

Leveraging Locality in Abstractive Text Summarization

Yixin Liu¹, Ansong Ni¹, Linyong Nan¹, Budhaditya Deb²,
Chenguang Zhu², Ahmed H. Awadallah², Dragomir Radev¹

¹Yale University, ²Microsoft Research

{yixin.liu, ansong.ni, linyong.nan, dragomir.radev}@yale.edu
{Budha.Deb, chezhu, hassanam}@microsoft.com

Abstract

Neural attention models have achieved significant improvements on many natural language processing tasks. However, the quadratic memory complexity of the self-attention module with respect to the input length hinders their applications in long text summarization. Instead of designing more efficient attention modules, we approach this problem by investigating if models with a *restricted* context can have competitive performance compared with the memory-efficient attention models that maintain a global context by treating the input as a single sequence. Our model is applied to individual *pages*, which contain parts of inputs grouped by the *principle of locality*, during both the encoding and decoding stages. We empirically investigated three kinds of locality in text summarization at different levels of granularity, ranging from sentences to documents. Our experimental results show that our model has a better performance compared with strong baseline models with efficient attention modules, and our analysis provides further insights into our locality-aware modeling strategy.¹

1 Introduction

Neural abstractive summarization (Rush et al., 2015; Nallapati et al., 2016) is mainly formulated as a sequence-to-sequence (Sutskever et al., 2014) (Seq2Seq) problem. Neural attention models, e.g., Transformers (Vaswani et al., 2017), have been widely used for such Seq2Seq tasks, allowing effective modeling of various dependencies in the input and output sequences. However, the *self-attention* module in such models introduces a quadratic memory growth with respect to the input sequence length. Consequently, for long-text summarization datasets,² recent works (Beltagy et al., 2020; Kitaev et al., 2020; Zaheer et al., 2020) have explored

¹We have made our code, results, and trained models publicly available at <https://github.com/yixinL7/PageSum>.

²For example, the average input document length in the arXiv dataset (Cohan et al., 2018) is more than 8,000 tokens.

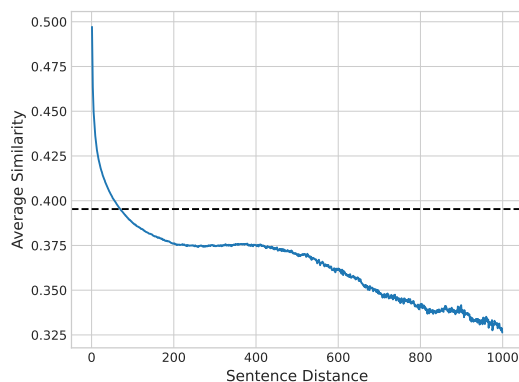


Figure 1: Intrinsic spatial locality in the arXiv dataset. The X-axis represents the distance of two sentences in source documents measured by the difference of their locations (indexes). Y-axis represents the average semantic similarity calculated by the cosine similarity between sentence embeddings, which are generated by a pre-trained sentence embedding model (Gao et al., 2021). The dash line shows the average similarity.

using *efficient attention* to reduce the memory footprint while still maintaining the same **global context** of a full-attention model – every input token can receive information from all the other input tokens. However, efficient attention is just an approximation of full attention and can show lower performance compared with its counterpart (Kitaev et al., 2020). To investigate an alternative memory-efficient modeling approach, we argue that models with a *restricted* context, where each token only receives a subset of tokens as its context during the entire computation, can be competitive with efficient attention models if they can effectively leverage **locality** in text summarization.

Locality, or the principle of locality, is one of the fundamental principles of virtual memory systems (Denning, 2005),³ and exists in a wide range

³A formal definition of locality coined by Denning (1980) is: “The concept that a program favors a subset of its segments during extended intervals (phases) is called locality.”

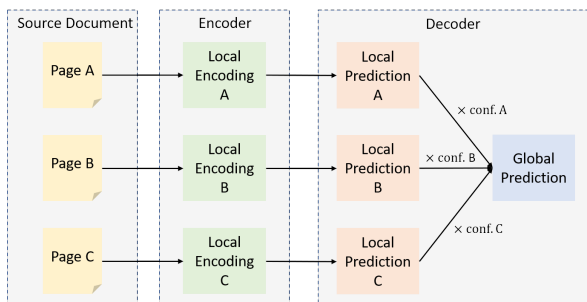


Figure 2: Model architecture. Our model views the source document as a number of *non-overlapping pages*, and the final output is a weighted combination of local predictions on the individual pages.

of domains (Koopman et al., 2013; Fonseca et al., 2003; Zamanian et al., 2015). A classic example of locality is the *spatial locality* in computer memory systems – data units that are stored closely on the disk are likely to be accessed during a short time period by a computer process, therefore it is beneficial to read a block of data as a *page* in the memory instead of reading only one data unit at a time. Such patterns also exist in text summarization. For example, on the arXiv dataset, we observe an *intrinsic spatial locality* in source documents – the closer in the document two sentences are, the more semantically similar they are (Fig. 1). This observation supports the inductive bias of *window attention* (Beltagy et al., 2020; Zaheer et al., 2020), which allows each token to interact with its neighboring tokens within the window size.

We introduce a framework of leveraging locality for text summarization, which reduces the memory complexity of full-attention models while still maintains competitive performance. Instead of viewing the input document as an entire sequence, we represent an input document as a number of *pages* which are constructed according to the principle of locality (Fig. 2). Each of these pages is encoded independently by the encoder of our abstractive model, and the decoder makes *local* predictions over each page along with *local* confidence scores of its predictions, which are used to combine the local predictions into final outputs. In this framework, tokens in different pages never directly interact with each other during encoding and decoding, which highlights the role of **locality** in text summarization. In contrast, one of the key assumptions of efficient attention models is that all tokens in the input text should interact with each other, which is made possible because (1) *global tokens* (Beltagy et al., 2020) or *overlapping win-*

down attention maintain a *global* context during encoding; (2) the encoder-decoder attention takes the source document embeddings as an entire sequence during decoding.

Using the proposed framework, we are able to investigate several types of locality in text summarization: (1) *spatial locality* or *sequential locality* – neighboring sentences are grouped into the same (non-overlapping) page; (2) *discourse locality* – different sections in a scientific paper may cover different aspects, therefore they are viewed as different pages (Cohan et al., 2018); (3) *document locality* – for multi-document summarization, each document in a document cluster can be viewed as an individual page (Jin and Wan, 2020). Our approach also has other advantages: (1) Our model can take the most advantage of pre-trained full-attention models (e.g. BART (Lewis et al., 2020)) because it preserves the same attention mechanism as the full-attention models, unlike most of the efficient attention models; (2) It reduces the overall complexity of encoder self-attention to a *linear* relationship with the input document length. We empirically demonstrate that our model outperforms strong baseline models built upon various efficient-attention modules on several summarization datasets. Furthermore, we conduct detailed analyses on different modeling options for our framework, shedding lights on its broader uses.

