

On Context Utilization in Summarization with Large Language Models

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Abstract

Large language models (LLMs) excel in zero-shot abstractive summarization tasks, delivering fluent and pertinent summaries. Recent advancements have extended their capabilities to handle long-input contexts, surpassing token limits of 100k. However, in the realm of multi-document question answering, language models exhibit uneven utilization of their input context. They tend to favor the initial and final segments, resulting in a U-shaped performance pattern concerning where the answer is located within the input. This bias raises concerns, particularly in summarization tasks where crucial content may be dispersed throughout the source document(s). This paper presents a comprehensive investigation encompassing 10 datasets, 5 LLMs, and 5 evaluation metrics to analyze how these models leverage their input for abstractive summarization. Our findings reveal a pronounced bias towards the introductory content (and to a lesser extent, the final content), posing challenges for LLM performance across a range of diverse summarization benchmarks.

1 Introduction

Large language models (LLMs) have drastically transformed the landscape of NLP recently. GPT-3 (Brown et al., 2020) first showed that pre-training Transformer-based (Vaswani et al., 2017) models of a sufficient scale (e.g., tens of billions of parameters) on enough data could lead to models capable of performing multiple tasks in zero-shot. Without the need of fine-tuning a pre-trained language model to adjust to a downstream task (such as abstractive news summarization), practitioners may just prompt the model to generate the desired output, keeping model weights fixed. With instruction tuning (InstructGPT or GPT-3.5) (Ouyang et al., 2022), LLMs made a major leap forward in generating content better aligning to the users’ intent as expressed in the prompt.

*Work done when the author was on leave from NTU.

In abstractive summarization specifically, LLMs opened a new paradigm (Goyal et al., 2022). Summaries generated by LLMs are highly grammatical, fluent and relevant. Despite noticeably lower scores on automatic metrics such as ROUGE (Lin, 2004) or BERTScore (Zhang et al., 2019), summaries generated by GPT-3 are largely preferred by humans over summaries from state-of-the-art fine-tuned models like BRIO (Liu et al., 2022b). In fact, on XSum, GPT-3.5 summaries are even on par with re-annotated human-written summaries, and much better than the dataset ground-truth, according to human evaluators (Zhang et al., 2023b). Popular summarization datasets CNN/DM (Hermann et al., 2015) and XSum (Narayan et al., 2018) were constructed by automatically scrapping online news sources and suffer from low-quality references, with frequent hallucinations (Maynez et al., 2020). For this reason, recent works go as far as to discard references and use the highest-performing LLMs (OpenAI, 2023) as references to train smaller LLMs (Liu et al., 2023b). LLMs also show promising capability to evaluate summaries generated by other systems, including other LLMs (Fu et al., 2023; Luo et al., 2023; Shen et al., 2023a).

Despite this success, a few major technological bottlenecks remain with LLMs, including the maximum length of their context window. The standard context window length for open-source LLMs is 2k tokens (Brown et al., 2020; Scao et al., 2022; Penedo et al., 2023; Touvron et al., 2023a), which drastically limits their usefulness for long-input summarization (Shaham et al., 2022). Several techniques were proposed to extend the context window of Transformer-based models, including ALiBi (Press et al., 2021), LeX (Sun et al., 2022), position interpolation (Chen et al., 2023) and YaRN (Peng et al., 2023). While some of them claim up to 128k tokens (Peng et al., 2023) processing capacity, it remains unclear how much such methods help

RQ1: Where do LLMs take their information from when they summarize?

- LLMs mostly take information from the beginning of the source.
- Existing summarization datasets are lead-biased, but LLMs are significantly more lead-biased than the reference.

RQ2: Where do LLMs look at within their context window?

- LLMs are more likely to re-phrase information from the beginning or (to a lesser extent) the end of their context window.

RQ3: Does LLMs summarization performance depend on the position of the information?

- LLMs summarization performance is sensitive to the position of salient information in the context window.
- Reference-based evaluation show a negative correlation between the position of salient information and performance.

Analysis:

- Control experiments show a strong U-shape (Liu et al., 2023a) in summarization: LLMs are good at processing information at the beginning or the end of their input, while the middle is largely ignored.
 - Inferring on more than 4k tokens shows no significant improvement in performance on long-input summarization tasks, questioning the interest of extending the context window.
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Table 1: Summary of our findings when applying LLMs in zero-shot to abstractive summarization tasks.

LLMs on long-context summarization.

Scaling up context length would only succeed if a key question gets addressed first: ***do LLMs make proper use of their entire context?*** Recent work (Liu et al., 2023a) suggested that, surprisingly, such a simple assumption may not hold: through experiments on multi-document question answering and key-value retrieval, the authors find that LLMs focus on the *beginning* and the *end* of the (long) context window. Plotting performance with regards to the position of the important information exhibits a *U-shape*, with performance high at first (beginning of the source), then dropping, and rising again at the end. Worryingly, in the middle of the context window, LLMs performance can drop to even *below random chance*, calling for greater examination of LLMs behaviour with regards to the position of information within the source.

