Understanding Long Documents with Different Position-Aware Attentions

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Abstract

Despite several successes in document understanding, the practical task for long document understanding is largely under-explored due to several challenges in computation and how to efficiently absorb long multimodal input. Most current transformer-based approaches only deal with short documents and employ solely textual information for attention due to its prohibitive computation and memory limit. To address those issues in long document understanding, we explore different approaches in handling 1D and new 2D position-aware attention with essentially shortened context. Experimental results show that our proposed models have the advantages for this task based on various evaluation metrics. Furthermore, our model makes changes only to the attention and thus can be easily adapted to any transformer-based architecture.

1 Introduction

The task of document understanding has recently gleaned many successes (Xu et al., 2020, 2021b; Appalaraju et al., 2021). This task requires multimodal input that makes it heavier than the text-only ones, resulting in most models only being capable of dealing with short documents, i.e. having up to 512 tokens. However, there exist long documents almost everywhere, e.g. contracts, scientific papers, newsletters, or Wikipedia articles, which are typically longer than 1,000 words. To automatically summarize and understand such long documents urges long document understanding to become an important task in both natural language processing and artificial intelligence.

Long document understanding faces several big challenges. 1) Recent document understanding approaches heavily rely on transformer (Vaswani et al., 2017). However, transformer suffers from the quadratic attention that usually limits the input to 512 words. Therefore, the correlation across long paragraphs/pages is yet to be learned. 2) Understanding long documents requires the power to model all long information available, not only just in text but also in other modalities such as spatial information. For example, LayoutLM (Xu et al., 2020) showed that short document understanding is largely improved by additionally embedding spatial into text information. How to efficiently make use of spatial information for long document understanding, however, is still an open and challenging problem regarding computation cost and adaptability.

Given the fact that long documents frequently appear in practice as well as in many datasets as shown in Figure 1, it is reasonable to assume that useful information is spanned across their lengths. Especially current OCR technology, which is essential for data preprocessing, only supports extracting spatial information on every page basis, without
the knowledge of other pages. This behavior poses yet another big challenge in dealing with long documents, which requires a proper method to connect information across pages for all input modalities.

In this paper, we discover new approaches to dealing with long document understanding, which addresses the aforementioned challenges. We carefully preprocess OCR data to establish the proper linkages across pages. Then we explore approaches for directly reducing the heavy attention cost while achieving high performance, flexibly using the typical 1D (textual) and/or novelly, 2D (spatial) reduced contextual information, without the need of adding more components into the already-heavy transformer (Appalaraju et al., 2021; Nguyen et al., 2021), employing additional pretraining tasks for better representation learning (Huang et al., 2022; Li et al., 2021) or employing complicated new encoding techniques (Hong et al., 2022; Wang et al., 2022). Despite being simple, we show through experiments that both 1D and 2D information can enhance the practicality of transformer-based models while achieving the needed power of handling long documents without introducing any new pretraining tasks other than the popular one: masked language modeling.

Our contributions In summary, we have three following contributions. 1) We newly motivate the simplistic, flexible use of spatial input into self-attention, making it plug-able to transformer-based and other architectures using attention. 2) We are able to tackle the document understanding task with input data up to 4096 words with several attention configurations. 3) Experimental results prove the advantages of our approaches on various long-document datasets in comparison to short models for both 1D and 2D contextual information.

2 Related Work

Transformer Attention For Long Documents

There are several methods that address the quadratic cost of the transformer attention and some of them narrow the focus on long documents for their practicality. Longformer (Beltagy et al., 2020) uses sliding windows to reduce the context, only retrained some sparse global connections. Similarly, ETC (Ainslie et al., 2020) embeds relative positions and adds contrastive predictive encoding. Bigbird (Zaheer et al., 2020) adds a few random connections on top of the sliding windows and sparse global connections and then arranges a long context into a few blocks to reduce the number of intermediate matrix re-arrangement and calculation steps. Our model similarly uses sliding windows to effectively handle long documents but differs in that it addresses the complication of multimodal, instead of text-only, data and exploits layout input along with the typical text input flexibly and directly into attention and thus enhancing the attention more power and flexibility in dealing with different data types.

