ATTENTION-BASED MULTI-HYPOTHESIS FUSION FOR SPEECH SUMMARIZATION

Takatomo Kano¹, Atsunori Ogawa¹, Marc Delcroix¹, and Shinji Watanabe²

¹NTT Corporation, Japan
²Language Technologies Institute, Carnegie Mellon University, Pittsburgh, USA

ABSTRACT
Speech summarization, which generates a text summary from speech, can be achieved by combining automatic speech recognition (ASR) and text summarization (TS). With this cascade approach, we can exploit state-of-the-art models and large training datasets for both subtasks, i.e., Transformer for ASR and Bidirectional Encoder Representations from Transformers (BERT) for TS. However, ASR errors directly affect the quality of the output summary in the cascade approach. We propose a cascade speech summarization model that is robust to ASR errors and that exploits multiple hypotheses generated by ASR to attenuate the effect of ASR errors on the summary. We investigate several schemes to combine ASR hypotheses. First, we propose using the sum of sub-word embedding vectors weighted by their posterior values provided by an ASR system as an input to a BERT-based TS system. Then, we introduce a more general scheme that uses an attention-based fusion module added to a pre-trained BERT module to align and combine several ASR hypotheses. Finally, we perform speech summarization experiments on the How2 dataset and a newly assembled TED-based dataset that we will release with this paper. These experiments show that retraining the BERT-based TS system with these schemes can improve summarization performance and that the attention-based fusion module is particularly effective.

Index Terms— Speech Summarization, Automatic Speech Recognition, BERT, Attention-based Fusion.

1. INTRODUCTION
Speech summarization generates a text summary from given speech data. It is challenging because it needs to process lengthy speech data (a sequence of utterances) and extract important information to create a compact representation of the content. Moreover, in contrast to a text input, speech contains fillers, disfluencies, redundancies (e.g., repetition of the same phrases), and colloquial language. There are two main types of summarization approaches, extractive and abstractive. Extractive summarization aims at identifying the most relevant segments of the input text/speech document and then concatenating them to assemble a summary. Abstractive summarization aims at directly generating a summary by paraphrasing the intent of the input document. Although the latter type is challenging, it has achieved great progress with the introduction of powerful deep learning models for text summarization (TS) such as Bidirectional Encoder Representations from Transformers (BERT) [1]. Moreover, abstractive summarization can potentially normalize spoken text to remove disfluencies, redundancies, and colloquial language, making the summary more understandable than extractive ones. Consequently, in this paper, we focus on abstractive summarization.

Speech summarization is achieved by combining two main submodules: an automatic speech recognition (ASR) module, which transcribes speech into a corresponding text document, and a TS system, which generates a compact representation of that document. Such a cascade connection permits using state-of-the-art modules optimized for each task individually, without requiring a large amount of paired data composed of speech data and associated summaries. Moreover, each module can operate on very different time resolution, i.e., ASR is performed for each utterance, while TS requires the entire text document. However, while generating the summary, a cascade connection discards speech-specific information [2,3], which has the potential to enrich the summary, such as intonation when generating the summary. Moreover, the TS system receives input text containing ASR errors that affect the performance of the speech summarization system [4]. This study focuses on the latter problem.

Many works have attempted to mitigate the influence of ASR errors on a natural language processing (NLP) back-end. For example, studies on speech translation [5–10] have reported that ASR errors could be mitigated during translation by considering multiple recognition hypotheses at the input of the translation back-end. Some studies [8,9] have used posterior probabilities to weight ASR hypotheses based on their confidence. Sperber et al. [10] proposed directing inputting recognition lattices to the back-end translation system. In general, the recognition lattices hold the approximated entire ASR search information representing word-level multi-hypotheses with a compact lattice form. Therefore, this approach helps mitigating ASR errors by considering alternative word candidates within the recognition lattices. However, it is difficult to use this approach directly with pre-trained state-of-the-art TS models like BERT, since the BERT model expects a sub-word sequence as an input instead of a lattice. For speech summarization, some studies built systems that are robust to ASR errors [11,13]. Weng et al. [4] achieved robust speech summarization by adding confidence scores associated with each recognized word to the input of a BERT-based TS system. The confidence scores help the TS system to ignore unreliable words in the ASR output. However, it provides a limited ability to recover the unreliable information from alternative word candidates as it derives from a single (the 1-best) ASR hypothesis rather than an N-best list or a lattice. Ogawa et al. [11] proposed inputting confusion networks (CNs) to a compressive (i.e., non-neural) TS system. Then, from the CNs, the TS system selects recognized words to form a summary that maximizes the ILP-based objective function. These studies confirmed that inputting multiple ASR hypotheses (e.g. lattices and CNs) and auxiliary information (e.g. confidence scores) to the NLP module is useful [4,10].