In this work, we propose to investigate in depth how position affect LLMs performance in abstractive summarization. We answer this question by examining LLMs-generated summaries, and what factors related to position affect their performance. We conduct a large-scale study with 5 open-source LLMs (of 7B, 13B or 20B parameters), 10 datasets covering many aspects of summarization (single and multi-document, standard and long input), and 5 highly diverse automatic metrics. Our research questions and findings are listed in Table 1. We exhibit a major weakness of LLMs as they largely ignore the content which is not in the beginning, or, to a lesser extend, the end of the input. We show that the U-shape exhibited by (Liu et al., 2023a) holds in abstractive summarization.

2 Experimental Setup

We cover a broad set of diverse abstractive summarization tasks, varying length and domain. We include 5 summarization datasets of standard length (source is below 2k tokens, which always fits in the LLM context window): **CNN/DailyMail** (Hermann et al., 2015), **XSum** (Narayan et al., 2018), **Reddit-TIFU** (Kim et al., 2019), **SAMSum** (Gliwa et al., 2019) and **Multi-XScience** (Lu et al., 2020). We also include another 5 long-input summarization datasets: **Arxiv** and **PubMed** (Cohan et al., 2018), **GovReport** (Huang et al., 2021), **SummScreen** (Forever Dreaming) (Chen et al., 2022), and **Multi-News** (Afli et al., 2017). A high-level view of each dataset is shown in Table 2, and detailed statistics are presented in Appendix A. For all datasets, we run experiments on the test set, subsampling 1,000 data points if its size is greater than 1,000, or using the entire test set otherwise.

We experiment with several popular high-performing *open-source* instruction-tuned LLMs. Instruction-tuning datasets such as Flan (Wei et al., 2021) include some of the datasets we study: CNN/DM, XSum, SAMSum and Multi-News. We download the following models though HuggingFace *transformers* (Wolf et al., 2020):

- **Flan-UL2** is a 20B parameters encoder-decoder model pre-trained on 1T tokens. It is based on the UL2 20B model (Tay et al., 2022), with the addition of Flan-T5 (Chung et al., 2022) instruction fine-tuning. The context window is 2k.
- **Llama-2** (Touvron et al., 2023b) is a recently introduced powerful decoder-only model pre-trained on 2T tokens, ranging from 7B to 70B parameters, and with 4k context window. We use

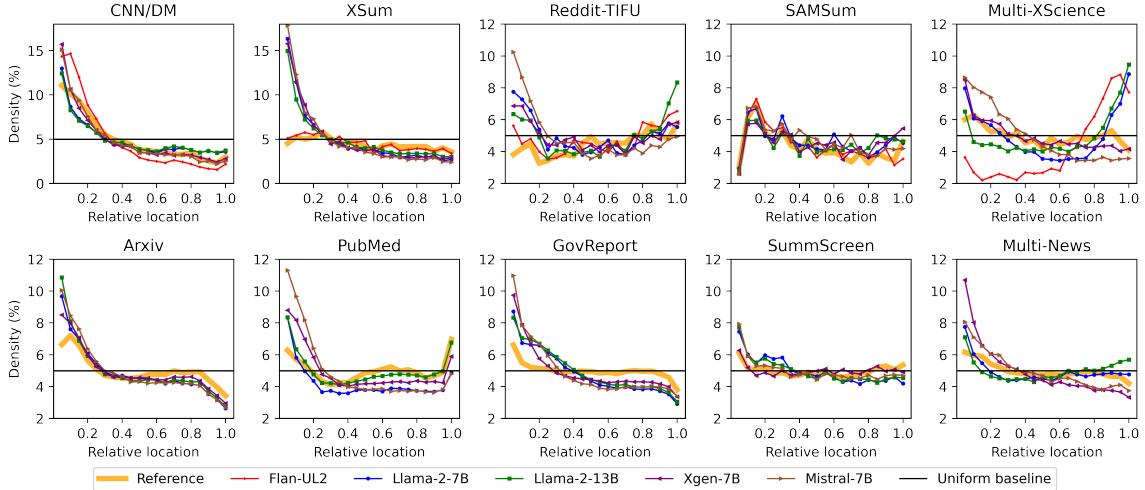


Figure 1: Distribution of the relative location of summary bigrams within the source. We split each source document into 20 bins of the same number of words.

Dataset	Input length		# Documents		In Flan? Yes No
	Standard	Long	Single	Multi	
CNN/DM (Hermann et al., 2015)	✓		✓		✓
XSum (Narayan et al., 2018)	✓		✓		✓
Reddit-TIFU (Kim et al., 2019)	✓		✓		✓
SAMSum (Gliwa et al., 2019)	✓		✓		✓
Multi-XScience (Lu et al., 2020)	✓			✓	✓
Arxiv (Cohan et al., 2018)		✓	✓		✓
PubMed (Cohan et al., 2018)		✓	✓		✓
GovReport (Huang et al., 2021)		✓	✓		✓
SummScreen (Chen et al., 2022)		✓	✓		✓
Multi-News (Aflai et al., 2017)		✓		✓	✓

Table 2: Summarization datasets under study.

the 7B and 13B models.

- **Xgen-7B** (Nijkamp et al., 2023) is a 7B decoder-only model pre-trained on 1.5T tokens with a long, 8k tokens context window.
- **Mistral-7B** (Jiang et al., 2023) is also an 8k-context 7B decoder-only model, with performance slightly better than Llama-2-13B.

