End-to-End Abstractive Summarization for Meetings

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Abstract

With the abundance of automatic meeting transcripts, meeting summarization is of great interest to both participants and other parties. Traditional methods of summarizing meetings depend on complex multi-step pipelines that make joint optimization intractable. Meanwhile, there are a handful of deep neural models for text summarization and dialogue systems. However, the semantic structure and styles of meeting transcripts are quite different from articles and conversations. In this paper, we propose a novel end-to-end abstractive summary network that adapts to the meeting scenario. We design a role vector to depict the difference among speakers and a hierarchical structure to accommodate long meeting transcripts. Empirical results show that our model considerably outperforms previous approaches in both automatic metrics and human evaluation. For example, in the ICSI dataset, the ROUGE-1 score increases from 32.00% to 39.51%.

1 Introduction

Meetings are a very common forum where people exchange ideas, make plans and share information. With the ubiquity of automatic speech recognition systems come vast amounts of meeting transcripts. Therefore, the need to succinctly summarize the content of a meeting naturally arises.

Several methods of generating summaries for meetings have been proposed (Mehdad et al., 2013; Murray et al., 2010; Wang and Cardie, 2013; Oya et al., 2014; Shang et al., 2018; Li et al., 2019). As Murray et al. (2010) points out, users prefer abstractive meeting summaries to extractive summaries. While these methods are mostly abstractive, they require complicated multi-stage machine learning pipelines, such as template generation, sentence clustering, multi-sentence compression, candidate sentence generation and ranking. As these approaches are not end-to-end optimizable, it is hard to jointly improve various parts in the pipeline to enhance the overall performance. Moreover, some components, e.g., template generation, require extensive human involvement, rendering the solution not scalable or transferrable.

Meanwhile, many end-to-end systems have been successfully employed to tackle document summarization, such as the pointer-generator network (See et al., 2017), reinforced summarization network (Paulus et al., 2017) and memory network (Jiang and Bansal, 2018). These deep learning methods can effectively generate abstractive document summaries by directly optimizing predefined goals.

However, the meeting summarization task inherently bears a number of challenges that make it more difficult for end-to-end training than doc-

| Meeting Transcript (162 turns) |
|--------------------------------|
| ... UI: So a touchscreen. and th the buttons the real buttons we have to use. We better use quite large buttons... PM: We have to be very attent in putting the corporate image in our product. ID: ... we should use default materials, simple plastics. ... |

| Summary from our model (21 sentences) |
|-------------------------------------|
| ... The user interface specialist will work together on the remote should be used buttons for the marketing concept. The corporate image must be used. The case will have to use plastic. ... |

Table 1: Example excerpt of a meeting transcript and the summary generated by our model in AMI dataset. Keywords are highlighted in colors. UI (user interface designer), PM (program manager), ID (industrial designer) are roles of the speakers. The meeting transcript contains word errors and grammatical glitches as it is the result from automatic speech recognition system.
ument summarization. We show an example of a meeting transcript from the AMI dataset and the summary generated by our model in Table 1.

First, a meeting is carried out between multiple participants. The different semantic styles, standpoints, and roles of each participant all contribute to the heterogeneous nature of the meeting transcript. For instance, in AMI meeting corpus (McCowan et al., 2005), there are 4 participants per meeting, including a program manager (PM), a marketing expert (ME), a user interface designer (UI) and an industrial designer (ID).

Second, the transcript and summary of a single meeting are usually much longer than those of a document. For instance, in CNN/Daily Mail dataset (Hermann et al., 2015), there are on average 781 tokens per article and 56 tokens per summary, while AMI meeting corpus contains meetings with 4,757 tokens per transcript and 322 tokens per summary on average. The example transcript in Table 1 has as many as 162 turns. This poses a great challenge to the time and space efficiency of meeting summarization methods.

