Abstract

Summarization of multimedia data becomes increasingly significant as it is the basis for many real-world applications, such as question answering, Web search, and so forth. Most existing multi-modal summarization works however have used visual complementary features extracted from images rather than videos, thereby losing abundant information. Hence, we propose a novel multi-modal summarization task to summarize from a document and its associated video. In this work, we also build a baseline general model with effective strategies, i.e., bi-hop attention and improved late fusion mechanisms to bridge the gap between different modalities, and a bi-stream summarization strategy to employ text and video summarization simultaneously. Comprehensive experiments show that the proposed model is beneficial for multi-modal summarization and superior to existing methods. Moreover, we collect a novel dataset and it provides a new resource for future study that results from documents and videos.

1 Introduction

Multi-modal summarization is conducted to refine salient information from different modalities (including text, image, audio, and video) and to represent key information through one or more modalities (Evangelopoulos et al. 2013; Li et al. 2017). Given the rapid increase of multimedia data dissemination over the Internet, this task has been widely exploited in recent years.

Early works on multi-modal summarization has dealt with sports video summarization (Tjondronegoro et al. 2011), meeting recordings summarization (Erol et al. 2003; Li et al. 2019), or multimedia micro-blog summarization (Bian et al. 2013). Most of these approaches concentrate on summarizing data that include synchronous information among different modalities. However, due to the lack of accurate alignment, summarizing the large volume of multi-modal data of the same topic is impractical. To address this issue, neural networks based methods have been introduced that search for the corresponding relations from different information resources. For example, Li et al. (2017) learn the joint representations of texts and images to identify the text that is relevant to an image. Zhu et al. (2018) and Chen and Zhuge (2018) propose an attention model to summarize a document and its accompanying images.

Although the aforementioned models have shown reasonable qualitative results, they still suffer from the following drawbacks: 1) Most existing applications extract visual information from the accompanying images, but they ignore related videos. We contend that videos contain abundant contents and have temporal characteristics where events are represented chronologically, which are crucial for text summarization. To the best of our knowledge,
the only work [Li et al., 2017] that considers video information, however, neglects temporal progression and simply treating videos as a bag of images. The authors use video frames for sentence matching in outputs rather than combining visual information with text processing. 2) Although attention mechanism [Bahdanau et al., 2014] and early fusion [Snoek et al., 2005] are used extensively, it adversely introduces noise as it is unsuitable for multi-modal data without alignment, which is characterized by a large gap that requires intensive communication. 3) Various multi-modal summarization works have focused on a single task, such as text or video summarization with added information from other modalities [Zhu et al., 2018; Wei et al., 2018]. We observe that both summarization tasks share the same target of refining original long materials, and as such they can be performed jointly due to common characteristics.

In this work, we propose a novel multi-modal summarization task which is depicted in Fig. 1. To remove the noise among different modalities and effectively integrate complementary information, we introduce a bi-hop attention mechanism to align features and induce an improved late fusion method for feature fusion. Moreover, we apply a bi-stream summarization strategy for training by sharing the ability to refine significant information from long materials in text and video summarization. Given the lack of relevant datasets for experiments, we create a novel multi-modal dataset from the Daily Mail and CNN websites, collecting articles and their corresponding summaries, videos, images.

The main contributions are as follows:

- We introduce a novel task that automatically generates a textual summary with significant images from the multi-modal data associated with an article and its corresponding video.
- We propose the bi-hop attention and improved late fusion mechanism to refine information from multi-modal data. Besides, we introduce a bi-stream summarization strategy that simultaneously summarizes articles and videos.
- We prepare a content-rich multi-modal dataset. Comprehensive experiments demonstrate that complementary information from multiple modalities is beneficial, and our general baseline model can exploit them more effectively than the existing approaches.

