Research on the Generation of Patented Technology Points in New Energy Based on Deep Learning

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ABSTRACT

Effective extraction of patent technology points in new energy fields is profitable, which motivates technological innovation and facilitates patent transformation and application. However, since patent data exists the ununiform distribution of technology points information, long length of term, and long sentences, technology point extraction faces the dilemmas of poor readability and logic confusion. To mitigate these problems, the article proposes a method to generate patent technology points called IGPTP—a two-stage strategy, which fuses the advantage of extractive and generative ways. IGPTP utilizes the RoBERTa+CNN model to obtain the key sentences of text and takes the output as input of UNILM (unified pre-trained language model). Simultaneously, it takes a multi-strategies integration technique to enhance the quality of patent technology points by combining the copy mechanism and external knowledge guidance model. Substantial experimental results manifest that IGPTP outperforms the current mainstream models, which can generate more coherent and richer text.

KEYWORDS

Text Extraction, Text Generation, RoBERTa

INTRODUCTION

New energy refers to various forms of energy other than traditional energy that is renewable energy developed and utilized on the basis of new technologies. In recent years, new energy technology has achieved great progress and all countries take to develop new energy as an important measure for industrial adjustment. Researches show that the number of new energy patent has increased rapidly, the annual patent applications up to 100,000 (Zhao. 2019). Although the total number of new energy

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patents has reached one million, the uneven quality of patents isn't conducive to technological innovation and the transformation and application of achievements. Therefore, it is of great practical significance to study the effective acquisition of patent technology points. The field of new energy is now an emerging industry. The technical point of the patent represents the core technical value in the patent. Therefore, the research on the generation of patent technology points has great practical significance for the transformation of patent achievements and the promotion of technological innovation in the field of new energy.

Patent technology points can cover concisely the core technology of the patent. Compared with traditional patent abstract information, it can present patent technical points more clearly and brightly. Generally, text generation technology can effectively obtain patented technology points, including extraction method and generation method. The extractive methods can ensure the grammatical structure of the text and not generate new words. But, the coherence of semantics in the generated text cannot be guaranteed. The generative methods can effectively maintain semantic coherence and readability. However, it can't guarantee the grammatical structure of the generated text. Therefore, to ensure the semantic coherence and the correctness of the grammatical structure in the text concurrently, it is practicable to combine the advantages of the two methods to complete the text generation task.

The patent data of new energy owns the characteristics of different information lengths, too long terms and words, more new words, and different text structure and syntax. Although the existing methods have well performance in the text generation task, it has performed poorly in the task of generating new energy patent technology points. To address the above problems, we propose a two-stage patent technology points generation method named IGPTP. It fuses the edge of extraction method and generation method. Meanwhile, it combines external knowledge and copy mechanism to guide the generation of patent technology points and improve the quality. The contributions made in this study are summarized as follows:

1. Authors build a corpus of patent technology points (about 5200) and a corpus of domain terms (about 3200) in the field of new energy, which bridges the gap in information on patented technologies in the field of new energy.
2. Authors propose a two-stage patented technology point generation method named IGPTP. It combines the advantages of extractive and generative method to generate the patent technology points.
3. IGPTP uses a multi-strategies ensemble method to improve the quality of patent technology points. In model training, it introduces adversarial training to promote the robustness of data. Simultaneously, the external knowledge is used to guide word segmentation and vectorization of input information. Finally, in the model decoding stage, the copy mechanism is introduced to embellish the text. The accuracy and readability of patent technology points have been promoted.
4. Substantial experiments are conducted to verify the proposed IGPTP can generate more accurate and coherent text that owns the performance edge over classical text generation methods.

The remaining parts of this paper are organized as follows. Section 2 briefly reviews some related work on text generation tasks. Section 3 elaborates on the design and implementation details of IGPTP. The experimental evaluation in which IGPTP is compared against the other classic text generation methods can be found in Section 4. Section 4 also discusses the wherefore about a few experimental results. Finally, we conclude this paper with future work in Section 5.

BACKGROUND

The patent technology point generation method is similar in principle to the summary generation method. Since there is no special patent technology point generation method, the traditional summary

generation method has marked reference significance. According to the different ways, the generating text summary methods can be divided into extraction, generation, and hybrid method.

Extractive Summary Generation Method

The extractive text summary method refers to selecting sentences from the text that can express the core idea of the original text as a text summary (Zhong et al. 2019). It can be divided into unsupervised and supervised according to the learning method. Unsupervised text summarization scores each sentence of the text and selects the sentence with the highest score as the summary. Chang et al. use the topic model to infer the topic distribution of the text content (Chang et al. 2009). However, the extracted text based on the word level ignores the importance of low-frequency keywords in the text. Inspired by the graph sorting algorithm, Mihalcea et al. proposed TextRank (Mihalcea et al. 2004), which uses sentences in the original text as nodes, constructs graphs with the similarity between sentences as weights, and calculates sentence importance. It selects sentences with higher scores as abstracts. However, the complete semantic information in the text paragraph is ignored. Supervised text summarization transforms the text summarization task into a sequence classification task. Nallapati et al. proposed a recurrent neural network (RNN) sequence model SummaRuNNer (Nallapati et al. 2017), which can visualize the pre-generated summaries without manually extracting labels. Zhang et al. proposed a multi-view augmented convolutional neural network (CNN) to obtain sentence features and then rank sentences (Zhang et al. 2016). Although the implementation of extractive summarization is simple and the coherence of words is stronger, it lacks the understanding of the full text structure and context information, and the generated text is less readable.