In this paper, we propose a speech summarization model that can exploit multiple ASR hypotheses to mitigate the influence of ASR errors and be used with pre-trained TS systems like BERT. We explore two approaches to combining the ASR hypotheses. First, we propose replacing the input sub-word embedding of BERT with a sum of sub-word embedding vectors weighted by their ASR posterior values, as done in previous studies on speech translation [6].
The second approach proposes to use an attention fusion mechanism to combine different ASR hypotheses within the BERT module. In the point of fusing multiple inputs with an attention mechanism, this attention fusion is similar to hierarchical attention [14, 15] proposed for multi-stream combinations [16] and audio-visual processing [17]. However, our proposal does not have a hierarchical architecture; it is an attention function that fuses multiple-hypothesis following the self-attention manner. The query is a 1-best hypothesis, and value and key are multiple-hypothesis. The attention fusion can be implemented at the input or within the BERT model. The latter can exploit BERT’s strong modeling capability to perform the hypotheses fusion.

Posterior fusion is similar to the confidence-based approach [1] in the sense that both approaches simply exploit the confidence of individual words or tokens within the 1-best hypothesis at token level and do not explicitly model multiple hypotheses at sequence level. In contrast, the attention fusion explicitly models multiple token sequence hypotheses by using two attention steps. First, we align the hypotheses with the 1-best hypothesis using an attention mechanism across the tokens of the 1-best and each hypothesis. This process allows using hypotheses with different lengths or redundant information. In the second step, we employ an attention mechanism over the aligned tokens and across the hypotheses to combine them. This attention fusion is similar to system combination approaches like ROVER [18], posterior probability decoding [19] and minimum Bayes risk decoding [20], but the combination is performed within the BERT encoding process.

We performed experiments to confirm the effectiveness of the proposed methods on two speech summarization datasets, i.e., YouTube How2 video and TED Talk summarization. The TED Talk summarization is a newly assembled corpus that associates the TEDLIUM ASR corpus with publicly available TED Talk summaries. We release this new corpus with this paper. Experimental results show that retraining a BERT-based TS system with the proposed multi-hypothesis combination schemes can improve summarization performance on both datasets.

2. SPEECH SUMMARIZATION

Let us consider a spoken document \( D \), which contains \( K \) utterances. Let \( X_k \) and \( S_k \) be the speech signal and the associated transcription of the \( k \)-th utterance of this spoken document. The summarization task consists of generating a compact document \( Y \) from the input spoken document \( D \). This problem is addressed in two stages. First, we use an ASR system to transcribe each speech utterance \( X_k \) into text. Then, we use a TS to generate the summary \( Y \) from the input speech document \( D \).

2.1. ASR system

We use a state-of-the-art Transformer model for ASR [21, 22]. The ASR system predicts the word sequence, \( \hat{S}_k \) associated with the speech signal \( X_k \) using beam search. This is achieved by combining the scores from the transformer and language model,

\[
\hat{S}_k = \arg\max_S \left( \log p_{\text{trans}}(S|X_k) + \lambda \log p_{\text{lm}}(S) \right),
\]

where \( p_{\text{trans}}(S|X_k) \) is the posterior probability of \( S \) given \( X_k \) obtained with the transformer model, \( p_{\text{lm}}(S) \) represents the language model, and \( \lambda \) is the shallow fusion weight of the language model.