2 Preliminaries

Abstractive summarization models aim to generate a shorter text sequence as the summary of an input document. Given an input document D and a reference summary S , the standard training algorithm of a neural abstractive summarization model g adopts the cross-entropy loss, which requires the model to predict the next token of the reference summary given the input document and the prefix of the reference summary before the current token:

$$\mathcal{L}_{xent} = - \sum_{i=1}^l \log p_{g_\theta}(s_i | D, S_{<i}; \theta), \quad (1)$$

where θ is the trainable parameters of the model g , p_{g_θ} is the predicted probability over the vocabulary, l is the length of the summary S , $\{s_1, \dots, s_i, \dots, s_l\}$ are tokens in S , $S_{<i}$ denotes the partial reference sequence $\{s_0, \dots, s_{i-1}\}$ and s_0 is a pre-defined start token.

Encoder-Decoder Model The encoder-decoder model formulates abstractive summarization as a Seq2Seq task,

$$h_i = \text{Decoder}(\text{Encoder}(D), S_{<i}), \quad (2)$$

where h_i is the hidden representation. The generation probability is

$$p_{g\theta}(\cdot|D, S_{<i}; \theta) = \text{softmax}(L_{vocab}(h_i)), \quad (3)$$

where L_{vocab} is a linear projection layer.

Neural Attention and Its Limitations Neural attention modules are essential to the success of Transformers (Vaswani et al., 2017) and pre-trained language models (Radford et al., 2019; Lewis et al., 2020; Zhang et al., 2020) for language generation tasks such as machine translation or text summarization. Given a query matrix Q , a key matrix K , and a value matrix V , the output of the dot-product attention is:

$$\text{Attention}(Q, K, V) = \text{softmax}(QK^T)V. \quad (4)$$

To compute Eq. 4 in a parallel manner, it requires $\mathcal{O}(l_Q \cdot l_K)$ memory space to store the intermediate result of QK^T where l_Q and l_K are the length of Q and K respectively. This becomes a bottleneck of the *self-attention* module for long input documents, where Q, K, V come from the same input D , and the space complexity becomes $\mathcal{O}(l_D^2)$, where l_D is the length of the input document and can be very large (e.g. more than 10,000 tokens).

3 Locality-aware Abstractive Text Summarization

To avoid the quadratic growth of memory with respect to the length of the input, we introduce a different view for modeling the input text. Specifically, instead of viewing the input document as an entire text sequence, we view it as a series of *non-overlapping pages* with a fixed maximum length:

$$D := \{P_1, \dots, P_i, \dots, P_n\}, \quad (5)$$

where P_i is the i -th page and n is the number of pages. We hypothesize that with the **principle of locality**, the abstractive summarizer can make local predictions about the output summary based on *individual* pages without having each input token interact with the entire input document:

$$h_i^{(j)} = \text{Decoder}(\text{Encoder}(P_j), S_{<i}), \quad (6)$$

where $h_i^{(j)}$ is the *local* hidden state of the i -th token of the summary given the j -th page. Apart from the hidden state, we also require the decoder to predict a confidence score of its local prediction:

$$c_{ij} = L_{conf}(h_i^{(j)}), \quad (7)$$

where L_{conf} is a linear layer projecting the hidden state $h_i^{(j)}$ to a scalar. The confidence scores are normalized:

$$\hat{c}_{ij} = \frac{\exp(c_{ij})}{\sum_{k=1}^n \exp(c_{ik})}, \quad (8)$$

and used to combine the local hidden states for predicting the final output:

$$p_{g\theta}(\cdot|D, S_{<i}; \theta) = \text{softmax}(L_{vocab}(\sum_{j=1}^n \hat{c}_{ij} \cdot h_i^{(j)})). \quad (9)$$

Fine-tuning from Pre-trained Models Our model can be directly initialized from a pre-trained language model (e.g. BART (Lewis et al., 2020)) except for an additional linear layer L_{conf} (Eq. 7). The cross-entropy loss (Eq. 1) with label smoothing (Szegedy et al., 2016) is used for training.

Space Complexity Our model has a linear space complexity with respect to the length of input documents. Specifically, given a pre-defined maximum page length L_{page} , a document of which the length is l_D will be split into at most $\lceil \frac{l_D}{L_{page}} \rceil$ pages. The space complexity of the encoder self-attention for one page is $\mathcal{O}(L_{page}^2)$, and the complexity for all pages is

$$\mathcal{O}(L_{page}^2 \cdot \lceil \frac{l_D}{L_{page}} \rceil) = \mathcal{O}(L_{page}l_D). \quad (10)$$

When $l_D \gg L_{page}$, the complexity is $\mathcal{O}(l_D)$.⁴

Locality in Abstractive Summarization We mainly explore three types of locality for abstractive summarization, which provide the principles of splitting an input document or document cluster (in the case of multi-document summarization) into different *pages*.

(1) **Spatial Locality**: in the most direct form, an input document can be sequentially split into different pages. The underlying intuition is that neighboring sentences are likely to focus on the same

⁴In practice, the page size L_{page} can be large (e.g. 512 tokens). However, we note that sparse attention models can also use window attention with large sizes (e.g. Longformer (Beltagy et al., 2020) uses either 512 or 1024 tokens).

topic. Under this setting, each document will be equally split into n_p pages, which is a pre-defined number.

(2) **Discourse Locality**: long documents usually have a hierarchical discourse structure, and discourse units at the same level have different focus. For example, a scientific paper usually has multiple sections with different purposes (e.g. introduction, related work, etc.), and this discourse structure can be a useful inductive bias (Cohan et al., 2018). Under this setting, each discourse unit (e.g. a section in a scientific paper) is viewed as a page.

(3) **Document Locality**: for multi-document summarization, we can view each single document in the document cluster as a page. Previous work (Jin and Wan, 2020) has shown that multi-document summarization can benefit from single-document summarization models by first summarizing each document then combining the predictions.

4 Related Work

4.1 Efficient Attention Models

Efficient attention models aim to reduce the memory complexity of full attention models, of which the most important and commonly used building blocks are window attention (Beltagy et al., 2020; Zaheer et al., 2020) and low-rank approximation (Liu* et al., 2018; Wang et al., 2020; Peng et al., 2021; Choromanski et al., 2021).

Window attention means that each token can only receive information from its neighboring tokens that are located in the same window. However, multi-layer models with **overlapping** window attention (Beltagy et al., 2020; Zaheer et al., 2020; Manakul and Gales, 2021; Guo et al., 2021) can still maintain a *global* context. On the other hand, **non-overlapping** window attention (local attention) with *fixed* windows (Liu* et al., 2018; Zhao et al., 2020; Pietruszka et al., 2020) has a *restricted* context since tokens in different windows cannot interact with each other. Instead of using fixed windows throughout the model, using window attention with **learnable** patterns (Kitaev et al., 2020; Tay et al., 2020; Huang et al., 2021) offer more flexibility because windows can be dynamically constructed at different layers of the model, which allows a larger context. Headwise sparse attention (Qiu et al., 2020; Huang et al., 2021) is another method of reducing memory usage while preserving global context.

