Resurrecting Submodularity in Neural Abstractive Summarization

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Abstract

Submodularity is a desirable property for a variety of objectives in summarization in terms of content selection where the encode-decoder framework is deficient. We propose ‘diminishing attentions’, a class of novel attention mechanisms that are architecturally simple yet empirically effective to improve the coverage of neural abstractive summarization by exploiting the properties of submodular functions. Without adding any extra parameters to the Pointer-Generator baseline, our attention mechanism yields significant improvements in ROUGE scores and generates summaries of better quality. Our method within the Pointer-Generator framework outperforms the recently proposed Transformer model for summarization while using only 5 times less parameters. Our method also achieves state-of-the-art results in abstractive summarization when applied to the encoder-decoder attention in the Transformer model initialized with BERT.

1 Introduction

Text summarization is the task of generating an abridged version of a source document (or multiple documents) while retaining the most salient information. There are two major paradigms of summarization: extractive and abstractive. Extractive methods directly extract salient content (e.g., sentences) from the original document, while abstractive methods attempt to generate novel words, which is more human-like. Extractive summarization is generally considered easier as direct copy of the source content ensures a certain degree of grammaticality and factual accuracy. However, with the advancements in natural language understanding and generation through deep learning, abstractive methods have also gained significant improvements in recent years. In this paper, we also consider abstractive summarization.

The dominant approach to abstractive summarization uses an encoder-decoder neural framework, where an encoder network first encodes the source text into a sequence of hidden states from which the decoder network generates the target summary text. Initial approaches adopt simple feed-forward or recurrent architectures for the encoder and decoder (Rush et al., 2015; Nallapati et al., 2016). Recent advancements to the basic model include advanced attention and copying mechanisms (See et al., 2017; Tan et al., 2017), reinforcement learning (Paulus et al., 2018; Pasunuru and Bansal, 2018), multitask learning (Guo et al., 2018), and hybrid extractive-abstractive models (Gehrmann et al., 2018; Chen and Bansal, 2018; Sharma et al., 2019; Liu and Lapata, 2019).

Among these models, Pointer-Generator with Coverage (See et al., 2017) has become a standard approach to abstractive summarization. Although many methods have surpassed it in terms of the ROUGE scores (Lin, 2004), it remains to be one of the methods that makes the fewest factual errors due to its copy mechanism (Falke et al., 2019). However, their coverage mechanism intended to prevent repetition in generation is not sufficient in terms of simplicity and appropriateness despite its effectiveness. Apart from the extra parameters required by the coverage model, a coverage loss function is needed to control the parameters and the coverage mechanism is added at a later stage during the training.

Lin and Bilmes (2010, 2011a) argue that monotone nondecreasing submodular functions are ideal for content selection in extractive summarization. Indeed, it can be shown that many popular extractive summarization methods (Carbonell and Goldstein, 1998; Berg-Kirkpatrick et al., 2011) optimize a submodular objective. Despite its appropriateness, submodular functions for content selection has so far been ignored in current
neural abstractive summarization methods.

In this paper, we propose novel attention mechanisms specifically designed for improving the coverage of neural abstractive summarization by leveraging submodular functions. By imposing submodularity on the coverage enforced by the decoder states on the encoder states, our diminishing attention method leads to more comprehensive overall coverage of the source document while maintaining conciseness of the summary and a focus on the most important content. We further enhance our basic diminishing attention and propose dynamic diminishing attention to enable even more appropriate coverage for abstractive summarization.

We show that without adding any extra parameters to the encoder-decoder attention, our method leads to 3.44, 2.02, 3.58 absolute improvements in ROUGE-1, ROUGE-2 and ROUGE-L compared with the Pointer-Generator baseline. Our attention method embedded within the Pointer-Generator framework also outperforms the recently proposed Transformer model (Liu and Lapata, 2019) on the CNN/Daily Mail dataset with 5x less parameters, and produces summaries with better quality.

To demonstrate the generalization ability of our methods, we also apply our proposed attention to the encoder-decoder attention in transformer-based model initialized with BERT (Devlin et al., 2019; Liu and Lapata, 2019) and achieve state-of-the-art in abstractive summarization.