2 Related Work

Text summarization selects salient information from long documents to form a concise summary. Existing approaches can be roughly categorized into two groups. Extractive-based methods, which extract key sentences and objects without modification, guarantee basic-level grammaticality and accuracy. For example, Jadhav and Rajan (2018) modeled the interaction between keywords and salient sentences by using a new two-level pointer network. The proposal of Narayan et al. [2018] and Hu (2018) extracted summary via deep reinforced learning. Abstractive-based methods, which paraphrase the significant contents after comprehending the original document, construct sophisticated summaries with newly-generated words and coherent expressions. Tan et al. (2017) presented a graph-based attention mechanism in a sequence-to-sequence framework. The work of Cao et al. (2018) retrieved proper existing summaries as candidate soft templates and extended the framework to jointly perform template reranking and summary generation. See et al. (2017) presented a pointer-generator network which can both copy words from articles and generate novel words. Recently, the sheer volume of fine-tuning approaches [Liu and Lapata, 2019; Zhang et al., 2019; Dong et al., 2019] boosted the quality of the generated summaries based on the pre-trained language models which have advanced a wide range of NLP tasks.

Video summarization is conducted to facilitate large-scale video browsing by producing concise summaries. Early works in video summarization have focused on videos of certain genres. They generated summaries by leveraging genre-specific information, i.e., salient objects of sports in (Ekin et al., 2003) and significant regions of egocentric videos in (Lu and Grauman, 2013). Furthermore, summarizing videos with auxiliary resources, such as web images and videos, has attracted considerable attention. Song et al. (2015) developed a co-archetypal analysis technique that learns canonical visual concepts shared between a video and images. Given that the above mentioned non-deep summarization methods are time-consuming, Zhou et al. (2018) modeled video summarization via a deep RNN to capture long-term dependencies in video frames and proposed a reinforcement learning-based framework to train the network end-to-end. Recently, a novel query-focused video summarization task was introduced in (Xiao et al., 2020).
Multi-modal summarization generates a condensed multimedia summary from multi-modal original inputs, such as text, images, videos, and etc. [UzZaman et al., 2011] introduced an idea of illustrating complex sentences as multimodal summaries that combine pictures, structure and simplified compressed text. [Libovicky et al., 2018; Palaskar et al., 2019] studied abstractive text summarization for open-domain videos. Besides, [Li et al., 2017] developed an extractive multi-modal summarization method that automatically generates a textual summary based on a set of documents, images, audios and videos related to a specific topic. [Zhu et al., 2018, 2020] combined image selection and output to alleviate the modality bias. Chen and Zhuge (2018) employed hierarchical encoder-decoder model to align sentences and images. Recently, aspect-aware model was introduced in [Li et al., 2020] to incorporate visual information for producing summary for e-commerce products.

3 Model

We introduce a novel multi-modal summarization model (M²SM) to automatically generate multi-modal summary from an article and its corresponding video. Fig. 2 illustrates the idea. Our proposed model consists of four modules: feature extraction, alignment, fusion, and bi-stream summarization, which are presented in Fig. 3.

3.1 Feature Extraction

Text Feature We utilize a hierarchical framework based on word and sentence levels to read the tokens of an article and induce a representation of each sentence. The bi-directional long short term memory (BiLSTM) which constitutes a forward and a backward LSTM is employed as recurrent unit. The first layer of the encoder, which extracts fine-grained information of a sentence, runs at the word level. The hidden state of the \( j^{th} \) word in the \( i^{th} \) sentence is represented by the BiLSTM, i.e., \( h_i^j = [h_i^j, h_i^j] \). Moreover, the encoder consists of a second layer conducted at the sentence level, which accepts the average-pooled, concatenated hidden states from the word level encoder as inputs. The hidden state of the \( i^{th} \) sentence is defined as

\[
s_i = [\phi(a_{pi}, s_{i-1}), \phi(a_{pi}, s_{i+1})], a_{pi} = \sum_{j=1}^{N_i} h_i^j,
\]

where \( N_i \) is the number of words in the \( i^{th} \) sentence and \( \phi(\cdot) \) represents LSTM.