Compared to these methods, our model has a dis-

tinct feature in that we maintain a **local** context of the input tokens at both the encoding and decoding stages. Zhao et al. (2020) proposed a similar block-wise encoder-decoder attention module which only uses a subset of input tokens (blocks) at each decoding stage. However, our method differs from theirs in that our model dynamically combines the local predictions based on all the individual *pages* into the final output (Eq. 9).

4.2 Hierarchical Summarization Models

Hierarchical attention (Yang et al., 2016) models aim to utilize the inherent structure of documents as a source of inductive bias. For text summarization, Ling and Rush (2017) proposes a coarse-to-fine structure consisting of word-level and chunk-level attention. Cohan et al. (2018); Xu et al. (2020a); Dong et al. (2021) introduce discourse-aware attention at the level of document sections or elementary discourse units. Related work (Xiao and Carenini, 2019; Xu et al., 2020b; Rohde et al., 2021; Ruan et al., 2022) use a similar structure that computes both token-level and sentence-level attention. Cao and Wang (2022) introduces learnable hierarchical biases into the attention module.

Hierarchical models have also been widely used for multi-document summarization. Hierarchical attention can focus on the sentence level (Fabri et al., 2019), paragraph level (Liu and Lapata, 2019), and document level (Zhang et al., 2018; Jin and Wan, 2020; Jin et al., 2020). Ernst et al. (2021) proposed a proposition-level clustering algorithm, which generates summaries from each of the proposition clusters extracted from source documents.

The multi-stage method of text summarization (Chen and Bansal, 2018; Xu and Durrett, 2019; Pilault et al., 2020) also has a hierarchical structure. In particular, Zhang et al. (2022) first generates a coarse summary for each part of the input document, then further summarizes the generated summaries. Mao et al. (2022) first extracts sentences from the source documents, and generates the summary based on the selected sentences.

Our method introduces **pages** as a new, unified abstraction for hierarchical models which can be instantiated as sentence clusters, scientific paper sections, and entire documents in a document cluster. Furthermore, unlike previous work, our model emphasizes the role of locality by preventing explicit interactions among different units (pages) at the higher levels of the hierarchy.

System	arXiv			PubMed			GovReport		
	R-1	R-2	R-L	R-1	R-2	R-L	R-1	R-2	R-L
LED* (4096)	44.40	17.94	39.76	-	-	-	-	-	-
LED* (16384)	46.63	19.62	41.83	-	-	-	-	-	-
LED [‡] (16384)	48.10	19.78	43.08	46.93	19.88	42.73	59.42	26.53	56.63
HEPOS* (7168)	48.24	20.26	41.78	48.12	21.06	42.72	55.00	21.13	51.67
HEPOS* (10240)	47.87	20.00	41.50	47.93	20.74	42.58	56.86	22.62	53.82
PRIMERA* (4096)	47.60	20.80	42.60	-	-	-	-	-	-
PRIMERA [‡] (4096)	47.65	20.76	43.19	-	-	-	-	-	-
HAT-BART* (3072)	46.68	19.07	42.17	48.36	21.43	37.00	-	-	-
PageSum (7168)	49.72 [†]	21.06 [†]	44.69 [†]	48.24 [†]	21.06 [†]	44.26 [†]	59.05	26.37	56.22
PageSum (20480)	-	-	-	-	-	-	59.91 [†]	27.20 [†]	57.07 [†]
PageSum* (7168/20480)	49.60 [†]	20.98 [†]	44.69 [†]	48.73 [†]	21.33 [†]	44.67 [†]	60.04 [†]	27.17 [†]	57.21 [†]

Table 1: System performance comparison for *spatial locality*. R-1/2/L are the ROUGE-1/2/L F_1 scores respectively. The numbers in parentheses indicate the maximum input length (tokens). *: results reported in the original papers. ‡: results from our own evaluation script (and own checkpoints). †: significantly better than LED[‡] ($p < 0.01$). PageSum denotes the model fine-tuned from a BART checkpoint pre-trained on the CNN/DailyMail dataset, while PageSum* is its counterpart without the CNN/DailyMail pre-training. For PageSum*, the maximum token number is 7168 on arXiv and PubMed, and 20480 on GovReport.

5 Experiments

5.1 Experimental Settings

Datasets We use four datasets (Tab. 10) in our experiments.

arXiv and PubMed are two scientific paper summarization datasets introduced by Cohan et al. (2018).⁵ The abstracts of the papers are used as the summaries of the main content of those papers.

GovReport⁶ (Huang et al., 2021) is a long document summarization dataset based on reports published by the U.S. Government Accountability Office and Congressional Research Service.

MultiNews⁷ (Fabbri et al., 2019) is a multi-document summarization dataset, with news articles and summaries collected from newser.com.

Baselines We use the following top-performing models as baselines for comparison.

- (1) **LED** (Longformer Encoder-Decoder) (Beltagy et al., 2020) is an encoder-decoder model with a sparse encoder self-attention module.
- (2) **HEPOS** (Huang et al., 2021) combines both efficient encoder self-attention and encoder-decoder attention in its encoder-decoder architecture.
- (3) **PRIMERA** (Xiao et al., 2022) shares the same architecture as **LED**, but has task-specific pre-training for multi-document summarization.
- (4) **HAT-BART** (Rohde et al., 2021) is built upon BART (Lewis et al., 2020) while it has additional

hierarchical layers for sentence-level interactions. It uses *full* attention and not sparse attention.

Implementation Details We use BART⁸ as the backbone of our model, except for the linear layer computing the confidence scores (Eq. 7). We initialize the model from either a checkpoint pre-trained on CNN/DailyMail dataset (Hermann et al., 2015; Nallapati et al., 2016), or its counterpart without the CNN/Dailymail pre-training. We select the model checkpoints based on their performance on the validation set, using cross-entropy loss (Eq. 1). We use ROUGE (Lin, 2004) as the automatic evaluation metric for performance comparison. More specifically, we report the F1 scores of ROUGE-1/2/L in our experiments.

We name our model as **PageSum** for the following experiments.

5.2 Exp-I: Spatial Locality

We first investigate the case of *spatial locality*, where the sentences in the source document are sequentially split into different *pages* with the same number of sentences. The maximum number of tokens for one page is 1,024.

We report the model performance⁹ in Tab. 1 on

⁸It contains around 400M parameters.

⁹For a fair comparison, we used public-available checkpoints of LED from Hugging Face’s Transformers (Wolf et al., 2020) on arXiv (‘allenai/led-large-16384-*arxiv*’) and PubMed (‘patrickvonplaten/led-large-16384-*pubmed*’) to generate the summaries and used our own evaluation script. The performance difference between the original result and the ours is likely because the original implementation uses window-attention with 512 tokens while HF uses 1,024 tokens.

