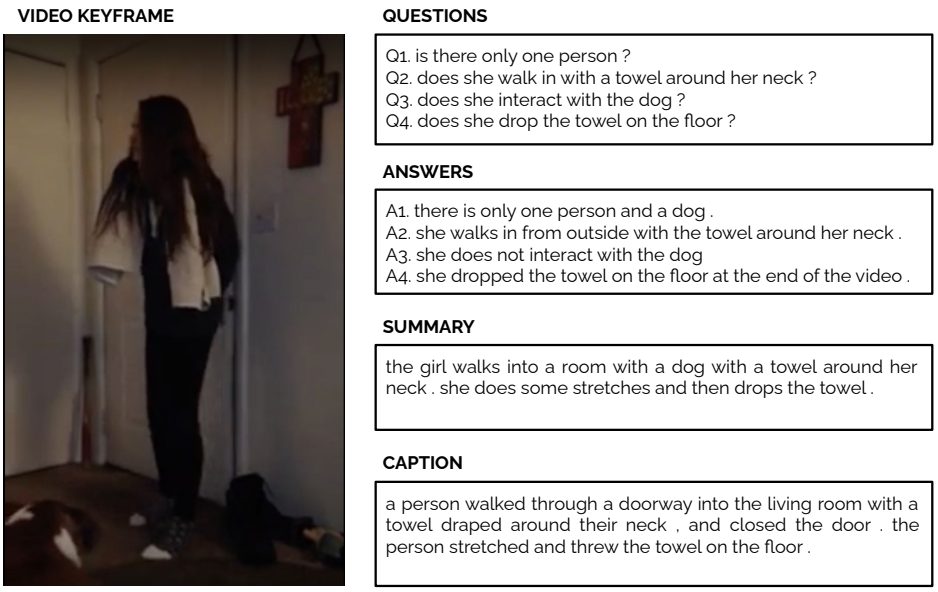


FIGURE 5.5: An example from the Charades dataset. For every video, there exists a video-dialog of 10 questions and answers each. The dataset additionally has the audio, summary and caption for each video.

5.3 Question Answering

5.3.1 Task Description

Inspired by the popular American word guessing game, Charades, where one player acts out a phrase and the other players guess what phrase it is, Sigurdsson et al. 2016 collect the *Charades* dataset of common human household activities. They ask annotators on Amazon Mechanical Turk to record their activities at home using their personal equipment, and upload the recorded video to their platform. They follow a set procedure for these recordings called the *Hollywood in Homes* approach: (1) script generation, (2) video direction and acting based on the scripts, and (3) video verification. At the time, this was the largest dataset of common household activities recorded *at home* and in an uncontrolled environment. They collect 10,000 videos in total, averaging 30 seconds each. There are 157 unique actions across the dataset. An example video from this dataset can be viewed at `https://youtu.be/x9AhZLDkbyc`.

Alamri et al. in 2019 extend this dataset to a Video Question Answering task, the Audio-Visual Scene-Aware Dialog (AVSD) task. They take the videos collected in the Charades dataset and collect 10 question-answer dialog sets for each, in addition to a video summary and a caption. The summary is a compressed version of the actions/activities in the video, whereas the caption is a more descriptive text of video content. This was one of the first video dialog datasets that contained the audio, video, summary, question, answer, and dialog modalities. The goal of the AVSD task is to automatically answer questions about a visual stream (*i.e.*, videos or images) and maintain dialog context across the various questions.

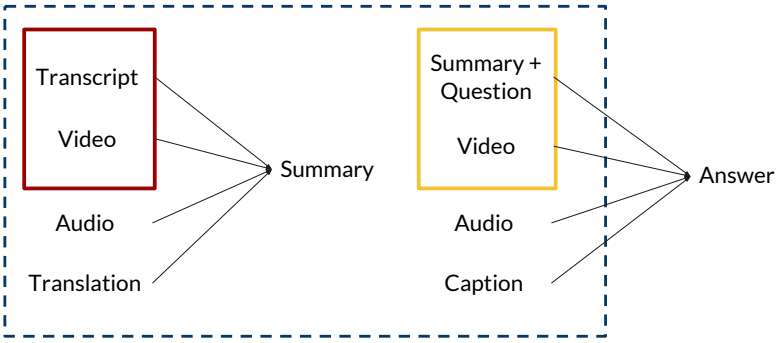


FIGURE 5.6: Our best performing model use the weights of a trained summarization model on the How2 dataset (left) to initialize the training of our DTSC7 challenge model (right).

5.3.2 Transfer Learning: Summarization to QA

There are many common modalities between the Charades dataset and the How2 dataset. To exploit this fact and increase the training data for this task, we first train models on the How2 data and then fine-tune (`FT`) them on the Charades dataset. The transfer learning setup and respective input modalities are shown in Figure 5.6. The models trained on How2 data use transcription of video (and/or video features) in the input and generate an abstractive textual summary of the video in the output. The methods used for training these are described in (Libovický et al., 2018). We initialize the training of a sequence-to-sequence model for the Charades data with the weights of this learned model, using summary+question (and/or video features) in the input and generating the answer in the output. While fine-tuning, we share the vocabulary for the two datasets and randomly initialize words that do not occur in both.

Although the two datasets have the same modalities, there are differences in the outputs. The main difference between the two datasets is that the summaries of the How2 dataset (usually 2-3 sentences) follow a particular pattern or template as described in (Sanabria et al., 2018), while the pattern of answers (usually single sentence) in the AVSD dataset do not follow any specific template, and are linguistically free-flowing[1]. Also, the videos in the How2 dataset are much longer and semantically-task specific (instructional) than the Charades dataset where they are about day-to-day activities, making the visual modality a semantically richer modality for How2.

We participated in the 7^{th} Dialog State Tracking Challenge (2019) which used this dataset and applied our video summarization models described in Section 5.2.2 via Transfer Learning to Dialog-based Video Question Answering. Our submissions ranked first in the automatic as well as human evaluation metrics of this challenge.

[1]The AVSD data collection procedure tried to avoid "Yes"-"No" answer biases and short answer biases by collecting more descriptive answers (Alamri et al., 2018)

5.3.3 Experimental Setup

Dataset The DSTC7 organizers crowdsourced human annotated questions, answers, captions, and summaries from videos belonging to the Charades dataset (Sigurdsson et al., 2016) to curate the Audio-Visual Scene Aware Dialog dataset (Alamri et al., 2017, 2018; Sigurdsson et al., 2016). The original videos of this dataset contain untrimmed and multi-action videos. In the DSTC7 dataset, each video has ten questions and answers pairs. The dataset statistics for training, validation, disclosed test and undisclosed evaluation test set are given in Table 5.5.

	Charades		How2
Split	**Sentences**	**Videos**	**Videos**
train	76590	7659	73993
val	17870	1787	2965
test	7330	733	2156
held_out	6745	1710	169*

TABLE 5.5: Dataset statistics for Charades and How2. The number of videos in the held_out test set of How2 is from the 300 hours subset of the data (*).

Multimodal Features To fully exploit the information provided in the videos we extract different representations from each modality. To do so, we use DNNs trained for a particular task to extract their internal representation. Based on empirical observations, we know that pre-trained DNNs capture specific characteristics to solve an specific task. Therefore we use DNNs trained for object recognition, place recognition, action recognition and audio even detection to extract meaningful representation of the data. We hypothesize that each of this features will capture information of the video that will be useful to answer each question.

Object Features: These feature are an intermediate representation of a CNN ResNet-50 trained with the ImageNet datset (Deng et al., 2009a)[2]. ImageNet is a dataset for object recognition with more than one milion of images annotated with 1000 classes.

Place Features: (Nallapati et al., 2016) extract scene feature representations from a static image. In this case, the network is trained to recognize scenes from an image. More specifically, (Nallapati et al., 2016) trained the network with Places dataset (Zhou et al., 2017) that contains 10 million images comprising with more than 400 classes.

I3D Flow: (Carreira and Zisserman, 2017) are video features extracted from an spatiotemporal CNN architecture trained for action recognition. The network is trained to recognize 400 different human actions. (Carreira and Zisserman, 2017) use a optical flow representation of the Kinetics Human Action Video dataset that contains 400 samples for class. We extract a 2048 dimensional representation from the `Mixed_5c` layer.

I3D RGB: are also video features from (Carreira and Zisserman, 2017) but instead of using optical flow, the network use video frames with three channels as input stream.

[2]https://github.com/KaimingHe/deep-residual-networks

3D ResNeXt: (Hara et al., 2018) is a 3 dimensional version of the traditional ResNet-101. The third dimensionality of the convolution allows us to extract features from the video instead from an image. The network, similar to VGGish and I3D Flow, is trained with the Kinetics Human Action Video dataset. From 3D ResNeXt, we extract a 2048 dimensional vector.

VGGish: (Hershey et al., 2017) are audio features that have been extracted from a CNN to perform audio even detection network. The network architecture is inspired by the traditional image classification network: VGG. This network works with log Mel spectrograms features extracted from 16 KHz audio recordings. The network was trained with 70M training videos (5.24 million hours) with a total of 30,871 target labels. We use a 128-dimensional embedding.

Evaluation We report the common natural language processing metrics like BLEU (Papineni et al., 2002), METEOR (Denkowski and Lavie, 2014), ROUGE-L (Lin and Och, 2004), and CIDEr (Vedantam et al., 2015). In addition to these objective evaluation metrics for this task, the organizers also evaluated some models on crowdsourced human scores. The human evaluators were asked to score model outputs based on how semantically, grammatically and factually correct the generated answers are.

Models We apply the same text-, video-, and text-and-video multimodal models as for summarization to this task. For the added audio modality via VGGish features, we apply the same hierarchical attention model. This is to evaluate the robustness of the hierarchical attention model on other abstractive tasks as well as to evaluate the fusion mechanism on a vast array of multimodal features. We additionally evaluate the benefits of transfer learning on datasets with shared modalities.

5.3.4 Results

Table 5.6 presents our different models trained using Charades and How2 data, and using various modalities one at a time (text-only, video-only) or together (text-and-video). First, we report the baseline results using the model architecture and code-base provided by the competition organizers (Alamri et al., 2017). We replicate their results using I3D RGB, I3D Flow and VGGish features. To compare the performance of different visual features, we use Objects, Places and 3D ResNeXt in the baseline and observe similar or slightly worse performance showing that all features are equally rich representations.

For text-only models (model #7 and #8 in Tables 5.6, 5.7), the input is a concatenation of the summary of the video followed by the question. The summary is repeated for every question following the assumption that it has relevant input information for each question. Further, we will see that improvements in the text-and-video models over text-only models show that only using the summary in the input may not be sufficient and visual features are useful in such scenarios. In the video-only models (model #9 and #10), we observe lower performance than

No.	Description	BL-1	BL-2	BL-3	BL-4	MET	R-L	C
Input: Text and Video (different features), Model: Baseline (Alamri et al., 2017)								
1	Charades & I3D RGB & I3D Flow	0.273	0.173	0.118	0.084	0.117	0.291	0.766
2	Charades & I3D RGB & I3D Flow & VGGish	0.271	0.172	0.118	**0.085**	0.116	**0.292**	**0.791**
3	Charades & Objects	0.272	0.173	0.117	0.083	**0.118**	0.287	0.742
4	Charades & Places	0.269	0.171	0.116	0.082	0.116	0.286	0.727
5	Charades & 3D ResNeXt	0.264	0.166	0.112	0.079	0.116	0.284	0.711
6	Charades & 3D ResNeXt & Objects & Places	**0.276**	**0.176**	**0.120**	**0.085**	**0.118**	0.287	0.752
Input: Text Only, Model: S2S								
7	Charades	0.297	0.200	0.142	0.105	0.138	0.330	1.079
8	How2 FT Charades	**0.311**	**0.212**	**0.152**	**0.114**	**0.146**	**0.337**	**1.169**
Input: Video Only (3D ResNeXt features), Model: Video-RNN								
9	Charades	0.264	0.170	0.118	0.085	0.116	0.294	0.804
10	How2 FT Charades	**0.279**	**0.179**	**0.122**	**0.086**	**0.122**	**0.300**	**0.833**
Input: Text and Video (different features), Model: Hierarchical Attention								
11	Charades & Objects	0.274	0.179	0.125	0.091	0.121	0.301	0.876
12	Charades & Places	0.287	0.191	0.136	0.101	0.133	0.320	1.036
13	Charades & VGGish	0.303	0.206	0.148	0.110	0.144	0.338	1.150
14	Charades & 3D ResNeXt	**0.306**	**0.209**	**0.150**	**0.112**	**0.144**	**0.338**	**1.161**
15	How2 FT Charades & 3D ResNeXt	**0.307**	**0.210**	**0.151**	**0.113**	**0.145**	**0.339**	**1.180**

TABLE 5.6: Automatic evaluation metrics on the test set provided by the organizers (groundtruth available). Models 1-6 are trained using the methods described in (Alamri et al., 2017) with different modalities. We treat them as our baselines. Models 7 and 8 are trained on text-only, models 9 an 10 on video-only and models 11-15 on text-and-video. Models 8, 10 and 15 are first trained on the How2 data and then fine-tuned FT on the Charades data.

the text-only model as expected. It is interesting to note that the video-only model is worse only by about 3-4 ROUGE-L points than the text-only model showing the richness of the visual features (3D ResNeXt). In text-and-video models (model #11-15), we use Hierarchical attention for multimodal adaptation with different visual features. We observe that 3D ResNeXt performs the best for adaptation models.

We fine-tune each of these models on the summarization models trained using the How2 data. In the text-only (model #8) and video-only (model #10), we see substantial gains using fine-tuning over models trained only on Charades data. For the text-and-video model, the gains are not too high, and further exploration of this behavior is necessary to understand why.