Third, the structure of a meeting transcript is very distinct from documents, as a meeting usually progresses according to an agenda. See et al. (2017) shows that simply taking the first 3 sentences from a CNN news article can achieve higher ROUGE scores than several sophisticated deep learning summarization methods. This is definitely not the case for meeting transcripts.

To tackle these challenges, we propose an end-to-end deep learning framework, Hierarchical Meeting summarization Network (HMNet). HMNet leverages the encoder-decoder transformer architecture (Vaswani et al., 2017) to produce abstractive summaries based on meeting transcripts. To adapt the structure to meeting summarization, we propose two major design improvements.

First, as meeting transcripts are usually lengthy, a direct application of the canonical transformer structure may not be feasible. For instance, conducting the multi-head self-attention mechanism on a transcript with thousands of tokens is very time consuming and may cause memory overflow problem. Therefore, we leverage a hierarchical structure to reduce the burden of computing. As a meeting consists of utterances from different participants, it forms a natural multi-turn hierarchy. Thus, the hierarchical structure carries out both token-level understanding within each turn and turn-level understanding across the whole meeting. During summary generation, HMNet applies attention to both levels of understanding to ensure that each part of the summary stems from different portions of the transcript with varying granularities.

Second, to accommodate the multi-speaker scenario, HMNet incorporates the role of each speaker to encode different semantic styles and standpoints among participants. For example, a program manager usually emphasizes the progress of the project and a user interface designer tends to focus on user experience. In HMNet, we train a role vector for each meeting participant to represent the speaker’s information during encoding. This role vector is appended to the turn-level representation for later decoding.

The training process for HMNet is end-to-end, optimizing the cross entropy of the generated summary. Therefore, HMNet makes it very convenient to jointly fine-tune each component to enhance summarization performance. To our knowledge, this is the first end-to-end deep learning method for meeting summarization entirely based on transcripts.

To evaluate our model, we employ the widely used AMI and ICSI meeting corpus (McCowan et al., 2005; Janin et al., 2003). Results show that HMNet significantly outperforms previous meeting summarization methods. For example, on ICSI dataset, HMNet achieves 7.51 higher ROUGE-1 points, 3.06 higher ROUGE-2 points, and 5.44 higher ROUGE-SU4 points compared with the previous best result. Human evaluations further show that HMNet generates much better summaries than baseline methods. We then conduct ablation studies to verify the effectiveness of different components in our model.

2 Problem Formulation

We formalize the problem of meeting summarization as follows. The input consists of meeting transcripts $X$ and meeting participants $P$. Suppose there are $s$ meetings in total. The transcripts are $X = \{X_1, ..., X_s\}$. Each meeting transcript consists of multiple turns, where each turn is the utterance of a participant. Thus, $X_i = \{(p_1, u_1), (p_2, u_2), \ldots, (p_{L_i}, u_{L_i})\}$, where $p_j \in P, 1 \leq j \leq L_i$, is a participant and $u_j = (w_1, \ldots, w_{L_j})$ is the tokenized utterance from $p_j$. The human-labelled summary for meeting $X_i$, de-
noted by $Y_i$, is also a sequence of tokens. For simplicity, we will drop the meeting index subscript. So the goal of the system is to generate meeting summary $Y = (y_1, ..., y_n)$ given the transcripts $X = \{(p_1, u_1), (p_2, u_2), ..., (p_m, u_m)\}$.

3 Model

Our hierarchical meeting summarization network (HMNet) is based on the encoder-decoder transformer structure (Vaswani et al., 2017), and its goal is to maximize the conditional probability of meeting summary $Y$ given transcript $X$ and network parameters $\theta$: $P(Y|X; \theta)$.

3.1 Encoder

3.1.1 Role Vector

Meeting transcripts are recorded from various participants, who may have different semantic styles and viewpoints. Therefore, the model has to take the speaker’s information into account while generating summaries.

