SUMM^N: A Multi-Stage Summarization Framework for Long Input Dialogues and Documents

Yusen Zhang[♣] Ansong Ni[†] Ziming Mao[†] Chen Henry Wu[‡]
Chenguang Zhu[♢] Budhaditya Deb[♢] Ahmed H. Awadallah[♢]
Dragomir Radev[†] Rui Zhang[♣]
[♣] Penn State University [†] Yale University
[‡] Carnegie Mellon University [♢] Microsoft Research
{yfz5488,rmz5227}@psu.edu, {ansong.ni,dragomir.radev}@yale.edu

Abstract

Text summarization is an essential task to help readers capture salient information from documents, news, interviews, and meetings. However, most state-of-the-art pretrained language models are unable to efficiently process long text commonly seen in the summarization problem domain. In this paper, we propose SUMM^N, a simple, flexible, and effective multi-stage framework for input texts that are longer than the maximum context lengths of typical pretrained LMs. SUMM^N first generates the coarse summary in multiple stages and then produces the final fine-grained summary based on them. The framework can process input text of arbitrary length by adjusting the number of stages, while keeping the LM context size fixed. Moreover, it can deal with both documents and dialogues, and can be used on top of any underlying backbone abstractive summarization model. Our experiments demonstrate that SUMM^N significantly outperforms previous state-of-the-art methods by improving ROUGE scores on three long meeting summarization datasets AMI, ICSI, and QMSum, two long TV series datasets from SummScreen, and a newly proposed long document summarization dataset GovReport. Our data and code are available at https://github.com/chatc/Summ-N.

1 Introduction

Abstractive summarization can help readers capture salient information from various sources such as documents, news, interviews, and meetings. Previous work has primarily focused on short texts of news (Gehrmann et al., 2018; Zhang et al., 2019), and short conversations (Gliwa et al., 2019; Chen and Yang, 2021). Recently, more long dialogue and document summarization tasks (Zhong et al., 2021b; Huang et al., 2021; Chen et al., 2021) have been proposed, posing challenges for current large pretrained language models due to the time and memory complexity of training. A common solution to summarizing the long input is to reduce the input source to a shorter one. This can be accomplished by truncating inputs or employing retrieve-then-summarize pipelines. Lewis et al. (2020) directly cut off the input at the limits of neural models. Zhong et al. (2021b) use a feature-based BERT and convolutional neural network to retrieve the salient information and then uses various neural summarization models to generate the summary. However, these methods break the dependency of the context and decrease the number of tokens that the model can read, i.e., the receptive field of the model. The cutting-off model depends on the leading bias of the source text, while the retrieve-then-summarize models heavily rely on the independence of retrieved units (turns or sentences) which are usually scattered.

Another solution is to modify the attention mechanism to accommodate longer inputs. This reduces the quadratic computational and memory complexities of large Transformers, such as Locality-sensitive hashing (LSH) attentions (Kitaev et al., 2020) and Sinkhorn attentions (Tay et al., 2020). Additionally, HMNet (Zhu et al., 2020) and HAT-BART (Rohde et al., 2021) use a hierarchical self-attention to extend the input limitation of typical self-attention models. However, these models weaken the external unsupervised knowledge from the Transformer model and sacrifice the performance of original Transformers to fit a longer input.

In this paper, we propose a multi-stage framework SUMM^N for long dialogue and document summarization. First, it divides the source text as well as the target text into segments such that the size of each segment can be fed into the neural summarization model. Then, the first coarse stage generates the coarse summary and concatenates them together as the input of the next stage. After multiple coarse stages of compression and summarization, the final stage produces the fine-grained summary. It has a full reception field, meaning that the proposed model can read the full input in the final stage no matter how long the input is. It seldom relies on the context because of the segmentation algorithm. It does not assume leading bias because each part of the source is fully used. In each stage, it leverages an underlying transformer model to recursively learn and generate the summaries. Therefore, it enjoys the full power of the pretrained language models because the framework preserve the intact structure of Transformers.