Table 5.7 shows the 4 best models from Table 5.6 which we submitted to the challenge. These were evaluated on the undisclosed evaluation test set by the challenge organizers. The baselines (model #1 and #2) are same as those in the previous table but evaluated on the undisclosed test

No.	Description	BL-1	BL-4	MET	R-L	C	Human
Input: Text and Video (different features), Model: Baseline (Alamri et al., 2017)							
1	Charades & I3D RGB & I3D Flow	0.621	0.305	0.217	0.481	0.733	-
2	Charades & I3D RGB & I3D Flow & VGGish	0.626	0.309	0.215	0.487	0.746	2.848
Input: Text Only, Model: S2S							
7	Charades *	0.692	0.364	0.254	0.543	1.006	-
8	How2 FT Charades *	**0.711**	**0.376**	**0.264**	**0.554**	**1.076**	3.394
Input: Text and Video (3D ResNeXt features), Model:Hierarchical Attention							
9	Charades *	0.718	**0.394**	**0.267**	**0.563**	**1.094**	**3.491**
15	How2 FT Charades *	**0.723**	**0.387**	**0.266**	**0.564**	1.087	3.459
-	Groundtruth	-	-	-	-	-	3.938

TABLE 5.7: **Automatic and Human evaluation** scores on the undisclosed evaluation test set prepared by DTSC7 organizers (we do not have access to groundtruth). Models 1 and 2 are the same baselines as in Table 5.6. Models 3 and 4 are trained on text-only. Models 5 and 6 are trained on text-and-video using Hierarchical attention. Models 4 and 6 are first trained on the How2 data and then fine-tuned FT on the Charades data. Systems marks with an asterisk (*) were the ones submitted to the challenge. Model 6 i.e. 'How2 FT Charades' was the best performing model. Note that the first column has a reference number to the model in Table 5.6.

set. The trends we observe on the prototype test set are same as those observed on the undisclosed test set. Additionally, this table also contains the human evaluation scores. The human evaluators were asked to rate the system generated answers as well as the groundtruth references answers which scored a topline of 3.938, using the human evaluation strategies designed by the challenge organizers. Our best model scores 3.491 on this metric while the baseline scores only 2.848. This further shows that our models score well not only in quantitative scores but also in qualitative scores.

Error Analysis We perform certain qualitative analysis of the different models: text-only, video-only and text-and-video, each with fine-tuning, to better understand the quality of the results and the model behavior (refer Table 5.8). We compute the number of unique words in the answers generated by each of the three models. We observe that multimodal fusion and fine-tuning with How2 both help increase the number of unique words. Another metric we use is the average length of outputs (avg.). Fine-tuning leads to longer outputs in text-only and video-only models. These models also led to higher gains over Charades only models in Table 5.6. Our final metric is the percentage (%) of sentences changed in a given system when compared with the text-only model trained only on Charades data. We compute this metric by counting all tokens changed, as well as by counting only content-based tokens, *i.e.* not counting stop words or punctuation as changed. We see the maximum percentage of changed sentences are in the video-only models. The difference percentage change by considering only content words is approximately 10-15% absolute.

Modality	Model	# unique words	Avg. o/p len	% sent. changed	% sent changed in content word
Text only	Charades	384	8.98	-	-
	How2 FT Charades	726	9.23	79.46%	65.30%
Video only	Charades	269	9.22	83.60%	72.35%
	How2 FT Charades	331	9.37	87.00%	74.91%
Text & Video	Charades	488	8.95	76.37%	59.00%
	How2 FT Charades	740	8.98	77.72%	60.21%

TABLE 5.8: Qualitative evaluation of different systems. % sentences (sent) changed are with respect to text-only Charades model.

5.4 Chapter Conclusion

We extend the series of learning tasks for video understanding to video summarization and video question answering in this chapter. We present models for the abstractive nature of these natural language generation tasks and explore a transfer learning method between the two to leverage common modalities and common task characteristics.

We present the Hierarchical Latent Representation Fusion model to design video-level control over the temporal sequences of inputs modalities: audio, video and text. This model is an evolution over the Monotonic Input Fusion and Latent Representation Fusion models. We discuss the drawbacks of these two models for abstractive tasks and the need and benefits of the Hierarchical model. We demonstrate the application of this model to the two abstraction tasks and show consistent improvement with Hierarchical multimodal modeling over established baselines as well as uni-modal models.

In the next chapter, we will address the last task of rationalization. We first introduce the task and its manifestations relevant to this thesis. We describe the different datasets used, and finally introduce the Hierarchical Interpretable Fusion model that is required for the rationalization task formulation. We describe how the previous models so far are not expressive enough for this task. Compared to summarization, rationalization manifests as two observable outputs, dependent information flow between the two outputs, and being able to generate information that was not explicitly mentioned in the input e.g. commonsense rationales for events around us.

Chapter 6

Rationalization

6.1 Introduction

In Chapters 3, 4, and 5, we discussed multimodal grounding for various video understanding tasks. Across chapters, task complexity and consequently multimodal modeling complexity and modalities involved increased. We now extend this further to a *Rationalization* task. With the rationalization task, we extend beyond abstract-learning tasks to also generate explainable rationales for the candidate answers in a question answering task or candidate summaries in s summarization task. These rationales can be a powerful interpretability tool as well as a user-targeted explanation technique that provides support for the model hypotheses.

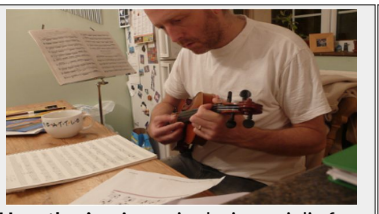
Visual Commonsense Reasoning (VCR) is an example of multimodal rationalization that has been introduced in recent years (Li et al., 2018; Zellers et al., 2019). VCR is designed as a question answering task: given an image and a set of questions, a correct answer is to be chosen from amongst four choices, and a corresponding rationale has to be chosen, again from four choices, that justifies or reasons about the chosen answer. All four (correct and incorrect) answer and rationale choices are human annotated and to simplify the reasoning task, this problem is designed as a classification problem in all early work (Zellers et al., 2019).

But such annotation of four answer-rationale choices, as well as a multiple choice question setup that explains model behavior is highly limiting. Barring annotation costs and time required, this setup is restricted to the datasets, domain of data, and limited choice of options for explainability. A more applicable approach is to train models to *generate* such rationales, i.e. open ended generation, that explains model behavior. This now increases the complexity of the task several fold as we have to train models to explain world behaviors. For example, in Figure 6.1, we demonstrate examples from three commonly used multimodal datasets in this field: VQA-X (Park et al., 2018) (visual question answering with explanations), E-SNLI-VE (Kayser et al., 2021) (explanations for visual language inference), and VCR (Zellers et al., 2019) (visual commonsense reasoning for realistic scenarios depicted through movies).

Question: Where is the bus going?

Answer: Union Station.

Explanation: The sign says Union Station.



Hypothesis: A man is playing a violin for the crowd.

Label: Contradiction

Explanation: There is no crowd listening to the man with the violin. He seems to be rehearsing alone in his room.

Question: Why is person looking aggravated?

Answer: The clerk is not helping him.

Rationale: He is waiting at the window and there is no clerk.

FIGURE 6.1: Examples demonstrating the rationalization task. The model is trained to generate the answers (or labels) as well as the commonsense rationales (or explanations) that justify the answers. Examples are ordered in increasing order of difficulty from three widely used multimodal datasets in this field: VQA-X (Park et al., 2019), E-SNLI-VE (Kayser et al., 2021), and VCR (Zellers et al., 2019).

As shown from the examples, open-ended generation of such explanations is a difficult task not only when compared with classification via a multiple choice set up, but also as a text generation problem. Often, explanations involve explaining real-world scenarios using commonsense reasoning or situational understanding that is very human-like. There could also be several correct answer-rationales combinations. As with other text generation problems, rationalization also suffers from poor automatic evaluation metrics. Related work has proposed human-evaluation metrics to evaluate the faithfulness (Wu and Mooney, 2018; Jain et al., 2020; Jacovi and Goldberg, 2020) and plausibility of generated rationales (Marasović et al., 2020), but this evaluation is difficult to use during training and for reproducibility of results.

From a modeling perspective, this type of data might not even be represented explicitly in the input (lack of a crowd in image two, or absence of the clerk in image 3), or could involve implicit inference that the model is not trained towards (identifying "Union Station" as an answer in image 1). Co-generation of answers and rationales is termed *Self-Rationalization* (), a newly formed term. To the best of our knowledge, we are the first ones to present results on such self-rationalization.

Rationalization need not be only via training models to predict or generate rationales. Rationalization is inherently a task of understanding model behavior. It aims to enhance explainability and interpretability. We propose that interpretability could also be achieved by generating auxiliary outputs from models trained to do a certain task. For instance, a list of noun and verb phrases as auxiliary outputs while image captioning or a list of semantic concepts as auxiliary outputs for video summarization. In theory, we propose to train models towards generating auxiliary outputs in addition to the main downstream task they are being trained towards, and these auxiliary outputs act as rationales to provide insight into model behavior.

Figure 6.2 depicts rationalization for existing multimodal generation tasks: captioning and summarization, without relying on external annotation (as in self-rationalization). From the visual

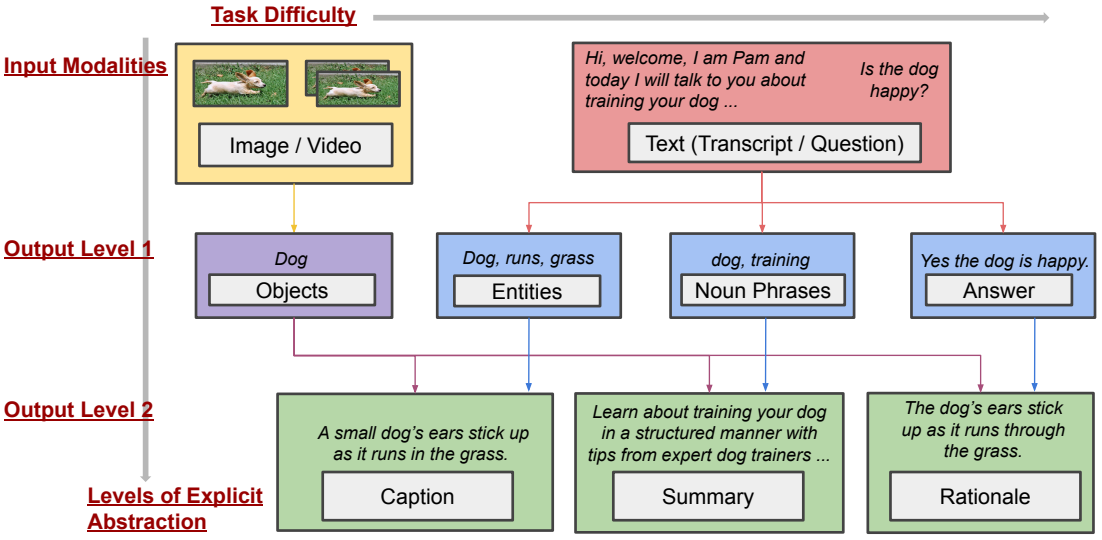


FIGURE 6.2: Demonstration of rationalization for existing multimodal generation tasks. Framework depicts three different multimodal generation tasks: captioning, summarization, and self-rationalization. For each, the auxiliary tasks are the entities, noun phrases, and answers respectively.

modality (image or video), the corresponding auxiliary task could be detecting the list of objects in the visuals. As the task gets more complex (left to right horizontally), the auxiliary task can be more complex as well. Each auxiliary task provides some explainability into model outputs. For example, entities *dog, runs, grass* lead to a caption containing these entities. Similarly, *dog, training* are noun phrases associated with the visual summary. The third task that generates answers and rationales is the self-rationalization task discussed earlier. Interpretability for this task can be achieved in two ways; first by generating an answer as an intermediate step before rationalization, and second by the generated rationale itself that explains the reasoning for a given answer to be the correct answer.

Figure 6.2 shows one particular example of how existing tasks could be broken into smaller components. In this case, language is decomposed using structure (linguistic and syntactic structure), but there could be other definitions. Along the vertical axis, there are explicit levels of outputs. These correspond with the degree of abstraction involved. These levels could also be defined in further detail or with further abstraction. In the following sections, we present results using the levels of abstraction shown decomposing via language structure.

While some of the text generation challenges involved in rationalization could be addressed using the models presented so far in this thesis, for example, multimodal fusion, abstraction, or information selection, rationalization involves dependent generation. Dependence between the answer and rationale, or the auxiliary outputs meant to aid interpretability. In this chapter, we present the Hierarchical Interpretable Fusion model that aims to tackle the newer challenges with rationalization.

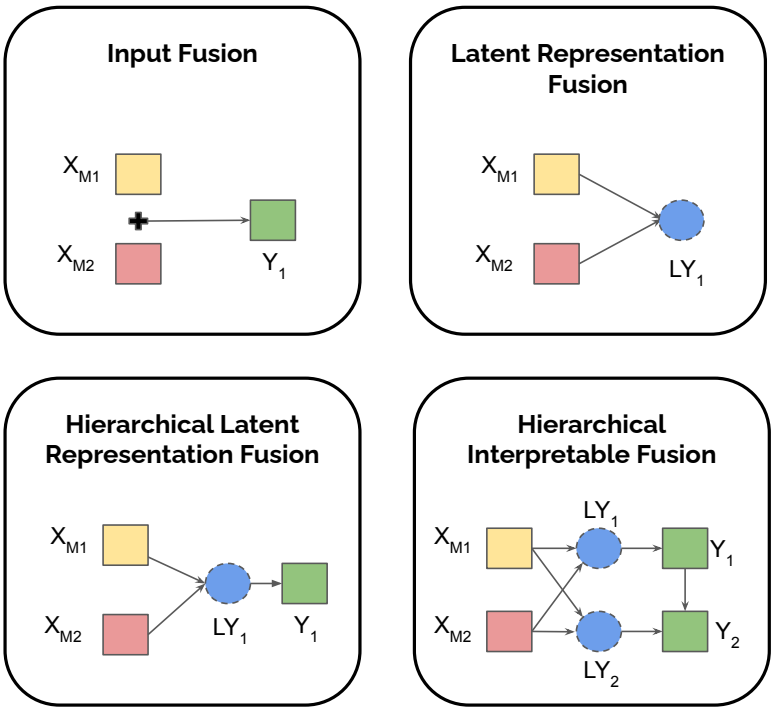


FIGURE 6.3: Expanding the fusion models to the fourth model: Hierarchical Interpretable Fusion model.