Multimodal Document Pretraining

Document understanding largely inherits from multimodal pretraining (Li et al., 2020; Chen et al., 2020; Luo et al., 2020) with the successes from LayoutLM (Xu et al., 2020, 2021a). Docformer (Appalaraju et al., 2021) and StructuralLM (Li et al., 2021) developed the task further by introducing a new two-pronged approach: having new pretraining tasks and suitable changes to the processing or embedding. Similarly, LayoutLMv3 (Huang et al., 2022) introduces two new, additional pretraining tasks on top of masked language modeling (MLM) to enrich the representation learned by the models. Yet another approach is to focus on encoding the spatial information properly with either relative spatial encoding (Hong et al., 2022) or having separate encoding flows for textual and spatial input, then flexibly fusing them (Wang et al., 2022). Unlike all of those approaches, our solution has a different focused motivation that is long documents, only employs MLM as the only pretraining objective, and tackles the attention directly—by efficiently handling the shortened contexts based on textual/spatial information to deal with long contexts—instead of resorting to further embedding and/or encoding all information properly, resulting in a more simple and lightweight solution that can be adapted easily for any architecture using the attention mechanism.

Finally, Skim-Attention (Nguyen et al., 2021) probably has the most related motivation for long documents, although we have a more memory-efficient, and faster way of handling layout input directly into attention and not from after the embedding like theirs, and consequently support longer input (4096 vs. 2048).

3 Our Model

The structure of this section is as follows. We will first introduce our MLM pretraining model with an emphasis on the novel attention that em-
Figure 2: Our pretrain model architecture. Unlike other models for this task, we keep a simple approach by only employing a single MLM pretraining objective and do not employ extra overhead into multimodal embedding or encoding methods. Instead, we tackle the attention module directly and make necessary changes to deal with our focus on long documents, by flexibly using 1D and 2D input.

3.1 Pretrain Model Architecture

To keep our solution simplistic and easy for studying the effects of each approach being proposed, we only employ Masked Language Model (MLM) architecture as in other document intelligence work, e.g. Xu et al. (2020, 2021a). However, we discover new attention approaches in MLM to enable its capability of handling long documents. In more detail, different from a typical MLM predominantly used in natural language processing, we have multimodal—instead of text-only—input, which inevitably makes the model heavier and hence cannot deal with long documents without proper changes, as we propose below.

First, we use the sliding-window inspired from Beltagy et al. (2020), given its lightweight and elegance in limiting the context window, making it significantly more memory friendly. Second, we introduce new spatial-based attention masks, in which each context window to a bounding box is determined by calculating its spatial neighbors, instead of the given neighboring words. Likewise, our model not only uses spatial input in the embedding but also in attention directly with preserved spatial correlation. The illustration of our MLM model is shown in Figure 1. Additionally, section 3.3 will elaborate on the establishment and usage of these new distance masks in comparison with others.

3.2 Post-OCR Processing

The task of document intelligence relies heavily on the quality of the OCR pre-processing as the first data processing. As a result, how to present the post-OCR data properly to the model is very important, as any mistake in this phase will be compounded later in the model. Especially in the case of long documents, this processing is more crucially important. While long documents have multiple pages, current OCR engines only generate single-page results, without any connections among pages. More current models are “short”
models that support up to 512 tokens, and thus typically make use of the very first page’s OCR results, discarding the rest of the valuable information. As a result, the further need for post-processing is usually unnecessary in those models.

Unlike those short models, to make our model capable of tackling long documents, we process and normalize the post-OCR data to establish the connections for all input components among the pages. For example, the bounding boxes on page \( n \) need adjusting the coordinates to include the previous \( n - 1 \) pages.

### 3.3 Different Attention Masks

We are motivated by the fact that in rich documents with multimodal contents, the relationship of words not only follows the consecutive, sequential nature of texts but also in the boxes or sections organized in many complicated forms, in which spatial input offers essential information in addition to text. Furthermore, we argue that in dealing with long documents, we should not put extra overhead on the already-heavy transformer-based models in both computation and memory perspectives. As a result, proper changes have to be made as described below in our proposed attention approaches.

#### Sliding-Window Masks (Figure 3a)

We use the sliding-window approach as inspired from Beltagy et al. (2020), which limits the context for each token from \( N \) down to a smaller \( M \), e.g. \( N = 4096, M = 512 \), and so the complexity is essentially reduced to \( O(NM) \).

