Length Control in Abstractive Summarization by Pretraining Information Selection

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Abstract

Previous length-controllable summarization models mostly control lengths at the decoding stage, whereas the encoding or the selection of information from the source document is not sensitive to the designed length. They also tend to generate summaries as long as those in the training data. In this paper, we propose a length-aware attention mechanism (LAAM) to adapt the encoding of the source based on the desired length. Our approach works by training LAAM on a summary length balanced dataset built from the original training data, and then fine-tuning as usual. Results show that this approach is effective in generating high-quality summaries with desired lengths and even those short lengths never seen in the original training set.

1 Introduction

Abstractive summarization (Nallapati et al., 2016; See et al., 2017; Çelikyilmaz et al., 2018; Dong et al., 2019; Lewis et al., 2020; Liu et al., 2021; Dou et al., 2021) aims at reproducing the semantics and topics of the original text in a concise and fluent summary by paraphrasing. In order to display the summary on different mobile devices or websites with space limitations, we have to produce summaries in different lengths. Length-controllable summarization is a multi-objective optimization problem, including generating complete summaries within desired lengths and selecting proper information to summarize based on desired lengths. The existing length-controllable summarization based on encoder-decoder models can be divided into two categories: (1) early-stop during decoding and (2) information selection before encoding.

Early-stop during decoding methods (Kikuchi et al., 2016; Liu et al., 2018; Makino et al., 2019; Yu et al., 2021) focus on when to output eos (end of sequence), indicating the end of the summary. An ad-hoc method (Rush et al., 2015) generates the eos by assigning a score of $-\infty$ to all candidate words at the position of the desired length during test. Ad-hoc can be applied to any seq2seq model. Others learn the relationship between length and the decoder state at training time. However, these methods simply add length requirements to the decoder and ignore the fact that encoding the content, or the information selection, from the source document must also adapt to different length requirements. Table 1 gives an example. The content of the reference summary with 10 tokens is the celebration of iranians. The reference summary with 30 tokens contains the reason for the celebration. Some generated summaries with short desired lengths are likely to be incomplete, similar to the truncated version of summaries generated by models without length constraints. The summaries of ad-hoc and LenAtten in Table 2 are not complete and lose the information about "deal".

Yu et al., 2021 focus on when to output eos (end of sequence), indicating the end of the summary. An ad-hoc method (Rush et al., 2015) generates the eos by assigning a score of $-\infty$ to all candidate words at the position of the desired length during test. Ad-hoc can be applied to any seq2seq model. Others learn the relationship between length and the decoder state at training time. However, these methods simply add length requirements to the decoder and ignore the fact that encoding the content, or the information selection, from the source document must also adapt to different length requirements. Table 1 gives an example. The content of the reference summary with 10 tokens is the celebration of iranians. The reference summary with 30 tokens contains the reason for the celebration. Some generated summaries with short desired lengths are likely to be incomplete, similar to the truncated version of summaries generated by models without length constraints. The summaries of ad-hoc and LenAtten in Table 2 are not complete and lose the information about "deal".

| Generated Summaries (Desired Length = 10) |
|------------------------------------------|
| BART (Lewis et al., 2020) + Ad-hoc (Rush et al., 2015) (10 tokens) |
| iranians erupted in celebration as young people waved flags from their sunroofs, blasted music from stereos and chatted online with the hashtag #iranTalks. The excitement came after a breakthrough nuclear deal with the united states and other world powers. |

| Source Document |
|-----|
| iranians erupted in celebration as young people waved flags from their sunroofs, blasted music from stereos and chatted online with the hashtag #iranTalks. The excitement came after a breakthrough nuclear deal with the united states and other world powers. |

Table 1: The reference summaries of one source document with lengths as 10 and 30.

| Table 2: The summaries generated by different models. |
|---------------------------------------------|
| LateStop (LenAtten) (12 tokens) |
| the agreement on the final day of persian new year festivities . |
| the agreement on the final day of persian new year festivities . |

Methods based on information selection are two-
In our approach, we can create an LBD from the original summarization dataset. We first train LAAM on this LBD to enhance the ability of LAAM on information selection with length constraints. Then we fine-tune the pretrained LAAM on original dataset to learn to paraphrase the selected information as abstractive summaries in different lengths. The task of generating short summaries by the models fine-tuned on datasets without short reference summaries can be seen as a zero-shot problem. Benefiting from the pretraining with LBD, our approach can solve the zero-shot length control problem. Our contributions are as follows:

1. We propose a new length-aware attention mechanism (LAAM) to generate high-quality summaries with desired length. LAAM outperforms the state-of-the-art length-controllable methods on CNN/Daily Mail and XSUM in terms of ROUGE scores, length variance and human evaluation (Table 5).

