Abstract

In recent years, abstractive text summarization with multimodal inputs has started drawing attention due to its ability to accumulate information from different source modalities and generate a fluent textual summary. However, existing methods use short videos as the visual modality and short summary as the ground-truth, therefore, perform poorly on lengthy videos and long ground-truth summary. Additionally, there exists no benchmark dataset to generalize this task on videos of varying lengths.

In this paper, we introduce AVIATE, the first large-scale dataset for abstractive text summarization with videos of diverse duration, compiled from presentations in well-known academic conferences like NDSS, ICML, NeurIPS, etc. We use the abstract of corresponding research papers as the reference summaries, which ensure adequate quality and uniformity of the ground-truth. We then propose FLORAL, a factorized multi-modal Transformer based decoder-only language model, which inherently captures the intra-modal and inter-modal dynamics within various input modalities for the text summarization task. FLORAL utilizes an increasing number of self-attentions to capture multimodality and performs significantly better than traditional encoder-decoder based networks. Extensive experiments illustrate that FLORAL achieves significant improvement over the baselines in both qualitative and quantitative evaluations on the existing How2 dataset for short videos and newly introduced AVIATE dataset for videos with diverse duration, beating the best baseline on the two datasets by 1.39 and 2.74 ROUGE-L points.

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respectively.

**Keywords:**
Abstractive text summarization, Multimodality, Attention, Factorized Multimodal Transformer, Language model

### 1. Introduction

Abstractive text summarization focuses on generating a summary of a text from its main ideas, not by replicating the most salient sentences, rather by generating new sentences and/or rephrasing existing sentences so that the key semantics and overall meaning of the original text remain intact in summary. It has a wide range of applications in our daily life — from media monitoring, search marketing, email filtering, newsletter production to question-answering chatbots, we are frequently exposed to abstractive summarization. Due to its ability to generate fluent and coherent summaries, abstractive summarization is an important and challenging area of research in Natural Language Processing and has got enough attention in the last few years. While most of the previous studies (See et al., 2017; Lebanoff et al., 2018; Gehrmann et al., 2018; Chowdhury et al., 2020; Chung et al., 2020) on abstractive summarization use only textual data as the input modality, some studies (Shah et al., 2016; Li et al., 2018; Zhu et al., 2018; Palaskar et al., 2019) have recently focused on incorporating multimodal signals as the input to enhance the quality of text summary. Intuitively, humans can comprehend the gist of an occurrence more quickly by watching relevant images or videos than by only reading a text document, and therefore we believe that multimodal data can also reduce the difficulties for machines to interpret the context.

**Motivation:** With the emergence of multimedia technology and the rapid growth of social media video-sharing platforms such as Youtube and Vimeo, multimedia data (including text, image, audio, and video) have increased dramatically. Specifically, during the COVID-19 outbreak in the last six months, there has been a steep rise in various e-learning platforms, resulting in a drastic increase of online video tutorials and academic presentation videos. However, such videos often do not have the text meta-data associated with them, or the existing ones fail to capture the subtle differences with related videos (Wang et al., 2012). Additionally, different modalities in most of these videos are asynchronous with each other, leading to the unavailability
of subtitles. In this work, we address the task of generating an abstractive text summary of a given academic presentation video so that the viewers can acquire the gist of the presentation in a short time, without watching the video from the beginning to the end. For this purpose, we incorporate automatic speech recognition (ASR) and optical character recognition (OCR) generated text transcripts and capture tonal-specific details of the speaker in addition to extracting semantics and sentsics from the video, which are jointly optimized to produce a rich and informative textual summary of the entire presentation. We also show the generalizability of our model on the non-academic dataset (instructional videos).

State-of-the-art and Limitations: The existing studies on abstractive text summarization with multimodal signals include multimodal news summarization (Li et al., 2018, 2016; Chen and Zhuge, 2018) and summarization of instructional videos (Palaskar et al., 2019). However, all of them use images and/or short videos as the visual modality, which do not generalize on long videos. The generated summaries by these systems are also one or two lines long, and therefore, not suitable for longer academic videos (such as course lecture, conference tutorials). Some other closely related studies include image and video captioning (Mun et al., 2017; Liu et al., 2018; Iashin and Rahtu, 2020; Shi et al., 2020; Shen et al., 2020), video story generation (Gella et al., 2018), video title generation (Zeng et al., 2016) and multimodal sentence summarization (Li et al., 2018); but all of them deal with short videos or images which are not appropriate for our application. The lack of previous studies on this task can be attributed to the absence of a suitable benchmark dataset. In a very recent work, Palaskar et al. (2019) studied the task of summarization of instructional videos on the How2 dataset (Sanabria et al., 2018), which is the only existing dataset for abstractive text summarization with multimodality. However, the How2 dataset consists of short videos, with an average duration of 90 seconds only. The ground-truth text summaries of this dataset have an average length of 33 words, which are very small as well.

Our Contributions: In this paper, we explore the role of multimodality in abstractive text summarization for academic presentation videos of diverse duration and introduce a new resource to further enable research in this area. More specifically, our main contributions in this work are as follows:

1. We curate the first large-scale dataset, **Audio VIdeo lAnguage daTasEt (AVIATE)**, for abstractive text summarization using multimodal inputs for academic presentation videos of diverse duration. To collect the videos
for this dataset, we scraped 6 publicly available websites and accumulated paper presentation videos from 28 well-known international conferences in computer science and social science. To obtain the transcripts of these videos, we apply Deep Speech \cite{hannun2014deep}, a pre-trained end-to-end automatic speech recognition (ASR) system. We use the abstracts of corresponding research papers as the ground-truth summaries, which ensure adequate quality and uniformity. In contrast to How2, AVIATE contains longer videos and larger ground-truth summaries, which help the deep learning models trained on AVIATE to generalize the performance on other datasets.

2. We introduce several baselines to show that multimodal frameworks are substantially more effective when compared to their unimodal variants for abstractive text summarization.

3. We propose **Factorized Multimodal Transformer based decoder-only Language Model** (**FLORAL**), which uses an increasing number of self-attentions to inherently capture inter-modal and intra-modal dynamics within the asynchronous multimodal input sequences. **FLORAL** demonstrates the utility of pre-trained language model (LM) for summary generation in relatively low-resource setups over traditional encoder-decoder based networks.

4. For the videos of AVIATE, we show the importance of OCR generated text transcripts, which contain keywords and informative phrases displayed on slides in academic presentations. To fuse ASR and OCR generated texts, we introduce a novel guided attention based fusion mechanism which attends the complementary features in both the sources and filters out repetitive and redundant words. After the incorporation of OCR transcript, the baselines and **FLORAL** yield $[0.7 - 3.6]$ ROUGE-L points performance improvement on AVIATE.

5. **FLORAL** reports benchmark results in terms of both automatic and manual evaluation metrics on How2 for short videos. It beats the best baseline by 1.39 ROUGE-L points. On AVIATE, **FLORAL** also turns out to be highly effective — it beats the best baseline by 2.74 ROUGE-L points.

6. Finally, we report the transferability of **FLORAL** between How2 and AVIATE. When trained on AVIATE and tested on How2, **FLORAL** yields 49.9 ROUGE-L score, which is only 6.9 points less than ROUGE-L obtained when
both trained and tested on How2. The diverse-length videos of AVIATE make the model transferable, which is tremendously effective for practical applications.

Reproducibility: To reproduce our results, we present detailed hyperparameter configurations in Table 1 and Section 5.1. Moreover, we also supplement our submission with full AVIATE dataset and source code of FLORAI.

2. Related Work

Abstractive text summarization with multimodal inputs has gained increasing attention in recent years with the surge of multimedia data on the Internet and social media. Unlike unimodal text summarization systems, which are vastly studied, multimodal approaches make use of visual and acoustic modalities in addition to the textual modality, as a valuable source of information for generating a fluent and informative summary. A few existing experiments (Li et al., 2017, 2018) have shown that compared to unimodal text summarization systems, multimodal summarization can improve the quality of generated summary by using the information in the visual modality.