#### Sliding-Window plus Random Token Masks (Figure 3b)

On top of sliding windows, we add a few random tokens to establish more connections to the attention, as done similarly by Zaheer et al. (2020). This operation essentially makes changes only to Equations 3 and 5, and replace them with Equations 7 and 8, respectively.

Using that intuition, the calculations are now changed to Equations (3–6), with the added get_window steps in Equations (3) and (5). This change is simplistic because while significantly reducing the heavy blueprint of the full attention, it retains a consistent pattern of token arrangement for fast implementation.

### Original Attention Masks

For the original transformer-based architectures (Vaswani et al., 2017), in each of their layers, the attention score is calculated by two main steps, as formulated in Equations (1) and (2).

\[
score(Q, K) = \text{softmax} \left( \frac{QK^T}{\sqrt{d_k}} \right) \\
attn\_score(Q, K, V) = score(Q, K) \cdot V
\]

where \( Q, K, V \) stand for the learnable Query, Key, and Value matrices respectively. Given the lengths of these three matrices are all \( N \), which is also the input length, the complexity of each step is \( O(N^2) \).

We usually refer to this attention mechanism as full attention because each single input token attends to all \( N \) available tokens including itself, which makes it impractical in terms of both computation and memory in the cases of long documents. As a result, proper changes have to be made as described below in our proposed attention approaches.

#### Sliding-Window Masks (Figure 3a)

We use the sliding-window approach as inspired from Beltagy et al. (2020), which limits the context for each token from \( N \) down to a smaller \( M \), e.g. \( N = 4096, M = 512 \), and so the complexity is essentially reduced to \( O(NM) \).

\[
K_w = \text{get_window}(K) \tag{3}
\]

\[
score(Q, K) = \text{softmax} \left( \frac{QK^T}{\sqrt{d_k}} \right) \tag{4}
\]

\[
V_w = \text{get_window}(V) \tag{5}
\]

\[
attn\_score(Q, K, V) = score(Q, K) \cdot V_w \tag{6}
\]

Using that intuition, the calculations are now changed to Equations (3–6), with the added get_window steps in Equations (3) and (5). This change is simplistic because while significantly reducing the heavy blueprint of the full attention, it retains a consistent pattern of token arrangement for fast implementation.

### Sliding-Window plus Random Token Masks (Figure 3b)

On top of sliding windows, we add a few random tokens to establish more connections to the attention, as done similarly by Zaheer et al. (2020). This operation essentially makes changes only to Equations 3 and 5, and replace them with Equations 7 and 8, respectively.

\[
K_w = \text{get_sliding_and_rand_window}(K) \tag{7}
\]

\[
V_w = \text{get_sliding_and_rand_window}(V) \tag{8}
\]
In more detail, the sliding-window contexts are enhanced by some random contexts added. While certainly being an extra overhead, the number of those random connections is limited to only a few, maintaining the practicality of the model in the face of long documents.\textsuperscript{2}

\begin{align}
K_{uv} &= \text{get\_2D\_spatial\_window}(K) \quad (9) \\
V_{uv} &= \text{get\_2D\_spatial\_window}(V) \quad (10)
\end{align}

\textbf{Spatial Distance Masks} (Figure 3c) Different from previous attention types, the $M$ contextual neighbors of each token are decided by spatial (2D) information instead of textual (1D) information. In the final result, however, the spatial attention mask has the same shape as sliding windows (if they both have the same number of contextual neighboring tokens). This process comprises a couple of steps.

First, we calculate the centers of all bounding boxes. Second, we fit the kNN algorithm to the sequence of those points based on L2 distance, resulting in a 2D distance matrix, in which each token now spatially attends to $M$ neighboring tokens. In summary, we replace Equations 3 and 5 with Equations 9 and 10. The resulting masks consequently have a non-consecutive neighboring relationship, unlike in the traditional text-based contexts. More illustrations of those distance-based masks for real examples are also shown in Figure 6 in Appendix C.

\textit{Implementation of Distance Masks} In terms of efficient implementation, there are certain considerations to enable the practical use of those newly proposed distance masks, which consume more computation and memory cost compared to the normal sliding window mechanism.

