Abstractive and mixed summarization for long-single documents

Roger Barrull Soler
University of Colorado, Colorado Springs
Autonomous University of Barcelona
College of Engineering and Applied Sciences
rbarrull@uccs.edu

Jugal Kalita
University of Colorado, Colorado Springs
College of Engineering and Applied Sciences
jkalita@uccs.edu

Abstract
The lack of diversity in the datasets available for automatic summarization of documents has meant that the vast majority of neural models for automatic summarization have been trained with news articles. These datasets are relatively small, with an average size of about 600 words, and the models trained with such data sets see their performance limited to short documents. In order to surmount this problem, this paper uses scientific papers as the dataset on which different models are trained. These models have been chosen based on their performance on the CNN/Daily Mail data set, so that the highest ranked model of each architectural variant is selected. In this work, six different models are compared, two with an RNN architecture, one with a CNN architecture, two with a Transformer architecture and one with a Transformer architecture combined with reinforcement learning. The results from this work show that those models that use a hierarchical encoder to model the structure of the document has a better performance than the rest.

1 Introduction
Summarization is the process of reducing the size of a document while preserving the meaning, and is one of the most researched areas in Natural Language Processing (NLP). Broadly, there are two approaches to summarization techniques on the basis of whether the exact sentences are considered as they appear in the original text or new text is generated. These techniques are called extractive and abstractive, respectively. Extractive summarization has been an extensively researched topic and has reached its maturity stage. So, the focus has shifted towards the more complex abstractive summarization. The current state-of-the-art models for abstractive summarization (Som Gupta 2018) have the limitation that they can only successfully summarize documents only up to a certain length. As a result, when summarizing long documents, we have to truncate the document to the threshold that we trained on. For CNN/Daily Mail, which is the biggest and most used dataset for summarization, this is typically around 600 words.

An alternative would be to summarize longer text in chunks. However, this limits the coherence of the final summary as semantic information may not flow well between chunks. In addition, finding the right chunking break points is non-trivial, as we have to ensure that at least locally semantic coherent phrases are within the same chunk.

2 Top perfoming models for CNN/Daily News

In Table 1, we list the ranking of the best models in terms of ROUGE for the CNN/Daily Mail dataset and their respective architectures. The ranking is based on comparison found on the website nlpprogress.com. As it can be seen, the ranking is clearly dominated by the models that use the Transformer
approach. The models in bold are some of the models that will be compared in this work using the arXiv data set. These models represent the best model for each architecture.

| Ranking | Model | Architecture |
|---------|-------|--------------|
| 1       | ProphNet | Transformers |
| 2       | PEGASUS(Zhang 2019a) | Transformers |
| 3       | BART(Lewis 2019) | Transformers |
| 4       | T5(Raffel 2019a) | Transformers |
| 5       | UniLM(Raffel 2019b) | Transformers |
| 6       | CNN seq2seq | CNN |
| 7       | BertSumExtAbs(Liu 2019) | Transformers |
| 8       | Bert-ext+abs+RL | Transformers + RL |
| ...     | ...     | ...           |
| 22      | PGN+Coverage | RNN |

Table 1: Ranking extracted from www.nlpprogress.com.

3 Recurrent Neural Networks (RNN)

In the past few years, the RNN, which is a type of neural network that can perform computations on sequential data (like sequences of words), has become the standard approach for many NLP tasks. In particular, the encoder-decoder model with attention (Nallapati 2016), has become popular for summarization. However, this model faces two significant problems (Dwivedi 2019).

1. The summaries sometimes reproduce factual details. Producing *He is 5 years old* - instead of *He is 20 years old*. This is because the model does not copy words from the source text. This happens if there is a word that appears infrequently during training and has a poor word embedding (Tomas Mikolov 2013), i.e., it is clustered with completely unrelated words. Then the word, from the perspective of the network, is indistinguishable from many other words, and thus impossible to reproduce.

