

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, Celikyilmaz 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,

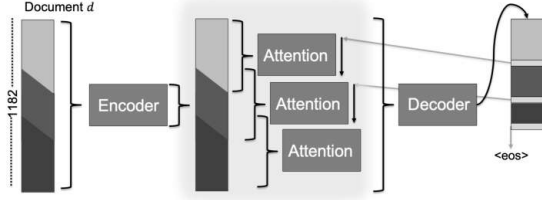


Figure 1: High-level illustration of the windowing model for long document summarization.

based on the training corpus statistics, the number of tokens the decoder is to generate from each source window; (2) for the Dynamic Windowing Model (DWM), we first heuristically, based on semantic similarity between source text and summary sentences, inject special *window-shift* tokens into the training reference summaries and then let the decoder learn to emit window-shift tokens during generation. Signaling the window shift by generating a special token, conceptually allows the DWM model to summarize arbitrarily long texts during inference. Evaluation on the WikiHow corpus (Koupae and Wang, 2018) of long texts with more even distribution of summary-relevant content renders our windowing models effective.

2 Windowing AS Models

Figure 1 contains the high-level depiction of the windowing AS model. We start from the attention-based Seq2Seq model with recurrent components (Bahdanau et al., 2015),¹ which maps the input sequence x_1, \dots, x_{T_x} into an output sequence y_1, \dots, y_{T_y} . A bidirectional LSTM (Bi-LSTM) encoder produces contextualized representations $h_j = [\vec{h}_j; \overleftarrow{h}_j]$ for each input token. Decoder’s state is initialized with the concatenation of the end states of encoder’s LSTMs ($s_0 = [\vec{h}_{T_x}; \overleftarrow{h}_1]$). We apply an attention mechanism similar to Luong et al. (2015). However, instead of learning a local attention span around each source text position – which would limit the model to a fixed-size input during training – we attend over a window of T_w tokens and sequentially slide the window over the long text. This way the decoder learns to model transitions between content windows, allowing to summarize arbitrarily long documents at inference.

Window size T_w and a stride step ss , divide the source text (T_x tokens) into overlapping windows.² We use the same decoder, retaining its

state, across all input windows. Sharing a decoder across input windows allows the flow of semantic information between adjacent windows and holds promise of retaining summary coherence. At each decoding step t , we attend over the window representations, using the decoder’s hidden state s_t as the attention query, and obtain the conditioned window encoding c_t (for the decoding step t): $c_t = \sum_{j \in T_w} \alpha_{t,j} h_j$, with attention weight $\alpha_{t,j}$ computed as the softmax-normalized value of the dot-product $s_t^\top h_j$ between the encoded token h_j and the decoder’s state s_t . Decoder outputs the embedding l_t via feed-forward projection of the concatenation of the attended input representation c_t and its own hidden state s_t : $l_t = W_l \tanh([c_t; s_t]) + b_l$, with $W_l \in \mathbb{R}^d \times {}^{2d}$, $b_l \in \mathbb{R}^d$ as parameters. 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 :

$$p_{gen} = \sigma(w_c^\top c_t + w_s^\top s_t + w_x^\top x_t + b_{ptr}) \quad (1)$$

with $w_c, w_s \in \mathbb{R}^d$, $w_x \in \mathbb{R}^{d_{emb}}$, $b_{ptr} \in \mathbb{R}$ 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:

$$P_{\hat{V}}(x) = p_{gen} \cdot P_V(x) + (1 - p_{gen}) \sum_{j: x_j = x} \alpha_{t,j} \quad (2)$$

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 $\{w_1, w_2, \dots, w_N\}$ 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:

¹We also experimented with Transformer (Vaswani et al., 2017) encoder/decoder, but obtained weaker performance.

²We pad the last window(s), if shorter than T_w tokens.

$e_s(w_i) = \exp(-k(1 + i \cdot d^i))$, with k and d as parameters defining the shape of the summary distribution over windows.³ 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:

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

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 $\mathbb{E}(|s|)_d$ 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.⁴

For every reference summary sentence, we identify the most similar source document sentence and determine its respective window.⁵ This way

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

⁴We 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; Zhelezniak et al., 2019, *inter alia*) in subsequent work.

⁵Depending on T_w and ss , a sentence be in more than

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 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 (Koupaei 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 ($\langle \text{eos} \rangle$) 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

one window. In such cases, we map the sentence to the last containing window.

⁶<https://tinyurl.com/y3y69h3z>

| Model | R-1 | R-2 | R-L |
|--------|-------|-------|-------|
| LEAD-3 | 39.89 | 17.22 | 36.08 |
| STAN | 37.85 | 16.48 | 34.95 |
| SWM | 37.11 | 16.01 | 34.37 |
| DWM | 36.02 | 15.67 | 33.28 |

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 | 200/180 | 26.15 | 8.63 | 25.48 |
| STAN | 400 | — | 27.54 | 9.59 | 26.85 |
| SWM | 780 | 400/380 | 28.25 | 9.71 | 27.55 |
| DWM | 780 | 400/380 | 27.23 | 9.51 | 26.49 |

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

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 windows 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