Video Feature Videos that accompany articles often capture news highlights and usually provide abundant complementary information from the perspective that is different from the article itself. We choose ResNet-50 [He et al., 2016] to extract frame features for its excellent performance. Furthermore, we train a BiLSTM to model the sequential pattern in video frames, where the distinctions between videos and bag of images are exhibited. The image feature of the \( i^{th} \) frame is a 2048 dimensional vector \( v_i \), which is obtained using \( v_i = \text{ResNet(frame}_i) \). Correspondingly, the representation of a frame is defined as

\[
m_i = [\varphi(v_i, m_{i-1}), \varphi(v_i, m_{i+1})],
\]

where \( \varphi(\cdot) \) represents BiLSTM.

Recently, inspired by the success of the language model BERT [Jacob et al., 2019], which pre-trains deep bidirectional representations on unlabeled texts, a few visual-linguistic joint models have been proposed, such as VideoBERT [Sun et al., 2019], ViLBert [Lu et al., 2019], and VLP [Zhou et al., 2020]. These models can induce superior features for summarization. Our model M²SM is devised from a new perspective to extract fine-grained features, which are orthogonal to the aforementioned BERT-based ones in a complementary manner.

3.2 Feature Alignment

Existing multi-modal models with high alignment cannot be used for capturing the correct common features among different modalities due to the asynchronism between modalities. Hence, we introduce two multi-modal attention mechanisms which focus on diverse parts of video frames in accordance to a current article sentence in order to search for aligned information.
Single-step Attention We fulfill the above-stated goal by adopting the attention mechanism which was introduced in (Bahdanau et al., 2014). Specifically:

\[ e_{ij} = V^T \tanh(W_s s_i + W_m m_j + b_{attn}), \]  

(3)

where \( e_{ij} \) is the attention value between the \( i \)th sentence and \( j \)th image, and \( V, W_s, W_m, \) and \( b_{attn} \) are learnable parameters. Although lots of multi-modal summarization models (Chen and Zhuge, 2018; Zhu et al., 2018; Li et al., 2018) follow this mechanism, we argue that it is unsuitable for a multi-modal task because one modality might dominate the summary resulting in substantial loss of information from other modalities. Therefore, we generalize over “bilinear” attention (Kim et al., 2017) and propose improvements such as:

- Single feature projection

Considering that features of different modalities are independent from each other, the projection can be separately calculated such that neither component dominates another. The feature mapping of each modality can be modified as follows:

\[ q_j = \tanh(W_m m_j + b_m), \]  

(4)

\[ r_i = \tanh(W_s s_i + b_s), \]  

(5)

where \( W_m, W_s, b_m, \) and \( b_s \) are parameters.

- Dual feature interaction

For close communication of different modalities, we further propose a dual interaction feature calculated using Hadamard product. The concatenation feature \( cf \) represents the feature of each modality, while dual interaction feature \( dif \) avoids insufficient interaction among modalities. The attention value is formulated as

\[ e_{ij} = V^T (q_j \odot r_i + q_j + r_i), \]  

(6)

After calculating the softmax of the attention value to obtain weight \( a_{ij} \) of each image state \( m_j \), and computing the weighted sum of these states, context value can be represented as follows:

\[ c_i = \sum_{j=1}^{NM} a_{ij} m_j, \quad a_{ij} = \softmax(e_{ij}), \]  

(7)

where \( NM \) is the number of filtered frames.

Bi-hop Attention Given that the transcript extracted from a video shares the same modality with an article and accurately aligns with a video, we induce it as a bridge to deepen the relationship between two modalities. We introduce bi-hop attention to produce a context by simultaneously combining text sentence with a transcript and video frames. Since a transcript is similar to an article text, we use the BiLSTM to extract its features \( t_1, t_2, ..., t_{NT} \), where \( NT \) is the number of words in transcripts. Moreover, the context vector of transcript \( ct2m \) is obtained by replacing \( s_i \) with \( t_i \) in Eq. (5) for a new attention value \( b_{t2} \), and the original context vector of article \( ca2m \) is improved as \( ca2t \) by replacing \( m_j \) with \( ct2m_j \) in Eq. (4) for \( d_{t2} \):

\[ (ct2m_k = \sum_{k=1}^{NT} b_{t2}^i t2m_k, \quad ct2m_k = \sum_{j=1}^{NM} d_{t2}^j m_j). \]  