Even if the word has a nice word embedding, the network may still have problems reproducing the word. For example, RNN summarization systems often replace a name with another name, e.g., *Anna* with *Emily*. This is because the word embeddings for female names tend to cluster to-gether, which may cause confusion when attempting to reconstruct the original word.

2. The summaries sometimes repeat themselves, e.g., *Germany beat Germany beat Germany beat* This is because the decoder does not store long-term information in the decoder state. The only information that it receives is the previous summary word. This is why a single repeated word commonly triggers an endless repetitive cycle.

3.1 Pointer-Generator with Coverage

The Pointer-Generator network is a hybrid network that can choose to copy words from the source text using an attention mechanism, while retaining the ability to generate words from a fixed vocabulary. By being able to copy from the source text, it solves the first problem presented earlier. To tackle the second problem of word repetition, it introduces a technique called Coverage. The idea is to keep track of what has been covered from the source text so far, and penalize the network for attending to the same parts again.

The PGN model with Coverage approach was the state of the art in text summarization from 2017 until models based on Transformers outperformed it in terms of ROUGE (Vaswani 2017), the standard metric in the performance evaluation of summaries. However, many people still argue that the PGN model with Coverage produces more readable summaries and with higher coherence when it comes to human evaluation, and there has been some work trying to combine the two (Jon Deaton 2019).

3.2 Discourse-aware attention model

The discourse-aware attention model can be seen as the adaptation of the PGN with coverage model for summarizing long-structured documents, e.g., scientific papers.

This model extends the Pointer Generator Network model with coverage by (i) introducing a hierarchical encoder for modeling long documents, and (ii) a discourse-aware decoder that captures the information flow from all discourse sections of the document.

Hierarchical encoder The RNN encoder is extended to a hierarchical RNN that captures the document discourse structure. It first encodes each discourse section and then encodes the document. The model uses a single bidirectional LSTM layer (following the LSTM formulation of (Graves 2013)) for both $RNN_{doc}$ and $RNN_{sec}$. The model combines the forward and backward LSTM states to a single state using a simple feed-forward network.

Discourse-aware decoder When humans summarize a long structured document, depending on the domain and the nature of the document, they incorporate important points from different discourse sections of the document. For example, scientific paper abstracts typically include the description of the problem, discussion of the methods, and finally results and conclusion (Suppe 1998). Motivated by this observation, the model proposes a discourse-aware attention method. Intuitively, at each decoding timestep, in addition to the words in the document, it also attends to the relevant discourse section (the “section attention” block in Figure 2).

4 Convolutional Neural Networks (CNN)

RNNs tend to be inefficient as they rely on the previous steps when training. An alternative is the usage of a CNN to create the representations for the source texts. However, traditional CNNs can only encode fixed size contexts. To address this issue, the model, which achieves the highest ROUGE using CNNs, stacks CNN layers over each other. By doing so, the length of the sequence being dealt with can be easily controlled, and each element in the sequence can be computed in parallel. In contrast, an RNN has to preserve the hidden state of the whole past, thus not able to perform parallelization operations.
Multi-layer CNNs create hierarchical representations of the input, i.e., close elements in a sequence interact at lower layers whereas distant elements interact at higher layers. Unlike the chain structure of an RNN, this multi-layer CNN model offers a shortcut to parallelly express long-range sequences.

4.1 Convolutional Seq2seq Model

In the evaluated model, the convolutional layer architecture is shared both by the encoder and the decoder, and they calculate intermediate states via the input elements. Each layer consists of a one-dimensional convolution and a non-linearity.

If a decoder has one layer with kernel width being $k$, its output compresses the information contained in the $k$ input elements. To enlarge the length of input elements, the model stacks blocks over one another; for example, stacking 6 blocks with $k=5$ can represent 25 input elements.

