LongT5: Efficient Text-To-Text Transformer for Long Sequences

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Abstract

Recent work has shown that either (1) increasing the input length or (2) increasing model size can improve the performance of Transformer-based neural models. In this paper, we present a new model, called LongT5, with which we explore the effects of scaling both the input length and model size at the same time. Specifically, we integrated attention ideas from long-input transformers (ETC), and adopted pre-training strategies from summarization pre-training (PEGASUS) into the scalable T5 architecture. The result is a new attention mechanism we call Transient Global (TGlobal), which mimics ETC’s local/global mechanism, but without requiring additional side-inputs. We are able to achieve state-of-the-art results on several summarization tasks and outperform the original T5 models on question answering tasks.

1 Introduction

Transformer models such as BERT (Devlin et al., 2019), and other variants (Liu et al., 2019; Radford et al., 2019; Raffel et al., 2019a; Lewis et al., 2020) have achieved state-of-the-art results on many challenging NLP tasks. Moreover, recent work in long-input transformers (Ainslie et al., 2020; Zaheer et al., 2020b; Beltagy et al., 2020; Tay et al., 2021) has shown that increasing the input length of a Transformer is able to process results in further performance gains. Additionally, it is also known that increasing model size also leads to performance gains in many tasks (Kaplan et al., 2020).

In this paper, we present a new model, called LongT5, with which we explore the effects of scaling both the input length and model size at the same time. To achieve this, we integrate long-input transformer attention and pre-training ideas into the scalable T5 (Raffel et al., 2019a) model architecture. The resulting model, as shown in Figure 1, achieved state-of-the-art performance on several summarization tasks like arXiv and PubMed (Cohan et al., 2018), which require handling long sequence inputs.

Regarding attention, we designed a new attention mechanism, which we call Transient Global (TGlobal), that mimics ETC’s local/global mechanism (Ainslie et al., 2020). Importantly, TGlobal attention removes the need for the additional side inputs in ETC, in order to fit within the T5 architecture. The main idea of ETC’s local/global mechanism is to introduce local sparsity in the attention mechanism to reduce the quadratic cost when scaling to long inputs. Specifically, ETC only allows tokens in the input (called the long input) to attend to a local neighborhood, and adds a secondary input called the global memory, through which tokens in the long input can attend to each other indirectly. One disadvantage of this mechanism is that it requires designing this secondary global input for each new problem. In order to adapt it to T5, our new TGlobal mechanism synthesizes these global tokens on the fly (as aggregations of groups of tokens in the input), at each attention layer. Our ex-
experiments show that this mechanism results in only a small degradation in performance with respect to full attention in the same input length but allows the model to scale to much larger input lengths, resulting in significant performance gains.

Regarding pre-training, we adopt the pre-training strategy in the PEGASUS (Zhang et al., 2019a) model. This pre-training strategy was originally designed for abstractive summarization, but in our experiments, we found it also improves model performance for other tasks, such as question answering, and hence we adopted it in LongT5. The key idea is to mask out key (principle) sentences from a document and ask the model to reproduce them as a single string, as if it was a summary.

We evaluate LongT5 on a collection of summarization and question answering tasks: CNN/Daily Mail, PubMed, arXiv, BigPatent, MediaSum, Multi-News, TriviaQA, and Natural Questions (see Sections 4.2.1 and 4.3.1 for a description of each of these datasets). Thanks to the scaling of both input length and model size, we achieve state-of-the-art results on four of the six evaluated summarization datasets, namely: arXiv, PubMed, BigPatent, and MediaSum. For the question answering tasks, we used a slightly different formulation than the original tasks, and hence we do not make any state-of-the-art claims.

The main contributions of this work are:

• A new Transformer architecture, LongT5, that allows for scaling both input length and model scale at the same time.

• A new attention mechanism (TGlobal), which mimics ETC’s local/global mechanism but is a drop-in replacement to regular attention and can be used within existing Transformer architectures like T5.

• An analysis of model performance when varying both input length and model size of vanilla T5 and LongT5 models (pushing both models up to the maximum lengths they can handle before encountering memory issues), to understand the trade-offs in both performance and computation cost.

