Dynamic Sliding Window for Meeting Summarization

Zhengyuan Liu, Nancy F. Chen
Institute for Infocomm Research, A*STAR, Singapore
{liu.zhengyuan,nfychen}@i2r.a-star.edu.sg

Abstract

Recently abstractive spoken language summarization raises emerging research interest, and neural sequence-to-sequence approaches have brought significant performance improvement. However, summarizing long meeting transcripts remains challenging. Due to the large length of source contents and targeted summaries, neural models are prone to be distracted on the context, and produce summaries with degraded quality. Moreover, pre-trained language models with input length limitations cannot be readily applied to long sequences. In this work, we first analyze the linguistic characteristics of meeting transcripts on a representative corpus, and find that the sentences comprising the summary correlate with the meeting agenda. Based on this observation, we propose a dynamic sliding window strategy for meeting summarization. Experimental results show that performance benefit from the proposed method, and outputs obtain higher factual consistency than the base model.

1 Introduction

Text summarization is studied in two paradigms: extractive and abstractive. Different from extractive models which directly select text spans from source content, abstractive approaches can generate summaries more concisely with flexible information aggregation and paraphrasing, but raise the higher requirement for context understanding and language generation. In the past few years, various neural sequence-to-sequence models are proposed and applied to abstractive summarization, from the vanilla attention-based summarizer (Rush et al., 2015), pointer-generator networks (See et al., 2017), to the recent large-scale pre-trained language models such as BERT and BART (Devlin et al., 2019; Lewis et al., 2020). These models have brought significant improvement on the generation quality especially in fluency and readability (Liu and Lapata, 2019).

While most prior work focuses on documents such as news articles (Hermann et al., 2015), summarizing conversations starts to raise more research interest (Goo and Chen, 2018; Zhu et al., 2020). One typical multi-party conversation scenario is meeting (McCowan et al., 2005). Since meetings often aim to cover several sub-topic discussions, the average number of their dialogue turns is much larger than that of short conversations such as social chat (Gliwa et al., 2019) and inquiring-answering (Liu et al., 2019). As the source content becomes longer, the summarizer may fall distracted on the massive contextual information, and the quality of neural generation tends to degrade when producing long text (Fan et al., 2018). Thus it is challenging for neural models to achieve the overall high quality for the long transcript summarization. Moreover, if adopting Transformer-based pre-trained language models like BART (Lewis et al., 2020), the transcript length often exceeds their maximum positional embedding limitations, and conducting text truncation will cause loss of some context.

Meetings usually consist of a set of agenda items (McCowan et al., 2005), and each item focuses on discussing a specific topic. Thus the whole meeting conversation is inherently organized at the topic level. This is also reflected in the summaries written by humans, which condense the key information on each discussion part. Therefore, we postulate the divide-and-conquer strategy can be useful to tackle the aforementioned challenges of meeting summarization. More specifically, our target is to split the long transcript into multiple segments, and obtain the final output by aggregating the summary snippets of each segment. To construct the ground-truth data for training, we first investigate the linguistic characteristics of meeting transcripts and reference summaries on the representative cor-
pus AMI (McCowan et al., 2005). Then, we propose to enhance the sequence-to-sequence summarizer with a dynamic sliding window strategy, to tackle the length limitation of Transformer-based language models. Unlike the conventional fixed window sliding (Devlin et al., 2019), the dynamic method makes a model learn to decide the start position of the next segment during the generation process. Experimental results show that the summary generation can benefit from adopting the dynamic window sliding, and achieves state-of-the-art performance. Further example analysis demonstrates that the enhanced framework performs better than the base model considering factual consistency.

In the contemporary studies, efficient attention schemes of the Transformer (Beltagy et al., 2020) and multi-block context aggregation (Grail et al., 2021) are proposed to support long text processing, and Schüller et al. (2020) investigate the fixed and automatic sliding window for processing long documents, and they focused on summarizing Wikipedia and news articles. Our proposed method is inspired by the organizational features of meeting transcripts, and is applicable for the language backbones with input length limitations.