Hierarchical Interpretable Fusion Model

With the three previous multimodal fusion models, we focused explicitly on methods of fusion and controllability, each gradually increasing in complexity to handle the task and modality complexities. With the *Hierarchical Interpretable Fusion* model, we combine the *Latent Representation Fusion* and *Hierarchical Latent Representation Fusion* together, while also aiming for interpretable generation. For the scope of this work, we define interpretable generation as the generation of some observable, not latent, intermediate output Y_1 followed by final observable output Y_2. Each of these outputs undergo latent modality fusion represented by LY_1 and LY_2. LY_1 and Y_1, or LY_2 and Y_2 could individually form the *Hierarchical Latent Representation Fusion* model from the previous chapter. The dependency between the two outputs Y_1 and Y_2 as shown in Figure 6.3 represents the combination of the previous fusion models into this one.

We will develop and apply this model to the rationalization task where X_{M1} and X_{M2} will be the input image and questions, Y_1 will be the answer, and Y_2 the corresponding rationale. Given the nature of the rationalization task, this particular model is well suited for the interpretability as well as dependency properties.

Chapter Structure

This chapter describes both approaches to rationalization. First, we talk about rationales through semantic concepts. These could be entities, objects, noun phrases, with relevant semantic correlations to the given downstream task. We describe in detail the process to obtain these from existing multimodal datasets without need for any additional annotation. We present models trained towards learning to predict or generate these concepts as auxiliary outputs in the process of building for the main downstream task. We will present a two-phase training approach that models the dependence between auxiliary outputs. This is one category of the Hierarchical Interpretable Fusion model.

Further, we present the task of self-rationalization. We describe the task setup, relevant datasets, state-of-the-art models, and necessary evaluation strategies. We also present another category of the Hierarchical Interpretable Fusion model that is trained end-to-end (as opposed to two-phase before). We perform extensive human evaluation for this task.

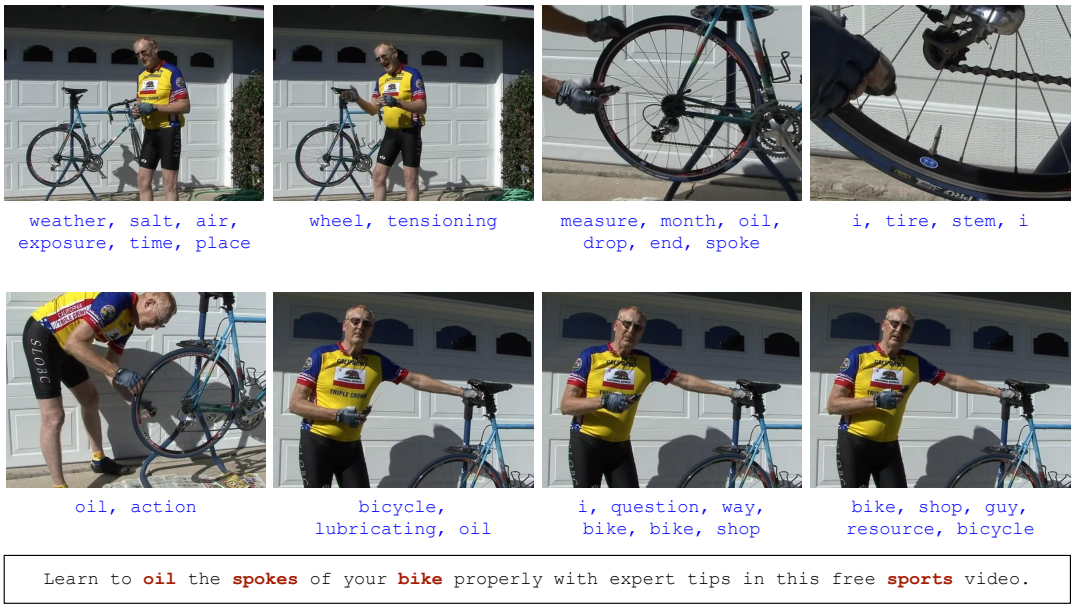


FIGURE 6.4: An example from the How2 dataset showing semantic concepts – specific concepts: granular, utterance-level, in blue, and abstract concepts: higher-level, video-level, in red.

6.2 Rationales through Semantic Concepts

Intermediate generation of observable auxiliary outputs can act as proxy for model explanations. While the main training task of the model may not be such output generation, co-generation, or multi-task generation of such outputs lead to model interpretability. In tasks where access to human annotated rationales or explanations is not available, such auxiliary generated could still be a viable approach. Below, we detail one such approach. We propose to increase model explainability through intermediate semantic concept generation. These concepts are automatically derived from existing annotations of multimodal data and do not rely on expensive external annotations. As these concepts are semantically rich representations from the model, they can act as proxies for rationales. This approach can be scaled to any amount of data and any downstream text generation task as it does not require added annotations. We start by defining semantic concepts and show its use case on the task of multimodal summarization covered in Chapter 5.

6.2.1 Defining Semantic Concepts

Figure 6.4 shows an example of an instructional video from the How2 dataset (**?**). The speaker describes verbally as well as demonstrates visually the steps he is going to perform in the video. The video comprises of relevant objects (bicycle, cycling gear), scenes (garage, outdoors), and actions (standing, bending, fixing things). Based on the granularity of the observed entities, we propose three levels of video understanding:

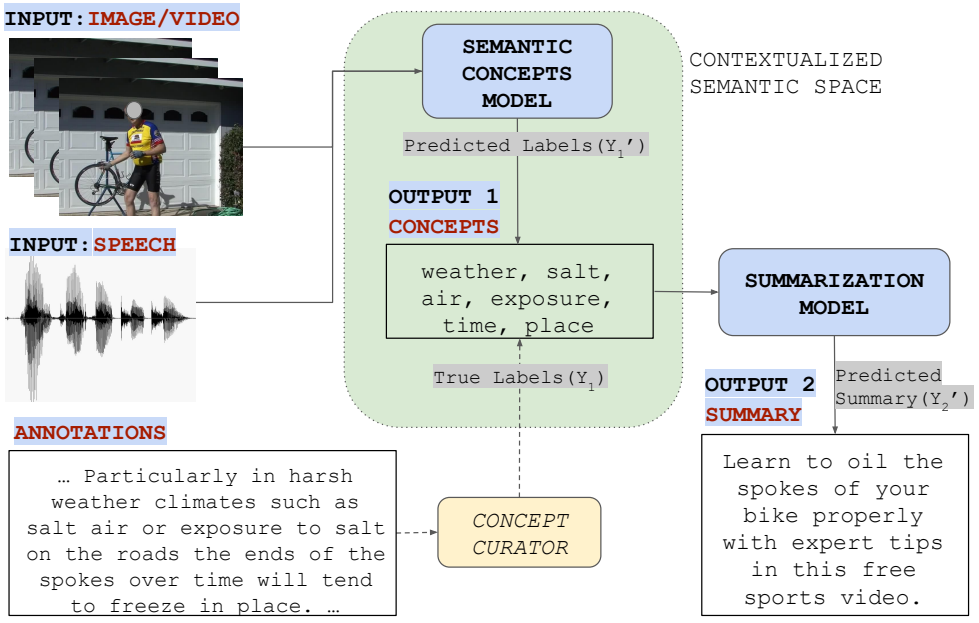


FIGURE 6.5: Learning Semantic Concepts from existing data. Flowchart shows the data curation process, and its relation with the remaining task setup.

Specific concepts are semantically-rich content words that represent low-level fine-grained details of the task. These are curated from the utterance-level transcript of the video. These are highly domain-specific and their vocabulary may contain rare but important domain words. Figure 6.6 shows 2 keyframes from the video corresponding to 2 utterances and each keyframe contains domain-specific words (e.g. weather, tensioning, spoke, etc.).

Abstract concepts are higher-level coarse-grained concepts that broadly represent the contents of the video, i.e. oil, spokes, bike, sports. These are curated from the human-annotated video summaries and are more generic and topic-based.

Video Summary is the natural language summary that provides a single sentence overview of the video. This summary consists of information gathered from all video modalities including speech, video, and text transcript.

6.2.2 Learning Semantic Concepts

Labeling Ground Truth Concepts

For the proposed concept extraction task, we use automatic methods to curate Specific and Abstract concept labels as collecting human annotation at this scale and granularity is expensive and difficult to standardize across annotators. To the best of our knowledge, no existing dataset contains these annotations, hence we curate this data.

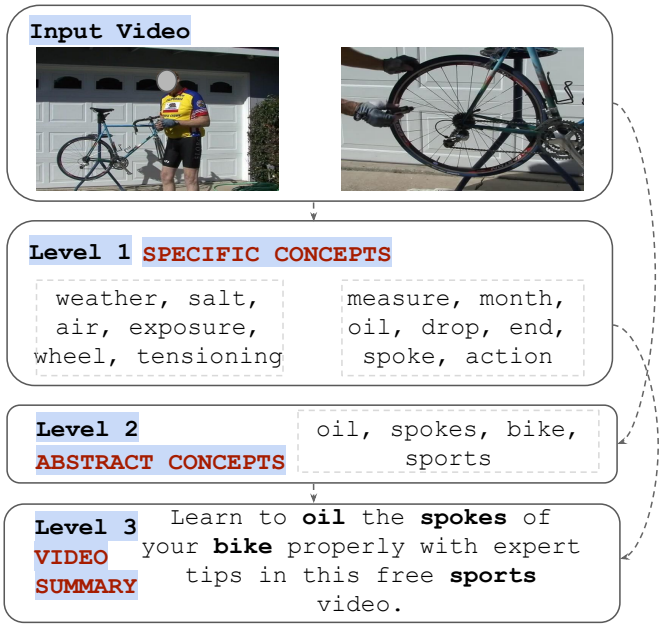


FIGURE 6.6: Hierarchical video understanding depiction: input is the video, outputs are a sequence of 3 levels of hierarchy: Specific concepts, Abstract concepts, and the Summary. Specific concepts are detailed, domain-specific. Abstract concepts provide a concise high-level overview. Summary is a textual overview of the video.

Video is often comprised of speech, video, and corresponding annotations (either transcriptions, translations, or other textual metadata). In such multimodal scenarios, some information is often repeated across modalities, for e.g. you might not have the necessity for captions if you understand the spoken language. This information repetition brings forth an opportunity to automatically curate ground truth labels for tasks where data annotation is expensive. In this work, we follow this technique and use the human-annotated video transcripts and summaries for Specific and Abstract concept curation respectively.

Noun and verb part-of-speech tags in a sentence form a major portion of meaningful and domain-specific actions and content words (Ghadiyaram et al., 2019). Dependency parses or subject-verb-object tuples are other methods of extracting content words from text automatically. The accuracy of any of these techniques for off-the-shelf usage depends on the type of dataset they are being applied to, e.g. models trained on written text do not perform as well on the spoken text. We use spaCy (Honnibal and Montani, 2017) to extract ground truth concept labels, and restrict our concepts to nouns and noun phrases as that worked best for both Specific concept extraction (which was on segmented speech utterances) as well as Abstract concept extraction (which was on long textual summaries of the video)[1].

Dataset	Concept	Modalities	Split	Samples	Vocab	Avg. #
Flickr8k	Specific	Speech, Image, Transcript	Train	30,000	**1,461**	2.0
			Test	5,000	-	2.0
How2-300h-Utt	Specific	Speech, Image, Transcript	Train	184,286	**9,014**	2.9
			Test	2,361	-	3.0
How2-300h-Video	Abstract	Speech, Video, Transcript, Summary	Train	13,172	**2,611**	5.9
			Test	127	-	5.6
How2-2000h-Video	Abstract	Speech, Video, Transcript, Summary	Train	73,993	**5,227**	5.9
			Test	2,156	-	5.8

TABLE 6.1: Table shows dataset statistics, available modalities, vocabulary and average number (#) of concepts for Flickr8k, How2-300h, and How2-2000h datasets. This table introduces the proposed task from a dataset size and vocabulary perspective. Note the large target vocabulary space.

6.2.3 Task Setup

Datasets & Statistics

Flickr8k The Flickr8k corpus (Hodosh et al., 2013) is a commonly used dataset for image captioning. Flickr8k-Audio is a subset of this that contains 3 parallel modalities: images, captions and spoken captions (read speech) (Harwath and Glass, 2015b). For each image, there are 5 captions leading to a total of 40,000 unique captions. The concept vocabulary is restricted to those that occur at least 3 times resulting in 1461 concepts. Table 6.8 summarizes the dataset statistics. Here, as captions are only available at the image-level, we can only learn Specific Concepts in this dataset (Abstract Concepts are modeled at video-level).

How2 Dataset The How2 dataset (Sanabria et al., 2018) is an open-source open-domain instructional videos corpus that contains 4 parallel modalities: speech, video, human-annotated transcription, and a summary. In this work, we use the following subsets of How2: How2-300h-Utt, How2-300h-Video, and How2-2000h-Video. The How2-300h-Utt contains speech utterances, corresponding transcripts, and images for Specific concept modeling. How2-300h-Video is the 300h video equivalent used for modeling Abstract concepts, which is then scaled to the larger How2-2000h-Video. The dataset has a large vocabulary of 9,014 Specific concepts, 2611 (300 h), and 5,227 (2000 h) Abstract concepts. This vocabulary size for video understanding tasks is much larger than prior work in speech/image/video classification tasks. While we use Flickr and How2 in this work, any other dataset that provides multi-way parallel data can also be used instead.

[1]Dependency parse does not perform well on spoken text.

Multimodal Features

Speech The speech features are extracted as dense time-series data following the standard feature extraction pipeline (Povey et al., 2011; Watanabe et al., 2017). We extract 80-dimensional filterbank features and 3-dimensional pitch features for every frame of the utterances sampled at 30 frames/second.

Image We extract ResNeXt-50 features (Xie et al., 2017) from images. The ResNeXt-50 model is trained on ImageNet (Deng et al., 2009b) for object detection. We extract a 1000-dimensional feature vector for every image from this model.