To incorporate the participants’ information, we integrate the speaker role component. In the experiments, each meeting participant has a distinct role, e.g., program manager, industrial designer. For each role, we train a vector to represent it as a role, e.g., program manager, industrial designer.

3.1.2 Hierarchical Transformer

Transformer. Recall that a transformer block consists of a multi-head attention layer and a feed-forward layer, both followed by layer-norm with residuals: LayerNorm$(x + Layer(x))$, where Layer can be the attention or feed-forward layer (Vaswani et al., 2017).

As the attention mechanism is position agnostic, we append positional encoding to input vectors:

$$PE_{i,j} = \sin(i/10000^{2j/10000})$$  \hspace{1cm} (1)

$$PE_{i,j+1} = \cos(i/10000^{2j/10000})$$  \hspace{1cm} (2)

where $PE_{i,j}$ stands for the $j$-th dimension of positional encoding for the $i$-th word in input sequence. We choose sinusoidal functions as they can extend to arbitrary input length during inference.

In summary, a transformer block on a sequence of $n$ input embeddings can generate $n$ output embeddings of the same dimension as input. Thus, multiple transformer blocks can be sequentially stacked to form a transformer network:

$$\text{Transformer} \{\{x_1, ..., x_n\}\} = \{y_1, ..., y_n\}$$  \hspace{1cm} (3)

Long transcript problem. As the canonical transformer has the attention mechanism, its computational complexity is quadratic in the input length. Thus, it struggles to handle very long sequences, e.g., 5,000 tokens. However, meeting transcripts are usually fairly long, consisting of thousands of tokens.

We note that meetings come with a natural multi-turn structure with a reasonable number of turns, e.g. 289 turns per meeting on average in AMI dataset. And the number of tokens in a turn is much less than that in the whole meeting. Therefore, we employ a two-level transformer structure to encode the meeting transcript.

Word-level Transformer. The word-level transformer processes the token sequence of one turn in the meeting. We encode each token in one turn using a trainable embedding matrix $D$ initialized by GloVe (Pennington et al., 2014). Thus, the $j$-th token in the $i$-th turn, $w_{i,j}$, is associated with a uniform length vector $D(w_{i,j}) = g_{i,j}$. To incorporate syntactic and semantic information, we also train two embedding matrices to represent the part-of-speech (POS) and entity (ENT) tags. Therefore, the token $w_{i,j}$ is represented by the vector $x_{i,j} = [g_{i,j}; POS_{i,j}; ENT_{i,j}]$. Note that we add a special token $w_{i,0} = [\text{BOS}]$ before the sequence to represent the beginning of a turn. Then, we denote the output of the word-level transformer as follows: $\text{Word-Transformer} \{\{x_{i,0}, ..., x_{i,L_i}\}\} = \{x_{i,0}^W, ..., x_{i,L_i}^W\}$.
**Turn-level Transformer.** The turn-level transformer processes the information of all \( m \) turns in a meeting. To represent the \( i \)-th turn, we employ the output embedding of the special token \([BOS]\) from the word-level transformer, i.e. \( x_{i,0}^W \). Furthermore, we concatenate it with the role vector of the speaker for this turn, \( p_i \). It follows that the output of the turn-level transformer is: \( \text{Turn-Transformer} (\{[x_{1,0}^W; p_1], \ldots, [x_{m,0}^W; p_m]\}) = \{x_1^T, \ldots, x_m^T\} \).

**3.2 Decoder**

The decoder is a transformer to generate the summary tokens. The input to the decoder transformer contains the \( k - 1 \) previously generated summary tokens \( \hat{y}_1, \ldots, \hat{y}_{k-1} \). Each token is represented by a vector using the same embedding matrix \( D \) as the encoder, \( D(\hat{y}_i) = g_i \).

The decoder transformer is different from its counterpart in the encoder in two ways. First, as the tokens are generated from left to right, the input to the self-attention layer has to be masked with a lower triangular matrix to avoid peeking at future information.