In this paper, we assume that we can obtain multiple ASR hypotheses. These hypotheses can be the \( N \)-best recognition hypotheses obtained using beam search decoding or \( N \) hypotheses obtained with different ASR systems as often done with system combination [23]. In the following, \( \hat{S}^n_k \) represents the \( n \)-th hypothesis obtained for a list of \( N \) hypotheses.

In practice, ASR operates on sub-word units such as byte pair encoding (BPE), and thus a recognition hypothesis can be expressed as \( \hat{S}^n_k = [\hat{s}^n_{k,1}, \ldots, \hat{s}^n_{k,M^n}]^T \in \mathbb{R}^{M^n \times V} \), where \( \hat{s}^n_{k,m} \) is a one-hot vector representing the \( m \)-th token of the \( n \)-th hypothesis and the \( k \)-th utterance, \( M^n \) is the length of the hypothesis, \( V \) is the vocabulary size (the number of sub-word units), and \( T \) is the transpose operation. To obtain recognition hypotheses for the entire spoken document, we can simply concatenate the hypotheses of all utterances as \( \hat{S}^n = [\hat{s}^n_{1,1}, \ldots, \hat{s}^n_{K,M^n}]^T \). By abuse of notation, we remove the utterance index \( k \) and redefine \( \hat{S}^n = [\hat{s}^n_{1,1}, \ldots, \hat{s}^n_{M^n}]^T \in \mathbb{R}^{M^n \times V} \), where \( M^n \) is the total length of the concatenated \( n \)-th hypotheses of the spoken document, i.e., \( M^n = \sum_k M^n_k \). With beam search, we can also obtain the posterior probabilities associated with each token in the hypothesis, which we denote as \( \hat{p}^n_m \).

2.2. TS system

Early works on text summarization used combinatorial optimization approaches to find important content in a text document [24–26]. It was difficult to generate consistent abstractive summaries with such approaches, so most research focused on extractive summaries. The success of the deep learning-based language models greatly improved the quality of abstractive summarization [27–29]. Recently, Transformer-based models have become state-of-the-art models for abstractive text summarization [30]. For example, BERTSum [29] leverages the strong language modeling capability of a pre-trained BERT [1] model to achieve high-quality abstractive summarization through transfer learning. Since, the original BERT model assumes single sentences as input instead of a sequence of sentences as in summarization tasks, BERTSum introduces BERT’s classification (CLS) tokens at the start of each sentence of the input document. BERTSum uses the BERT model as an encoder and adds a Transformer-based decoder to generate the summary. The model is then fine-tuned on the text summarization task.

The TS system accepts the entire transcription of the spoken document as an input. In general, we can simply use the 1-best hypothesis \( \hat{S}^1 \). We employ a BERTSum model to generate a summary from \( \hat{S}^1 \) as

\[
E = \text{Emb}(\hat{S}^1),
\]

\[
Z = \text{Enc}_{\text{bert}}(E),
\]

\[
Y = \text{Dec}_{\text{trans}}(Z),
\]

where \( \text{Emb}(\cdot) \) is an embedding layer that converts the one-hot token sequence into a sequence of embedding vectors \( E = [e_1, \ldots, e_{M^n}]^T \in \mathbb{R}^{M^n \times B} \), \( B \) is the size of the embedding, \( \text{Enc}_{\text{bert}}(\cdot) \) represents a BERT encoder, \( Z \) is an intermediate representation of the document, and \( \text{Dec}_{\text{trans}}(\cdot) \) represents a transformer-based decoder that generates a summary based on \( Z \). BERTSum takes advantage of the strong language modeling capability of the pre-trained BERT model to generate high-quality summaries. By inserting CLS symbols between consecutive sequences, the BERT encoder can process a sequence of multiple utterances that forms a long document.

There are two issues with the cascade connection of ASR and BERTSum. First, the BERT model assumes discrete features representing the IDs of the sub-word units as inputs. Thus it cannot accept an uncertain input such as posteriors of the ASR system directly, and recognition errors will directly affect the summary. We discuss some proposals to address this problem in Section 3.