2 Background

In this section, we give a brief overview of submodular functions, Pointer-Generator networks, and BERT-based Transformer architecture in the context of text summarization.

2.1 Submodular Functions

Let \( \mathcal{V} = \{v_1, \ldots, v_n\} \) denote a set of \( n \) objects and \( f : 2^\mathcal{V} \to \mathbb{R} \) is a set-function that returns a real value for any subset \( S \subseteq \mathcal{V} \). We also assume \( f(\phi) = 0 \). Our goal is to find the subset:

\[
S^* = \arg\max_{S \subseteq \mathcal{V}} f(S) \quad \text{s.t.} \quad |S^*| \leq m \quad (1)
\]

where \( m \) is the budget; e.g., for summarization, \( m \) is the maximum summary length allowed. Note that \( f : 2^\mathcal{V} \to \mathbb{R} \) can also be expressed as \( f : \{0, 1\}^n \to \mathbb{R} \), where a subset \( S \subseteq \mathcal{V} \) is represented as a one-hot vector of length \( n \), that is, \( S = (I(v_1 \in S), \ldots, I(v_n \in S)) \) with \( I \) being the indicator function that returns 1 if the argument is true otherwise 0.

In general, solving Equation 1 is NP-hard. If \( f \) is monotone submodular (defined below), it is still NP-complete. However, there is a greedy algorithm that finds an approximate solution with an optimality of \( (1 - 1/e) \approx 0.63 \) or higher (Nemhauser et al., 1978).

Definition 1 \( f \) is submodular if \( f(S + v) - f(S) \geq f(T + v) - f(T) \) for all \( S \subseteq T \subseteq \mathcal{V} \), \( v \notin S \).

This property is also known as diminishing returns, which says that the information gain given by a candidate object (e.g., a word or sentence) is larger when there are less objects already selected (as summary). The function \( f \) is monotone non-decreasing if for all \( S \subseteq T \), \( f(S) \leq f(T) \). In this paper, we will simply refer monotone non-decreasing submodular functions as submodular functions.

In some sense submodular functions can be considered as the discrete analogue of concave functions in that \( f(\theta) : \mathbb{R}^n \to \mathbb{R} \) is concave if the derivative \( f'(\theta) \) is non-increasing in \( \theta \), and \( f(S) : \{0, 1\}^n \to \mathbb{R} \) is submodular if for all \( i \) the discrete derivative, \( \partial_i f(S) = f(S + v_i) - f(S) \) is non-increasing in \( S \). Furthermore, if \( g : \mathbb{R}_+ \to \mathbb{R} \) is concave, then the composition \( f'(S) = g(f(S)) : 2^\mathcal{V} \to \mathbb{R} \) is also submodular. The convex combination of two submodular functions is also submodular. Submodular functions have received much attention in the combinatorial optimization, machine learning and computer vision community (Krause et al., 2008; Jegelka and Bilmes, 2011). It has also been used in NLP for the tasks of extractive summarization and word alignment in machine translation (Lin and Bilmes, 2011a,b).

2.2 Pointer-Generator Network

Pointer-Generator (PG) network (Gu et al., 2016; See et al., 2017) is a hybrid seq2seq architecture that can copy words from the source by a pointing mechanism (Vinyals et al., 2015), while retaining the ability to generate new words from a vocabulary. The copy mechanism helps improving factual accuracy and handling out-of-vocabulary (OOV) words. See et al. (2017) also computes a coverage vector\(^1\) to keep track of what has been covered so far, and discourage the network from repeatedly

\(^1\)Coverage here and in our model refers to the coverage imposed on the encoder state by the decoder states
attending to same parts, thereby, avoiding repetitions in the summary. Since our work is about improving the coverage mechanism, here we mainly focus on PG’s coverage computation and omit the architectural details for brevity.

