GMAT: Global Memory Augmentation for Transformers

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Abstract

Transformer-based models have become ubiquitous in natural language processing thanks to their large capacity, innate parallelism and high performance. The contextualizing component of a Transformer block is the pairwise dot-product attention that has a large $\Omega(L^2)$ memory requirement for length $L$ sequences, limiting its ability to process long documents. This has been the subject of substantial interest recently, where multiple approximations were proposed to reduce the quadratic memory requirement using sparse attention matrices. In this work, we propose to augment sparse Transformer blocks with a dense attention-based global memory of length $M$ ($\ll L$) which provides an aggregate global view of the entire input sequence to each position. Our augmentation has a manageable $O(M \cdot (L + M))$ memory overhead, and can be seamlessly integrated with prior sparse solutions. Moreover, global memory can also be used for sequence compression, by representing a long input sequence with the memory representations only. We empirically show that our method leads to substantial improvement on a range of tasks, including (a) synthetic tasks that require global reasoning, (b) masked language modeling, and (c) reading comprehension.

1 Introduction

The Transformer architecture [26] has been widely successful in achieving state-of-the-art performance on a wide range of natural language processing (NLP) tasks, including machine translation [4], language modeling [24], question-answering [8], and many more. In particular, Transformers pre-trained on large amounts of text with a language modeling (LM) objective, have become the de-facto standard in NLP, exhibiting surprising amounts of linguistic and world knowledge [18, 3, 12, 19, 6, 24]. Moreover, Transformers with tailored attention patterns have been successfully used to replace convolutions in computer vision [16, 15], and have also been useful in music generation [7], symbolic mathematics [11] and other modalities.

One of the most powerful features in Transformers is (pairwise) self-attention, where all positions in an input sequence aggregate information from the entire sequence in parallel. However, this requires computing a similarity score for all pairs of positions simultaneously, leading to a $\Omega(L^2)$ memory requirement for length $L$ sequences, which is prohibitively expensive for long sequences. To alleviate this issue, several sparsifications of vanilla self-attention have been recently proposed; each restricting the number of positions that a given position can attend to [28, 2, 21, 20, 9, 1]. For example, in BLOCKBERT [20], the sequence is split into $L/M$ chunks of length $M$ and positions in chunk $i$ only attend to positions in chunk $\sigma(i)$ for some pre-determined permutation $\sigma$, thereby having a $O(M \cdot L)$ memory requirement. The REFORMER [21] uses locality-sensitive hashing (LSH) to arrange similar vectors close to one another and then chunks them. Each chunk then attends to only a couple of chunks leading to a $O(M \cdot L)$ memory requirement. While such sparsifications often lead to performance that is comparable to vanilla Transformers, they have some undesirable consequences:
A position can require many layers to accumulate information from the entire input, and thus struggle when aggregating global information is necessary. For example, in §3.1, we show that a LSH Transformer (REFORMER without reversible connections) struggles on a simple tagging task that requires information from the entire sequence.

Most sparsification schemes pose an inductive bias based on the locality of natural language, by restricting a position to only attend to its nearby tokens. While this is often a reasonable assumption, it raises several concerns. First, it is trivial to construct examples where locality is violated. For example, vanilla attention is invariant to input permutation, and thus can handle tasks such as “word deshuffling”, where a randomly shuffled sequence needs to be mapped to the original order. On the other hand, any locality-based inductive bias would be detrimental. Second, progress in natural language understanding has led to increasing interest in handling global dependencies in long documents and even entire books [10], where a locality-based inductive bias is sub-optimal.

In this work, we propose **Global Memory Augmentation for Transformers (GMAT)**. We augment sparse variants of the Transformer with a small global memory which is read and updated by all the positions using vanilla attention. Specifically, we prefix every input sequence (of length $L$) with a list of $M$ memory tokens. At each multi-head attention layer, for each head (Figure 1a), the $L$ tokens of the main sequence attend to other tokens of the main sequence using any sparse variant of attention, whereas they attend to the $M$ memory tokens using vanilla dense attention. Moreover, the $M$ memory tokens attend to all $M + L$ tokens using vanilla attention. This results in a $O(M \cdot (L + M))$ memory overhead which is manageable for $M \ll L$. Because the number of parameters in Transformers does not depend on the length of the input (modulo learned positional embeddings), the number of parameters grows by only a negligible $M \cdot E$ parameters, for an embedding size $E$.

We propose also to use GMAT for sequence compression (Figure 1c). After encoding an input sequence with $N_c$ GMAT layers, we discard the vectors corresponding to the main sequence $X$, and keep only the global memory vectors, which are now a compressed representation of the entire input. The memory vectors are then processed and decompressed using $N_d$ layers back to the original input length. The sequence can now be stored using only $M (\ll L)$ vectors, and decompression is done with a small number $(N_d)$ of GMAT layers.