We conduct extensive experiments on various datasets in multiple domains. The results demonstrate that the proposed model significantly outperforms previous state-of-the-art methods through automatic evaluations on three long meeting summarization datasets (AMI, ICSI, QMSum) and one long TV series summarization dataset (SummScreen). It also achieves state-of-the-art performance on a long document summarization dataset (GovReport). Additionally, these datasets include both query-based and non-query-based long dialogue summarization tasks.

Compared with the baselines, the proposed framework is more flexible. SUMM^N can flexibly change the number of coarse stages according to the compression ratio between source and target, the input limit of the underlying model, and the input source length. We give the empirical formula to decide the number of needed stages for every tested dataset. Experiments show that the ROUGE scores increases on all datasets when increasing from one stages to a proper number. Additionally, the flexibility of SUMM^N also resides in that the underlying model can be replaced easily, and models do not have to be identical in every stage.

Our contributions can be listed as follows: 1) We propose SUMM^N, a simple but effective framework for long dialogue and document summarization. 2) We evaluate SUMM^N on both dialogue and document domains and improve the baseline model by a large margin. 3) We analyze and compare the proposed framework with baselines discuss its merits with high interpretablity.

2 Related Work

Long Document Summarization Document summarization has been widely studied in multiple domains, such as news (Nallapati et al., 2016), patterns (Trappey et al., 2009), books (Kryściński et al., 2021; Wu et al., 2021), scientific publications (Qazvinian and Radev, 2008), and medical records (Cohan et al., 2018). However, the input of these datasets is often shorter than several thousand words. Huang et al. (2021) propose the GovReport dataset that contains more than 9000 words, greatly challenging the capability of current models such as PEGASUS (Zhang et al., 2019), TLM (Subramanian et al., 2019), and BIGBIRD (Zaheer et al., 2020). Other models such as Longformer (Beltagy et al., 2020) adjust attention mechanisms in Transformers to consume longer inputs. However, these models can only deal with relatively short inputs, and they are specifically designed for either dialogues or documents. By contrast, our framework eliminates the upper bound restriction of the input length by adding more stages, performing well on both long dialogues and documents. Besides, the performance of our framework can be further improved by using more powerful or task-specific underlying summarization models.

Long Dialogue Summarization Dialogue summarization has been extensively studied using skip-chain CRFs (Galley, 2006), SVM and SDA (Wang and Cardie, 2013) and sentence gating mechanism (Goo and Chen, 2018). However, such models usually struggle with long inputs including long meetings (McCowan et al., 2005; Janin et al., 2003; Zhong et al., 2021b), TV series (Chen et al., 2021), and Interviews (Zhu et al., 2021). This is due to the significant time and space consumption and the difficulty in modeling the context-dependency of the dialogue. HMNet (Zhu et al., 2020) and HAT-BART (Rohde et al., 2021) leverage a two-level transformer-based model to obtain word level and sentence level representations. DialLM (Zhong et al., 2021a), Longformer-BART-arg (Fabbri et al., 2021) use Transformer models to incorporate the external knowledge while maintaining the accuracy of lengthy input via fine tuning or data augmentation.

Multi-Stage Text Generation The multi-stage pipeline has been studied in many other text generation tasks. Some coarse-to-fine frameworks generate the intermediate sketches or the coarse text to help the final generation, such as dialogue state tracking (Chen et al., 2020), neural story generation (Fan et al., 2018), and extractive summarization (Xu and Lapata, 2020). More specifically, multi-stage summarization produces the salient in-