Second, the decoder transformer block includes two additional cross-attention layers. After self-attention, the embeddings first attend with token-level outputs \( \{x_{i,j}^W\}_{i=1,j=1}^{m,L} \), and then with turn-level outputs \( \{x_i^T\}_{i=1}^m \), each followed by layer-norm with residuals. This makes the model attend to different parts of the inputs with varying scales at each inference step.

The output of the decoder transformer is denoted as: \( \text{Decoder-Transformer} (\{g_1, \ldots, g_{k-1}\}) = \{v_1, \ldots, v_{k-1}\} \).

To predict the next token \( \hat{y}_k \), we reuse the weight of embedding matrix \( D \) to decode \( v_{k-1} \) into a probability distribution over the vocabulary:

\[
P(\hat{y}_k | \hat{y}_{<k}, X) = \text{softmax}(v_{k-1}D^T) \quad (4)
\]

We illustrate the Hierarchical Meeting summary Network (HMNet) in Fig. 1.

**Training.** During training, we seek to minimize the cross entropy:

\[
L(\theta) = -\frac{1}{n} \sum_{k=1}^{n} \log P(y_k | \hat{y}_{<k}, X) \quad (5)
\]
We use teacher-forcing in decoder training, i.e. the decoder takes ground-truth summary tokens as input.

**Inference.** During inference, we use beam search to select the best candidate. The search starts with the special token \langle BEGIN \rangle. We employ the commonly used trigram blocking (Paulus et al., 2017): during beam search, if a candidate word would create a trigram that already exists in the previously generated sequence of the beam, we forcibly set the word’s probability to 0. Finally, we select the summary with the highest average log-likelihood per token.

## 4 Experiment

### 4.1 Datasets

We evaluate our model on the widely used AMI (McCowan et al., 2005) and ICSI (Janin et al., 2003) meeting corpora. The two datasets contain meeting transcripts from automatic speech recognition (ASR), respectively. We follow Shang et al. (2018) to use the same train/development/test split. Each meeting has an abstractive summary written by human annotators. Furthermore, each participant has an associated role, e.g. project manager, marketing expert. Since there is only one speaker per role in each meeting and no other speaker identification information, we use a single role vector to model both speaker and role information simultaneously.

In AMI, there are on average 4,757 words with 289 turns in the meeting transcript and 322 words in the summary. In ICSI, there are on average 10,189 words with 464 turns in the meeting transcript and 534 words in the summary. As the transcript is produced by the ASR system, there is a word error rate of 36% for AMI and 37% for ICSI (Shang et al., 2018).

### 4.2 Baseline models

For comparison, we select a variety of baseline systems from previous literatures:

- **Basic baselines:** Random and Longest Greedy (Riedhammer et al., 2008)
- **Template-based method:** Template (Oya et al., 2014)
- **Ranking systems:** CoreRank & PageRank submodular (Tixier et al., 2017), TextRank (Mihalcea and Tarau, 2004) and Cluster-Rank (Garg et al., 2009)
- **Unsupervised method:** UNS (Shang et al., 2018)
- **Document summarization:** Pointer-Generator Network (PGNet) (See et al., 2017)
- **Multi-modal model:** MM (Li et al., 2019)

In addition, we implement the baseline model Extractive Oracle, which concatenates top sentences with highest ROUGE-1 scores with the golden summary. The number of sentences is determined by the average length of golden summary: 18 for AMI and 23 for ICSI. The performance of Extractive Oracle can be seen as the upper bound for extractive summarization.

### 4.3 Metrics

Following Shang et al. (2018), we employ ROUGE-1, ROUGE-2 and ROUGE-SU4 metrics (Lin, 2004) to evaluate all meeting summarization models. These three metrics respectively evaluate the accuracy on unigrams, bigrams, and unigrams plus skip-bigrams with a maximum skip distance of 4. These metrics have been shown to highly correlate with the human judgment (Lin, 2004).

### 4.4 Training Details

We train HMNet using the Adam optimizer (Kingma and Ba, 2014) with an initial learning rate of 0.0005, \( \beta_1 = 0.9, \beta_2 = 0.999 \). We employ spaCy (Honnibal and Johnson, 2015) as the tokenizer and embed POS and NER tags into 12-dim and 8-dim vectors, respectively. All transformers have 2 layers and 2 heads in attention. We use a dropout probability of 0.1 on all layers. The beam search width is 12 for AMI and 9 for ICSI. We set the minimum number of tokens per summary to be 280 in AMI and 340 in ICSI. The batch size is 1 and we use gradient clipping with a maximum norm of 2.

During training, we pick the model with the highest ROUGE-1 score on the development set (Shang et al., 2018). Since UNS includes 4 model variants, we select the best result from all variants for comparison. PGNet treats the whole meeting transcript as an article and generates the summary.
Table 2: ROUGE-1, ROUGE-2, ROUGE-SU4 scores of generated summary in AMI and ICSI datasets. Numbers in bold are the overall best result. Numbers with underscore are the best result from previous literature. * The two baseline MM models require additional human annotations of topic segmentation and visual signals from cameras. ** Results are statistically significant at level 0.05.

| Model                        | AMI          | ICSI         |
|------------------------------|--------------|--------------|
|                              | ROUGE-1      | R-2          | ROUGE-1      | R-2          |
|                              | R-SU4        |              | R-SU4        |              |
| Random                       | 35.13        | 6.26         | 13.17        | 29.28        | 3.78         | 10.29        |
| Longest Greedy               | 33.35        | 5.11         | 12.15        | 30.23        | 4.27         | 11.14        |
| Template                     | 31.50        | 6.80         | 11.40        | /            | /            | /            |
| CoreRank Submodular          | 36.13        | 7.33         | 14.18        | 29.82        | 4.00         | 10.61        |
| PageRank Submodular          | 36.10        | 7.42         | 14.32        | 30.0         | 4.42         | 11.14        |
| TextRank                     | 35.25        | 6.90         | 13.62        | 29.70        | 4.09         | 10.64        |
| ClusterRank                  | 35.14        | 6.46         | 13.35        | 27.64        | 3.68         | 9.77         |
| UNS                          | 37.86        | 7.84         | 14.71        | 31.60        | 4.83         | 11.35        |
| Extractive Oracle            | 34.99        | 9.65         | 13.20        | 34.66        | 8.00         | 10.49        |
| PGNet                        | 40.77        | 14.87        | 18.68        | 32.00        | 7.70         | 12.46        |
| MM (TopicSeg+VFOA)*          | **53.29**    | 13.51        | /            | /            | /            | /            |
| MM (TopicSeg)*               | 51.53        | 12.23        | /            | /            | /            | /            |

HMNet (ours) 52.09 **19.69** **24.11** **39.51** **10.76** **17.90**

Table 2: ROUGE-1, ROUGE-2, ROUGE-SU4 scores of generated summary in AMI and ICSI datasets. Numbers in bold are the overall best result. Numbers with underscore are the best result from previous literature. * The two baseline MM models require additional human annotations of topic segmentation and visual signals from cameras. ** Results are statistically significant at level 0.05.

and report the result on the test set. We train the model for 50 epochs. The training is on a single Tesla V-100 GPU with 32G memory.

4.5 Results

Table 2 shows the ROUGE scores of generated summaries in AMI and ICSI datasets. As shown, except for ROUGE-1 in AMI, HMNet outperforms all baseline models in all metrics, and the result is statistically significant at level 0.05, under paired t-test with the best baseline results. On ICSI dataset, HMNet achieves 7.51, 3.06 and 5.44 higher ROUGE points than previous best results.