We evaluate GMAT on a wide range of tasks and show: (a) large improvements on synthetic tasks where global reasoning is required, (b) it improves masked language modeling (MLM) accuracy (used in Transformer pre-training), (c) improvements on two reading comprehension (RC) tasks, and last (d) moderate reductions in MLM and RC performance when using GMAT for compression.

To summarize, GMAT is a simple extension of the Transformers architecture, that can be seamlessly combined with any sparse attention variant. We show GMAT is useful for reducing memory requirements as well as for sequence compression, and demonstrate performance enhancements on a wide range of tasks. Our code and data can be downloaded from [https://github.com/ag1988/gmat](https://github.com/ag1988/gmat).

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1For brevity, we use the word *token* to refer both to the input token and its contextualized representation interchangeably.
2 Global-Memory Augmented Transformers

A Transformer [26] is a stack of layers each consisting of sub-layers such as multi-head attention, feed-forward, etc. Its contextualizing component is the multi-head attention defined as follows.

**Multi-head Attention** Given a query $Q \in \mathbb{R}^{L_Q \times d}$, key $K \in \mathbb{R}^{L_K \times d}$ and value $V \in \mathbb{R}^{L_K \times d}$, the output of scaled dot-product attention is defined as:

$$\text{Attention}(Q, K, V) = \text{softmax} \left( \frac{QK^T}{\sqrt{d}} \right) V.$$  \hspace{1cm} (1)

In multi-head attention, instead of computing a single attention output with $d_{\text{model}}$ dimensional keys, queries, and values, these are linearly projected down in parallel $h$ times to $d = d_{\text{model}}/h$ dimensions, using different learned projection matrices. Attention is applied to each of the $h$ new queries, keys and values, yielding $d$ dimensional outputs which are concatenated and again projected to obtain the $d_{\text{model}}$-dimensional output.

The attention function (Eq. 1) requires the computation of $QK^T$ containing $L_Q \cdot L_K$ entries and can be expensive for long sequences. To alleviate this issue, sparse attention variants relax this requirement and compute only a few entries of $QK^T$, masking out the rest. For a binary mask $B \in \{0, -\infty\}^{L_Q \times L_K}$,

$$\text{SparseAttention}(Q, K, V, B) = \text{softmax} \left( \frac{QK^T}{\sqrt{d}} + B \right) V.$$  \hspace{1cm} (2)

**Global Memory** As explained in §1, sparse attention variants have some undesirable properties. To remedy this, we augment such models with a small global memory which is read and updated by all the positions using vanilla attention (Figure 1b). Specifically, we prefix every token sequence $X$ (of length $L$) with a sequence of $M$ memory tokens $[m_1], \ldots, [m_M]$. At each multi-head attention layer of the model, at each head, the $L$ representations $X$ corresponding to the tokens of the main sequence attend to the other positions in $X$ using any sparse attention variant, but attend to the representations of all memory tokens $X_M$ normally (Eq. 3). Moreover, the memory tokens attend to all the $M + L$ tokens normally.

$$\widetilde{X} = \text{SparseAttention} \left( X, \left[ \begin{array}{c} X \\ X_M \end{array} \right], \left[ \begin{array}{c} X \\ X_M \end{array} \right], \left[ \begin{array}{c} B \\ 0 \end{array} \right] \right), \quad \widetilde{X}_M = \text{Attention} \left( X_M, \left[ \begin{array}{c} X \\ X_M \end{array} \right], \left[ \begin{array}{c} X \\ X_M \end{array} \right] \right).$$  \hspace{1cm} (3)

This results in an $O(M \cdot (L + M))$ memory overhead (manageable for $M \ll L$). Moreover, this does not add any parameters to the model, except for a negligible $M \cdot E$ parameters used to embed the $M$ new memory tokens with an embedding size of $E$.

**Chunked self-attention** To explore the limits of GMAT and highlight its ability to contextualize over multiple fragments via a memory, we work with chunked self-attention (Figure 1b), a simple sparsification method. In $C \times k$ chunked self-attention (Figure 1b), a sequence of length $C \times k$ is partitioned into $k$ contiguous chunks of length $C$. Each token within a given chunk uses vanilla (multi-head) attention to attend to tokens in its chunk in addition to the global memory but does not attend to other chunks. Hence, chunks interact with each other only via the memory. Without memory, training with $C \times k$ attention is equivalent to training with vanilla Transformer over a length-$C$ sequence. While more complex sparsification schemes are possible, this setup focuses on the ability to contextualize disjoint segments through the global memory only. Note that a single model can be used with different values of $C$ and $k$, as Transformer models are invariant to the length of their input, aside for positional embeddings, which we handle below. We use the notation $(C \times k, M)$ to denote a chunked self-attention model where the input sequence $X$ has length $C \times k$ with a global memory of size $M$.