Second, although both systems use sub-word units, the definition of sub-word units usually differs. Typically, ASR performs better with much smaller BPE units than the conventional BERT
value, which we map to a hidden vector using a linear mapping as $\hat{e}_m$. We use vectors of BERTSum to be the sum of the sub-word embedding vectors of BERTSum to be the sum of the sub-word embedding vectors and a confidence embedding. Here, we implemented a similar method. We use $p_n^1$, as introduced in Section 2.1, as a confidence value, which we map to a hidden vector using a linear mapping as

$$c_m = \text{Emb}_\text{conf}(p_n^1),$$

where $c_m \in \mathbb{R}^B$ is a confidence embedding and $\text{Emb}_\text{conf}()$ is a linear embedding layer, where $B$ is the dimension of the projected embedding vectors. Then the modified embedding vector $e_{m}^{\text{conf}}$ is obtained as the summation of confidence and word embeddings:

$$e_{m}^{\text{conf}} = e_{m} + c_m.$$

### 3. MULTI-HYPOTHESIS SUMMARIZATION

In this paper, we propose a BERT-based summarization model that takes into account multiple speech recognition hypotheses. We propose combining several ASR hypotheses to mitigate the influence of ASR errors. Conceptually, the combined hypothesis can be obtained as a weighted-sum as,

$$e_m^* = \sum_{n=1}^{N} \alpha_n^m e_m^n,$$

where $\alpha_n^m$ denotes a weight of each hypothesis, $e_m^*$ denotes a modified embedding vector.

First, we apply a method of incorporating posterior probability that was originally proposed for speech translation to the BERT summarization model. Next, we explain the hypothesis fusion method using an attention mechanism.

#### 3.1. Speech summarization with posterior fusion

The posterior fusion consists of summing the embedding vectors of all sub-words weighted by their posterior probabilities, $p_n^m$, as

$$e_{m}^{\text{post}} = \sum_{n=1}^{N} p_n^m e_m^n,$$

where $e_m^\text{post}$ is a modified embedding vector and $e_m^n$ is the $n$-th embedding vector of the $n$-th hypothesis obtained with Eq. (2). The modified embedding $e_m^\text{post}$ can include the uncertainty in the ASR system. Computing $e_m^\text{post}$ requires that all hypotheses are aligned and have the same length. We thus create the $N$ hypotheses as follows. First, we save the sequence of output log-softmax values from the ASR and the language models for the best beam-search path. After decoding, for each step in the 1-best path, we select the $N=10$ tokens with the top 10 values of saved output vectors in the path. This way of creating $N$ hypotheses may generate more diverse hypotheses than simply obtaining the $N$-best list from beam search decoding. Note that since the posterior-based fusion modifies the input of the TS model, we need to retrain the BERTSum model using ASR hypotheses.

#### 3.2. Attention-based multi-hypothesis fusion

Posterior probability fusion trusts the ASR weighting and may mitigate the influence of unreliable tokens when performing summarization. However, in the case of the ASR outputs the correct word at 10-th hypotheses, it may be difficult to recover information from the modified embedding of Eq. (8) because the correct word’s weight $p_n^1$ is too small. On the other hand, our proposal re-calculate all hypothesis weight based on BERT representation. Thus, even if the correct word is 10-th hypotheses, our proposal can provide high weight to the correct word.

Attention-based fusion consists of two steps. In the first step, we pick up a representative ASR hypothesis and align the other hypotheses to it. We use the most confident ASR hypothesis, i.e., the 1-best hypothesis, $S^1$. If we use multiple ASR systems, we use a hypothesis of a possible best performing ASR system as $S^1$.

We obtain the embedding vectors for the $n$-th hypothesis,

$$\tilde{E}^n = \left[\tilde{e}_1^n, \ldots, \tilde{e}_{N1}^n\right] \in \mathbb{R}^{M \times B},$$

which is time-aligned with the $M^1$-length hypothesis $S^1$, based on the attention mechanism as:

$$\tilde{E}^n = \text{softmax} \left( (E^n W_Q)(E^n W_K)^T \right) E^n W_V,$$

$E^n = \left[\tilde{e}_1^n, \ldots, \tilde{e}_{N1}^n\right] \in \mathbb{R}^{M \times B}$ is the sequence of embedding vectors associated with the $n$-th hypothesis. $E^n$ is the sequence of the 1-best embedding vectors and is used as a query. $\text{softmax}(.)$ is the softmax operation and $W_Q \in \mathbb{R}^{B \times B'}$, $W_K \in \mathbb{R}^{B \times B'}$, $W_V \in \mathbb{R}^{B' \times B'}$ are the query, key, and value projection matrices, respectively.