The advantage of the model is that it conducts parallel computation, which is much more efficient than the traditional RNN model, which computes element by element. To represent a sentence with $n$ words, CNNs only need $O(n/k)$ operations, while RNNs need $O(n)$ operations. However, this hierarchical CNN model is not more efficient than traditional CNN models as it has to stack CNN layers to represent a sequence more expressively, while a traditional CNN model only needs one layer to explore a whole sentence.

In the source document, the sentences could be very long; hence, a summary could be drawn from not only the key-words, but also the key sentences. So, firstly, the model applies two CNNs on the source text, at word level and sentence level, respectively. Then, to capture the hierarchical document structure, the model implements a hierarchical attention mechanism applied at both levels simultaneously. It first calculates the word-level attention, which is then re-weighted by its corresponding sentence-level attention. In the summarization task, it is common that the named-entities and keywords in the test text are essential to the summary, but in the training data they may actually be rare or even unseen, and therefore these words are out-of-vocabulary (OOV) words. To address the issue, the model introduces a copying mechanism, which enables the seq2seq model to extract the OOV words. It can distinguish the keywords based on their position or syntactic information from the original
In the encoder side at the left, the word-level RNN is shown in blue and the section-level RNN is shown in green. The decoder, seen on the right side, consists of an RNN - in orange- and a predict network for generating the summary. At each decoding time step $t$ (in the figure $t=3$ is shown), the decoder forms a context vector $c_t$ which encodes the relevant source context ($c_0$ is initialized as a zero vector). Then, the section and word attention weights are respectively computed using the green section attention and the blue word attention blocks. The context vector is used as another input to the decoder RNN and as an input to the predict network which outputs the next word using a joint pointer-generator network.

Text, even without knowing much other information.

**Copying Mechanism** Similar to the Pointer Generator Model, this CNN model introduces a copying mechanism that allows the model to copy words from the source text. This is especially useful when such words are rare words that the model is unable to predict. Each word is assigned a weight in the original document by the copying mechanism. Such a weight is able to evaluate the words importance via a positional attention score, and determine if the word should be copied or not.

**Hierarchical Attention Mechanism** The model applies the convolutional seq2seq model on both word and sentences levels. Then, it adopts the hierarchical attention mechanism to generate the keywords and the key sentences simultaneously.

5 Transformers

The Transformer is a novel architecture that aims to solve sequence-to-sequence tasks by handling long-range dependencies with ease (Vaswani 2017). The Transformer relies entirely on self-attention to compute representations of its input and output without using RNNs or CNNs.

Recent work on pretrained language models made significant advances in NLP tasks. BERT (Devlin 2018) is a bidirectional encoder that is pretrained by predicting randomly masked tokens in sentences, and by predicting next sentences. GPT (Radford 2018), GPT-2 (Radford 2019) and GPT-3 (Brown 2020) are auto-regressive LMs. BART is a pre-trained language model that combines a bidirectional Transformer as an encoder and an auto-regressive Transformer as a decoder. The models based on Transformer used in this work are ProphetNet, a model that is the current state of the art when it comes to abstractive summarization on the CNN/Daily Mail data set, and a model that performs an extractive step before generating the summary.

5.1 ProphetNet

ProphetNet is a pre-trained seq2seq large-scale model that introduces a self-supervised objective named *future n-gram prediction* and a proposed *n-stream self-attention mechanism*. Instead of the optimization for one-step ahead prediction in a traditional sequence-to-sequence model, ProphetNet is optimized by $n$-step ahead prediction, which predicts the next $n$ tokens simultaneously based on previous context tokens at each time step. The ProphetNet model is based on a Transformer encoder-decoder architecture and has two goals: (a) the model should be able to simultaneously predict the future $n$-grams at each time step in an efficient way during the training phase, and (b) the model should be easily converted to predict the next token only as the original seq2seq model for the inference or finetuning phase. To achieve this, the model extends the two-stream self-attention proposed in XLNet (Yang 2019) to $n$-stream self-attention. ProphetNet contains a mainstream self-attention mechanism.
which is the same as the self-attention in the original Transformer. Besides, it introduces $n$ extra self-attention predicting streams for future $n$-gram prediction. During training, the $i$-th predicting stream attends to the hidden states of the main stream to predict the next $i$-th future token, which guarantees every $n$ continuous tokens in the target sequence are trained to predict at one time step.

