Reinforced Abstractive Summarization with Adaptive Length Controlling

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Abstract
Document summarization, as a fundamental task in natural language generation, aims to generate a short and coherent summary for a given document. Controllable summarization, especially of the length, is an important issue for some practical applications, especially how to trade-off the length constraint and information integrity. In this paper, we propose an Adaptive Length Controlling Optimization (ALCO) method to leverage two-stage abstractive summarization model via reinforcement learning. ALCO incorporates length constraint into the stage of sentence extraction to penalize the over-length extracted sentences. Meanwhile, a saliency estimation mechanism is designed to preserve the salient information in the generated sentences. A series of experiments have been conducted on a wildly-used benchmark dataset CNN/Daily Mail. The results have shown that ALCO performs better than the popular baselines in terms of length controllability and content preservation.

Introduction
Document summarization is a fundamental task of natural language generation, which targets to condense the given document into a short and coherent version with the important information. Summarization has attracted much attention and has a wide-ranging application with the explosive growth of text information. For example, summarization, in search engines, can help users to catch the main concepts of the desired documents quickly. In this paper, we focus on controllable summarization, especially of the length, to generate a condensed summary and retain the salient information as much as possible. It is a challenging issue to control the summary length in the real application, especially when no prior is provided. As shown in Figure 1, both document length and summary length have significant variance. In this case, adaptive controllable summarization becomes necessary to generate a summary with appropriate length and without sacrificing the salient information.

In literatures, various summarization methods have been proposed. Among them, extractive methods (Nallapati, Zhai, and Zhou 2017; Narayan, Cohen, and Lapata 2018) try to select proper sentences from the source document. Abstractive methods (See, Liu, and Manning 2017; Chen and Bansal 2018; You et al. 2019) aim to generate new sentences for providing more fluent and readable summary. These traditional methods focus on improving semantic accuracy. Controlling summary length, however, is an essential aspect of summarization in some practical applications and recently has been pointed out as a challenging issue in the area of neural language generation (Kikuchi et al. 2016).

To consider length constraint, a popular way is to incorporate length embedding in the decoder module of abstractive summarization model (Kikuchi et al. 2016; Fan, Grangier, and Auli 2018; Liu, Luo, and Zhu 2018; Bian et al. 2019; Makino et al. 2019). Their main goal is to determine the appropriate position where the decoding process can be stopped according to the length constraint. However, it is difficult for them to decide what information should be covered in summary with a particular length. Recently, Saito et al. (2020) introduce a word-level extractive module with length constraint to provide proper information for the subsequent encoder-decoder abstractive model. Although these
In this paper, we propose an adaptive length controllable abstractive summarization model via reinforcement learning. ALCO incorporates length constraint into the stage of sentence-level extraction module to penalize the overlength sentences, so that only a few short sentences are extracted. Meanwhile, ALCO introduces a saliency estimation mechanism to evaluate the significance of sentences, so that the most related sentences are selected. As shown in Table 1, rather than the sentence [18], the sentence [21] containing salient information and less words should be selected to generate the corresponding sentence in summary.

To the best of our knowledge, this is the first work to control summary length in sentence-level for two-stage abstractive summarization. Our contributions are summarized as follows.

- A novel adaptive length controllable abstractive summarization model is proposed with the aid of reinforcement learning. It has ability to effectively guide the sentence extraction and adaptively control the size of extracted sentences.
- ALCO can effectively coordinate the balance between the length of the generated summary and the information attenuation of the original document. Moreover, it is much more practical and flexible because users need not predefine the desired length.
- ALCO empirically achieves a higher ROUGE score and better length controllability. Furthermore, it is faster (more than $40\times$) than the existing length controllable abstractive models to generate summary in the testing phase.

### Related Work

In this section, we briefly describe the related work from three aspects: neural document summarization, length controllable abstractive summarization, and reinforcement learning for summarization.