⁵<https://github.com/armancohan/long-summarization>

⁶<https://github.com/luyang-huang96/LongDocSum>

⁷<https://github.com/Alex-Fabbri/Multi-News>

System	R-1	R-2	R-L
PageSum-Spatial (7168)	49.72	21.06	44.69
PageSum-Discourse (8192)	49.84	21.19[†]	44.89[†]

Table 2: System performance comparison for *discourse locality* on arXiv. R-1/2/L are the ROUGE-1/2/L F₁ scores respectively. The numbers in the parentheses indicate the maximum input length. **PageSum-Spatial** is with spatial locality. **PageSum-Discourse** is with discourse locality. †: significantly better ($p < 0.05$).

reference	random	spatial	discourse
0.9800	0.9543	0.9734	0.9798

Table 3: Semantic coherence (Eq. 11) of summaries on arXiv. **reference** is the reference summary. **random** is an oracle which randomly shuffles reference summary sentences. **spatial** is PageSum with spatial locality while **discourse** is with discourse locality. **discourse** has significantly higher ($p < 0.01$) coherence than **spatial**.

the arXiv, PubMed, GovReport datasets. We make the following observations. (1) **PageSum** achieves better ROUGE scores on all three long text summarization datasets compared with the baselines that leverage efficient attention modules. (2) On Pubmed, **HAT-BART** achieves slightly better performance than **PageSum**, likely because HAT-BART uses *full* attention instead of *efficient* attention. (3) On GovReport, increasing the maximum input length helps to improve **PageSum**’s performance.

5.3 Exp-II: Discourse Locality

We use the arXiv dataset to explore another locality principle – *discourse locality*. Specifically, we view each section of the input document as an individual *page*. The maximum number of tokens for one *page* is still 1,024, however, here we allow each example to have a different number of pages because documents can have different numbers of sections. For each page, we concatenate the name of the section and the content together as the input.

The results in Tab. 2 show that PageSum with *discourse locality* achieves higher ROUGE scores than PageSum with *spatial locality*. In addition, we note that with discourse locality, PageSum can also generate more coherent summaries. Specifically, following [Bommasani and Cardie \(2020\)](#), we evaluate the *semantic coherence* of the generated summaries using the next sentence prediction task ([Devlin et al., 2019](#)) with a pre-trained BERT

System	R-1	R-2	R-L
PRIMERA*	49.90	21.10	25.90
PRIMERA [‡]	50.29	21.20	46.23
BART-Long-Graph*	49.24	18.99	23.97
PageSum-Spatial	49.03	19.10	44.73
PageSum-Document	51.17[†]	21.39[†]	46.88[†]

Table 4: System performance comparison for *document locality* on MultiNews. R-1/2/L are the ROUGE-1/2/L F₁ scores respectively. **PageSum-Spatial** is PageSum with spatial locality. **PageSum-Document** is with document locality. *: results reported in the original papers. ‡: results from our own evaluation script. †: significantly better than PRIMERA[‡] ($p < 0.05$).

model¹⁰ to predict the probability (p_{BERT}) of one sentence $S^{(i-1)}$ in the summary S being followed by the next sentence $S^{(i)}$:

$$\text{SC}(S) = \frac{\sum_{i=2}^{N_S} p_{\text{BERT}}(S^{(i)} | S^{(i-1)})}{N_S - 1}, \quad (11)$$

where N_S is the number of sentences in the summary. Tab. 3 shows the average semantic coherence of summaries. The summaries generated by PageSum with discourse locality have higher semantic coherence, suggesting that grouping the sentences based on discourse structures helps to generate more well-structured summaries.

5.4 Exp-III: Document Locality

For multi-document summarization, we evaluate PageSum with *document locality* on MultiNews, where we view each document in the document cluster as a page. The other experiment setting is the same as in §5.3. In addition to the baseline systems in §5.1, we add another model BART-Long-Graph ([Pasunuru et al., 2021](#)) for comparison, which is specifically designed for multi-document summarization and achieves top performance on MultiNews. The results are shown in Tab. 4.¹¹ PageSum achieves strong performance in this setting, outperforming the previous state-of-the-art models. We also note that PageSum with *document locality* achieves much better performance than its counterpart with *spatial locality*, suggesting the importance of choosing the suitable locality for a specific task.

¹⁰We use the checkpoint (“bert-large-uncased”) from HuggingFace Transformers ([Wolf et al., 2020](#)).

¹¹We reported the performance fine-tuned from the BART model pre-trained on CNN/DailyMail dataset while we found the model without this pre-training having similar performance. We notice a large difference between ROUGE-L scores reported by the original paper and as calculated using our evaluation script for PRIMERA. This may be due to different versions of ROUGE-L.

Page Size	#Pages	R-1	R-2	R-L
128	32	47.67	18.76	42.82
256	16	48.29	19.32	43.38
512	8	48.82	19.80	43.85
1024	4	48.66	19.90	43.74

Table 5: Performance comparison of different *page sizes* on arXiv. **Page Size** denotes the number of tokens in one page. **#Pages** denotes the number of pages. R-1/2/L are the ROUGE-1/2/L F_1 scores respectively.

System	R-1	R-2	R-L
arXiv			
Global-Decoding	48.57	19.92	43.71
PageSum-Spatial	48.66	19.90	43.74
MultiNews			
Global-Decoding	48.75	19.03	44.48
PageSum-Document	51.17	21.39	46.88

Table 6: Comparison of page-wise decoding and global decoding on arXiv and MultiNews. R-1/2/L are the ROUGE-1/2/L F_1 scores respectively.

5.5 Analysis

We analyze several important aspects of our method to gain further insights.

Page Size To investigate how the maximum length of a *page* affects the model performance, we conduct experiments with different page sizes on arXiv. For a fair comparison, we first truncate each document in arXiv to 4,096 tokens, then split the document into different pages based on the page size. The results are shown in Tab. 5. We observe that increasing the page size generally helps to improve model performance. However, model performance stops increasing after the page size reaches 512 tokens.

Page-wise v.s. Global Decoding Both the encoder and decoder in PageSum are designed to follow the principle of locality. Specifically, the decoder in PageSum first makes *local* predictions based on each encoded page (Eq. 6), which are later combined into final predictions. An alternative approach is to directly make *global* predictions based on the entire input document – the encoded pages are concatenated as a single sequence, which serves as the input to the decoder. We compare this option with our modeling strategy in Tab. 6.¹² The results show that on arXiv, page-wise decoding with *spatial locality* has a similar performance

¹²On arXiv, we compare the models with this setting: 4 pages, 1,024 tokens for each page.