We use the instruction-tuned or *chatbot* checkpoints for Llama-2, Xgen-7B and Mistral-7B. To run inference, we use the following prompt: Read the following text and summarize it: [text]. Summarize the above text in [n] sentences. Summary: where n is set to an average number of sentences per dataset (see Appendix A). We sample summaries with top-k sampling (Fan et al., 2018) using $k = 50$.

Summarization evaluation is especially challenging in the LLM era, as most automatic metrics poorly correlate with human preference (Goyal et al., 2022). To get a broad picture of performance, we evaluate with metrics as diverse as

possible. First, we consider **reference-based** metrics: **ROUGE-2** (Lin, 2004), which measures bigrams overlap, **BERTScore** (Zhang et al., 2019), which measures semantic similarity with BERT (Devlin et al., 2018) embeddings, and **A3CU** (Liu et al., 2023c), which extracts facts in the form of Atomic Content Units (ACUs) (Liu et al., 2022a), and checks the presence of ACUs between prediction and reference. As **reference-free** metrics, we include **SummaC** (Laban et al., 2022), a leading factual consistency evaluation metric relying on entailment scores between pairs of source and summary sentences. We also leverage **GPT-3.5**¹ as a summarization evaluator, which is proven to be a strong natural language generation evaluator (Wang et al., 2023b; Shen et al., 2023a; Jain et al., 2023). We prompt the model with the source and generated summary, and ask to output a score on a likert scale from 1 (low-quality) to 5 (high-quality). We refer to Appendix B for the full prompt template. For GPT-3.5 evaluation, we subsample 300 data points per dataset in order to reduce costs. We report the performance achieved by LLMs on all 10 datasets, alongside a comparison to SOTA models, in Appendix C. FLan-UL2 dominates on standard-length datasets, but Llama-2-13B has the upper hand on the long-input ones. Performance itself is not our focus in this paper, but rather which position-related factors influence it. Flan-UL2 performance on long-input datasets being very low due to its short 2k context window, we discard it on such datasets.

¹We use the gpt-3.5-turbo-instruct checkpoint.

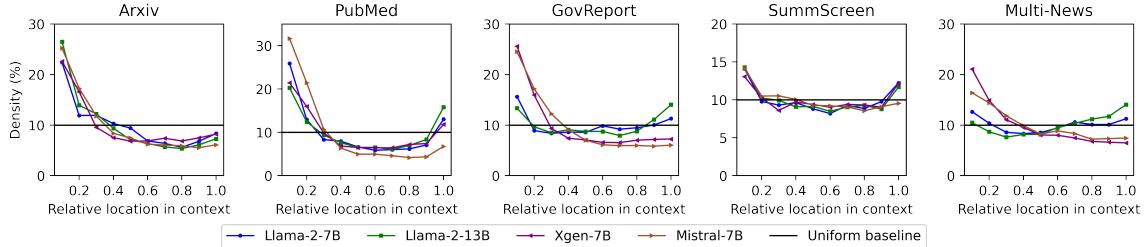


Figure 2: Distribution of relative location of input context sentences aligned with sentences from summaries. We split each input context into 10 bins with the same number of *sentences* (x-axis), and plot the fraction of aligned sentences coming from each bin (y-axis).

3 Experiments

In this section, we describe our experiments aimed at understanding how do LLMs treat information in their input depending on the position.

3.1 RQ1: Where do LLMs take their information from?

We investigate summaries generated by LLMs, and map them to specific parts of the input. Unlike in question-answering or extractive summarization, mapping salient information from a summary to the source is not trivial in abstractive summarization.

We follow the approach used in (Kim et al., 2019; Zhao et al., 2022a) and compute the relative position of bigrams from generated summaries within the source documents, as a proxy for position of salient information. We only use unique bigrams from summaries, and for each bigram, find all its occurrences within the source, if there are any. We then split each source into 20 bins of the same number of words, and compute the fraction of matched bigrams found in each bin. On top of the LLMs described above, we include position of bigrams from reference summaries, and a uniform baseline.

As seen in Figure 1, all summarization datasets except XSum and Reddit-TIFU have some lead bias: salient bigrams from the reference (orange curves) are more likely to be found at the beginning of the source. However, LLMs show a significantly stronger lead bias on all datasets: bigrams from LLMs summaries are much more likely to be found in the first 20% words of the source. It is especially striking on XSum (except for Flan-UL2), Reddit-TIFU, Arxiv, PubMed and GovReport. On XSum, Flan-UL2 closely matches the reference distribution, which we attribute to its better instruction tuning. We conclude that ***LLMs focus on content in the beginning of source documents.***

3.2 RQ2: Where do LLMs look at within their context window?

In the previous experiment’s design, LLMs may not see the entire source in long-input summarization datasets, due to their limited context window. We now focus on input information accessible to LLMs, and only consider salient information if it falls within the context window. Besides, since the same bigram may occur multiple times throughout the source, we adjust the methodology for saliency estimation. Specifically, we align sentences in generated summaries to sentences in the source, following the procedure described in (Zhou et al., 2018) and used in (Adams et al., 2023). We employ a greedy approach selecting source sentences until the ROUGE-1 F1 score between the set of selected source sentences and the summary stops increasing. The resulting set of source sentences forms a proxy of the visible salient input information being rephrased by the model when summarizing. We split each truncated source document into 10 bins of the same number of sentences, and map each aligned source sentence to its bin. Note that bins are not directly comparable across models, as inputs vary with each model’s context length.