2. We design a heuristics to create a length-balanced dataset (LBD) from original dataset. After pretraining LAAM on LBD, the pretrained LAAM performs better than LAAM and can effectively solve the zero-shot length control problem (Table 10).

2 Approach

In this section, we first introduce the length-controllable summarization (LCS) problem, then introduce the length-aware attention mechanism (LAAM), which attends the existing transformer seq2seq model (Vaswani et al., 2017) as our basis. Suppose that the encoder output is \( h = \{h_0, h_1, \ldots, h_n\}, h \in \mathbb{R}^{n \times d} \) and the output of the decoder’s masked self-attention sub-layer is \( z = \{z_0, z_1, \ldots, z_n\}, z \in \mathbb{R}^{n \times d} \). The normal cross attention is calculated as:

\[
A = \text{softmax}(z \cdot h^T)
\]  

where \( A \in \mathbb{R}^{n \times m} \) is an attention matrix. \( A_t = \{a_{t,0}, a_{t,1}, \ldots, a_{t,m}\} \) shows the attention scores of \( y_t \). \( a_{t,i} \) is the attention score between \( y_t \) and \( x_i \).
2.2 Length-aware Attention Mechanism

In the transformer seq2seq model, the cross attention of an output token \( y_t \) is likely to summarize those tokens with high attention scores in the input (source document). By formulating the cross attention as a function of the desired length \( l \), we can manipulate the input information selection according to \( l \). This is the intuition behind LAAM, which is illustrated in Figure 1.

LAAM is made up of two parts: attention for input selection (Attn\(i_t\)) and attention for eos token (Attn\(eos\)), each optimized for information selection and length control, the two objectives in LCS.

\( Attn_{i_t} \). At decoding, given the initial desired length \( l \), \( l + 1 \) is the number of tokens in the output with \( eos \), the remaining length budget \( (l_t) \) decreases as more tokens are generated. Specifically, at step \( t \),

\[
l_t = \begin{cases} 
  l + 1 - t, & 0 \leq t \leq l \\
  1, & \text{otherwise}
\end{cases}
\]

Intuitively, at each decoding step, the decoder should plan its output \( y_t \) given the remaining number \( l_t \) of tokens it will generate. Our key idea is to increase the attention scores of the top \( l_t \) tokens with the highest attention scores in \( A_t \), which gives a boost to the chance of these tokens to be selected and summarized. The interesting effect of this is that i) the longer \( l \), the more source information will be selected for summarization; and ii) as the decoder generates more tokens, the number of tokens to be mainly attended in input decreases. We use one-hot vector \( p = \{ p_0, p_1, ..., p_m \} \) to label the indices of the top \( l_t \) tokens with the highest attention scores in \( A_t \) as 1 and others as 0, and then the length-aware attention score is computed as:

\[
a_{t,i}^l = w_{t,i} \times a_{t,i}^l \tag{4}
\]

where \( w_{t,i} \) is the weight for boosting the attention between \( x_i \) and \( y_t \). According to Eq. (5), the weight for cross attention decreases as the remaining length decreases, resulting in a decrease in the gap between the enhanced tokens and other tokens. This makes the model evenly attend to tokens related to the enhanced tokens and output general words to end the decoding. The model can learn to select information to be summarized by desired length.

\( Attn_{eos} \). At each decoding step \( t \), to enhance the ability of model to generate \( eos \) at the desired length, we modify the attention score between \( y_t \) and \( eos \) in source document \( x_m \) as follows:

\[
a_{t,m}^{l+1} = (l + 1 - l_t) \times a_{t,m} \tag{6}
\]

The length-aware attention of \( eos \) increases step by step, which demonstrates the probability of stopping decoding will increase as the length of the output close to the desired length.