**Positional Embeddings** As attention is invariant to order, it is important to supply the model with positional information corresponding to the individual tokens. Rather than have a distinct learnable vector for each position [26], we represent a position $p$ as a tuple $(q, r)$ where $r = p \mod 512$, and $q = [p/512]$. Each $0 \leq r < 512$ and $0 \leq q < 64$ has a distinct learnable vector.\footnote{The sparsity of $B$ can be leveraged via customized implementations of matrix product [2][1]. The positional} These particular values allow us to initialize the vectors for $r$ with the learned 512 positional embeddings of pre-trained LMs such as BERT.
embedding of $p$ is represented by the sum of the vectors corresponding to $q$ and $r$ and allows us to model positions up to $2^{15}$. Memory tokens have a fixed position, and thus positional embeddings are used only for the main sequence $X$.

### 2.1 Sequence Compression

Contextualized word representations \[18, 13\] improve performance compared to fixed word embeddings such as GloVe \[17\]. Unfortunately, some large models that compute contextualized representations do not fit on popular GPUs and need specialized hardware \[22\]. Instead of leaving this computation to the users, an appealing option might be to release pre-computed contextualized representations, at least for popular benchmarks, similar to word embeddings \[17\]. However, storing a vector for each position in a large corpus is expensive. A second natural motivation for GMAT is for sequence compression, i.e., using a small memory to represent a long sequence. This can dramatically reduce the overhead in storing pre-computing contextualized representations for large corpora.

Consider a $N$-layer GMAT with a memory of size $M$. We apply the $N$ model layers in 3 steps as shown in Figure 1. Given a length $L$ input sequence, let $W$ and $P$ denote its word and positional embeddings. First, the bottom $N_c$ layers are applied for compressing the entire information of the input sequence into just $M$ memory vectors $X^{(c)}_M$. The next $N_m$ layers are then applied only on the $M$ memory vectors resulting in richer representations $X^{(m)}_M$. This length $M$ sequence is restored to the original length $M + L$ by concatenating the positional embeddings $P$ and, finally, the remaining $N_d = N - N_c - N_m$ layers are applied for decompressing the information packed in $X^{(m)}_M$ into the final representations. Here, the positional embeddings $P$ act as queries for restoring the original input information from $X^{(m)}_M$.

The $M(\ll L)$ vectors $X^{(m)}_M$ can be efficiently serialized for later use and are decompressed using minimal post-processing into representations of length $L$. In §4.3 and §4.4, we show that using the decompressed representations leads to only a small performance degradation on masked language modeling and reading comprehension. We use positional embeddings $P$ in the decompression step and not the contextualized representation $X^{(c)}$ (Figure 1c), since we want the output to depend only on $M$ vectors instead of $M + L$.

**Comparison to Longformer** In contemporaneous work \[11\], the authors demonstrate the effectiveness of a sparse sliding window attention pattern combined with a global memory on multiple natural understanding tasks. In contrast to our work, the contribution of the global memory component is not evaluated, and is designed on a task-by-task basis. Moreover, attention scores for the memory and the main sequence are computed using separate sets of projection matrices, thereby introducing new parameters. In comparison, we demonstrate the utility of a global memory for various sparse attention patterns on synthetic, NLP and compression tasks, introducing a minimal set of new parameters.

### 3 Global Reasoning on Synthetic Data

We consider two synthetic datasets, where global reasoning over the entire input is required.

#### 3.1 Majority Tagging

Recently proposed sparse attention schemes exploit the locality of natural language \[8, 14\]. One exception is locality sensitive hashing (LSH) attention \[9\]. While in LSH attention, tokens are not bound to attend only within their proximity, it does limit the number of positions a token can attend to at each head. We examine the utility of adding GMAT to a LSH Transformer \[9\], that is, a Transformer that uses LSH attention, for a sequence tagging task.

MAJORITY($L, p$): Let $X = (x_1, \ldots, x_L)$ be a sequence of $L$ integers from the set $\{1, \ldots, 2p\}$. Let $N_i$ denote the number of occurrences of $i$ in $X$. For every even integer $i$ in the domain, define

$$\text{maj}(i - 1) = \text{maj}(i) = \begin{cases} i - 1 & N_{i-1} \geq N_i \\ i & \text{otherwise} \end{cases}.$$ 

Then the majority sequence is defined to be $(\text{maj}(x_1), \ldots, \text{maj}(x_L))$. Note that for $p = 1$, the task requires tagging all tokens of $X$ by their mode.
Figure 2: Evaluation exact match (EM) of LSH Transformer on the MAJORITY($L, p$) task of §3.1. $M$ denotes the memory size. Models in the same figure use the same hyperparameters.