Formally, the coverage computation and pointing methods can be expressed as follows.

\[ c^t_i = \sum_{t'=0}^{t-1} a^t_i \]  
\[ \tilde{a}^t_i = u^T \tanh (\mathbf{W}_e e_i + \mathbf{W}_d d_i + \mathbf{W}_c c^t_i + b_i) \]  
\[ a^t = \text{softmax}(\tilde{a}^t) \]

where \( e_i \) is the encoder state for token \( i \) and \( d_i \) is the decoder state at time \( t \); \( a^t_i \) is the attention that token \( i \) receives at decoding step \( t \) with \( \mathbf{W}_e, \mathbf{W}_d, \mathbf{u} \) and \( b \) being learnable weights in the attention module. Notice that the coverage \( c^t_i \), which represents the “total” attention that token \( i \) has received so far, is also an input to the attention module and has learnable weights \( \mathbf{W}_c \).

The training loss for a target (or summary) word \( \hat{y}^t_i \) at decoding step \( t \) is the negative log probability, \(- \log P(\hat{y}^t_i)\). However, See et al. (2017) found it also necessary to add an explicit coverage loss in addition to feeding the coverage vector \( c^t \) as an additional input to the attention function (Eq. 4). The overall training loss with the coverage loss weighted by \( \lambda \) at time \( t \) is expressed as follows.

\[ \text{loss}_t = - \log P(\hat{y}^t_i) + \lambda \sum_i \min(a^t_i, c^t_i) \]  

The coverage loss penalizes the model to repeatedly attend to the same tokens.

### 2.3 Transformer and BERT

Liu and Lapata (2019) take advantages of recent advancements in representation learning to boost the performance of both extractive and abstractive summarization. They modify BERT (Devlin et al., 2019) to encode multiple sentences and use it for summarization. A ‘[CLS]’ token is appended at the beginning of every sentence, which is used to learn the sentence-level representation. Their proposed extractive-abstractive model (BERTSUMEXTABS) follows a two-stage training strategy. First, they train an extractive model BERTSUMEXT, which has a 2-layer sentence-level transformer encoder on top of BERT’s final layer to capture the document-level semantics.

The output layer of BERTSUMEXT is a sigmoid classifier that predicts if a sentence \( i \) should be included in the extractive summary as:

\[ \hat{y}_i = \sigma(\mathbf{W}_c h^L_i + b_o) \]

where \( h^L_i \) is the representation of sentence \( i \) from the final layer of the encoder.

BERTSUMEXTABS then adopts the pre-trained BERTSUMEXT as the encoder and a 6-layer randomly initialized Transformer decoder, and is trained with an abstractive summarization objective. However, since the decoder is randomly initialized while the encoder is pretrained, a new fine-tuning schedule with two different optimizers has been proposed as follows.

\[ lr_E = \hat{lr}_E \cdot \min(\text{step}^{-0.5}, \text{step} \cdot \text{warmup}_E^{-1.5}) \]  
\[ lr_D = \hat{lr}_D \cdot \min(\text{step}^{-0.5}, \text{step} \cdot \text{warmup}_D^{-1.5}) \]

where \( \hat{lr}_E = 2e^{-3} \) and \( \text{warmup}_E = 20000 \) for the encoder learning rate \( lr_E \), and \( \hat{lr}_D = 0.1 \) and \( \text{warmup}_D = 10000 \) for the decoder learning rate \( lr_D \). BERT sub-word tokenizer eliminates OOV problems mostly and trigram-blocking (Paulus et al., 2018) is applied during inference to help avoiding repetitve words.

### 3 Diminishing Attention

Given an input document, the goal of summarization is to generate an abstractive summary that covers the most important concepts in the document. In the neural encoder-decoder framework, the input document is represented as a set of latent states (concepts) by an encoder, and the decoder constructs the summary autoregressively by generating one token at a time. While generating a token, the decoder computes an attention distribution over the encoded latent states, which represents the relevance of the corresponding input tokens to the output token.

#### 3.1 Submodular Coverage

Following Tu et al. (2016) and See et al. (2017), we quantify degree of coverage as the total attention that the decoder puts on the input tokens in the course of generating the summary. We hypothesize that the coverage function should be monotone nondecreasing, as coverage should improve with more words generated in the summary. Importantly, it should also be submodular. Consider adding a new word \( w \) into two summaries \( S \) and
where the concepts covered by \( S' \) is a subset of \( S \). Intuitively, the information gain by adding \( w \) to \( S' \) should be higher than adding it to \( S \), as the new concepts carried by \( w \) might have already been covered by those that are in \( S \) but not in \( S' \). This is indeed the diminishing return property.