Finally, we re-normalize the modified attention scores \( A_t^l = \{ a_{t,0}^l, a_{t,1}^l, ..., a_{t,m}^l \} \) to get the context vector \( c_t \) and compute the probability distribution of predicted tokens via:

\[
p(y_t | y_{<t}, x, l) = \text{softmax}(Wc_{t-1} + b) \tag{7}
\]

\[
c_t = \sum_{i=0}^{m} \tilde{a}_{t,i} h_i \tag{8}
\]

\[
\tilde{a}_{t,i} = \frac{a_{t,i}^l}{\sum_{i=0}^{m} a_{t,i}^l} \tag{9}
\]

where \( W \) and \( b \) are trainable parameters.

2.3 LBD Creation for Pretraining LAAM

Since the summary lengths of a training dataset may be highly concentrated in a small range (see Table 4), neural-based abstractive summarization models tend to select source information according to the summary lengths they have seen in training data and generate summaries with similar lengths. In order to make the model learn to select proper information according to different desired lengths, we propose a heuristics to create a length-balanced dataset (LBD) by extracting summaries with various lengths from each document in original dataset.
and making lengths of these extractive summaries evenly distributed in different ranges.

Given an abstractive summarization dataset $D$, which consists of a training set $T$ and a validation set $V$, we create the training set $T'$ and validation set $V'$ of LBD. To create $T'$, we set the discrete bins $B = \{b_1, b_2, \ldots, b_k\}$ to represent the ranges of summary length of $T'$. $k$ is the number of the bins. For example, $B = \{(0, 10], (10, 20], \ldots\}$ and $b_0 = (0, 10]$. For each document $src$ and its reference summary $ref$ in $T$, we produce length-controllable pairs (LCPs) consisting of $src$ and its extractive summaries in various length ranges. Let $e$ be the extractive summary of length $b \in B$. We apply a greedy approach, where we add one sentence at a time incrementally to the $e$, until the length of $e$ is within the proper range of $b$ and has the highest ROUGE-1 (R-1) recall with respect to $ref$. Generally, the more training data, the greater the impact on the model. To make $T'$ effective, the number of samples in $T'$ should be close to $|T|$. $S(b)$ is the subset of $T'$, including LCPs with extracted summaries with length in $b$. We add top $\lceil |T'|/k \rceil$ extractive summaries (length $\in b$) with the highest R-1 recall and their source documents to $S(b)$, which makes the summaries equally distributed in the bins or length ranges. The details are in Algorithm 1.

**Algorithm 1 Creating Training Set of LBD**

**Input:** the training set $T$

**Output:** the training set $T'$

1: $rec()$ computes the R-1 recall score between two texts.
2: $len()$ computes the length of token sequence.
3: for each training pair $(src, ref) \in T$ do
4: $src = \{s_1, s_2, \ldots\}$, where $s_i$ is the $i^{th}$ sentence in $src$.
5: for $i = 0 \rightarrow |e|$ do
6: $min$ and $max$ denote minimum and maximum length of length range $b_i$, respectively.
7: $e_i \leftarrow 0$
8: while $S = \{s \in src \cap len(e_i \cup s) \leq max\}$ do
9: Select the $s_{red}$ with best $rec(e_i \cup s_{red}, ref)$ from $S$.
10: if $rec(e_i \cup s_{red}, ref) > rec(e_i, ref)$ then
11: $e_i \leftarrow s_{red}$; $src \leftarrow src - s_{red}$
12: else
13: break
14: if $len(e_i) > min$ then
15: $Add((src, e_i, rec(e_i, ref))$ to $S(b_i)$.
16: $S(b_i) \leftarrow top(\lceil |T'|/k \rceil)$ samples from $S(b_i)$ sorted by $rec(e_i, ref)$
17: $T' \leftarrow S(b_1) \cup S(b_2) \cup \cdots \cup S(b_k)$
18: return $T'$

For $V'$, we create an extractive reference summary by selecting one sentence at a time until we get a subset of sentences from $src$ that maximizes the R-1 F1 with respect to $ref$. Given an original source document and reference summary pair, R-1 recall computes the similarity between extracted sentences and reference without considering the length of extracted sentences. This meets our requirements for creating $T'$, that is, we can extract multiple summaries within different length ranges for one document. To evaluate the model at training, each document in $V'$ only needs one extractive summary. R-1 F1 considers the difference between the lengths of compared summaries, which can select an extractive summary most similar to the reference in length and content.