#### Neural Document Summarization

Neural encoder-decoder models (Bahdanau, Cho, and Bengio 2015) enable the end-to-end framework for the natural language process, which inspires the research on neural extractive and abstractive summarization models. The former usually creates a summary by directly selecting sentences from the given document via scoring or classification (Cheng and Lapata 2016; Nallapati, Zhai, and Zhou 2017). Although the extractive method can generate summary quickly and precisely, it suffers from fluency and coherence. Rush, Chopra, and Weston (2015) proposed an attentional encoder-decoder model for abstractive summarization to generate summary from scratch, which is extended via recurrent neural networks (Chopra, Auli, and Rush 2016), convolutional neural networks (Fan, Grangier, and Auli 2018), and copy mechanism (See, Liu, and Manning 2017). However, the best result of See, Liu, and Manning (2017) does not quite surpass the ROUGE scores of the lead-3 baseline (extract first three sentences), nor the previous best extractive model (Nallapati, Zhai, and Zhou 2017). Later, Chen and Bansal (2018) proposed a two-stage (extract-then-compress) abstractive summarization model, which takes advantages of both extractive and abstractive method. Concretely, it first extracts a critical sentence and then rewrites it to a short one, which is similar to human making summaries. Meanwhile, this model is much efficient in both training and testing phases, which inspires several new studies (Ba et al. 2019; Sharma et al. 2019; Moroshko et al. 2019). Therefore, we take the two-stage abstractive model as our basic learning framework.

#### Length Controllable Abstractive Summarization

To control summary length, Kikuchi et al. (2016) propose methods for controlling the output sequence length for neural encoder-decoder models. It mainly includes four methods: EOS tags, discarding out-of-range content, length embedding as additional input for the decoding network, and length-based memory cell for the LSTM initialization. To efficiently parallelize the learning process and improve the

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**Table 1: Source document and reference summary example in CNN/Daily Mail dataset**

| Source Document | Reference Summary |
|-----------------|-------------------|
| [0] lapd apologizes after son of sen. robert f. kennedy objects to las vegas display. | [0] lapd apologizes after son of sen. robert f. kennedy objects to las vegas display. |
| [1] tie, jacket, shirt senator wearing when slain removed from exhibit. | [1] tie, jacket, shirt senator wearing when slain removed from exhibit. |
| [2] chief calls exhibit, which includes evidence from other high-profile crimes, educational. | [2] chief calls exhibit, which includes evidence from other high-profile crimes, educational. |
| [3] in editorial, maxwell taylor kennedy calls clothing display “a macabre public-ity stunt” | [3] in editorial, maxwell taylor kennedy calls clothing display “a macabre public-ity stunt” |

**Methods:**

- EOS tags
- Discarding out-of-range content
- Length embedding as additional input for the decoding network
- Length-based memory cell for the LSTM initialization
length controlling, the Convolutional sequence to sequence model was extended for controllable abstractive summarization (Liu, Luo, and Zhu 2018; Fan, Grangier, and Auli 2018; Bian et al. 2019). Later, Makino et al. (2019) further reduce the summary length and speed the summary generation by incorporating global training based on a minimum risk training under the length constraint. However, the length constraint is usually embedded in the decoder side, which may miss important information because they hardly determine which content should be included in a summary for certain length constraints. Saito et al. (2020) proposed a prototype extractor for a two-stage abstractive model to simultaneously control the summary length and capture important content in summary. Even though the above methods obtain impressive performance, they require a predefined length or the length of the gold summary as constraint, which is not practical in a real application, primarily when users cannot provide such information. Thus, in this paper, we focus on adaptive length controllable summarization.

Reinforcement Learning for Summarization

Reinforcement learning (RL) has attracted increasing attentions in the field of natural document summarization due to its superiorities on optimizing the non-differential metrics and mitigating the exposure bias. Narayan, Cohen, and Lapata (2018) designed a reinforcement learning objective to globally optimize the ROUGE evaluation metric and learn to rank sentences for extractive summarization. Paulus, Xiong, and Socher (2018); Pasunuru and Bansal (2018) use policy gradient algorithm and multi-reward optimization to leverage abstractive summarization. To take advantages of both extractive and abstractive methods, Chen and Bansal (2018) proposed a two-stage reinforced abstractive summarization method. These reinforced methods usually design a reward according to the ROUGE score. In this case, the length of generated summaries will depend on the type of ROUGE score. For example, the summary length will be long if ROUGE recall is adopted, while the summary length will be short once ROUGE precision is used. Even though the ROUGE F1 score can balance the length of a generated summary, it cannot decide whether or not the summary is over-length (Makino et al. 2019). To bring reinforcement learning into full play, we incorporate an adaptive length constraint to the reward for length controllable two-stage abstractive summarization. It is expected to avoid generating verbose summaries with unnecessarily long sentences and redundant information.