As we can see in Figure 2, sentences from the first 10% or last 10% of source documents are much more represented than others. A clear U-shape emerges on PubMed and SummScreen for all LLMs. This is intriguing knowing that Llama-2 LLMs and the other two LLMs have different context window lengths, and the last 10% of each context window may contain content of varying saliency. In other words, ***LLMs seem to be mostly re-phrasing information from the beginning or the end of their context window.***

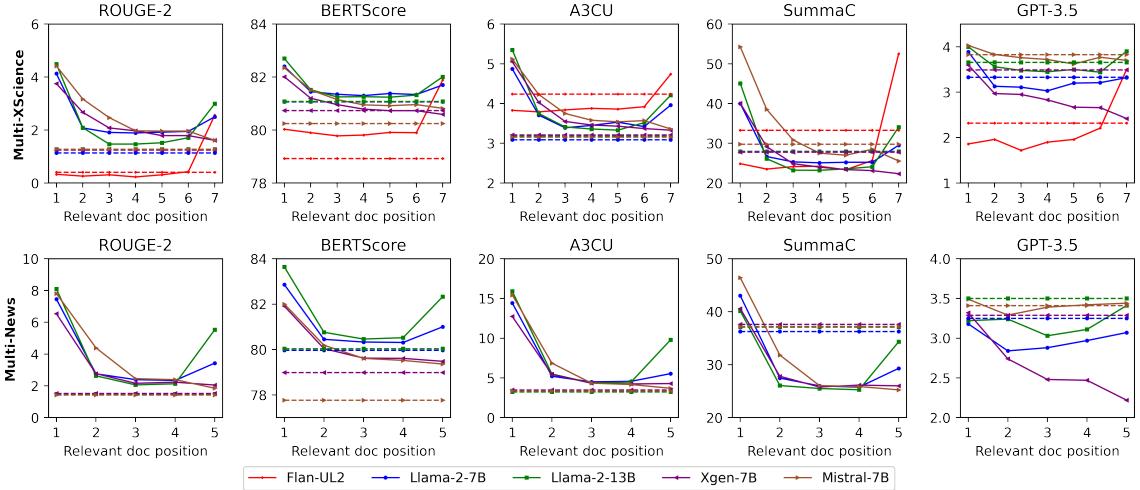


Figure 3: Multi-document summarization performance on Multi-XScience (top row) and Multi-News (bottom row) when a unique relevant document is used, and its position is varied (x-axis). Dashed horizontal lines correspond to the random baseline.

document and vary its position. As salient document, we keep the abstract of the query paper on Multi-XScience, while on Multi-News, we keep the document with the highest similarity (measured with BERTScore) with regards to the reference. We replace the $k - 1$ other documents with documents from another random data point also with k documents. We run inference k times, each time placing the most relevant document at position k , and using relevancy markers in front of each document, to encourage the LLM to only focus on the unique relevant document. In this experiment and the following, we also include a *random* baseline: this is the score achieved when running inference on the subset of data points being used (using all input documents), but shuffling predicted summaries before scoring them. In Figure 3, we see a noticeable drop in performance for all metrics when the salient document is not in the first or final position. Flan-UL2 seems to focus on the *end* of the context, Xgen-7B and Mistral-7B on the *beginning*, and Llama-2 models on *both*. Performance can fall quite below random range, especially for SummaC, confirming the worrying trend from (Liu et al., 2023a).

In the second experiment, we take the opposite approach, and instead of filling noise around a salient document, we keep the first and last documents, and fill with noise (random documents) in between. As baseline, we use once again randomness, and just using the first and last documents as input. In light of previous experiments, we expect the latter baseline to be close to the result with random documents in between. As seen in

Dataset	Model	Input documents	R-2	BS	A3CU	SummaC	GPT-3.5
Multi-XScience	Llama-2-7B	All 7	4.79	82.80	5.82	49.13	4.09
		First + last	4.76	82.80	5.68	48.84	4.04
		First + 5 random + last	4.40	82.58	5.22	53.87	3.94
		Random	1.14	81.07	3.09	27.99	3.33
		All 7	4.78	82.89	6.21	46.97	4.11
	Llama-2-13B	First + last	4.58	82.84	5.81	44.23	4.17
		First + 5 random + last	4.56	82.77	5.65	57.27	4.04
		Random	1.28	81.08	3.18	27.95	3.66
	Xgen-7B	All 7	5.37	82.68	6.59	44.34	4.18
		First + last	5.01	82.73	5.86	49.08	4.03
		First + 5 random + last	3.89	82.16	5.03	55.29	3.64
	Mistral-7B	Random	1.25	80.74	3.21	27.77	3.49
		All 7	5.39	82.61	6.23	63.06	4.16
		First + last	5.17	82.66	6.07	60.44	4.04
		First + 5 random + last	4.55	82.43	5.31	55.47	3.97
		Random	1.28	80.65	3.16	29.76	3.83
Multi-News	Llama-2-7B	All 5	10.12	79.86	17.84	60.92	4.07
		First + last	9.72	84.47	16.25	56.06	4.09
		First + 3 random + last	7.15	76.84	12.49	50.47	3.36
		Random	1.48	75.40	3.29	36.27	3.25
		All 5	10.81	84.81	18.54	59.05	4.33
	Llama-2-13B	First + last	9.50	84.53	16.64	50.18	4.15
		First + 3 random + last	7.78	83.65	14.46	50.34	3.64
		Random	1.49	80.04	3.25	37.11	3.50
	Xgen-7B	All 5	9.04	83.18	17.05	60.55	4.18
		First + last	7.82	83.27	14.18	51.59	4.15
		First + 3 random + last	6.30	81.85	11.66	49.02	3.74
		Random	1.52	78.99	3.48	37.62	3.29
	Mistral-7B	All 5	9.01	83.33	16.63	63.31	3.85
		First + last	9.38	83.42	15.97	68.62	4.21
		First + 3 random + last	6.58	82.08	11.96	52.45	3.97
		Random	1.43	77.77	3.36	37.22	3.41