Unimodal Text Summarization: Unimodal text summarization systems can be broadly classified into two approaches – extractive and abstractive summarization. Extractive summarization systems, which are robust and straightforward, involve the selection of phrases and sentences from the source document to generate the summary. Existing literature on extractive summarization has structured the decision either as binary classification over sentences (Cheng and Lapata, 2016; Nallapati et al., 2017) or classification followed by ranking (Fang et al., 2017; Narayan et al., 2018; Zhou et al., 2018; Du et al., 2020). On the other hand, abstractive text summarization systems involve generating novel sentences either by rephrasing or using new words to capture the overall meaning of the source document, making it more advanced and closer to human-like interpretation. Rush et al. (2015) was the first to apply modern neural networks to abstractive text summarization. Their approach is based on the attention mechanism and has later been augmented with recurrent decoders (Chopra et al., 2016), hierarchical attention networks

\footnote{The resources are available in the following link: \url{https://github.com/LCS2-IIITD/multimodal_summ}}
(Nallapati et al., 2016), variational autoencoders (Miao and Blunsom, 2016) and pointer-generator (PG) (See et al., 2017) architecture, further improving performance of the summarization task. Song et al. (2018) proposed a PG-derived structure that tends to preserve structural dependencies from the source into the summaries. Chowdhury et al. (2020) improved the work of Song et al. (2018) by adding a structural attention based encoder to implicitly capture long term dependency relations in the summarization of lengthy documents. Recently, transformers (Vaswani et al., 2017) have been used to effectively encode sequential data with great success when pre-trained for language modeling or language masking and subsequently fine-tuned (Radford et al., 2018; Devlin et al., 2019) and thus, can be used on relatively low-resource setup without overfitting.

**Text Summarization with Multimodality:** Abstractive text summarization with multimodality deals with the fusion of textual, acoustic and visual modalities for summarizing a video document with a text precise that outlines the content of the entire video. Multimodal information is very useful in learning human-like meaning representations (Baroni, 2016; Kiela, 2017; Pramanick et al., 2021a,b). Since text rarely occurs in isolation in the real world, it becomes very effective to use all available information to optimize the quality of the summary jointly. The existing literature on multimodal text summarization include multimodal news summarization (Li et al., 2018; Chen and Zhuge, 2018; Li et al., 2016) and summarization of instructional videos (Palaskar et al., 2019). Li et al. (2017) were the first to collect a multimodal corpus of 500 English news videos and articles with manually annotated the summaries. However, the size of this dataset is very small. Zhou et al. (2018) presented the YouCookII dataset, containing instructional videos for cooking recipes with temporarily localized annotations for the procedures. Zhu et al. (2018) introduced the notion of multimodal summarization with multimodal output, which takes the news with images as input, and finally outputs a pictorial summary. Most recently, Palaskar et al. (2019) studied the task of summarization of instructional videos on the How2 dataset (Sanabria et al., 2018), which can be considered as the closest task to ours. However, all existing multimodal text summarization methods focus on summarizing images and/or short videos and generate one- or two-line long summary, and thus, can not be generalized to longer videos.
3. Dataset

To enable the exploration of abstractive text summarization using multimodal signals and to generalize the task for videos of different lengths, we introduce AVIATE, the first large-scale multimodal text summarization dataset with videos of diverse duration, compiled from academic paper presentations. Currently, the only existing benchmark dataset relevant to our task is the How2 dataset [Sanabria et al., 2018], which includes short instructional videos on different topics like cooking, sports, indoor/outdoor activities, music, etc. Our study reveals that deep neural models trained on such short videos fail to produce satisfactory results on longer videos. Moreover, the facial expression of the speakers in academic talks and presentations often plays an important role to preserve the most informative frames, which is not always the case for the How2 dataset.

3.1. How2 Dataset

The How2 dataset consists of 2,000 hours of short instructional videos, where the training, validation, and test set contain 73,993, 2,965, and 2,156 videos respectively, with an average length of 90 seconds. Each video in this dataset is accompanied by a human-generated transcript and a 2 – 3 sentence ground-truth summary. The average length of transcripts and summaries is 291 and 33 words respectively.

3.2. AVIATE Dataset

To collect conference presentation videos, we identified 28 academic conferences in computer science and social science, spanning over various domains such as Machine Learning, Natural Language Processing, Data Mining, Computer Vision, Computational Linguistics, Semantic Web, and Complex Systems. Most of the videos of our dataset come from conferences like NDSS,
ICML, NeurIPS, ACL, NAACL, CVPR, EMNLP, ISWC, KDD, etc. To collect the oral and spotlight presentations of these conferences, we scrapped six different academic online video repositories, namely Videolectures.NET\(^2\), ACL Anthology\(^3\), CVF Open Access\(^4\), ICML\(^5\), NeurIPS\(^6\), and NDSS Symposium\(^7\) websites. All the paper presentation videos are accompanied by an abstract, which we use as the ground-truth summary. Thus, unlike the How2 dataset, we did not annotate the summaries ourselves, which significantly improved the quality of ground truth summaries, and hence of the entire dataset.

AVIATE consists of a total of 8,201 videos, which spans over almost 2,300 hours. Among them, we use 6,680 videos for training, 662 for validation, and 859 for testing. The length of summaries is mostly between 100 − 300 words, with an average of 168 words. A brief source and duration statistics of AVIATE is presented in Figure 1.

**Transcription:** Since we collected all the videos from six different sources, not all of them had subtitles or transcripts readily available. This is particularly the case for videos from ACL Anthology and Videolectures, which contribute the majority of the AVIATE dataset. In the case of videos from NDSS, ICML, NeurIPS, and CVF Open Access corpus, subtitles are available for those videos which are present on Youtube. To maintain uniformity in the quality of transcripts, we apply Deep Speech \(^{[\text{Hannun et al. 2014}]}\), a pre-trained end-to-end speech recognition algorithm, to extract transcripts for all the videos. To ensure the quality of Deep Speech generated transcripts, we manually transcribe 300 randomly selected videos from our dataset. A low word error rate (24.19\%) of the Deep Speech model for those videos indicates the satisfactory standard of the transcripts. An additional normalization step, which includes formatting\(^8\) entities like numbers, dates, times, and addresses, helps us to further reduce the error rate to 20.12\%.

Figure 2 shows a comparison of video length and ground-truth summary length distribution for AVIATE and How2. For both datasets, longer videos

\(^2\)http://videolectures.net/
\(^3\)https://www.aclweb.org/anthology/
\(^4\)https://openaccess.thecvf.com/
\(^5\)https://icml.cc/
\(^6\)https://nips.cc/
\(^7\)https://www.ndss-symposium.org/
\(^8\)For example, labeling ‘September 16, 2017’ as ‘september sixteenth twenty seventeen’. 
Figure 2: Correlation between duration of videos and ground-truth summary length for AVIATE and How2 datasets.

Generally have a longer ground-truth summary, which leads to an overall positive correlation between video duration and ground-truth summary length. The average length of AVIATE videos is almost 12 times more than that of How2 videos. The longer videos and lengthier summaries in AVIATE make it harder than How2 to train on, which is explained in Section 6.

4. FLORAL: Our Proposed System

In this section, we describe our proposed system, Factorized Multimodal Transformer (Zadeh et al., 2020) based Language Model (FLORAL) for abstractive text summarization using multimodal signals. Figure 3 shows the overall architecture of FLORAL. It takes a video, its corresponding audio and text transcript as input and generates an abstractive textual summary. A video generally has three distinct modalities – visual, textual, and acoustic, which supplement each other by providing complementary information, and thus when fused, separately contribute to generating richer and more fluent summaries. The first part of FLORAL extracts unimodal features using respective unimodal feature extraction networks. This phase does not
consider the contextual relationship between the three different modalities. In the next part, unimodal features are processed using the Factorized Multimodal Transformer (FMT) based decoder-only network over multiple steps, which in turn generates one summary word in each step. After every step, the generated word is appended to the source text with a delimiter. Therefore, FLORAL considers the entire summarization problem as a language modeling task, simplifying traditional encoder-decoder architecture. The remaining part of this section discusses individual modules of FLORAL in detail.

4.1. Video Feature Extraction

The visual features are extracted using a pre-trained action recognition model, ResNeXt – 152 3D Convolutional Neural Network (Hara et al., 2018) trained on the Kinetics dataset (Kay et al., 2017) to recognize 400 different human actions. All the frames, computed at a rate of 5 FPS, are first preprocessed by resizing, center-cropping, and normalization to have a resolution of 112 × 112. For every 16 non-overlapping frames in a video, ResNeXt – 152 extracts a 2048 dimensional feature vector. Therefore, the result is a sequence of feature vectors per video rather than a global one. The sequential feature vector, $u_v = \{u_v^i\}_{i=1}^l$, is then used as the visual embedding input to the FMT.
4.2. Speech Feature Extraction

The acoustic modality is expected to contribute information related to tonal-specific details of the speaker [Tepperman et al., 2006]. To achieve this, we obtain low-level features from the audio stream for each video. Similar to Castro et al. (2019), we use the popular speech processing library, Librosa [McFee et al., 2018] and perform the steps mentioned next. First, the audio sample for a video is stacked as a time-series signal with a sampling rate of 16000 Hz. Next, we remove the echos and background noise from the audio signals by integrating it with Audacity instance [9], which is a free and open-source audio editor. Then, we segment the audio signals into \( d_w \) non-overlapping windows with a window size of 25 ms and successive window shift of 10 ms to extract low-level features that include Mel Frequency Cepstral Coefficients (MFCCs) with hamming window and the related temporal derivatives. Padding and segmentation are performed to achieve a fixed-length representation of the audio sources which are otherwise variable in length. At last, we concatenate all the extracted features to compose a \( d_a = 512 \) dimensional joint representation for each window. Final MFCC features are obtained by applying a log Mel frequency filter bank over 0 to 8000 Hz and applying discrete cosine transformation (DCT). Similar to the visual features, the audio features, \( u_a = \{ u_{ai} \}_{i=1}^{l_a} \), are also sequential for every video sample and are then used as the acoustic embedding input of FMT.