Methodology

This section will start with the problem definition, and then describe the basic two-stage model, extract-then-compress. Finally, the proposed adaptive length control optimization method will be described in detail.

Given a document–summary pair \((D, S)\) with sentences \([d_1, d_2, ..., d_D]\) in \(D\) and sentences \([s_1, s_2, ..., s_S]\) in \(S\), a summarization model aims to generate a concise and readable multi-sentence summary \(S'\) (approach to \(S\)) for \(D\) (where \(S'\) consists of \([S']\) sentences \([s_1', s_2', ..., s_{S'}']\)).

Basic Two-Stage Model

The two-stage summarization is used as the basic model in our work because it is more in line with the thinking of human beings when making summaries (Chen and Bansal 2018). It firstly uses an extractive agent as a sentence extractor to select the important sentences from the given document, and then leverages an abstractive module to rewrite and compress the extracted sentences, thus it is called as extract-then-compress model and denoted as SentenceRewriting. In this case, the extractor agent can be taken as a stochastic policy \(π_a\) (with parameters \(θ_a\)) to select actions (sentences) according to the corresponding ROUGE scores for reinforced summarization. Specially, the reward of the \(t\)-th generated sentence \((s'_t)\) can be calculated as

\[
r_t = R(s'_t, s_t),
\]

where \(R\) indicates the ROUGE-L score between the generated sentence \((s'_t)\) and reference sentence \((s_t)\), and \(s'_t\) is obtained by rewriting the extracted sentence \(d_t\). At the current step \(t\), the total discounted future reward can be defined as

\[
R_t(s'_t) = \sum_{t=0}^{N-t} γ^τ r_{t+τ}.
\]

Here \(γ\) is the discounted factor. To learn the optimal policy \(π_a\), SentenceRewriting exploits a critic network to predict a baseline \(b_t\), which is used to estimate the advantage value for each action (extracted sentence). \(A_t(s'_t) = R_t(s'_t) − b_t\). The critic network can be trained by minimizing the square loss \(L_{θ_c} = (b_t − R_t(s'_t))^2\). The final goal is to maximize the advantage value along all actions:

\[
L_{θ_c} = −\frac{1}{N_s} \sum_{i=1}^{N_s} \log π_{θ_a} A_t(s'_t),
\]

where \(N_s\) is the number of extracted sentences. SentenceRewriting exploits the Advantage Actor-Critic (A2C, a synchronous variant of A3C (Mnih et al. 2016)) as the optimization method to learn the parameters \(θ_a\) and \(θ_c\).

This kind of two-stage model takes advantages of both extractive method and abstractive method via policy-based reinforcement learning, so that a readable summary can be generated efficiently. In this paper, we target to extending this two-stage model to perform length controllable summarization.

The Proposed ALCO Method

To control the summary length, a reinforced two-stage abstractive summarization with adaptive length constraint is designed in this subsection, as shown in Figure 2. The proposed model consists of two parts: Adaptive Length Controlling (ALC) and Saliency Estimation Mechanism (SEM). Among it, ALC aims to penalize the overlength extracted sentences, i.e., prefer to the shorter sentences. SEM is introduced to guarantee the extracted sentences contain salient information as much as possible. Our main idea is to incorporate the length constraint and saliency estimation into the reward function \(r_t\) in (1)).
Adaptive Length Controlling In two-stage summarization, the extractive module is used to select sentences, while the abstractive module will generate summary according to the extracted sentences. In this case, the extracted sentences will dominate the performance of summarization, after all, the abstractive model can not output a good summary without high-quality input. This observation motivated us to focus on enhancing the extractive module by cooperating adaptive length constraint.