Generative Summary Generation Method

The generative text summary method refers to the contextual information of the text and uses a deep learning model to regenerate abstract text summaries. Generative text summarization is mainly modeled based on Seq2Seq proposed by Sutskever et al. (Sutskever et al. 2004). There are some problems in generative text summarization, such as out of vocabulary (OOV) and repetitive generation. OOV means that the model cannot generate words beyond the scope of the fixed vocabulary. For this reason, See et al. proposed a pointer generation network (PGN) to support copying words from the original text, which greatly solves the OOV problem (See et al. 2017). Nallapati et al. proposed to introduce text statistics as an auxiliary input to improve the model's ability to learn contextual information (Nallapati et al. 2016). This method solved the problem of factual errors and incomplete coverage of the generated text. Duan et al. enhanced text generation by parse tree embeddings, using a parse tree encoder to extract rich information from structure trees (Duan et al. 2022). Diverse grammatical texts conditioned on text structural features were generated. Ma et al. proposed a topic-aware generative model, using a layered encoder based on multi-layer attention (Ma et al. 2022). Combined with the Copy mechanism to generate text, the model is helpful for the generation of new words. Liu et al. introduced keywords into generative text summarization as guidance information in the process of generating summarization (Liu et al. 2019). The accuracy of words in related fields has been improved to a certain extent. Srivastava et al. proposed data augmentation using subsampled point cloud representations to deal with data scarcity (Srivastava et al. 2022). Anil et al. proposed a deep learning technique using the GoogleNet architecture for object detection (Anil et al. 2022). Kuppusamy et al. propose a social spider optimization (DOLSSO) algorithm based on reinforcement policy dynamic adversarial learning to enhance individual strengths and scheduling workflows in fog computing (Kuppusamy et al. 2022). Hu et al. proposed the PLANET model, which uses a novel autoregressive generative framework for content dynamic planning to guide the generation of output sentences (Hu et al. 2022). It has better results in long text generation tasks. However, the above problems are not fundamentally solved. It not only relies on the large-scale corpus, but also the new words in the generated text are not highly relevant and logical to the original text.

Hybrid Summary Generation Method

The hybrid text summary method combines the advantages of both extractive and generative methods, extracts the core content from the text, and generates summaries based on this. Wang et al. used a hybrid text similarity calculation method based on graph structure to extract key sentences in long texts (Wang et al. 2018). The extraction results are sent to seq2seq based on pointer and attention mechanism for summary generation. Chen et al. used the TextRank algorithm and fused topic similarity to extract key sentences (Chen et al. 2021). Then the extracted information is fused, and the Seq2Seq model is used for text generation. Zhu et al. proposed a two-stage model TWAG, which first predicted the topic distribution of each sentence (Zhu et al. 2016). Then a pointer generation network is used to present the decoded sentences from the topics. The implementation of such methods is relatively complex, and the research is not deep enough. There is still a large room for improvement. Related studies are compared as shown in Table 1.

Application of Summary Generation Method in Patent Data

On the task of patent abstract generation, Li et al. proposed an automatic method for generating patent abstracts based on graph convolutional networks to generate patent abstracts (Li et al. 2022). The patent abstract is generated through the claims of patents and their structural information, but the vocabulary of the generated text is not similar to the original text. Shu et al. construct three different similarity calculation methods to select the sentence with the highest score and use it as the patent abstract (Shu et al. 2020). However, the generated abstract is not highly readable. There are problems such as low readability and low factuality of the above-mentioned text generation tasks. To obtain more complete patent technical information than patent abstracts, we propose a patent technical point generation model that combines extraction and generation methods. Moreover, in order to improve the performance, the method introduces external knowledge and the copy mechanism to guide text generation. The generated technology point information has higher readability and accuracy.

MODEL

A two-stage text generation model IGPTP is proposed, which combines extraction and generation methods. The original text is input, and the key technology point sentences are obtained through the extraction model. The output of the extracted model is used as the input of the generated model to generate patent technology points that can be read smoothly. The extractive model adopts a sentence-based sequence annotation model. The sentence vector part is generated by RoBERTa + Average Pooling. The main body of the annotation model is constructed by the DGCNN (Dilate Gated Convolutional Neural Network) model. The generative model is the seq2seq model, which uses NEZHA (Neural contextualized representation for Chinese language understanding) + UNILM

Table 1. Related research comparison

Category	Work	Logic	Readability	Completeness
Extractive	Zhong et al. 2019	low logic	high readability	high Completeness
Extractive	TextRank	low logic	high readability	high Completeness
Generative	Nallapati et al. 2016	high logic	low readability	low Completeness
Generative	Nallapati et al. 2016	high logic	low readability	low Completeness
Hybrid	Chen et al. 2021	high logic	high readability	low Completeness
Hybrid	TWAG,	high logic	low readability	high Completeness
Hybrid	Our work	high logic	high readability	high Completeness

(Unified pre-trained Language Model). The model uses the Copy mechanism and external knowledge to guide the model to generate patented technical points. 1.The flow chart of the method is shown in Figure 1.

IGPTP is a two-stage text generation method. In the first stage, the original text of the patent is used as input, and the core technical point sentences are extracted through the extraction model. This stage can be seen as a pruned overview of the patent source text, reducing irrelevant information for the text generation stage. In the second stage, the output of the extraction model is used as the input of the generation model to generate technical points. And the model is tuned by combining the Copy mechanism and external knowledge. Finally, the patent technology points are obtained through the generative model. The logic of the text obtained only by using the information extraction method is poor, and the readability of the text obtained by only using the text generation method is poor. Therefore, IGPTP is used to combine the two methods to obtain high-quality patented technology points. The frame diagram of the IGPTP model is shown in Figure 2.

Extractive Model

The extraction model uses a sentence-based sequence annotation model. RoBERTa+ average pooling is used to generate sentence vectors, which are fixed and unchanged. The main body of the annotation model is constructed of the DGCNN model. First, learn the text context information according to Roberta and get the embedding representation. Then DGCNN is used to perform feature learning on Roberta's output to obtain the final text features. DGCNN is a variant of CNN that improves the ability of feature learning through a larger visible range. Then the output result is obtained through similarity calculation and judgment.The extracted results should be sent to the Seq2Seq model for optimization. Therefore, the principle of extracting the model is to "seek for completeness", and try to cover all the information needed by the final technical point. To this end, the original training corpus is converted into an extracted corpus according to the following rules: 1. We construct a function to split sentences to make sentences more granular; 2. The sentence match with the highest similarity to the artificial technical point in the original text (it can be matched repeatedly); 3. All matched original sentences are used as extracted sentence labels. The specific structure of the extraction model is shown in Figure 3.

The extraction task is transformed into a classification task. The sentence input to the model is judged by the model to determine whether the output sentence is a patent technology point sentence. In the binary classification task, 0 indicates that it is not a patent technology point sentence, and
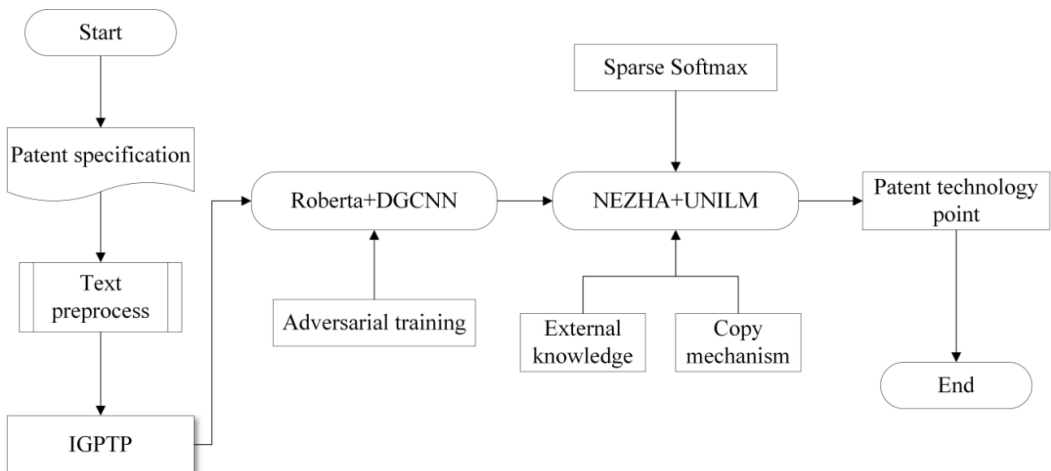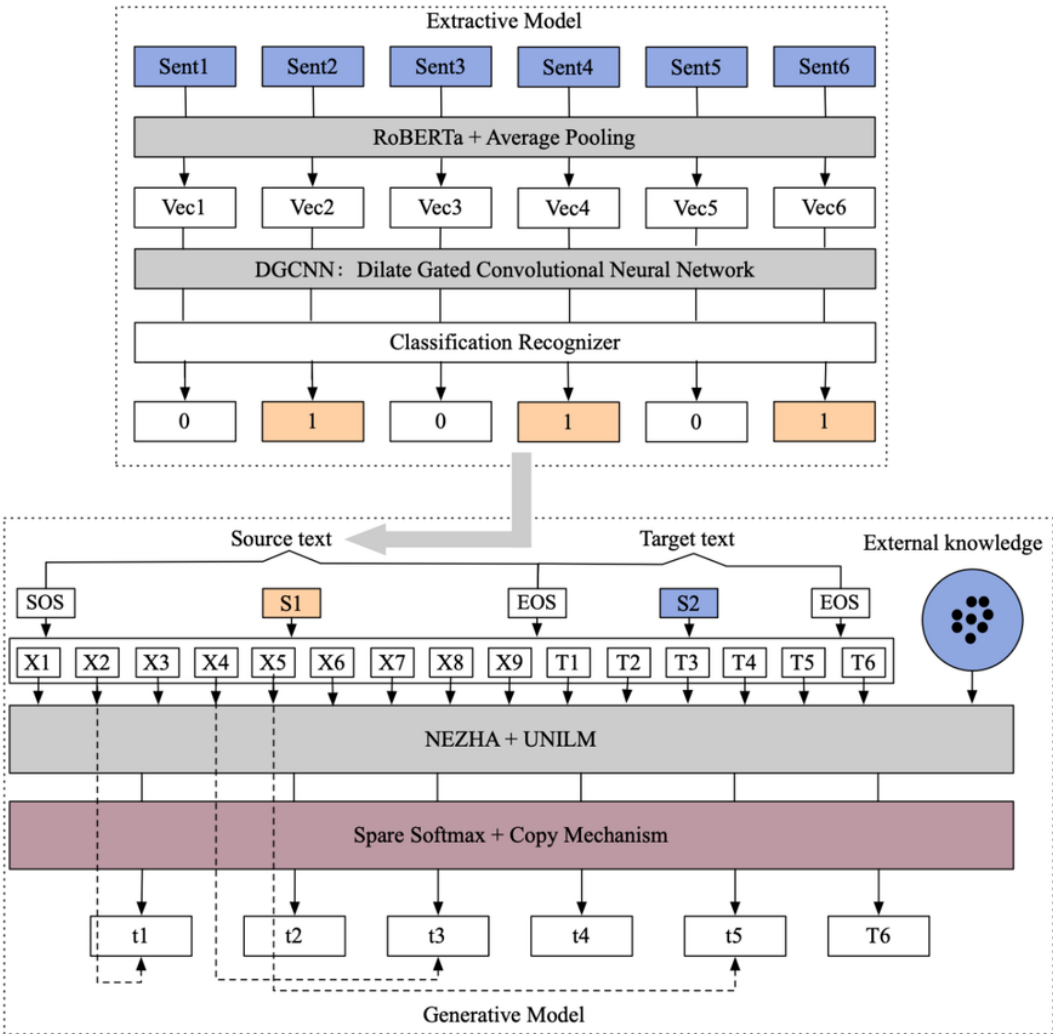
Figure 1. IGPTP flow chart

Figure 2. The framework of IGPTP

1 indicates a patent technology point sentence. Specific steps are as follows: The sentences are subdivided according to finer granularity. Vectorization is performed using RoBERTa to fully learn the semantic information of the text. RoBERTa is an improved model of BERT (Liu et al. 2019), which uses the dynamic mask mechanism and has better performance; Average pooling is used to reduce the dimensionality of the features and remove redundant information. The invariance of the features should be kept as much as possible while reducing the parameters. It can prevent overfitting and improve the speed of operation.

Then the vector is passed to DGCNN for feature extraction. DGCNN (Gehring et al. 2017) is a model based on CNN and Attention, which fuses the dilated convolutional network (DCNN) and the gated convolutional neural network (GCNN). Because of the advantages of the two components, DGCNN has better feature learning ability than convolutional neural network model. The model has fast efficiency. As shown in Figure 2, GCNN adds a gate to each output of Conv1D. The weights of the two Conv1D are not shared, one uses a sigmoid activation function, and the other does not add an activation function. The method reduces the risk of gradient disappearance. DCNN can capture more

Figure 3. Detailed structure of the extractive model
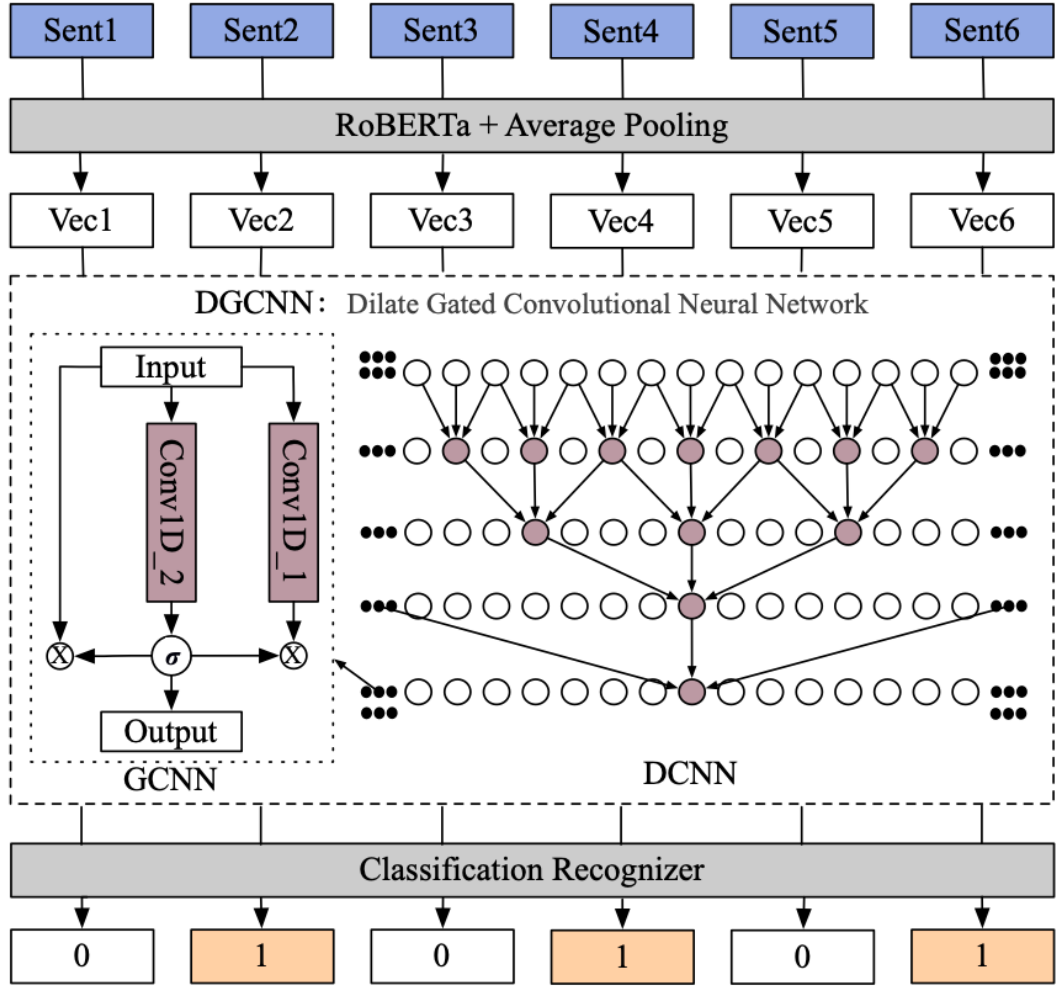
inputs and farther distance than ordinary convolution without changing the number of parameters and speed. Ordinary convolution can only capture three inputs adjacent to the centre when it is in the current layer, and has nothing to do with other inputs. As shown in Figure 2, DCNN can skip the input adjacent to the centre, directly capture the centre and non-adjacent input, and can capture more input in the current layer but the number of parameters does not change; After that, the full connected layer is used as a classifier to obtain the extracted patent technology point sentences; The formula is shown in formula 1 below.

Adversarial training (Madry et al. 2017) is introduced during training to construct some adversarial samples by adding disturbances. As a method of defending against attacks, the idea of adversarial training is very simple and direct. There are many ways of confrontation training. Carl et al. established the relationship between confrontation training and regularization in detail (Carl et al. 2019). Zhang et al. pointed out that the use of normal samples can increase the accuracy of the model (Zhang et al. 2019). The FGM adversarial training method (Miyato et al. 2016) is used to make the direction of perturbation consistent with the direction of gradient boosting. FGM scales according to specific

gradient to obtain better confrontation samples. We use FGM for confrontation training. The method can improve the robustness and generalization performance of the model:

$$Y = Conv1D_1\left(X\right) \otimes \sigma\left(Conv1D_2\left(X\right)\right) \tag{1}$$

The two *Conv1D* forms are the same, but the weight value is not shared, that is, the parameters are doubled. One of them is activated with a sigmoid function σ, and the other does not add an activation function. Then they are multiplied bit by bit.

Generative Model

The generative model is the seq2seq model. The output of the extraction model is used as the input. The manually labelled technical point information is used as the output for training. The model is a further embellishment of the extraction results. The overall structure of the model is shown in Figure 4.

The Seq2Seq model uses the classic UNILM model (Dong et al. 2019). UNILM uses a shared Transformer network and uses a specific self-attention mask mechanism to effectively learn contextual information. The formula for calculating attention and extracted features is shown in formulas 2-4 below. The source and target are input together into the model for training. Since the total length of input + output may exceed 512, the NEZHA (Wei et al. 2019) model introduced by Huawei is chosen as the base model architecture instead of BERT. The NEZHA model uses relative position encoding, which is not limited to length. It can effectively solve the problem of long text. At the same time of the model input, the external knowledge is integrated into the model to guide the word segmentation and vectorization. The method makes the word vector with specialized information and performs better in the generation of long words and terms. The performance of the model is improved due to the incorporation of more semantic knowledge. In the decoding stage, the copy mechanism (Liu et al. 2021) is introduced, which can directly copy words from the input text to the output text. An additional sequence prediction task is added to the decoder part. Originally, the decoder models the distribution of each token. But now, one more copy label distribution is predicted. The copy mechanism can

Figure 4. The structure of the generative model
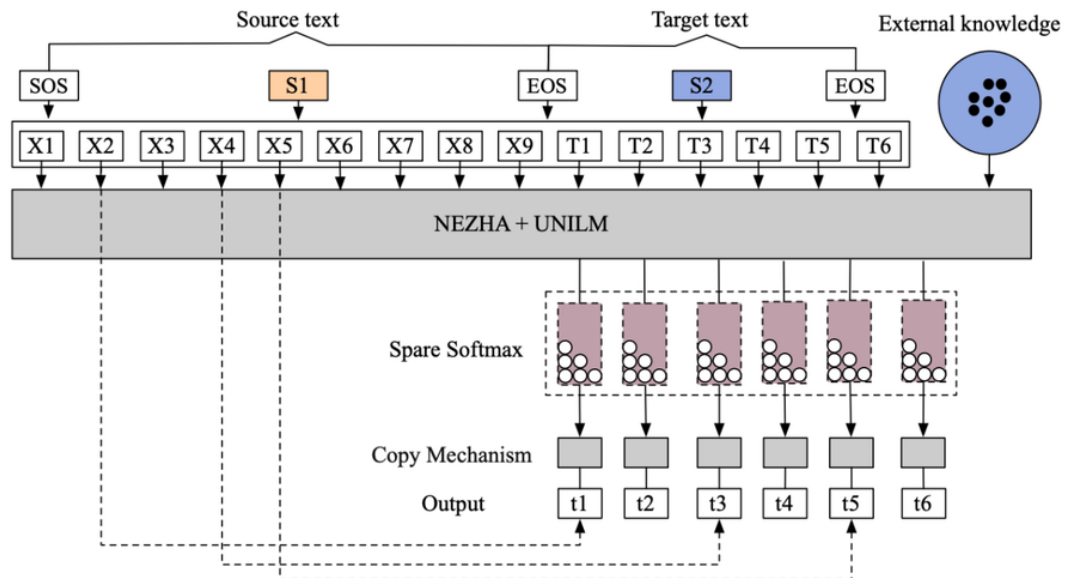
ensure the fidelity of the generated technical point text and the original text. The method can avoid professional errors. Spare Softmax replaces the regular Softmax to avoid the over-learning problem of Softmax. The method can enhance the interpretability of the model and improve the generation effect. Finally, the embellished patent technology point text is generated:

$$Q = H^{l-1}W_l^Q, K = H^{l-1}W_l^K, V = H^{l-1}H^{l-1}W_l^V \tag{2}$$

$$M_{ij} = \begin{cases} 0, allow \ \ to \ \ attend \\ -\infty, prevent \ \ from \ \ attending \end{cases} \tag{3}$$

$$A_l = softmax\left(\frac{QK^T}{\sqrt{d_k}} + M\right)V_l H^{l-1} \in \mathbb{R} \tag{4}$$

where the previous layer's output $H^{l-1} \in \mathbb{R}^{|x| \times d_h}$ is linearly projected to a triple of queries, keys and values using parameter matrices $W_l^Q, W_l^K, W_l^V \in \mathbb{R}^{d_h \times d_k}$, respectively, and the mask matrix $M \in \mathbb{R}^{|x| \times |x|}$ determines whether a pair if tokens can be attended to each other.

External Knowledge

It is observed that there are many types of data terms in the new energy field, and the terms represent similar data characteristics, which is important for the patent technology points generating. BERT-BiLSTM-CRF is used to extract term information in the new energy field. Firstly, the labelled texts are input into the BERT pre-training model, each character is converted into a low-dimensional word vector, then the context information are learned fully; The word vectors output from the BERT layer are input to BiLSTM (Bi-directional Long Short-Term Memory) for semantic encoding and extraction of sentence features; Finally, CRF (Conditional Random Fields) is used to decode the predicted label sequences with the highest probability, extract the entities in the sequences; The extraction of patent terms in the fields of new energy is realized. About 3200 knowledge of domain terms was extracted. The extracted term information is used as external knowledge to guide the word segmentation and vectorized representation of the model input. It makes the domain terminology of the input texts more professional and improves the authenticity and professionalism of the generated texts. The external knowledge extraction model is shown in Figure 5.

EXPERIMENTS

Data Set

The experimental data adopts the patents in the new energy field obtained from the SooPAT[1] website. The patent specification is used as the source text. The patent technology points that are manually annotated by experts are used as the target text. The technology points generation dataset[2] is constructed with a dataset size of 5158. The self-constructed sentence function is used to make the granularity of the sentence finer as the original input of the model. The overall data length is shown in Table 2, and the data length distribution is shown in Figure 6.

It can be observed from Table 1 that the maximum length of the source text is 24869, the minimum length is 532, and the average length is 4246. The maximum length of the target text is 384, the minimum length is 102 and the average length is 276. It can be observed from Figure 4 that the source text data is mostly distributed between the lengths of 2500-5000, and the target text data is mostly distributed between the lengths of 250-300.

Figure 5. The BERT-BiLSTM-CRF model
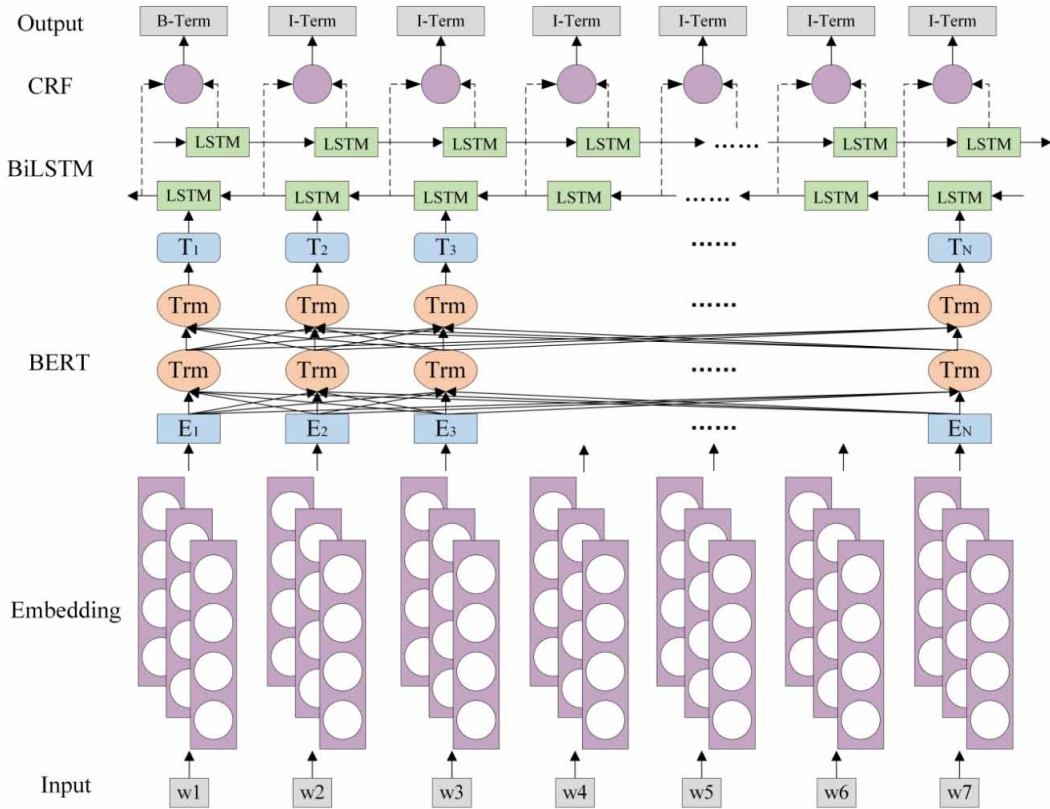
## Evaluation Indicators

Automatic Evaluation

ROUGE is used as evaluation index, which is a commonly used evaluation index in the field of text generation (Lin. 2004). It contains ROUGE-1, ROUGE-2 and ROUGE-L. ROUGE-N is the N-gram recall between the reference text and the target text. The calculation formula of ROUGE-N is shown as formula 5:

$$ROUGE-N = \frac{\sum_{S \in \{Reference\}} \sum_{gram_n \in S} Count_{match}\left(gram_n\right)}{\sum_{S \in \{Reference\}} \sum_{gram_n \in S} Count\left(gram_n\right)} \tag{5}$$

Table 2. Data length overview in the corpus

Data	Average Length	Maximum Length	Minimum Length
Source	4246	24869	532
Target	276	384	102

Figure 6. Data length distribution
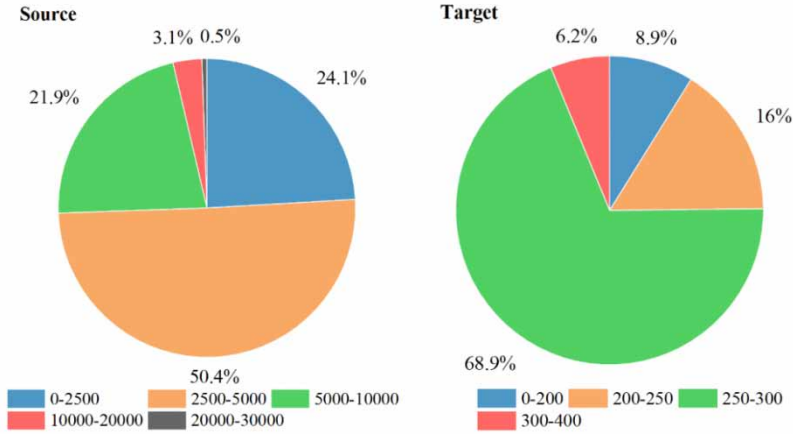
The denominator is the number of *n-grams*. The numerator is the number of *n-grams* shared by the reference text and the target text. And *n* is the number of the *n-grams* (the number of consecutive words).

ROUGE-L: Longest Common Subsequence. The text sentences as word sequences. It judges the degree of similarity by the co-occurrence units of two sentences. The calculation formula is shown in the following formula:

$$R_{lcs} = \frac{LCS(X,Y)}{m} \qquad (6)$$

$$P_{lcs} = \frac{LCS(X,Y)}{n} \qquad (7)$$

$$F_{lcs} = \frac{(1+\beta^2) R_{lcs} P_{lcs}}{R_{lcs} + \beta^2 P_{lcs}} \qquad (8)$$

$\beta = P_{lcs}/R_{lcs}$. $LCS(X, Y)$ represents the length of the longest common subsequence of *X* and *Y*. And m, n represent the length of the reference text and the target text respectively. When *X = Y, ROUGE-L = 1*; When *LCS(X, Y) = 0, ROUGE-L = 0*.

Human Evaluation

In addition to the ROUGE evaluation index, manual evaluation is used to evaluate the quality of the generated text. Ten scholars in related fields were selected to score and average the generated text. The following criteria are required to evaluate the quality of the generated text: 1. Evaluate the accuracy of the generated text vocabulary and sentences; 2. Evaluate the coherence and expressive fluency of the generated text; 3. Determine the grammatical structure of the generated text. The score ranges from 0 to 100, with 0 indicating that the generated text is not correct, and 100 indicating that the generated text is accurate, faithful, and semantically coherent.

Experimental Parameters

The experimental model training is based on Ubuntu 18.04. The hardware environment is Intel(R) Xeon(R) Gold 5218 CPU @ 2.30GHz. The GPU is 4 * NVIDIA A40 (48GB). The deep learning framework Tensorflow 1.14. Python version is 3.6. The specific parameters are shown in Table 3.

Table 3. Parameter settings

Parameter Name	Parameter Value
Roberta	chinese_roberta_wwm_ext_L
hidden_size	768
max_position_embeddings	512
optimizer	Adam
activation	sigmoid
batch_size	32
ResidualGatedConv1D	6
kernel_size	3
dropout	0.1
NEZHA	NEZHA-base
batch_size	64
max_len	1024
loss	CrossEntropy
lr	2e-5
EarlyStop	5

In the model training process, the extraction model uses Roberta chinese_roberta_wwm_ext_L provided by Harbin Institute of Technology. The hidden_size is 768. The word vector dimension is 512. Adam is used for model optimization. Sigmoid function is used for activation function. The number of ResidualGatedConv1D is 6-layer. The convolution kernel is set to 3. The dropout rate is set to 0.1. The k-fold cross-validation is used for training to solve the problem with a small amount of data. The optimal model is selected. And k is set to 15. The generated model uses NEZHA-base provided by Huawei. The batch size is set to 64. The maximum length is set to 1024. Adam is used for model optimization. Cross Entropy Loss is used for computing the loss, and the learning rate is set to 2e-5. The number of training rounds adopts dynamic early stops. If the effect is not improved for five consecutive times, the training will be stopped.

Experiments

Comparative Experiment Settings

1. PGN (Pointer Generation Network) copies words from the source text via pointers, which improves the accuracy and processing power of OOV words while retaining the ability to generate new words. It can copy some important and low-frequency words from the original text into the generated text;
2. mT5 (Xue et al. 2020) is a multilingual version of the T5 (Raffel et al. 2020) model. Based on the idea of transfer learning, mT5 designs a standard input format to obtain text output. Its positional encoding relies on self-attention expansion to compare relations;
3. BART (Lewis et al. 2019) absorbs the respective characteristics of BERT's bidirectional encoder and GPT's left-to-right decoder. The model is based on the standard seq2seq Transformer model. It is more suitable for text generation scenarios than BERT (Devlin et al. 2018). Compared with GPT (Radford et al. 2019), it also has more bidirectional contextual information.
4. IGPTP: A two-stage strategy, which fuses the advantage of extractive and generative ways.

Experimental Results

To verify the validity of our proposed models, we selected the three mainstream and classical models in the generic domain as the baseline. They are PGN, mT5, and BART, respectively. The comparative experimental results shown in Table 4.

Table 3 shows the ROUGE scores and manual scores of different models on the new energy patent data set. It can be found that the performance of this model on the ROUGE score is better than all baseline models. In order to clearly demonstrate the superiority of the model, the evaluation scores of different models are shown in Figure 7.

In the comparison of IGPTP with PGN, ROUGE-1, ROUGE2, and ROUGE-L are 14.42%, 18.25%, and 17.25% higher than PGN, respectively. Since the volume of the dataset is around 5000, we infer that the convergence of IGPTP is better under the condition of small sample data than PGN. In the comparison between IGPTP and BART, ROUGE-1 scores increased by 3.5%, ROUGE-2, and ROUGE-L increased by 10.17% and 3.78% respectively. In the text generation part, external knowledge is integrated to guide the word segmentation and vectorization of the model. The model can perform better in word level. In addition, a combination of extraction and generation is used. The generated

Table 4. Experimental results of the different models

Model	Rouge-1	Rouge-2	Rouge-L	Human Scores
PGN	57.73	41.51	51.69	62.41
mT5	65.71	50.74	61.03	83.82
BART	68.65	49.23	65.16	73.80
IGPTP	72.15	59.40	68.94	89.01

Figure 7. Histogram of evaluation scores for different models
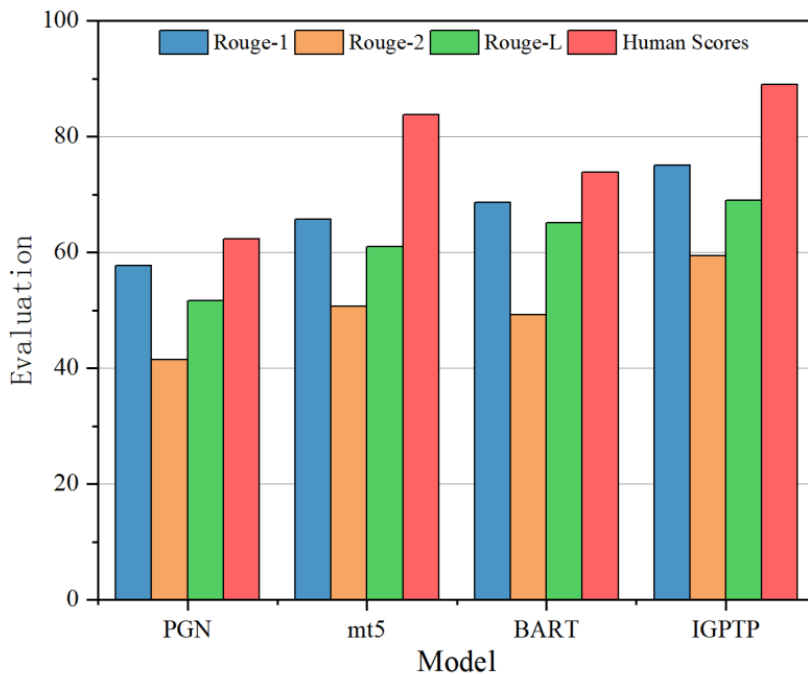
text is embellished and rewritten to make it read more fluently. In terms of manual scoring, the scores of IGPTP are 26.60%, 5.19%, and 15.21% higher than those of PGN, mT5, and BART models. It fully verifies that the generated text of this model is closer to the real sentence in readability, syntax structure, etc. The significant improvement in the ROUGE-2 and ROUGE-L scores indicates that IGPTP has better similarity at the word level and common subsequences. These phenomena also fully prove that the patent technology point generated by the IGPTP model is more complete and closer to the standard patent technology point. It reflects the effectiveness and advantages of the IGPTP model. Examples The generation examples of different models are shown in Table 5.

The purple font represents the text generation results of our IGPTP method. It can be observed from the blue text in Table 4, "also includes a temperature sensor, the socket connection end is provided with a heat conducting element," has low sentence fluency and poor contextual relevance. Both the PGN and the mT5 model have incoherent and inaccurate sentence patterns. The generated text has poor logic. As shown in the red text in Table 4, "the temperature sensor is in contact with the heat-conducting element" this sentence appears twice in a row. The generated text has serious redundant information. The BART model has the phenomenon of vocabulary repetition and incompleteness. The IGPTP model combines extraction and generative methods to effectively reduce the problem of poor logic in the generated text. It integrates the copy mechanism to ensure the accuracy of the text. The patent technology points generated by the IGPTP model are more accurate at both coarse and fine grain. There is no sentence redundancy, the sentence structure performs well and the text is more readable. It is also better in the generation of long terms. The reliability of the text generated by the model in this paper is verified.

Ablation Experiments

To verify the effectiveness of each component of the proposed model, each component of the model was disassembled for ablation experiments. The results are shown in Table 6 and Figure 8.

1. Extraction method: RoBERTa+DGCNN model is used. The task is transformed into a classification task to determine whether the sentence is a patented technology point. Roberta is used for vectorization. The vector is passed into DGCNN for feature extraction. The patented technology points are extracted using classification recognizer.
2. Generation method: NEZHA+UNILM model is used. The method uses the NEZHA pre-training model introduced by Huawei, which is combined with the classical UNILM model to generate patented technology points.
3. Extraction + Generation: The method fuses method 1 and 2, which use the extraction result of the extraction model as the input of the generation model.
4. Extraction + generation + external knowledge: Based on method 3, the external knowledge term is added to guide the vector representation of the input of the generation model. The generation effect of domain terms is improved.
5. Extraction + generation + adversarial training: Based on method 3, adversarial training is added. The robustness of the model is improved by adding perturbations to enhance the generalization performance of the model.
6. Extraction + Generation + Sparse Softmax: Based on method 3, Sparse Softmax is used to enhance interpretability. The method can avoid the over-learning problem of Softmax and improve the model performance.
7. Extraction + Generation + Copy mechanism: Based on method 3, the Copy mechanism is added. The Copy mechanism can directly copy words from the input text to the output text, ensuring fidelity between technology points and original text and avoiding professional errors.
8. Extraction + Generation + External Knowledge + Adversarial Training: 3+4+5.
9. Extraction + Generation + External Knowledge + Adversarial Training + Sparse Softmax: 3+4+5+6.
10. The model of this paper: extraction + generation + external knowledge + confrontation training + Sparse Softmax + Copy mechanism. 3+4+5+6+7.