4.3. Textual Feature Extraction

Both How2 and AVIATE datasets contain textual transcripts corresponding to video samples. For How2, the transcripts are manually annotated, while for AVIATE, a pre-trained automatic speech recognition (ASR) algorithm, Deep Speech [Hannun et al., 2014], is used to extract the transcripts for all the videos (as discussed in Section 3.2). Since the AVIATE dataset consists of conference presentation videos, we observe that in the majority of video samples of AVIATE, the speaker uses presentation slides that contain the most informative key-phrases. Thus, we extract the text shown in the slides using Google OCR Vision API [10] and fuse the OCR-generated text with ASR-generated text using a novel guided attention mechanism to attend complementary and non-redundant words of both sources.

[9] https://github.com/officeonlinesystems/audacityonline_audioeditor/
[10] https://cloud.google.com/vision/docs/ocr#vision_text_detection-python
Guided Attention: At first, we represent the text in both ASR and OCR-generated transcripts using pre-trained BERT (Devlin et al., 2019), which provides dynamic embedding for every word. In particular, we use the sequence of 768-dimensional hidden states at the output of the last layer of the BERT model. Let \( F \in \mathbb{R}^{n \times 768} \) and \( H \in \mathbb{R}^{m \times 768} \) be the BERT representations for ASR and OCR texts respectively, where \( n \) and \( m \) are the respective token counts. The guided attention mechanism begins with defining an affinity matrix \( C \in \mathbb{R}^{n \times m} \), whose element \( c_{ij} \) denotes the similarity between the feature vector pairs, \( h_i \in \mathbb{R}^{768} \) and \( f_i \in \mathbb{R}^{768} \):

\[
C = \tanh(H W_b F^\top) \tag{1}
\]

where \( W_b \in \mathbb{R}^{768 \times 768} \) is a correlation matrix to be learned during training.

Subsequently, we compute a normalized weight \( \alpha_{ij}^h \) to denote the relevance of the \( i^{th} \) ASR-generated word to \( j^{th} \) OCR-generated word. Therefore, the weighted summation of the ASR transcript, \( a_j^h \), can be represented as,

\[
a_j^h = \sum_{i=1}^{n} \alpha_{ij}^h h_i \tag{2}
\]

where, \( \alpha_{ij}^h = \exp(c_{ij}) / \sum_{i=1}^{n} \exp(c_{ij}) \) \tag{3}\]

Since our goal is to emphasize the dissimilar features between the ASR and OCR transcripts, we define the relevance matrix \( R(f_i, a_j^h) \) as cosine distance between the attended ASR sentence vector \( a_j^h \) and OCR word embedding \( f_i \) –

\[
R(f_i, a_j^h) = 1 - \frac{f_i^\top \cdot a_j^h}{\|f_i\| \|a_j^h\|} \tag{4}
\]

Now, the weighted summation of all word embeddings produces the modified ASR representation \( U \) computed as,

\[
U = \sum_{j=1}^{m} R(f_i, a_j^h) \cdot f_i \tag{5}
\]

where \( R(f_i, a_j^h) \) acts as a filter for the ASR encoding \( f_i \).

Finally, we concatenate the attended ASR word representations with OCR word embeddings to get the sequential textual features \( u_t = \{u_t^i\}_{i=1}^{l_t} \), which is used as the textual embedding input of FMT.
4.4. Language Model Pre-training

The pre-trained Language Model (LM) has recently been shown to have superior performance in abstractive summarization, particularly to enhance sample efficiency (Khandelwal et al., 2019). This decoder-only network, known as Transformer LM, takes a pre-trained transformer (Vaswani et al., 2017) as its base module and treats summarization as a language modeling task where each generated summary word in every step is appended to its source article. We extend the concept of Transformer LM to a multimodal setting, where we use Factorized Multimodal Transformer (Zadeh et al., 2020) based Language Model (FLORAL) for multimodal sequential learning. After each step of summary generation, we append the generated summary word to its source text transcript, along with a delimiter, and train the transformer on this reformulated data. FLORAL has three crucial advantages over traditional encoder-decoder based summarization networks:

1. In contrast to encoder-decoder architecture, FLORAL uses a single network to encode the source and generate the target, and thus, avoids the loading of same pre-trained weights into separate encoder and decoder.

2. Compared to the encoder-decoder network, FLORAL has fewer number of parameters.

3. Most critically, all the parameters of FLORAL can be pre-trained.

Since there is no available large-scale multimodal corpus, we pre-train FLORAL on the text-only 2-billion word corpus based on Wikipedia, called WikiLM (Khandelwal et al., 2019), and fine-tune on the AVIATE and How2 datasets.

4.5. Factorized Multimodal Transformer LM

Factorized Multimodal Transformer (FMT) (Zadeh et al., 2020), which is the current state-of-the-art model for multimodal emotion recognition and multimodal speaker traits recognition on well-studied IEMOCAP (Busso et al., 2008) and POM (Park et al., 2014) datasets, applies seven distinct self-attention mechanisms to simultaneously capture all possible uni-modal, bi-modal, and tri-modal interactions across its multimodal input. We use

\footnote{https://github.com/tensorflow/tensor2tensor}
Figure 4: Overview of a single Factorized Multimodal Self-attention (FMS) in MTL. Each FMS consists of 7 distinct self-attention layers, which inherently capture inter-modal and intra-modal dynamics within the asynchronous multimodal input sequence. Blue, red and green colors are used to illustrate the propagation of visual, acoustic and textual features within FMS.

Before feeding into FMT, the unimodal embeddings are resampled using a reference clock so that modalities can follow the same frequency. Additionally, zero paddings are used to unify the length of all samples of the entire dataset to a desired fixed length $L$. Hence, the $i^{th}$ data point consists of three distinct sequences of embeddings corresponding to three modalities – visual, acoustic, and language:

$$D = \{ x_i = [x_{(t,i)} = \langle u_v^{(t,i)}, u_v^{(t,i)}, u_v^{(t,i)} \rangle_{t=1}^{L}, \text{tar}_i ]_{i=1}^{N}\}$$

where $x_i \in \mathbb{R}^{L \times d_x}$ and $\text{tar}_i \in \mathbb{R}^{M \times d_y}$ are the inputs and target summaries respectively, $M$ is the length of the summary; $d_x, d_y$ denote the input and output dimensionality at each time step respectively; $N$ is the total number of samples within the dataset. Positional embeddings are also added to the input.

The FMT consists of a stack of Multimodal Transformer Layers (MTL), which captures factorized dynamics within multimodal data and aligns the time asynchronous information both within and across modalities using multiple Factorized Multimodal Self-attentions (FMS), each of which has 7 distinct self-attention layers. Each attention has a unique receptive field with
respect to modalities \( f \in F = \{L, V, A, LV, LA, VA, LVA\} \). The high dimensional output of FMS is controlled by a summarization network \( S_1 \) to have a reduced dimension \( \mathbb{R}^{L \times d_x} \) which goes through feedforward and normalization layers. If there are a total of \( P \) number of FMS units inside MTL, the dimensionality of the normalization layer is \( \mathbb{R}^{P \times L \times d_x} \) which is again mapped to \( \mathbb{R}^{L \times d_x} \) using a secondary summarization network \( S_2 \). The output of the last MTL of FMT, thus computed, is fed into a Gated Recurrent Unit (GRU) to have a \( d_y \) dimensional predicted summary word embedding, \( \text{Summ}_i \). An overview of a single Factorized Multimodal Self-attention (FMS) block in MTL is presented in Figure 4.

The summary word predicted by the FMT in the first step, \( \text{Summ}_1 \), is appended to the text transcript and fed into the same FMT in the next step to predict the second summary word, \( \text{Summ}_2 \). This process is continued until the model generates a stop-word or a predetermined summary length is reached. We only compute loss over the target sequence, as suggested by Khandelwal et al. (2019).

5. Experiments

To explore the role of multimodality in abstractive text summarization, we conduct multiple experiments evaluating textual and visual modalities separately and jointly on both How2 and AVIATE datasets. Additionally, we investigate the role of OCR-generated text for the academic presentation videos in AVIATE for improving summary generation.