In this paper, we first pretrain LAAM on LBD for the ability to select information from source document to be summarized according to length constraint. Then we fine-tune the pretrained LAAM (PtLAAM) on original dataset. At this stage, armed with the ability to select information from source document, the model further learns to paraphrase the selected information into extractive summaries with desired length.

## 3 Evaluation

We first introduce the datasets and the experimental setup. We design two experiments, **general length control** and **zero-shot length control**, to compare our approach with baselines. General length control experiment trains and tests the models on the entire original dataset. Zero-shot length control experiment tests the model on a subset of the test set whose summary lengths fall within a certain range, and trains the model on training data with summary lengths outside this range. In each of the two experiments, we evaluate methods’ ability to do **length control and information selection**.

### 3.1 Datasets

We use two popular summarization datasets, **CNNDaily Mail** (CNNDM) (Hermann et al., 2015) consists of pairs of a single source document and a multi-sentence summary. The dataset includes 286,817 training pairs, 13,368 validation pairs and 11,487 test pairs. **XSUM** (Narayan et al., 2018) is composed of article and single-sentence summary pairs. The number of samples in training/validation/test sets are 204,045/11,332/11,334.

### 3.2 Baselines

The existing length-controllable models with good performance are listed in Table 3.

In the experiments, LAAM and PtLAAM are im-
implemented on top of BART2, because BART (Lewis et al., 2020) is one of the SOTA models in summarization, and it uses less memory and training time than its peers (Shleifer and Rush, 2020). Exact is not a summarization model but is used here to achieve hard length control on any seq2seq models to produce summaries of exact lengths.

### 3.3 Experimental Setup

We follow Liu et al. (2018) and Saito et al. (2020) to segment datasets by different length ranges and set the discrete bins $B$ of summary length ranges in Sec. 2.3. The $B$ of CNNDM is $B_c = \{(0, 10], (10, 30], ... , (90, +\infty]\}$ and that of XSUM is $B_x = \{(0, 10], (10, 30], (30, +\infty]\}$. Bx has only 3 ranges as the summaries in XSUM are shorter. In zero-shot length control experiments, test length ranges for CNNDM and XSUM is $\{(0, 30]\}$ and $\{(0, 10]\}$, containing 488 and 176 samples respectively. The length distribution of the datasets is in Table 4. During training, we set the lengths of gold summaries as desired lengths and take them as input. During test, there are two different setups. The gold length test (Saito et al., 2020) asks the models to generate summaries with desired lengths equal to the reference summaries. The arbitrary length test asks the models to generate summaries with arbitrary lengths, regardless of the reference summary lengths. The output lengths are set at 10, 30, 50, 70 and 90 for CNNDM and at 10, 30 and 50 for XSUM due to the latter’s shorter summaries.

In each experiment, to evaluate the ability to control length, we do soft length control tests, which sets minlen and maxlen to 0 and 200 respectively during decoding, covering a very large range. It is up to individual models to generate summaries as close as possible to the target length. To evaluate the ability to select information, we utilize

\begin{equation}
\text{Variance of the summary lengths against the desired length } l = \text{var} = 0.001 \times \frac{1}{n} \sum_{i=0}^{n} |l_i - l|^2,
\end{equation}

where $n$ is the number test cases, and $l_i$ is the length of generated summary for case $i$.

**Human Evaluation:** We randomly select 50 samples from CNNDM and 50 samples from XSUM. We ask three human annotators who are native or proficient English speakers to score the generated summaries under 3 aspects: Grammatically correct (Gram.): How grammatical the sentences of a summary are?; Informativeness (Info.): How much important information about the source document are?; Overall: How good is the overall quality of the summary on you criterion? The score of each aspect will be judged as: Poor (1.0), Barely Acceptable (3.0) and Good (5.0).