(8)

Similarly, bi-hop attention can be reversed to obtain an article context for video summarization.
3.3 Feature Fusion

In terms of combining complementary information from multiple modalities, we develop a method that not only smoothly suppresses the effect of modality in unfavorable situations, but also captures synergies between the modalities that share reliable complementary information. Methodologically, we use two common strategies for taking cross-modal correlations: Early fusion, which concatenates various features directly, has been explored in multi-modal tasks extensively (Zhu et al., 2017; Chen and Zhuge, 2018). The fusion feature of $i^{th}$ sentence of text summarization can be represented as $p_{ts} = [s_i, ca2m_i]$. Tensor fusion (Zadeh et al., 2017) disentangles unimodal and bi-modal dynamics by modeling each of them explicitly for intra-modality and inter-modality dynamics. $p_{ts} = [s_i, 1] \otimes [ca2m_i, 1]$ is denoted as fusion feature, where $\otimes$ indicates the outer product. Further, the label of each sentence can be predicted by $p_{ts}^i$.

Both the above-mentioned strategies are based on a strong assumption that each modality is accurately aligned, yet multi-modal summarization always contains asynchronous information. Hence, we consider that late fusion, which uses unimodal decision values and fuses them with a fusion mechanism, suits multi-modal summarization well. $F(f(s), g(ca2m))$ is the fusion process where $f(\cdot)$, $g(\cdot)$ is a conventional feed forward network, and $F(\cdot)$ can be a function, such as averaging, voting or other learned models. We use a feedforward network in this work. Given that each modality is not useful all the time, e.g., frames of accompanied interview video may contribute only to a small extent to visual features, we restrain the noise from a certain modality by following the ideas in (Liu et al., 2018) and induce late+ fusion. Its fusion process is improved as $F(W_s f(s), W_c g(ca2m))$ and $W_s, W_c$ are calculated as follows:

$$W_s = [1 - g(ca2m_i)]^\beta, W_c = [1 - f(s_i)]^\beta,$$ (9)

where $\beta$ is a smoothing coefficient determining the penalty intensity. For example, if a frame comes from an interview video and its visual features are irrelevant for classification, $g(ca2m_i)$ becomes small which bases the prediction mainly on article.

3.4 Bi-stream Summarization Training

Given that text and video summarization aim to extract salient information from the original redundant content, we propose bi-stream summarization training strategy. It indicates that they are learned jointly and simultaneously, which improve the generalization performance by holding similar objectives and sharing complementary information.

We consider extractive-based text summarization as a sentence classification task, in which the binary label of each sentence is imperative. Given that most corpora only contain abstractive summaries written by humans, we construct the label of each sentence following the methods in (Nallagattu et al., 2017). Sentences are selected to maximize the ROUGE with respect to the gold summary by a greedy approach. Furthermore, we use cross entropy for training:

$$L_{ts} = -\frac{1}{NS} \sum_{n=1}^{NS} \left[y_n \log \hat{y}_n + (1 - y_n) \log (1 - \hat{y}_n)\right],$$ (10)

where $y_n$ and $\hat{y}_n$ represent the true and predicted labels, respectively.

Video summarization can also be considered as a classification task; we use unsupervised learning by RL methods proposed in (Zhou et al., 2018). Its loss can be separated into diversity reward $R_{div}$ and representativeness reward $R_{rep}$. The former measures the dissimilarity among selected frames in the feature space, whereas the latter measures how well the generated summary can represent the original video. The calculations are as follows:

$$R_{div} = \frac{1}{|M|(|M| - 1)} \sum_{j \in M} \sum_{j' \in M, j' \neq j} d(m_j, m_{j'})$$

$$R_{rep} = \exp \left(-\frac{1}{NM} \sum_{j=1}^{N} \sum_{j' \in M} \min_{j \in M} \|m_j - m_{j'}\|_2\right)$$ (11)

where $M$ is the set of selected video frames, and $d(\cdot)$ is the dissimilarity function, which employed as one minus cosine similarity in this work.

