Windowing Models for Abstractive Summarization of Long Texts

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Abstract

Neural summarization models suffer from the fixed-size input limitation: if text length surpasses the model’s maximal number of input tokens, some document content (possibly summary-relevant) gets truncated. Independently summarizing windows of maximal input size disallows for information flow between windows and leads to incoherent summaries. We propose windowing models for neural abstractive summarization of (arbitrarily) long texts. We extend the sequence-to-sequence model augmented with pointer generator network by (1) allowing the encoder to slide over different windows of the input document and (2) sharing the decoder and retaining its state across different input windows. We explore two windowing variants: Static Windowing precomputes the number of tokens the decoder should generate from each window (based on training corpus statistics); in Dynamic Windowing the decoder learns to emit a token that signals encoder’s shift to the next input window. Empirical results render our models effective in their intended use-case: summarizing long texts with relevant content not bound to the very document beginning.

1 Background and Motivation

While extractive summarization selects and copies the most relevant source phrases and sentences to the summary, abstractive summarization (AS) aims to capture the source meaning and generate summaries not necessarily containing portions of the source texts (Nenkova and McKeown, 2011), holding promise of producing summaries more like human created ones. State-of-the-art neural AS models (Nallapati et al., 2016; See et al., 2017; Paulus et al., 2018; Tan et al., 2017; Makino et al., 2019; You et al., 2019) extend a standard sequence-to-sequence (Seq2Seq) architecture, using either recurrent (RNN) (Bahdanau et al., 2015) or Transformer-based (Vaswani et al., 2017) encoder and decoder components. See et al. (2017) extend the standard Seq2Seq model with a pointer-generator network (PG-Net), providing the model with extractive capabilities, i.e., allowing it to choose between generating a token and copying source text tokens. Tan et al. (2017) propose a hierarchical model that introduces an additional graph-based attention mechanism which serves to model interactions between encoded sentence representations. Paulus et al. (2018) incorporate a reward expectation based on reinforcement learning into a mixed training objective to steer the model towards predicting globally meaningful sequences.

With respect long-document summarization, Celiyilmaz et al. (2018) distribute the encoding task to multiple collaborating encoder agents, whereas Cohan et al. (2018) propose a hierarchical encoder that captures the document’s discourse structure, and an attentive discourse-aware decoder that generates the summary. The latter requires a predefined discourse structure and is designed for domain-specific texts (e.g., scientific publications). Despite multiple encoders operating on different document segments, these models still limit the maximal document length at inference.

In this work, we address a prominent limitation of neural AS models: they cannot summarize texts longer than the maximal input length \( T_x \) set during model training. At inference, documents longer than \( T_x \) tokens are truncated, which renders the (potentially summary-relevant) truncated content inaccessible to the model. We propose novel AS models based on windowing of source text: we sequentially shift encoder’s attention over different windows of source text. The decoder is shared across windows, thereby preserving semantic information from a previous window when decoding the next. We investigate two windowing strategies: (1) Static Windowing Model (SWM) precomputes,
We apply an attention mechanism similar to Luong which would limit the model to a fixed-size input windowing AS model. We start from the attention-based Seq2Seq model with recurrent components (Bahdanau et al., 2015), but obtained weaker performance. During training – we attend over a window of tokens and sequentially slide the window over the text words) interpolates between generation and copying a token from the extended vocabulary \( \hat{V} \) (union of \( V \) and source text words) interpolates between generation and copying a token from the extended vocabulary \( \hat{V} \) (union of \( V \) and source text words). The output probability distribution \( P_V \) (over training vocabulary \( V \)) is then simply computed by applying the softmax function on the vector of dot-product values computed between \( l_t \) and each of the (pretrained) word embeddings.

We augment the base Seq2Seq model with the pointer-generator network (PG-Net), as in (See et al., 2017), allowing the decoder to choose, in each step, between generating a token from the training vocabulary and copying a token from the source document. Generation probability is based on the context vector \( c_t \), decoder’s hidden state \( s_t \), and decoder’s input \( x_t \):

\[
p_{gen} = \sigma(w_c^T c_t + w_s^T s_t + w_x^T x_t + b_{ptr})
\]

with \( w_c, w_s, w_x \in \mathbb{R}^d, w_x \in \mathbb{R}^{d \times d}, b_{ptr} \in \mathbb{R} \) as parameters. The output probability for a word \( x \) from the extended vocabulary \( \hat{V} \) (union of \( V \) and source text words) interpolates between generation and copying distributions:

\[
P_V(x) = p_{gen}P_V(x) + (1-p_{gen}) \sum_{j:x_j=x} \alpha_{t,j}
\]

This specifies the PG-Net-augmented Seq2Seq AS model that operates on a window (\( T_w \) tokens). We next need to specify when to transition from one window of source text to another.