Video Hara et al. (2018) propose a 3-dimensional version of the traditional ResNet-101 model (He et al., 2016a), 3D ResNeXt, with a third dimension of convolution that represents the sequential video information. The network is trained with the Kinetics Human Action Video dataset (Kay et al., 2017). From 3D ResNeXt, we extract a 2048-dimensional vector for every keyframe.

Evaluation and Pseudo Toplines

Evaluation We evaluate the quality of the concepts as well as summaries. For concept evaluation, Precision (P), Recall (R), and F1 are reported. This is at the corpus level to remove any input/output length variation dependencies. For summaries, we use standard text generation metrics: METEOR (Denkowski and Lavie, 2014) and ROUGE (Lin and Och, 2004).

Pseudo-Toplines In addition to the proposed models, we design certain pseudo-topline models to gain perspective on the proposed task. These pseudo-toplines are designed with text in the input, either annotated text or predicted text using a speech recognizer (ASR), hence their nomenclature *pseudo-toplines*. Annotated text uses the same inputs as were used during concept data curation. Predicted text using ASR is again very close to the target concepts, and is a text-based input. For predicted text, we use two ASRs, a large-scale out-of-domain `ASPIRE` model (Peddinti et al., 2015) which is widely-used as an off-the-shelf English recognizer, and a smaller in-domain model trained on Flickr and How2 using methods by Palaskar and Metze (2018). Despite the presence of such toplines for this proposed task, the reason to use other input modalities like speech and vision instead of text is to try to capture subtle semantic information available through these modalities that is often lost in text. In the next section, we show a comparison of multimodal inputs versus pseudo-text inputs for the proposed task of video understanding.

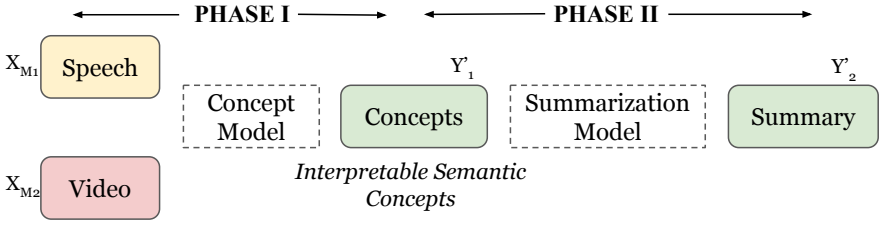


FIGURE 6.7: Hierarchical Interpretable Fusion through two phase training. Two phase cascaded model for multimodal summarization via semantic concept learning.

6.2.4 Models

We develop a cascaded input-to-concept and concept-to-summary model in two phases. Phase I is the concept generation model that takes various multimodal inputs. Phase II is the concept-to-summary model that takes as inputs the concepts generated in Phase I. Phase I Concept models are modality-specific fusion models that are trained towards generating contextual semantic concepts. Phase II Summarization models are text-to-text generation models for unstructured to structured generation. The dependence between concepts (output 1) and summary (output 2) is modeled during phase II. This is the two-phased training approach for the Hierarchical Interpretable Fusion model.

Classification vs. Generation of Concepts

Specific or Abstract concept outputs could either be extracted as a classification task (no order or correlation across concepts) or as a generation task (modeling concept order to build more context). We explore different models for this task below.

BiLSTM Classification A Bi-directional Long Short Term Memory (BiLSTM) (Hochreiter and Schmidhuber, 1997) encoder processes the sequential inputs into a high-level representation followed by a binary cross-entropy loss. The binary cross-entropy loss designs this task as a multi-label classification (MLC) problem where each input can have multiple independent concepts (or classes) as outputs. This model predicts a probability of occurrence for each concept in the vocabulary independent of each other.

Attentive BiLSTM Classification The BiLSTM encoder is followed by an attention layer (Bahdanau et al., 2014b) in this model (`Attn BiLSTM`). This model uses the embedding of each concept in the vocabulary as a query to the attention model, retrieves the corresponding context vector, and performs classification.

Attentive ConvNet Classification Instead of a BiLSTM encoder, we use a convolutional network as encoder in this model, followed by an attention layer (`Attn ConvNet`).

Attentive S2S Generation An attentive sequence-to-sequence model (`Attn S2S`) is used to model the order of concepts. Concepts are *generated* as a sequence using an LSTM decoder (Sutskever et al., 2014b) instead of a classifier. While there is no syntactical structure between concepts, there is a strong semantic correlation in their order. Additionally, the concepts generated in this task are not mutually exclusive as assumed by a classifier, motivating generation.

Phase I: Concept Models

Speech-to-Concept (S2C) We use a Bidirectional Long Short Term Memory (Hochreiter and Schmidhuber, 1997) encoder with pyramidal subsampling and an attention decoder (LSTM) for concept generation with speech inputs (Sutskever et al., 2014b; Chan et al., 2016). This model learns to directly map speech to corresponding concepts, extending the work on direct acoustic-to-word speech recognizers (Palaskar and Metze, 2018) to directly generate concepts from speech (much like spoken language understanding). Speech inputs are very dense sequence vectors; using a pyramidal BiLSTM encoder converts low-level speech signals into higher-level features with input subsampling, a common technique for sequence-based speech models (Chan et al., 2016). Additionally, we also use weights from a pre-trained acoustic-to-word speech recognizers in a transfer learning approach to boost speech-based model performance for direct speech-to-concept mapping.

Visual Adaptive Training (VAT) Visual Adaptive Training is a multimodal adaptation model to combine the speech and vision modalities. We adapt the S2C model using the VAT strategy previously applied to multimodal speech recognition (Miao and Metze, 2016a; Caglayan et al., 2019). The VAT model learns an embedding shift transform between the low-level input speech signals and the corresponding video features leading to a transformed low-level audio-visual multimodal signal, which then proceeds through the pyramidal BiLSTM encoder (and decoder) of the S2C model. The VAT submodule is trained end-to-end with the S2C model.

VideoRNN The given sequence of features from multiple frames for every utterance or video are represented into higher-level features using a BiLSTM encoder.

Hierarchical Attention (HierAttn) Hierarchical Attention is a multimodal adaptation model to combine text and vision modalities applied to machine translation (Libovický and Helcl, 2017) and summarization (Palaskar et al., 2019a). In this model, there are separate BiLSTM encoders for each input, with an encoder-specific attention layer for each. This is followed by another attention layer, the hierarchical attention layer, applied on top of the encoder-specific attention layers, generating a multimodal context vector. Via this the hierarchical attention layer learns to weigh each input modality. The output of this hierarchical attention layer is fed into an LSTM decoder.

Task	Model	P	R	F1
Clf	BiLSTM	70.6	53.3	60.8
Clf	Attn BiLSTM	82.3	56.0	66.6
Clf	Attn ConvNet	**82.8**	67.6	74.4
Gen	Attn S2S	80.7	**79.4**	**80.0**

TABLE 6.2: Concept extraction results as a classification (Clf) or generation (Gen) task on Flickr8k captions.

Pred. Text-to-Concept (S′2C) For video-level concept generation, the speech lengths are too long to build a single S2C model. For current computational limitations, we represent long speech by predicted text (S′) using an off-the-shelf ASR (Peddinti et al., 2015). This is the predicted-text-to-concept model (S′2C).

Phase II: Summarization Models

S2S This model takes the Specific and Abstract concepts predicted by concept extraction models as inputs and converts them into a natural language summary (video Summary in Figure 6.5). Outputs of the semantic concept extraction model pass through a standard BiLSTM encoder followed by an attention layer and an LSTM decoder (Sutskever et al., 2014b).

6.2.5 Results

Classification vs. Generation

We evaluate the classification and generation-based concept extraction models in Table 6.2 on the Flickr8k dataset. Generation-based S2S model with attention (Attn S2S) significantly outperforms all the classification-based approaches in Recall and F1 scores. This establishes the strong role of context for concept extraction in the proposed task. Based on this, we use generation based models for concept extraction with modifications as required based on modalities (as described in Section 6.2.4).

Specific Concepts Generation

Table 6.3 contains results for Specific concept generation on the How2-300h-Utt dataset. Speech-based Direct S2C model outperforms the video-based VideoRNN model on all metrics. The Direct S2C model achieves a huge boost in performance by transfer learning using a pre-trained ASR. On top of this improvement, the VAT model gives significant improvements over the Direct S2C model – an absolute improvement of 3 F1 points. As speech is a noisy signal in the How2 dataset, grounding with the vision modality improves performance.

No.	I/P Modalities	Models	Train	Vocab	P	R	F1
1	Video	VideoRNN	✓	9014	13.3	4.7	7.0
2	Speech	Direct S2C	✓	9014	26.0	21.5	23.5
3	Speech	Direct S2C (transfer lrng)	✓	9014	62.8	62.7	62.7
4	Speech + Video	VAT (transfer lrng)	✓	9014	**66.6**	**64.7**	**65.7**
5	Pred. Text	S′2C OOD ASR	✗	102750	75.1	69.6	72.3
6	Pred. Text	S′2C In-Domain ASR	✗	9644	66.1	64.7	65.4
7	Ann. Text	Ground truth concepts	✗	9014	100	100	100

TABLE 6.3: Specific concepts generation on the How2-300h-Utt data at utterance level. Train column indicates whether the model is trained for concept generation. I/P modalities shows the model-specific input modalities. OOD: out-of-domain.

No.	I/P Modalities	Models	Train	Vocab	P	R	F1
1	Image	ImageRNN	✓	1461	16.9	14.3	15.5
2	Speech	Direct S2C	✓	1461	50.6	49.5	50.0
3	Speech	Direct S2C (transfer lrng)	✓	1461	**67.7**	**65.0**	**66.4**
4	Speech + Image	VAT (transfer lrng)	✓	1461	**67.7**	64.5	66.1
5	Pred. Text	S′2C OOD ASR	✗	102750	76.7	67.1	71.6
6	Pred. Text	S′2C In-Domain ASR	✗	1664	83.4	76.6	79.9
7	Ann. Text	ground truth concepts	✗	1461	100	100	100

TABLE 6.4: Specific concepts generation results on the Flickr8k dataset. OOD: out-of-domain.

Additionally, the VAT model performs competitively with the predicted text with an in-domain ASR, *without* any text signal in its input. This emphasizes that using speech as the primary modality and vision as the adapting signal captures crucial semantic information. With the VAT model, we demonstrate the power of learning multimodal semantic concepts using the speech and vision modalities of a video, that perform competitively with a pseudo-topline without any loss in performance.

To check if the model learns to produce rare concepts, we drop the 20 most frequently occurring concepts leading to F1 drop 65.7 to 56.2 in the VAT model. While this is significant, it still shows that the model is learning meaningful semantic concepts and is capable of generating rare concepts. Out-of-domain ASR performs better than in-domain on the How2 data due to its larger vocabulary, more training data, and the relatively high OOV rate (11.2%) of the in-domain ASR.

Similarly, Table 6.4 contains results of equivalent Specific concept generation experiments on the Flickr8k dataset. Again, the speech modality by itself outperforms the image only model on all metrics. The Direct S2C model with transfer learning performs much better; the F1 score increases from 50 to 66.4. The VAT model in this case does not lead to any significant difference compared to the speech-only model as the audio signal of the Flickr dataset is much cleaner than the How2 data, and multimodal adaptation using the visual modality does not lead to further gain.

I/P Modalities	Models	Train	How2-300h-Video			How2-2000h-Video		
			P	R	F1	P	R	F1
Pred. Text	S′2C OOD ASR	✓	16.4	40.6	23.5	52.5	57.3	54.8
Video	VideoRNN	✓	40.8	46.7	43.6	58.6	**64.0**	61.2
Pred. Text + Video	HierAttn	✓	**47.9**	**47.0**	**47.4**	**66.2**	63.2	**64.7**
Ann. Text	S2S	✓	46.6	49.1	47.8	66.2	66.4	66.3
Ann. Text + Video	HierAttn	✓	54.1	54.9	54.4	71.5	69.1	70.3

TABLE 6.5: Abstract concepts generation on the How2-300h-Video and How2-2000h-Video data. Train column indicates whether the model is trained for concept generation on the given input modalities (I/P modalities). OOD: out-of-domain.

In conclusion, multimodal fusion via VAT performs at par with the predicted text pseudo-topline, demonstrating a method to leverage the speech and vision modalities towards learning semantic concepts without loss in performance. Further, we contend that the How2 corpus is a better example of real-world open-domain data, and results on this data demonstrate the applicability of the proposed approach to open-domain "in the wild" data.

Abstract Concepts Generation

Table 6.5 shows the Abstract concept generation at video-level on the How2-300h-Video and How2-2000h-Video sets. The video-only model for Abstract concept generation performs better as it is not downsampled at an utterance-level anymore, as was required for Specific concepts models. Overall, the Hierarchical Attention (HierAttn) model for predicted text and video achieves significantly higher performance than either modality by itself. Having access to a reliable ASR is not as useful for Abstract concept modeling as was for Specific concepts – the predicted text model achieves lowest F1 in Table 6.5 and the performance difference between annotated and predicted text models is lower than Specific concepts models. This highlights the importance of other modalities and Hierarchical Attention based multimodal fusion for Abstract concept generation. Using more training data with How2-2000h-Video boosts the performance of all models while maintaining the same trends as the How2-300h-Video set.

Concepts to Summarization

For the summarization task, our two baselines are, (1) a language model (LM) trained on the target summaries, and (2) a strong sequence-to-sequence (S2S) abstractive summarization model, the current state-of-the-art on this data (Palaskar et al., 2019a), which takes the complete human-annotated video transcript as the input and summarizes it without any intermediate concepts (results obtained by running their code). Table 6.6 contains results for Specific and Abstract concept to summary generation on the How2-300h-Video data. Both Specific and Abstract concept models outperform the LM baseline significantly. The Hierarchical Attention (HierAttn) Abstract concepts model outperforms the S2S baseline on METEOR with 3 absolute points,

Concept	Concept Model in Cascade	M	RG
No	LM	15.0	32.3
No	S2S (Palaskar et al., 2019a)	27.6	**54.5**
Specific	S2C	20.9	43.6
Specific	VAT	21.8	45.9
Abstract	Out-of-Domain ASR	21.2	44.6
Abstract	VideoRNN	24.3	49.2
Abstract	HierAttn	**30.4**	51.2

TABLE 6.6: Summarization using Specific and Abstract concept generation models evaluated using METEOR (M) and ROUGE-L (RG). Concept model in cascade denotes the particular concept generation model used for summarization.