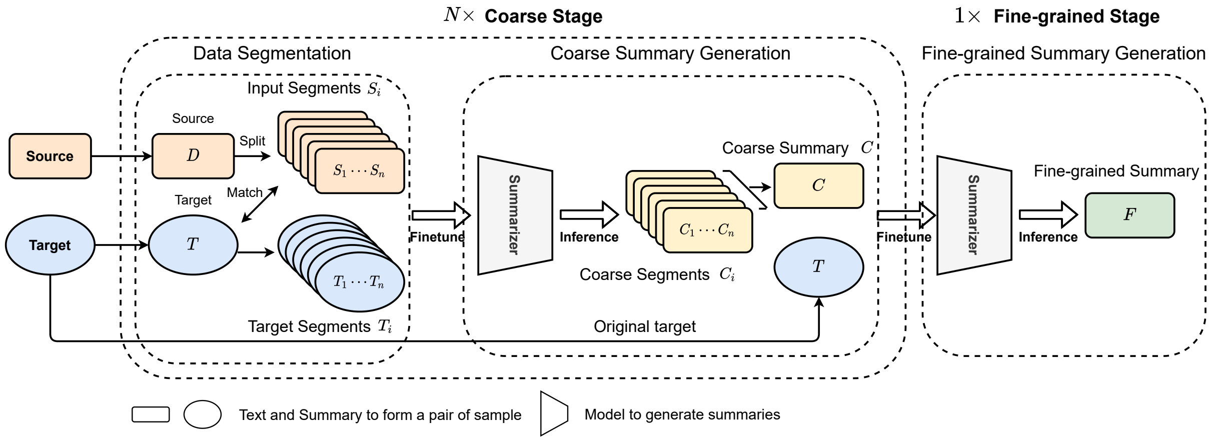

Figure 1: Workflow of proposed framework SUMM^N. It contains N coarse stage and 1 fine-grained stage. In each stage, a summarizer is trained from beginning to generate the summary. Finally, the fine-grained summary is the output of SUMM^N.

formation step by step, such as the extract-and-summarize pipeline (Zhang et al., 2019; Subramanian et al., 2019; Zhao et al., 2020). Our framework is different because SUMM^N aims at summarizing long input summarization which is not explored by these work.

3 Method

To formulate our task, we denote one sample of the source text in the dataset as $D = \{D_1, D_2, \cdots, D_m\}$, where D_i indicates one sentence in either document or dialogue. For query-based summarization, there is a query Q. The target is to produce a well-formulated summary T, given D and the optional Q.

Figure 1 shows the workflow of our proposed framework SUMM^N. There are two types of stages in the workflow, N coarse stages and one fine-grained stage. In the first coarse stage, the input source text D is compressed by a segment-then-combine method. The output of this coarse stage C is then fed to the next same coarse stage (with different model parameters) or the final fine-grained stage. This is decided by the length of the coarse summary C. If it does not exceed the limit of the fine-grained summarization model, we feed the data to the fine-grained stage to generate the final summary. Besides, the summarizer of every stage is initialized separately and then trained with different data. The coarse stage consists of two steps, data segmentation, and coarse summary generation. In the first step, both source and target data from the original dataset or previous stage are segmented to form a new dataset. Then, it is used to train a summarizer in the next step and generate the coarse summary C. In the final fine-grained stage, the coarse summary together with the targets was trained on a summarizer again without segmentation and produce the fine-grained summary as the output of the entire framework.

3.1 Data Segmentation

In long text summarization, the number of tokens in source data usually exceeds the limit of the underlying summarization models which will reduce the summary quality. To make sure that the model is able to capture information of all tokens in the input source, we apply a segmentation algorithm for long input summarization datasets. First, we segment the source text so that the data input to underlying model does not exceed the length limit. Then, we apply a greedy algorithm to find the best target that matches the source segments.

Source Segmentation Assuming the number of the maximum input tokens of underlying model is K. To completely receive the source information, we cut the input D into multiple segments such that each segment contains fewer than K tokens with the maximum number of complete sentences. Given the input D, we will have n segments $S = \{S_1, S_2, \cdots, S_n\}$ where $S_i \in D$ is continuous sentences in D. For query-based summarization tasks, we simply concatenate the query to the beginning of the the S, i.e. $S_i \leftarrow Q \bigoplus S_i$. In both cases, the number of the tokens in each segment is less than the hyper-parameter K.

Target Segmentation After segmentation of the source text, n source pieces S_i are obtained. We

Algorithm 1 Greedy Target Segmentation

Input: $S_i, T_s = \{T_{s_1}, T_{s_2}, \cdots, T_{s_k}\}$
Output: (S_i, T_i)

```
T_i ← Φ
loop
    T'_i ← T_i
    for T'_s ∈ T_s − T_i do
        τ' ← ROUGE_1(S_i, T'_i)
        τ ← ROUGE_1(S_i, T_i ⊕ T'_s)
        if τ' < τ then
            T'_i ← T_i ⊕ T'_s
        end if
    end for
    if T'_i = T_i then
        Break the loop.
    else
        T_i ← T'_i
    end if
end loop
return (S_i, T_i)
```

assign each S_i a target $T_i \in T$ so that the underlying model could be trained on the new pair (S_i, T_i). We use the following two strategies for target segmentation.