Table 4: Performance in multi-document summarization on Multi-XScience (7 documents) and Multi-News (5 documents) when infilling the middle of the context window with random documents. **R-2** is ROUGE-2, **BS** refers to BERTScore.

Table 4, filling with random noise between the first and last document (which amounts to a set of input documents which are in majority irrelevant to the reference summary) only leads to a moderate drop in performance. For instance, on Multi-XScience, with 5 random documents between the first and last leads to Llama-2-13B maintains at least 97% on all 5 metrics compared to running inference on just the two relevant documents.

We conclude from these two experiments that **LLMs can focus on the beginning and/or the end of their input, but largely ignore the middle. The U-shape or middle curse from (Liu et al., 2023a)**

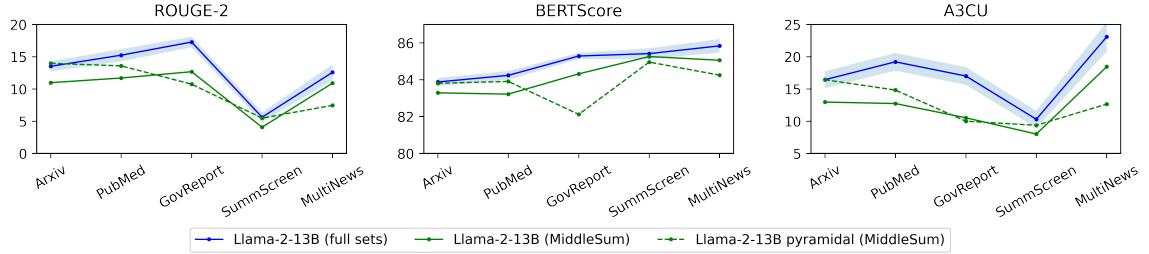


Figure 4: **Llama-2-13B** performance on MiddleSum. The blue curve and shaded area corresponds to the expected value of sampling full datasets with a subset of the same size as in the MiddleSum subset.

also applies to summarization.

4.2 Towards a better understanding of the middle curse

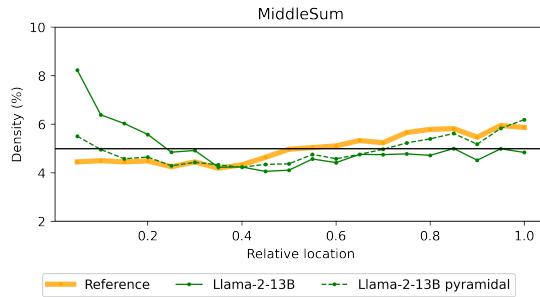


Figure 5: Relative location of summary bigrams within the source on MiddleSum for **Llama-2-13B**.

To evaluate loss of performance due to the *middle curse* in a natural setup, we subsample data points from each of the 5 long-input summarization datasets. Specifically, we obtain source sentences aligned with reference summaries, following the procedure from Section 3.2. Only data points where the start index of the earliest aligned source sentence is at least 1,200 words, are kept. This procedure aims to ensure that there is no salient information within the first roughly 1,500 tokens (no matter the tokenization being used). We randomly sample 50 data points from each of Arxiv, PubMed, GovReport and Multi-News, and 25 from SummScreen, forming an evaluation dataset of 225 samples which we name **MiddleSum**².

We evaluate Llama-2-13B on MiddleSum in Figure 4, breaking down results by dataset subset. Since MiddleSum is built using saliency with regards to reference summaries, only reference-based evaluation metrics are considered. As expected, the LLM performs noticeably worse on MiddleSum (green curve) as compared to the full set (blue

curve), confirming that MiddleSum is a more challenging task on which LLMs summaries drift away more from reference summaries. To bypass the *middle curse*, we craft an alternative inference method: we split source documents in blocks of 2k tokens, truncating at a maximum of 5 blocks, then ask the LLM to summarize each block, and lastly ask the LLM to combine all block summaries into a final summary. We note that in this setup, inference cost is increased, as the LLM may need to generate up to 6 summaries. This process, which we refer to as **pyramidal inference**, is shown in Figure 4 (dashed green curves), and sensibly improves performance on Arxiv, PubMed and SummScreen, almost matching the average performance on the full datasets. We show MiddleSum results for the other LLMs in Appendix D: pyramidal inference drastically improves Mistral-7B, but is not effective on Xgen-7B.

Figure 5 replicates the analysis from Section 3.1 on MiddleSum with Llama-2-13B. The green curve highlights the LLM’s strong lead bias, which pyramidal inference seems to noticeably repress. Distribution of location of reference bigrams confirms that MiddleSum is built to avoid an excess of salient information at the beginning of the source.

4.3 Is scaling context length useful for summarizing?

Both previous experiments confirm that LLMs struggle to summarize information contained in the middle of their context window. This poses issues for long-input summarization: due to their context window maximum length, LLMs can only access information up to a point in the middle of the source document. Since salient information is more present in the beginning of the source (see Figure 1), summarizing long documents may become challenging: after the initial part with a lot of salient content, information is less salient and may

²We will release it alongside our code to reproduce experiments

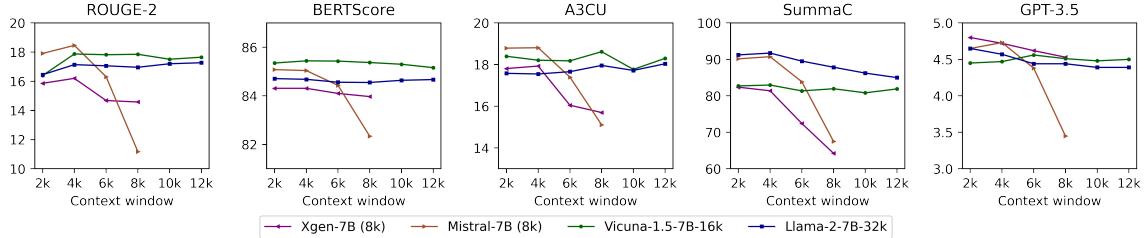


Figure 6: Long-input summarization performance on GovReport with 4 models and all 5 metrics. X-axis represents the truncated maximum source length. Xgen-7b and Mistral-7b cannot infer beyond 8k tokens.

be harder to synthesize, and LLMs summarization capability weakens. To investigate this issue, we truncate long-document summarization datasets up to length $m * 2k$ tokens, varying m from 1 to 6^3 , and perform inference. We use our longest context LLMs Xgen-7B and Mistral-7B, as well as two LLMs extending Llama-2-7B context window with **position interpolation** (Chen et al., 2023), a method gaining traction as an efficient way to scale the context window of Transformer-based LLMs. The idea is very straightforward: writing M as the desired context length, and N as the pre-trained context length (thus, $M > N$), position interpolation multiplies position indices by $\frac{N}{M}$ to force them back into the pre-trained range of $[0, N]$. We use two LLMs applying position interpolation on top of Llama-2-7B: Vicuna-7B-1.5-16k⁴, and Llama-2-7B-32k⁵, with context window 16k tokens and 32k tokens, respectively.

Results for GovReport in Figure 6 confirm our intuition: all metrics plateau or even decrease (for Xgen-7B and Mistral-7B) from 4k context window upwards. Two conflicting forces are at play when increasing context length in summarization: giving more information to the model helps it to retrieve key elements to make a summary, while reasoning over a longer context is more challenging. Yet, such a drop of ROUGE-2, BERTScore, A3CU and SummaC for Xgen-7B and Mistral-7B at 8k inference length is concerning. Our results suggest that *in the current evaluation framework, there is no need to use more than 4k context window for abstractive summarization with LLMs*.

5 Related Work

Summarization with LLMs It is widely acknowledged that LLMs have enabled a large step

³Our academic setup with two A100 80GB does not enable us to exceed 12k tokens at inference.

⁴In HuggingFace: `lmsys/vicuna-7b-v1.5-16k`

⁵In HuggingFace: `togethercomputer/LLaMA-2-7B-32K`

forward in summarization research (Pu et al., 2023). Indeed, summaries generated by instruction-tuned LLMs are now highly rated by human annotators (Goyal et al., 2022; Zhang et al., 2023b). (Liu et al., 2023b) proposes to train smaller models like BART (Lewis et al., 2020) or BRIO (Liu et al., 2022b) with contrastive learning using LLMs like Chat-GPT as evaluator providing signal on which generated summary candidate is better. Summary chain-of-thought (Wang et al., 2023d) designs a custom chain-of-thought method which first prompts the LLM to list important facts, then integrates these facts into a coherent summary. Iterative approaches are successful when applying LLMs to summarization. SummIt (Zhang et al., 2023a) utilizes Chat-GPT to write then refine summaries given feedback from an evaluator LLM. Chain-of-density (Adams et al., 2023) gradually makes GPT-4 generated summaries contain more and more entities while keeping length budget constant, creating more informative albeit a bit less readable summaries. (Ravaut et al., 2022) noticed that data points with higher compression are generally harder to summarize with pre-trained language models.

Position bias in LLMs It is known that for Transformer-based models, most recent tokens play a greater role compared to older tokens on tasks such as next-token prediction (Sun et al., 2021). However, how LLMs make use of their entire context window remains poorly understood and under-explored, especially for complex, reasoning generation tasks such as abstractive summarization, which do not involve merely copying blocks of tokens from the input. (Liu et al., 2023a) shows that for multi-document question answering, LLM performance may drastically drop if the document containing the answer is the middle of the input context, leading to a U-shape of performance with regards to the position of the important document. Performance in the middle of the context window

may drop to below random chance which is very concerning. Even very powerful models like GPT-4 are influenced by the position of elements within their input (Wang et al., 2023a); recent studies (Wang et al., 2023c; Xu et al., 2023) reported that when used as an evaluator comparing two systems, GPT-4 has a preference for the first element in the prompt. Reliance on positional information also affects LLMs capabilities in arithmetic (Shen et al., 2023b).

6 Conclusion

Behind the hype around LLMs, our study showcases a major weakness in abstractive summarization: LLMs suffer from the *middle curse* and struggle to use information in the middle of their context window. LLMs do not make a consistent use of their context window as they mostly look at the beginning and (to a lesser extent) the end. Extending context window beyond 4k tokens, which has been an intense area of focus lately, is not justified in the current inference and evaluation setup in abstractive summarization. We explored an alternative inference method, breaking down source blocks and merging each block’s summary in a pyramidal manner. Despite promising results on scientific paper datasets, it is far from a silver bullet to the *middle curse*, and makes inference considerably more computationally intensive.

We call for a better evaluation of LLMs taking into account the use of the entire context window. New fine-grained evaluation metrics may measure how consistent LLMs are at processing such salient information throughout the source, and not only at the whole document(s) level. We acknowledge the difficulty in assessing saliency of input content: our methodology approximates salient content through either summary bigrams or aligned source sentences with the summaries (where quality of reference summaries is not always ideal), and approximates the position of such content by averaging position of aligned sentences. Future work may also develop more robust tools to detect salient content in the input of summarization datasets.

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A Statistics

In Table 5, we include statistics on each of the abstractive summarization datasets under consideration. We use the non-anonymized version for CNN/DM (See et al., 2017). For Reddit-TIFU, we use the Long subset, and for SummScreen, we only consider the ForeverDreaming (FD) subset. GovReport and SummScreen are part of the long-input benchmarks Scrolls (Shaham et al., 2022) and ZeroScrolls (Shaham et al., 2023).

In Figure 7, we illustrate how much of the source document(s) is visible with a 4k context window (Llama-2).

B GPT-3.5 Evaluation

To evaluate LLM-generated summaries with GPT-3.5, we use the following prompt template:

Score the following summary generated by another system given the source on a scale from 1 to 5 with regards to overall general summary quality. 1-point indicates a low-quality summary, and 5 points a very high quality summary. A high-quality summary is grammatical, fluent, informative, relevant, coherent and factually consistent with the source. Let's think step-by-step and just output the score.

Dataset	Domain	# Docs	# Data points			# Sentences			# Words		# Tokens	
			Train	Val	Test	Doc.	Summ.	Inf.	Doc.	Summ.	Doc.	Summ.
CNN/DM (Hermann et al., 2015)	News	1.00	287,113	13,334	11,490	33.37	3.79	3	773.23	57.75	994.56	84.47
XSum (Narayan et al., 2018)	News	1.00	204,045	11,332	11,334	19.11	1.00	1	433.05	23.19	566.79	31.63
Reddit-TIFU (Long) (Kim et al., 2019)	Social Media	1.00	33,701	4,214	4,221	22.21	1.45	2	444.20	23.37	532.18	29.82
SAMSum (Kim et al., 2019)	Dialogue	1.00	14,732	818	819	8.96	2.01	2	126.93	23.12	175.54	29.69
Multi-XScience (Liu et al., 2020)	Science	5.06	30,369	5,066	5,093	30.55	4.86	5	773.36	120.65	965.99	157.77
Arxiv (Cohan et al., 2018)	Science	1.00	203,037	6,436	6,440	250.37	6.23	6	6,446.11	166.72	8,940.00	225.58
PubMed (Cohan et al., 2018)	Science (medical)	1.00	119,924	6,633	6,658	101.61	7.59	7	3,142.92	208.03	4,602.62	324.97
GovReport (Huang et al., 2021)	Legal	1.00	17,517	973	973	282.86	23.14	22	8,363.22	649.01	11,025.02	879.10
SummScreen (FD) (Chen et al., 2022)	TV Transcripts	1.00	3,673	338	337	727.06	5.26	5	7,618.20	123.34	10,067.39	157.44
Multi-News (Affi et al., 2017)	News	2.73	44,972	5,622	5,622	79.02	9.88	10	2,101.49	256.55	2,998.52	324.29

Table 5: Statistics on the 10 datasets used for experiments. Doc. is the source document, Summ. the ground-truth summary, Inf. refers to the number of desired sentences to be in the summary prompted to each LLM during inference. Statistics are computed on the entire test set. # Tokens is calculated with Llama-2 tokenizer.