5.1. Training

We train FLORAL using Pytorch framework on NVIDIA Tesla V100 GPU, with 32 GB dedicated memory, with CUDA-10 and cuDNN-7 installed. We pre-train all the parameters of FLORAL using WikiLM (Khandelwal et al., 2019), and fine-tune on the summarization datasets (How2 and AVIATE). Similar to encoder-decoder models, we only compute loss over the target sequence. In Table 1, we present the details of hyper-parameters used in the baselines and in FLORAL.

5.2. Baselines

We compare the performance of the following extractive and abstractive unimodal and multimodal text summarization models both on How2 and AVIATE datasets.
### Table 1: Hyperparameters of different abstractive baseline models compared to FLORAL.

| Modality                        | Models                  | Batch-size | #Steps | Peak LR | Optimizer | Dropout | #Parameters |
|---------------------------------|-------------------------|------------|--------|---------|-----------|---------|-------------|
| Unimodal (Text Only)            | PG                      | 16         | 230K   | 0.01    | Adagrad   | 0.2     | 42m         |
|                                 | PG-MMR                  | 16         | 230K   | 0.01    | Adagrad   | 0.2     | 42m         |
|                                 | Hi-MAP                  | 32         | 200K   | 0.01    | Adagrad   | 0.1     | 36m         |
|                                 | Copy Transformer        | 16         | 200K   | 0.05    | Adam      | 0.2     | 105m        |
| Multimodal (Text + Audio + Video) | Multimodal HA          | 64         | 300K   | 0.05    | Adam      | 0.3     | 8m          |
|                                 | MuIT En-De              | 24         | 300K   | 0.01    | Adam      | 0.2     | 477m        |
|                                 | FMT En-De               | 32         | 300K   | 0.04    | Adam      | 0.2     | 495m        |
|                                 | MuIT LM                 | 32         | 500k   | 0.04    | Adam      | 0.1     | 242m        |
|                                 | FLORAL                  | 16         | 500k   | 0.01    | Adam      | 0.1     | 260m        |

**5.2.1. Extractive Summarizers (Text Only)**

- **Lead3** is the most common baseline which simply selects the leading three sentences of the document as its summary.

- **KLSumm** ([Haghighi and Vanderwende, 2009](#)) is a greedy algorithm that minimizes the Kullback-Lieber (KL) divergence between the original document and the ground-truth summary.

- **TextRank** ([Mihalcea and Tarau, 2004](#)) runs a modified version of PageRank on a weighted graph, consisting of nodes as sentences and edges as similarities between sentences.

- **LexRank** ([Erkan and Radev, 2004](#)) is a graph-based algorithm that represents sentences as vertices, and edges represent the similarity.

**5.2.2. Abstractive Summarizers (Text Only)**

- **Pointer Generator (PG)** ([See et al., 2017](#)) network is one of the most popular sequence to sequence (seq2seq) summarization architectures. PG allows both generating words from the vocabulary or copying from the source document.

- **Pointer Generator-MMR** ([Lebanoff et al., 2018](#)) uses MMR along with PG for better coverage and redundancy mitigation. Here MMR computes a similarity score of sentences with the source text and modifies the attention weights for a better summary generation.

- **Hi-MAP** ([Fabbri et al., 2019](#)) is a hierarchical MMR-attention based PG model, which extends the work of PG and MMR. Here, MMR scores are calculated at word level and incorporated in the attention weights for a better summary generation.
• **CopyTransformer** (Bottom-up Abstractive Summarization) (Gehrmann et al., 2018) uses the transformer parameters proposed by Vaswani et al. (2017). It uses a content selection module that over-determine phrases in the source document.

5.2.3. *Abstractive Summarizers (Video + Audio + Text)*

• **Multimodal Hierarchical Attention** (Palaskar et al., 2019) extends the work of Libovický and Helcl (2017), which was originally proposed for multimodal machine translation. This model fuses visual and textual modalities and captures the context of visual and textual features along with hierarchical attention to generate summaries.

• **MulT Encoder-Decoder** is an encoder-decoder based summarization architecture, which uses MulT (Multimodal Transformer for Unaligned Multimodal Language Sequences) model (Tsai et al., 2019) as its encoder and decoder unit.

• **FMT Encoder-Decoder** is an encoder-decoder network, similar to MulT encoder-decoder. This baseline uses Factorized Multimodal Transformer (Zadeh et al., 2020) as the encoder and decoder units.

• **MulT LM** is MulT-based architecture. This is most akin to our proposed FLORAL model; only the FMT module of FLORAL is replaced by MulT (Tsai et al., 2019) to have this multimodal summarization baseline.

6. Experimental Results

We present a quantitative analysis of the summaries using the standard metrics for abstractive summarization – ROUGE-1 (R-1), ROUGE-2 (R-2), and ROUGE-L (R-L) (Lin, 2004; Graham, 2015) that measure the unigrams, bigrams, and longest common sequence between the ground-truth and the generated summaries, respectively. Additionally, we perform extensive qualitative analysis using human experts to primarily understand the fluency and informativeness of the summaries. We also analyze the word distributions in the transcriptions and summaries.

6.1. Quantitative Analysis

At first, we evaluate the performance of commonly used extractive and abstractive text summarization models both on the How2 and AVIATE
| Model         | Modality   | AVIATE Dataset |
|--------------|------------|----------------|
|              |            | R-1  | R-2  | R-L  |
| KLSumm       | ASR        | 22.19| 2.05 | 15.59|
|              | ASR+OCR    | 24.27| 2.31 | 16.92|
| TextRank     | ASR        | 22.15| 2.71 | 16.42|
|              | ASR+OCR    | 24.55| 2.72 | 22.1 |
| LexRank      | ASR        | 22.63| 2.49 | 15.68|
|              | ASR+OCR    | 24.55| 2.72 | 22.1 |
| PG           | ASR        | 26.27| 2.01 | 22.96|
|              | ASR+OCR    | 27.77| 2.05 | 23.81|
| PG-MMR       | ASR        | 27.34| 2.72 | 22.63|
|              | ASR+OCR    | 27.82| 3.97 | 23.93|
| Hi-MAP       | ASR        | 27.62| 3.16 | 22.1 |
|              | ASR+OCR    | 28.13| 3.87 | 22.5 |
| CopyTransformer | ASR    | 29.93| 3.73 | 25.13|
|              | ASR+OCR    | 30.27| 3.94 | 27.06|
| Multimodal HA | ASR+V+A  | 27.51| 4.83 | 25.32|
|              | (ASR+OCR)+A+V | 28.14| 4.91 | 26.12|
| Multit Encoder-Decoder | ASR+V+A | 29.65| 4.12 | 26.47|
|              | (ASR+OCR)+A+V | 30.89| 4.34 | 27.2 |
| FMT Encoder-Decoder | ASR+V+A | 31.8 | 4.49 | 26.1 |
|              | (ASR+OCR)+A+V | 32.85| 4.6  | 27.65|
| MulT LM      | ASR+V+A    | 31.71| 4.07 | 27.58|
|              | (ASR+OCR)+A+V | 33.47| 4.12 | 28.73|
| FLORAL       | ASR+V+A    | 33.26| 6.38 | 28.52|
|              | (ASR+OCR)+A+V | **37.13**| **11.04** | **31.47**|

Table 2: Ablation results after incorporating OCR generated text into the ASR generated text transcript using guided-attention for different extractive and abstractive unimodal and multimodal text summarization systems on AVIATE.

datasets. Note that the average length of text transcripts in How2 is much less than that of AVIATE. Following our intuition, PG-based text summarization networks perform relatively well on How2 as shown in Table 3 but their performance drastically drops on AVIATE. This result can be attributed to the fact that attention-based encoder-decoder networks often fail to capture long-term dependencies when the source text is long and noisy. Hence, we decide to use transformer-based pre-trained BERT (Devlin et al., 2019) as the text-embedding layer in our model.

In addition to text-only models, we train two video-only models – the first one uses a single convolutional and pooling layer for feature extraction from the entire video, while the second one applies a single layer RNN over these vectors in time. We observe in Table 3 that even using only action features in the videos leads to almost competitive R-1, R-2, and R-L scores compared...
to text-only models, in some cases often better than extractive text-only systems. This result demonstrates the importance of both modalities for summarization.

Table 3: FLORAL achieves highest performance in ROUGE-1, ROUGE-2 and ROUGE-L over text based extractive system (Lead3, KLSumm, TextRank and LexRank) and abstractive systems (Seq2Seq, PG, PG-MMR, Hi-MAP and CopyTransformer) and multimodel baselines (Multimodal HA, MuT based encoder decoder, FMT based encoder decoder, MuT based language model and FLORAL) in How2 and AVIATE datasets.