## 2 Meeting Transcript Analysis

In this section, we conduct data analysis on the AMI meeting corpus (McCowan et al., 2005), in which the participants work in a team and conduct meetings to discuss product design, development, and planning. There are four main speaker roles: a project manager (PM), a marketing expert (ME), an industrial designer (ID), and a user interface designer (UI). Following previous work (Shang et al., 2018), we split the whole dataset into train (97 transcripts), validation (20 transcripts), and test (20 transcripts) sets. The data statistics are shown in Table 1, where we count one utterance in the conversation as one sentence, and conduct word-level tokenization. Compared with the news summarization benchmarks, the average length of meeting transcripts as well as the reference summaries are much larger (In our settings, we use the long version abstracts in the AMI corpus, as previous work (Feng et al., 2020)). Moreover, human-written summaries of news articles often concentrate on the first few parts of source content (Liu et al., 2020), thus the truncation with a fixed length does not affect the final performance significantly (Jung et al., 2019). However, summarizing meetings requires grasping useful contextual information across the whole conversation, in this case, simple text truncation will lead to certain information loss.

### 2.1 Organization Analysis

Since meetings are usually taken with a set of sub-topics, we analyze the organizational co-relation of these sub-topics and sentences in meeting sum-

|            | CNN | DailyMail | NYT | AMI |
|------------|-----|-----------|-----|-----|
| Average Source Content Length: |     |           |     |     |
| Sentence Level | 33.98 | 29.33 | 35.55 | 288.7 |
| Word Level    | 760.5 | 653.3 | 800.1 | 4757 |
| Average Reference Summary Length: |     |           |     |     |
| Sentence Level | 3.59  | 3.86 | 2.44  | 17.55 |
| Word Level    | 45.8  | 54.65 | 45.54 | 323.3 |

Table 1: Data statistics of the news summarization benchmarks and the AMI meeting corpus.
In the AMI corpus, for each meeting transcript, aside from a human-written abstractive summary, there is an additional extractive annotation. As shown in Figure 1, human annotators were asked to choose sentences from the source conversation, as the supporting segments for each abstractive summary sentence. Based on this extractive annotation, we obtained the start/end supporting utterance indices in the conversation of each summary sentence. Then we sorted them by their occurrence order in the source content, and observed that 80% sentences in reference summaries match the same agenda order as in the source content. This indicates that when humans write a summary, they often read the source content and record the key points sequentially.

### 2.2 Segmentation Analysis

Summarization is a process to write a shorter version of a text span, and context integrity is essential. When adopting a divide-and-conquer strategy, only a part of the conversation will be extracted. To assess information integrity, we calculate the word level coverage with the extractive annotations (Figure 1) in the AMI. With the start/end supporting utterance indices described in Section 2.1, we split the original transcripts into a number of segments. Then the word-level recall is calculated between each summary sentence and its corresponding segment. Summaries are often written via paraphrasing and introducing novel words, and the overall word-level coverage in our observation is 74%.

### 2.3 Summary Conversion

As the final output under a divide-and-conquer strategy is produced by aggregating summary snippets, to build the training ground-truth, we split each reference summary into multiple parts based on the analysis in Section 2.1 and Section 2.2. For each summary sentence, we constructed its context segment by using the corresponding extractive annotation. Then we ordered the summary sentences by their occurrence indices in the source conversation, and merged adjacent summary sentences to summary snippets if their context segments had a certain overlap. For summary sentences without extractive annotation, we reorganized them via calculating word-level overlap with existing content segments. Furthermore, we observed that some summary snippets are started with a pronoun that refers to a precedent personal named entity, as shown in Figure 2. To maximize the semantic integrity when producing one snippet, we used coreference resolution on the original summary, and if one summary snippet is started with a personal pronoun, it will be replaced by its referring.

### 3 Neural Meeting Summarizer

In this section, we elaborate our framework for meeting summarization with the dynamic sliding window strategy.

#### 3.1 Dynamic Sliding Window

The sliding window is to split a long input into a number of shorter spans, process the spans in order (e.g., from left to right), and adopt aggregation for final output. It is a straightforward but useful method that is commonly applied to long sequence encoding (Devlin et al., 2019), and it is generally controlled by two parameters: window size denotes the context span size, and stride size is the amount of movement at each sliding step. In previous work,
the proposed dynamic sliding window strategy, where the stride size at each sliding step is predicted by the model. More specifically, given the window size \( k \), at each sliding step, one index \( j \) is selected (equals stride size is \( j \)) in the range of \([0, k - 1]\) as the start position of next window.