To take into account the length constraint, the number of words in reference summary is adopted to penalize the ROUGE scores of overlength extracted sentences via

\[
 a_{alc}^t(s'_t, s_t) = -\rho \times \max(\epsilon, L(s'_t) - L(s_t)) \times R(s'_t, s_t),
\]

where \( R(s'_t, s_t) \), like (1), indicates the ROUGE-L_{F1} score between \( s'_t \) and \( s_t \). \( L() \) counts the number of words for the given sentence. The parameter \( \epsilon \) is introduced to enforce the length controlling (even if the length of the generated sentence is shorter than the reference sentence) and empirically set as 0.0001, and parameter \( \rho \) is for adjusting the strength of length constraint. The proposed length constraint \( a_{alc}^t(s'_t, s_t) \) will be small once the long sentence is extracted, i.e., it will output a large value on short selected sentence.

Saliency Estimation Mechanism In the basic reinforced two-stage abstractive model, the extractor agent is usually trained according to the ROUGE-based reward. Due to the characteristics of ROUGE, this strategy is insufficient to extract informative sentences, especially under length constraint (See, Liu, and Manning 2017; Makino et al. 2019). Thus, we design a saliency estimation mechanism to evaluate the saliency of each generated sentence, so that only the sentences with salient content are extracted in the extractive module.

To implement this, a paraphraser network (with the same architecture as the as the abstractor) is trained with the set sentence pairs (the generated sentences (\( s'_t \)) and the extracted sentences (\( d_t \))), so that the paraphrased sentences \( d'_t \) (transforming from \( s'_t \)) approach to \( d_t \). In this case, we can estimate the extent to which the salient content of \( d_t \) is maintained by \( s'_t \).

\[
a_{sem}^t = R(d'_t, d_t).
\]

Higher \( a_{sem}^t \) indicates that the generated sentence \( s'_t \) retain more salient content from the extracted sentence \( d_t \).

Adaptive Length Controlling Optimization Towards controllable summarization, control length and remain saliency in summarization, we improve the basic two-stage model via a reinforcement learning with the introduction of two rewards from adaptive length controlling (\( a_{alc}^t \)) and saliency estimation mechanism (\( a_{sem}^t \)) respectively. The proposed multi-reward for adaptive length controlling optimization can be formalized as

\[
r^t_{ALCO} = a_{sem}^t \times r^t_{basic} + a_{alc}^t.
\]

Here, \( r^t_{basic} \) is the traditional metric (ROUGE) reward \( r_t \) (as shown in Eq.(1)). In this case, the novel reward simultaneously considers length constraint, saliency maintained, and the traditional metric ROUGE. The learning process of RL aims to maximize \( r^t_{ALCO} \), which generates short sentences with salient content and a higher ROUGE score.

Experiments

In this section, the proposed ALCO model is evaluated on the widely-used benchmark dataset (CNN/Daily Mail) from two aspects (length controllability and summary completeness) in terms of various evaluation metrics.

CNN/Daily Mail Dataset

This corpus was originally constructed for reading comprehension tasks by collecting news stories from CNN and Daily Mail websites (Hermann et al. 2015). There are two versions of the dataset, non-anonymized and entity anonymized version. Following (See, Liu, and Manning 2017), we use the non-anonymized version, which has 286,939 training pairs (remove invalid pairs), 13,368 validation pairs, and 11,490 test pairs. Table 3 shows the statistics in detail.

Evaluation Metric

ROUGE & METEOR In experiments, the standard ROUGE evaluation metric (Lin 2004) on F1 score is adopted, including ROUGE-1 (R-I), ROUGE-2 (R-2), and ROUGE-L (R-L). The averaged value on these three values is also calculated, denoted as R-AVG. Meanwhile, to do more thorough analysis, we also evaluate on METEOR (MT) (Banerjee and Lavie 2005). Larger values on ROUGE and METEOR indicate better performance.