6.1.1. Incorporation of OCR

Since the AVIATE dataset is composed of conference presentation videos, we observe that in almost 94.8% videos in the entire dataset, the speaker shows slides during the presentation. The text in these slides is succinct and contains the most important key-phrases which are crucial for summary generation. Table 2 shows the performance improvement for every summarization model when the OCR is fused with ASR transcript using our guided attention mechanism. We also consider direct concatenation of OCR transcript with the ASR-transcript; however, it resulted in lower performance as compared to guided attention fusion. The guided attention ensures the filtering of redundant and repetitive words in OCR and ASR transcripts. For every summarization model, we only use the first 500 tokens of the OCR transcript. We did not consider incorporating OCR for How2 as this dataset only contains
instructional videos, and there is no text shown in the frames of instructional videos.

Table 2 shows that unimodal extractive text summarization models, namely KLSumm, TextRank and LexRank, yield an improvement of $[2.1 - 2.3]$ R-1 points, $[0.1 - 0.3]$ R-2 points and $[0.6 - 6.5]$ R-L points after incorporating OCR-generated text. Similarly for abstractive summarization, the very popular PG-MMR network produces $0.5, 1.25,$ and $2.3$ points performance improvement in terms of R-1, R-2, and R-L scores, respectively. The other abstractive summarization networks, namely PG, Hi-MAP, CopyTransformer, also support our hypothesis and show an improvement of $[0.5 - 4]$ points in terms of all three evaluation metrics.

Influenced by the performance of unimodal summarization models, we incorporate the OCR transcripts into all of our multimodal baselines. Supporting our intuition, the multimodal systems obtain significant performance enhancement with OCR transcripts as shown in Table 2. The multimodal hierarchical attention model, MulT, and FMT-based encoder-decoder models show $[0.8 - 1.5]$ points improvement in the R-L score. Our proposed FLORAL model yields the highest performance boost with OCR among all the multimodal systems, showing $3.87, 4.66,$ and $2.95$ point enhancement in R-1, R-2, and R-L scores respectively. The performance boost can be easily attributed to the keywords in the OCR-generated transcript, which guides the text-embeddings to attend the most important portions in a very long ASR transcript. Hence, in the rest of our discussion, we always report results with (ASR + OCR) transcript, fused with guided attention, as the textual modality.

6.1.2. Complementarity of Multiple Modalities

Table 3 shows the ROUGE scores for different unimodal and multimodal text summarization systems on the How2 and AVIATE datasets. Among the unimodal variants, the abstractive text summarization systems generally perform much better than the extractive systems, especially on AVIATE. Note that despite being a very strong extractive baseline, Lead3 does not perform well on AVIATE, as the text transcripts of academic presentation videos do not tend to be structured with the most important information at the beginning. The two video-only models, simple conv-pool action features and action features with RNN perform very close to the abstractive text-only baselines, which clearly indicates the necessity of visual modality in
addition to the textual modality. As presented in Table 3, the MulT, and FMT multimodal baselines and the proposed FLORAL model beat most of the unimodal systems by a large margin, on both the datasets. This result is expected because of the inherent ability of MulT and FMT to capture the intra-model and inter-modal dynamics within asynchronous multimodal sequences and incorporate diverse information in a single network. Overall, the combination of visual, acoustic, and textual signals significantly improves over the unimodal variants, with an improvement of 1.57, 3.04, and 3 R-1, R-2, and R-L points on How2 and 6.86, 7.1 and 4.41 on AVIATE.

We manually investigate some video samples of AVIATE where the multimodal system generates a better summary than the unimodal system. In most of these samples, the textual transcript is very noisy and contains many irrelevant words that are not much required for the summary generation. Figure 6 shows an example training instance of the AVIATE dataset with three different modalities. A closer look into the ASR and OCR transcripts reveals the presence of irrelevant and noisy words. For example, the very first sentence of the ASR transcript "hi i’m lisa ann hendricks and today" does not contribute to the summary generation. As a result, these samples require additional cues for performance improvement, which are availed from the multimodal signals. The variation of outputs from various unimodal and multimodal summarization networks for a single video sample is shown in Table 9.

6.1.3. Comparative Study on How2

Table 3 shows that the performance of unimodal and multimodal summarization systems on How2 as compared to AVIATE. In contrast to prior work on news-domain summarization (Nallapati et al., 2016), the seq2seq model performs the best among all unimodal systems on How2, achieving 55.32, 23.06, and 53.9 R-1, R-2, and R-L scores, respectively. As indicated by Palaskar et al. (2019), the PG model performs lower than seq2seq on How2 due to the lack of overlaps between input and output, which is the important feature of PG networks. Among the multimodal systems, our proposed FLORAL model yields the best results; however, the other multimodal

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12 We do not evaluate the performance of acoustic modality separately, as the MFCC audio features are typically incorporated to capture the pitch, intonation, and other tonal-specific details of the speaker, which do not contribute individually to the summarization task.
baselines reach almost competitive ROUGE scores compared to FLORAL on this dataset. Noticeably, despite having a simple structure, the multimodal hierarchical attention model performs very well on How2. On this dataset, FLORAL achieves 56.89, 26.93, and 56.80 R-1, R-2, and R-L scores, respectively, which are [0.1 – 2] points higher than the scores achieved by other multimodal baselines.

6.1.4. Comparative Study on AVIATE

AVIATE contains longer videos than How2, resulting in longer transcripts and ground-truth summaries. As shown in Table 3, the best performing unimodal summarization model on AVIATE is CopyTransformer. As the ASR and OCR generated summaries are very long, the extractive systems do not perform well on this dataset. While PG and seq2seq yield 23.32 and 23.81 R-L scores respectively, CopyTransformer produces a 27.06 R-L score, outperforming all other unimodal systems. The superior performance of CopyTransformer over PG and seq2seq can be attributed to the self-attention mechanism of transformers which helps to capture long-term dependencies. The incorporation of visual and acoustic modalities significantly improves the ROUGE scores on this dataset. FLORAL beats all the transformer-based encoder-decoder networks and language models. FLORAL produces 37.13, 11.04 and 31.47 R-1, R-2 and R-L scores respectively, where the second-ranked model on AVIATE, MuLT-LM obtains 33.47 R-1, 4.12 R-2, 28.73 R-L scores, which are almost [2.7 – 7] points lower than that of FLORAL. Since AVIATE contains 6,680 training samples, which may not be enough for today’s deep neural models, the factorization mechanism on FMT, which allows an increasing number of self-attention to better model the multimodal phenomena, results in its superior performance, without encountering difficulties even on the relatively low-resource setup of AVIATE. Pre-training of all the parameters of FLORAL also has an immense impact, which helps in beating all other baselines by a significant margin.

Table 3 also shows that all the unimodal and multimodal summarization models obtain almost [18 – 25] points higher R-1 and R-L scores and [3 – 6] points higher R-2 score on How2 over AVIATE. For example, FLORAL yields 56.89, 26.93, and 56.80 R-1, R-2, and R-L scores on How2 and 37.13, 11.04 and 31.47 R-1, R-2 and R-L scores on AVIATE. We can observe from Table 3 that all the baseline models as well as FLORAL yield higher R-1, R-2 and R-L scores on How2 than AVIATE. The overall better performance of every system on How2 than AVIATE can be attributed to two factors – firstly, the text
transcripts of How2 are manually annotated. In contrast, we use ASR and OCR outputs as the transcripts for AVIATE. The large margin of ASR and OCR errors in some of the train and test samples significantly affect the model performance. Secondly, since the video length, transcript length, and reference summary length are much longer in AVIATE than How2, the summarization task becomes more challenging in AVIATE. Furthermore, since AVIATE comprises many scientific presentation videos, the audio transcript contains complex academic words, leading to a larger dictionary for the language generation task. Overall, the results in Table 3 conclude that the AVIATE dataset is more exacting than How2, indicating room for further research with fine-grained and sophisticated multimodal models for long videos.

In our next experiment, we demonstrate how the summarization task becomes more challenging with longer videos. We divide the AVIATE dataset into three portions - short videos (duration less than 10 minutes), medium videos (duration between 10 minutes and 30 minutes) and long videos (duration more than 30 minutes). We split each portion in 4 : 1 ratio and train and test all the multimodal systems on each segment. Table 4 shows the performance reduction of each model with the increase in video length. In general, we observe that all four multimodal baselines yield R-L score in the range of [27.03 – 34.09] on the short videos. However, the score reduces to [23.19 – 28.69] for the long videos. The performance of FLORAL also decreases from short to medium and long videos; however, the span of reduction of R-L score is only [0.39 – 0.64], which is relatively less than all other baselines. We also notice that the LM-based systems generally capture long-term dependencies better than traditional encoder-decoder based systems.