- **Duplication** Each segment S_i is simply paired with the target T, i.e. $T_i = T$. This method matches each source segment with full information of the summary which is good for learning global features. However, the duplication of the target will lead to the confuses of the model, making the model focus on the generation of some duplicated content.

- **Greedy Algorithm** We first split T into separated sentences $T_s = \{T_{s_1}, T_{s_2}, \cdots, T_{s_k}\}$. Then, each segment S_i is matched with a subset of T_s such that the ROUGE-1 score between T_s and S_i is maximized. However, the cost of finding the optimal set is not feasible. We apply a simple greedy approximation to find such subset. From a null set T_i, we iteratively add into the subset the sentence with the highest ROUGE-1 gain between T_s and S_i. Algorithm 1 shows the detailed algorithm to obtain the new training pair (S_i, T_i). $\bigoplus$ indicates the concatenation of sentences while keeping the order of them in the original text. We use ROUGE-1 as the matching criteria because the ROUGE-1 score usually coincides with the other metrics such as ROUGE-2 or ROUGE-L, but enjoys lower time complexity.

3.2 Number of Coarse Stages

In regard to text length, the source text of each stage should be compressed gradually to ensure that the summary with proper length could be generated in the final stage. Also, the compression rate determines the number of needed stages, which is a significant indicator of time cost. Suppose the source of stage i contains N_s^i words, while the target contains N_t^i words, and the maximum input length of the model is K, the compress rate of the target segmentation algorithm is $C_r = \frac{|T_i|}{N_t}$. N_t^i can be expressed by the number of segment $\frac{N_s^i}{K}$ times $|T_i|$. In each stage, we have:

$$N_t^i = \frac{N_s^i}{K} \times N_t \times C_r$$

$$N_s^i = N_t^{i-1}$$

By iterating this equation for L_c time, the number of needed coarse stages L_c for a dataset can be decided in this way:

$$\frac{N_s^0}{K^{L_c}} \times N_t^{L_c} \times C_r^{L_c} \leq K$$

$$L_c \geq \frac{\log K - \log N_s^0}{\log N_t + \log C_r - \log K}$$

Where $*^{L_c}$ indicates the L_c-th power of $*$, while N_s^0 indicates the source text of original dataset. C_r of duplication segmentation is 1 and greedy segmentation is 0.5 to 0.9. So the target segmentation algorithm is a key step for reducing the number of stages.

3.3 Coarse Summary Generation

In coarse summary generation, we train a summarization model, that takes the segmented data as input. Data segmentation helps the summarizer to better learn the task of the current stage. We first collect the training samples (S_i, T_i) generated by data segmentation to form a new dataset. This augments the source data to N_s/K times compared with the cut-off methods. Also, it eliminates the leading bias to a great extent, unlike the cut-off method which only takes as input the first segment S_1. Then, we use these data to train a neural summarizer. In this way, our model treats each part of the source texts as equally important.

We pick BART (Lewis et al., 2020) model as our underlying model because it performs well on the short text summarization but not as good on the long text, illustrating the benefits by introducing our framework. Compared with other pretrained parameters, the BART-large model pretrained on the CNN/DM dataset yields the best performance (Zhang et al., 2021). So we use BART-large-cnn parameter as a better starting point .

It is worth noting that the BART model was initialized and separately finetuned in each stage. We experiment with reusing the model parameters in multiple stages but obtained a lower score on the final summaries, e.g. the ROUGE-1 score of stage 2 in QMSum dataset decreases around two points if we use the best parameters of stage 1 summarizer as the starting point of training stage 2 summarizer. This is because the tasks of different stages differ significantly. For instance, the input to the first stage of dialogue summarization is dialogue turns while the input to the latter stages is documents.