### 3.5 Experiment 1: General Length Control

Length control. We use soft length control here. As shown in Table 5 and Figure 2, LAAM and Pt-LAAM achieve higher ROUGE scores and lower variance than all other approaches, which means our approaches can generate good quality summaries with tighter length control. LAAM and

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Table 3: The abbreviation and description of methods.

| Abbrev. | Description |
|---------|-------------|
| Exact | Ignore eos before generated summary within the desired length and insert eos at the desired length. |
| LenEmb | Input remaining length. (Kikuchi et al., 2016) |
| LC | Take desired length as input. (Liu et al., 2018) |
| GDEE | Apply length-aware loss. (Makino et al., 2019) |
| LenAtten | Add length attention unit. (Ye et al., 2021) |
| LenEmb | Apply length-aware loss. (Makino et al., 2019) |
| Extract proto on top of BART | Extract prototype summary. (Saito et al., 2020) |
| BART+Proto | Apply length-aware loss. (Makino et al., 2019) |
| XSUM | Apply length-aware loss. (Makino et al., 2019) |

Table 4: Length distributions of two datasets.

| Data | Length | Train | Val | Test |
|------|--------|-------|-----|------|
| CNNDM | (0, 10] | 421 | 1 | 1 |
| | (10, 30] | 20,429 | 573 | 487 |
| | (30, 50] | 114,521 | 4,255 | 4,144 |
| | (50, 70] | 101,461 | 4,746 | 4,380 |
| | (70, 90] | 31,470 | 2,321 | 1,509 |
| | (90, +\infty] | 18,925 | 1,472 | 969 |
| | Total | 287,228 | 13,059 | 11,491 |
| XSUM | (0, 10] | 6,049 | 167 | 176 |
| | (10, 30] | 193,237 | 10,732 | 10,729 |
| | (30, +\infty] | 77,605 | 433 | 429 |
| | Total | 204,046 | 11,332 | 11,334 |
PtLAAM outperform BART, indicating that by controlling lengths effectively, summary quality can be improved, too. LPAS performs better than LenAtten on ROUGE scores but worse on Var, because LPAS focuses more on information selection under the length constraint and overlooks where to stop decoding. BLPAS is better than LPAS as using the pretrained BART as the basic model. BART and BLPAS are considered the previous SOTA methods for length-agnostic summarization and length-controllable summarization respectively. Therefore, we compare our approaches with BART and BLPAS in the remaining experiments.

Table 6 also confirms that compared with BART and BLPAS, our best approach PtLAAM gives the best quality summaries by human judges. The summaries generated by PtLAAM achieve better scores in grammatically correct, informativeness and overall. The human evaluation scores of XSUM are lower than those of CNNDM because the summaries in XSUM are much shorter. It is more difficult for a shorter summary to ensure that it is grammatically correct and contains enough information.

|                      | CNNDM      | XSUM       |
|----------------------|------------|------------|
|                      | R-1  | R-2  | R-L  | R-1  | R-2  | R-L  |
| BART                 | 4.13 | 20.05| 39.32| 44.61| 21.19| 36.00|
| LenEmb               | 32.74| 13.78| 24.50| 28.45| 8.92 | 23.13|
| LC                   | 35.45| 14.50| 26.02| 31.87| 11.23| 25.94|
| GOLC                 | 38.27| 16.22| 34.99| 32.94| 14.38| 26.11|
| LenAtten             | 39.82| 17.31| 36.20| 37.20| 16.05| 31.24|
| LPAS                 | 42.55| 20.09| 39.36| 43.64| 19.81| 35.22|
| BLPAS                | 42.95| 20.29| 39.76| 44.94| 20.31| 35.98|
| LAAM                 | 43.55| 20.44| 40.61| 45.30| 21.77| 36.64|
| PtLAAM               | 44.17| 20.63| 40.97| 45.48| 21.80| 36.84|

Table 5: Gold length test with soft length control. The LAAM and PtLAAM are statistically significantly better than BLPAS with p<0.05 according to t-test.

Table 6: Human evaluation. Average Cohen’s Kappa is 0.62 among judges, indicating good agreement.

We fine-tune the bart.large on CNNDM and XSUM via released code in https://github.com/pytorch/fairseq/. Due to incompleteness of the data preprocessing code and possible variance in computing resources and parameters, the results of BART in Table 5 are slightly lower than published version but similar to the numbers reported by others, such as https://github.com/pytorch/fairseq/issues/2541.

Figure 2: Variance of generated summary lengths in gold length test with soft length control.