Compared to the original Transformer seq2seq model, ProphetNet introduces four modifications: (a) The novel self-supervised objective called future $n$-gram prediction. (b) The $n$-stream self-attention mechanism, (c) A modified positional embedding, and (d) A mask based auto-encoder denoising task for seq2seq pre-training.

5.2 Transformer Language Model with Extraction

This model uses a single GPT-like Transformer language model to generate the summary. The interesting thing about this model is that before generating the summary, it does an extractive step, which is then used to condition the Transformer language model on relevant information before being tasked with generating an abstractive summary.

The model comprises two distinct and independently trainable components.

- A hierarchical document representation model that either points to or classifies sentences in a document to build an extractive summary.
- A Transformer language model that conditions on the extracted sentences as well as a part of the entire document.

Extractive step The model first performs sentence extraction using two different hierarchical document models: one based on pointer networks (Vinyals 2015), and the other based on a sentence classifier (Nallapati 2017). This extracts important sentences from the document that can be used to better condition the Transformer language model on relevant information before being tasked with generating a summary.

The model described in the paper, demonstrates that using the ground truth extracted sentences during training and the model extracted sentences at inference performs better than using the model extracted sentences everywhere.

Abstractive step: Transformer Language Model (TLM)

The model is made up of a single Transformer language model that is trained from scratch. The architecture of this Transformer is identical to the model developed by Radford (Radford 2019). The training data is organized for the language model such that the ground-truth summary follows the information used by the model to generate a system summary. This way, it models the joint distribution of document and summary during training, and sample from the conditional distribution of the summary, given the document at inference. When dealing with extremely long documents that may not fit into a single window of tokens seen by a Transformer language model, such as an entire scientific article, the model uses its introduction as a proxy for having enough information to generate an abstract (summary) and uses the remainder of the paper as in domain language model training data (Figure 5).

6 Reinforcement Learning (RL)

Reinforcement Learning (RL) is a widely used learning technique for text summarization. Paulus (Paulus 2017) showed that the loss function commonly used in a supervised model is not closely related to the evaluation metric, and introduced an end-to-end RL model that employs the ROUGE metric (Lin 2004) as a rewarder.

Bhm (Bhm 2019) highlighted the limitations of ROUGE-based rewarders and proposed neural network-based rewarders to predict the similarity between document and summary. Specifically, the model is trained to predict the similarity score between the document and summaries of various qualities. The pretrained language model BERT is used to encode the input sequences so that the semantics of the two inputs are adequately reflected in the model.

6.1 Summary Level Training of Sentence Rewriting

The model consists of two neural network modules, an extractor and an abstractor. The extractor encodes a source document and chooses sentences from the document, and then the abstractor paraphrases the selected ones to generate a summary. The model also presents a novel training signal that directly maximizes summary-level ROUGE scores through reinforcement learning.

Extractor Network The extractor is based on the encoder-decoder framework. BERT is adapted for the encoder to exploit contextualized representations from pretrained Transformers. BERT, as the encoder, maps the input sequences to sentence representation vectors.

Sentence Selection The model uses an LSTM Pointer Network as the decoder to select the extracted sentences based on the sentence representations. The decoder extracts sentences recurrently, producing a distribution over all of the remaining sentence representations, excluding those already selected. Since the sequential model selects one sentence at a time step, the decoder can consider the previously selected sentences. This property is needed to avoid selecting sentences that have overlapping information with the sentences extracted already.
Abstractor Network  The abstractor network compresses and paraphrases an extracted document sentence to a concise summary sentence. It uses the standard attention based sequence-to-sequence model with the copying mechanism for handling out-of-vocabulary words.