Given source segment S_i and an optional query Q, we obtain the coarse summary segments using a BART model:

$$\hat{T}_i^l = \text{BART}_l(Q, S_i)$$

Where l is the index of the current stage. Then, the n coarse summaries corresponding to the original source $S = \{S_1, S_2, \cdots, S_n\}$ are concatenated: $\hat{T}^l = \hat{T}_1^l \bigoplus \hat{T}_2^l \bigoplus \cdots \bigoplus \hat{T}_n^l$. We use $\hat{T}^l$ as the new source text of next stage, which compresses the input source data D^l. i.e. $D^{l+1} = \hat{T}^l$. To pair with the D^{l+1}, the target to the next stage is copied from the original dataset, i.e. $T^{l+1} = T$.

3.4 Fine-Grained Summary Generation

When the length of input source is shorter then K, we can use a single summarization model to obtain the finally summary. The segment-then-summary is not needed in this stage because the lengthy issue is resolved.

The workflow of fine-grained stage is the same as the coarse summary generation except for the combination of the coarse summary. In fine-grained stage, the model is directly trained on dataset (D^{L_c}, T) from last coarse stage, and inference on the test set to obtain the summary:

$$\hat{T}^{L_c+1} = \text{BART}_{L_c+1}(Q, D^{L_c})$$

4 Experiment Setup

4.1 Datasets and Metrics

Table 1 shows the statistics for the datasets we used in this paper.

AMI & ICSI (McCowan et al., 2005; Janin et al., 2003) are meeting scripts generated by Automatic Speech Recognition (ASR) system. AMI is collected from product design meetings in company while ICSI is collected from academic group meetings in school. As the transcript is produced by the ASR, there is a word error rate of 36% for AMI and 37% for ICSI.

QMSum (Zhong et al., 2021b) is a query-based meeting summarization dataset. It consists of the meetings from three domains, including AMI and ICSI, and the committee meetings of the Welsh Parliament and Parliament of Canada. Each query and sample are written by experts.

SummScreen (Chen et al., 2021) consists of community contributed transcripts of television show episodes from The TVMegaSite, Inc. (TMS) and ForeverDream (FD). The summary of each transcript is the recap from TMS, or a recap of the FD shows from Wikipedia and TVMaze.

GovReport (Huang et al., 2021) is a large-scale long document summarization dataset, containing 19,466 long reports published by U.S. Government Accountability Office to fulfill requests by congressional members, and Congressional Research Service covering researches on a broad range of national policy issues.

ROUGE (Lin, 2004) is used as the automatic evaluation metrics throughout all experiments. We use `pyrouge` library [1] as the implementation. We split the sentence in each generated summary to obtain the full ROUGE-L scores.

4.2 Baselines

We compare the proposed framework with various baselines. **PGNet** (See et al., 2017) uses a pointer mechanism to copy the token from training sample. **TopicSeg** (Li et al., 2019) is multi-modal model jointly modeling the segmentation and summarization. **HMNet** (Zhu et al., 2020) utilizes hierarchical attention structure and cross-domain pre-training for meeting summarization. **TextRank** (Mihalcea and Tarau, 2004) is a graph-based ranking model

[1] https://github.com/bheinzerling/pyrouge

Dataset	Type	Domain	Size	Source length	Target length	Query
AMI	Dialogue	Meetings	137	6007.7	296.6	✗
ICSI	Dialogue	Meetings	59	13317.3	488.5	✗
QMSum	Dialogue	Meetings	1808	9069.8	69.6	✓
SummScreen	Dialogue	TV shows	26851	6612.5	337.4	✗
GovReport	Document	Reports	19466	9409	553.4	✗

Table 1: The summarization datasets for evaluation. The source length and target length is the averaged number across the dataset.

for text processing. **HAT-BART** (Rohde et al., 2021) is a new hierarchical attention transformer-based architecture that outperforms standard Transformers. **DDAMS** (Feng et al., 2021) uses a relational graph to model the interaction between utterances in a meeting by modeling different discourse relations.

For SummScreen dataset, we use the neural and hybrid model scores reported by Chen et al. (2021). We rename these two baselines as **Longformer+ATT** and **NN+BM25+Neural** to clarify the difference between other baselines.

The baseline scores we report on GovReport dataset are from the original paper (Huang et al., 2021). **BART Variant** indicates self-attention variants with full encoder-decoder attention. **BART HEPOS** indicates encoder variants with head-wise positional strides (HEPOS) encoder-decoder attention.