Length Controllability To evaluate length controllability, we use three types of metrics. The first type is the variance of the \( t \)-th generated summary length \( L(S'_t) \) against
| Summarization Model | R-1 | R-2 | R-L | R-AVG | C-Var | W-Var | W-Over% | Avg-Time (sec.) |
|---------------------|-----|-----|-----|-------|-------|-------|---------|-----------------|
| **Summarization Model Without Length Controlling** |     |     |     |       |       |       |         |                 |
| Lead-3              | 40.34 | 17.70 | 36.57 | 31.54 | 66.55 | 2.32 | 90.46% | -               |
| PG (w/c)            | 39.53 | 17.28 | 36.38 | 31.06 | 23.58 | 0.84 | 58.84% | -               |
| SentenceRewriting   | 40.88* | 17.80* | 38.54* | 32.41* | 19.58* | 0.68* | 74.26% | 0.36            |
| **Length Controllable Abstractive Model** |     |     |     |       |       |       |         |                 |
| PG w/LE (MLE)      | 37.45 | 15.31 | 34.28 | 29.01 | 4.10  | -    | 19.11% | 12.83          |
| PG w/LE (MRT)      | 38.47 | 16.30 | 35.30 | 30.02 | 18.74 | -    | 43.32% | 24.13          |
| PG w/LE (GLOC)     | 38.27 | 16.22 | 34.99 | 29.83 | 5.13  | -    | 6.70%  | 10.31          |
| LC (MLE)           | 30.67 | 11.00 | 28.97 | 23.55 | -     | 0.17 | 44.67% | 16.93          |
| LC (MRT)           | 31.02 | 11.29 | 28.54 | 23.62 | -     | 0.21 | 61.67% | 17.19          |
| LC (GLOC)          | 29.38 | 10.38 | 27.18 | 22.31 | -     | 0.22 | 21.55% | 16.41          |
| ALCO (w/o ALC)     | 41.41 | 18.30 | 38.94 | 32.88 | 17.39 | 0.62 | 66.56% | 0.33           |
| ALCO (w/o ALC) & ρ = 1.00 | 41.52 | 18.47 | 39.09 | 33.03 | 21.48 | 0.75 | 74.15% | 0.35           |
| ALCO (w/o ALC) & ρ = 4.00 | 37.04 | 15.90 | 34.66 | 29.10 | 22.58 | 0.82 | 23.30% | 0.22           |
| ALCO & ρ = 1.00   | 38.59 | 16.80 | 36.10 | 30.50 | 22.27 | 0.81 | 23.65% | 0.23           |
| ALCO & ρ = 0.10   | 41.30 | 18.24 | 38.82 | 32.79 | 17.11 | 0.61 | 64.10% | 0.28           |

Table 2: Comparing performance on CNN/Daily Mail in terms of ROUGE, C-Var, W-Var, W-Over%, and Avg-Time (sec.).

Figure 3: Comparing performance of five methods (PG (w/coverge) (PGC2), SentenceRewriting (SR3), ALCO (w/o ALC) (ALCOALC), ALCO (w/o SEM) & ρ = 2.00 (ALCOSEM), ALCO & ρ = 0.01 (ALCO)) on CNN/Daily Mail testing sets in terms of R-AVG, W-Total, IG-R-AVG (Improvement Gain of R-AVG), W-Total-Over, IG-R-AVG / W-Total-Over. The values in (c) and (d) are calculated according to PG (w/coverge) (the corresponding recorded results are R-AVG: 28.51, W-Total: 656151).

The reference summary length $L(S_i)$ in terms of word-level, character-level and sentence-level (Liu, Luo, and Zhu 2018), denoted as W-Var, C-Var and S-Var respectively.

$$W-Var(S'_i, S_i) = 0.001 \times \frac{1}{T} \sum_{i=0}^{T} |L(S'_i) - L(S_i)|^2,$$  \hspace{1cm} (7)

where $T$ is the number of documents in the testing set. $S'_i$ and $S_i$ are respectively the generated summary and reference summary for the $i$-th document. $L(S_i)$ indicates the number of words in $S_i$. Following the previous work (Liu, Luo, and Zhu 2018), the length variance C-Var on characters is also counted with the same method as W-Var. Additionally, our proposed methods focus on controlling length in the stage of sentence extraction, thus, the length variance on sentences is designed to evaluate the final performance as follows.

$$S-Var(S'_i, S_i) = 0.1 \times \frac{1}{T} \sum_{i=0}^{T} ||S'_i|| - ||S_i||^2.$$  \hspace{1cm} (8)

Here $||S_i||$ indicates the number of sentences in $S_i$.