The complementarity of multiple modalities in the performance of FLORAL is shown in Table 5. To understand the importance of visual modality,

| Model       | AVIATE Dataset |
|-------------|----------------|
|              | Short Videos   | Medium Videos | Long Videos | Whole Dataset |
|             | R-1 | R-2 | R-L | R-1 | R-2 | R-L | R-1 | R-2 | R-L | R-1 | R-2 | R-L |
| Multimodal HA | 30.11 | 5.12 | 27.03 | 26.54 | 4.97 | 25.31 | 24.18 | 4.65 | 23.19 | 28.14 | 4.91 | 26.12 |
| MultiEn-De  | 31.44 | 5.32 | 27.38 | 27.73 | 4.93 | 26.89 | 25.62 | 4.67 | 24.12 | 30.89 | 4.34 | 27.2 |
| FMT En-De   | 33.02 | 5.81 | 31.06 | 32.1 | 5.91 | 28.31 | 31.48 | 4.96 | 27.02 | 32.85 | 4.6 | 27.65 |
| MultiLM     | 33.13 | 5.65 | 30.58 | 34.09 | 5.05 | 29.27 | 33.37 | 5.31 | 28.69 | 33.47 | 4.12 | 28.73 |
| FLORAL      | 36.13 | 11.62 | 31.44 | 35.59 | 11.64 | 31.05 | 34.31 | 10.39 | 30.8 | 37.13 | 11.04 | 31.47 |

Table 4: Performance of multimodal baseline models and FLORAL on short (< 10 min), medium (> 10 min & < 30 min) and long (> 30 min) videos of AVIATE. As the video length and the corresponding reference summary length increase, the performance of all baseline models decreases heavily. However, FLORAL performs well across all video lengths.
Table 5: Significance of multimodal cues in FLORAL. The combination of visual, textual, and acoustic signals significantly improves over the unimodal variants, with a relative improvement of R-1, R-2 and R-L scores of 9.99%, 8.11% and 11.80% respectively over the best unimodal variant.

we feed zero input in other two modality channels of FLORAL and continue the process for all three modalities. We observe that the textual modality provides the best performance among unimodal variants. The addition of visual and acoustic features improves significantly over the unimodal baselines and achieves the best performance - with an increase in R-1, R-2 and R-L score of 9.99, 8.11 and 11.80 respectively over the best unimodal variant.

Table 6: Transferability of the proposed FLORAL model on the two available multimodal abstractive text summarization datasets - How2 and AVIATE. The network is trained on the dataset in each row, and is tested on the dataset shown in each column. The second row indicates the performance of FLORAL on the How2 videos whose transcripts are generated from ASR.

Table 7: Transferability of the proposed FLORAL model on videos of different length in the AVIATE dataset. The network is trained on the videos in each row, and tested on the videos shown in each column.
6.1.5. **Transferability of FLORAL**

Table 6 shows the transferability property of FLORAL between How2 and AVIATE. When trained and tested on the same dataset, FLORAL produces the best ROUGE scores, which is expected. However, when trained on AVIATE and tested on How2, FLORAL yields an R-L score of 49.90, which is just 6.9 decrease in R-L score (11.83% reduction in performance) than the one when trained and tested on How2. The vice-versa is not true, i.e., when trained on How2 and tested on AVIATE, the performance drop is drastic (26.56% reduction in performance). As the videos in How2 have human-annotated transcripts and those in AVIATE have ASR-generated transcripts, for fair comparison of transferability, we extract the ASR transcripts of the How2 videos and train FLORAL. The results of this experiment are shown in the second row of Table 6. We observe that the ASR transcript reduces the test performance on How2, which is expected due to the noise in the ASR output. The transferability score on AVIATE improves a bit, but the performance drop is still heavy (25.51% reduction in performance). From all these experiments, we can conclude that since the videos of How2 are very short, the learned weights do not perform well for longer videos. However, AVIATE consists of diverse-length videos, and thus, the trained model on AVIATE yields good results on How2 as well.

Table 7 shows the transferability of FLORAL across short, medium and long videos of AVIATE. When trained on the long videos, FLORAL performs the best across all three portions. However, when trained on short videos, the model can not learn long-term dependency for lengthier videos. The same property supports the results on Table 6. Since the How2 dataset contains only short videos, the model does not perform well when trained on How2 and tested on AVIATE. The longer videos in the training set helps the model to generalize well across videos of various lengths.

6.2. **Qualitative Analysis**

In addition to ROUGE scores, we conduct a qualitative analysis by performing a human evaluation to understand the standard of the summary outputs. Following the abstractive summarization human annotation work of Grusky et al. (2018), the summaries were evaluated by five annotators.\(^{13}\)

\(^{13}\)We employed five annotators who are experts in NLP, and their age ranges between 24-35 years.
Table 8: Scores for human evaluated metrics - Informativeness (INF), Relevance (REL), Coherence (COH), Fluency (FLU) over text based extractive systems (KLSumm and TextRank), abstractive systems (PG and CopyTransformer), video based abstractive systems (Action features with RNN) and multimodel systems (FMT Encoder Decoder, MulT Language Model and FLORAL) on How2 and AVIATE datasets.

| Modality                      | Model       | How2          | AVIATE        |
|-------------------------------|-------------|---------------|---------------|
| Extractive Systems (Text only)| KLSumm      | 2.82          | 2.98          |
|                               | TextRank    | 2.92          | 2.82          |
| Abstractive Systems (Text only)| PG          | 3.45          | 3.32          |
|                               | CopyTrans.  | 3.46          | 3.36          |
| Abstractive Systems (Video only)| Action     | 3.54          | 3.40          |
|                               | Ft. + RNN   | 3.52          | 3.31          |
| Multimodel Systems (Video + Audio + Text)| FMT En-De | 3.61          | 3.67          |
|                               | MulT LM     | 3.57          | 3.68          |
|                               | FLORAL      | **3.62**      | **3.71**      |

Figure 5: Word distribution of machine-generated summaries in comparison with the ground-truth summaries for different unimodal and multimodal systems on How2 and AVIATE datasets.

(a) Density curve on How2 dataset. (b) Density curve on AVIATE dataset.

to rate the generated summaries on a scale of [1 − 5] on four parameters - informativeness, relevance, coherence, and fluency. For the evaluation, we randomly sampled 300 videos from the test sets of How2 and AVIATE. Table 8 shows the average human evaluation scores for 4 text-only, 1 video-only and 3 multimodal models. In general, we observe that PG has difficulty in summarizing articles with repetitive information and tends to assign a lower priority to less occurring important keywords. The extractive summarization systems sometimes pick sentences extraneous to the summary. For example, we notice some summaries generated by KLSumm starting with “Good afternoon everyone, I am . “, which is the very first line of the transcript. In contrast, the
multimodal summarization models generate summaries with greater relevance and informativeness. Our proposed FLORAL model obtains high scores on informativeness, relevance, and coherence on AVIATE, but sometimes seems to generate less fluent summaries. This fluency problem mostly stems from errors in ASR and OCR generated text. Some of these phenomena are illustrated with instances from AVIATE in Table 9.

We also analyze the word distributions of the ground-truth summaries and different system-generated summaries. The density curves in Figure 5 shows that for both How2 and AVIATE, the abstractive unimodal and multimodal summarization models generate summaries shorter than the ground-truth summary. The average length of summaries is highest for CopyTransformer. Interestingly, FLORAL and PG generated summaries are similar in length. However, FLORAL outperforms PG by a large margin, which illustrates that for improvements in ROUGE scores, an informative summary is more crucial than a lengthier summary.

7. Conclusion

In this paper, we explore the role of multimodality in abstractive text summarization. All the previous studies in this direction have used either images or short videos as the visual modality and generate one or two lines long summary, and thus, fail to perform on longer videos. Moreover, there exists no benchmark dataset for abstractive text summarization of medium and long videos. In this work, we introduce AVIATE, the first large-scale dataset for abstractive text summarization with videos of diverse duration, compiled from paper presentation videos in renowned academic conferences. We then propose FLORAL, a Factorized Multimodal Transformer based decoder-only Language Model, which uses an increasing number of self-attentions to inherently capture inter-modal and intra-modal dynamics within the asynchronous multimodal sequences, without encountering difficulties during training even on relatively low-resource setups. To evaluate FLORAL, we perform extensive experiments on How2 and AVIATE datasets and compare them against several unimodal and multimodal baselines. Overall, FLORAL achieves superior performance over previously proposed models across two datasets.

Acknowledgement

The work was partially supported by Ramanujan Fellowship (SERB) and the Infosys centre for AI, IIIT Delhi, India.
Table 9: Comparison of ground-truth summary and outputs of 7 different unimodal and multimodal abstractive text summarization systems - FLORAL, MultT LM, MultT Encoder-Decoder, CopyTransformer, multimodal hierarchical attention (HA), Pointer Generator (PG) and Pointer Generator with MMR (PG-MMR) - arranged in the order of best to worst ROUGE-L scores in this table. Red highlighted text indicates a positive correlation of context w.r.t. ground-truth summary while blue color represents a negative correlation with ground-truth summary.
Figure 6: Example of AVIATE dataset with three different modalities. To obtain the text transcripts from the acoustic modality, we apply Deep Speech ([Hannun et al., 2014]), a pre-trained end-to-end automatic speech recognition (ASR) system. We extract the text shown in the slides in the presentation videos using Google OCR Vision API. We use the abstracts of corresponding research papers as the ground-truth summaries.