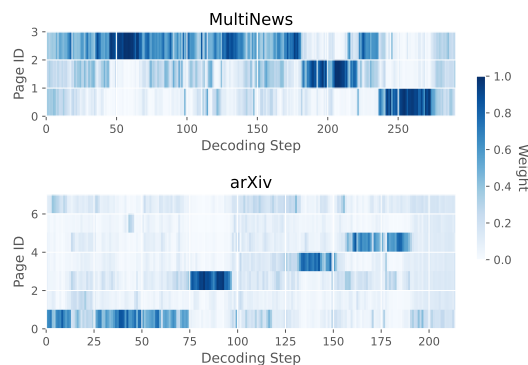


Figure 3: Visualization of importance scores of different pages at each decoding step on MultiNews and arXiv. Darker colors represent greater importance.

compared with global decoding. On the other hand, *document locality* on MultiNews is proven to be a very useful inductive bias because PageSum with document locality has a large improvement over the model with global decoding.

Visualizing Locality The confidence scores calculated by PageSum’s decoder (Eq. 7) can be interpreted as the importance scores of different *pages* at each decoding step. That is, a page associated with a higher score will contribute more to the decision at the current step. Fig. 3 depicts how the importance scores changed during the decoding of the *reference summaries* on MultiNews and arXiv using two examples. We observe two phenomena: (1) *space locality* – at each decoding step only a subset of pages are making large contributions to the current prediction; (2) *time locality* – PageSum’s decoder tends to focus on the similar subset of pages at neighboring decoding steps.

5.6 Human Evaluation for Coherence

Summary coherence is a critical aspect of the summary quality, especially when the summaries are very long. Fabbri et al. (2021) shows that automatic metrics have a low correlation with human evaluation results w.r.t. summary coherence, while Goyal et al. (2022) demonstrates that recent state-of-the-art summarization models can still make many coherence errors on long text summarization datasets. Therefore, we conduct human evaluation for the coherence of system-generated summaries on GovReport¹³ dataset to investigate this important aspect.

¹³We choose GovReport dataset because it has the longest summaries.

Error Type	Example	Explanation
RefE	The Part D program, administered by the Centers for Medicare & Medicaid Services (CMS), pays Part D plan sponsors to provide drug coverage, and plan sponsors may charge beneficiaries monthly premiums in exchange for coverage. Plan sponsors and PBMs negotiate reimbursement rates for the drugs provided to beneficiaries. ... Seventy-four percent of the drug benefits management services provided under 624 Part D plans sponsors' contracts were performed by a pharmacy benefit manager (PBM) alone or in conjunction with a plan sponsor in 2016.	The word, PBM , is an abbreviation for <i>pharmacy benefit manager</i> , which is mentioned without first introducing the full name.
TopicE	... The President may implement the recommendations suggested in the Commerce report, take other actions, or decide to take no action. After making a decision, the President has 15 days to implement the action and 30 days to submit a written statement to Congress explaining the action or inaction; he must also publish his findings in the Federal Register. <i>While there is no specific definition of national security in the statute</i> , it states that the investigation must consider certain factors, such as domestic production needed for projected national defense requirements; domestic capacity; ...	The topic abruptly changes from the President and recommendations to the specific definition of national security.
InconE	... To do this work, GAO selected <i>seven</i> states Arizona, Florida, Kansas, New Jersey, Pennsylvania, Tennessee, New York, Virginia, and Pennsylvania based on factors such as population size, Medicaid enrollment, and geographic location and interviewed CMS officials. ...	There are nine states mentioned instead of <i>seven</i> .
RepE	... The high productivity helped the operation come in under budget by \$118 million a 36 percent reduction while the operation's cost was \$185 million, 36 percent below the anticipated cost. ...	The 36 percent reduction are mentioned twice in one sentence.

Table 7: Examples of different coherence errors on GovReport dataset. **RefE**: Missing Information/Reference about an Event/Object. **TopicE**: Abrupt Transition from the Previous Topic. **InconE**: Inconsistent, Conflicting Information. **RepE**: Repetition.

Following Goyal et al. (2022), we use a fine-grained human evaluation protocol which requires the annotators to identify different types of *span-level* coherence errors in the summaries. We adopted the taxonomy of coherence errors proposed by Goyal et al. (2022) and modified it for GovReport, which results in four types of coherence errors (the definitions are taken and modified from the definitions in Goyal et al. (2022)):

(1) Missing Information/Reference about an Event/Object (**RefE**). These refer to coherence errors where an event or object is mentioned the first time without the proper context or introduction. On GovReport, a common error is referring an entity using its abbreviation without introducing the entity and its whole name before.

(2) Abrupt Transition from the Previous Topic (**TopicE**). These refer to coherence errors where there is a sudden topic shift in the summary.

(3) Inconsistent, Conflicting Information (**InconE**). These refer to text spans that contradict previous content.

(4) Repetition (**RepE**). These refer to text spans where content is repeated.

We show examples of these types of errors in Tab. 7. We randomly sampled 30 examples from the test set of GovReport, and counted the number of text spans containing the coherence errors in the summaries generated by PageSum and LED. All examples are annotated by three of the authors.¹⁴ We anonymized the examples for a fair comparison. The results are shown in Tab. 8.

¹⁴The Krippendorff's alpha (Krippendorff, 2011) is 0.5719.

System	RefE	TopicE	InconE	RepE	Total
LED	41.7	19	8.3	9.7	78.7
PageSum	32.3	14	10	8.3	64.7

Table 8: Human Evaluation for Coherence on GovReport. We report the number of different coherence errors made by PageSum and LED on 30 examples (averaged across three annotators). **RefE**: Missing Information/Reference about an Event/Object. **TopicE**: Abrupt Transition from the Previous Topic. **InconE**: Inconsistent, Conflicting Information. **RepE**: Repetition.

Aligned with the findings in Goyal et al. (2022), we found that both LED and PageSum make a non-trivial amount of errors. However, PageSum is able to make fewer errors for each of the error types except for the InconE error type.

5.7 Case Study: Long-Distance Dependencies

A global context can be much more important in the presence of long-distance dependencies for text summarization models (Fernandes et al., 2019; Xu et al., 2020a). To study this phenomenon, we leverage the notion of *sentence fusion* (Barzilay and McKeown, 2005) to investigate sentence-level dependencies. Specifically, following Lebanoff et al. (2019a,b), we define a **fusion sentence** in the *reference summary* to be a sentence that has significant overlaps with two or more sentences¹⁵ in the *source document*. Then, we define two sentences \hat{s}_1, \hat{s}_2 in the source document D to be **interdependent** if they have the most significant contribution to a

¹⁵We focus on the case of two sentences.

Fusion Sentence	ED issued a notice of <i>proposed rulemaking</i> in late 2018, after revoking some of its previous guidance to schools in 2017.
14th Source Sentence	And ED recently issued another notice of <i>proposed rulemaking</i> , after having revoked some of its prior guidance to schools in 2017.
410th Source Sentence	On November 29, 2018, ED issued a notice of <i>proposed rulemaking</i> in the Federal Register.
PageSum Output	ED recently issued another notice of proposed rulemaking, after having revoked some of its prior guidance to schools in 2017.