In the second step, we perform attention over the different hypotheses for every aligned sub-word position $m$ in a similar way as the hierarchical attention \[14\] [34] [38]. Let $C_m = \left[\tilde{e}_1^m, \ldots, \tilde{e}_{N1}^m\right] \in \mathbb{R}^{B' \times N}$ be a matrix containing the $N$ aligned embedding sequences for the $m$-th sub-word position in a sequence. We can perform attention over the hypotheses to obtain a modified embedding vector $e_m^\text{att}$ as

$$\alpha_m = \text{softmax} \left( (e_m^T) W_Q C_m \right),$$

$$e_m^\text{att} = \alpha_m e_m^T,$$

where $\alpha_m \in \mathbb{R}^{1 \times N}$ are attention weights over the recognition hypotheses. Eq. (11) performs a similar summation over embedding vectors as in Eq. (8), but using the attention mechanism to compute the weights and time-aligned embedding vectors.

The proposed attention fusion can also be extended to multi-head attention. In that case, we can obtain an aligned hypothesis for each attention head, $E_k^n$, using a similar equation as Eq. (9), with different projection matrices for each head, i.e., $W_{Qk}$, $W_{Kk}$, and $W_{Vk}$.
We created this corpus by associating TED Talks included in the TED corpus with videos, allowing multi-modal summarization. Here, we only use the audio content of the corpus. Although the corpus also includes videos, we focus on summarizing the brief video description provided on YouTube. The target for summarization consists of the speech content of the video, which is extracted using automatic speech recognition (ASR) technology. Note that others have also used TED Talks from speech summarization tasks, but those corpora were smaller. Furthermore, they did not publicly release their corpus.

### 4. TED SPEECH SUMMARIZATION CORPUS

We used three corpora to train and test our speech summarization systems. In particular, we assembled a new corpus derived from TED Talks that we will release upon acceptance of the paper. Table 1 compares the characteristics of the TED corpus with the two other corpora used in this paper.

#### 4.1. Descriptions of the corpora

| Corpora          | Text documents | Speech documents | Compression rate | Word overlap | Source lengths | Target lengths | Word error rate |
|------------------|----------------|------------------|------------------|--------------|----------------|----------------|-----------------|
| CNN-DailyMail    | Yes            | Yes              | Intermediate     | High         | Long           | Long           | Low             |
| TED              | Yes            | Yes              | Low              | High         | Short          | Short          | High            |
| How2             | Yes            | Yes              | Very Low         | Very High    | Short          | Short          | Very High       |

The TED corpus consists of a summation of TED Talks. We created this corpus by associating TED Talks included in the TEDLIUM corpus with summaries obtained from the TED website. For the TED summarization task, we add the speaker name to the speech document to allow the TS systems to output the speaker names, which commonly appear in the reference summaries. The target summary consists of the title and abstract of the talk. Note that others have also used TED Talks from speech summarization tasks, but those corpora were smaller. Furthermore, they did not publicly release their corpus.

### 4.2. Analysis of the complexity of the TED summarization task

Table 1 shows the number of text and speech documents, the compression rate, the source and target lengths, and the word error rate (WER) of the three corpora. The compression rate is expressed as the ratio between the output and input document lengths. Thus, a lower value means higher information compression. This table shows that our proposed TED summarization task is challenging because it has a relatively small amount of training data and consists of long input speech documents that require higher information compression than needed for existing datasets. Note that the WER is about 8.5%, which makes it slightly easier than the How2 corpus in terms of the ASR performance.

In our experiments, we measure ideal extractive summarization scores on the reference summaries. We use the ROUGE scores [42] and word overlap of the ideal extractive summaries for the three datasets. The word overlap measures the percentage of words from the target summaries that are in the source documents. CNNDM, which consists of a summary of news articles, is well suited for extractive summarization; therefore, oracle scores and word overlap are relatively high. In contrast, the How2 corpus consists of relatively casual speech, which leads to much lower oracle scores and word overlap. The TED summarization task consists of relative formal speech and its oracle extractive summarization scores are between those of CNNDM and How2.