• State-of-the-art results on the arXiv, PubMed, BigPatent, and MediaSum datasets.

2 T5

T5 (Raffel et al., 2019a) is a transformer based text-to-text pre-trained language model that is gaining popularity for its unified framework that converts all text-based language problems into a text-to-text format, and its ease to scale up in number of parameters (from 60M to 11B parameters) with model parallelism. With full attention transformer, T5 has been successfully applied to many NLP tasks, but the tasks only require shorter input sequence. This is due to the limitation of quadratic computation growth with respect to input sequence length, resulting in larger memory consumption and longer training time. Recently, Press et al. (2021) explored scaling up T5 style models at inference time to longer sequences than seen during training, but how to scale up T5 style models in the input sequence length during training remains underexplored.

3 LongT5

3.1 Architecture

We extend the original T5 encoder with global-local attention sparsity patterns (Ainslie et al., 2020; Zaheer et al., 2020a) to handle long inputs. For the work reported in this paper, we used a standard T5 decoder since all of the tasks we considered require relatively short output sequence lengths.

Architecturally, the main difference between T5 and LongT5 lies in the attention mechanism. We experiment with two attention mechanism variations for LongT5, illustrated in Figure 2: (1) Local Attention and (2) Transient Global Attention (TGlobal). Both variations preserve several properties of T5: relative position representations, support for example packing, and compatibility with T5 checkpoints.

3.1.1 Local Attention

For Local Attention, we simply replace the encoder self-attention operation in T5 with a sparse sliding-window local attention operation following the implementation in ETC (Ainslie et al., 2020). Specifically, for a given local radius r, this formulation only allows each token to attend r tokens to the left and right of it (see Figure 2.a). We found r = 127 to be sufficient in practice, where r is the number of neighboring tokens to the left and to the right.

Local Attention does not introduce any new parameters and easily accommodates the attention masking required for example packing. For a

1Example packing refers to packing more than one short
Each input token can attend to its neighborhood \( r \) tokens to the left, and \( r \) tokens to the right.

The rest of the parameters are identical to T5, and we accommodate sequence packing by additionally masking attention from input tokens to global tokens of other examples. We found block size \( k = 16 \) to be sufficient in practice. Notice thus, that TGlobal attention introduces a block of \( l \times l/k \) additional attention key-value pairs to calculate on top of Local Attention (\( l \) input tokens, attending to \( l/k \) global tokens; represented by the right most rectangle in Figure 2.b), hence for input sequence length \( l \), complexity is \( O(l(r + l/k)) \).

3.2 **PEGASUS Principle Sentences Generation Pre-training**

T5 is pre-trained with a span corruption objective, where consecutive spans of input tokens are replaced with a mask token and the model is trained to reconstruct the masked-out tokens. While it is effective, recent work on masked language modeling (MLM) (Liu et al., 2019; Zhang et al., 2019b) shows that carefully selecting the prediction objective could lead to significantly better performance. One argument is that predicting more informative tokens from the text could force the model to learn better semantics of the text. Motivated by that, we explore masking and generating the principle sentences from the text. In particular, we adopt the Gap Sentences Generation with **Principle Ind-Uniq** strategy from Zhang et al. (2019a), which was used for summarization pre-training.

Following Zhang et al. (2019a), we select top-\( m \) scored (**Principle**) sentences based on ROUGE-F1 score (Lin, 2004) using formula 

\[
s_i = \text{rouge}(x_i, D \setminus \{x_i\}, V_i),
\]

where \( i \) is the sentence...
index, $D$ is the collection of sentences in the document. Each sentence is scored independently (Ind), and each $n$-gram is only counted once (Uniq) during the calculation.

4 Experiments

4.1 Configurations

LongT5 is implemented using JAX$^3$ and the Flaxformer$^4$ library. Following the same setup as T5.1.1$^5$, we consider models of 3 sizes: base ($\sim 220M$), large ($\sim 770M$), and xl ($\sim 3B$), and use the same cased English SentencePiece vocab model used by T5.1.1, which contains 32000 sentence pieces. We use batch size of 128 and Adafactor as the optimizer in all experiments.