4.3 Implementation Details

We report the scores of SUMM^N on different stages. **Stage 1** indicates the model with only one coarse stage and no fine-grained stage. In this model, We directly use the first segment of the coarse summary as the output, i.e. $\hat{T}_1^1$ of each sample. **Stage i** ($i > 1$) model contains $i - 1$ coarse stage and one fine-grained stage, the generated summary is from fine-grained summarization models, i.e. $\hat{T}^i$.

We fit all models into a single RTX A6000 GPU with a 48 GiB memory. We adopt the fairseq[2] implementation for BART. The learning rate is set to 2e-5 and the beam width is set to 2 for coarse stages and 10 for fine-grained stages. The maximum number of tokens in each batch is set to 2048. The maximum number of tokens in each source text is set to 1024 because we tried to extend the positional embeddings to 2048 or longer but obtained worse performance. For the output of each intermediate stage, we use <s> and </s> to separate each generated target segments $\hat{T}_i^l$.

[2]https://github.com/pytorch/fairseq

5 Results and Analysis

In this section, we first describe the overall results of SUMM^N on meeting, TV series and document dataset. Next, we introduce the ablations on AMI test set. Then, we discuss the model replacement, stage improvement, and backbone models.

Meeting Summarization Table 2 show the ROUGE scores on AMI, ICSI and QMSum datasets. Compared with baseline models, SUMM^N achieves state-of-the-art on almost all metrics. Specifically, SUMM^N improves ICSI by **2.9** ROUGE-1, and **0.83** ROUGE-2 scores, improves QMSum-Gold by **4.14** ROUGE-1, **3.96** ROUGE-2, and **4.35** ROUGE-L scores. These results demonstrate the effectiveness of SUMM^N on long dialogue summarization tasks.

TV Series Summarization Table 3 shows ROUGE score on SummScreen dataset. SUMM^N outperforms almost all metrics on two SummScreen dataset. Especially, we improve **6.58** ROGUE-1, **1.92** ROUGE-2, and **3.34** ROUGE-L scores on SummScreen-FD dataset. This result demonstrates the robustness of SUMM^N, showing it can be generalized to various domains, including both meetings and TV series.

Document Summarization Table 5 shows ROUGE score on GoveReport dataset. SUMM^N achieves state-of-the-art performance on ROUGE-2 and ROUGE-L scores, and compatible results on ROUGE-1 score. In long document summarization task, the improvements between different stages and the boosting from backbone model (Full (1024) is identical to the BART-large backbone in GovReport) is also explicitly obtained. SUMM^N can be generalized to long document summarization tasks, and regarding performance boosting, the properties in long dialogue summarization also exists.

	AMI			ICSI			QMSum-All			QMSum-Gold		
	R-1	R-2	R-L	R-1	R-2	R-L	R-1	R-2	R-L	R-1	R-2	R-L
PGNet	42.60	14.01	22.62*	35.89	6.92	15.67*	28.74	5.98	25.13	31.52	8.69	27.63
TopicSeg	51.53	12.23	25.47*	-	-	-	-	-	-	-	-	-
HMNET	52.36	18.63	24.00*	45.97	10.14	18.54*	32.29	8.67	28.17	36.06	11.36	31.27
TextRank	35.19	6.13	16.70*	30.72	4.69	12.97*	16.27	2.69	15.41	-	-	-
HAT-BART	52.27	20.15	50.57	43.98	10.83	41.36	-	-	-	-	-	-
DDAMS	53.15	**22.32**	25.67*	40.41	11.02	19.18*	-	-	-	-	-	-
Ours (SUMM^N)	**53.44**	20.30	**51.39**	**48.87**	**12.17**	**46.38**	**34.03**	**9.28**	**29.48**	**40.20**	**15.32**	**35.62**

Table 2: ROUGE scores on three meeting summarizing tasks, AMI, ICSI, and QMSum. QMSum-ALL and QMSum-Gold indicates that the input contains all turns or only the gold turns. * denote the ROUGE-L scores without sentence split.