To further test the models’ length control ability in different target length ranges, we divide the test data into different sets according to length range in Table 4, and test the models on these sets separately. Figure 3 shows that LAAM and PtLAAM still achieve the lowest Var. For the same length range in Figure 3 and Table 4, the more training data in this range, the lower Var of the generated summaries with respect to the reference summaries within this length range. This denotes that the imbalance length distribution in training data interferes with controlling length. In Figure 3, LAAM and PtLAAM have better and more stable ROUGE scores in all length ranges, illustrating that our approaches are not affected by the summary length distribution in training set and can generate better summaries with desired lengths.

Figure 3: Var and R-2(F1) scores of gold length test with soft length control on divided test sets.

The results of arbitrary length test are listed in Figure 4, the lower Var of LAAM and PtLAAM illustrate our approach can control summary length better. As R-2 is the most popular metric in summarization, we report the R-2 related scores of generated summaries. We compute R-2 Precision.
(Pre) of generated summaries instead of F1, because when the desired length of generated summaries is shorter than reference summary lengths, precision can reflect the accuracy of information selection within that limited budget. In Figure 4, LAAM and PtLAAM get better R-2 (Pre) on both datasets, which means our approaches can select more accurate information. As the desired length increases, the length-controllable models are more likely to select accurate information, causing the gap between our approach and BLPAS to gradually decrease. Bart is not designed to control length, resulting in unchanged R-2 (Pre). Although the arbitrary length test provides a unique perspective in the evaluation of the models, its automatic metric, i.e., R-2 (Pre) is only partial. Therefore, in the rest of the section, we will not do arbitrary length test unless the result is evaluated by human.

Figure 4: Var and R-2 (Pre) of arbitrary length test with soft length control on complete test sets.

Information selection. Next, we apply hard length control on all models to strictly enforce the exact desired length which is equal to the gold length. The better performance of our proposed approaches in Table 7 indicates that our approaches can cover more important information while producing exactly the same length of the reference summary. Compared to Table 5, our approaches also demonstrate more consistency.

Table 7: The ROUGE scores of models in gold length test with hard length control.

| Approach | CNNDM | XSUM |
|----------|-------|------|
|          | R-1   | R-2  | R-L  | R-1   | R-2  | R-L  |
| BART     | 43.43 | 20.11 | 39.52 | 44.82 | 21.34 | 36.23 |
| BLPAS    | 43.15 | 20.52 | 40.01 | 45.03 | 20.57 | 36.02 |
| LAAM     | 43.63 | 20.76 | 40.63 | 45.38 | 21.77 | 36.64 |
| PtLAAM   | 44.21 | 20.77 | 40.97 | 45.53 | 21.82 | 36.85 |

Ablation Studies. We evaluate the effectiveness of the pretraining LAAM on LBD and length-aware attention mechanism.

Pretraining on LBD. Compared with LAAM only training on original datasets, PtLAAM performs better on R-2 and Var in Figure 4 and Figure 3. The better R-2 scores indicates that the PtLAAM can select more important information with pretrained LAAM on our created dataset LBD. As one source document of LBD may have different extracted summaries within different length ranges, the model trained on LBD can learn to select different information from source document according to the length constraints. Besides, in LBD, the number of summaries with lengths in different ranges is balanced. PtLAAM gets lower Var, which denotes it can control length better. The Var scores in different length ranges are stable, which weakens the negative impact caused by the imbalanced length distribution of training data.

Length-aware attention mechanism. The length-aware attention consists of $\text{Attn}_{is}$ and $\text{Attn}_{eos}$. Table 9 shows the results of LAAM test on gold length test with soft length control. Compared with LAAM, the LAAM without $\text{Attn}_{is}$ has a big drop in ROUGE scores and a small drop in Var score, demonstrating that $\text{Attn}_{is}$ mainly focuses on select information with length constraint. The LAAM without $\text{Attn}_{eos}$ gets the much lower Var scores but not much difference in ROUGE scores than LAAM, which means that $\text{Attn}_{eos}$ is useful in limiting the output length. LAAM outperforms its
variant because of the effectiveness of length-aware attention mechanism. Thus, in our experiments, we use PtLAAM model, which trains LAAM with both $Att_{is}$ and $Att_{cos}$ on LBD first and then fine-tunes the original datasets, as our best approach.