4.1.1 Pre-training

We pre-train LongT5 models for 1M steps on 4096 input sequence length and 910 output sequence length. We use the same inverse square-root learning rate schedule as T5, with learning rate set to $1/\sqrt{\text{max}(\text{step}, \text{warm}_\text{up \ steps})}$, where warm_up steps is set to 1000. The same as T5.1.1, we pre-train LongT5 only on the C4 dataset (Raffel et al., 2019b), and we do not apply dropout during pre-training. As described in section 3.2, we use the PEGASUS Principle Sentences Generation objective as our pre-training objective. The configuration is similar to what was described by Zhang et al. (2019a) for their larger models, except for the masked sentence ratio in which we use a value of 0.2 instead of 0.45$^6$. In section 5.3, we will show our ablation study between Principle Sentences Generation and Span Corruption.

4.1.2 Fine-tuning

For fine-tuning, we use a constant learning rate of 0.001 and dropout rate of 0.1 for all tasks. For summarization tasks, we experiment with values of 4096, 8192, and 16384 for input lengths and 512 for output lengths. For QA tasks, we experiment with values starting at 512 and scale up to 36864 for input lengths and 128 for output lengths.

4.2 Evaluation on Summarization Tasks

We choose to benchmark our models on summarization tasks that cover various context lengths, because of their long context understanding and generative nature.

4.2.1 Datasets

LongT5 was benchmarked on the following six datasets.

**CNN / Daily Mail** (Nallapati et al., 2016) News articles from CNN and Daily Mail are used as input and the article’s summary bullets used as the target summary.

**PubMed** (Cohan et al., 2018) Scientific documents were collected from PubMed, with a document’s content used as input and its corresponding abstract as the target summary.

**arXiv** (Cohan et al., 2018) Similar task to PubMed, with the collection of documents taken from arXiv.

**BigPatent** (Sharma et al., 2019) U.S. patent documents were collected, with the patent’s details used as input and the patent’s abstract as the target summary.

**MediaSum** (Zhu et al., 2021) Interview transcripts from CNN and NPR were used as input and their corresponding topic and overviews used as the target summary.

**Multi-News** (Fabbri et al., 2019) The task involves summarizing multiple news documents about a topic into a human-written summary.

4.2.2 Dataset Stats

Table 1 provides statistics for the number of examples in train, validation, and test splits, and the average, median, max, and 90th percentile input sequence length. As can be seen, these datasets are long in input length, and would benefit from models that can model lengthier inputs. We included the CNN / Daily Mail dataset to benchmark on a common task, especially to see how using TGlobal attention impacts the model, despite the length of the inputs being smaller than the other datasets.

4.2.3 Results

We compare LongT5 with various top approaches: BigBird-PEGASUS (Zaheer et al., 2020b), HAT-BART (Rohde et al., 2021), DANCER PEGASUS (Gidiotis and Tsoumakas, 2020), PRIMER (Xiao et al., 2021), TG-MultiSum (Cui and Hu, 2021), LED (Beltagy et al., 2020), and an application of BART by Zhu et al. (2021). For these comparisons, we use common evaluation metrics of ROUGE-1, ROUGE-2, and ROUGE-L.

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$^3$https://github.com/google/jax  
$^4$https://github.com/google/flaxformer  
$^5$https://github.com/google-research/text-to-text-transfer-transformer/blob/main/released_checkpoints.md#t511  
$^6$We briefly experimented with other values, but found 0.2 to work best with the downstream tasks of interest.
| Dataset                  | Example Count | Input Length |
|-------------------------|---------------|--------------|
|                         | Train | Validation | Test | Average | Median | Max  | 90th percentile |
| **CNN / Daily Mail**    | 287,113 | 13,368 | 11,490 | 982.39 | 894 | 5268 | 1659 |
| **arXiv**               | 203,037 | 6,436 | 6,440 | 10,720.18 | 8,519 | 378,825 | 20,170 |
| **PubMed**              | 119,924 | 6,633 | 6,658 | 4,747.97 | 3,883 | 452,915 | 8,883 |
| **BigPatent**           | 1,207,222 | 67,068 | 67,072 | 6,537.32 | 5,236 | 294,004 | 11,328 |
| **MediaSum**            | 443,596 | 10,000 | 10,000 | 2,302.02 | 1,748 | 125,974 | 4,128 |
| **Multi-News**          | 44,972 | 5,622 | 5,622 | 2,593.81 | 1,902.5 | 683,544 | 4,853 |