Table 9: Case Study on GovReport about long-distance dependencies. Both 14th and 410th sentences contribute to the same reference sentence. PageSum’s output fails to capture this long-distance dependency.

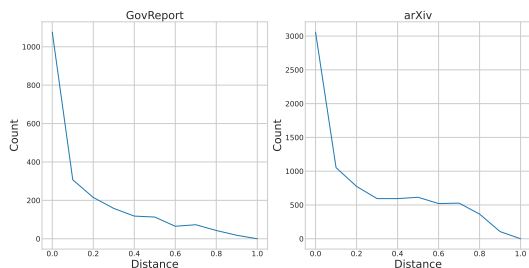


Figure 4: Number of interdependent sentences with different distances on GovReport and arXiv datasets. X-axis represents the ratio of sentence distances normalized by the number of sentences in the entire document.

fusion sentence h :

$$(\hat{s}_1, \hat{s}_2) := \arg \max_{(s_i, s_j), s_i, s_j \in D} \text{ROUGE}_{\text{Recall}}(h, s_i \oplus s_j). \quad (12)$$

More details can be found in Appendix B.

We found that PageSum can fail to capture the dependencies where two interdependent sentences are far away from each other. We show such an example in Tab. 9, where the 14th sentence and 410th sentence in the source document both contribute to the same fusion sentence. PageSum’s output only captures the information in the 14th sentence. However, the impact of the potential failures is restricted. As shown in Fig. 4, there are much fewer interdependent sentence pairs with long distances.

6 Conclusions

We empirically investigate three kinds of locality in abstractive text summarization by using them as important inductive biases. Using a new abstraction of viewing the input document as a series of *pages*, our model emphasizes the role of locality in both encoding and decoding stages. The experimental results show that our model has strong performance by following the principle of locality. We also show that it is important to select the suitable kind of locality for different application

scenarios. We note that the fact that our model has better or competitive performance comparing with the models equipped with efficient attention modules suggests that those models may fall short of their designing objectives. Therefore, for future work, our findings call for more rigorous examinations of the memory-efficient abstractive summarization models that aim to capture global features (e.g. long-distance dependencies) and maintain a global input context.

7 Limitations

Computation Resources While our approach can reduce the memory footprint of full-attention models, it still requires GPUs with large memory sizes (e.g. 48 GBs) and long time (more than 7 days with a single GPU) to train our model. We note that our model has a similar memory footprint as the efficient-attention models such as Longformer (Beltagy et al., 2020). Therefore, the requirement of computation resources is a common challenge in long text summarization.

Long-Distance Dependencies The inductive bias of our approach is to emphasize the role of *locality* in abstractive text summarization. As a result, our approach can fail to capture long-distance dependencies. We have discussed this potential problem in §5.7. While we have shown that the ratio of sentence-level long-distance dependencies are relatively low in the datasets we investigated for this work, it is worthwhile to be aware of this limitation when extending our method to other datasets.

Human Evaluation While we have presented a fine-grained human evaluation on summary coherence in §5.6, there are other important aspects of summary quality such as factual consistency (Maynez et al., 2020). However, it is even a more non-trivial task to evaluate an input-document-based aspect such as factual consistency on the datasets we used as it requires reading the entire input documents which can be more than 10K words long and having domain-specific knowledge to understand the context of scientific papers or government reports. We believe the research of long text summarization will benefit greatly from better human and automatic evaluation.

Acknowledgements

We thank the anonymous reviewers for helpful suggestions. This work is supported in part by a grant from Microsoft Research.

References

- Regina Barzilay and Kathleen R. McKeown. 2005. [Sentence fusion for multidocument news summarization](#). *Computational Linguistics*, 31(3):297–328.
- Iz Beltagy, Matthew E. Peters, and Arman Cohan. 2020. [Longformer: The long-document transformer](#). *CoRR*, abs/2004.05150.
- Rishi Bommasani and Claire Cardie. 2020. [Intrinsic evaluation of summarization datasets](#). In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 8075–8096, Online. Association for Computational Linguistics.
- Shuyang Cao and Lu Wang. 2022. [HIBRIDS: Attention with hierarchical biases for structure-aware long document summarization](#). In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 786–807, Dublin, Ireland. Association for Computational Linguistics.
- Yen-Chun Chen and Mohit Bansal. 2018. [Fast abstractive summarization with reinforce-selected sentence rewriting](#). In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 675–686, Melbourne, Australia. Association for Computational Linguistics.
- Krzysztof Marcin Choromanski, Valerii Likhoshesterov, David Dohan, Xingyou Song, Andreea Gane, Tamas Sarlos, Peter Hawkins, Jared Quincy Davis, Afroz Mohiuddin, Lukasz Kaiser, David Benjamin Belanger, Lucy J Colwell, and Adrian Weller. 2021. [Rethinking attention with performers](#). In *International Conference on Learning Representations*.
- Arman Cohan, Franck Dernoncourt, Doo Soon Kim, Trung Bui, Seokhwan Kim, Walter Chang, and Nazli Goharian. 2018. [A discourse-aware attention model for abstractive summarization of long documents](#). In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers)*, pages 615–621, New Orleans, Louisiana. Association for Computational Linguistics.
- Peter J. Denning. 2005. [The locality principle](#). *Commun. ACM*, 48(7):19–24.
- P.J. Denning. 1980. [Working sets past and present](#). *IEEE Transactions on Software Engineering*, SE-6(1):64–84.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. [BERT: Pre-training of deep bidirectional transformers for language understanding](#). In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.
- Yue Dong, Andrei Mircea, and Jackie Chi Kit Cheung. 2021. [Discourse-aware unsupervised summarization for long scientific documents](#). In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 1089–1102, Online. Association for Computational Linguistics.
- Ori Ernst, Avi Caciularu, Ori Shapira, Ramakanth Pasunuru, Mohit Bansal, Jacob Goldberger, and Ido Dagan. 2021. [A proposition-level clustering approach for multi-document summarization](#). *ArXiv*, abs/2112.08770.
- Alexander Fabbri, Irene Li, Tianwei She, Suyi Li, and Dragomir Radev. 2019. [Multi-news: A large-scale multi-document summarization dataset and abstractive hierarchical model](#). In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1074–1084, Florence, Italy. Association for Computational Linguistics.
- Alexander R. Fabbri, Wojciech Kryściński, Bryan McCann, Caiming Xiong, Richard Socher, and Dragomir Radev. 2021. [SummEval: Re-evaluating Summarization Evaluation](#). *Transactions of the Association for Computational Linguistics*, 9:391–409.
- Patrick Fernandes, Miltiadis Allamanis, and Marc Brockschmidt. 2019. [Structured neural summarization](#). In *International Conference on Learning Representations*.
- R. Fonseca, V. Almeida, M. Crovella, and B. Abraham. 2003. [On the intrinsic locality properties of web reference streams](#). In *IEEE INFOCOM 2003. Twenty-second Annual Joint Conference of the IEEE Computer and Communications Societies (IEEE Cat. No.03CH37428)*, volume 1, pages 448–458 vol.1.
- Tianyu Gao, Xingcheng Yao, and Danqi Chen. 2021. [SimCSE: Simple contrastive learning of sentence embeddings](#). In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 6894–6910, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Tanya Goyal, Junyi Jessy Li, and Greg Durrett. 2022. [Snac: Coherence error detection for narrative summarization](#). *ArXiv*, abs/2205.09641.
- Mandy Guo, Joshua Ainslie, David C. Uthus, Santiago Ontañón, Jianmo Ni, Yun-Hsuan Sung, and Yinfei Yang. 2021. [LongT5: Efficient text-to-text transformer for long sequences](#). *ArXiv*, abs/2112.07916.
- Karl Moritz Hermann, Tomáš Kočiský, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. 2015. [Teaching machines to read and comprehend](#). In *Proceedings of the 28th International Conference on Neural Information Processing Systems - Volume 1, NIPS’15*, page 1693–1701, Cambridge, MA, USA. MIT Press.