First, identifying spatial neighbors for each token usually takes quadratic time, which is a great deterrent to our solution. So we choose to use scikit-learn's kNN library\textsuperscript{3} for its well-regarded efficiency and speed.

Second, “where to create distance masks: in dataset loader or in model computation” is a key problem. We choose to create distance masks in the dataset loader for the following reasons. On one hand, the main obstacle to applying long-document attention methods is that the transformer-based models are inherently heavy. If placing the quadratic computation of those distance masks in the main model phase, the model will be significantly slower (in proportion to document lengths) and the risk of out-of-memory will be much higher (given the limitation of GPU memory). On the other hand, by preemptively computing the distance mask in the dataset loader, e.g. using Pytorch Dataloader\textsuperscript{4} and exploiting its data buffering mechanism, the data loading will not be slower by running multiple loader processes simultaneously.

Finally, for the sliding-window attention, we detail the implementation notes for those new attention masks.

\begin{footnotesize}
\begin{itemize}
    \item[\textsuperscript{3}]https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.KNeighborsClassifier.html
    \item[\textsuperscript{4}]https://pytorch.org/docs/stable/_modules/torch/utils/data/dataloader.html#DataLoader
\end{itemize}
\end{footnotesize}
herit the implementation from Huggingface, then implement our distance-based solution on top of it.

3.4 Pretrain Model Variants

We build out MLM pretraining architecture with various attention mechanisms for long documents as described in Section 3.3 and compare their performances in several tasks. Since this change is only made directly to the attention, our method can be used off-the-shelf for transformer-based architecture with multimodal input.

SW Model This model directly uses Sliding-Window (SW) masks for attention, which significantly reduces the computation and was shown to be effective for long documents in text-based tasks (Figure 3a).

SW+R Model This model uses blocked Sliding-Window plus some random blocks on top (Figure 3b).

DISTANCE Model This model uses Spatial Distance Masks, with all neighboring contexts being preemptively computed using kNN, and is implemented in the data loading instead of transformer encoding phase, not to slow down the main process (Figure 3c).

DISTANCE+SW Model. In this model, we combine the spatial and textual attention masks together in a single attention pass. In detail, it is done via two steps, as shown in Equations (3–6), with Equation (3) now being replaced by Equation (9). This is a possible adjustment since these two steps are separated and both preserve the logic and shapes of matrices in their calculation. Our motivation and intuition are to combine the benefits of both textual and spatial information in a single attention pass (Figure 3d).

4 Experiments

In this section, we describe our experimental methodology to evaluate our proposed approach of flexible attention using different contextual input information.

4.1 Tasks and Datasets

Pretraining We use IIT-CDIP Test Collection 1.0 dataset for our MLM pretraining task. This is a large-scale dataset with over 6M multi-page documents and around 11M pages in total (each page is stored as a scanned image and is preprocessed by an OCR engine).

Document Classification This document classification task uses RVL-CDIP (Harley et al., 2015) dataset, which is a subset of the pretraining dataset IIT-CDIP. It comprises 16 classes and each class equally has 25K grayscale images. All of these 400K images in combination are split into 320K images for training and 40K images each for validation and testing. For more statistics on this dataset, the document length distribution is shown in Figure 1.

Sequence Labeling There are two datasets for this task, namely Kleister-NDA and FunSD.

1) FunSD (Guillaume Jaume, 2019) This is a lightweight dataset that has 199 noisy scanned forms, which contain around 31K words and 9.7K entities with 7 given token classes. Although it is not a long-document dataset (all documents have < 512 words), it is a popular dataset used by many document intelligence models and is also useful for ablation studies on how long document models perform on a short document dataset, as we show in Section 4.4.

2) Kleister-NDA (Grąlski et al., 2020; Stanisławek et al., 2021) This dataset has 540 documents in total (254 train, 83 validation, and 203 test) with 2,160 entities annotated and an average of 2,540 words per document. Due to the difficulty in reproducibility with unclear results post-processing, this task is cast similarly to FunSD with 4 classes. Consequently, we report the evaluation results of our models along with all other methods’ reproduced outcomes using the same preprocessing steps and metrics, in order to maintain fair comparisons.