The second type is %over that is calculated by dividing the number of the overlength summaries with the number of test data in word-level and sentence-level, denoted as W-Over% and S-Over% respectively.

The last type of metric includes W-Comp.% and S-Comp.% indicating the compression ratio in terms of word and sentence respectively from document to summary.

Table 3: Statistics of CNN/Daily Mail. Averaged S-Len / Averaged W-Len indicate the averaged number of sentences / words in document or summary. S-Comp.% / W-Comp.% indicates the compression ratio (summary vs. document) on sentence-level / word-level.

| Training Set / Testing Set | Averaged S-Len (Document) | Averaged W-Len (Document) | Averaged S-Len (Reference) | Averaged W-Len (Reference) | S-Comp.% | W-Comp.% |
|----------------------------|---------------------------|---------------------------|---------------------------|---------------------------|-----------|-----------|
| Averaged S-Len (Document)  | 26.88                     | 25.63                     |                           |                           |           |           |
| Averaged W-Len (Document)  | 785.44                    | 741.95                    |                           |                           |           |           |
| Averaged S-Len (Reference) | 3.72                      | 3.71                      |                           |                           |           |           |
| Averaged W-Len (Reference) | 54.91                     | 55.63                     |                           |                           |           |           |
| S-Comp.%                   | 13.84                     | 14.48                     |                           |                           |           |           |
| W-Comp.%                   | 7.00                      | 7.50                      |                           |                           |           |           |
(Sharma, Li, and Wang 2019). Smaller values \( \rho \) on length evaluation metrics indicate better length controllability.

**Baseline**

We compare ALCO with three popular summarization models (Lead-3, PG (w/ coverage) (See, Liu, and Manning 2017) and SentenceRewriting (Chen and Bansal 2018)) that are not capable of controlling summary length, and three length controllable models (PG w/ LE (Kikuchi et al. 2016), LC (Liu, Luo, and Zhu 2018), and GLCO (Makino et al. 2019)). Concretely, Lead-3 is used because it is an efficient extractive model, which extracts the first three sentences from a source text as a summary. For the abstractive model, SentenceRewriting is taken as one baseline since ALCO is proposed by extending this basic model. Meanwhile, PG (w/ coverage) and SentenceRewriting showed SOTA performances on the abstractive summarization task. The reported scores of Lead-3 and PG (w/ coverage) in See, Liu, and Manning (2017) on CNN/Daily Mail is directly used. The results of other baselines are reported in the corresponding articles. Due to page limited, please refer to Chen and Bansal (2018) for the detail of implementation settings about various hyperparameters and training strategies.

**Results and Discussions**

For easy comparison, we separate the experimental results into two parts. The first part focuses on comparing ALCO with baselines. The other is to discuss the importance of adaptive length controlling and the effectiveness of the evaluation metric.

**ROUGE Results**

Table 2 shows ROUGE (F1-scores of full length summaries without trimming), C-Var, W-Var, and W-Over\% on CNN/Daily Mail. The best results of baselines without length controlling are marked by star, and the best results of the existing length controllable abstractive model are underlined. The best results of ALCO and its variants are marked in bold. It can be seen that the basic model SentenceRewriting (Chen and Bansal 2018) performs the best among all baselines in terms of ROUGE. This confirms the effectiveness of reinforced two-stage abstractive summarization. An interesting phenomenon is that the length controllable abstractive models obtain the best performance on length controllability, however, they sacrifice the ability to generate summaries (obtaining lower ROUGE scores). As expected, the proposed model is helpful to improve the performance of summarization, e.g., ALCO (w/o SEM) \& \( \rho = 1.00 \), ALCO (w/o ALC) and ALCO \& \( \rho = 0.10 \) consistently outperform baselines in terms of ROUGE scores. This indicates that both adaptive length controlling (ALC) and saliency estimation mechanism (SEM) leverage summary generation.