| Data    | Model | R-1       | R-2       | R-L       | Var(%) |
|---------|-------|-----------|-----------|-----------|--------|
| CNNDM   | LAAM  | 43.63     | 20.76     | 40.63     | 0.05   |
|         | w/o $Att_{is}$ | 42.77     | 19.32     | 39.13     | 0.06   |
|         | w/o $Att_{cos}$ | 43.10     | 20.17     | 37.45     | 0.13   |
| XSUM    | LAAM  | 45.38     | 21.77     | 36.64     | 0.03   |
|         | w/o $Att_{is}$ | 43.45     | 20.64     | 34.79     | 0.03   |
|         | w/o $Att_{cos}$ | 44.62     | 21.32     | 35.03     | 0.08   |

Table 9: Usefulness of two kinds of attentions.

### 3.6 Experiment 2: Zero-shot Length Control

In this experiment, we use the modified dataset for zero-shot length control (Sec. 3.3). Zero-shot task can test a model’s ability to generalize to summary lengths that it has never seen in the original training data before.

| Dataset | Length | Approach | R-1 | R-2 | R-L | Var(%) |
|---------|--------|----------|-----|-----|-----|--------|
| CNNDM   | (0, 30) | BLPAS    | 33.54 | 14.83 | 29.42 | 0.14   |
|         |        | LAAM     | 33.52 | 15.20 | 30.54 | 0.05   |
|         |        | PtLAAM   | 33.65 | 15.77 | 31.26 | 0.03   |
| XSUM    | (0, 10) | BLPAS    | 34.37 | 19.54 | 31.66 | 0.10   |
|         |        | LAAM     | 34.49 | 20.07 | 32.10 | 0.03   |
|         |        | PtLAAM   | 35.16 | 20.55 | 32.47 | 0.02   |
|         | (0, 10) | BLPAS    | 30.25 | 12.51 | 26.98 | -      |
|         |        | LAAM     | 33.64 | 15.23 | 30.76 | -      |
|         |        | PtLAAM   | 33.78 | 15.89 | 31.30 | -      |
| XSUM    | (0, 10) | BLPAS    | 32.55 | 17.16 | 29.52 | -      |
|         |        | LAAM     | 34.83 | 20.15 | 32.10 | -      |
|         |        | PtLAAM   | 35.16 | 20.58 | 32.49 | -      |

Table 10: Results of zero-shot length control.

Table 10 shows the performance of PtLAAM on ROUGE scores and Var on different datasets are the best. For soft length control experiment, the ROUGE scores of different models are similar, because the lengths of summaries generated by BLPAS are longer than reference summary lengths (BLPAS has higher Var scores), which causes the generated summaries to match more tokens in the reference. Because ROUGE (F1) scores usually penalize summaries with longer lengths, PtLAAM, which controls the length better, is still better than other approaches. The lowest Var of our approaches means that our approach can better control summary length. In the hard length control experiment, the ROUGE scores of BLPAS drop a lot since the hard control shortens the length of summaries generated by BLPAS. The best performance of PtLAAM on ROUGE indicate PtLAAM learns to select information based on desired lengths. The ROUGE scores of our approaches are similar to those in soft length control experiment, which indicates our approaches are stable in controlling length. The LAAM performs worse than PtLAAM on ROUGE and Var denotes that the ability of LAAM to control length is impacted by length distribution of the training data. The pretraining on LBD is useful in generating high-quality summaries under desired summary length since the summaries are balanced in different length ranges of LBD.

### 3.7 Case Study

In this section, we analyze the performance of different models in controlling length.

#### Input Document

A gym teacher in New Hampshire has been accused of posing as a young girl on a social media site and persuading an elementary school student to share inappropriate images of herself. He was senting the photos to a grown man. Paul Johnson-Yarosevich of Acton, Maine, on Monday with prohibited use of computer after they say they discovered he’d been fooling a pre-teen girl into sending him inappropriate photos of herself by posing as a young girl on social media. Authorities soon learned that the girl was sending the photos to a grown man.

| Len | Generated summaries                                                                 |
|-----|-------------------------------------------------------------------------------------|
| 10  | police charged 34-year-old Paul Johnson-Yarosevich of Acton, Maine, on Monday with prohibited use of computer after they say they discovered he ‘d been fooling a pre-teen girl into sending him inappropriate photos of herself by posing as a young girl on social media.
| 30  | police charged 34-year-old Paul Johnson-Yarosevich of Acton, Maine, on Sunday with prohibited use of computer after discovering he ‘d been fooling a pre-teen girl into sending him inappropriate photos of herself by posing as a young girl on social media.