In the encoder-decoder framework, diminishing return property ensures that given the same amount of attention, encoder states with higher coverage from previous steps would have less gain in coverage than those with lower coverage. This prevents over-coverage where repetition ensues. At the same time, those encoder states that are important would still receive larger amount of coverage than those that are less important because the coverage function is monotone non-decreasing.

To achieve this, in the following we propose diminishing attention with which coverage becomes monotone non-decreasing and submodular.

### 3.2 Diminishing Attention

As mentioned, for monotone nondecreasing submodular coverage functions, the greedy algorithm approximates the solution to the maximum-budgeted problem of summarization (Eq. 1) with an optimality of 0.63. For that purpose, the attention scores should be added to the coverage in a greedy manner. However, greedy search among all the decoder states is not possible in the encoder-decoder framework since the decoder states are generated autoregressively, one at a time. We therefore propose a compromised yet simple and effective workaround where we compute the coverage values by summing up the attention scores, after which we model new attention scores with a diminished old attention score. The formal definition of our proposed attention scores is as follows.

Let \( A_i = \{a_i^0, \ldots, a_i^T\} \) denote the set of attention scores that an input token \( x_i \) receives from the first \( t = 0 \) till the last \( t = T \) decoding step. \( F : 2^k \rightarrow \mathbb{R} \) is a set function that maps the set of attention scores to a score which we define as submodular coverage at the current step \( t \). Formally,

\[
F(A_i^t) = f(\sum_{t'=0}^{t} a_{i}^{t'}) + C
\]

where \( f \) is a concave and non-decreasing function (e.g., \( \log(x+1) \), \( \sqrt{x+1} \)) and \( C \) is a constant. By imposing a concave function on the modular coverage function, we obtain a submodular coverage function (Bach, 2011). The diminishing attention (DimAttn) can thus be defined as:

\[
\text{DimAttn}_i^t = F(A_i^t) - F(A_i^{t-1})
\]

which models diminishing return directly, and will be used as the attention weight corresponding to the encoder state \( e_i \) (or token \( x_i \)) to produce the context vector at decoding step \( t \). Note that unlike traditional attention, diminishing attention does not conform to a probability distribution.

With diminishing attention, we can derive that the effective coverage (i.e., the sum of diminishing attention scores) is equal to the submodular coverage that we just defined in Eq. 9. Note that at the first decoder step the previous coverage is \( F(\emptyset) \), i.e., \( f(0) \), which is a constant.

\[
C_i^t = \sum_{t'=0}^{t} \text{DimAttn}_i^{t'} = F(A_i^t) = F(A_i^{t-1}) + (-F(\emptyset))
\]
In other words, the effective coverage that each encoder state gets from the decoder is submodular at every decoding step while coverage is apparently modular with attention. Additionally, the coverage is monotone nondecreasing. This means that although the coverage has been changed, the encoder states which receive the largest coverage with the original attention still receive the largest coverage with the diminishing attention.

3.3 Dynamic Diminishing Attention

While our diminishing attention yields a submodular coverage function, using a single coverage function alone may not guarantee the most appropriate diminishing return effect of the coverage for all the encoder states in the decoding process. We thus propose to enhance the diminishing attention further to enable dynamic diminishing effect at different decoding steps.

Ideally, the model should be capable of further adopting varied degree of diminishing effect as the decoding proceeds — if an encoder state has been ranked as the most important token at a certain decoding step, the more aggressive diminishing effect should be applied to it afterwards. We model this with a soft ranking approach, thus adaptively applying the appropriate coverage function.

As before, let $A_i = \{a_i^0, \ldots, a_i^T\}$ denotes the set of attention scores that an input token $x_i$ receives from the first till the last time step. Let $F_1$ and $F_2$: $2^{|A_i|} \rightarrow \mathbb{R}$ be two different set functions that map the attention scores to a coverage score with different diminishing effect. For a concave function, the more negative (i.e., lower) the second-order derivative is, the faster the first derivative changes. In other words, the diminishing attention corresponding to lower second-order derivative has a stronger diminishing effect.