Note that MM is a multi-modal model which requires human annotation of topic segmentation (TopicSeg) and visual focus on attention (VFOA) collected from cameras, which is rarely available in practice. In comparison, our model HMNet is entirely based on transcripts generated from ASR pipelines. Still, on AMI dataset, HMNet outperforms MM(TopicSeg) by 0.56 points in ROUGE-1 and 7.46 points in ROUGE-2, as well as MM(TopicSeg+VFOA) by 6.18 points in ROUGE-2.

Compared with the document summarization model, Pointer-Generator Network (PGNet), HMNet has a clear advantage in both datasets. This result indicates that traditional summarization models must be carefully adapted to meeting scenarios.

Our model also significantly outperforms the extractive oracle, showing that human summaries are more abstractive rather than extractive for meetings.

In the supplementary materials, we show example summaries generated by our model and baseline models. Compared to baselines, HMNet can summarize both individual actions and group activities, similar to the reference’s structure. Also, the language by HMNet is much smoother and contains fewer grammatical errors.

Ablation Study. We conduct an ablation study of HMNet to verify the effectiveness of its various components. As shown in Table 3, when the part-of-speech and entity embeddings are removed, the ROUGE-1 score drops 2.8 points. When the role vector is removed, the ROUGE-1 score drops 4.3 points. The “+role text” setting removes the role vector. Instead, it prepends the role name to each turn’s transcript. Its performance is higher than that of “-role vector” setting in ROUGE-2 and ROUGE-SU4, but still falls behind HMNet. This indicates the effectiveness of the vectorized representation of speaker roles. When HMNet is without the hierarchy structure, i.e. the turn-level transformer is removed and role vectors are appended to word-level embeddings, the ROUGE-1 score drops as much as 7.0 points. Thus, all these components we propose both play an important
| Model         | ROUGE-1 | R-2 | R-SU4 |
|--------------|---------|-----|-------|
| HMNet        | 52.1    | 19.7| 24.1  |
| − POS&ENT    | 49.3    | 18.8| 23.5  |
| − role vector | 47.8    | 17.2| 21.7  |
| + role text  | 47.4    | 18.8| 23.7  |
| − hierarchy  | 45.1    | 15.9| 20.5  |

Table 3: Ablation results of HMNet on AMI’s test set. “+role text” means the role vector is not used, but the role name is prepended to each turn’s transcript.

role in the summarization capability of HMNet.

### 4.6 Human Evaluation

We conduct a human evaluation of the meeting summary to assess its readability and relevance. Readability measures how fluent the summary language is, including word and grammatical error rate. Relevance measures how well the summary sums up the main ideas of the meeting.

As MM model (Li et al., 2019) does not have summarization text or trained model available, we compare the results of HMNet and UNS (Shang et al., 2018). For each meeting in the test set of AMI and ICSI, we have 5 human evaluators from Amazon Mechanical Turk label summaries from HMNet and UNS. We choose labelers with high approval rating (>98%) to increase the credibility of results.

Each annotator is presented with the meeting transcript and the summaries. The annotator needs to give a score from 1 to 5 (higher is better) for readability (whether the summary consists of fluent and coherent sentences and easy to understand) and likewise for relevance (whether the summary contains important information from the meeting). The annotators need to read both the meeting transcript and the summary to give evaluations. To reduce bias, for each meeting, the two versions of summaries are randomly ordered.

As shown in Table 4, HMNet achieves much higher scores in both readability and relevance than UNS in both datasets. The scores for HMNet are all above 4.0, indicating that it can generate both readable and highly relevant meeting summaries.

| Dataset | AMI | ICSI |
|---------|-----|------|
| Source  | HMNet | UNS |
| Readability | 4.17 (.38) | 2.19 (.57) |
| Relevance | 4.08 (.45) | 2.47 (.67) |

Table 4: Average scores (1-5) of readability and relevance of summaries on AMI and ICSI’s test sets. Each summary is judged by 5 human evaluators. Standard deviation is shown in parenthesis.