For bi-stream summarization, we mix the loss from dual summarization tasks, whose contribution relies on their weight $\alpha_{ts}$ and $\alpha_{vs}$:

$$L = \alpha_{ts} L_{ts} + \alpha_{vs} (R_{div} + R_{rep}).$$ (12)

4 Experiments

4.1 Dataset and Evaluation Metrics

There is no existing dataset that contains articles, corresponding videos and references for multimodal summarization, we construct a new corpus called MM-AVS. To obtain high quality summaries, we collect data from Daily Mail and CNN websites same as in (Hermann et al., 2015). We also preserve the related titles, images and their captions
for multi-modal research. Samples which miss any elements mentioned above or which video duration is less than 30 seconds are removed. The detailed statistics of the corpus are shown in Table 1. Notice that the videos in CNN are much longer than that in Daily Mail, we collect less samples from the former and we mainly use them during testing.

ROUGE (Lin, 2004) with standard options is used for text summary evaluation. We apply the ROUGE-1 (R-1), ROUGE-2 (R-2), and ROUGE-L (R-L) F1-score to evaluate the overlap of uni-grams, bi-grams, and the longest common subsequences between the decoded summary and the reference. To evaluate the quality of the generated video summaries (images), we employ ResNet to construct image feature vectors and calculate the cosine image similarity (Cos) between image references and the extracted frames from videos.

4.2 Baseline Methods

Multi-modal based:
VistaNet (Truong and Lauw, 2019) prioritizes visual information as alignment to point out the important sentences of an article to detect the sentiment of a document.

MM-ATG (Zhu et al., 2018) is a multi-modal attention model generating text and selecting the relevant image from the article and alternative images.

Img+Trans (Hori et al., 2019) applies multi-modal video features including video frames, transcripts and dialog context for dialog generation.

TFN (Zadeh et al., 2017) learns both intra and inter modalities by modeling a new multi-modal tensor fusion approach.

HNNattTI (Chen and Zhuge, 2018) aligns the sentences and accompanying images by attention.

Pure video summarization:
Random extracts the key video frames randomly.

Uniform samples video frames uniformly.

VSUMM (De Avila et al., 2011) extracts color features from video frames via k-means clustering.

DR-DSN (Zhou et al., 2018) proposes a reinforcement learning framework equipped with a reward function for diverse and representative summaries.

Pure text summarization:
lead3 picks the first three sentences as summary.

SummaRuNNer (Nallapati et al., 2017) is an interpretable RNN-based sequence model, and it can be trained in both extractive and abstractive manners.

NN-SE (Cheng and Lapata, 2016) consists of a hierarchical document encoder and an attention-based extractor that can extract sentences or words.

4.3 Experimental Settings

The dataset is split by 70%, 10%, 20% for train, validation and test sets, respectively. The hidden dimension of Bi-LSTM is 64, beta in late+ fusion is 0.3, and the proportion of each modality in loss is 3.33. To remove the redundancy of videos, one of five consecutive frames is randomly selected. The last layer of ResNet-50 with 2048 dimension is used for image feature extraction. We perform training by Adagrad with learning rate 0.0001. We use early stop to avoid overfitting.

5 Results

5.1 Quantitative analysis

As shown in Table 2, M2SM outperforms the best performing baseline for both text and video summaries on the Daily Mail dataset. These improvements are achieved thanks to the bi-hop attention mechanism, improved late+ fusion, and bi-stream summarization strategy, which are all jointly incorporated in M2SM. Table 2 also shows that VistaNet underperforms other models by a large margin. We consider that the learning strategy of VistaNet wherein image information is considered prior to text information may bring noise.