**Length Controllability**

Comparing with the existing models without length controlling, from Table 2, it can be seen that ALCO significantly compresses the summary length. However, the recorded values on length evaluation metrics obtained by PG-type and LC-type methods are better than ours. According to their experimental settings, we found that these methods set the desired length as the length of the gold summary during the testing phase. In other words, they take the ground-truth length as prior, while our proposed ALCO does not use such information because they are not previously known in real applications.

In ALCO, parameter \( \rho \) in (4) is introduced to adjust the strength of ALC on summary generation. To investigate the effect of \( \rho \) on ALCO, a series of experiments under varying \( \rho \) were conducted and the results are recorded in Table 4. Among it, Extract-Result is obtained according to the extracted summary without rewriting, while Abstract-Result is from the two-stage (extract-then-rewrite). It can be seen that, in both cases, ALCO generates summaries with different lengths (both in word-level and sentence level) by tuning \( \rho \). Large \( \rho \) prefers to short summary because it promotes penalizing the overlength extracted sentence to a large extent. To be excited, ALCO \& \( \rho = 1.00 \) has ability to obtain proper compression ratio in terms of word-level (7.25\%) and sentence-level (14.09\%), which is closest to the ground-truth W-Comp.\% value (7.5\%) and S-Comp.\% value (14.48\%). This result confirms that ALCO is good at generating summary with appropriate length.

**Summarization Speed**

The column Avg-Time (sec.) in Table 2 lists the average time (in second) to generate summary for one input document. Benefiting from two-stage summarization model, SentenceRewriting (Chen and Bansal 2018) and our proposed ALCO-type models are obviously efficient. Especially, ALCO (w/o SEM) \& \( \rho = 4.00 \) faster than 40× (0.22 vs. 10.31) the other length controlled baselines. ALCO performs better than its basic model (0.22 vs. 0.36). The main reason, we believe, is that the length controlling strategies (ALC and SEM) can effectively avoid selecting the unnecessarily long sentences with redundant information.

**Discussion about Two Main Issues**

An Adaptive Length or A Desired Length? In most real applications, it is hard to previously know the concrete information about summary such as length, complexity and etc, but it is required to output a correct and salient summary. In this case, if the summary is generated according to the given length (e.g., a desired length), it may be incomplete and even ambiguous. As shown in Figure 1, documents with different lengths should have the corresponding summaries with different lengths. This observation motivated us to design ALCO with adaptive length controlling during summarization.

Length or ROUGE? ROUGE is usually adopted to evaluate the performance of summarization models. According to its computation mechanism, we know that higher ROUGE recall prefers a long summary, while higher ROUGE precision promotes outputting a short summary. Although ROUGE F1 trades off these two metrics, higher ROUGE F1
is always accompanied by higher ROUGE recall (Makino et al. 2019), which will result in a long summary. Comparing with the popular and efficient abstractive model PG (See, Liu, and Manning 2017), we demonstrate the gain on R-AVG and %over on word length in Figure 3 (c) and (d). Note that only baselines without length constraints are used here because the authors of other baselines do not provide code. It can be seen that the basic model SentenceRewriting obtains a great ROUGE gain but the longest summary in word-level. Here, a novel evaluation metric is designed, called as ROUGE under Explicit Length Constraint (RELC) to simultaneously consider length and ROUGE. Concretely, RELC is the ratio between R-AVG (on ROUGE with F1 score) and W-Total-Over. From Figure 3, it can be seen that the proposed ALCO significantly outperforms the baselines.

### Conclusions and Future Work

An adaptive length controlling optimization method is proposed to leverage reinforced two-stage abstractive summarization. Benefiting from the designed adaptive length controlling and saliency estimation mechanism, ALCO has the ability to extract short sentences with salient content. A series of experiments have demonstrated that ALCO outperformed the popular summarization methods in terms of ROUGE, while maintaining the length controllability.

In the future, it will be interesting to incorporate modern language model in ALCO to learn much more informative representation for document and summary.
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