### 3.2 Base Neural Architecture

For the neural summarizer, we use a Transformer-based sequence-to-sequence architecture (Vaswani et al., 2017), and select the large-scale pre-trained language backbone BART (Lewis et al., 2020) for initialization. The encoder consists of 6 stacked Transformer layers, and each layer has two sub-components: a multi-head self-attention layer and a position-wise feed-forward layer. Between the two sub-components, residual connection and layer normalization are used. The \( u \)-th encoding layer is formulated as:

\[
\tilde{h}^u = \text{LN}(h^{u-1} + \text{MHAttention}(h^{u-1}))
\]

\[
h^u = \text{LN}(\tilde{h}^u + \text{FFN}(\tilde{h}^u))
\]

where \( h^0 \) is the first layer input. MHAttention, FNN, LN are multi-head attention, feed-forward, and layer normalization, respectively.

The decoder consists of 6 stacked Transformer layers as well. In addition to the two encoding sub-components, the decoder performs another multi-head attention over the previous decoding hidden states and all the encoded representations. Then, the decoder generates tokens in an auto-regressive manner from left to right.

### 3.3 Adopting Dynamic Sliding Window for Meeting Summarization

The proposed dynamic sliding window is a general design that can be applied to various neural architectures. In our summarization setting, the source content is a sequence with \( n \) tokens \( C = \{ w_1, w_2, ..., w_n \} \), and the summary is composed of \( m \) snippets \( S = \{ s_1, s_2, ..., s_m \} \). In a traditional sequence-to-sequence process, the whole source content \( C \) is fed to a model as input, and the output summary is generated at one decoding stage. With the dynamic sliding window strategy, the encoding-decoding process will be conducted in a number of steps, as shown in Figure 3. Given the window size \( k \), at \( i \)-th sliding step, the start token index is \( i_{\text{left}} \), and the end token index \( i_{\text{right}} \) is \( i_{\text{left}} + k \). Then the input sequence of encoder at \( i \)-th step is \( c_i = \{ w_{i_{\text{left}}}, ..., w_{i_{\text{right}}} \} \). After encoding, the contextualized hidden representation \( h_i = \{ h_{i_{\text{left}}}, ..., h_{i_{\text{right}}} \} \) is fed to the decoder to generate a summary snippet, and all snippets will be merged to form the final output.

To obtain the dynamic sliding prediction, one way is to directly predict the value of stride size as in (Gong et al., 2020), where reinforcement learning is used to decide the stride value, and Schüller et al. (2020) proposed to generate a special indicator for the moving operation. Here, based on the analysis in Section 2, we introduce a learning-efficient method named Retrospective. More specifically, as shown in Figure 3, at \( i \)-th step, the decoder will not only generate the summary snippet \( s_i \), but also the last supporting utterance of its context segment that is described in Section 2.1 (concatenated with a “(SEP)” token). Since the predicted supporting utterance provides the context boundary of the current generation step on the right, it is used to determine the amount of sliding movement. After all sliding steps, the generated snippets are concatenated as the output summary.

### 4 Experiment Results and Analysis

#### 4.1 Configuration

The proposed framework was implemented using PyTorch (Paszke et al., 2019) and Hugging Face (Wolf et al., 2020). The learning rate was set at \( 2e-5 \), and AdamW (Loshchilov and Hutter, 2019) optimizer was applied. We trained each model for 20 epochs, and selected the best checkpoints on the validation set based on ROUGE-2 score (Lin, 2004). All input sequences were processed with the sub-word tokenization scheme as in (Lewis et al., 2020), and repeated output sentences were removed. Based on the summary conversion described in Section 2.3, we obtained 598/131/143 snippet-level samples as the train, validation, and test set, respectively. In the training stage, to simulate the input noise during inference time, we randomly added \( k \) adjacent utterances \((5 < k < 15)\) in each context chunk. In the testing stage, for each example, the generation process of our BART-SW-Dynamic model was started with the first chunk of a default window size, which is initialized as 1024.\(^1\) Then we used the sliding prediction described in Section 3.3 to form the next chunk, until the whole transcript was processed. We also as-

\(^1\)The token-level maximum input length of BART (Lewis et al., 2020) is 1024 by default.
Table 2: ROUGE F1 scores on the AMI test set from baseline models and our framework. * Results of baselines are reported as in (Feng et al., 2020).