### 2.1 Static Windowing Model

The Static Windowing Model precomputes the number of tokens the decoder needs to generate for each input window. Let \{\( w_1, w_2, \ldots, w_N \)\} be the equally-sized source windows (determined with \( T_w \) and \( ss \)). We use the following function to determine the importance (weight) for each window:
window-shift token ($w_i$), with $k$ and $d$ as parameters defining the shape of the summary distribution over windows. The unnormalized weights $e_s(w_i)$ are converted into probabilities using the softmax function. We next compute the expected summary length for a given document, based on the document length and training corpus statistics. Let $D$ be the set of documents and $S$ the set of their respective reference summaries in the training corpus. We compute the expected summary length for a new document $d$ as:

$$E(|s|)_d = \text{majority}(|S|) \cdot \frac{|d|}{\text{majority}(|D|)}$$ (3)

where $\text{majority}(|D|)$ is the length that covers 90% of training documents (i.e., 90% of $d \in D$ are at most $\text{majority}(|D|)$) and $\text{Majority}(|S|)$ is the length that covers 90% of reference summaries from $S$. The number of tokens the decoder is to generate for a window $w_i$ is now simply a product of $E(|s|)_d$ and the normalized weight $e_s(w_i)$.

2.2 Dynamic Windowing Model

SWM still relies on the document (and summary) lengths of the training corpus, and the number of summary tokens decoded for a window does not it’s content. Dynamic Windowing Model (DWM) aims to be more flexible, by allowing the decoder to dynamically signal, via a special token, the saturation of the current window and shift to the next. Because (1) the decoder needs to learn to emit this window-shift token ($\rightarrow$), and (2) we still want an end-to-end trainable AS model, we need to somehow inject window-shift tokens ($\rightarrow$) into reference summaries of the training corpus. We achieve this heuristically, by computing semantic similarity scores between source text sentences and reference summary sentences. For simplicity, we obtain the sentence embedding as a sum of its respective word embeddings and compute the cosine similarity between sentence embeddings.

For every reference summary sentence, we identify the most similar source document sentence and determine its respective window. This way we map each reference summary sentence to one source window. The order of windows assigned to summary sentences is, however, not necessarily sequential (e.g., $[1, 3, 2, 4, 3]$ for some reference summary with five sentences). Since our model allows only sequential window shifts, we first make the window order sequential by replacing sequence-breaking windows with accumulated maximums (e.g., $[1, 3, 2, 4, 3]$ becomes $[1, 3, 3, 4, 4]$). We then inject window-shift tokens ($\rightarrow$) between summary sentences with different assigned source windows (e.g., for the window assignment $[1, 3, 3, 4, 4]$ we inject $\rightarrow \rightarrow$ between the first and second summary sentence and $\rightarrow \rightarrow$ between the third and fourth sentence). During inference, the input window is shifted whenever the decoder outputs the $\rightarrow$ token.

3 Evaluation

Data. We evaluate our windowing models on two benchmark datasets: (1) CNN/Dailymail news corpus, created by (Nallapati et al., 2016) from the question answering dataset of Hermann et al. (2015) and (2) WikiHow corpus (Koupaee and Wang, 2018). News place the most relevant information at the beginning (the so-called lead-and-body principle): the standard models that truncate long documents are thus likely to perform well in the CNN/Dailymail evaluation. The WikiHow dataset does not have such a construction bias – summary-relevant information is more evenly distributed across the texts.

Experimental Setup. We use the negative log likelihood objective and optimize the models by maximizing the ROUGE-L performance on development sets. We use a batch-level beam search decoder with beam size $B = 3$. Unlike standard beam search, $B$ does not decrease when the end-of-summary token ($<\text{eos}>$) is predicted. Longer yet incomplete partial hypotheses can thus take over completed beams whenever they prevail in terms of length-normalized log probability. We set the hidden state sizes for both encoder’s LSTMs and decoder’s LSTM to 256. We employ the Adam optimizer (Kingma and Ba, 2015) ($\beta_1=0.9$, $\beta_2=0.999$, and $\epsilon=1e-8$). For word representations, we use pretrained 300-dim. fastText embeddings (50,000 most frequent words)\(^6\)

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\(^3\)For example, with $d = 1.2$ and $k = 0.8$, the early windows will receive larger weights than the later windows.