Training  To optimize the ROUGE metric directly, the model assumes the extractor as an agent in the reinforcement learning paradigm (Sutton 1998). The extractor has a stochastic policy that generates actions (sentence selection) and receives the score of the final evaluation metric (summary-level ROUGE in our case) as the return.

7 Datasets
The dataset containing scientific documents for this work was collected from the scientific repository arXiv.org and pre-processed by Cohan and Dernoncourt (Arman Cohan 2017). They removed figures and tables to only preserve the textual information as well as normalized all the math formulas and citation markers with special tokens. The arXiv data set is approximately seven times larger than the popular CNN and Daily Mail dataset of news articles.

Table 2, some statistics of the comparision between the said datasets can be seen.

| Dataset           | #docs | avg. doc length (words) | avg. summary length (words) |
|-------------------|-------|-------------------------|-----------------------------|
| CNN               | 92k   | 656                     | 43                          |
| Daily Mail        | 219K  | 693                     | 52                          |
| arXiv (this work) | 215K  | 4938                    | 220                         |

Table 2: Comparison among the most popular datasets and the one used in this work.

8 ROUGE
The set of metrics called ROUGE stand for Recall-Oriented Understudy for Gisting Evaluating (Lin 2004), and ROUGE is the standard software package used for evaluating automatic summarization. The metrics compare an automatically produced summary against a human-produced one.
8.1 ROUGE-N
ROUGE-N is based on the amount of overlap of $n$-grams between the system generated summaries and the reference summaries.

8.2 ROUGE-L
It takes into account the longest common subsequences between the system and the reference summaries. It identifies longest co-occurring subsequence in a sequence of $n$-grams.

8.3 Warning
As stated in www.nlpprogress.com, automatic metrics for summarization such as ROUGE have serious limitations, as outlined below.
1. They only assess content selection and do not account for other quality aspects, such as fluency, grammaticality, coherence, etc.
2. To assess content selection, they rely mostly on lexical overlap, although an abstractive summary could express the same content as a reference without any lexical overlap.
3. Given the subjectiveness of summarization and the correspondingly low agreement between annotators, the metrics were designed to be used with multiple reference summaries per input. However, recent datasets such as CNN/DailyMail and Gigaword provide only a single reference.

Therefore, tracking progress and claiming state of the art based only on these metrics is questionable.

9 Results
The results obtained in this work can be seen in Table 3. As it can be observed, the model that uses Transformer language models with an extractive step has the best performance in ROUGE-1 and ROUGE-2, and the Discourse-aware attention model has the best performance in ROUGE-L. The interesting thing about these results is that both models use a hierarchical encoder to capture the document discourse structure. These two models are not even within the top 10 models in the CNN/Daily Mail data set; however, they clearly outperform those top 10 models when the data set is made up of scientific papers. Regarding the four models selected from their performance on the news datasets, their performance on the arXiv dataset relative to each other is similar to that in the CNN/Daily Mail and there are no big surprises. This work shows that introducing a hierarchical encoder that models the document is key when it comes to summarize long structured documents such as scientific papers.

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Figure 6: The overview architecture of the extractor network from the Summary Level Training of Sentence Rewriting model. Figure extracted from (Bae 2019).

| Model                     | RG-1 | RG-2 | RG-L |
|---------------------------|------|------|------|
| PGN + coverage            | 32.06| 9.04 | 25.16|
| Disc-aware                | 35.8 |      |      |
| CNN seq2seq               | 35.09| 12.34| 27.26|
| ProphetNet                | 41.01| 11.19| 23.28|
| TLM-I+E (G,M)             | **42.43** | **15.24** | **24.08** |
| Bert + RL                 | 39.00| 12.09| 22.34|

Table 3: Comparison between the most popular datasets and the one used in this work.

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