4.2 Baselines

We pretrain our 4 model variants (Figure 3) with the MLM objective and then compare them with the following baseline groups:

Text: This group consists of models that only accept text input including BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019), and other long models including Bigbird (Zaheer et al., 2020) and Longformer (Beltagy et al., 2020).

Our SW and SW+R models share the similarity with those last two ones, with the difference of handling multimodal
Table 1: Classification accuracy for RVL-CDIP. For this long-document dataset, the models capable of using 4096 words uniformly beat other models and layout information helps with the task compared with using Text input. All our long models show their advantages on this long dataset.

| Type               | Model          | SeqLen | Acc (%) |
|--------------------|----------------|--------|---------|
| Text               | BERT-base      | 512    | 89.81   |
|                    | RoBERTa-base   | 512    | 90.06   |
|                    | BERT-large     | 512    | 89.92   |
|                    | RoBERTa-large  | 512    | 90.11   |
|                    | Bigbird-base   | 4096   | 93.48   |
|                    | Longformer-base| 4096   | 90.85   |
|                    | Bigbird-large  | 4096   | 93.34   |
|                    | Longformer-large| 4096  | 93.73   |
| Text+Layout        | LayoutLM-base  | 512    | 91.88   |
|                    | LayoutLM-large | 512    | 91.90   |
|                    | Ours SW        | 4096   | 94.50   |
|                    | Ours SW+R      | 4096   | 95.25   |
|                    | Ours DISTANCE  | 4096   | 94.79   |
|                    | Ours DISTANCE+SW| 4096 | 94.69   |

Table 2: Results on Kleister-NDA. Although this dataset is challenging, long models still show advantages over short ones.

| Type               | Model          | SeqLen | F1 |
|--------------------|----------------|--------|----|
| Text               | BERT-base      | 512    | 47.06 |
|                    | BERT-large     | 512    | 52.66 |
|                    | Longformer-base| 4096   | 61.78 |
|                    | Bigbird-base   | 4096   | 46.98 |
| Text+Layout        | LayoutLM-base  | 512    | 55.69 |
|                    | LayoutLM-large | 512    | 61.95 |
|                    | Ours SW        | 4096   | 64.06 |
|                    | Ours SW+R      | 4096   | 58.92 |
|                    | Ours DISTANCE  | 4096   | 57.01 |
|                    | Ours DISTANCE+SW| 4096 | 44.70 |

Table 3: Results on FunSD dataset. As usual, layout information is helpful in boosting performance. However, long models do not perform well compared with short models on this small, short-document dataset.

| Type               | Model          | SeqLen | F1 |
|--------------------|----------------|--------|----|
| Text               | BERT-base      | 512    | 60.3  |
|                    | RoBERTa-base   | 512    | 66.5  |
|                    | BERT-large     | 512    | 65.6  |
|                    | RoBERTa-large  | 512    | 70.7  |
|                    | Bigbird-base   | 4096   | 45.8  |
|                    | Longformer-base| 4096   | 71.4  |
|                    | Bigbird-large  | 4096   | 46.8  |
|                    | Longformer-large| 4096 | 73.5  |
| Text+Layout        | LayoutLM-base  | 512    | 78.7  |
|                    | LayoutLM-large | 512    | 79.0  |
|                    | Ours SW        | 4096   | 69.9  |
|                    | Ours SW+R      | 4096   | 77.1  |
|                    | Ours DISTANCE  | 4096   | 64.0  |
|                    | Ours DISTANCE+SW| 4096 | 61.8   |

Sequence Labeling with Kleister-NDA

Comparing the “base” versions (separated from their “large” counterparts), Table 2 shows that most of our models, which are also the “base” ones, clearly have better scores. Particularly, our SW model is the best performer.

Furthermore, our DISTANCE+SW is not performing equally well. Our hypothesis is that the OCR engine cannot understand the decoying annotation in this dataset, and thus generates spatial results that do not correlate well with the text. Consequently, the combination of textual and spatial information does not result in the benefits of those two.

4.4 Ablation: Long Models on Short Dataset

The purpose of this study is to explore how long models perform on short documents, which also appear in practice, to see whether they can generalize their performance to shorter data.