PREDICTED SUMMARY:
 ↳ Lionel Messi has won a club-record 34 trophies with a record six European | the footballer won the 2009 Ballon d'Or | the footballer has won a club-record 34 trophies | ↳ the former world no 1 has won the tournament in the 2014 world | ↳ he is now a professional footballer and has a son named in his brother | ↳ the former England man is now a professional footballer | ↳ he is also known for his work as a player of the tournament | ↳ he has played five games with the team for the first time | ↳ he has played nine games for the first team that season | ↳ the 19-year-old has scored 17 goals in 30 games for the club | ↳ the match was played in a match against Getafe | ↳ the new season is the fourth highest in the world | ↳ the match is the fourth highest in the world | ↳ the is the first club to achieve the feat | ↳ the win is the second consecutive year of the season | ↳ the win is the fourth consecutive year of the season | ↳ the club won the last 16 of the world cup | ↳ the win is the highest level of 180 league goals in the last five years | ↳ the game is the first leg of the world to reach the semi-finals | ↳ the is the first player to win the season | ↳ the is the top scorer in the world | ↳ the trio scored a total of 122 goals in all competitions that season | ↳ the top scorer with ten goals earned him the top scorer in the 2014 category | ↳ he won the tournament | ↳ with a record fifth time in his career | ↳ the victory against Real Betis is the second most successful season | ↳ the 2016 will be held on 14 January in the next round of the 2016 qualifier between and | ↳ is the first player to achieve the feat in the 2017 | ↳ the 2016 will be appearance maker in the club | ↳ the is the second most successful player in the world | ↳ the scored a hat-trick in a thriller against Levante | ↳ the club also won the title for the first time in the last eight years | ↳ the game is the fourth consecutive year for the | ↳ the match was the first time the tournament was held in the last eight | ↳ the match was the first match of the tournament in the world | ↳ the match was the first time the group won the match in the last eight | ↳ the match was the first match to finish in the group | ↳ the match was the first match of the tournament in the last eight years | ↳ the game between the two sides ended in September 2011 | ↳ the match was the first game of the tournament in the final | ↳ the match was the first time since the tournament in the quarter-finals | ↳ the final match saw a penalty shootout with a win over Paraguay | ↳ the win gives him the best chance of the victory in the final | ↳ he won the tournament in the semi-final of the season | ↳ he was also included in the squad for the national team in 2016 qualifiers | ↳ the match was held by composed Hernan Crespo in the 2016 World world cup final match | ↳ the match finished second in the second round of the world cup | ↳ the match was the first time the team has won a title with Argentina | ↳ the win is the second most successful season in the world | ↳ the 18-year-old is the best player in the world | ↳ he is the oldest player to ever play in the world | ↳ he is also a professional footballer and three professional | ↳ he is the first player to exceed the € 100m benchmark for a calendar year | ↳ the is the third highest in the world | ↳ the is the most mobile person in the world | ↳ the is a goodwill ambassador for the children | ↳ the Leo Messi is a talent scout for young players | ↳ the judge has ruled out the future of the world |

Figure 2: Summary for the Wikipedia page “Lionel Messi” (13.607 tokens) produced by DWM trained on CNN/Dailymail ($T_x = 1.160$ tokens). Colors correspond to different source text windows over which the decoder attended during generation.

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.

References

- Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. [Neural machine translation by jointly learning to align and translate](#). In *Proceedings of ICLR*.
- Asli Celikyilmaz, Antoine Bosselut, Xiaodong He, and Yejin Choi. 2018. Deep communicating agents for abstractive summarization. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 1662–1675.
- Arman Cohan, Franck Dernoncourt, Doo Soon Kim, Trung Bui, Seokhwan Kim, Walter Chang, and Nazli Goharian. 2018. A discourse-aware attention model for abstractive summarization of long documents. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers)*, pages 615–621.
- Alexis Conneau, Douwe Kiela, Holger Schwenk, Loïc Barrault, and Antoine Bordes. 2017. Supervised learning of universal sentence representations from natural language inference data. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 670–680.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186.
- Karl Moritz Hermann, Tomas Kocisky, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. 2015. Teaching machines to read and comprehend. In *Advances in neural information processing systems*, pages 1693–1701.
- Diederik P. Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In *ICLR*.
- Mahnaz Koupaee and William Yang Wang. 2018. [Wikihow: A large scale text summarization dataset](#). *CoRR*, abs/1810.09305.
- Matt Kusner, Yu Sun, Nicholas Kolkin, and Kilian Weinberger. 2015. From word embeddings to document distances. In *International conference on machine learning*, pages 957–966.
- Minh-Thang Luong, Hieu Pham, and Christopher D. Manning. 2015. [Effective approaches to attention-based neural machine translation](#). In *Proceedings of EMNLP*, pages 1412–1421.
- Takuya Makino, Tomoya Iwakura, Hiroya Takamura, and Manabu Okumura. 2019. [Global optimization under length constraint for neural text summarization](#). In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1039–1048.
- Ramesh Nallapati, Bing Xiang, and Bowen Zhou. 2016. [Sequence-to-sequence rnns for text summarization](#). In *Proceedings of ICLR: Workshop Track*.
- Ani Nenkova and Kathleen R. McKeown. 2011. Automatic summarization. *Foundations and Trends in Information Retrieval*, 5(2-3):103–233.
- Romain Paulus, Caiming Xiong, and Richard Socher. 2018. [A deep reinforced model for abstractive summarization](#). In *Proceedings of ICLR*.
- Abigail See, Peter J Liu, and Christopher D Manning. 2017. Get to the point: Summarization with pointer-generator networks. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1073–1083.
- Jiwei Tan, Xiaojun Wan, and Jianguo Xiao. 2017. [Abstractive document summarization with a graph-based attentional neural model](#). In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1171–1181. Association for Computational Linguistics.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Proceedings of NeurIPS*.
- Yongjian You, Weijia Jia, Tianyi Liu, and Wenmian Yang. 2019. [Improving abstractive document summarization with salient information modeling](#). In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 2132–2141.
- Vitalii Zhelezniak, Aleksandar Savkov, April Shen, Francesco Moramarco, Jack Flann, and Nils Y Hammerla. 2019. Don’t settle for average, go for the max: Fuzzy sets and max-pooled word vectors. In *Proceedings of ICLR*.