To create the data, we sampled the elements of $X$ independently and uniformly from the domain. After training a 2-layer LSH Transformer on the above task (Figure 2a) we compared its performance with and without a global memory of size $M = 8$. Hyperparameters for LSH attention (bucket size, rounds of hashing, etc.) were used as suggested by [9] and the other hyperparameters (hidden size, etc.) were taken from BERT-base (without dropout). As shown in Table 1, we found that LSH attention failed to do well on the MAJORITY($8192, 1$) task. On much shorter inputs of length 512, it managed to do well on MAJORITY($512, 1$) but again struggled on a slightly more complex task of MAJORITY($512, 3$). Conversely, GMAT obtains near perfect performance on these tasks.

| $M$ | MAJORITY($8192, 1$) | MAJORITY($512, 1$) | MAJORITY($512, 3$) |
|-----|---------------------|---------------------|---------------------|
| 0   | 0.15                | 0.92                | 0.86                |
| 8   | 0.98                | 1.0                 | 0.98                |

Table 1: Evaluation exact match (EM) of a 2-layer LSH Transformer on majority tagging. EM for an example is 1 iff every position is tagged correctly. $M$ denotes the memory size.

To determine if GMAT also leads to lower sample complexity in deeper models, we trained (Figure 2b) a 12-layer model on MAJORITY($1792, 4$) and found GMAT obtains better performance with lower sample complexity. This suggests that in LSH attention, while a certain level of sparsity works well when information is mostly local, it can be too restrictive for inherently global tasks.

### 3.2 Numerical Reasoning Over Text

Having shown the utility of GMAT on a combinatorial task, we now transition towards language tasks. We create a pseudo-textual task that requires global mathematical reasoning by generating examples from a rule-based generator from [5]. The generator generates examples that include a passage $P$, describing a sequence of related events, and a question $Q$ that requires aggregating information from various parts of $P$ and performing numerical reasoning to arrive at a numeric answer $A$ (see Table 2).

**P:** The commander recruited 358 households and 9669 Italian troops. The commander lost 812 of the households. The commander recruited 542 households in France. The commander recruited 3075 households in France. The commander recruited 2843 households and 5413 Native American troops.

**Q:** How many more Italian troops did the commander have than Native American troops? $A$: 4256

Table 2: An example from the textual synthetic data used in §3.2

Following [5], we train a generative encoder-decoder model, GENBERT, on the generated data after replacing the encoder self-attention [26] with chunked self-attention [2], and compare the performance before and after GMAT augmentation (see training and data details in §A.1). We summarize the results in Table 3. Compared to vanilla attention over the entire input (i.e., ($140 \times 1$, 0)), chunking the encoder input into 2 chunks significantly reduced the performance (i.e., ($70 \times 2$, 0)), in line with the global nature of the task. Surprisingly, adding a global memory of size 30 reduced accuracy even further. We hypothesize this is due to the strict weight-tying strategy employed by GENBERT, where the parameters of the Transformer encoder and decoder are tied, leading to underfitting. To handle that, we untie the parameters of the projection matrices that update the memory representations $X_M$ in all attention heads (Eq. [3] right), initializing them randomly. This separates the attention heads that update the main sequence from the heads that update the memory. In this setup, accuracy improved substantially, almost recovering the performance of vanilla attention.
4 Masked Language Modeling

One of the biggest success stories of Transformers is as an architecture for pre-training LMs. We now investigate pre-training GMAT with a masked language modeling objective, as a memory-efficient replacement for models such as BERT \cite{devlin2018bert, radford2019language}. Past work has shown strong correlation between performance on the MLM task and that on downstream applications \cite{devlin2018bert, jain2019transformer}. For our experiments, we use the BERT-base architecture \cite{devlin2018bert} after making the modifications described in §2.

We form examples by sampling sequences of length \( L \) from English Wikipedia and the PG19 dataset, and replacing sub-words with the [MASK] token following the procedure in \cite{devlin2018bert} (details in §A.2). The model is trained to maximize the log probability of the masked out tokens. We evaluate the error of the model as the fraction of tokens predicted incorrectly, and the MLM “perplexity” as the reciprocal of the geometric mean of probabilities of all masked out tokens.\footnote{Equivalently, the natural exponential of the average loss over the development set.}

PG19 contains 29K long books, and is thus likely to benefit from modeling long context, while in Wikipedia most articles are short and can fit into the 512 word pieces that are the input of BERT. We experiment with training a Transformer from scratch, as well as initializing with BERT-base.

\subsection{Random Initialization}

As shown in Figure 3a, we train 3 models on Wikipedia. The setting \((512 \times 1, 0)\) corresponds to standard MLM training on instances of length 512 without global memory. Similarly, \((1024 \times 1, 0)\) denotes training with vanilla attention over a context of size 1024, incurring a large memory penalty.\footnote{We do not train in the \((2048 \times 1, 0)\) setting due to memory constraints.}

Lastly, in \((512 \times 4, 64)\), a 2048-long context is chunked into four 512-chunks that have to interact via a global memory of size 64. Increasing the context size to 1024 improves MLM performance on Wikipedia (Table 4). Using global memory improves sample complexity and performance compared to training on 512-long instances, albeit only moderately. Thus, the chunks are able to leverage global memory to exchange information, alleviating the context fragmentation problem \cite{radford2019language}.