	SummScreen-FD			SummScreen-TMS		
	R1	R2	RL	R1	R2	RL
Longformer+ATT	25.90	4.20	23.80	42.90	**11.90**	41.60
NN+BM25+Neural	25.30	3.90	23.10	38.80	10.20	36.90
Ours (SUMM^N)	**32.48**	**6.12**	**27.14**	**44.64**	11.87	**42.53**

Table 3: ROUGE scores on SummScreen datasets including TV MegaSite, Inc. (TMS) and ForeverDreaming (FD).

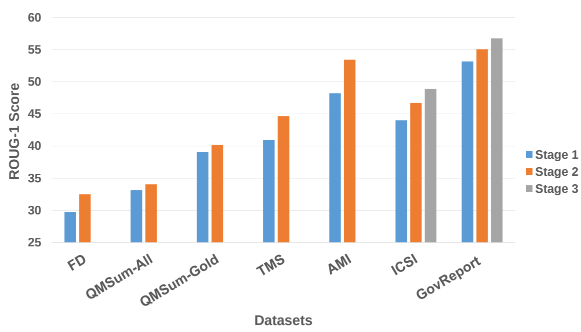

Figure 2: ROUGE-1 score of various dataset of different stages. FD and TMS indicate two SummScreen datasets. ICSI and GovReport has 3 stages while the others has 2 stages.

5.1 Ablations

Table 6 show the ablation study of SUMM^N on test set of AMI dataset. As shown in the table, removing stage 2 (using the first segment of the coarse summary $\hat{T}_1^1$ as generated summary) will lead to a 5.23 ROUGE-1 score drop. When the data segmentation is removed, the ROUGE-1 score decrease 6.61 although the fine-grained stage still exsists in the framework. Also, removing both stage 2 and taget segmentation (use duplication algorithm instead) will further decearse the performance of SUMM^N which even hurts the performance of original BART model because the simple duplication of target will introduce some biases towards the common part of the targets.

5.2 Replacement of Underlying Models

To evaluate the robustness of SUMM^N towards underlying models, we first replace the BART-large-cnn model in previous experiments with BART-base, and then train and evaluate the new model on AMI dataset. We obtain 41.54, 13.8, 38.75 ROUGE-1/2/L scores in stage 1, and 46.6, 18.8, 45.23 ROUGE-1/2/L scores in stage 2. Although BART-base is a weaker summarizer compared with BART-large model, the framework is still able to improve the ROUGE-1 score by **5.06**.

5.3 Performance of Different Stages

We also notice that the performance improves greatly with increasing number of stages. Figure 2 shows the ROUGE-1 scores of different tasks across stages. Although stage 2 of SUMM^N on ICSI dataset has already outperformed the baselines, the scores can be further improved by adding one more coarse stage. In fact, in all datasets, increasing the number of stages leads to performance gain. This gain is highly interpretable in SUMM^N: if the input to the next stage is larger than K, adding one more coarse stage will be helpful since the model will receive more information from the source text rather than cutting off them. On the contrary, if the the input is smaller than K, there is no need to add more stages, because the fine-grained model is already able to process the information from last layer.

5.4 Improvement of Underlying Model

SUMM^N also boosts the performance of backbone model by a large margin. As shown in Table 7, it improves the BART-large model by

	ICSI
SUMM^N	The project manager opens the meeting by recapping the events of the previous meeting. The marketing expert presents the results of market research , which shows that users want a fancy-looking remote control that is easy to use and has a fancy look and feel. The user interface designer presents the user interface concept for the remote , which is based on the idea that a remote should be simple and user-friendly. The industrial designer presents about the internal components of a remote control. The group discusses using kinetic energy to power the device , using a simple battery for the LCD screen , and using an advanced chip for the advanced chip. The project manager closes the meeting , telling the team members what their tasks will be for the next meeting. $\cdots$ The Marketing Expert will research how to produce a remote that is technologically innovative. The User Interface Designer will look at how to make a remote out of wood or plastic with either a wooden or plastic cover. The Group will not work with teletext. There was a lack of information on the cost of components and materials.
Gold	The project manager opened the meeting and recapped the decisions made in the previous meeting. The marketing expert discussed his personal preferences for the design of the remote and presented the results of trend-watching reports , which indicated that there is a need for products which are fancy , innovative , easy to use , in dark colors , in recognizable shapes , and in a familiar material like wood. The user interface designer discussed the option to include speech recognition and which functions to include on the remote. The industrial designer discussed which options he preferred for the remote in terms of energy sources , casing , case supplements , buttons , and chips. The team then discussed and made decisions regarding energy sources , speech recognition , LCD screens , chips , case materials and colors, case shape and orientation , and button orientation.$\cdots$ The case covers will be available in wood or plastic. The case will be single curved. Whether to use kinetic energy or a conventional battery with a docking station which recharges the remote. Whether to implement an LCD screen on the remote. Choosing between an LCD screen or speech recognition. Using wood for the case.