Text: This group contains models that accept both text and layout information, including LayoutLM (Xu et al., 2020) variants.

4.3 Results and Discussions

Document Classification As shown in Table 1, long models (SeqLen10 4096) clearly outperform short ones in both baseline groups, with or without layout information added to the input. Furthermore, all our 4 model variants outperform all the baselines.

This result concurs with our observation that long documents have valuable information spanned across the length. And importantly, our models show advantages of handling long multimodal input, and hence are more practical with real data that are usually longer than 512 tokens.

input for document intelligence.

10SeqLen is short for Sequence Length
input to the model is zero padding and thus not enough for contributing for better scores.

Another reason is that long models have their embedding representations trained for the length of 4096 tokens and hence are hard to adapt to 512-token input with just a few fine-tuning steps. As a result, analyzing the data well to design suitable pretraining and fine-tuning models is very important.

The next 2 studies will explore the implications of the newly-added spatial attention masks in our models.

4.5 Ablation: Different-Length Documents

This study aims to explore how the models work if we do not cut any information from documents (the models take input up to their maximum length limit). Out of 40K test samples in RVL-CDIP, there are 9268 samples with length $\geq 512$, 2312 with length $\geq 1024$, and only 106 with length $\geq 2048$.

Figure 4 shows the consistent observation that our models are much better than LayoutLM, and yet perform slightly worse as the original document length increases. There could be several possible reasons for this behavior: the models are not well pretrained and/or fine-tuned, many long documents have lots of confusing parts, or there are many noises in OCR results.

4.6 Ablation: Different Max Input Lengths

Given the pretrained models that can accept input up to 4096 tokens, we finetune them with the input of different maximum lengths, i.e. excess will be purged. As a result, we use all 40K test samples in RVL-CDIP for this study.

As shown in Figure 5, our models are better and better as more tokens are absorbed, thus once again confirming our intuition that valuable information is spanned across the length. As a result, if the model capacity permits, we should not limit the capacity to 512 tokens as in most current models in the literature.

4.7 Further Discussion on Spatial Masks

As seen in the above experimental results, direct usage of 2D layout context information in the transformer attention has some advantages. However, its performance does not match the typical usage of 1D textual information. This might be discouraging at first since introducing spatial masks brings heavier computation compared to textual ones. We hypothesize the drawbacks are due to some objective limitations. First, the kNN suffers some inaccuracy compared with normal (and slow) calculations. Second, the performance of the whole pipeline heavily depends on OCR quality, e.g., in Kleister-NDA with decoy design, OCR results are not well aligned with the text. Consequently, we conjecture that with future development in OCR technologies, the use of spatial masks would be more and more helpful in practice.

5 Conclusion and Discussion

We propose a versatile solution for long document understanding, in which the shortened context can be used in the form of textual and/or layout input for the attention mechanism in a flexibly pluggable manner. We keep our approach simple by not putting extra overhead on complicated encoding methods. Despite its simplicity, our solution has shown promising experimental results on document understanding tasks with long, multimodal input. In the future, we will further reduce the memory consumption of models.
with given multimodal input and speed up the pre-training. Similar to LayoutLM, pretraining usually takes 80 hrs/epoch with 8 V100 GPUs. Thus there are certainly lots of room for improvement to make these models more efficient and practical.

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A More Information on the Pretrain Task

Pretrain Data Preprocessing As described, for pretrain model we retain the same OCR engine for generating and aligning layout and text information from LayoutLM (Xu et al., 2020). The task is also the same, which is Masked Language Modeling (MLM). To deal with long documents, we have to implement the additional sliding-window, random-block and distance-based masks.

Pretrain Model Implementation Our solution only makes changes to the attention module, in which uses can choose to use any types of attention masks from the 4 variants illustrated in Figure 3. For the SW and SW+RAND models which are also our new pretrain models, we implement the layout-related part on top of the original BigBird and Longformer implementations from Huggingface’s transformers, respectively. Otherwise the distance-based masks, which are employed in DISTANCE AND DISTANCE+SW models, are newly implemented as a pluggable module.

Training MLM We pre-train the task on the IIT-CDIP datasets, using a single-node multi-GPU mode. Each job was run on a server with 8 V100 Nvidia GPUs, each of which has 32GB of memory and fast processors. For text-only models, please refer to LayoutLM’s github.