References

A. See, P. J. Liu, C. D. Manning, Get to the point: Summarization with pointer-generator networks, in: Proceedings of the 55th Annual Meet-
L. Lebanoff, K. Song, F. Liu, Adapting the neural encoder-decoder framework from single to multi-document summarization, in: Proceedings of the 2018 Conference on EMNLP, ACL, Brussels, Belgium, 2018, pp. 4131–4141. URL: https://www.aclweb.org/anthology/D18-1446. doi:10.18653/v1/D18-1446.

S. Gehrmann, Y. Deng, A. Rush, Bottom-up abstractive summarization, in: Proceedings of the 2018 Conference on EMNLP, ACL, Brussels, Belgium, 2018, pp. 4098–4109. URL: https://www.aclweb.org/anthology/D18-1443. doi:10.18653/v1/D18-1443.

T. Chowdhury, S. Kumar, T. Chakraborty, Neural abstractive summarization with structural attention, in: C. Bessiere (Ed.), Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence, IJCAI-20, IJCAI, 2020, pp. 3716–3722. URL: https://doi.org/10.24963/ijcai.2020/514. doi:10.24963/ijcai.2020/514, main track.

T. Chung, Y. Liu, B. Xu, Monotonic alignments for summarization, Knowledge-Based Systems 192 (2020) 105363. URL: http://www.sciencedirect.com/science/article/pii/S0950705119306197. doi:https://doi.org/10.1016/j.knosys.2019.105363.

R. R. Shah, Y. Yu, A. Verma, S. Tang, A. D. Shaikh, R. Zimmermann, Leveraging multimodal information for event summarization and concept-level sentiment analysis, Knowledge-Based Systems 108 (2016) 102–109.

H. Li, J. Zhu, C. Ma, J. Zhang, C. Zong, Read, watch, listen, and summarize: Multi-modal summarization for asynchronous text, image, audio and video, IEEE Transactions on Knowledge and Data Engineering 31 (2018) 996–1009.

J. Zhu, H. Li, T. Liu, Y. Zhou, J. Zhang, C. Zong, MSMO: Multimodal summarization with multimodal output, in: Proceedings of the 2018 Conference on EMNLP, ACL, Brussels, Belgium, 2018, pp. 4154–4164. URL: https://www.aclweb.org/anthology/D18-1448. doi:10.18653/v1/D18-1448.
S. Palaskar, J. Libovický, S. Gella, F. Metze, Multimodal abstractive summarization for how2 videos, in: Proceedings of the 57th Annual Meeting of the ACL, ACL, Florence, Italy, 2019, pp. 6587–6596. URL: https://www.aclweb.org/anthology/P19-1659 doi:10.18653/v1/P19-1659.

M. Wang, R. Hong, G. Li, Z.-J. Zha, S. Yan, T.-S. Chua, Event driven web video summarization by tag localization and key-shot identification, IEEE Transactions on Multimedia 14 (2012) 975–985.

Z. Li, J. Tang, X. Wang, J. Liu, H. Lu, Multimedia news summarization in search, ACM Transactions on Intelligent Systems and Technology (TIST) 7 (2016) 1–20.

J. Chen, H. Zhuge, Abstractive text-image summarization using multi-modal attentional hierarchical rnn, in: Proceedings of the 2018 Conference on EMNLP, 2018, pp. 4046–4056.

J. Mun, M. Cho, B. Han, Text-guided attention model for image captioning, in: AAAI, 2017, pp. 4233–4239.

S. Liu, Z. Ren, J. Yuan, Sibnet: Sibling convolutional encoder for video captioning, in: Proceedings of the 26th ACM International Conference on Multimedia, MM ’18, ACM, New York, NY, USA, 2018, p. 1425–1434. URL: https://doi.org/10.1145/3240508.3240667 doi:10.1145/3240508.3240667.

V. Iashin, E. Rahtu, Multi-modal dense video captioning, in: Proceedings of the IEEE/CVF Conference on CVPR Workshops, 2020, pp. 958–959.

X. Shi, J. Cai, J. Gu, S. Joty, Video captioning with boundary-aware hierarchical language decoding and joint video prediction, Neurocomputing 417 (2020) 347–356.

X. Shen, B. Liu, Y. Zhou, J. Zhao, M. Liu, Remote sensing image captioning via variational autoencoder and reinforcement learning, Knowledge-Based Systems (2020) 105920.

S. Gella, M. Lewis, M. Rohrbach, A dataset for telling the stories of social media videos, in: Proceedings of the 2018 Conference on EMNLP, 2018, pp. 968–974.
K.-H. Zeng, T.-H. Chen, J. C. Niebles, M. Sun, Title generation for user generated videos, in: European conference on computer vision, Springer, 2016, pp. 609–625.

H. Li, J. Zhu, T. Liu, J. Zhang, C. Zong, Multi-modal sentence summarization with modality attention and image filtering, in: Proceedings of the Twenty-Seventh IJCAI-18, IJCAI, 2018, pp. 4152–4158. URL: https://doi.org/10.24963/ijcai.2018/577 doi:10.24963/ijcai.2018/577.

R. Sanabria, O. Caglayan, S. Palaskar, D. Elliott, L. Barrault, L. Specia, F. Metze, How2: a large-scale dataset for multimodal language understanding, in: Proceedings of the Workshop on Visually Grounded Interaction and Language (ViGIL), NeurIPS, 2018, pp. 26.1–26.12. URL: http://arxiv.org/abs/1811.00347.

A. Y. Hannun, C. Case, J. Casper, B. Catanzaro, G. Diamos, E. Elsen, R. Prenger, S. Satheesh, S. Sengupta, A. Coates, A. Y. Ng, Deep speech: Scaling up end-to-end speech recognition, CoRR abs/1412.5567 (2014). URL: http://arxiv.org/abs/1412.5567.

H. Li, J. Zhu, C. Ma, J. Zhang, C. Zong, Multi-modal summarization for asynchronous collection of text, image, audio and video, in: Proceedings of the 2017 Conference on EMNLP, 2017, pp. 1092–1102.

J. Cheng, M. Lapata, Neural summarization by extracting sentences and words, in: Proceedings of the 54th Annual Meeting of the ACL (Volume 1: Long Papers), ACL, Berlin, Germany, 2016, pp. 484–494. URL: https://www.aclweb.org/anthology/P16-1046 doi:10.18653/v1/P16-1046.

R. Nallapati, F. Zhai, B. Zhou, Summarunner: A recurrent neural network based sequence model for extractive summarization of documents, in: Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence, AAAI’17, AAAI Press, 2017, p. 3075–3081.

C. Fang, D. Mu, Z. Deng, Z. Wu, Word-sentence co-ranking for automatic extractive text summarization, Expert Systems with Applications 72 (2017) 189 – 195. URL: http://www.sciencedirect.com/science/article/pii/S0957417416306959 doi:https://doi.org/10.1016/j.eswa.2016.12.021.
S. Narayan, S. B. Cohen, M. Lapata, Ranking sentences for extractive summarization with reinforcement learning, in: Proceedings of the 2018 Conference of the North American Chapter of the ACL: Human Language Technologies, Volume 1 (Long Papers), ACL, New Orleans, Louisiana, 2018, pp. 1747–1759. URL: https://www.aclweb.org/anthology/N18-1158 doi:10.18653/v1/N18-1158.

Q. Zhou, N. Yang, F. Wei, S. Huang, M. Zhou, T. Zhao, Neural document summarization by jointly learning to score and select sentences, in: Proceedings of the 56th Annual Meeting of the ACL (Volume 1: Long Papers), ACL, Melbourne, Australia, 2018, pp. 654–663. URL: https://www.aclweb.org/anthology/P18-1061 doi:10.18653/v1/P18-1061.

Y. Du, Q. Li, L. Wang, Y. He, Biomedical-domain pre-trained language model for extractive summarization, Knowledge-Based Systems (2020) 105964.

A. M. Rush, S. Chopra, J. Weston, A neural attention model for abstractive sentence summarization, in: Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, Association for Computational Linguistics, Lisbon, Portugal, 2015, pp. 379–389. URL: https://www.aclweb.org/anthology/D15-1044 doi:10.18653/v1/D15-1044.

S. Chopra, M. Auli, A. M. Rush, Abstractive sentence summarization with attentive recurrent neural networks, in: Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, 2016, pp. 93–98.