For the sake of explanation, let us assume diminishing attention $F_1$ has a stronger diminishing effect than $F_2$, which is realized by $f_1$ having a lower second-order derivative than $f_2$ (e.g., $f_1 = \sqrt{x + T}$ and $f_2 = \log(x + 1)$). At any decoding step $t$, the attention score $a_{i}^{t}$ can be seen as the probability of the token $x_i$ (or encoder state $e_i$) being the most important token with respect to the decoder state $d_t$. Therefore, the probability that the encoder state $e_i$ has been seen as the most important state until step $t$ can be computed as:

$$P_t^i = \max_t (A_{i}^{t})$$ (12)

The dynamic diminishing attention (DyDimAttn) is defined as:

$$\text{DyDimAttn}_t^i = P_t^i [F_1(A_i^t) - F_1(A_i^{t-1})] + (1 - P_t^i) [F_2(A_i^t) - F_2(A_i^{t-1})]$$ (13)

which is a convex combination of two diminishing attention functions. Thus it keeps the submodular coverage property of diminishing attention.

Remark 1 The coverage vector we compute is the same as the PG + Coverage model. Critically, however, instead of letting the coverage vector inform the attention, we define a new attention that is the diminishing return measured by the submodular coverage values at the current and previous decoder step. This has the advantages that coverage loss is not needed to control the attention and that no extra parameters are added to the model.

Remark 2 As pointed out by See et al. (2017), PG models tend to copy words from the source documents instead of generating novel words from the vocabulary. The reason could be that in each decoding step the source token size on which the attention (or pointing) distribution is computed is much smaller than the full vocabulary size. As a result, the pointing distribution over the source tokens tends to dominate the final distribution over the vocabulary. However, when our diminishing attentions are applied to the model, the pointer distribution tends to become smaller and flatter, which in turn, encourages the model to generate more novel words from the vocabulary. This increases the abstractiveness of our models as shown later in the experiments.

4 Experiments

In this section, we first present experiments and analysis of our proposed attention mechanisms based on the Pointer Generator model. Subsequently, we also evaluate our methods on a recently proposed BERT-based Transformer model (Liu and Lapata, 2019) to further validate the generalizability of our approach.

4.1 Datasets

CNN/Daily Mail. The CNN/Daily Mail dataset (Hermann et al., 2015; Nallapati et al., 2016) contains news articles from CNN and Daily Mail with several concatenated highlights as the summary associated with each article. The average length
of the articles is 781 tokens and the summaries includes 56 tokens (or 3.75 sentences) on average. We use entity non-anonymized version of the dataset.

### 4.2 Experimental Settings

**Point-Generator** We retrain the Pointer-Generator (PG)\(^2\) as our baseline by replicating the settings from See et al. (2017). The model uses randomly initialized word embeddings and the coverage mechanism is added to the model after 230k iterations of training. For a fair comparison, we train a PG model without coverage loss and coverage vector and apply our proposed DimAttn and DyDimAttn attentions from 230k iteration onward and train it for less than 10k iterations.

For our diminishing attentions, we use concave functions \(f = \log(x + 1)\) in DimAttn and \(f_1 = \sqrt{x + 1}, f_2 = \log(x + 1)\) in DyDimAttn. We found that increasing the beam size from 4 to 6 has led to significant improvements to our model while it did not give any improvement to the baseline. In addition, we apply length normalization (Wu et al., 2016) with \(\alpha = 1.5\) during inference.

Following the standard, the input document was truncated to 400 tokens in training the baseline PG model. We exposed the models to more input tokens when diminishing attentions were employed in training.\(^3\) Specifically, we truncated the article to 600 (200 more) tokens for training with DimAttn and 800 (200 more) tokens for DyDimAttn. We also adopt trigram-blocking (Paulus et al., 2018) during inference.

**BERT-Based Model** We obtained trained BERTSUMEXTABS checkpoint from the author\(^4\) and fine-tune the model with our proposed attentions. We apply our attentions only to the encoder-decoder cross attention of the final layer of the transformer. The hyper-parameters remain the same as Liu and Lapata (2019) and we use the same concave functions for diminishing attentions as in PG models.