Model	Output Concepts/Summary
Groundtruth	side, stretch, exercise, video
OoD ASR	exercise, **fitness**, **trainer**, video
VideoRNN	**press**, exercise, video
Groundtruth	learn a side stretch exercise with small weights for your pilates routine in this free exercise video .
OoD ASR	learn how to do pilates exercise with tips from a **fitness trainer** in this free exercise video .
VideoRNN	learn a **chest press** exercise with tips from a pilates instructor in this free exercise video .
S2C	learn how to do the weekend yoga pose with tips from a **fitness** instructor in this free yoga lesson video .
VAT	learn more about this exercise with tips from a **fitness instructor** in this free exercise video .

TABLE 6.7: Example model outputs showing creative generation. OoD stands for out-of-domain ASR.

demonstrating the benefit of modeling concept generation as an intermediate task. An important advantage of the METEOR score is its evaluation of synonyms in addition to exact n-gram match in language generation (Denkowski and Lavie, 2014). A significant improvement in METEOR with this model suggests the generation of creative summaries, containing semantically relevant words, which can be measured with METEOR but not with ROUGE-L that expects exact match for the longest common subsequence, hence a corresponding decrease in ROUGE-L score. Finally, summarization using multimodal concepts models leads to an absolute improvement of 2-7 Rouge points in Specific and Abstract concepts respectively, over unimodal models.

Qualitative Evaluation

Table 6.7 shows model outputs for certain concept generation and summarization models. In ASPIRE and VideoRNN, concept models predict novel, semantically relevant concepts such as *press, fitness, trainer* which are not in the ground truth but match the topic of the video.

Similarly in other examples, we see higher word diversity in generated summaries by using the learned semantic concepts as inputs for e.g. *chest press exercise, pilates exercise, weekend yoga pose*, etc.

6.3 Self-Rationalization

In the past few years, there has been a growing interest in explainablility and/or interpretability of neural models for language tasks (Liu et al., 2019; Tang et al., 2020; Danilevsky et al., 2020), as well as for multimodal tasks (Hendricks et al., 2016; Kim et al., 2018; Hancock et al., 2018; Camburu et al., 2018; Ehsan et al., 2018; Wu and Mooney, 2019; Narang et al., 2020; Wiegreffe et al., 2021; Kayser et al., 2021). One common method in interpretable AI (XAI) (Arrieta et al., 2020) is to generate post-hoc explanations; given a fully trained and tested model, generate useful approximations of the models inner workings using certain metrics or natural language (Jacovi and Goldberg, 2021; Camburu et al., 2018; Kayser et al., 2021; Clinciu et al., 2021). Such approaches do not alter the models training itself. Another approach is to integrate such explanation learning into the model itself, along with the specific downstream tasks. Free-text rationales, that can potentially extend beyond the scope of datasets and tasks they were collected for. Such interpretability aims towards making the often black-box neural models understandable, especially useful when deployed in safety-critical scenarios, such as autonomous navigation or medical decision support. Beyond increasing interpretability, free-text rationales can also be used to improve given downstream tasks, by using auto-generated free-text rationales as another representation of inputs.

Open-ended generation of rationales pushes the boundaries of reasoning tasks to beyond annotated data, and beyond the tasks for which this data was collected. In particular, it enables the models to potentially be deployed "in-the-wild" for other NLP systems requiring interpretability. To bound such open-ended rationale generation, we explore models that also generate answers to visual questions or entailment labels as an intermediate anchoring step before rationale generation, shown in Figure 6.1. Wiegreffe et al. (2021) introduce the term "Self-Rationalization" for this class of models that perform such open-ended generation of two associated outputs. In this work, we explore various existing vision-language models as well as propose a model for the task of vision-language self-rationalization.

Interpretable NLP through free-text rationalization automatically implies that models possess worldly "knowledge", "commonsense", or "reasoning" capabilities, similar to humans. Figure 6.1 shows examples from three different vision-language reasoning datasets. The example explanations represent straightforward reasoning or commonsense capabilities that humans use, but current models lack.

There is a rapid, concurrent growth in multimodal representation learning and text generation many core questions regarding multimodal self-explainability are not answered.

For instance, what is more beneficial for generating text from multimodal inputs: training text decoders from scratch using multimodal data that contains only text that is much simpler than text used for training massive pretrained language models (LMs), that on the other hand have not seen images during their extensive pretraining, or finetuning the LMs?

Dataset	Task	# Samples train/val/test	Avg. Answer Len train/val/test	Avg. Explanation Len train/val/test
VCR	Visual Commonsense Reasoning	212.9K / 26.5K / 25.2K	7.54 / 7.65 / 7.55	16.16 / 16.19 / 16.07
E-SNLI-VE	Visual Entailment	402K / 14K / 15K	1/1/1	12.3/13.3/13.2
VQA-X	Visual Question Answering	29.5K / 1.5K / 2K	1.03/1.05/1.03	8.6/9.0/9.2

TABLE 6.8: Specifications of the target datasets. VCR explanations and answers are notably more longer which makes them more challenging to generate automatically. Sources: VCR (Zellers et al., 2019), E-SNLI-VE (Kayser et al., 2021), VQA-X (Park et al., 2018).

Does the answer changes with (1) The size of finetuning data because a text-only language model can be changed sufficiently if we have a lot of visual-textual data, but what if we don't, does it behave like a text-only model then? (2) How about the model size? These multimodal transformers are still small relative to the our largest language models and larger the model typically larger the improvements.

6.3.1 Background

The sub-areas of *Explainable NLP* (ExNLP) or Interpretable Machine Learning involve tasks that use explanations: either as an additional data signal to improve downstream task performance, or as outputs themselves that provide model explainability. The task of Self-Rationalization falls under the second category. With this task, we hope to push current ExNLP models to not only perform said downstream tasks but also generate free-text explanations for the same. The ultimate goal of such models would be in-the-wild explanations for human-computer decision-support systems of any kind.

We start with exploring the feasibility of this task, from simple to more difficult datasets. Design and evaluate on relevant metrics as existing automated language generation evaluation faces further challenges for evaluating explanations, and finally compare with two main class of models for vision-language generation: unified pre-trained models and adapted models.

6.3.2 Tasks and Datasets

The complexity of a Vision-Language Self-Rationalization task can be controlled in two forms: (1) the complexity of the answer, and (2) the complexity of the explanation. The complexity of the answer is defined by certain answer properties such as single-word or multi-word, single-sentence or multi-sentence, type of answer, dependence on visual signal, etc. The complexity of the explanations are governed by whether it was automatically sourced or human annotated, free-form or structured text, single-sentence or multi-sentence, and overall the "difficulty" of the given image/question pair. We work with three datasets with increasing order of complexity of answers and explanations.

VQA-X VQA-X (Park et al., 2018) is the extension of the widely-used Visual Question Answering (Antol et al., 2015) and the Visual Question Answering v2 (Goyal et al., 2017) datasets, with the addition of corresponding explanations. The images here are originally sourced from the MSCOCO dataset (Lin et al., 2014), and the answers are collected for open-ended questions about these images that require vision, language, and commonsense knowledge to answer. The explanations annotated provide textual justifications with relevant visual grounding. VQA-X contains one explanation per question-image pair in the training set and three per question-image pair in the test set.

E-SNLI-VE E-SNLI-VE (Kayser et al., 2021) is a visual-textual dataset for entailment. E-SNLI-VE combines annotations from two datasets: (1) SNLI-VE (Xie et al., 2019), collected by replacing the textual premises of SNLI (Bowman et al., 2015) with Flickr30K images (Young et al., 2014), and (2) E-SNLI (Camburu et al., 2018), a dataset of crowdsourced explanations for SNLI. This procedure of automatic combinations has led to some errors in this data collection (Vu et al., 2018) as hypothesis of SNLI were originally annotated without the context of corresponding images. Despite these challenges, as the entailment task builds on top of "simple" question answering in VQA-X, we present this as our second task/dataset.

VCR VCR (Zellers et al., 2019) is a carefully crowdsourced dataset of answers and explanations for visual scenes extracted from Hollywood movies. Given that, the visual context in this data is much more complex than MSCOCO or Flickr30K images, leading to correspondingly complex answers and explanations. Zellers et al. carefully instructed crowdworkers to first annotate answers for a given question-image pair, and then showed the annotated answer along with the question-image pair to a different set of annotators to get the corresponding explanation. In this task, the explanations are more like rationales for why a given answer is correct, but in essence, explanations and rationales mean the same in our context.

The dataset statistics with average answer and explanation length as given in Table 6.8 highlights differences and complexities of each task.

6.3.3 Automatic & Human Evaluation

Accuracy (and proxy accuracy) is an automated metric to evaluate quality of answer generation. BERTscore (Zhang* et al., 2020) is an automated metric to evaluate explanations. Both these automated metrics are useful for intermediate evaluation but human evaluation of explanations has been the widely used and widely adapted metric for explanation generation (Jacovi and Goldberg, 2021; Camburu et al., 2018; Kayser et al., 2021; Clinciu et al., 2021).

Accuracy Accuracy (for E-SNLI-VE, VQA-X) and proxy Accuracy (for VCR). E-SNLI-VE and VQA-X answers being short 1-2 words, can be directly evaluated as an accuracy metric,

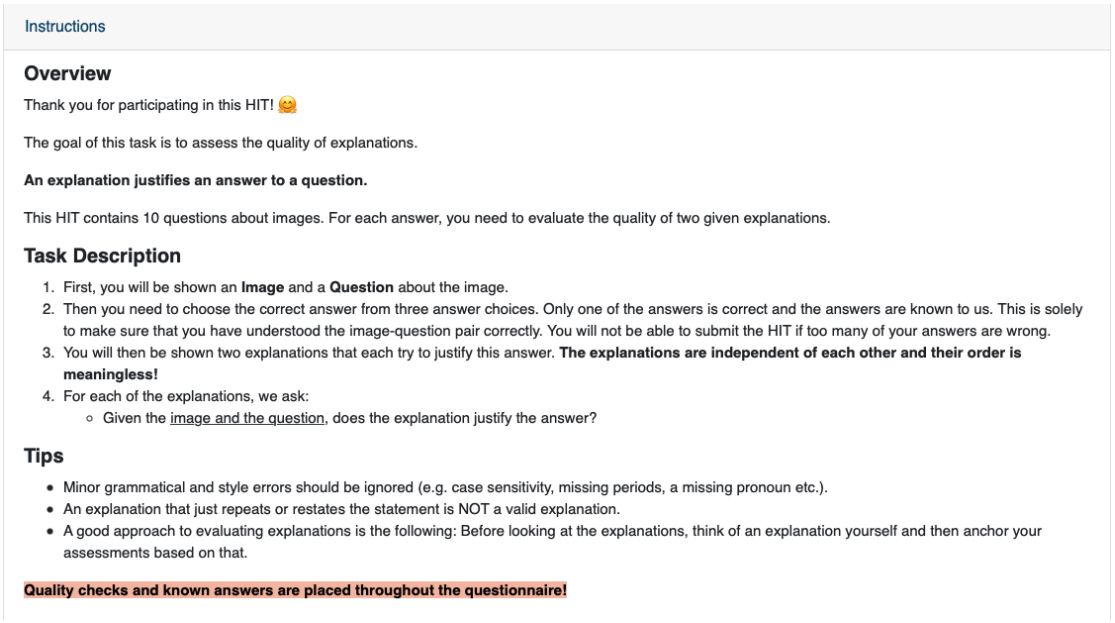
whereas VCR being natural language answers, we can best estimate accuracy using a *proxy* metric. Given a generated answer, we normalize text (remove articles, punctuation, lowercase), and count the number of overlapping words with the ground truth answer choice. We further perform human evaluation for VCR answers and measure correlation between proxy accuracy and human evaluation.

BERTscore BERTscore (Zhang* et al., 2020) is useful for intermediate automatic evaluation of generated explanations before we move to human evaluation, following (Kayser et al., 2021).

Human Plausibility Human evaluation of Plausibility (Camburu et al., 2018; Kayser et al., 2021; Clinciu et al., 2021) has been proposed as a measure of human agreement on the quality of automatically generated explanations. Plausibility measures the quality of generated explanations, given images, corresponding text (questions/hypothesis), and generated answers. Human evaluators categorize generated rationales into four categories: strong yes, weak yes, strong no, and weak no, following (Marasović et al., 2020). We perform similar evaluations for VCR answers.

Figures 6.8 and 6.9 are screenshots of the human evaluation instructions and a sample example from VQA-X. Based on Fleiss Kappa evaluation, we found better inter-annotator agreement with 5 annotators per sample rather than 3. We perform all human evaluation using Amazon Mechanical Turk. Each batch of evaluation contains 10 samples. We pay $1.5 per batch to each annotator for VCR evaluations and $1 per batch for E-SNLI-VE and VQA-X each. For VCR answers, we evaluate 600 samples. We represent each of the 244 unique movies in this sample set of 600. For explanations, we sample 300 question-image-answer sets for which the answer is correctly generated for all three datasets. For E-SNLI-VE, we do a uniform sampling from each of the three classes of entailment, neutral and contradiction. Our setup closely follows that of (Kayser et al., 2021). We additionally evaluate VCR answers. The four categories are assigned numerical values: strong yes (1), weak yes (2/3), weak no (1/3), and no (0). Human annotations of these categories are mapped to these numerical scores and averaged per annotator across the entire evaluation set. This is the Plausibility score reported in the following sections.

We evaluate 6 models for each of the four tasks: (1) VCR answers, (2) VCR explanations, (3) E-SNLI-VE explanations, and (4) VQA-X explanations. The six models are: VLP, VL-BART, VL-T5, VA-T5-BASE, VAT5-LARGE, VAT5-3B. We repeat all these experiments for all three datasets for a low-resource setting evaluation. Additionally, for VA-T5 we evaluate four multimodal features in addition to above experimental combinations. Further details on these exact experiments and corresponding Plausibility evaluations are in the sections below.



Instructions

Overview

Thank you for participating in this HIT! 🤗

The goal of this task is to assess the quality of explanations.

An explanation justifies an answer to a question.

This HIT contains 10 questions about images. For each answer, you need to evaluate the quality of two given explanations.

Task Description

1. First, you will be shown an **Image** and a **Question** about the image.
2. Then you need to choose the correct answer from three answer choices. Only one of the answers is correct and the answers are known to us. This is solely to make sure that you have understood the image-question pair correctly. You will not be able to submit the HIT if too many of your answers are wrong.
3. You will then be shown two explanations that each try to justify this answer. **The explanations are independent of each other and their order is meaningless!**
4. For each of the explanations, we ask:
    - Given the image and the question, does the explanation justify the answer?

Tips

- Minor grammatical and style errors should be ignored (e.g. case sensitivity, missing periods, a missing pronoun etc.).
- An explanation that just repeats or restates the statement is NOT a valid explanation.
- A good approach to evaluating explanations is the following: Before looking at the explanations, think of an explanation yourself and then anchor your assessments based on that.

Quality checks and known answers are placed throughout the questionnaire!

FIGURE 6.8: Screenshot of instructions to human evaluators for the VQA-X dataset.

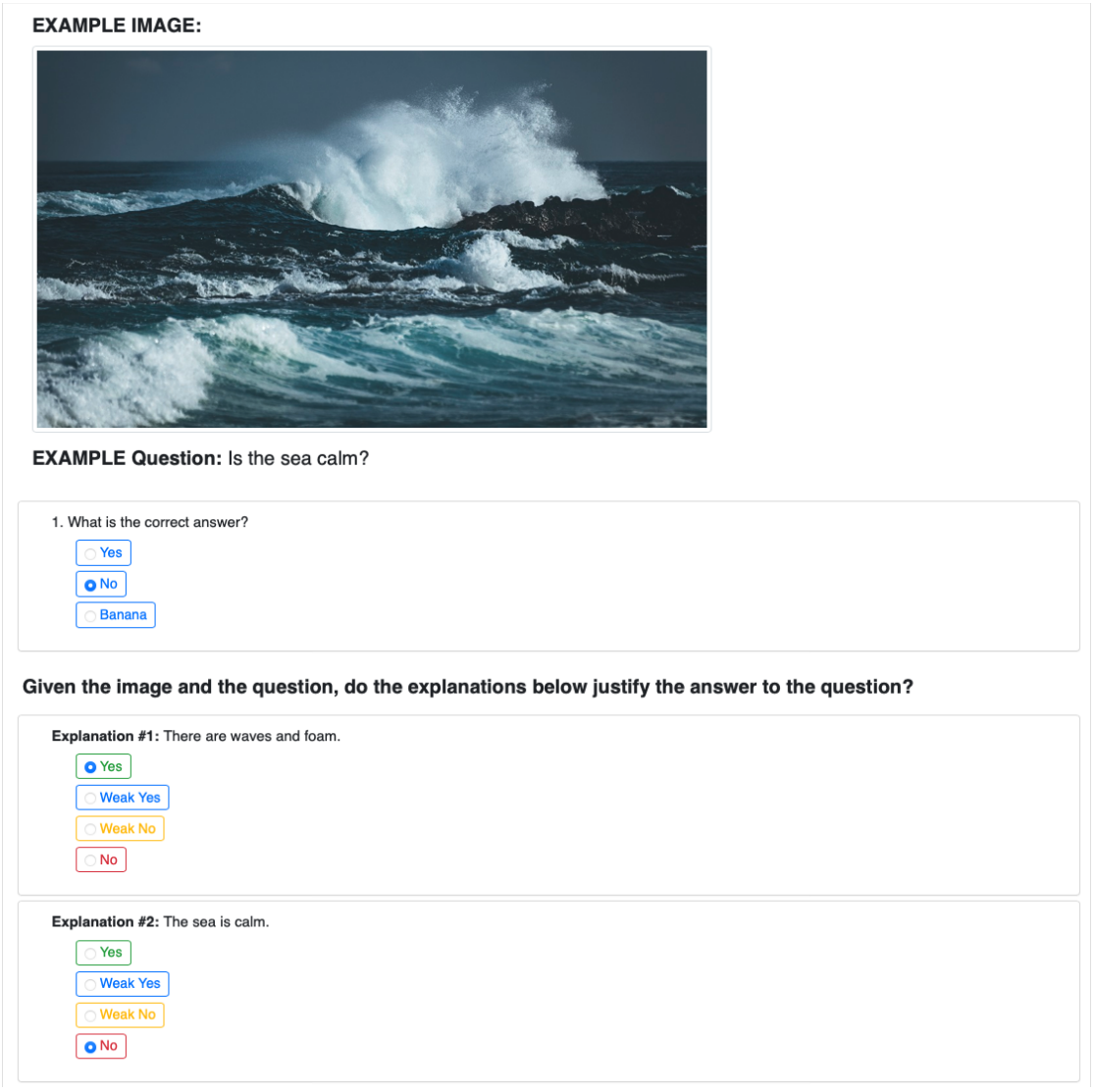


FIGURE 6.9: Screenshot of an example HIT shown to human evaluators. This image, question, and answer are from the VQA-X dataset. Evaluators are asked to categorize the model generated explanation into four categories as shown.

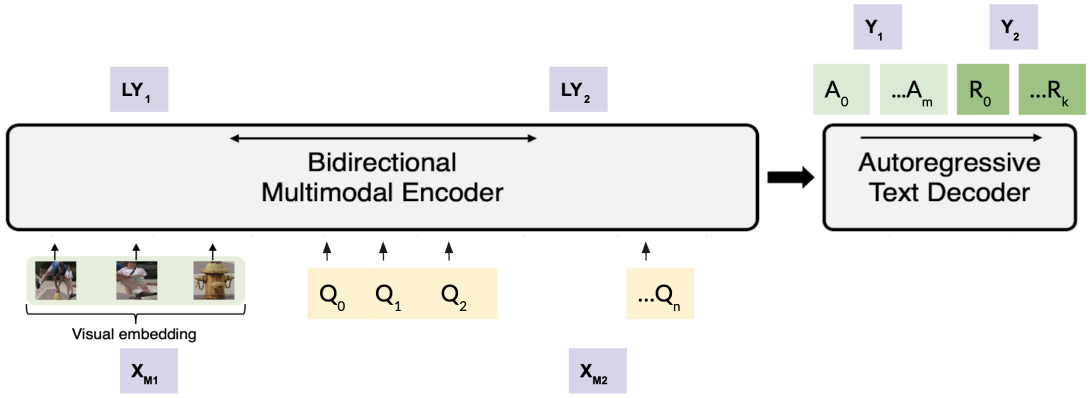


FIGURE 6.10: Depiction of the Vision Adapted T5 (VA-T5) model. The encoders and decoders are first pre-trained on complex text. In the next stage, finetuned with visual features. This is the stage shown in this image.

6.3.4 Models

The backbone archictecture for the Hierarchical Interpretable Fusion model is a bidirectional encoder-decoder model. It is a sequence-to-sequence model with Transformer layers (Vaswani et al., 2017). This core architecture can be used for unimodal or multimodal sequence learning. In the following sections, we discuss unimodal/multimodal fusion strategies for this model. Figure 6.10 shows the core bidirectional encoder (multimodal here) and the autoregressive text decoder.

There are two inputs in the Figure above: image (X_{M1}) and text (X_{M2}) corresponding to the notation in Figure 6.3. Correspondingly, depending on different pre-training strategies discussed below, we learn the corresponding multimodal latent representations LY_1 and LY_2 via a shared bidirectional encoder. The decoder outputs concatenated Y_1 and Y_2, which is the answer and explanation for self-rationalization. We found concatenation to be the best dependency modeling strategy (modeling discussion and results below).

Below, we compare various modeling strategies for Vision Language pre-training towards this Hierarchical Interpretable Fusion model. Pre-trained models finetuned towards the task of Self-Rationalization via the model described above out performed non-pretained Transformer or BLSTM based model. The Hierarchical Interpretable Fusion model is independent of the learning layer used (RNN-based BLSTM/GRU or Transformer). The model architecture proposed could be implemented via either. The development of this model on top of Hierarchical Latent Representation Fusion is the dependency modeling of the two outputs, and the concatenation method is independent of the learning layer used.

There are two main techniques to pre-train the Vision Language Transformers. We describe them in detail below.

	Unified VL Models Joint pretraining of visual and textual features	**PLM Visual Adaptation** Adapting language-only pretraining with vision features
Pros	Tightly coupled multimodal grounding beneficial for proper image understanding.	1. Available PLM are much larger than unified VL models. This is beneficial since text generation improves with increasing model size (Brown et al., 2020), including self-rationalization (Marasović et al., 2022). 2. Due to huge pretraining corpora, PLMs have been shown to capture some world (Petroni et al., 2019) and commonsense knowledge (Davison et al., 2019) which is beneficial for self-rationalization as it often requires *inferring* relevant information from the inputs (see Fig. 6.1).
Cons	1. Text inputs in multimodal pretraining dataset are often simple language captions. 2. Unified models are smaller than PLMs.	Visual information may get over-powered, especially when finetuning multimodal data is limited.

TABLE 6.9: Summary of benefits and downsides of training unified vision-language (VL) models (VLP or GPV) versus adapting pretrained language models (PLM) to visual features (VA-T5). Some models are combination of these two approaches (VL-T5, VL-BART).

Model	**Text for Pre-training**	**Images for Pre-training**
VLP	Conceptual Captions	Conceptual Captions
GPV	MS COCO, VQA v2, RefCOCO+	MS COCO
VL-T5 & VL-BART	MS COCO, Visual Genome, VQA v2, GQA, Visual 7W	MS COCO, Visual Genome
VA-T5	None	None

TABLE 6.10: Overview of text and image datasets used for pre-training by the different models.

Vision Language Pre-training

Vision-Language pre-training can be performed in the following two ways: (1) **Unified Pre-training**: Pre-train models from scratch with vision-language data, (2) **Vision-adapted Training**: Adapt unimodally trained models (often text) to the other modality (often vision).

Open Research Questions

Table 6.9 highlights the pros and cons of the two approaches we discussed above. For multimodal self-rationalization, and overall vision-language generation tasks, there is no consensus on training strategies, picking the best base models, or deciding fine-tuning strategies. We explore some of these questions, providing quantifiable results to support future research decisions in this direction.

I. Models Pretrained for VL from Scratch

Pre-training from scratch allows the model to learn from each modality equally without starting with any priors. This joint pre-training establishes tighter coupling between modalities. A limitation of this approach is the data availability of pre-training is now restricted to cases where each modality is present. Further, in the case of vision-language, the textual annotations corresponding to images/videos are simpler sentences compared to text-only data that can be scraped from several sources. In unified pre-training, vision-language data is used in the pre-training step itself, and the models are later fine-tuned on VQA-X, E-SNLI-VE, or VCR. There may, or may not be an overlap between the datasets used for pre-training and fine-tuning; an artefact we will explore further in the results section below.

VLP VLP is a Unified vision-language model that uses a shared multi-layer transformer network as encoder and decoder (Zhou et al., 2020). VLP is pre-trained for classification as well as generation tasks. Input images are first sampled into fixed number of regions and then passed through an off-the-shelf object detector (Wu et al., 2019a). These pre-extracted object features are the image representations for this model. VLP is pre-trained on the Conceptual Captions dataset (Sharma et al., 2018) containing about 3 millions web-accessible images and associated captions.

GPV General Purpose Vision (GPV-I) (Gupta et al., 2021) proposes a task-agnostic vision-language system that takes an image and corresponding textual task identifier as input; for question-answering the textual input is the question itself whereas for captioning the textual input is "Describe the image". The authors train GPV on Visual Question Answering, Captioning, Object Classification, Object Localization and Referring Expressions with the COCO (Lin et al., 2014), VQA v2 (Goyal et al., 2017), and the RefCOCO+ (Kazemzadeh et al., 2014) datasets. The total image-text training instances for GPV sum to about 1.3M. During training, either the localized image region features or the ground truth text is passed as the supervision signal. The authors propose GPV as a task-agnostic system, extendable to any new task other than the ones it is pre-trained on.

Images in GPV are encoded using an end-to-end trainable object detector DETR (Carion et al., 2020) and text is represented through a BERT encoder (Devlin et al., 2019). DETR is a Resnet-50 (He et al., 2016a) backend that is fine-tuned on-the-go with every new dataset, making GPV much slower but with more robust representations than VLP that uses pre-extracted features. GPV follows an encoder-decoder approach as well with no parameter sharing between the two, but with a cross-attention layer connecting the encoder-decoder.

II. Models Pretrained with Complex Text

Vision-adapted Training involves starting with text-only pre-trained language models (PLMs) and adapting them to vision-language data as a fine-tuning step. There are several benefits of this approach. First, the size of available data for pre-training is now potentially uncapped as we only need textual data. We can also source more complex textual data for pre-training for the task of open-ended Self-Rationalization where explanations are often complex sentences. A limitation of this approach is that the textual signal may overpower the vision signal during the fine-tuning step, leading to a lack of multimodal grounding. Further, any visual grounding is only obtained via the VQA-X, E-SNLI-VE, or VCR datasets during the fine-tuning stage, which is not as strong a visual signal as for the Unified Pre-training models.

VL-BART / VL-T5 VL-BART (Cho et al., 2021) also follows an encoder-decoder architecture but does not share the parameters between the encoder and decoder as is done in VLP. VL-BART is a multimodal extension of the BART$_{Base}$ (Lewis et al., 2020) model. There are separate transformer blocks with multi-head self attention and fully connected layers with residual connections in the encoder and decoder each. Similar to GPV, a cross-attention layer connects the encoder outputs and decoder at each decoding time-step. Input images are represented using a Faster R-CNN model (Ren et al., 2015) for a fixed set of region features. The outputs of this Faster R-CNN models are concatenated with text embeddings and fed into the VL-BART model, which is then trained using the same objective as the BART$_{Base}$. The input is also prefixed with a task identifier, similar to GPV, that indicates the task to be performed, for e.g., vqa, visual grounding, captioning, etc.

VL-BART is also trained using data for various tasks making it a task-agnostic model, unified via text-generation and classification objectives. The difference with GPV is the input image representations and fusion, along with the base model used. VL-BART starts from a unimodal text-only pre-trained language model, adapted to visual information in a second pass of pre-training (not fine-tuning).

VL-T5 (Cho et al., 2021) is similar in spirit to VL-BART, where it is initialized with a T5$_{Base}$ model (Raffel et al., 2020) correspondingly. These two models represent and help evaluate base differences between T5 and BART training approaches, as applied to multimodal language. T5 is trained for various downstream tasks jointly, whereas BART exploits a task-specific encoder-decoder set up for sequence generation tasks; we explore which of these is a good base model for vision-language self-rationalization.

Both VL-BART and VL-T5 are pre-trained with MS COCO (Lin et al., 2014), Visual Genome (Krishna et al., 2017b), VQA v2 (Goyal et al., 2017), GQA (Hudson and Manning, 2019), and Visual7W (Zhu et al., 2016), leading to a total of 9.18M image-text pairs on 180K unique images.

III. Visually Adapting Language Models: Proposed VA-T5

Visually adapting pre-trained language models could be a best of both worlds approach. Training, or hot-starting from existing large-scale text-only language models, and adapting them to multimodal datasets, could help capture complex language structures, and adapt them to visual inputs. Such training gives us the flexibility of picking task-based and domain-specific unimodal or multimodal datasets, suitable model sizes, suitable dataset sizes, and visual features. In the following Section, we explore such adaptation with varying visual features, model sizes, and datasets.

IV. Dependency Modeling

We try four main approaches to dependency modeling: (1) Concatenating the two output sequences (2) Multi-task learning with two separate decoders, and (3) Masked Language modeling, and (4) Two-pass decoding. For multi-task learning, we compare multi-task decoders attached at various encoder levels (from layers 6, 8, 10, and 12). This is to test if an easier task (often Y_1) can be learnt earlier. We also attempt a two-pass generation model that uses two decoders. The first decoder is meant for Y_1-only generation. This decoder output is passed as input in the second-pass to a linked decoder that generates Y_2. This architecture is trained in pipeline. In early experiments, end-to-end training of the two-pass decoding model led to time latency due to the decoding constraint during training.

6.3.5 Results

Below, we first discuss results supporting the open-research questions discussed. We present studies on using different visual features with the proposed VA-T5 model and different model size for the same. We also present an ablation study of various Layernorm techniques for VA-T5. Further, we compare various model performance in a limited data setting using only 30% training data. Finally, we present comparison of various dependency modeling techniques.

Unified VL Models vs Visually Adapted Language Models

Table 6.11 contains Rouge-L scores for the various models discussed on VCR answer generation evaluation. We present these automated metrics only for answer generation as it is a widely accepted image question answering task. On automated metrics, VA-T5-Base performs much better than all other models. Also, the models presented in this study are overall better than the previous baseline of Dua et al..

With the choice of models pre-trained for VL from scratch, and models pre-trained with complex text, we try to provide some quantifiable understanding of pros and cons of using either for future VL language generation tasks. Depending on the style of datasets, from VCR with complex

Models	Rouge-L
BASELINE (DUA ET AL., 2021)	26.2
VLP	35.5
VL-BART	26.5
VL-T5	27.2
VA-T5-BASE	**41.3**

TABLE 6.11: Comparison of unified pre-training (VLP) and pre-trained language model adaptation methods (VL-BART, VL-T5, VA-T5) with baseline from (Dua et al., 2021) on VCR answer generation. VA-T5-Base significantly outperforms other models on this metric.

	VCR			**E-SNLI-VE**			**VQA-X**		
	Acc	BERT	Plau	Acc	BERT	Plau	Acc	BERT	Plau
VLP	55.5	85.7	34.0	75.4	87.7	63.8	79.4	89.6	73.5
VL-BART	57.8	86.6	29.5	75.6	89.3	71.5	86.3	91.2	75.9
VL-T5	58.4	85.5	28.7	76.3	89.1	69.0	84.9	91.0	72.2
VA-T5-BASE	58.1	86.0	15.6	74.7	89.3	65.4	74.7	90.9	70.8

TABLE 6.12: Comparison of unified pre-training (VLP) and pre-trained language model adaptation methods (VL-BART, VL-T5, VA-T5) on all three datasets VCR, E-SNLI-VE, and VQA-X. We report on proxy or task accuracy (Acc.), BERTscore for self-rationalization (BERT) and human evaluation of generated natural language rationales/explanations (Plausibility).

answers and complex rationales, to VQA-X with short answers and simple explanations, we compare various models available.

Table 6.12 presents a comparison of all models, datasets, and the three evaluation metrics. Pure unified pre-training with VLP often under performs. With VL-T5 and VL-BART, we get a best-of-both-worlds setting, as is also evidenced by their strong performance. There is no particular benefit to picking one over the other in this comparison. VA-T5 while the most malleable, is a strong competitor to VLP, but under performs compared to VL-T5 or VL-BART. We scale down the amount of available fine-tuning data to 30% for each dataset to test this trend in a limited-data setting, Table 6.18. We also present results with data size scaled down to 20%, 10% and 5%. We observe the same trends as with access to full training data. In particular, VL-T5 and VL-BART performance holds steady on VQA-X while VLP and VA-T5 drop. On VCR, the trends in accuracy do not match trends on E-SNLI-VE and VQA-X either across models or data sizes, leading us to believe the proxy accuracy metric not a good representative of model performance. Currently, we strongly rely on plausibility to evaluate performance on VCR.

Table 6.13 presents three methods to compute plausibility from the 5 human annotations per question.

	VCR			E-SNLI-VE			VQA-X		
	Avg	Agg	Vote	Avg	Agg	Vote	Avg	Agg	Vote
VLP	34.0	34.9	29.0	63.8	69.4	73.3	73.5	76.6	78.3
VL-BART	29.5	30.8	27.0	71.5	76.0	81.3	75.9	79.3	80.7
VL-T5	28.7	29.3	22.7	69.0	73.0	76.0	72.2	76.0	79.0
VA-T5-BASE	21.0	21.8	18.0	65.2	70.3	74.7	75.8	78.5	79.0
VA-T5-LARGE	24.4	25.7	21.7	65.0	71.4	76.3	72.3	76.0	77.3
VA-T5-3B	25.8	27.1	21.3	64.1	69.9	71.3	69.3	73.3	74.0

TABLE 6.13: Different Plausibility computation methods to compare unified pre-training (VLP) and pre-trained language model adaptation methods (VL-BART, VL-T5, VA-T5) on all three datasets VCR, E-SNLI-VE, and VQA-X. We report average plausibility (Avg), aggregated plausibility (Agg), and majority vote plausibility (Vote).

- Plausibility Average: Averages all 5 annotations, keeping 4 categories yes, weak yes, weak no, and no.
- Plausibility Aggregate: Averages all 5 annotations but with aggregation into two categories. weak yes and yes are counted as yes, whereas weak no and no are counted no.
- Majority Vote: If majority annotators say yes, then it is counted yes, otherwise no.

Results presented in Table 6.13 are for all models and datasets for explanation evaluation.

Analysis of Vision Features

The VA-T5 model brings in flexibility of visual feature adaptation. Unlike unified models, we can choose visual features for adaptation while fine-tuning without the need to pre-train on large-scale data again. Here, we make three main comparisons: (1) Is multimodal adaptation helpful at all for such a generation task?, (2) Is it better to textually represent images while adapting a text-only T5?, and (3) Quantifying the gains by the different visual features. In Tables 6.14 and 6.15, we compare Accuracy, BERTScore, and Plausibility for text-only generation (*None*; no multimodal adaptation), textual representation of visual features (*Captions*; auto-generated captions from pre-trained VL-T5 for image captioning), image features (*Objects*; object features from a pre-trained R-CNN model (Ren et al., 2015)), and image-text features (*CLIP*; from a jointly trained vision-language model CLIP (Radford et al., 2021)).

We see consistent and significant improvements in accuracy across all three datasets with multimodal adaptation (with Captions, Objects, or CLIP) as compared with no adaptation (None). Further, we see that adapting with textual features that represent images (Captions) is also a strong multimodal signal. When we replace auto-generated captions with human annotated gold captions, we observe further gain in performance, beating Objects and CLIP performance. With stronger automatic captioning models, this performance gain can be explored further. Overall,

Task \ Feats	Accuracy				BERTScore			
	None	Captions	Objects	CLIP	None	Captions	Objects	CLIP
VCR	54.5	56.2	57.8	**58.1**	85.3	85.7	85.6	**86**
E-SNLI-VE	67.6	71.7	72.5	**74.7**	89.1	**89.3**	**89.3**	**89.3**
VQA-X	43.4	73.8	72.3	**74.7**	90.7	**91.2**	91.1	90.9

TABLE 6.14: Analysis of various visual features. We use the proposed VA-T5-BASE as the common model. None indicates no multimodal features; this is a text-only model. Caption indicates automatically generated natural language captions from a pre-trained image captioning model. As captions are natural language, this is a text-text adaptation model. Object features are extracted from an R-CNN object detector. CLIP features are extracted from a pre-trained CLIP model and are the latest off-the-shelf visual features. CLIP consistently outperform other features.

Task \ Feats	Plausibility			
	None	Captions	Objects	CLIP
VCR	15.6	19.6	21.0	21.0
E-SNLI-VE	65.4	66.6	65.7	65.2
VQA-X	70.8	75.5	76.4	75.8

TABLE 6.15: Analysis of various visual features evaluating using human plausibility. We use the proposed VA-T5-BASE as the common model.

	VCR			E-SNLI-VE			VQA-X		
	Acc	BERT	Plau	Acc	BERT	Plau	Acc	BERT	Plau
VA-T5-BASE	58.1	86.0	21.0	74.7	89.3	65.2	74.7	90.9	75.8
VA-T5-LARGE	59.1	86.0	24.4	74.4	89.3	65.0	75.6	90.6	72.3
VA-T5-3B	59.1	85.8	25.8	68.0	89.2	64.1	75.1	90.0	69.3

TABLE 6.16: Comparing model size for the VA-T5 model for all three datasets. Each model uses CLIP features for adaptation. Acc: Accuracy, BERT: BERTscore, Plau: Human evaluation of Plausibility.

with the currently available features, we see the best performance with CLIP embeddings. All comparisons are made on the VA-T5-BASE model.

Analysis of Model Size

In Table 6.16, we explore three model sizes for the VA-T5 model: Base, Large, and 3 billion (3B), with 60 million, 220 million, and 3 billion parameters respectively. With this comparison, we hope to quantify self-rationalization performance and the benefits of multimodal adaptation, especially for the fully-generational VCR setting. Further, each of the unified models VLP, VL-T5, and VL-BART are pre-trained with the corresponding Base versions of BERT, T5 and BART.

	Acc	BERT
No LayerNorm	72.4	89.3
LayerNorm (vision)	73.0	89.3
LayerNorm (vision;text)	72.6	89.3

TABLE 6.17: LayerNorm analysis for the VA-T5-BASE model using CLIP-based adaptation on the E-SNLI-VE dataset.

LayerNorm Analysis

The VA-T5 model not being pre-trained jointly, there might be normalization required for the textual and visual representations that are obtained from different pre-trained models (hence different latent representation spaces), we do an analysis of adding additional LayerNorm (Ba et al., 2016) upon fusion in the VA-T5 model. Table 6.17 contains results of no layer normalization upon fusion, LayerNorm only for vision (as the T-5 backbone automatically normalizes text during pre-training), and LayerNorm of both text and vision upon fusion. The visual representations used here are from a pre-trained CLIP model and LayerNorm over those leads to most improvement over no LayerNorm. The results presented here are for the E-SNLI-VE test set and VA-T5-BASE model.

Analysis of Limited Data Setting

With the increase in scale of the text-only base model, we are able to quantify the benefits achievable through visual adaptation. In particular, we see that the visual information gets overpowered with the VA-T5-3B model. VA-T5-Large often performs slightly better or comparable with VA-T5-Base. The improvement in performance comes at the cost of larger number of parameters; future decisions to use either of these models should be made considering the trade-off between performance gains and number of parameters used. We also observe stagnation in the proxy accuracy metric for VCR. Overall, we observe that simply increasing the model size of the base model being used, either in unified pre-training or visual adaptation might not lead to corresponding performance gains for self-rationalization. In both cases, we need to maintain a balance between information obtained from either modality. Model size results are reported in Tables 6.12 and 6.18. Table 6.18 performs same comparisons as Table 6.12 but with a limited data setting, i.e. with using only 30% of training data. This comparison helps us establish whether visual information gets overpowered by textual information in the VA-T5 models. Tables 6.19, 6.20, and 6.21 contain results for 20%, 10%, and 5% data scale down respectively. We see similar trends as with 30% scaling.

	VCR			E-SNLI-VE			VQA-X		
	Acc	BERT	Plau	Acc	BERT	Plau	Acc	BERT	Plau
VLP	54.7	85.9	25.1	73.5	87.6	63.6	71.8	89.4	72.9
VL-BART	57.4	86.4	22.7	74.4	89.3	66.1	85.6	90.9	72.9
VL-T5	58.5	85.2	22.5	74.2	89.3	66.6	83.5	90.5	71.3
VA-T5-BASE	57.2	85.7	23.1	66.5	89.1	64.5	66.5	90.8	75.8
VA-T5-LARGE	57.3	85.8	21.1	68.3	89.2	62.0	67.3	90.4	73.6
VA-T5-3B	57.0	85.3	19.0	68.7	89.2	63.6	53.7	90.6	69.8

TABLE 6.18: Different modeling and model size comparison for all three datastes on a limited data setting. We train with only 30% randomly shuffled data. For E-SNLI-VE we sample evenly across Entailment, Neutral and Contradiction classes. Acc: Accuracy, BERT: BERTscore, Plau: Human evaluation of Plausibility.

	VCR		E-SNLI-VE		VQA-X	
	Acc	BERT	Acc	BERT	Acc	BERT
VLP	54.3	85.6	72.5	87.6	72.4	89.3
VL-BART	56.5	86.4	74.0	89.3	85.4	90.8
VL-T5	58.3	85.4	72.6	89.4	83.3	90.4
VA-T5-BASE	56.8	85.7	64.5	89.4	64.9	90.3
VA-T5-LARGE	57.5	85.8	62.1	89.0	52.3	90.1

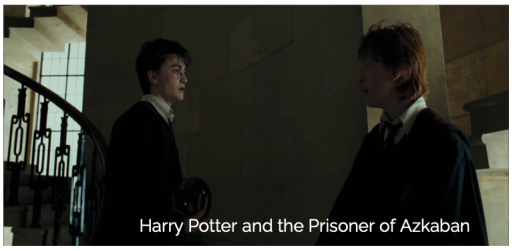
TABLE 6.19: Different modeling and model size comparison for all three datastes on a limited data setting. We train with only 20% randomly shuffled data. For E-SNLI-VE we sample evenly across Entailment, Neutral and Contradiction classes. Acc: Accuracy, BERT: BERTscore.

	VCR		E-SNLI-VE		VQA-X	
	Acc	BERT	Acc	BERT	Acc	BERT
VLP	53.5	85.6	71.3	87.6	67.5	89.1
VL-BART	56.2	86.3	72.6	89.3	85.0	90.6
VL-T5	58.3	85.7	70.9	89.4	82.7	90.4
VA-T5-BASE	55.7	84.7	63.5	89.1	62.4	90.5

TABLE 6.20: Different modeling and model size comparison for all three datastes on a limited data setting. We train with only 10% randomly shuffled data. For E-SNLI-VE we sample evenly across Entailment, Neutral and Contradiction classes. Acc: Accuracy, BERT: BERTscore.

	VCR		E-SNLI-VE		VQA-X	
	Acc	BERT	Acc	BERT	Acc	BERT
VLP	53.7	86.2	69.5	87.6	63.7	89.0
VL-BART	56.2	86.3	70.8	89.3	83.1	90.2
VL-T5	58.3	85.5	69.0	89.3	81.4	90.5
VA-T5-BASE	55.7	84.7	62.9	88.7	57.9	89.8

TABLE 6.21: Different modeling and model size comparison for all three datastes on a limited data setting. We train with only 5% randomly shuffled data. For E-SNLI-VE we sample evenly across Entailment, Neutral and Contradiction classes. Acc: Accuracy, BERT: BERTscore.



Question: Is everyone at school?

Answer: Yes , everyone is at school .

Rationale: Everyone is wearing a school uniform .

Question: Why is person wearing a hat?

Answer: It is cold outside .

Rationale: People wear hats when it is cold .

Question: Why is chair empty?

Answer: person is leaving the room .

Rationale: person is walking away from the chair .

FIGURE 6.11: Qualitative examples showing model generated answers and rationales for two sample images from the VCR dataset.

Qualitative Examples

Figure 6.11 shows qualitative examples from two samples images from the VCR dataset. These images are scenes from two different movies. For each of the three questions shown, you can observe that the answers and rationale are dependent on each other. The rationale explains the answer. In the first image, the answer is correct and relevant to the context. In the second image though, context of the scene is required to answer correctly, and explain the answer. For instance, the first answer seems incorrect as the hat worn by the actor is not meant to protect against cold. Whereas, the last answer is correct as relevant to the scene and someone who has seen the movie will be able to answer it correctly. VCR as a dataset is ripe for the task of self-rationalization but still a very difficult dataset for this task. There are several dependencies and outside knowledge being used to describe movie scenes and lots more work needs to be done in this space to make more progress on this task.

6.4 Chapter Conclusion

We proposed two methods for Rationalization in this Chapter: (1) Through explicit interpretable semantic concepts, and (2) Generation of free-text explanations that rationale about model behavior. As both these tasks setups are relatively new, we presented detailed task setup, and performed extensive evaluation of existing models. We proposed the Hierarchical Interpretable Fusion model that captures the nature of both these rationalization tasks. This model was necessary to model the multi-output nature of this task, either as a concept learning problem or as a self-rationalization problem. Models proposed so far in this thesis, as well as relevant related work did not explicitly model for this phenomenon. In one formulation of this model, we train it as a pipeline model connecting the two outputs. In the other formulation, we train this end-to-end for self-rationalization. Self-rationalization, a task of generating open-ended answers and explanations to visual questions, is a relatively recent task for multimodal literature.

Overall, we saw that the proposed approach of Rationalization through semantic concepts led to an absolute gain of 5 Rouge-L points and 7 Meteor points in Summarization performance. Additionally, we saw that concepts learnt through multimodal data (speech and video) performed strongest compared to unimodal setup. We also saw qualitative examples of how concepts generated as a first step directly reflected in the downstream summary. With Self-Rationalization, we compared performance of unified VL and visually-adapted language models, and found training both together could potentially be a best of both worlds approach. Over three datasets of increasing difficulty, pretraining with different data and model sizes led to more gains on easier datasets but also improvements on VCR, the difficult dataset. We also compared different visual features for VA-T5 and found good improvement with the increasing quality of visual features. Through extensive human evaluation, we found good correlation with the proxy metrics we used.

In the last four Chapters, we showed how increasingly complex models were necessary to handle task-based characteristics. In this Chapter, both the tasks needed novel architectural design, which led to the Hierarchical Interpretable Fusion model. We hope to have shown the increasing order of complexity. In the next Chapter, we will discuss broader impact and limitations of such complexity or model design, along with a summary of contributions.

Chapter 7

Conclusions and Future Directions

7.1 Summary of Contributions

We identify four learning tasks with increasing complexity that fall in the umbrella of Multimodal Video Understanding. For each of these tasks, we build multimodal fusion models based on the nature of the tasks and modalities involved. We start by defining the four learning tasks, and highlight their similarities and differences. We design incrementally increasing complexity in the input modalities involved and downstream tasks. The contributions of this thesis are:

- **Learning Tasks** We present four learning tasks using audio, video, and language modalities. We order them in increasing order of complexity defined by input output modalities and downstream tasks. This order spans surface-level tasks such as Speech Recognition or Translation and expands into interpretable and explanatory tasks such as Summarization, QA, and Rationalization.
- **Learning Architectures** We also propose relevant model architectures based on the task (monotonic, non-monotonic, abstractive, explanatory), complexity of the task (utterance-level, video-level), modalities involved (from audio, video, text) and the expected downstream output (transcription, translation, summarization, rationalization). We propose the Multimodal Input Fusion model, Latent Representation Fusion model, Hierarchical Latent Representation Fusion model, and Hierarchical Interpretable Fusion model for the four learning tasks.

1. **Speech Recognition**
    - **Audio Visual Speech Recognition** We propose a Monotonic Input Fusion model for end-to-end audio-visual speech recognition at the semantic level that can improve ASR performance using relevant objects and scenes detected in the video. We

demonstrate a relative improvement of about 9% in the token error rate over unimodal models. The related publication is: Palaskar et al. 2018 which was later extended by Caglayan et al. 2019.

- **Acoustic-to-Word Speech Recognition** To fuse information in the semantic space, we need to first handle the time-scale alignment issue between the speech signal (acoustic frames), video signal (word-level latent representation), and text sequences (characters or word-level units). Towards this goal, we build acoustic-to-word models to match speech frames with visual and textual representations. The proposed approach leads to semantically-rich acoustic word embeddings that match textual representations from corresponding transcriptions. The related publication is: Palaskar and Metze 2018.
- **Model:** Input Fusion

2. **Speech Translation**

   - **Multiview Learning** We present a multi-view representation learning model trained via Deep Correlation Analysis to perform semi-supervised speech recognition and translation. Upon evaluation of a retrieval-based metric, the semi-supervised learning method achieves within 3% word error rate of a fully supervised model for speech recognition and within 7 BLEU points for speech translation. The corresponding publications for this are Palaskar et al. 2019b and Holzenberger et al. 2019.
   - **Model:** Latent Representation Fusion

3. **Summarization**

   - **Video Summarization** We present a Hierarchical Latent Representation Fusion model for video summarization that leads to a relative improvement of 3% in contentful word generation, measured by a Content F1 score, over unimodal models. Our proposed hierarchical fusion model outperforms the state-of-the-art summarization models at that point, showing the need for the hierarchical architecture. The associated publication for this work is Palaskar et al. 2019a.
   - **Video QA** We explore transfer learning techniques in this task for the Hierarchical Latent Representation Fusion model used for abstractive summarization. We compare learnings between the `How2`and another dataset with similar modalities, the Audio-Visual Scene-aware Dialog (AVSD) dataset (Alamri et al., 2019). We observe significant consistent improvement with transfer learning from How2 to AVSD with gains ranging from 5-10 points absolute improvement on standard text generation metrics. With our best multimodal transfer learning model based on Hierarchical Latent Fusion, we ranked first in the 7^{th} Dialog Systems Technology Challenge. The associated publications for this work are Sanabria et al. 2019 and Palaskar et al. 2020b.
   - **Model:** Hierarchical Latent Representation Fusion

4. **Rationalization**

   - **Rationales from Semantic Concepts** We propose a method to increase interpretability and rationalization of existing multimodal tasks by learning to generate intermediate semantic concepts. We demonstrate results for the video summarization task discussed previously. We present a new architecture to execute this task where we have dependent information flow between the semantic concepts and downstream summary: the Hierarchical Interpretable Fusion model. The proposed approach in this work can be applied to any language generation task and we have evaluated it on image captioning and question answering. On summarization, we observe an absolute gain of 5 Rouge-L points and 7 Meteor points using the said approach. The associated publication for this work is Palaskar et al. 2020a.
   - **Self-Rationalization** The Hierarchical Interpretable Fusion model trained for self-rationalization is an end-to-end model that relates input modalities and dependent information flow between outputs in the same model. We present a comparison on various methods to model dependent information flow, and compare with two main approaches to multimodal language generation. We present a thorough study on a new task of self-rationalization that generates explanations for model behavior. The main task for self-rationalization is question answering. We establish first results and baselines on this task for future work to build off of on three datasets: VQA-X, ESNLIVE, and VCR.
   - **Model:** Hierarchical Interpretable Fusion

7.2 Broader Impact and Limitations

With this thesis, we hope to have laid a foundation for the type of thinking going ahead in this field, especially for soon-to-be applications that require seamless multimodal and human-machine interaction. One approach that we touched upon in this thesis is to perform hierarchical modeling with modalities, and consistently build tasks one on top of another. If we view learning tasks as building blocks that can be combined to learn from each other, and lead to increased "understanding" using multimodal correlations, it could be one approach towards holistic video understanding.

With this thesis, we hope to have shown how increasingly complex multi-modal problems require increasingly complex fusion methods. For the purposes of this PhD thesis, we restrict ourselves to the speech, vision, and langauge modalities which is good because consumer video is often comprised of these. In the long term, we hope this thesis can contribute to soon-to-be applications such as meeting summarization, or multimodal personal assistant interaction, or hateful content generation, or more long term applications such as multimodal aspects of self-driving, accessibility related applications, or Augmented and Virtual Reality. The main limitations are: we don't define "understanding" and complexity is a contextual term.

In the context of video understanding, defining meaning of the term "understanding" is a limitation of this thesis. Here, we use the term as colloquially as is done with concurrent works in computer vision and speech and natural language processing communities. While it is out of the scope of this thesis, and the colloquial definition suffices, a widely accepted definition can lead to more concerted efforts, and in-turn lead to emergence of definitions for learning tasks. More focused efforts could be taken towards addressing niche of research that arise.

On the other hand, complexity of a problem could have different meanings in different contexts. For instance, in the context of this thesis, complexity related to the nature of input modalities and downstream task. It could even be approached from a purely modality-based perspective: complexity of perception in the visual modalities, or complexity of language in the textual modality. It could even be approached from the perspective of type of task; we focused on generation tasks but there are classification-based, regression-based, reinforcement learning related, or even interactive learning problems to name a few that would change how complexity is defined. Finally, complexity could even relate to the model creation itself. Here, task characteristics and model creation were linked, but the model complexity by itself need not be defined by the task, for e.g. generative adversarial networks for multimodal tasks.

This thesis also broadly focused on language-generation tasks. All models and learning tasks, including speech recognition, are inherently sequence-generation problems given various granularities of data (utterance-level, video-level, speech frames, phonemes, words, sentences, etc). This could be expanded to classification tasks, generative tasks, unsupervised representation learning, regression tasks, etc. The order of learning task difficulty would need to be evaluated based on the given downstream problems of other tasks.

There are several other modalities of data that provide relevant context. Emotions, actions, context of dialog for virtual assistants, eye gaze information for screens with cameras under necessary privacy conditions, human pose, categorical data, etc are some of the streams of information that could be expanded upon in current speech, vision, and language settings for multimodal learning. This thesis broadly covered speech, vision, and natural language data as the main modalities but for applications beyond discussed in this thesis, several other modalities provide relevant context. Most of the methods proposed in this thesis are independent of the modality and number of modalities being used, and could be scaled easily to other and/or more modalities as required.

7.3 Future Directions

While multimodal learning as an area of machine learning has been explored for several decades, Multimodal Video Understanding has been relatively new due to compute constraints until recently. Researchers from Computer Vision, Natural Language Processing, and Speech Recognition communities have studied various aspects of interaction of the different modalities: audio, images, video, text, speech, emotions, etc. In this thesis, we covered four tasks that could be ordered given certain constraints, but there are several other tasks and applications.

Video understanding has several different application areas; short-term such as long-video summarization, semantic search through large-scale video data being generated data, or automatic hate speech flagging, and long-term such as healthcare, accessibility, Augmented Reality/Virtual Reality, autonomous vehicles, etc. For each application area, video understanding would encompass different meanings. At the core, this area deals with multimodal interaction, modality alignment, fusion, addressing missing or noisy modalities, and so on. Future work in this direction could be focused towards specific applications of video understanding.

Similarly, video understanding is a field of machine learning that has abundance of data available in the current world, even if it is noisy and not annotated as per requirements. Some recent work has begun exploring one-model-for-all type general purpose models for multimodal tasks that can learn off of each other in this setting, but this work could be expanded further to learn from the large amount of multimodal data that is being generated daily. With more modalities, more tasks, more data, and more models, we can expand to more complicated learning tasks than those covered in this thesis.

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