| Extractive baselines* | R-1 | R-2 | R-L |
|-----------------------|-----|-----|-----|
| TextRank              | 35.19 | 6.13 | 15.70 |
| SummaRunner           | 30.98 | 5.54 | 13.91 |

| Abstractive baselines*: | R-1 | R-2 | R-L |
|------------------------|-----|-----|-----|
| Seq2Seq+Attention      | 36.42 | 11.97 | 21.78 |
| Pointer-Generator      | 42.60 | 14.01 | 22.62 |
| Sentence-Gated         | 49.29 | 19.31 | 24.82 |
| TopicSeg               | 51.53 | 12.23 | 25.47 |
| HMNet                  | 53.02 | 18.57 | 24.85 |
| DDA-GCN                | 53.15 | 22.32 | 25.67 |

Our models:
- BART-SW-GoldSeg: 53.42 22.57 28.52
- BART-Truncate: 48.31 17.52 20.13
- BART-SW-Fixed: 50.02 19.86 23.98
- BART-SW-Dynamic: 52.83 21.77 26.01

Table 2: ROUGE F1 scores on the AMI test set from baseline models and our framework. * Results of baselines are reported as in (Feng et al., 2020).

4.2 Results on the AMI Corpus

Following previous work (Chen and Yang, 2020; Feng et al., 2020), we used the ROUGE score (Lin, 2004) for generation assessment, and reported ROUGE-1 (R-1), ROUGE-2 (R-2) and ROUGE-L (R-L) scores. We selected a set of strong baseline models for extensive comparison including Pointer-Generator (See et al., 2017), Sentence-Gated (Goo and Chen, 2018), TopicSeg (Li et al., 2019), HMNet (Chen and Yang, 2020), and DDA-GCN (Feng et al., 2020). As shown in Table 2, for meeting summarization, abstractive approaches generally perform much better than extractive ones.

In our settings, the model with the dynamic sliding window strategy (BART-SW-Dynamic) outperforms the model with the fixed window (BART-SW-Fixed), and the model with text truncation (BART-Truncate). This shows the effectiveness of the sliding window approach. Moreover, our proposed framework achieves the comparable performance of the contemporary state-of-the-art models.

4.3 Sample Analysis

We first conducted a text quality analysis on the generated summaries across models. As shown in Figure 4, based on the strong generation capability of the language backbone, all BART-based models can produce fluent and grammatically correct summaries. While the model with text truncation achieves relatively acceptable ROUGE scores (as reported in Table 2), it produces sentences that are factually inconsistent with the source content, as shown in Figure 4. We speculate that this is caused by over-fitting the training samples. In contrast, since our proposed framework can produce the final summary based on relevant context segments without truncation, it performs better than the base model considering the factual consistency.

We then conducted a stride prediction assessment. For the Retrospective method described in Section 3.3, the predicted context boundaries are expected to be located closely to the ground-truth. With the best checkpoint, we observed that the average utterance-level distance between gold boundary span and model prediction is 2.7 (48 characters), and this shows that the model is able to predict the correct start position at each sliding step.

5 Conclusion

In this paper, to tackle the challenges from lengthy meeting transcript inputs, we proposed a dynamic sliding window strategy for abstractive summarization. Experimental results demonstrate that the neural sequence-to-sequence models can benefit from the proposed method, and suggest that the long transcript summarizing can be conducted in a divide-and-conquer manner. One of the future works can be extending the proposed method to other corpora with larger sample sizes.
References

Iz Beltagy, Matthew E Peters, and Arman Cohan. 2020. Longformer: The long-document transformer. arXiv preprint arXiv:2004.05150.

Jiaao Chen and Diyi Yang. 2020. Multi-view sequence-to-sequence models with conversational structure for abstractive dialogue summarization. In Proceedings of EMNLP2020, pages 4106–4118. Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of NAACL2019, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Angela Fan, Mike Lewis, and Yann Dauphin. 2018. Hierarchical neural story generation. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 889–898.

Xiaochong Feng, Xiaocheng Feng, Bing Qin, Xinwei Geng, and Ting Liu. 2020. Dialogue discourse-aware graph convolutional networks for abstractive meeting summarization. arXiv preprint arXiv:2012.03502.