\(^4\)We acknowledge that this is a rudimentary method for computing semantic similarity between sentences. We intend to experiment with more advanced sentence embedding models and more accurate sentence similarity measures (Kusner et al., 2015; Conneau et al., 2017; Devlin et al., 2019; Zheljzniak et al., 2019, inter alia) in subsequent work.

\(^5\)Depending on $T_w$ and $ss$, a sentence be in more than one window. In such cases, we map the sentence to the last containing window.

\(^6\)https://tinyurl.com/y3y69h3z
Table 1: Results on the CNN/Dailymail test set: summaries of $T_y = 125$ tokens; STAN trained with fixed-size input of $T_x = 400$ tokens; SWM $(d = 1.2, k = 0.8)$ & DWM trained on $T_x = 1160$ tokens, with windows of $T_w = 400$ tokens (stride $ss = 380$).

| Model | $T_x$ | $T_w/ss$ | R-1  | R-2  | R-L  |
|-------|-------|----------|------|------|------|
| LEAD-3 | -     | -        | 24.24| 5.31 | 21.86|
| STAN  | 200-  | 22.84    | 7.89 | 22.38|
| DWM   | 740/180 | 26.15 | 8.63 | 25.48|
| STAN  | 780/380 | 28.25 | 9.71 | 27.55|
| DWM   | 780/380 | 27.23 | 9.51 | 26.49|

Table 2: Results on the WikiHow dataset ($T_y = 125$, $d = 0$ for SWM).

| Model | $T_x$ | $T_w/ss$ | R-1  | R-2  | R-L  |
|-------|-------|----------|------|------|------|
| LEAD-3 | -     | -        | 24.24 | 5.31 | 21.86|
| STAN  | 200-  | 22.84    | 7.89 | 22.38|
| DWM   | 740/180 | 26.15 | 8.63 | 25.48|
| STAN  | 400/180 | 27.54 | 9.59 | 26.85|
| DWM   | 780/380 | 27.23 | 9.51 | 26.49|

**Baselines.** We compare different variants of SWM and DWM against the standard PG-Net Seq2Seq model (STAN) with the fixed-size input (See et al., 2017), as well as against the commonly employed LEAD-3 baseline, which simply copies the first three document sentences to the summary.

**Results and Discussion.** Table 1 contains the results on the CNN/Dailymail dataset. Unsurprisingly, the simple LEAD-3 baseline outperforms STAN and both our static and dynamic windowing models. This is because in CNN/Dailymail documents almost all of the summary-relevant content is found at the very beginning of the document. The ability to process all windows does not benefit to SWM and DWM in this setting as there is virtually no summary-relevant content in later windows.

In Table 2 we display the results on the WikiHow dataset, which is bound to be more appropriate for the windowing models, because of the more even distribution of the summary-relevant content across the source documents. On the WikiHow dataset, the windowing models – SWM and DWM – generally have an edge over the standard PG-Net Seq2Seq model (STAN) when the fixed-size input for STAN matches the window size of the windowing models. For a larger input size $T_x = 400$, STAN performs comparably to DWM with the same window size $T_w = 400$. Notably, the DWM has the advantage of being able to process longer overall input. Lowering $T_x$ for STAN to 200 and comparing it against SWM/DWM with windows of the same size $T_w = 200$, we see that the windowing models clearly prevail. This renders our windowing models as a more appropriate solution for summarization of documents for which the following two properties hold: (1) the document length massively surpasses the maximal number of tokens we can feed to the fixed-input-size model and (2) summary-relevant information is present all across the document, and not just at its beginning.

While SWM seems to outperform DWM, in practice SWM cannot really summarize arbitrarily long texts at inference. Despite transitioning across content windows, SWM adapts to the summary lengths seen in the training corpus and generates the $<$eos$>$ token too early during inference on the long texts. In contrast, by learning to emit window transitions, the Dynamic Windowing Model can truly generate summaries for arbitrarily long texts at inference time, regardless of the observed lengths of training document and their respective reference summaries. Figure 2 depicts the summary of a very long document (13,607 tokens), produced by a DWS model trained on an order of magnitude shorter documents ($T_x = 1,160$ tokens).

**4 Conclusion**

Neural summarization models fix the length of the source texts in training (e.g., based on the average source document length in the training set), forcing documents longer than this threshold to be truncated at inference. In this work, we proposed windowing summarization models, which allow to process arbitrarily long documents at inference, taking into account full source text. Our models are effective in summarizing long texts with evenly distributed summary-relevant content.
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