**Evaluation Metrics** We evaluate our methods using F1 ROUGE (Lin, 2004), which was suggested for evaluating abstractive systems (Nallapati et al., 2016).\(^5\) We report unigram and bigram overlap (ROUGE-1, ROUGE-2) as well as the longest common subsequence (ROUGE-L). Since ROUGE is insufficient for evaluating the summarization quality in terms of capturing synonyms and paraphrases, we also evaluate with model based evaluation metrics including BERTScore\(^6\) (Zhang et al., 2019) which uses the pre-trained contextual embeddings from a large-scale language model and matches words in sentences of system and gold summaries by cosine similarity, and MoverScore (Zhao et al., 2019) which computes Earth Mover Score based on contextual embeddings from BERT.

### 4.3 Experimental Results

Table 1 shows the performance of baselines as well as our models on the CNN/DM dataset.

| Model               | R-1 | R-2 | R-L | # Param |
|---------------------|-----|-----|-----|---------|
| LEAD-3              | 40.00 | 17.50 | 36.28 | -       |
| **Single Model**    |     |     |     |         |
| PG\(^1\)            | 36.69 | 15.92 | 33.63 | 27.9M   |
| PG + Cov.\(^†\)     | 39.08 | 17.09 | 35.92 | 27.9M + 512 |
| 6-layer Transformer\(^§\) | **40.21** | **17.76** | **37.09** | **128.2M** |
| PG + DimAttn        | 40.01 | 17.74 | 36.94 | 27.9M   |
| PG + DyDimAttn      | 40.13 | 17.94 | 37.21 | 27.9M   |
| **BERT-based**      |     |     |     |         |
| BSEA\(^¶\)          | 41.88 | 19.42 | 38.93 | 180.2M  |
| BSEA + DimAttn      | 42.05 | **19.53** | 39.09 | 180.2M  |
| BSEA + DyDimAttn    | **42.09** | 19.47 | **39.16** | **180.2M** |

Table 1: ROUGE scores on the CNN/DM dataset. \(^1\) denotes the models we retrain. \(^†\) means we take the numbers from the paper (Liu and Lapata, 2019). \(^§\) denotes the pre-trained BERTSUMEXTABS model obtained from the author.

\(^2\)We used PyTorch implementation from https://github.com/atulkum/pointer_summarizer

\(^3\)Inclusion of more input tokens did not give any additional gain for the PG + Coverage model.

\(^4\)https://github.com/nlpyang/BertSum

\(^5\)We used pyrouge, a Python wrapper for the ROUGE package (Lin, 2004), to compute all ROUGE scores.

\(^6\)hash code of the model we used is “roberta-large-xl_17_no-idf_version=0.2.1”
consists of a one-layer Bi-LSTM and whose decoder is a one-layer LSTM.

We also include the performance of the Transformer model taken from (Liu and Lapata, 2019) in Table 1 for comparison. This is a 6-layer encoder and decoder model, and is randomly initialized. Our DyDimAttn model, with five times less parameters, outperforms the transformer model by a good margin in ROUGE-2 and ROUGE-L despite a slightly lower score in ROUGE-1.

When applied to the cross attention in the Transformer model initialized with BERT, our method further pushes the state-of-the-art performance. We achieve 42.09, 19.47 and 39.16 in ROUGE-1, ROUGE-2 and ROUGE-L. This indicates that even with the power of better word representations brought by a large-scale language model, the existing attention mechanism may not incorporate the most appropriate inductive bias for the summarization task while our diminishing attentions are a better fit as they explicitly model the submodularity of the coverage.

4.4 Analysis and Discussion

To gain more insights into the performance of our method, we conduct extensive analysis mainly based on the PG model with our attention methods including (a) quality analysis, (b) abstractiveness analysis, and (c) ablation study of model components (d) comparison with trigram-blocking.

Quality Analysis  We empirically show that submodularity imposed on the coverage enables our model to generate summaries with better quality from the following three aspects.

First, to evaluate the summary quality from a semantic perspective, we calculate the BERTScore (Zhang et al., 2019) and MoverScore (Zhao et al., 2019) of the summaries produced by our models and baselines. Table 2 shows that our attention consistently outperforms the baselines and is better at capturing the overall meaning of the source article than the baseline method.