Bogdan Gliwa, Iwona Mochol, Maciej Biesek, and Aleksander Wawer. 2019. SAMSum corpus: A human-annotated dialogue dataset for abstractive summarization. In Proceedings of the 2nd Workshop on New Frontiers in Summarization, pages 70–79. Association for Computational Linguistics.

Hongyu Gong, Yelong Shen, Dian Yu, Jianshu Chen, and Dong Yu. 2020. Recurrent chunking mechanisms for long-text machine reading comprehension. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 6751–6761, Online. Association for Computational Linguistics.

Chih-Wen Goo and Yun-Nung Chen. 2018. Abstractive dialogue summarization with sentence-gated modeling optimized by dialogue acts. In 2018 IEEE Spoken Language Technology Workshop (SLT), pages 735–742. IEEE.

Quentin Grail, Julien Perez, and Eric Gaussier. 2021. Globalizing bert-based transformer architectures for long document summarization. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 1792–1810.

Karl Moritz Hermann, Tomas Kocisky, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. 2015. Teaching machines to read and comprehend. In Proceedings of NeurIPS2015, pages 1693–1701.

Taehee Jung, Dongyeop Kang, Lucas Mentch, and Edward Hovy. 2019. Earlier isn’t always better: Sub-aspect analysis on corpus and system biases in summarization. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3324–3335.

Mike Lewis, Yinhao Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7871–7880. Association for Computational Linguistics.

Manling Li, Lingyu Zhang, Heng Ji, and Richard J. Radke. 2019. Keep meeting summaries on topic: Abstractive multi-modal meeting summarization. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 2190–2196, Florence, Italy. Association for Computational Linguistics.

Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In Text Summarization Branches Out: Proceedings of the ACL-04 Workshop, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.

Yang Liu and Mirella Lapata. 2019. Text summarization with pretrained encoders. In Proceedings of EMNLP2019, pages 3721–3731, Hong Kong, China. Association for Computational Linguistics.

Zhengyuan Liu, Angela Ng, Sheldon Lee, Ai Ti Aw, and Nancy F Chen. 2019. Topic-aware pointer-generator networks for summarizing spoken conversations. In IEEE ASRU2019, pages 814–821. IEEE.

Zhengyuan Liu, Ke Shi, and Nancy Chen. 2020. Conditional neural generation using sub-aspect functions for extractive news summarization. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: Findings, pages 1453–1463.

Ilya Loshchilov and Frank Hutter. 2019. Decoupled weight decay regularization. The International Conference on Learning Representations (ICLR2019).

Iain McCowan, Jean Carletta, Wessel Kraaij, Simone Ashby, S Bourban, M Flynn, M Guillemot, Thomas Hain, J Kadlec, Vasilis Karaikos, et al. 2005. The ami meeting corpus. In Proceedings of the 5th International Conference on Methods and Techniques in Behavioral Research, volume 88, page 100. Cite-seer.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca
Antiga, et al. 2019. Pytorch: An imperative style, high-performance deep learning library. In Proceedings of NeurIPS2019, pages 8026–8037.

Alexander M. Rush, Sumit Chopra, and Jason Weston. 2015. A neural attention model for abstractive sentence summarization. In Proceedings of EMNLP2015, pages 379–389, Lisbon, Portugal. Association for Computational Linguistics.

Leon Schüller, Florian Wilhelm, Nico Kreiling, and Goran Glavaš. 2020. Windowing models for abstractive summarization of long texts. arXiv preprint arXiv:2004.03324.

Abigail See, Peter J Liu, and Christopher D Manning. 2017. Get to the point: Summarization with pointer-generator networks. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, pages 1073–1083.

Guokan Shang, Wensi Ding, Zekun Zhang, Antoine Tixier, Polykarpos Meladianos, Michalis Vazigiannis, and Jean-Pierre Lorré. 2018. Unsupervised abstractive meeting summarization with multi-sentence compression and budgeted submodular maximization. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 664–674, Melbourne, Australia. Association for Computational Linguistics.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In Proceedings of NeurIPS2017, pages 5998–6008.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierrick Cistac, Tim Rault, Remi Louët, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. 2020. Transformers: State-of-the-art natural language processing. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 38–45, Online. Association for Computational Linguistics.

Chenguang Zhu, Ruochen Xu, Michael Zeng, and Xuedong Huang. 2020. A hierarchical network for abstractive meeting summarization with cross-domain pretraining. Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing.