Reinforcing Semantic-Symmetry for Document Summarization

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ABSTRACT
Document summarization condenses a long document into a short version with salient information and accurate semantic descriptions. The main issue is how to make the output summary semantically consistent with the input document. To reach this goal, recently, researchers have focused on supervised end-to-end hybrid approaches, which contain an extractor module and abstractor module. Among them, the extractor identifies the salient sentences from the input document, and the abstractor generates a summary from the salient sentences. This model successfully keeps the consistency between the generated summary and the reference summary via various strategies (e.g., reinforcement learning). There are two semantic gaps when training the hybrid model (one is between document and extracted sentences, and the other is between extracted sentences and summary). However, they are not explicitly considered in the existing methods, which usually results in a semantic bias of summary. To mitigate the above issue, in this paper, a new reinforcing semantic-symmetry learning model is proposed for document summarization (ReSyM). ReSyM introduces a semantic-consistency reward in the extractor to bridge the first gap. A semantic dual-reward is designed to bridge the second gap in the abstractor. The whole document summarization process is implemented via reinforcement learning with a hybrid reward mechanism (combining the above two rewards). Moreover, a comprehensive sentence representation learning method is presented to sufficiently capture the information from the original document. A series of experiments have been conducted on two wildly used benchmark datasets CNN/Daily Mail and BigPatent. The results have shown the superiority of ReSyM by comparing it with the state-of-the-art baselines in terms of various evaluation metrics.

CCS CONCEPTS
• Computing methodologies → Information extraction; Natural language generation; • Information systems → Summarization.

KEYWORDS
Document Summarization, Semantic Consistency, Reinforcement Learning, Representation Learning

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1 INTRODUCTION
Document summarization has attracted much attention and has a wide-ranging application with the explosive growth of text information. For example, summarization, in a search engine, can help users to catch the main concepts of the desired documents by automatically generating appropriate summaries. Its main goal is to automatically create summaries by capturing the central information from a given long document so that machine-generated summary matches with the human-made summary. Therefore, the main objective should be taken into account, the semantic accuracy of the generated summary.

Since late fifties [11], a large number of summarization approaches have been developed to meet these requirements. They can be roughly divided into two groups: extract-based and abstract-based summarization model. Early, more attentions of researchers were paid to obtain the salient information from the given document via the extract-based method [14, 16], which focuses on selecting proper sentences from the given document. Although this kind of method can create summaries quickly, the semantic information contained in the summaries may be different from that of the given document due to the discontinuous sentence content extracted. In contrast, the abstract-based methods [3, 9, 15, 20, 23] aim to generate a summary by employing words and phrases that do not appear in the given document. Still, they usually suffer from information bottleneck and accumulated errors, which lead to the semantic bias in the generated summary, especially for long documents.

To mitigate the above issues, a novel two-stage policy-based summarization framework (extract-then-compress) is proposed by Chen and Bansal [2] to take advantage of both extractive and abstractive methods, which uses an extractor network to select salient sentences from the long given document as the first stage and then exploits an abstractor network to compress and rewrite them into a more readable version as the second stage. Compared with the traditional one-stage abstractive method, the extract-then-compress framework not only effectively alleviates the information bottleneck and accumulated errors, but also improves the ROUGE evaluation scores of the generated summary. Later, various improvements have been proposed, such as summary-level ROUGE evaluation instead of sentence-level, extract-then-compress / not compress, etc. These above excellent methods have proved the effectiveness of the extract-then-compress models.

For the two-stage abstractive summarization models, semantic information changes in three forms: the given document, the extracted content, the generated summary. In the process of semantic
To better capture the main information, a novel comprehensive sentence representation learning method is proposed to characterize the source document and reference summary.

The main contributions of this paper include:

- To mitigate the semantic asymmetry issue, a reinforcing semantic-symmetry document summarization method is proposed with the aid of consistency attention mechanism and dual-abstractor module, which aims to preserve the semantic consistent between source document and generated summary.
- To capture the main information from the source document and reference summary, a novel comprehensive sentence representation learning method is proposed, which has ability to sufficiently represent the given document in several levels (including word, sentence, topic and document).
- A series experiments are conducted on CNN/Daily Mail and BigPatent datasets, and the results have shown the superiority of the proposed method in terms of several evaluation metrics.

### 2 RELATED WORK

Neural document summarization has been widely studied recently. Existing popular summarization methods are mainly two types: extractive and abstractive. The former creates summaries by directly selecting sentences, and the latter generates novel words not copied from the given document. Document summarization is usually taken as a classification task due to the given reference summary in training data. In this subsection, we will briefly review the supervised neural-network extractive and abstractive summarization.

To extract the proper sentences to build summary, Nallapati et al. [14] adopted a recurrent neural network (RNN) to represent each sentence as a fixed dimension vector and select the important sentences according to the reference summary. Narayan et al. [16] conceptualized the extractive summarization as a sentence ranking task and optimized the ROUGE evaluation metric [10] between the extracted sentences and the reference summary through a policy-based reinforcement learning method. Shi et al. [24] proposed a contrastive training strategy to learn the salience estimation network, and then used the learnt salience score as a guide to iteratively extract the salient sentences from the document. Although these extractive summarization methods obtain high ROUGE scores because they extract the salient sentences according to the reference summary, they can not make sure the extracted sentences have semantic consistency with the original document. This situation will become worse when giving low-quality reference summary. Furthermore, the output summary is usually lack of readability.

To generate readable summary, researchers adopted the basic attention-based Seq2Seq framework for abstractive summarization [15]. Later, various strategies are used for the neural abstractive summarization, such as copy-pointer [20, 23], hierarchical attention [3, 6], policy-based reinforcement learning [17, 18], and etc. Recently, researchers take advantage of both extractive and abstractive methods to improve the performance of summarization, as shown in Figure 1 (a). Similar to how humans summarize long documents, this proposed model first uses an extractor module to

| Source document (Original document): |
|-------------------------------------|
| a passenger on an atlanta-bound air canada flight told a cnn reporter on the plane friday that a stranger sitting behind him tried to choke him. [oliver minatel, 22, said he was sleeping on air canada flight 8623 from toronto when he felt something around his neck. ] "with a rope, something that he has, he just jumped on me. that's what happened. " minatel said cnn's paula newton moments after the incident. she was seated four rows behind, a professional soccer player traveling with his team. [the incident occurred about a half-hour before the flight landed, after the pilots had begun their descent. ] "i forced it down and then other people came to help, and then i got out and he started saying that we were here to kill him," minatel said. [the man was not restrained for the rest of the trip, but the flight crew told him to stay seated with his seat belt on. the man kept trying to get out of his seat but other passengers yelled at him whenever he tried to stand up. [ (... ) several witnesses said they saw the suspect try to choke minatel with the cord of his headphones. (...) ] |

| Ground truth summary (Reference summary): |
|-------------------------------------------|
| (1) oliver minatel, a 22-year-old player from brazil, was attacked from behind, he says. (2) witnesses say suspect tried to choke him with the cord from his headphones. (3) team says forward is ok, will play saturday night; suspect was taken for evaluation. |

| SentRewriting [2] (Baseline model) |
|------------------------------------|
| (1) oliver minatel, 22, said he was sleeping on canada flight 8623 from toronto. (2) the man was not restrained for the rest of the trip. (3) "with a rope, something that he has, he just jumped on me," minatel says. (4) passenger on an atlanta-bound air canada flight told a cnn reporter on the plane friday that a stranger sitting behind him tried to choke him. |

Table 1: Examples (from CNN/Daily Mail testing data) about Original / Source document, Ground truth summary, and Generated summary by the baseline model, which makes the semantic inconsistency of the extracted sentences and the semantic inconsistency of the generated summary with the original document and the reference.
extract salient sentences, and then exploits an abstractor module to rewrite each of the extracted sentences by the reference summary. For example, Hsu et al. [6] constructed an inconsistency loss function by combining the sentence-level and word-level attention to train the whole model. Later, Chen and Bansal [2] proposed a hybrid extractive-abstractive architecture via a policy-based reinforcement learning method, which optimizes the ROUGE evaluation between the extracted sentences and the reference summary. As expected, these methods [2, 6, 13, 21] have ability to generate fluent summaries. Like other supervised summarization methods, they focus on matching generated summary and reference summary. However, they ignore the semantic consistency between the generated summary and the original document, which will output readable but unimportant even irrelevant content.

3 PRELIMINARY

In this section, the baseline policy-based reinforced summarization model will be briefly described, please refer to [2] for details. Let’s begin with the problem definition.

Given a training set of document-summary pairs \( \{x_i, y_i\}_{i=1}^T \), where \( T \) denotes the total number of training pairs, and \( x_i \) and \( y_i \) are the document and reference summary of the \( i \)-th training pair. For a long text document \( x_i \) with a sequence \( x_i = (x_{i,1}, ..., x_{i,m}, ... x_{i,N}) \) containing \( N \) sentences, summarization aims to output a readable multi-sentence summary. Each sentence \( x_{i,n} \) is made up of a sequence of \( M \) words \( (w_{i,1}, ..., w_{i,m}, ..., w_{i,M}) \). For training data, each document has the corresponding supervised information, i.e., a sequence of \( J \) sentences \( y_i = (y_{i,1}, ..., y_{i,j}, ..., y_{i,J}) \), to form the ground truth summary. The goal of summarization task, for a given document, is to predict the summary \( \hat{y}_i = (\hat{y}_{i,1}, ..., \hat{y}_{i,j}, ..., \hat{y}_{i,J}) \), so that the prediction \( \hat{y}_i \) approaches to \( y_i \) as much as possible.

For neural reinforced summarization, a successful framework is hybrid extractive-abstractive architecture with actor-critic reinforcement learning [2]. At the \( t \)-th step, the extractor agent receives \( x_i \) and \( a_{i,t-1} \) as state \( s_{i,t} \) and extracts its one sentence as an action \( a_{i,t} \). The optimal action is selected according to a policy \( \pi_B \) (a mapping from states to actions). The reward can be quantified by comparing the generated sentence \( \hat{y}_{i,t} \) with the ground-truth sentence \( y_{i,t} \) in terms of some evaluation metric such as ROUGE score,

\[
    r_{i,t+1} = \text{ROUGE-L} \left( \hat{y}_{i,t}, y_{i,t} \right). \tag{1}
\]

In this case, for a simple episode, the total accumulated return from the \( t \)-th step can be calculated with discounted factor \( \gamma \),

\[
    R_{i,t}(s_{i,t}, a_{i,t}) = \sum_{t=0}^{N_i-1} \gamma^t r_{i,t+1}. \tag{2}
\]

Then, the final reward of the \( t \)-th step is defined as \( A^B_{i,t}(s_{i,t}, a_{i,t}) = R_{i,t}(s_{i,t}, a_{i,t}) - b_{i,t} \), which is usually called as advantage value. Specifically, the optimal model can be constructed by minimizing the following loss function,

\[
    L^*_t = -\frac{1}{N_s} \sum_{i=1}^N \sum_{t=1}^{N_t} \log \pi_B(s_{i,t}, a_{i,t}) A^B_{i,t}(s_{i,t}, a_{i,t}) \tag{3}
\]

where \( N_s \) is the number of sentences that the agent extracts for the current document.

4 THE PROPOSED MODEL

A qualified and capable summarization system needs to simultaneously ensure that the semantic information of the generated summary is consistent with the original document and the reference summary. In this paper, the task of document summarization is regarded as a two-stage task, which contains the first-stage as an extractive module to select salient sentences and the second-stage as an abstractor module rewrites selected sentences to a more fluent and readable form. Here, we denotes the first-stage as \( f_e(\cdot) \) and the second-stage as \( f_a(\cdot) \). Specifically, \( f_e(x_i) = \hat{y}_i \).

In this section, we first give the introduction of three different semantic-symmetry models: a semantic-consistency reward for extractor module (SCREM), a semantic dual-reward for abstractor module (SDRAM), a hybrid semantic-symmetry reward mechanism (HSSRM). Secondly, a new comprehensive sentence representation learning method is proposed to model different levels of semantic information.
4.1 Semantic-Consistency Reward for Extractor Module (SCREM)

In this section, we introduce the proposed semantic-consistency reward for the extractor module to guarantee the semantic consistency of the extracted sentences. As shown in Figure 2, our semantic-consistency reward contains several major parts: comprehensive sentence representation (details will be given in Section 4.3), an extractor module, a consistency attention network, and the reward calculation.

Generally, a traditional policy-based reinforced extractive summarization model calculates the reward of \( t \)-th extracted sentence via sentence-level ROUGE-L F-1 score [10]:

\[
\hat{r}_{\text{ext}}^{\text{e}} = \text{ROUGE-L}_F(x_i, y_i). \tag{4}
\]

The above reward function Eq.(4) only considers the semantic consistency between the extracted sentences and the reference summary but does not consider the original document simultaneously. However, keeping the semantic-consistency with the original document is the premise of generating a reliable summary. Similar to how human summarizes document, we need to pay attention to several aspects when selecting content, such as whether the selected sentences are salient, whether it can cover enough semantic information, and whether it can simultaneously ensure the semantic consistency between the original document, the reference summary, and the extracted sentences.

In the NLP field, a widespread method is to calculate the semantic similarity between texts through some strategies to deal with downstream tasks. Recently, Numerous studies have proved that attention mechanism [1, 25] is very significant for NLP and RL tasks [3, 6, 23], which provides a new and efficient similarity measurement method. For the summarization model, it also can use the attention mechanism to calculate the semantic similarity between the extracted sentences, the original document, and the reference summary, and then judge the semantic consistency among them. Hence, most extractive summarization models use attention mechanisms to calculate similarity and then regard the information with high similarity as the salient content. However, above models only use attention mechanisms to focus on the importance of extracted sentences, ignoring whether the extracted sentences are semantically consistent with the original document and the reference summary at the same time, resulting in the semantic inconsistency of the extracted sentences.

Inspired by these above issues and methods, we propose a novel consistency attention mechanism, which uses attention mechanism to measure the semantic similarity of extracted sentences between the original document and the reference summary. Specifically, we combine the consistency attention and the traditional reward function and expect to use the attention value as a constraint term for the reward to ensure the semantic consistency.

Firstly, the source document and the reference summary are represented in sentence-level. Given the sequence of sentences, the input sentence of the \( i \)-th document at the \( n \)-th step is represented by a hidden state \( h_{i,n}^z \), and the document is represented by the last hidden state \( h_{i,N}^z \) (details were given in the previous section). Then we calculate the semantic similarity as follows:

\[
\alpha_{i,n}^d = \text{sigmoid} \left( \frac{g(h_{i,n}^z)W_d h_{i,N}^z/N}{\sum_{k=1}^N g(h_{i,k}^z)h_{i,N}^z/N} \right), \tag{5}
\]

where \( \alpha_{i,n}^d \) denotes the similarity between the \( n \)-th sentence representation \( h_{i,n}^z \) and the \( i \)-th document representation \( h_{i,N}^z \), and \( W_d \) is a learnable matrix. Similarly, we calculate the semantic similarity \( \alpha_{i,n}^s \) between the \( n \)-th sentence representation \( h_{i,n}^z \) and the \( i \)-th reference summary representation \( p_{i,j}^z \):

\[
\alpha_{i,n}^s = \text{sigmoid} \left( \frac{g(h_{i,n}^z)W_s p_{i,j}^z}{\sum_{k=1}^N g(h_{i,k}^z)p_{i,j}^z/N} \right), \tag{6}
\]

where \( W_s \) is a learnable matrix. In order to keep the semantic consistency among the extracted summary, the original document, and the reference summary, the attention \( \alpha_{i,n}^s \) and \( \alpha_{i,n}^d \) can be aligned by the following mean square loss,

\[
L_s = \frac{1}{T} \sum_{i=1}^T \frac{1}{N} \sum_{t=1}^N (\alpha_{i,n}^d - b_{i,t})^2, \tag{7}
\]

\[
L_d = \frac{1}{T} \sum_{i=1}^T \frac{1}{N} \sum_{t=1}^N (\alpha_{i,n}^s - \alpha_{i,n}^d)^2, \tag{8}
\]

\[
L_u = \delta_u L_s + (1 - \delta_u)L_d, \tag{9}
\]

where \( \delta_u \) denotes a scaling factor accounting for the difference in magnitude between two loss functions. In the above formula, first, aligning the attention score \( \alpha_{i,n}^d \) and sentence extraction score \( b_{i,t} \) by minimizing the loss function of \( L_s \), the semantic consistency between the extracted content and the original document is ensured. Secondly, aligning attention score \( \alpha_{i,n}^s \) and \( \alpha_{i,n}^d \) by minimizing the loss function of \( L_d \), the semantic consistency between extracted content and reference summary is ensured. Finally, the consistency attention is used as a bridge to make the source document, extracted content, and reference summary have semantic consistency.

After that, we exploit the \( t \)-th extracted sentence’s attention \( \alpha_{i,t}^e \) to constraint the \( t \)-th extracted sentence’s reward \( \hat{r}_{i,t+1} \) for keeping the semantic consistency when extracting sentences from the source document.

\[
r_{i,t+1}^{\text{ext}} = \alpha_{i,t}^e \hat{r}_{i,t+1}. \tag{10}
\]
As we known, the return $R_{i,t}$ can be calculated as $\sum_{t=0}^{N-1} y_{i,t}^e f_{e}^e$, which exists high variance in the policy-based reinforcement learning method. Therefore, for Eq (10), we except that the consistency attention $\alpha^e_{i,t}$ can also reduce the variance of reward estimation. Finally, we optimize the whole model follow the introduction of the preliminary.

### 4.2 Semantic Dual-Reward for Abstractor Module (SDRAM)

![Diagram](image)

**Figure 3**: Overview of the Abstractive Semantic-Symmetry Reward Mechanism.

In this section, we introduce how to keep the semantic consistency of the generated summary by the abstractor module. Usually, after rewriting a sentence in the second stage, we expect the abstractor module can not only compress and rewrite the extracted sentences to a short version but also keep the semantic information of the summary consistent with that before rewriting. In short, to ensure the semantic consistency of the rewritten content of the abstractor module is to reconstruct the rewritten content into the extracted sentences by ensuring the semantic unchanged. Inspired by the above issue and [4, 27], we propose a semantic dual-reward for abstractor module (as shown in Figure 3). Here, we only introduce three mainly parts: an abstractive module, a dual-abstractive, and a reward calculation.

Firstly, an abstractive module rewrites the extracted sentences to a more concise summary. Then the reward of the rewritten sentences can be calculated as follows:

$$r_{i,t+1}^{abs} = ROUGE-L_F(y_{i,t}, x_{i,t}).$$  \hspace{1cm} (11)

In general, partial semantic information will be lost when rewriting sentences, which may be an important part of the factual descriptions, thus it will lead to the semantic inconsistency between the rewritten sentence and the extracted sentence. Intuitively, if the rewriting sentences can be restored to ensure that the core semantic information is consistent with the extracted sentences, then the rewriting process is effective. Hence, we propose a dual-abstractor module to reconstruct the extracted sentences by the rewritten sentences. Especially, $f_d(\cdot)$ denotes the generation process of the dual-abstractor. The key difference between the original abstractor module and the dual-abstractor module is that the original abstractor module uses the extracted sentences as input and the reference summary as supervision information. In training process of the dual-abstractor module, the reference summary is used as input and the extracted sentence as supervision information. Hence, the reward of the $t$-th reconstructed sentence can be calculated as follows:

$$r_{i,t+1}^{dual} = ROUGE-L_F(f_d(y_{i,t}), x_{i,t}).$$  \hspace{1cm} (12)

Then, we treat the reward of the $t$-th reconstructed sentence $r_{i,t+1}^{dual}$ as a penalty term to constraint the reward of the $t$-th extracted sentence $r_{i,t+1}^{abs}$, which expects to keep the semantic consistency of the generated summary. Then, we propose to explicitly combine above two reward functions by simple scalar multiplication. The computation of the semantic dual-reward as follows:

$$r_{i,t+1}^{dual} = r_{i,t+1}^{abs} r_{i,t+1}^{dual}.$$  \hspace{1cm} (13)

The multiplication ensures that only when the semantic information between the reconstructed sentence and the extracted sentence is consistent, the semantic dual-reward can be high. Finally, for our abstractor and dual-abstractor module, we follow the pointer-generator network proposed by See et al. [20].

In this paper, the difference between the first stage and the second stage is that the first stage is to extract sentences from the source document, which can be regarded as a compression task from document-to-paragraph. The second stage is to rewrite the extracted sentences separately, which can be regarded as a sentence-to-sentence paraphrase task. For the second stage, it can be regarded as a sentence-to-sentence paraphrase task, that’s why we use a dual-abstractor to generate the reconstructed sentence. For the first stage, it is challenging to use the similar method with the second stage to ensure the semantic consistency, thus it is more effective to use an consistency attention mechanism to control the semantic consistency.

### 4.3 Comprehensive Sentence Representation Learning

Due to the extractor module uses the semantics of sentences as the discrimination information when extracting sentences, the comprehensive sentence representation can better capture the semantic information effectively. To capture the semantic information much more efficiently, both document and summary are represented in word, sentence, document, and topic levels, which has been powerful to measure the semantics and further improve summarization performance [6, 8]. Thus, we propose a new comprehensive sentence representation learning method to simultaneously capture the latent semantic information and recurrent dependencies among sentences.

The representation model consists of three parts. The first part aims to obtain the individual sentence information from word vectors in the documents. Specifically, the $m$-th word in the $n$-th sentence can be pre-embedded as a vector $w_{n,m} \in \mathbb{R}^{d_1}$. The global semantic dependency ($x_{i,n}^{g} \in \mathbb{R}^{d_2}$) of the $n$-th sentence can be modeled by:

$$x_{i,n}^{g} = relu(W_p(\frac{1}{M} \sum_{m=1}^{M} w_{i,n,m})).$$  \hspace{1cm} (14)
where $W_p$ is a learnable matrix. Meanwhile, the local semantic dependency $x_{i,n}^{l,g} \in \mathbb{R}^{d_1}$ of this sentence can be computed by the temporal convolutional approach [7]. Finally, the initial representation of the $n$-th input sentence ($x_{i,n}^{l,g} \in \mathbb{R}^{d_1}$) can be projected as follows,

$$x_{i,n}^{l+g} = f_{g}(x_{i,n}^{l+g} \circledast x_{i,n}^{l}),$$

where $f_{g}$ is a learnable mapping matrix to combine both local and global semantic dependency information.

The second part tries to capture the long-term semantic dependencies among sentences. Thus, a Bi-LSTM layer is exploited to further improving the sentence representation as follows,

$$h_i = f_{l}(x_{i,1}^{l+g}, \ldots, x_{i,m}^{l+g}, \ldots, x_{i,N}^{l+g}),$$

where $h_i = \{h_{i,1}, \ldots, h_{i,m}, \ldots, h_{i,N}\}$, and $f_{l}(\cdot)$ denotes the operation in the Bi-LSTM layer. $h_{i,1} \in \mathbb{R}^{d_5}$ is the latent state of the first sentence. $h_{i,N}$ indicates the representation of the $i$-th document, and the whole training document set can be represented via $H = \{h_{i,N}\}_{i=1}^L$. Similarly, for the $i$-th document, its the summary with $J$ sentences can be encoded as $P = (p_{i,j})_{j=1}^J$ in a $d_2$-dimensional latent space which is same with the latent space of document.

Our goal in the third part is to capture the high-level latent concepts (e.g., topic) in the original document. Inspired by Wang et al. [26], we apply variation autoencoder [19] on the documents $H$. Each document is encoded via a latent random variable $z_i \in \mathbb{R}^{d_2}$ which is assumed to be sampled from a standard Gaussian prior, i.e., $z_i \sim N(0, I_d)$. Such variable has ability to determine the high-level latent concepts in the documents and will be useful for the summarization task [8]. During the encoding process, $z_i$ can be sampled via a reparameterization trick for Gaussian distribution, i.e., $z_i \sim q(z|h_{i,N}) = N(\mu_i, \sigma_i)$. Specifically, we sample an auxiliary noise variable $\epsilon \sim N(0, I_1)$ and reparameterize $z_i = \mu_i + \sigma_i \circ \epsilon$, where $\circ$ denotes the element-wise multiplication. The mean vector $\mu_i \in \mathbb{R}^{d_3}$ and variance vector $\sigma_i \in \mathbb{R}^{d_3}$ will be inferred by a two-layer network with ReLU-activated function, i.e., $\mu_i = \phi_b(h_{i,N})$ and $\sigma_i = \sigma_b(h_{i,N})$ where $\phi$ is the parameter set. During the decoding process, the document can be reconstructed by a multi-layer network ($f_k$) with Tanh-activated function, i.e., $h_{i,N} = f_k(z_i)$.

To simultaneously minimize the reconstruction loss and penalize the discrepancy between prior distribution and posterior distribution about the latent variable $z$, the VAE process can be implemented by optimizing the following objective function,

$$L_z = -\mathbb{E}_{q(z|H)}[p(H|z)] + D_{KL}(p(z)|q(z|H)).$$

where $D_{KL}$ indicates the Kullback-Leibler divergence between two distributions.

Once having the latent document representation $z_i$, the sentence representation $h_{i,n}$ can be enhanced by considering the high-level latent semantic information as follows,

$$h_{i,n}^z = \text{relu}(W_f(h_{i,n}; z_i)).$$

Here, $h_{i,n}^z \in \mathbb{R}^{d_5}$ and $W_f \in \mathbb{R}^{d_c \times (d_2 + d_3)}$ is a learnable mapping matrix. For training data, the reference summary representation $p_{i,j}$ can be enhanced with the same strategy into $p_{i,j}^z \sim N(z_i, \sigma_z)$, and $p_{i,j}^z$ will be used to evaluate the semantic similarity between sentences and summary as shown in Eq.(6).
4.4 ReSyM with Hybrid Semantic-Symmetry Reward Mechanism

In the previous sections, we enhanced the semantic consistency of the extracted sentences and the original document through the consistency attention mechanism and the semantic consistency before and after sentences rewriting through the dual-abstractor module. Although the SCREM and SDRAM model can ensure the semantic consistency in salient extraction and sentence rewriting, for the two-stage summary model, it is necessary to take into account the semantic gap in the extraction and rewriting at the same time to ensure the semantic consistency of the generated summary, and then get a high-quality summary. Obviously, through the integration of the two parts, we will adequately consider the semantic gap from the original document to the generated summary, to get a high-quality summary. Here, we introduce a hybrid semantic-symmetry reward mechanism to maintain the semantic consistency of the generated summary by considering the semantic similarity of the two stages simultaneously. Therefore, we combine the semantic-consistency reward and the semantic dual-reward, which expects to keep the semantic consistency of the generated summary with the original document and the reference summary. Thus the hybrid semantic-symmetry reward can be calculated as follows:

\[ r_{it+1}^u = \delta_e r_{it+1}^e + (1 - \delta_e) r_{it+1}^d, \] (19)

where \( \delta_e \) denotes a scaling factor accounting for the difference in magnitude between two parts. After that, we follow the description in the preliminary and exploit the policy-based reinforcement learning method to optimize the whole reinforced summarization model, thus the loss function as follows:

\[ L_{rl} = -\frac{1}{T} \sum_{i=1}^{T} \frac{1}{N_t} \sum_{t=1}^{N_t} \left[ \log \pi_q(s_{it}, a_{it}) \right] \left( \sum_{r=0}^{N-1} y_{r, it+t} r_{t, it+t} - b_{it+t} \right). \] (20)

5 EXPERIMENTS

5.1 Benchmark Datasets

We evaluate our proposed method on two large-scale datasets of CNN/Daily Mail [5] and BIGPATENT [22]. Next, we introduce the two datasets briefly.

Table 2: Statistics of CNN/Daily Mail and BIGPATENT summarization datasets. # Document: raw number of documents in each dataset. For all other columns, mean values are reported over all documents.

| Dataset          | # Document | # word | # sentence | # word |
|------------------|------------|--------|------------|--------|
| CNN/Daily Mail   | 312,085    | 789.9  | 3.8        | 55.6   |
| BigPatent        | 1,341,362  | 3572.8 | 3.5        | 116.5  |

5.1.1 CNN/Daily Mail Dataset. This corpus was proposed by Hermann et al. [5] for reading comprehension task, which includes news stories in CNN and Daily Mail websites. There are two versions of the dataset, non-anonymized and entity anonymized version. Our experiment follow [20] and use the non-anonymized version of this dataset which has 287,227 training pairs, 13,368 validation pairs and 11,490 test pairs. Each pair of data in this dataset is divided into two parts, a news stories as input document of about 800 tokens on average, and a human-written multi-sentence summary of up to 200 tokens.

5.1.2 BigPatent Dataset. This large-scale summarization dataset was proposed by Sharma et al. [22], which consists of 1,341,362 U.S. patent documents collected from Google Patents Public Datasets with human-written abstractive summaries. It contains patents filed after 1971 across nine different technological areas. In this dataset, each patent’s abstract as a gold-standard summary and description as the input document to construct pairs of training data.

5.2 Experimental Settings

There are several hyperparameters in the proposed ReSyM, which are set as follows. Each word is pre-trained and represented as a 128-dimension vector. Meanwhile, the size of sentence vector in different layers are set by \( d_1 = d_2 = 128, d_3 = d_4 = 300, d_5 = 512 \). For each dataset, the 30000 most frequently words are kept as the vocabulary. The trade-off parameters in Eq.(19), (9), (7) are set as \( \delta_e = \delta_l = 0.5 \) and \( \delta_r = \delta_u = \delta_v = 1/3 \). We use Adam optimizer with learning rate \( 10^{-4} \) for RL training, and the mini-batches size is 32. When calculating the reward, the discount factor is set as \( \gamma = 0.95 \). The extractor and abstractor were trained similarly to [2] (including the same settings). We compare our model with some baselines and state-of-the-art methods. Because the datasets are quite standard, so we just extract the results from their papers. Therefore the baseline methods on different datasets may be slightly different. Moreover, in our experiments, ReSyM-SCREM denotes the proposed method with the semantic-consistency reward mechanism, ReSyM-SDRAM denotes the proposed method with the semantic dual-reward mechanism, and ReSyM-HSSRM denotes the proposed method with hybrid semantic-symmetry reward mechanism. To save space, in the result display of all figures, we abbreviate SentRewriting, SCREM, SDRAM, and HSSRM to SR, SC, SD, and HS Following the previous studies [20], we evaluate the proposed model on standard ROUGE [10] evaluation metrics, reporting the F1 scores for ROUGE-1, ROUGE-2, and ROUGE-L (which respectively measure the word-overlap, bigram-overlap, and longest common sequence between the reference summary and the summary to be evaluated). Moreover, we also evaluate with the METEOR evaluation metric in full mode (which additionally rewards matching stems, synonyms, and paraphrase).

6 RESULTS AND ANALYSIS

6.1 Overall Performance of the ReSyM

The experimental results on CNN/Daily Mail and BigPatent are given in Table 3 and Table 4. Overall, our proposed ReSyM achieves advantages of ROUGE F1 scores over all of the other baselines (reported in their own articles) and two extensions we proposed both improve the performances based on our basic model (has the same structure as SentRewriting [2] except for the encoding
Table 3: ROUGE F-1 scores of the generated summaries on the CNN/Daily Mail test set. The best results are in bold and the best results obtained by baselines are underlined.

| Baseline Models               | ROUGE-1 | ROUGE-2 | ROUGE-L |
|------------------------------|---------|---------|---------|
| Inconsistency [6]            | 40.68   | 17.97   | 36.54   |
| JECS [6]                     | 41.70   | 18.50   | 37.90   |
| SENECA [6]                   | 41.52   | 18.36   | 38.09   |
| EditNet [6]                  | 41.42   | 19.03   | 38.76   |
| ML+RL+intra-attention [18]   | 39.87   | 15.82   | 36.90   |
| SentRewriting [2]            | 40.88   | 17.80   | 38.54   |

| Our Proposed Models          | ROUGE-1 | ROUGE-2 | ROUGE-L |
|------------------------------|---------|---------|---------|
| ReSyM-SCREM                  | 41.01   | 18.31   | 38.76   |
| ReSyM-SDRAM                  | 41.17   | 18.26   | 38.83   |
| ReSyM-HSSRM                  | 41.53   | 18.51   | 39.11   |

Table 4: ROUGE F-1 scores of the generated summaries on the BigPatent test set. The best results are in bold and the best results obtained by baselines are underlined.