Table 1: Statistics for the summarization datasets. Input length is in terms of the number of tokens after tokenizing with a SentencePiece Model.

| Dataset                  | Example Count | Input Length |
|-------------------------|---------------|--------------|
|                         | Train | Validation | Test | Average | Median | Max  | 90th percentile |
| **NQ**                  | 307,373 | 7,830 | 6,695.92 | 4,486 | 151,519 | 15,290.8 |
| **TriviaQA**            | 87,622 | 11,313 | 10,832 | 69,082.51 | 45,011 | 1,174,918 | 150,643 |

Table 3: Statistics for the QA datasets. Input length is in terms of the number of tokens after tokenizing with a SentencePiece Model.
As can be seen in Table 2, LongT5 is able to achieve state-of-the-art rouge scores for arXiv, PubMed, BigPatent, and MediaSum. For arXiv and PubMed, which are composed of longer inputs, being able to scale up to 16k input length helps LongT5 achieve strong results.

One dataset where LongT5 is not able to achieve state-of-the-art results is with Multi-News. LongT5 is the 2nd best model, slightly worth than PRIMER. This is understandable as the PRIMER model was pre-trained on a large corpus of documents related to news events, thus exposing the model to a similar corpus as that seen in Multi-News.

When looking at CNN / Daily Mail, we can see that LongT5 was comparable with HAT-BART, despite not having full attention. LongT5 did at least get stronger scores in the ROUGE-2 metric.

4.3 Evaluation on QA Tasks

For the evaluation on QA tasks, we choose two popular benchmarks, Natural Questions and TriviaQA, that require long context understanding. Our evaluation method differs slightly from the leader boards: (1) Since only the train and dev sets are publicly available, in TriviaQA we use 90% of the official training set for training while using 10% as hold-out dev set to fine-tune the hyperparameters and training epoch, and use the official dev set as our test set. In NQ, we used the official training set, and report dev set results with early stopping. (2) We benchmark LongT5 variants against the corresponding T5.1.1 models instead of directly comparing to the leader boards.

4.3.1 Datasets

NaturalQuestions (NQ) Questions are real queries issued by multiple users to Google search that retrieve a Wikipedia page in the top five search results. Answer text is drawn from the search results (Kwiatkowski et al., 2019). The original NQ dataset asks models to predict short answer (including no-answer or yes/no) and a long answer. We framed the task as a seq2seq task, and ignored the long answer. Hence, our results focus only on short answer. Moreover, since our models predict answer texts instead of answer spans, our results are not directly comparable to other existing approaches.

TriviaQA Trivia enthusiasts authored question-answer pairs. Answers are drawn from Wikipedia and Bing web search results, excluding trivia websites (Joshi et al., 2017).

| Approach | NQ | TriviaQA |
|----------|----|----------|
| base:    |    |          |
| T5.1.1 (512) | 56.83 | 60.84 | 48.91 | 52.89 |
| T5.1.1 (6k)  | 60.18 | 64.69 | 59.09 | 63.31 |
| large:    |    |          |
| T5.1.1 (512) | 58.19 | 62.45 | 53.26 | 57.01 |
| T5.1.1 (3k)  | 61.84 | 66.67 | 60.15 | 64.15 |
| xl:        |    |          |
| T5.1.1 (4k)  | 65.33 | 69.43 |

Table 4: QA results comparing T5.1.1 and LongT5 at different sequence lengths. Base and large models are trained on 4x8 TPUv3 with no model partitioning, and xl models are trained on 8x16 TPUv3 with 8 partitions.

4.3.2 Dataset Stats

Table 3 shows the dataset statistics for the number of examples in train and validation splits, and the average, median, max, and 90th percentile input sequence length.