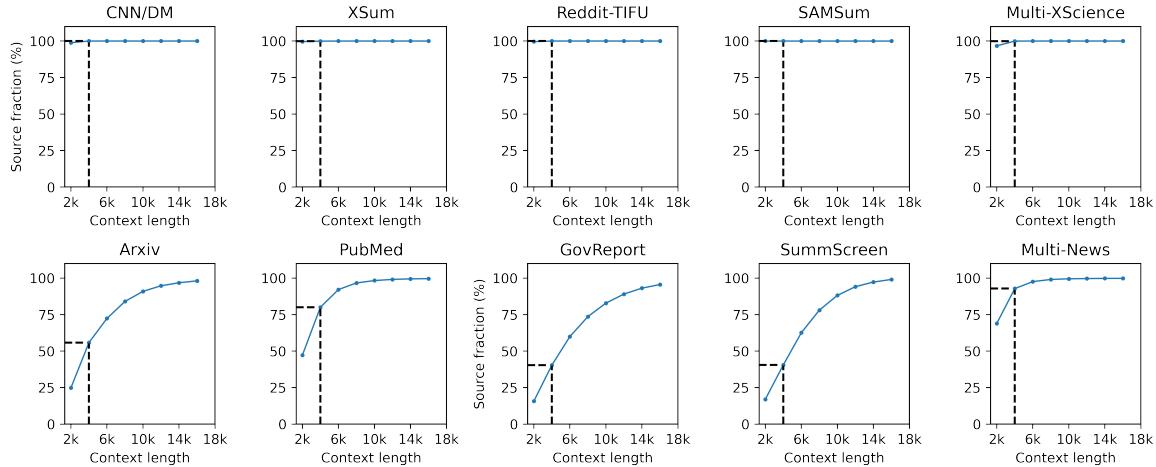


Figure 7: Fraction of the source which fits into the context window, for several context window lengths with Llama-2 tokenization. The black dashed lines correspond to Llama-2 context window length of 4k tokens. On standard-length datasets, 4k is enough to access 100% of all source documents ; but on the long-input datasets such as GovReport or SummScreen, such a context window may not even fit 50% of the source.

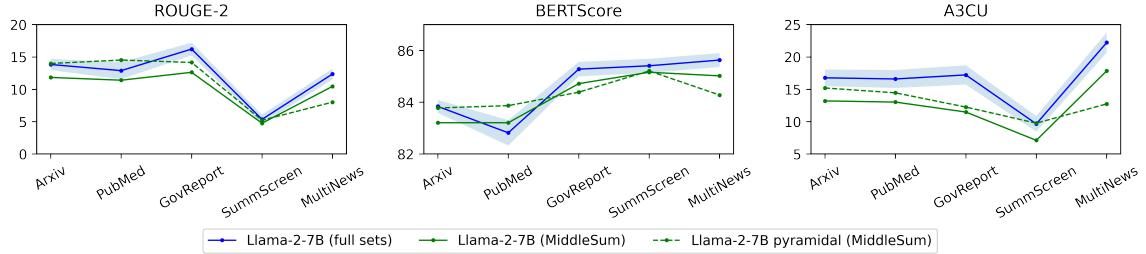


Figure 8: **Llama-2-7B** performance on MiddleSum. The blue curve and shaded area corresponds to the expected value of sampling full datasets with a subset of the same size as in the MiddleSum subset.

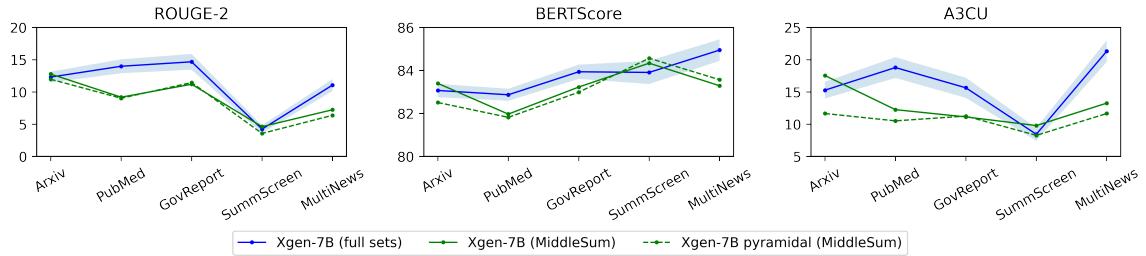


Figure 9: **Xgen-7B** performance on MiddleSum. The blue curve and shaded area corresponds to the expected value of sampling full datasets with a subset of the same size as in the MiddleSum subset.

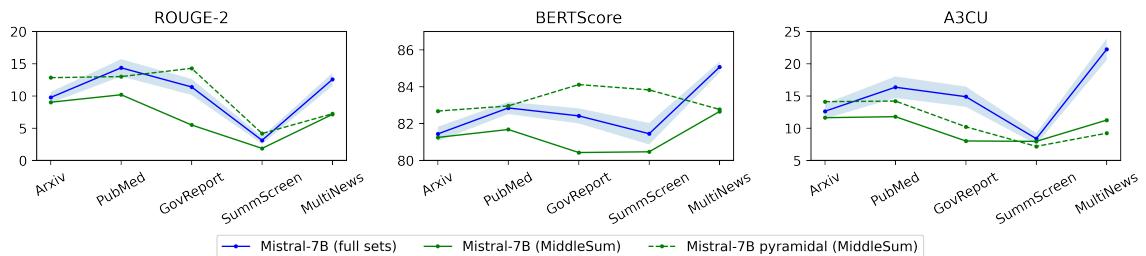


Figure 10: **Mistral-7B** performance on MiddleSum. The blue curve and shaded area corresponds to the expected value of sampling full datasets with a subset of the same size as in the MiddleSum subset.