Table 11: The generated summaries of Table 1 of various desired length Len. The italicized tokens repeat significant parts the shorter summaries. The red is the tokens longer than desired length. Here Exact refers to the BART using Exact at test, to be fair.

We use the example in Table 11 to analyze different length-controllable methods since the summaries of this example generated by different models are obviously different in length control and information selection.

As shown in Table 11, BART itself cannot control the length of generated summaries. So, the
length of the summary generated by BART is always much longer for covering more information from source document. After adding Exact at test time, BART can generate summary with length exactly the same as desired length. But, as a early-stop during decoding methods, Exact always produce incomplete summaries. The summary with 30 tokens of Exact repeats its summary with 10 tokens during generation. Because such methods ignore that the summaries with different lengths of one document should represent different information of source document. BLPAS tends to select more information with length constraints, which may generate summaries with length longer than desired length (the red part in Table 11). The lengths of summaries generated by LAAM and PtLAAM in Table 11 are the same as the desired lengths.

Compared with PtLAAM, given the desired length as 10, LAAM loses the important information about the reason why Paul was charged as there are few training pairs with summary lengths as 10. PtLAAM pretrained on LBD can select information according to various desired lengths as the summary lengths in LBD are evenly distributed in different length ranges. The summaries with desired length as 30 of LAAM and PtLAAM are more similar than their summaries with desired length as 10. This is because there are many more summaries with length about 30 than those with length about 10 in original dataset. Thus, PtLAAM is more effective in generating summaries of lengths that do not appear in the original datasets.

4 Related Work

Previously, most length-controllable approaches in abstractive summarization focused on stopping decoding at a particular time. Ad-hoc (Rush et al., 2015) generated the eos token by assigning a score of -∞ to the tokens in vocabulary and generated a fixed number of words. LenEmb and LenInit (Kikuchi et al., 2016) input length embeddings to decoder respectively. Bian et al. (2019) took LenEmb and LenInit as an agent and adjusted the reward incorporating with the desired length. LC (Liu et al., 2018) added the desired length into the first layer of CNN encoder. GOLC (Makino et al., 2019) optimized LenEmb and LC by normalizing loss with an overlength penalty. Fan et al. (2018) predefined some special markers to denote different length ranges and prepended the input with such markers during training and testing. Takase and Okazaki (2019) extended the sinusoidal positional encoding (Vaswani et al., 2017) to take account of stepwise remaining length. LenAtten (Yu et al., 2021) added a length attention unit to exploit proper length information based on the stepwise remaining length.

Other length-controllable approaches decided the content to be summarized by length-aware intermediate summaries. LPAS (Saito et al., 2020) extracted a word sequence with the desired length from source document and generated summary by a non-length-controllable model with document and extracted summary as input. MLS (Sarkhel et al., 2020) generated a general summary and then input it to a length-controllable model.

Compared with previous methods, our approach can effectively control the length of generated summaries by pretraining the length-controllable information selection model on length-balanced dataset. Meanwhile, it can generate summaries with length approximate to the desired length in zero-shot controlling length problem.

Recently, the approaches fine-tune the pretrained transformer seq2seq models (Lewis et al., 2020; Zhang et al., 2020; Dou et al., 2021; Liu and Liu, 2021) on summarization datasets. They achieve outstanding performances on summarization tasks. Our approach is applied to transformer seq2seq model, which is orthogonal to above pretrained transformer models and can be added to them.

5 Conclusion

We present a novel approach to produce summaries in desired length that are fluent and coherent. This approach pretrains a transformer seq2seq model whose cross attention between input and output are re-normalized accordingly to the length requirement. The pretraining is done over synthetic summarization data extracted from the original training set but with summary lengths evenly distributed. Our results show that the framework achieves a good balance between information selection from input documents and length control when producing summaries.
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