4.3.3 Results

As mentioned above, for TriviaQA, we split the public train set as our training and dev sets, and use the public dev set as our test set, and for NQ we train on the official training set and report results on the dev set with early stopping. As a baseline we decided to run T5.1.1 (1) with the default 512 input sequence length and (2) with the largest input sequence length that can fit into device memory on the same exact setup (topology, batch size, and number of partitions) used for LongT5, and use

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7For base and large models.
8For base and large models, we used 4X8 TPUv3 and no model partitioning; for xl model, we used 8x16 TPUv3, and 8 partitions.
those as our baselines.

Table 4 shows results for the NQ and TriviaQA datasets. For each dataset, we show two metrics: EM (Exact Match) and F1 score (evaluating precision and recall of individual words in the answer compared to the ground truth, ignoring stop words). We compare three models: T5.1.1, LongT5 with Local Attention and LongT5 with TGlobal attention. Since we are comparing against T5.1.1, for base and large LongT5 experiments we report results starting at 512 input length, and then up to the largest input length allowed by each model before running out of memory on the hardware configuration used in our experiments (4x8 TPUv3 slice). But for xl models, due to resource limit, we only ran the largest input length allowed by memory limit on the hardware configuration (8x16 TPUv3).

As the table shows, increasing input length results in significant benefits in NQ, with models with larger input lengths significantly outperforming those with smaller input lengths. Moreover, while LongT5 with Local Attention underperforms T5.1.1, LongT5 with TGlobal attention significantly outperforms T5.1.1 thanks to being able to scale to longer input lengths (at the same input length, LongT5 with TGlobal attention performs very similar to T5.1.1 at the same input length). For example, considering the base size models, T5.1.1 was able to scale up to an input length of 6k tokens, while the TGlobal model was able to reach 12k tokens, giving it an edge.

We derive our observations from NQ while evaluating on TriviaQA, and only test on our best setup for all three model sizes. We draw the same conclusion on TriviaQA, where the ability to scale up input sequence lengths gives LongT5 an advantage to outperform the corresponding T5.1.1 models.

5 Analysis

5.1 Input Length vs Speed

In order to evaluate the training speed and memory consumption of LongT5, compared to T5.1.1, we performed a series of training runs in the NQ data set starting at input length 512, and increasing the input length steadily until models ran out of memory on a 4x8 TPUv3 slice. Results are shown in Figure 3, which compares 6 different model configurations: T5.1.1 base, T5.1.1 large, LongT5 (base Local), LongT5 (large Local), LongT5 (base TGlobal), and LongT5 (large TGlobal). For each model configuration, we show a curve plotting the number of sequences per second processed during training (speed, in the vertical axis) for each input length (horizontal axis). Both axes are shown in logarithmic scale.

We can see that at shorter lengths (512), T5.1.1, LongT5 Local, LongT5 TGlobal have similar speeds, but as we increase the sequence length, LongT5 becomes significantly faster. For example at sequence length 2048, T5.1.1 base can only process 479 sequences per second, while LongT5 (base TGlobal) can process 765 and LongT5 (base Local) can process 860. The differences grow even larger as sequence length increases.

Another important fact that Figure 3 shows is that T5.1.1 models reach their out of memory point much earlier. For example, we could only scale up to 6k tokens for T5.1.1 base. On the other hand, LongT5 (base Local) can go up to 36k tokens in length, and LongT5 (base TGlobal) up to 12k. Large models show a similar picture with T5.1.1 large going only up to 3k, but the LongT5 variants going to 10k (large Local) and 6k (large TGlobal).

5.2 Input Length vs Performance

This section presents a similar analysis, but where we plotted model speed versus performance in NQ (F1 score). Results are shown in Figure 4. Each point in the curves is also annotated with the corresponding sequence length. Hence, the ideal point
in this plot would be the top-right-most corner.

As Figure 4 shows, performance increases significantly as input length increases, highlighting the benefits of LongT5. Moreover, input length by itself is not enough to achieve good performance in all datasets, and in particular, in the NQ dataset (used in this figure), using Local Attention significantly hurts performance. So, even at very long input lengths, LongT5 with Local Attention does not outperform T5.1.1 in NQ. However, LongT5 with TGlobal attention achieves similar performance as T5.1.1 models at the same input lengths, but since LongT5 is faster and can reach input lengths longer than T5.1.1, we can see how the purple LongT5 plots overtake T5.1.1 starting at 2k lengths for the base models, and at 1k lengths for the large models.