R. Nallapati, B. Zhou, C. dos Santos, Ç. Güçlüçehre, B. Xiang, Abstractive text summarization using sequence-to-sequence RNNs and beyond, in: Proceedings of The 20th SIGNLL Conference on Computational Natural Language Learning, ACL, Berlin, Germany, 2016, pp. 280–290. URL: https://www.aclweb.org/anthology/K16-1028 doi:10.18653/v1/K16-1028.

Y. Miao, P. Blunsom, Language as a latent variable: Discrete generative models for sentence compression, in: Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, Association for Computational Linguistics, Austin, Texas, 2016, pp. 319–328. URL: https://www.aclweb.org/anthology/D16-1031 doi:10.18653/v1/D16-1031.
K. Song, L. Zhao, F. Liu, Structure-infused copy mechanisms for abstractive summarization, in: Proceedings of the 27th International Conference on Computational Linguistics, Association for Computational Linguistics, Santa Fe, New Mexico, USA, 2018, pp. 1717–1729. URL: https://www.aclweb.org/anthology/C18-1146.

T. Chowdhury, S. Kumar, T. Chakraborty, Neural abstractive summarization with structural attention, International Joint Conferences on Artificial Intelligence (IJCAI) (2020) 3716–3722.

A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, I. Polosukhin, Attention is all you need, in: Advances in neural information processing systems, 2017, pp. 5998–6008.

A. Radford, K. Narasimhan, T. Salimans, I. Sutskever, Improving language understanding by generative pre-training, 2018.

J. Devlin, M.-W. Chang, K. Lee, K. Toutanova, BERT: Pre-training of deep bidirectional transformers for language understanding, in: Proceedings of the 2019 Conference of the North American Chapter of the ACL: Human Language Technologies, Volume 1 (Long and Short Papers), Association for Computational Linguistics, Minneapolis, Minnesota, 2019, pp. 4171–4186. URL: https://www.aclweb.org/anthology/N19-1423, doi:10.18653/v1/N19-1423.

M. Baroni, Grounding distributional semantics in the visual world, Language and Linguistics Compass 10 (2016) 3–13.

D. Kiela, Deep embodiment: grounding semantics in perceptual modalities, Technical Report, University of Cambridge, Computer Laboratory, 2017.

S. Pramanick, M. S. Akhtar, T. Chakraborty, Exercise? i thought you said’extra fries’: Leveraging sentence demarcations and multi-hop attention for meme affect analysis, in: Proceedings of the International AAAI Conference on Web and Social Media, volume 15, 2021a, pp. 513–524.

S. Pramanick, D. Dimitrov, R. Mukherjee, S. Sharma, M. S. Akhtar, P. Nakov, T. Chakraborty, Detecting harmful memes and their targets, in: Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021, Association for Computational Linguistics, Online, 2021b, pp.
L. Zhou, C. Xu, J. J. Corso, Towards automatic learning of procedures from web instructional videos, in: AAAI Conference on Artificial Intelligence, 2018, pp. 7590–7598. URL: https://www.aaai.org/ocs/index.php/AAAI/AAAI18/paper/view/17344.

A. Zadeh, C. Mao, K. Shi, Y. Zhang, P. P. Liang, S. Poria, L.-P. Morency, Factorized multimodal transformer for multimodal sequential learning, Elsevier Information Fusion Journal (2020).

K. Hara, H. Kataoka, Y. Satoh, Can spatiotemporal 3d cnns retrace the history of 2d cnns and imagenet?, 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition (2018) 6546–6555.

W. Kay, J. Carreira, K. Simonyan, B. Zhang, C. Hillier, S. Vijayanarasimhan, F. Viola, T. Green, T. Back, P. Natsev, et al., The kinetics human action video dataset, CoRR (2017).

J. Tepperman, D. Traum, S. Narayanan, Yeah right: Sarcasm recognition for spoken dialogue systems, 2006, pp. 1838–1841.

S. Castro, D. Hazarika, V. Pérez-Rosas, R. Zimmermann, R. Mihalcea, S. Poria, Towards multimodal sarcasm detection (an obviously perfect paper), 2019, pp. 4619–4629. doi:10.18653/v1/P19-1455.

B. McFee, M. McVicar, S. Balke, C. Thomé, V. Lostanlen, C. Raffel, D. Lee, O. Nieto, E. Battenberg, D. Ellis, et al., Wzy, Rachel Bittner, Keunwoo Choi, Pius Friesch, Fabian-Robert Stter, Matt Vollrath, Siddhartha Kumar, nehz, Simon Waloschek, Seth, Rimvydas Naktinis, Douglas Repetto, Curtis” Fjord” Hawthorne, CJ Carr, Joo Felipe Santos, JackieWu, Erik, and Adrian Holovaty,”librosa/librosa: 0.6 2 (2018).

U. Khandelwal, K. Clark, D. Jurafsky, L. Kaiser, Sample Efficient Text Summarization Using a Single Pre-Trained Transformer, arXiv preprint arXiv:1905.08836 (2019) 1,7.

C. Busso, M. Bulut, C.-C. Lee, A. Kazemzadeh, E. Mower, S. Kim, J. N. Chang, S. Lee, S. S. Narayanan, Iemocap: Interactive emotional dyadic
motion capture database, Language resources and evaluation 42 (2008) 335.

S. Park, H. S. Shim, M. Chatterjee, K. Sagae, L.-P. Morency, Computational analysis of persuasiveness in social multimedia: A novel dataset and multimodal prediction approach, in: Proceedings of the 16th International Conference on Multimodal Interaction, 2014, pp. 50–57.

M. Chen, S. Wang, P. P. Liang, T. Baltrušaitis, A. Zadeh, L.-P. Morency, Multimodal sentiment analysis with word-level fusion and reinforcement learning, in: Proceedings of the 19th ACM International Conference on Multimodal Interaction, 2017, pp. 163–171.

A. Haghighi, L. Vanderwende, Exploring content models for multi-document summarization, in: Proceedings of Human Language Technologies: The 2009 Annual Conference of the North American Chapter of the Association for Computational Linguistics, ACL, Boulder, Colorado, 2009, pp. 362–370. URL: https://www.aclweb.org/anthology/N09-1041.

R. Mihalcea, P. Tarau, TextRank: Bringing order into text, in: Proceedings of the 2004 Conference on EMNLP, ACL, Barcelona, Spain, 2004, pp. 404–411. URL: https://www.aclweb.org/anthology/W04-3252.

G. Erkan, D. R. Radev, Lexrank: Graph-based lexical centrality as salience in text summarization, Journal of Artificial Intelligence Research 22 (2004) 457–479. URL: http://dx.doi.org/10.1613/jair.1523 doi:10.1613/jair.1523.

A. Fabbri, I. Li, T. She, S. Li, D. Radev, Multi-news: A large-scale multi-document summarization dataset and abstractive hierarchical model, in: Proceedings of the 57th Annual Meeting of the ACL, ACL, Florence, Italy, 2019, pp. 1074–1084. URL: https://www.aclweb.org/anthology/P19-1102 doi:10.18653/v1/P19-1102.

A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. u. Kaiser, I. Polosukhin, Attention is all you need, in: I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, R. Garnett (Eds.), Advances in NeurIPS 30, Curran Associates, Inc., 2017, pp. 5998–6008. URL: http://papers.nips.cc/paper/7181-attention-is-all-you-need.pdf
J. Libovický, J. Helcl, Attention strategies for multi-source sequence-to-sequence learning, in: Proceedings of the 55th Annual Meeting of the ACL (Volume 2: Short Papers), ACL, Vancouver, Canada, 2017, pp. 196–202. URL: https://www.aclweb.org/anthology/P17-2031. doi:10.18653/v1/P17-2031.

Y.-H. H. Tsai, S. Bai, P. P. Liang, J. Z. Kolter, L.-P. Morency, R. Salakhutdinov, Multimodal transformer for unaligned multimodal language sequences, in: Proceedings of the conference. ACL. Meeting, volume 2019, NIH Public Access, 2019, p. 6558.

C.-Y. Lin, Rouge: A package for automatic evaluation of summaries, in: Text summarization branches out, 2004, pp. 74–81.

Y. Graham, Re-evaluating automatic summarization with bleu and 192 shades of rouge, in: Proceedings of the 2015 conference on EMNLP, 2015, pp. 128–137.

M. Grusky, M. Naaman, Y. Artzi, Newsroom: A dataset of 1.3 million summaries with diverse extractive strategies, in: Proceedings of the 2018 Conference of the North American Chapter of the ACL: Human Language Technologies, Volume 1 (Long Papers), ACL, New Orleans, Louisiana, 2018, pp. 708–719. URL: https://www.aclweb.org/anthology/N18-1065. doi:10.18653/v1/N18-1065.