### 5 Insights

#### 5.1 How abstractive is our model?

An abstractive system can be innovative by using words that are not from the transcript in the summary. Similar to See et al. (2017), we measure the abstractiveness of a summary model via the ratio of novel words or phrases in the summary. A higher ratio could indicate a more abstractive system.

Fig. 2 displays the percentage of novel n-grams, i.e. that do not appear in the meeting transcript, in the summary from reference, HMNet, and UNS. As shown, both reference and HMNet summaries have a large portion of novel n-grams ($n > 1$). Almost no 4-grams are copied from the transcript. In contrast, UNS has a much lower ratio of novel n-grams, because it generates a summary mainly from the original word sequence in transcripts.

#### 5.2 Error Analysis

We qualitatively examine the outputs of HMNet on AMI dataset and summarize two major types of errors:

- Due to the nature of long meeting transcripts,
the system sometimes summarizes salient information from parts of the meeting different from the reference summaries.

- Our system tends to summarize meetings at a high level (e.g., topics, decisions) and not to describe details as much as that in the reference.

6 Related Work

Meeting Summarization. There are a number of studies on generating summaries for meetings and dialogues (Zhao et al., 2019; Liu and Chen, 2019; Chen and Metze, 2012; Liu et al., 2019b,a). Mehdad et al. (2013) uses utterance clustering, an entailment graph, a semantic word graph and a ranking strategy to construct meeting summaries. Murray et al. (2010) and Wang and Cardie (2013) focus on various aspects of meetings such as decisions and action items. Oya et al. (2014) employs multi-sentence fusion to construct summarization templates for meetings, leading to summaries with higher readability and informativeness. Recently, Shang et al. (2018) leverages a multi-sentence compression graph and budgeted submodular maximization to generate meeting summaries. In general, these approaches first semantically group utterances, then over-generate candidate summary sentences via word graph. This is followed by ranking and selecting top sentences into the summary. As a result, this multi-step pipeline makes joint optimization intractable, and any modification to one component often requires changing other components in the pipeline. Li et al. (2019) proposes an encoder-decoder structure for end-to-end multi-modal meeting summarization. However, their method depends on manual annotation of topic segmentation and visual focus, which is not usually available in practice. In comparison, our model only requires meeting transcripts directly from speech recognition.

Document Summarization. End-to-end abstractive document summarization has received considerable attention in recent literature. The primarily employed neural structures are seq2seq models (Sutskever et al., 2014). Rush et al. (2015) first introduces an attention-based seq2seq model to the abstractive sentence summarization task. However, the quality of the generated multi-sentence summaries for long documents is often low, and out of vocabulary (OOV) words cannot be efficiently handled. To tackle these challenges, See et al. (2017) proposes a pointer-generator network that can both produce words from the vocabulary via a generator and copy words from the source text via a pointer. Paulus et al. (2017) further adds reinforcement learning to improve the result. Gehrmann et al. (2018) uses a content selector to over-determine phrases in source documents that helps constrain the model to likely phrases and achieves state-of-the-art results in several document summarization datasets. Recently several work on using large-scale pretrained language models for summarization are proposed and achieves very good performance (Liu, 2019; Devlin et al., 2018; Raffel et al., 2019; Lewis et al., 2019; Zhang et al., 2019).

Hierarchical Neural Architecture. As a variety of NLP data (e.g., conversation, document) has an internal hierarchical structure, there have been many works applying hierarchical structures in NLP tasks. Li et al. (2015) proposes a hierarchical neural auto-encoder for paragraph and document reconstruction. It applies two levels of RNN: one on tokens within each sentence and the other on all sentences. Lin et al. (2015) applies a hierarchical RNN language model (HRNNLM) to document modeling, which similarly encodes token-level and turn-level information for better language modeling performance. Serban et al. (2016) puts forward a hierarchical recurrent encoder-decoder network (HRED) to model open-domain dialogue systems and generate system responses given the previous context. Nallapati et al. (2016) proposes the hierarchical attention mechanism on word-level and turn-level in the encoder-decoder structure for abstractive document summarization.