We evaluate the error for the MLM task in 3 different setups.

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|}
\hline
setting & \((512 \times 1, 0)\) & \((512 \times 4, 64)\) & \((1024 \times 1, 0)\) \\
\hline
best evaluation error / perplexity & 33.67 / 5.14 & 33.25 / 5.11 & 31.53 / 4.64 \\
\hline
\end{tabular}
\caption{MLM training on Wikipedia from random initialization for 431K steps. Error denotes the percentage of masked tokens predicted incorrectly.}
\end{table}

\subsection{BERT Initialization}

To show that GMAT can be easily integrated into existing pre-trained LMs, we take a pre-trained BERT-base model, and further train it using GMAT. Because BERT was pre-trained on Wikipedia, improving performance on Wikipedia itself could be difficult, as it already has high confidence on tokens from this corpus. Hence, we also train on PG19, which was not part of BERT’s training data.
Table 5 summarizes the results. On Wikipedia, increasing the context size to 1024 provides a significant improvement (Figure 5b), but global memory does not improve performance compared to standard MLM training on 512-long instances. However, on PG19 (Figure 3e) using global memory substantially improves perplexity from 4.4 → 4.35, closing roughly half the gap from using a context of size 1024, which obtains an MLM perplexity of 4.3. This hints that the lack of improvement on the Wikipedia data might be due to the fact that BERT was pre-trained on Wikipedia.

| setting | BERT (no training) | (512 × 4, 0) | (512 × 4, 64) | (1024 × 2, 0) | (8 × 64, 0) | (8 × 64, 64) |
|---------|--------------------|--------------|---------------|---------------|------------|-------------|
| Wikipedia | 35.2 / 6.856 | 29.163 / 3.953 | 29.15 / 3.956 | 28.74 / 3.87 | 29.163 / 3.953 |
| PG19 | 42.5 / 10.37 | 31.90 / 4.40 | 31.72 / 4.35 | 31.44 / 4.30 | - | - |

Table 5: Evaluation error / perplexity for MLM training. Models are initialized with BERT-base, except for (8 × 64, 0), (8 × 64, 64), which are initialized with the trained models (512 × 4, 0), (512 × 4, 64) respectively.

The above results indicate that disjoint text segments can exchange useful information via global memory. However, because natural language has a locality bias, the utility of memory diminishes as the chunk length C increases. To determine the efficacy of GMAT when C is small, where contextualization should highly depend on the memory, we experiment with chunks of size 8. As expected, without access to a reasonably-large surrounding context, the model (8 × 64, 0) fails to predict masked tokens (Table 5). Interestingly, a small global memory of size 64 significantly improves performance (53.11 → 32.98 error, 20.68 → 4.94 perplexity), reaching performance that is close to (512 × 4, 0). We further evaluate the pre-trained GMAT models on reading comprehension tasks in §4.4.

### 4.3 Sequence Compression

We turn to sequence compression, where our goal is to compress a sequence of length L into M vectors that can be saved and later decompressed back into a sequence of length L, with minimal drop in performance. Using the setup described in §2.1 we use Nc compression layers, followed by Nd = N − Nc decompression layers, and train with the same data and MLM objective as above on Wikipedia. As shown in Table 6, we found that Nc = 9 outperforms Nc = 3 (which also happens to be well-aligned with our need for a small number of decompression layers). Compared to a model without compression, we observe a moderate degradation in performance (29.163 → 32.98 error, and 3.953 → 5.017 MLM perplexity), showing that a global memory of size just 64 provides a compact and useful representation for the entire sequence of length 512.

| setting | (512 × 4, 0) | (512 × 1, 64), Nc = 3 | (512 × 1, 64), Nc = 9 |
|---------|--------------|-------------------|-----------------|
| initialization | BERT | (512 × 4, 64) | (512 × 4, 64) |
| best evaluation error / perplexity | 29.163 / 3.953 | 33.44 / 5.112 | 32.98 / 5.017 |

Table 6: MLM training on Wikipedia with compression. Compressed models were initialized with the (512 × 4, 64) model trained in §4.2 and further trained for 440K steps.

### 4.4 Reading Comprehension Performance

While MLM performance is known to correlate well with downstream applications [13, 22], we take Wikipedia-based GMAT models trained with the MLM objective in §4.2 and §4.3 and further fine-tune them on reading comprehension (RC) tasks.