Second, we measure the repetition ratio by calculating the duplicate n-grams in a summary. Figure 2 shows the repetition ratio of summaries generated by PG baselines, our model and gold summaries. Compared to the PG model, our method is able to yield significantly less repetition in terms of 1-gram and 2-gram, outperforming the PG+Cov. model as well. 3-gram repetition is completely eliminated as tri-gram blocking is applied.  

Table 2: BERTScore F1 and 1-gram and 2-gram MoverScore (Zhao et al., 2019).

Table 3: n-gram overlaps with the lead-3 reference.

Last but not the least, lead bias is a common issue in news datasets (Kryscinski et al., 2019). Truncating the documents to 400 tokens caters to the lead bias of the dataset. By increasing the maximum encoding steps (600 for DimAttn and 800 for DyDimAttn), we feed the model more information and let the model automatically learn to extract the most crucial information from the source. Table 3 demonstrates that our models lead to lower n-grams overlaps with the lead-3 reference compared to the baseline even though it uses a larger maximum encoding steps, and they do so without compromising the ROUGE scores.

Recall that the average article length in CNN/DM is 781.
Abstractiveness

As mentioned earlier, our diminishing attentions helps to reduce copying words from the input sequence and encourages abstractiveness in the summary. Figure 3 presents the abstractiveness of the summaries generated by the PG model, our models, as well as the reference summaries. Both our DimAttn and DyDimAttn generate a higher ratio of novel n-grams compared to PG + Cov. model, especially when \( n \) is larger than 2. However, they are still lacking in abstractiveness when compared to the ground truth summaries, and abstractiveness still remains to be a challenge for PG-based models.

Ablation Study

We conduct an ablation study to analyze how each component weighs in our model. Table 4 shows the improvements for our attention methods and other components as they are added once at a time. It can be seen that by adding DimAttn or DyDimAttn only, our model outperforms the baselines. Length normalization further boosts the performance which accords with the observation that our method tends to generate shorter summaries with PG-based models.

Comparison with Tri-Gram Blocking

Tri-gram blocking is a widely accepted method for eliminating redundancy. However, the quality of the summaries generated is not guaranteed by applying tri-gram blocking only. We experiment on the PG baseline and observe that although adopting tri-gram blocking during inference could decrease the repetition level and increase ROUGE scores by a large margin, the summaries generated are excessively extractive and their BERTScore (Zhang et al., 2019) and MoverScore (Zhao et al., 2019) are much lower than that of our summaries.

5 Conclusions

We have proposed a class of diminishing attentions which, by leveraging the hypothesis of submodular coverage property in neural abstractive summarization, is shown to be empirically more effective than the previous coverage mechanism. They are also architecturally simpler.

Experimental results and a series of analysis on the CNN/DailyMail dataset on different neural architectures demonstrate that our method produces summaries of good quality, outperforms comparable baselines and achieves state-of-the-art performance. In future, we would like to evaluate our methods on other datasets, and perform a user study to evaluate the models on different linguistic aspects (e.g., coherence, grammaticality). We also plan to extend this work by exploring other approaches to utilizing submodularity in the neural sequence-to-sequence framework and the applicability of our attention to other text generation tasks across areas such as machine translation, image captioning, dialogue generation, and automatic speech recognition.

References

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| Model                  | ROUGE-1 | ROUGE-2 | ROUGE-L |
|------------------------|---------|---------|---------|
| PG + Cov.              | 39.08   | 17.09   | 35.92   |
| DimAttn                | 39.30   | 17.48   | 36.31   |
| + Length Norm.         | 39.64   | 17.51   | 36.64   |
| + Trigram Blocking     | 39.92   | 17.64   | 36.88   |
| PG + Cov. only         | 39.08   | 17.09   | 35.92   |
| DyDimAttn only         | 39.70   | 17.80   | 36.67   |
| + Length Norm.         | 39.92   | 17.80   | 36.89   |
| + Trigram Blocking     | 40.13   | 17.87   | 37.09   |

Table 4: Ablation study. All the models have the same setting as our PG baseline, i.e., the maximum encoding steps are all set to 400 (thus the difference in ROUGE scores from Table 1).
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