- Luyang Huang, Shuyang Cao, Nikolaus Parulian, Heng Ji, and Lu Wang. 2021. [Efficient attentions for long document summarization](#). In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1419–1436, Online. Association for Computational Linguistics.
- Hanqi Jin and Xiaojun Wan. 2020. [Abstractive multi-document summarization via joint learning with single-document summarization](#). In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 2545–2554, Online. Association for Computational Linguistics.
- Hanqi Jin, Tianming Wang, and Xiaojun Wan. 2020. [Multi-granularity interaction network for extractive and abstractive multi-document summarization](#). In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 6244–6254, Online. Association for Computational Linguistics.
- Diederik P. Kingma and Jimmy Ba. 2015. [Adam: A method for stochastic optimization](#). In *3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings*.
- Nikita Kitaev, Lukasz Kaiser, and Anselm Levskaya. 2020. [Reformer: The efficient transformer](#). In *International Conference on Learning Representations*.
- Hilda Koopman, Dominique Sportiche, and Edward Stabler. 2013. *An introduction to syntactic analysis and theory*. John Wiley & Sons.
- Klaus Krippendorff. 2011. Computing krippendorff’s alpha-reliability.
- Logan Lebanoff, John Muchovej, Franck Dernoncourt, Doo Soon Kim, Seokhwan Kim, Walter Chang, and Fei Liu. 2019a. [Analyzing sentence fusion in abstractive summarization](#). In *Proceedings of the 2nd Workshop on New Frontiers in Summarization*, pages 104–110, Hong Kong, China. Association for Computational Linguistics.
- Logan Lebanoff, Kaiqiang Song, Franck Dernoncourt, Doo Soon Kim, Seokhwan Kim, Walter Chang, and Fei Liu. 2019b. [Scoring sentence singletons and pairs for abstractive summarization](#). In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 2175–2189, Florence, Italy. Association for Computational Linguistics.
- Mike Lewis, Yinhan 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, Online. Association for Computational Linguistics.
- Chin-Yew Lin. 2004. [ROUGE: A package for automatic evaluation of summaries](#). In *Text Summarization Branches Out*, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.
- Jeffrey Ling and Alexander Rush. 2017. [Coarse-to-fine attention models for document summarization](#). In *Proceedings of the Workshop on New Frontiers in Summarization*, pages 33–42, Copenhagen, Denmark. Association for Computational Linguistics.
- Peter J. Liu*, Mohammad Saleh*, Etienne Pot, Ben Goodrich, Ryan Sepassi, Lukasz Kaiser, and Noam Shazeer. 2018. [Generating wikipedia by summarizing long sequences](#). In *International Conference on Learning Representations*.
- Yang Liu and Mirella Lapata. 2019. [Hierarchical transformers for multi-document summarization](#). In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 5070–5081, Florence, Italy. Association for Computational Linguistics.
- Potsawee Manakul and Mark Gales. 2021. [Long-span summarization via local attention and content selection](#). In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 6026–6041, Online. Association for Computational Linguistics.
- Ziming Mao, Chen Henry Wu, Ansong Ni, Yusen Zhang, Rui Zhang, Tao Yu, Budhaditya Deb, Chenguang Zhu, Ahmed Awadallah, and Dragomir Radev. 2022. [DYLE: Dynamic latent extraction for abstractive long-input summarization](#). In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1687–1698, Dublin, Ireland. Association for Computational Linguistics.
- Joshua Maynez, Shashi Narayan, Bernd Bohnet, and Ryan McDonald. 2020. [On faithfulness and factuality in abstractive summarization](#). In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 1906–1919, Online. Association for Computational Linguistics.
- Ramesh Nallapati, Bowen Zhou, Cicero dos Santos, Çağlar Gulçehre, and Bing Xiang. 2016. [Abstractive text summarization using sequence-to-sequence RNNs and beyond](#). In *Proceedings of The 20th SIGNLL Conference on Computational Natural Language Learning*, pages 280–290, Berlin, Germany. Association for Computational Linguistics.
- Ramakanth Pasunuru, Mengwen Liu, Mohit Bansal, Sujith Ravi, and Markus Dreyer. 2021. [Efficiently summarizing text and graph encodings of multi-document clusters](#). In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 4768–4779, Online. Association for Computational Linguistics.