**SQUAD** We first fine-tune on SQUAD v1 [23], using the simple sliding-window based approach of [3]. Similar to past work [12], we limit the input size to 384 tokens, as most paragraphs are relatively short. We train all models using identical hyperparameters. Summarized in Table 7, the model (512 × 4, 64) improves performance over BERT (88.6 → 89.2 F1), indicating global memory helps even with vanilla self-attention. The performance of (512 × 4, 0) is very similar to BERT, ruling out the possibility that the performance of (512 × 4, 64) was a result of extra pre-training on Wikipedia. Surprisingly, the model (8 × 64, 64) reported 84.2 F1, a moderate drop in performance given that, with chunks of size 8, the contextualization depends almost entirely on the memory. Interestingly, the compression model with Nc = 9 reported 87.1 F1 (compared to BERT’s 88.6) an impressive score given that, after 9 layers, the information of the entire input must pass through only 64 vectors.
### Table 7: Evaluation EM/F₁ on SQUAD v1.

| Model       | (512 × 4, 0) | (512 × 4, 64) | (64 × 64, 64) | (8 × 64, 0) | (512 × 1, 64) | (512 × 1, 64) |
|-------------|--------------|--------------|--------------|------------|--------------|--------------|
| EM          | 81.09 / 88.60 | 80.93 / 88.47 | 81.77 / 89.16 | 75.64 / 84.17 | 9.82 / 14.60 | 61.6         |
| F₁          | 79.55 / 87.05 | 71.68 / 86.95 | 79.35 / 87.05 | 78.02 / 86.95 | 64.0         | 68.3         |

### Table 8: F₁ scores on HOTPOTQA GS development set.

| model | SF task included | BERT (512 × 4, 64) |
|-------|------------------|--------------------|
|       | no               | yes                |
| all   | 66.3             | 66.3               |
| only-comparison | 61.6             | 61.6               |

### Table 9: F₁ on HOTPOTQA GS+QR and ADV-HOTPOTQA GS+QR development sets.

| model             | (512 × 4, 0) | (512 × 4, 64) |
|-------------------|--------------|--------------|
| SF task included  | no           | yes          |
| HOTPOTQA GS+QR    | 65.4         | 66.4         |
| ADV-HOTPOTQA GS+QR| 62.6         | 64.0         |

### 5 Conclusion

In this work, we proposed GMAT, a simple extension to the Transformer architecture that allows a better trade-off between compute and performance and can be naturally used for sequence compression. Our approach can be seamlessly integrated with the increasingly-popular sparse Transformer variants. We show GMAT (a) leads to performance improvements on a wide range of tasks, and (b) can be used to compress long sequences by factor of 8× with only a small degradation in performance.


**Broader Impact**

Transformers have become a popular architecture for sequence processing and generation in natural language processing and outside of it. The goal of this paper it to reduce the memory requirement and thereby allow for longer sequences to be processed. Moreover, our compression technique can facilitate the use of pre-computed contextualized representations, allowing users access to an approximation of these representations even if they cannot compute the representations from scratch themselves. As such, we consider a positive impact of this work to be the ability of more users with constraints on their computational resources to use the Transformer architecture and its pre-trained representations. Moreover, being able to process long documents can open the door to new applications in natural language processing, such as multiple-document understanding, and perhaps also processing of sequences outside of NLP, for example in Biology. As Transformers are becoming ubiquitous in machine learning, naturally any negative impact that can be attributed to Transformers (fake news generation, classifiers in sensitive domains such as the justice system and healthcare) are also inherited by our approach, and perhaps enhanced when long sequences need to be processed.

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**References**

[1] I. Beltagy, M. E. Peters, and A. Cohan. Longformer: The long-document transformer. *arXiv preprint arXiv:2004.05150*, 2020.
[2] R. Child, S. Gray, A. Radford, and I. Sutskever. Generating long sequences with sparse transformers. *arXiv preprint arXiv:1904.10509*, 2019.
[3] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In *North American Association for Computational Linguistics (NAACL)*, pages 4171–4186, Minneapolis, Minnesota, June 2019.
[4] S. Edunov, M. Ott, M. Auli, and D. Grangier. Understanding back-translation at scale. In *Empirical Methods in Natural Language Processing (EMNLP)*, 2018.
[5] M. Geva, A. Gupta, and J. Berant. Injecting numerical reasoning skills into language models. In *ACL*, 2020.
[6] J. Hewitt and C. D. Manning. A structural probe for finding syntax in word representations. In *North American Association for Computational Linguistics (NAACL)*, pages 4129–4138, 2019.
[7] C.-Z. A. Huang, A. Vaswani, J. Uszkoreit, I. Simon, C. Hawthorne, N. Shazeer, A. M. Dai, M. D. Hoffman, M. Dinculescu, and D. Eck. Music transformer. In *International Conference on Learning Representations*, 2019.
[8] V. Karpukhin, B. Oğuz, S. Min, L. Wu, S. Edunov, D. Chen, and W.-t. Yih. Dense passage retrieval for open-domain question answering. *arXiv preprint arXiv:2004.04906*, 2020.
[9] N. Kitaev, L. Kaiser, and A. Levskaya. Reformer: The efficient transformer. In *International Conference on Learning Representations*, 2020.
[10] T. Kočiský, J. Schwarz, P. Blunsom, C. Dyer, K. M. Hermann, G. Melis, and E. Grefenstette. The narrativeqa reading comprehension challenge. *Transactions of the Association for Computational Linguistics*, 6:317–328, 2018.
[11] G. Lample and F. Charton. Deep learning for symbolic mathematics. In *International Conference on Learning Representations*, 2020.
[12] Z. Lan, M. Chen, S. Goodman, K. Gimpel, P. Sharma, and R. Soricut. Albert: A lite bert for self-supervised learning of language representations. In *International Conference on Learning Representations*, 2020.
[13] Y. Liu, M. Ott, N. Goyal, J. Du, M. Joshi, D. Chen, O. Levy, M. Lewis, L. Zettlemoyer, and V. Stoyanov. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*, 2019.
[14] S. Min, E. Wallace, S. Singh, M. Gardner, H. Hajishirzi, and L. Zettlemoyer. Compositional questions do not necessitate multi-hop reasoning. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4249–4257, 2019.
[15] N. Parmar, P. Ramachandran, A. Vaswani, I. Bello, A. Levskaya, and J. Shlens. Stand-alone self-attention in vision models. In Advances in Neural Information Processing Systems, pages 68–80, 2019.