7 Conclusion

In this paper, we present an end-to-end hierarchical neural network, HMNet, for abstractive meeting summarization. We employ a two-level hierarchical structure to adapt to the long meeting transcript. Furthermore, we design a role vector to represent the different viewpoints and semantic styles of each participant. Experiments on public datasets show that HMNet achieves significantly better results than baseline models in both automatic metrics and human evaluation. Through an ablation study, we show that both the role vector and hierarchical architecture significantly contribute to the model’s performance.
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Appendix

Example of Meeting Summary

We demonstrate in Table 5 an example AMI meeting transcript with speaker information and three versions of summaries: reference, HMNet and UNS (Shang et al., 2018). As the transcript results from ASR pipelines, there are some word errors and grammatical glitches. Moreover, compared with document summarization tasks like CNN/Daily Mail (Hermann et al., 2015; Nallapati et al., 2016), the meeting transcript is pretty long and lacks the important-information-first structure. All of these add to the complexity of meeting summarization tasks.

The summary generated by HMNet includes both individual actions/proposals and group activities, which is similar to the reference. In contrast, the result from UNS does not have a clear structure. Also, HMNet is more effective in selecting salient information from the lengthy transcript. Furthermore, the language of summary from HMNet is smoother and has many fewer grammatical errors than UNS. The reason is that HMNet learns the language pattern from the reference summary during training while UNS generates summaries by concatenating transcript word sequences.
Meeting Transcript (162 turns)

PM: Everybody found his place again?
ME: ... But it might be a good idea to make a docking station ... Then a surprisingly great deal of people w indicated that an LCD screen in the remote control would be preferred.
UI: So a touchscreen. and th the buttons the real buttons we have to use. We better c use quite large buttons for Everybody have to use it so ol even old people young people. we must keep buttons quite s simple and quite large. That was my part of it.
PM: We have to see what requirements we need for those remote controls. what you told is the channel selection is important. Volume selection, power and teletext.
ID: ... And when a button gets pressed, its goes to the chip. The chip controls the infrared bulb and perf perhaps a normal bulb... we should use default materials , simple plastics...
PM: We have to be very attent in putting the corporate image in our product.
...

Reference Summary (25 sentences)

The project manager stated the agenda and the marketing expert discussed what functions are most relevant on a remote, what the target demographic is, and what his vision for the appearance of the remote is.
The marketing expert also brought up the idea to include a docking station to prevent the remote from getting lost and the idea to include an LCD screen.
The user interface designer pushed for a user-friendly interface with large buttons, a display function, a touchscreen, and the capability of controlling different devices.

The corporate image must be visible in the design of the remote.
The remote will feature a small LCD screen.
Whether to include a scroll button.

Summary from HMNet (ours, 21 sentences)

... He suggested that users want a remote and discussed options for the remote.
He discussed the user requirements to include a remote, and discussed how to include in an LCD screen.
The user interface specialist will work together on the remote should be used buttons for the marketing concept.
Whether the group had problems with the design, and a simple chip.
The corporate image must be used.
The remote control device.
The case will have to use plastic.

Summary from UNS (26 sentences)

... Fancy design easy to learn few buttons on the right places.
Source you got i missed the remote controls and youngsters.
Suggest let’s have a discussion on the control functions.
Point of advantage in our remote control for elderly people are they can think of I wanna subtitles in push the button.
Banana’s questions about the technical functions instead of a few roof less buttons.
Addition we did some market research see what the market consists of what ages are involved.

Table 5: Example of meeting transcript and summary from reference, HMNet, and UNS. Roles of participants are coded as follows: PM - project manager, ME - marketing expert, ID - industrial designer, UI - user interface designer. We manually capitalize some words in the summaries from HMNet and UNS for better demonstration.