| Baseline Models               | ROUGE-1 | ROUGE-2 | ROUGE-L | AVG   |
|------------------------------|---------|---------|---------|-------|
| SentRewriting [2]            | 37.12   | 11.87   | 32.45   | 27.15 |

| Our Proposed Models          | ROUGE-1 | ROUGE-2 | ROUGE-L | AVG   |
|------------------------------|---------|---------|---------|-------|
| ReSyM-SCREM                  | 37.61   | 12.13   | 32.92   | 27.55 |
| ReSyM-SDRAM                  | 37.75   | 12.20   | 33.01   | 27.65 |
| ReSyM-HSSRM                  | 38.75   | 12.97   | 33.89   | 28.54 |

Comparing with the reinforced one-stage extract-based Refresh and abstract-based ML+RL+intra-attention and ROUGESal+Ent baselines, our models are capable of achieving better performance. For the above three baselines, the proposed ReSyM has a more significant improvement in the ROUGE-1 and ROUGE-L scores, which shows that our model can not only capture the salient information better but also ensure the readability of the generated summary. We believe it gives credit to the capability of semantic modeling by an end-to-end two-stage summarization framework. According to our statistics, compared with the best results of our model and the best results of the baseline models in the CNN/Daily Mail dataset, we have achieved 1.59%, 1.70%, and 1.48% improvement in ROUGE-1, ROUGE-2, and ROUGE-L F-1 scores respectively. Since the document and summary of BigPatent are longer and more complicated than that of CNN/Daily Mail, all models produce lower ROUGE scores. However, compared with the best results of our model and the best results of the baseline models in the BigPatent dataset, we have achieved 4.39%, 9.27%, and 4.44% improvement in ROUGE-1, ROUGE-2, and ROUGE-L F-1 scores respectively. Hence, it can be seen from the above analysis that the results of our proposed ReSyM on the BigPatent have a more significant improvement than the results of our proposed ReSyM on the CNN/Daily Mail. It can be found that our model has more advantages in dealing with long documents than dealing with short document, which is mainly due to the comprehensive sentence representation learning method, which fully considers the semantic information of various levels in documents.

6.2 Results of Saliency Extraction

Note that the extracted sentences mentioned here will be taken as the input of the abstractor module. Thus the quality of extraction information largely determines the quality of the generated summary. Therefore, it is necessary to observe the quality of the extracted sentences by the extractor module to evaluate the performance of the proposed model on the first stage. To evaluate whether our extractor module extracts enough salient content, we exploit full-length ROUGE recall scores between the extracted sentences and the reference summary. High ROUGE recall scores can be obtained if the extracted sentences include more words or sequences overlapping with the reference summary. We show the results of the baseline model SentRewriting and our models on the test set of the CNN/Daily Mail and BigPatent datasets in Figure 6. The extractor of three different models proposed by ours performs the best ROUGE recall scores than the baseline model.

Compared with the concurrent only extract-based RL model by Narayan et al. [16], showing that our reinforced salient extractor is very useful when combined with the semantic-consistency reward mechanism. For the results in the Figure 6, we can find that SCREM model is more effective in extracting salient information for long document content, which can surpass SDRAM model, mainly due to the advantage of semantic-consistency attention mechanism. For the results in the Figure 7, compared with the SCREM, the sentences extracted from the SDRAM has higher ROUGE F1 scores, which is mainly due to the rewriting of the summary content by the SDRAM model. Moreover, from the results of the meteor evaluation
metric in the Figure 6, we can see that the ReSyM has a significant improvement compared with the baseline model.

6.3 Results of Abstractive Summary
Our two-stage model improves the readability and fluency of the generated summary by rewriting the extracted sentences. From Figure 7 and Figure 8, we can see that our model has a significant improvement in the sentence’s ROUGE F-1 scores compared with rewriting the sentence. As shown in Figure 8 (a) and (b), it is found that for short sentence and document, SDRAM performs better than SCREM, and it is found that for long sentence and document, SCREM performs better than SDRAM. Therefore, the SDRAM proposed in this paper has more advantages in processing relatively short sentences, and SCREM is more effective in treating long sentences or document information. On the whole, the proposed ReSyM has an excellent performance in dealing with a short document and lengthy document.

7 CONCLUSIONS AND FUTURE WORK
In this paper, to ensure the semantic-symmetry of the generated summary, we treat the summarization task as a two-stage task and propose three kinds of semantic-symmetry models to keep the semantic consistency. Furthermore, we propose a novel comprehensive sentence representation learning method to capture semantic information adequately. The experimental results demonstrated that our model could well capture the essential semantic information of documents and also achieve better performance than the state-of-the-art baselines. In future work, we would like to extend our model on a multi-document summarization task.

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