[16] N. Parmar, A. Vaswani, J. Uszkoreit, L. Kaiser, N. Shazeer, and A. Ku. Image transformer. CoRR, abs/1802.05751, 2018.

[17] J. Pennington, R. Socher, and C. D. Manning. GloVe: Global vectors for word representation. In Empirical Methods in Natural Language Processing (EMNLP), pages 1532–1543, 2014.

[18] M. E. Peters, M. Neumann, M. Iyyer, M. Gardner, C. Clark, K. Lee, and L. Zettlemoyer. Deep contextualized word representations. In North American Association for Computational Linguistics (NAACL), 2018.

[19] F. Petroni, T. Rocktäschel, P. Lewis, A. Bakhtin, Y. Wu, A. Miller, and S. Riedel. Language models as knowledge bases? In Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP), 2019.

[20] J. Qiu, H. Ma, O. Levy, S. W.-t. Yih, S. Wang, and J. Tang. Blockwise self-attention for long document understanding. arXiv preprint arXiv:1911.02972, 2019.

[21] J. W. Rae, A. Potapenko, S. M. Jayakumar, C. Hillier, and T. P. Lillicrap. Compressive transformers for long-range sequence modelling. In International Conference on Learning Representations, 2020.

[22] C. Raffel, N. Shazeer, A. Roberts, K. Lee, S. Narang, M. Matena, Y. Zhou, W. Li, and P. J. Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. arXiv preprint arXiv:1910.10683, 2019.

[23] P. Rajpurkar, J. Zhang, K. Lopyrev, and P. Liang. SQuAD: 100,000+ questions for machine comprehension of text. In Empirical Methods in Natural Language Processing (EMNLP), 2016.

[24] A. Roberts, C. Raffel, and N. Shazeer. How much knowledge can you pack into the parameters of a language model? ArXiv, abs/2002.08910, 2020.

[25] A. Roy, M. Saffar, A. Vaswani, and D. Grangier. Efficient content-based sparse attention with routing transformers. arXiv preprint arXiv:2003.05997, 2020.

[26] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin. Attention is all you need. In Advances in Neural Information Processing Systems (NIPS), pages 5998–6008, 2017.

[27] T. Wolf, L. Debut, V. Sanh, J. Chaumond, C. Delangue, A. Moi, P. Cistac, T. Rault, R. Louf, M. Fundtowicz, and J. Brew. Huggingface’s transformers: State-of-the-art natural language processing. ArXiv, abs/1910.03771, 2019.

[28] Z. Yang, Z. Dai, Y. Yang, J. Carbonell, R. R. Salakhutdinov, and Q. V. Le. Xlnet: Generalized autoregressive pretraining for language understanding. In Advances in neural information processing systems, pages 5754–5764, 2019.

[29] Z. Yang, P. Qi, S. Zhang, Y. Bengio, W. W. Cohen, R. R. Salakhutdinov, and C. D. Manning. Hotpotqa: A dataset for diverse, explainable multi-hop question answering. In EMNLP, 2018.

[30] Z. Ye, Q. Guo, Q. Gan, X. Qiu, and Z. Zhang. Bp-transformer: Modelling long-range context via binary partitioning. arXiv preprint arXiv:1911.04070, 2019.
A Supplemental Material

A.1 Details of the Numerical Reasoning Task

For creating the textual synthetic data for the generative QA task of §3.2, we used the data generation set-up of [5] (§4.2 of [5]). Default templates and vocabulary were used to create passages containing 5 sentences. While instantiating the templates, the probability of sampling from one of the previously used values was set to 0.999 to promote inter-sentence dependencies. This gave us 629906/15K train/dev passage-question-answer triples. Among these, we only kept the samples where the answer was a number not appearing in the passage, and discarded the rest. This gave us 223067 training and 5146 evaluation instances.