5.3 Principle Sentences Generation vs. Span Corruption

As mentioned in section 3.2, we use PEGASUS Principle Sentences Generation instead of default Span Corruption used in T5 as our pre-training objective. Table 5 shows our ablation study with the default Span Corruption pre-training objective, compared to Principle Sentences Generation for both NQ and arXiv. The comparison is done on the dev set of the tasks, and with TGlobal base models. Fine-tuning is done with input sequence length 4096. The table shows, even though Principle Sentences Generation was developed by Zhang et al. (2019a) as a pre-training strategy for summarization, it benefits both summarization and QA tasks.

6 Related Work

Language model pre-training followed by task specific fine-tuning has proven to be a powerful tool for numerous NLP tasks (Devlin et al., 2019; Liu et al., 2019; Zhang et al., 2019b; Radford et al., 2019; Raffel et al., 2019a; Lewis et al., 2020; Joshi et al., 2020). BERT (Devlin et al., 2019) introduced Mask Language Model (MLM), where a model predicts masked tokens given a sequence of text input. Fine-tuning a pre-trained BERT model has led to improved performance on various NLP tasks. However, MLM predictions are not made auto-regressively, which limits the capability of the BERT family for generation tasks. Raffel et al. (2019a) introduced the span corruption task in T5 as the pre-training objective, where a model predicts the masked token span using an autoregressive model. It can handle the generation tasks as the pre-training is done in a generative way. BART (Lewis et al., 2020) is similar to T5 but used a slightly different pre-training objective, in which spans are masked from the input but the complete output is predicted. However, none of these works tried to investigate pre-training for very long sequence inputs. They often use a transformer (Vaswani et al., 2017) architecture as backbone, the complexity of which is quadratic to the input length, making them impractical to model very long sequence input.

Long text modeling An extensive amount of work has also been done for modeling long text like documents. The work from Roy et al. (2016); Chen (2017); Wu et al. (2018) obtained document embeddings from word-level embeddings. Another line of research tries to model long document through hierarchical training. The work from Yang et al. (2016);
Miculicich et al. (2018) employed Hierarchical Attention Networks for document classification and neural machine translation, and Guo et al. (2019) proposed using a hierarchy network to build document embeddings on top of sentence embeddings for parallel document mining.

More recent research has been focusing on improving the memory and computation efficiency of transformer models (Tay et al., 2020b, 2021) for handling long input. One type of such approaches is using non-full attention patterns to restrict the attention field range, so that it reduces the attention complexity from $O(n^2)$ to $O(n \log n)$ or $O(n)$, including Sinkhorn (Tay et al., 2020a), Longformer (Beltagy et al., 2020), ETC (Ainslie et al., 2020), and BigBird (Zaheer et al., 2020a). Another type of approaches is leveraging the low-rank approximation of the attention matrix, such as Linformer (Wang et al., 2020), Performer (Choromanski et al., 2021), Random Feature Attention (Peng et al., 2021), and LUNA (Ma et al., 2021).

7 Conclusion

This paper presented a new Transformer-based neural model called LongT5, with which we have explored the effects of scaling both input length and model size at the same time. Specifically, the main differences of LongT5 with respect to T5.1.1 are (1) a new scalable attention mechanism called Transient Global attention, which is a drop-in replacement to the standard T5 attention mechanism, and hence can be used without needing additional side inputs to the model or modifications to the model inputs; and (2) using a PEGASUS-style Principle Sentences Generation pre-training objective.

Via experimentation in several challenging summarization and question answering datasets, we have explored the performance gains that can be achieved by scaling both input length and model size, resulting in state-of-the-art results on several summarization datasets: arXiv, PubMed, BigPatent, and MediaSum.

As part of our future work, we would like to pursue several directions such as studying efficient attention mechanisms in the decoder and decoder-to-encoder attention pieces of the model (both Local Attention and TGlobal attention are only applied to the encoder in LongT5 for now). Additionally, we would like to incorporate additional long-input transformer ideas into the LongT5 architecture, that could further improve model efficiency.

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