In addition, Table 2 shows that the results on CNN are inferior to those on Daily Mail. We consider this may be attributed to the longer length of original materials, especially of videos, as shown in Table 1. Given that it is difficult to extract visual features from long videos, summarizing the articles in the CNN dataset is more challenging. Besides, we ignore image evaluation in CNN due to the lack of reference from the original website, and explore video summaries by comparing with pure video summarization in Section 5.3.

5.2 Ablation Study

To verify the effectiveness of each component of our model, we conduct ablation experiments. We construct a hierarchical framework which concentrates on word and sentence level to generate summaries as our baseline. Based on the hierarchical text component, three constituents of M2SM are
Table 2: Comparisons of proposed M\textsuperscript{2}SM model with the multi-modal baselines. All of the text encoder parts in multi-modal approaches are modified as hierarchical framework for fair comparison.

| Model       | R-1   | R-2   | R-L   | Daily Mail | CNN       |
|-------------|-------|-------|-------|------------|-----------|
| VistaNet    | 18.62 | 6.77  | 13.65 | -          | 3.24      | 6.33      |
| MM-ATG      | 35.38 | 14.79 | 25.41 | 69.17      | 26.83     | 8.11      | 18.34     |
| Img+Trans   | 39.28 | 16.64 | 28.53 | -          | 27.04     | 8.29      | 18.54      |
| TFN         | 39.37 | 16.38 | 28.09 | -          | 27.68     | 8.69      | 18.71      |
| HNNattTI    | 39.58 | 16.71 | 29.04 | 68.76      | 27.61     | 8.74      | 18.64      |
| M\textsuperscript{2}SM | 41.73 | 18.59 | 31.68 | 69.22      | 27.81     | 8.87      | 18.73      |

Table 3: Comparisons of M\textsuperscript{2}SM model with video summarization baselines.

| Model      | R-1   | R-2   | R-L   |
|------------|-------|-------|-------|
| VSUMMM     | 68.74 |       |       |
| Random     | 67.69 |       |       |
| Uniform    | 68.79 |       |       |
| DR-DSN     | 68.69 |       |       |
| M\textsuperscript{2}SM | 69.22 |       |       |

Table 4: Text summary comparisons of proposed M\textsuperscript{2}SM model with the text summarization baseline.

| Model      | R-1   | R-2   | R-L   |
|------------|-------|-------|-------|
| lead3      | 41.07 | 17.87 | 30.90 |
| SummaRuNNer| 41.12 | 17.92 | 30.94 |
| NN-SE      | 41.22 | 18.15 | 31.22 |
| M\textsuperscript{2}SM | 41.73 | 18.59 | 31.68 |

Table 5: Ablation study to evaluate the effects of different components of M\textsuperscript{2}SM.

| Model      | R-1   | R-2   | R-L   |
|------------|-------|-------|-------|
| text-only(baseline) | 39.11 | 16.42 | 28.56 |
| +video frames | 40.86 | 17.48 | 30.23 |
| +transcripts  | 41.26 | 17.95 | 30.98 |
| +bi-stream   | 41.73 | 18.59 | 31.68 |

5.3 Evaluation on Single Modalities

To assess the gains of the proposed method coming from the multi-modal information, we compare it with the popular single-modal approaches on Daily Mail dataset, including the video only summarization and text only summarization.

The video summary comparisons are shown in Table 3. We collect the related images as references in an online manner, because manually labeling each video frame is labor-intensive and time-consuming. As shown in Table 3, M\textsuperscript{2}SM performs better than the video only methods. It can be attributed to its capability to derive comprehensive insights from multi-modal materials.

In terms of the text summary as shown in Table 4, M\textsuperscript{2}SM is also competitive, although it does not achieve as much large margin as in the case of the multi-modal summary comparisons. We speculate this may be due to the noisy information. Using an effective information filter is a promising way which worth in-depth exploration in the future.