Table 4: Sample output summary SUMM^N on ICSI dataset. Tokens marked in grey indicates the out-of-boundary contents of truncation models. Brown tokens are the keywords emerged in the gold summary. Tokens marked in red indicate the concepts of out-of-boundary text.

	R-1	R-2	R-L
BART Variants			
Full (1024)	52.83	20.50	50.14
Stride (4096)	54.29	20.80	51.35
LIN. (3072)	44.84	13.87	41.94
LSH (4096)	54.75	21.36	51.27
Sinkhorn (5120)	55.45	21.45	52.48
BART HEPOS			
LSH (7168)	55.00	21.13	51.67
Sinkhorn (10240)	**56.86**	22.62	53.82
Ours (SUMM^N)	56.77	**23.25**	**53.90**

Table 5: Results on GovReport. For each baseline model, the number in the parentheses is the maximum length of input tokens.

	R-1	R-2	R-L
SUMM^N	**53.44**	**20.30**	**51.39**
- stage 2	48.21	18.59	46.46
- data seg.	46.83	15.91	45.0
- stage 2 & tar. seg.	46.24	16.03	44.45
only BART	46.57	16.41	44.61

Table 6: Ablations on test set of AMI. "-data seg." indicates removing data segmentation (the same as cutoff at limitation), "-tar. seg." indicates source segmentation paired with duplicated targets.

6.87 ROUGE-1, **3.89** ROUGE-2, **6.78** ROUGE-L on AMI dataset. This indicates the capability of SUMM^N to boost performance of a weak learner on long summarization tasks. Especially, when the backbone model is well pretrained on short input texts and performs well on short summarization tasks, SUMM^N could greatly increase the capability of the backbone model to process and read long source texts. Also, each stage of SUMM^N can be easily replaced by some other models, and models are not necessarily identical to be identical for every stage. One can try different learners such as T5 as the backbone model and replace the model in stage 1 with a model designed for dialogue-to-document tasks.

	R-1	R-2	R-L
AMI			
Backbone (BART)	46.57	16.41	44.61
SUMM^N	**53.44**	**20.30**	**51.39**
ICSI			
Backbone (BART)	39.91	9.98	38.17
SUMM^N	**48.87**	**12.17**	**46.38**
QMSum-All			
Backbone (BART)	29.20	6.37	25.49
SUMM^N	**34.03**	**9.28**	**29.48**
QMSum-Gold			
Backbone (BART)	32.18	8.48	28.56
SUMM^N	**40.20**	**15.32**	**35.62**

Table 7: ROUGE scores of underlying BART model and SUMM^N on AMI, ICSI and QMSum dataset.

5.5 Case Study

Table 4 shows a concrete sample summary generated by SUMM^N. It captures the topics of the source text and smoothly follows the outline of the gold summary. Also, SUMM^N is able to evenly generate the information of the whole summary, including the last part of source text which is truncated in the standard BART-large models.

6 Conclusion

In this paper, we propose SUMM^N, a simple, flexible, and effective framework for long dialogue and document summarization. It consists of multiple coarse stages and one fine-grained stage to iteratively compress the long source input to the desired length. It enjoys the full power of underlying models while ensuring the full receptive field of the summarization model. We evaluate the model on various datasets and improve the baselines by a large margin.

The future work includes 1) applying SUMM^N to other tasks with long input, such as long form question answering and response generation with long dialogue history, 2) modifying the framework to improve the performance on various tasks.

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