We only kept the decoder/generative head of GENBERT (§3 of [5]) and allowed the decoder to attend to all the encoder outputs in the cross-attention layers. As the weights of the encoder and decoder are tied, we used segment ids 0 for the encoder input sequence and 1 for the decoder inputs.

A.2 Data for Masked LM task

The instances for the MLM task (§4) were formed separately using 5.2M pages from English Wikipedia (October 2017 dump) and the training set of PG19 dataset containing ∼29K books from Project Gutenberg [21]. For each dataset, after appending a special symbol at the end of each document, the documents were arranged in a random order and concatenated into a single long text which was then tokenized into a list of tokens. Depending upon the input length $L$ of the experiment (512/1024/etc) this list was chunked into full length $L - 2$ sequences which were then masked randomly following [3] and enclosed within [CLS] and [SEP] tokens. For each dataset, the first 2.55B tokens (i.e. $510 \times 5M$) were used to form the respective training set, next 10.20M tokens ($510 \times 20K$) the dev set and the rest were discarded.

A.3 Finetuning on HOTPOTQA

Given the question $Q$ and 10 arranged paragraphs $P_i$’s, each $P_i$ is extended by prefixing it with its title. Moreover, to handle yes/no questions, a special string $<$a> yes no </a> is also prefixed. The context $D$ is formed by simply concatenating the resulting paragraphs. Following [3], given a window/chunk $P$ from tokenized $D$, the corresponding instance is formed as $[CLS] Q [SEP] P [SEP]$.

Supporting Facts Tagging Task (SF): Besides the standard span extraction loss, we also include another task using the supporting facts supervision. Contextualized representations of the model are linearly projected to 2 scores (for 0/1) per token and normalized to obtain log-probabilities. For an input, loss is computed as negative log probability of the correct tag averaged over the positions. As supporting facts positions are fewer, log-probabilities are weighted according to the respective class (0/1) size.

Adversarial data generation: After training the single-paragraph model of [14] on HOTPOTQA, for each sample in the training and development sets, we retrieved top 50 introductory paragraphs from Wikipedia according their TF-IDF similarity with the question. The 50 paragraphs were then re-ranked using the "no-answer-logit" score predicted by the trained model and 8 adversarial distractors were chosen accordingly. When evaluated on the adversarial version of the development set the performance of the trained model reduced from 64.4 $\rightarrow$ 57.8 F1. Re-training on the adversarial data increased the performance to 61.3. In both cases, we trained for 10 epochs with batch size 36, maximum sequence length 300 and learning rate $5e-5$ with linear warmup proportion 0.1.

A.4 Hyperparameters

For all our experiments, we used an older version of Hugging Face’s Transformers library [27]. For convenience, we denote the training hyperparameters using the following abbreviations, INS: number of training instances, BSZ: number of instances in a batch, ISZ: instance size, SQL: final input sequence length, LR: learning rate, WRM: linear LR warm-up proportion, EP: number of epochs, STP: number of optimizer steps, GAC: gradient accumulation steps, POSq: whether (y/n) q part is included in positional embeddings defined in §2.
The hyperparameters for majority tagging are in Table 12, for GENBERT finetuning in Table 13, for MLM trainings in Table 10, for SQUAD finetuning in Table 11, and for HOTPOTQA finetuning in Table 14.

Table 10: Training hyperparameters for MLM training (§4). Common parameters: INS=5M, dropout-rate=0.1, optimizer=Bert-Adam, weight-decay=0.01, max-grad-norm=1.0, seed=42. If STP specified, training is terminated after STP many optimizer steps.

Table 11: Training hyperparameters for SQUAD v1 finetuning (§4.4). POSq for a model is same as during its pre-training. Common parameters: maximum query length=64, window-stride-length=128, dropout-rate=0.1, optimizer=Bert-Adam, weight-decay=0.01, max-grad-norm=1.0, seed=42.

Table 12: Training hyperparameters for majority tagging task (§3.1). Common parameters: init=random, dropout-rate=0.0, optimizer=Bert-Adam, weight-decay=0.01, max-grad-norm=1.0, seed=42.

Table 13: Training hyperparameters for GENBERT finetuning (§3.2). Common parameters: init=BERT, INS=223067, POSq=n, dropout-rate=0.1, optimizer=Bert-Adam, weight-decay=0.01, max-grad-norm=1.0, seed=42.

Table 14: Training hyperparameters for finetuning on HOTPOTQA variants (§4.4). Common parameters: maximum query length=64, dropout-rate=0.1, optimizer=Bert-Adam, weight-decay=0.01, max-grad-norm=1.0, seed=42.