- Hao Peng, Nikolaos Pappas, Dani Yogatama, Roy Schwartz, Noah Smith, and Lingpeng Kong. 2021. [Random feature attention](#). In *International Conference on Learning Representations*.
- Michal Pietruszka, Łukasz Borchmann, and Lukasz Garncarek. 2020. Sparsifying transformer models with trainable representation pooling.
- Jonathan Pilault, Raymond Li, Sandeep Subramanian, and Chris Pal. 2020. [On extractive and abstractive neural document summarization with transformer language models](#). In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 9308–9319, Online. Association for Computational Linguistics.
- Jiezhong Qiu, Hao Ma, Omer Levy, Wen-tau Yih, Sinong Wang, and Jie Tang. 2020. [Blockwise self-attention for long document understanding](#). In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 2555–2565, Online. Association for Computational Linguistics.
- Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners.
- Tobias Rohde, Xiaoxia Wu, and Yinhan Liu. 2021. [Hierarchical learning for generation with long source sequences](#). *CoRR*, abs/2104.07545.
- Qian Ruan, Malte Ostendorff, and Georg Rehm. 2022. [HiStruct+: Improving extractive text summarization with hierarchical structure information](#). In *Findings of the Association for Computational Linguistics: ACL 2022*, pages 1292–1308, Dublin, Ireland. Association for Computational Linguistics.
- Alexander M. Rush, Sumit Chopra, and Jason Weston. 2015. [A neural attention model for abstractive sentence summarization](#). In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 379–389, Lisbon, Portugal. Association for Computational Linguistics.
- Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. [Neural machine translation of rare words with subword units](#). In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1715–1725, Berlin, Germany. Association for Computational Linguistics.
- Ilya Sutskever, Oriol Vinyals, and Quoc V. Le. 2014. Sequence to sequence learning with neural networks. In *NIPS*.
- C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna. 2016. [Rethinking the inception architecture for computer vision](#). In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2818–2826, Los Alamitos, CA, USA. IEEE Computer Society.
- Yi Tay, Dara Bahri, Liu Yang, Donald Metzler, and Da-Cheng Juan. 2020. [Sparse Sinkhorn attention](#). In *Proceedings of the 37th International Conference on Machine Learning*, volume 119 of *Proceedings of Machine Learning Research*, pages 9438–9447. PMLR.
- 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 *Advances in Neural Information Processing Systems*, volume 30. Curran Associates, Inc.
- Sinong Wang, Belinda Z. Li, Madian Khabsa, Han Fang, and Hao Ma. 2020. Linformer: Self-attention with linear complexity. *ArXiv*, abs/2006.04768.
- Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, 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.
- Wen Xiao, Iz Beltagy, Giuseppe Carenini, and Arman Cohan. 2022. [PRIMERA: Pyramid-based masked sentence pre-training for multi-document summarization](#). In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 5245–5263, Dublin, Ireland. Association for Computational Linguistics.
- Wen Xiao and Giuseppe Carenini. 2019. [Extractive summarization of long documents by combining global and local context](#). 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 3011–3021, Hong Kong, China. Association for Computational Linguistics.
- Jiacheng Xu and Greg Durrett. 2019. [Neural extractive text summarization with syntactic compression](#). 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 3292–3303, Hong Kong, China. Association for Computational Linguistics.
- Jiacheng Xu, Zhe Gan, Yu Cheng, and Jingjing Liu. 2020a. [Discourse-aware neural extractive text summarization](#). In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5021–5031, Online. Association for Computational Linguistics.
- Shusheng Xu, Xingxing Zhang, Yi Wu, Furu Wei, and Ming Zhou. 2020b. [Unsupervised extractive summarization by pre-training hierarchical transformers](#). In

Findings of the Association for Computational Linguistics: EMNLP 2020, pages 1784–1795, Online. Association for Computational Linguistics.

Zichao Yang, Diyi Yang, Chris Dyer, Xiaodong He, Alex Smola, and Eduard Hovy. 2016. [Hierarchical attention networks for document classification](#). In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1480–1489, San Diego, California. Association for Computational Linguistics.

Manzil Zaheer, Guru Guruganesh, Kumar Avinava Dubey, Joshua Ainslie, Chris Alberti, Santiago Ontanon, Philip Pham, Anirudh Ravula, Qifan Wang, Li Yang, and Amr Ahmed. 2020. [Big bird: Transformers for longer sequences](#). In *Advances in Neural Information Processing Systems*, volume 33, pages 17283–17297. Curran Associates, Inc.

Erfan Zamanian, Carsten Binnig, and Abdallah Salama. 2015. [Locality-aware partitioning in parallel database systems](#). In *Proceedings of the 2015 ACM SIGMOD International Conference on Management of Data*, SIGMOD ’15, page 17–30, New York, NY, USA. Association for Computing Machinery.

Jianmin Zhang, Jiwei Tan, and Xiaojun Wan. 2018. [Adapting neural single-document summarization model for abstractive multi-document summarization: A pilot study](#). In *Proceedings of the 11th International Conference on Natural Language Generation*, pages 381–390, Tilburg University, The Netherlands. Association for Computational Linguistics.

Jingqing Zhang, Yao Zhao, Mohammad Saleh, and Peter Liu. 2020. [Pegasus: Pre-training with extracted gap-sentences for abstractive summarization](#). In *International Conference on Machine Learning*, pages 11328–11339. PMLR.

Yusen Zhang, Ansong Ni, Ziming Mao, Chen Henry Wu, Chenguang Zhu, Budhaditya Deb, Ahmed Awadallah, Dragomir Radev, and Rui Zhang. 2022. [Summⁿ: A multi-stage summarization framework for long input dialogues and documents](#). In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1592–1604, Dublin, Ireland. Association for Computational Linguistics.

Yao Zhao, Mohammad Saleh, and Peter J. Liu. 2020. [Seal: Segment-wise extractive-abstractive long-form text summarization](#). *ArXiv*, abs/2006.10213.

A Experimental Settings

A.1 Datasets Statistics

We report the dataset statistics in Tab. 10.

Datasets	# Examples			Avg. Tokens	
	Train	Valid	Test	Doc.	Sum.
arXiv	203K	6.4K	6.4K	8154.3	197.8
PubMed	120K	6.7K	6.6K	3983.6	261.3
GovReport	17.5K	973	974	10726.1	681.6
MultiNews	45.0K	5.6K	5.6K	2526.4	277.2

Table 10: Dataset Statistics. We report the average number of tokens generated by the BPE tokenizer (Sennrich et al., 2016) used by BART (Lewis et al., 2020) on the *validation* set. For MultiNews dataset, we report the *sum* of lengths of the individual source document in a document cluster as it is a multi-document dataset.

A.2 Implementation Details

We use the Adam optimizer (Kingma and Ba, 2015) with learning rate scheduling as follows:

$$lr = 2 \times 10^{-3} \min(\text{step}^{-0.5}, \text{step} \cdot \text{warmup}^{-1.5}). \quad (13)$$

warmup is the number of warmup steps, which is set to 10000. step is the number of update steps taken so far. Our models are trained on one NVIDIA A6000 GPU, and it takes around 5-25 hours (depending on the size of the dataset) for one training epoch. All models converged in 10 epochs. For ROUGE score computation, we use the summary-level ROUGE-L score which is the default choice of the standard ROUGE Perl script.

B Long-Distance Dependencies

We define two sentences \hat{s}_1, \hat{s}_2 in the source document D to be **interdependent** if they have the most significant contribution to a fusion sentence h in the reference summary:

$$(\hat{s}_1, \hat{s}_2) := \arg \max_{(s_i, s_j), s_i, s_j \in D} \text{ROUGE}_{\text{Recall}}(h, s_i \oplus s_j). \quad (14)$$

where we use ROUGE Recall to measure the sentence contribution by viewing h as the reference. We define two filtering rules:

$$\text{ROUGE}(h, s) > t_1, \quad (15)$$

$$\text{ROUGE}(h, \hat{s}_1 \oplus \hat{s}_2) - \text{ROUGE}(h, s) > t_2, \quad (16)$$

where $s \in \{\hat{s}_1, \hat{s}_2\}$. t_1 and t_2 are two threshold values which are set to 20 and 10 respectively based on our empirical observations. Eq. 15 ensures that each sentence has a non-trivial overlap with the fusion sentence, while Eq. 16 ensures that each sentence has a unique contribution.