For SW model, we use the public pretrained weights from Longformer (Beltagy et al., 2020). Other of our models employ the same set of parameters, except for the pretrained weights, in which SW+RAND model uses the weights from Bigbird (Zaheer et al., 2020) and the last two models having distance masks (DISTANCE and DISTANCE+SW models) use the same pretrained weights as SW model, as demonstrated in Table 4.

It is also worth noting that the pretrained weights from Longformer and Bigbird models are useful even for the models using distance masks because those two model families support documents with length 4096, so the position embeddings are helpful. For speed and memory tradeoff, we limit the context for distance masks to only 128 (vs. 512 in textual contexts), without sacrificing much performance, as reported in Section 4.3.

Training Notes Although not reported in the main content, we note some lessons learned from the pretraining task. As we observe, the Ours SW model consistently achieves the best results, while consuming the least GPU memory. For the base model, it only consumes about 7 GB GPU memory and Ours DISTANCE+SW that uses sliding-window attention on its half processing also consumes about 9 GB memory. Both models, as a result, can be deployed well on a broad range of GPUs in the market.

Unlike those conveniences, Ours SW+RAND and Ours DISTANCE do not share the same advantages. In fact, they consumes about more than 30GB GPU memory each, limiting their practicality. We hypothesize the main reason for such drawbacks is that they have random, inconsistent patterns, and hence there is no efficient way to take advantage of fast memory-efficient and fast matrix operations.

Finally, although showing promising practical behaviors, all baselines and our models, and almost any transformer-based ones are certainly not lightweight models. And although there are advancements in compressing those heavy models (e.g. (Touvron et al., 2021; Frankle and Carbin, 2019), there seems to be a considerable way to go for making these model run on mobile devices in the near future.
B More information on Finetuning Tasks

As described in the main content, after pretraining, the saved models are the backbone for the respective fine-tuning model types. For that reason, the parameters are mostly shared with their pretrain counter-part models, e.g. Table 4 for Ours SW models. Generally, we keep the same optimizer and batch size of 32 (combined across all used parallel GPUs).

For RVL-CDIP in the document classification task, we use the SequenceClassification model type. On top of the pretrain skeleton, we add a small classifier with 2 fully-connected layers and a drop-out layer in between. The final output is the single class for the whole sequence/document.

For FunSD and Kleister-NDA datasets, we instead use the TokenClassification model type, which is designed to classify all-document entities. The similar classifier is added to the pre-trained skeleton, now with a different usage in which each token/entity is to be classified into one of the number of given classes.

What’s more, to preprocess these two datasets, we have to ingest all available document tokens. Likewise, with documents longer than the maximum lengths, we need to cut those documents, and recursively treat the overflowing parts in the same way. In terms of implementation, unlike FunSD that is lightweight, we always want to avoid loading the whole dataset into the memory but rather taking advantage of the data buffering in feeding to the models. As a result, we pre-process all data first, save them to disks and only load the respective parts when needed.

Additional Information for Kleister-NDA

It is worth recalling that the evaluation of it is tricky if using the provided official GEval evaluation script (Grajński et al., 2020). In detail, given the predicted tokens, one has to retrieve the associated texts in a group. For example, the beginning of an entity group usually starts with a class beginning with “B-”, followed by a series of “I-” tokens. However, there is no guarantee that the prediction will always return a group having this meaningful pattern, let alone many other complicated cases that can happen. Such complications make the post-processing of the prediction— before feeding to GEval—very difficult and importantly, not easily reproducible. In fact, amongst recent papers that report performance on this dataset (e.g. in Xu et al. (2021a); Appalaraju et al. (2021)), there is reference code with which for us to compare.

Consequently, we treat this dataset the same as FunSD, given their similarity in annotation. In addition, because this dataset is larger and much more difficult (due to decoying texts) compared to FunSD, we analyze the train dataset and employ the weighted loss based on the distribution the given labels. As a result, our method is more transparent and reproducible.

C Additional Samples on Distance Masks

Complementary to Figures 3c and 3d, we present more distance masks based on real samples taken from RVL-CDIP with the same setting in Figure 6.