Finally, we compare the performance of abstractive text summarization on the ground-truth transcriptions. The results indicate an upper-bound value for the speech summarization systems we investigated. Table 2 shows the ROUGE scores obtained with BERTSum models for the three tasks. We found that the difficulty of abstractive summarization is highly dependent on the length of the input and the compression rate, which makes the proposed TED summarization task challenging for abstractive summarization.

Comparing the results of Table 2 and 3 shows that ideal extractive summarization's scores on TED talk, in particular ROUGE-2 and -L scores, are higher than abstractive summarization ones. We will investigate extractive summarization on the TED corpus and comparing it with abstractive summarization in future works.

### 5. EXPERIMENTS

We performed experiments using two speech summarization datasets, TED and How2 described in Section 4.

#### 5.1. System configuration

Our baseline consists of a cascade of ASR and TS systems trained separately. We built Transformer-based ASR models using the ESPnet toolkit [38] by following the published recipes for the TEDLIUM2 [43] and How2 [40] tasks, except that we varied the BPE size. For the TS model, we built a BERTSum model using a pre-trained BERT model as an encoder and a Transformer decoder in the same way as [38]. We used the pre-trained BERT model provided by hugging-face. We pre-trained the BERTSum model using CNNDM data, which is a large-volume corpus used for text summarization.
Table 1. Comparison of the text and speech summarization corpora.

| Dataset | Text documents | Speech documents | Compression rate word | Source lengths word | Target lengths word | WER |
|---------|----------------|------------------|-----------------------|---------------------|---------------------|-----|
| CNNDM   | 162,018        | n/a              | 14%                   | 9%                  | 35                  | 853 | 3 | 60 | n/a |
| How2    | 72,983         | 12,798           | 16%                   | 16%                 | 14                  | 303 | 1 | 34 | 13.0% |
| TED     | 4,001          | 1,495            | 6%                    | 5%                  | 102                 | 2210| 4 | 79 | 8.5% |

Table 2. ROUGE scores of ideal extractive summaries and word overlap.

| Dataset | ROUGE-1 | ROUGE-2 | ROUGE-L | Word overlap |
|---------|---------|---------|---------|--------------|
| CNNDM   | 45.0    | 29.9    | 42.8    | 83%          |
| How2    | 27.9    | 10.4    | 23.3    | 58%          |
| TED     | 34.4    | 19.8    | 33.5    | 72%          |

Table 3. ROUGE scores of abstractive summarization with BERTSum using the ground-truth transcriptions (BERTSum (oracle)).

| Dataset | ROUGE-1 | ROUGE-2 | ROUGE-L |
|---------|---------|---------|---------|
| CNNDM   | 41.7    | 19.4    | 38.8    |
| How2    | 56.5    | 37.8    | 59.3    |
| TED     | 32.1    | 6.2     | 19.0    |

Note that we confirmed the validity of our implementation of BERTSum except that we used attention fusion described in Section 5.2.1 instead of Eq. (6). We used five hypotheses ($N=5$) for attention fusion due to GPU memory constraints of our experimental environment. We trained all BERTSum models following the original recipe except that we used a learning rate of 0.0002 and warm-up steps of 20k when retraining on the ASR outputs (systems (4) to (7)). We compared the summarization performance of each method with ROUGE [42].

5.2. Effect of BPE size

ASR and BERT models use both BPE to represent sub-words; however, the BPE unit definitions used for the two systems differ. Typically, ASR systems achieve optimal performance at a smaller BPE size than that of the BERT model. However, since our proposed method requires that the BPE unit definition of the ASR system must match that of the BERT model, we expect to have some ASR degradation due to too large BPE sizes. Thus, we first investigate the effect of BPE size on ASR performance.

Table 4 shows WER as a function of different BPE sizes for the How2 and TED corpora. We observe a relative WER increase of 12% for How2 and by more than 20% for the TED corpus when adopting the BPE definition used by BERT. Although this is a significant WER increase, we discuss its impact on summarization in the following subsection.