5.4 Sub-module Evaluation

We evaluate the effectiveness of each module of the proposed model. Fig. 4 illustrates the performance of four feature fusion approaches, which are early, tensor, late, and late+ fusion. All these feature fusion methods are trained under three strategies: cross entropy minimizing the binary cross entropy, +video-loss adding video summarization loss for optimization, and +weighted that gives weights to each task in consideration of their different contributions. As demonstrated in Fig. 4 early fusion, which is most commonly used in practice, is inferior to other fusion approaches. Due to the asynchrony of multi-modal feature and the various significance of each modality, simple feature concatenation in early fusion may introduce noise and...
Table 6: Comparison of three feature alignment strategies on the basis of early fusion.

| Method              | R-1  | R-2  | R-L  |
|---------------------|------|------|------|
| no-attention        | 40.13| 17.21| 29.85|
| concat-product      | 39.59| 16.71| 29.04|
| bilinear-attention  | 40.86| 17.48| 30.23|

Table 7: Words overlap statistics of video transcripts with articles and references.

|           | Inform | Satis |
|-----------|--------|-------|
| article   | 3.65   | 3.76  |
| video     | 2.73   | 2.78  |
| article+video | 3.87  | 4.30  |

Table 8: Manual Summary quality evaluation.

| Evaluation    | Inform | Satis |
|---------------|--------|-------|
| article       | 3.65   | 3.76  |
| video         | 2.73   | 2.78  |
| article+video | 3.87   | 4.30  |

Figure 5: Evaluation of the smoothed value $\beta$ in late+ fusion and $\alpha_{ts}/\alpha_{vs}$ of each modality in loss.

lose its effectiveness for handling complex cases. Moreover, Fig. depicts that weighted achieves the best results. We consider that it successfully avoids unfavorable influence of irrelevant modalities.

In addition, three attention mechanisms are tested: no attention which uses the last state as video feature directly, concat-product which uses the common mechanism introduced in (Bahdanau et al., 2014) and bilinear-attention which we propose in this paper. Table 6 presents the results and indicates a stimulating phenomenon that concat-product attention mechanism performs poorly, even worse than models without attention. We speculate that conventional attention which lacks communication between modalities will mislead the model, as it focuses on irrelevant parts and brings noise.

5.5 Balance between modalities

A particular characteristic of multi-modal summarization is that the related data are complementary and thus different modalities contribute differently to summarization. Hence, we restrain the noises from irrelevant modalities through the improved late fusion and balance the loss function in different tasks. The left graph in Fig. illustrates the penalty of irrelevant information, which shows that $\beta = 0.3$ yields the best results. The other graph depicts the proportion of each modality in a loss function, and illustrates that the text summarization gives approximately 70% attention to the text modality. However, this graph also reveals that nearly 30% of useful information is searched and complemented by other modalities.

Effectiveness of Transcript

$M^2$SM incorporates video transcripts to bridge videos and texts with appropriate alignments. This is one of the critical factors for proper summarization, as demonstrated in Table 5. To further investigate the nature of transcripts, we quantitatively evaluate their relationships with the articles and references, as shown in Table 7. The results demonstrate that video transcripts are distinct from articles with low overlaps, indicating that they are not repeating of articles but provide extra and useful information. Table 7 also illustrates that they poorly correlate with references, which suggests that transcripts assist summary generation by capturing the key information of videos, however they are not enough for final summaries.

5.7 Manual Evaluation

200 examples with text and video summarization results were selected, and 5 graduate students were volunteered to evaluate them based on informativeness (Inform) and satisfaction (Satis). Each sample was graded on the scale from 1 to 5, where a higher score is better. We calculate the average score of each evaluation (Table 8) shows it further demonstrates the proposed method.

6 Conclusion

In this work, we have proposed a multi-modal summarization task that generates summaries from documents and the related videos. We have also constructed a content-rich video-containing dataset for future study. A comprehensive evaluation has demonstrated the effectiveness of the proposed model and individual introduced strategies.

Our work can be extended in some ways. For example, acoustic features could be extracted from acoustic signals and incorporated into our model to provide additional complementary information, i.e., sentiment and tone. In another example, to further advance user satisfaction, it would be worthwhile to explore generation techniques, such as generating a small video accompanied with text description as a summary.
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