5.3. Speech summarization results

Table 5 shows the ROUGE scores for the baseline systems (1) to (5)) and the proposed method with (6) posterior and (7) attention-based fusion. We observe a large performance gap in summarization performance when using ASR transcriptions (system (2)) instead of ground-truth transcription (system (1)). As we discussed in section 5.2 using BERT’s BPE definition for ASR (system (3)) induces more recognition errors, which clearly degrades summarization performance on both tasks compared to using the BPE definition from BERTSum.

5Note that we confirmed the validity of our implementation of BERTSum as it achieved a similar level of performance on the How2 corpus [29], which reported ROUGE-1 and ROUGE-L scores of 48.3 and 44.0, respectively, although the systems cannot be directly compared because of differences in the training data and ASR front-end.
In this paper, we proposed a speech summarization system that can exploit multi-hypotheses generated by an ASR system to mitigate the impact of recognition errors. We proposed two schemes, i.e., posterior and attention-based fusion, which could be integrated into a BERT-based TS model. We showed that both approaches could handle hypotheses with different lengths. We plan to further investigate such a combination by using more diverse ASR systems to generate the hypotheses in future work.

## 6. CONCLUSION

In this paper, we proposed a speech summarization system that can exploit multi-hypotheses generated by an ASR system to mitigate the impact of recognition errors. We proposed two schemes, i.e., posterior and attention-based fusion, which could be integrated into a BERT-based TS model. We showed that both approaches could reduce the impact of ASR errors on summarization and achieved competitive results on two tasks.

Future works will include investigating tighter interconnection of the ASR front-end and TS back-end to mitigate ASR errors and exploit speech-specific information such as intonation and create richer and more informative speech summaries.

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### Table 5. ROUGE scores for the different speech summarization systems. Systems (6) and (7) are the proposed methods.

| Method               | ROUGE-1 | TED ROUGE-2 | ROUGE-L | Reference                        | Example                                                                 |
|----------------------|---------|-------------|---------|----------------------------------|------------------------------------------------------------------------|
| (1) BERTSum (oracle) | 32.1    | 6.2         | 19.0    |                                  | learn how to form a b sound for ventriloquists with expert voice throwing tips from a professional comedian in this free online ventriloquism lesson video clip |
| (2) BERTSum (ASR-BPE)| 29.9    | 6.9         | 18.3    |                                  | practice your ventriloquists with expert voice throwing tips from a professional comedian in this free online ventriloquism lesson video clip |
| (3) BERTSum (BERT-BPE)| 28.9    | 6.2         | 17.8    |                                  | how2 obtain a good summary on our webpage                            |
| (4) BERTSum retrain | 31.5    | 5.6         | 20.4    |                                  | learn how to make b sound for ventriloquists with expert voice throwing tips from a professional comedian in this free online ventriloquism lesson video clip |
| (5) BERTSum confidence| 30.1    | 6.8         | 20.4    |                                  | learn how to make b sound for ventriloquists with expert voice throwing tips from a professional comedian in this free online ventriloquism lesson video clip |
| (6) BERTSum Pos. fusion| 31.6    | 6.1         | 20.3    |                                  | learn how to make b sound for ventriloquists with expert voice throwing tips from a professional comedian in this free online ventriloquism lesson video clip |
| (7) BERTSum Att. fusion| 31.9    | 6.0         | 19.3    |                                  | learn how to make b sound for ventriloquists with expert voice throwing tips from a professional comedian in this free online ventriloquism lesson video clip |

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### Table 6. How2 dataset summarization examples. The red collar highlights the different main parts.

| Method               | Example                                                                 |
|----------------------|------------------------------------------------------------------------|
| Reference            | learn how to form a b sound for ventriloquists with expert voice throwing tips from a professional comedian in this free online ventriloquism lesson video clip |
| (5) BERTSum confidence| practice your ventriloquists with expert voice throwing tips from a professional comedian in this free online ventriloquism lesson video clip |
| (7) BERTSum Att. fusion| learn how to make b sound for ventriloquists with expert voice throwing tips from a professional comedian in this free online ventriloquism lesson video clip |

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