Table 5. Sample generate texts by different models

Source text	Technical field: The utility model relates to electric vehicles, in particular to a charging gun core piece, a charging gun plug and a charging gun capable of monitoring temperature. …… The specific embodiment also discloses a charging gun, including a charging gun plug, the charging gun plug has a core piece, and the core piece adopts the above-mentioned charging gun core piece capable of monitoring temperature.
Target text	The utility model discloses a charging gun core piece capable of monitoring temperature, which comprises a core piece body, the head end of the core piece body is a socket connection end, the tail end of the core piece body is a cable connection end, and further comprises a temperature sensor, and the socket connection end is provided with a heat-conducting element, and the temperature sensor is in contact with the heat-conducting element. In the utility model, a heat-conducting element is arranged at the connecting end of the socket, and the temperature sensor is in contact with the heat-conducting element, so that the temperature of the socket can be measured when the charging gun core piece is in contact with the socket. The utility model also discloses a charging gun plug and a charging gun using the above-mentioned charging gun core piece.
Technology points generated by PGN	The utility model discloses a charging gun core piece capable of monitoring temperature, a charging gun plug and a charging gun. The charging gun core piece capable of monitoring temperature comprises a core piece body, and the head end of the core piece body is a socket connection end, and the tail end of the core body is a cable connection end, and also includes a temperature sensor, including a charging gun plug and a charging gun. The socket connection end is provided with a heat-conducting element, and the temperature sensor is in contact with the heat-conducting element. The temperature sensor has an insulating shell, the socket connecting end is also provided with an insulating part, and the side wall of the heat conducting element is wrapped by the insulating part, so that the heat conducting element does not contact the socket connecting end, and the head end of the heat conducting element is exposed on the insulating part.
Technology points generated by T5	The utility model discloses a charging plug and a charging bin for a core piece of a charging gun. A positioning mechanism is arranged between the core piece body and a flow guide. The positioning mechanism is used to fix the position of the flow guide in a cavity, and includes a core piece. The body also includes a temperature sensor, the socket connection end is provided with a heat conducting element, and the temperature sensor is in contact with the heat conducting element. The utility model discloses a charging gun core piece capable of monitoring temperature. A heat-conducting element is arranged at the connection end of a socket, and a temperature sensor is in contact with the heat-conducting element. In this way, the heat-conducting element can be prevented from contacting with the socket connection end, and the temperature sensor housing is also insulated, which can directly reduce the heat generated by the socket connection end during operation.
Technology points generated by BART	The utility model discloses a charging gun core piece capable of monitoring temperature. The charging gun core piece capable of monitoring temperature comprises a core piece body, the head end of the core piece body is a socket connection end, and the tail end of the core piece body is It is a cable connection end, and also includes a temperature sensor, the socket connection end is provided with a heat-conducting element, the temperature sensor is in contact with the heat-conducting element, and the temperature sensor is in contact with the heat-conducting element. The temperature sensor has an insulating shell, the socket connection end is further provided with an insulating part, the side wall of the heat conducting element is wrapped by the insulating part, and the head end of the heat conducting element is exposed outside the insulating part.
Our work: Technology points generated by IGPTP	The utility model discloses a charging gun core piece capable of monitoring temperature, which comprises a core piece body, the head end of the core piece body is a socket connection end, the tail end of the core piece body is a cable connection end, and further comprises a temperature sensor, and the socket connection end is provided with a heat-conducting element, and the temperature sensor is in contact with the heat-conducting element. The temperature sensor has an insulating shell, and the socket connection end is also provided with an insulating member. By arranging a heat conduction element at the socket connection end, the temperature sensor is in contact with the heat conduction element. The charging gun plug of the charging gun core piece and the charging gun are used, and the temperature sensor shell is also insulated, which can directly reduce the heat generated by the socket connection end during operation.

Through the experimental results, it can be found that the combination of extraction and generation can achieve better results for patented technology point generation. Compared with the separate extraction and generation methods, the Rouge score has a high improvement. It verifies the

Table 6. Ablation experiments results

Method	Rouge-1	Rouge-2	Rouge-L
1	59.12	38.65	47.15
2	61.13	47.69	56.67
3	67.23	51.25	65.22
4	67.85	55.69	66.76
5	67.30	53.41	65.74
6	67.41	52.67	66.26
7	68.71	57.13	67.10
8	69.97	56.42	67.23
9	71.76	57.81	67.71
10	72.15	59.40	68.94

Figure 8. Ablation experiments results
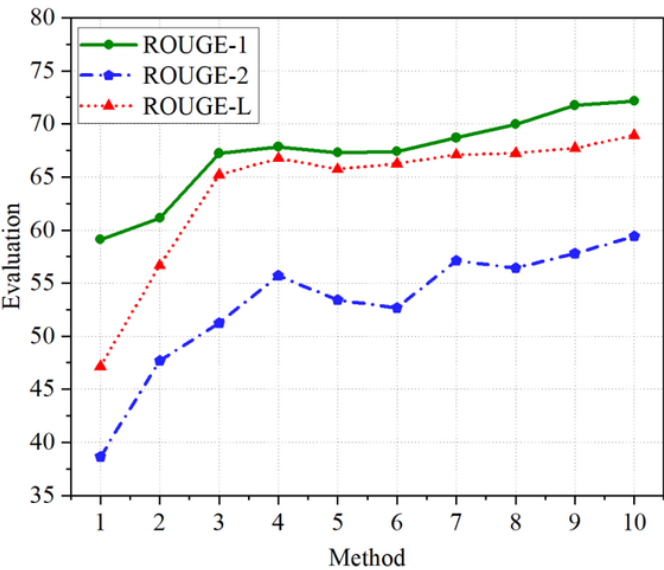
effectiveness of the idea of using the extraction results as the input of the generation model for patented technology points generation. Comparing methods 4 and 3, it can be found that the introduction of external knowledge to guide the input of the generation model can effectively improve the generation effect of the long terms. It makes the generated text more similar to the standard answer. The Rouge-2 and Rouge-L scores are improved by 4.44% and 1.54% respectively. It proves the results superiority of introducing external knowledge approach on the public sequence; Comparing methods 5 and 3, it can be found that adding adversarial training during the extraction model training can fully improve the robustness of the model. Thereby, the generation quality of the model is improved and the Rouge score is improved. Comparing method 6 and method 3, it can be found that sparse Softmax can effectively improve the interpretability of the model and enhance the generation quality. The Rouge score increases by 0.18%, 1.42%, and 1.04% respectively; Comparing methods 7 and 3, it can be

found that the introduction of Copy mechanism can effectively ensure the fidelity of the generated text and the original text and embellish the generated text. The Rouge score is increased by 1.48%, 5.88%, and 1.88% respectively; Comparing experiments 8, 9, and 10 can verify the reliability of the combination of the various components of the model proposed in this paper, which all improved in the Rouge scores; After the verification of the ablation experiments, all types of components provide positive effects on the model effect. It is well demonstrated that the model IGPTP proposed in this paper can effectively combine extractive and generative methods. The generated patent technology points have a high quality through the embellishment of each component.

CONCLUSION

In this paper, to solve the dilemmas faced by traditional text generation methods in the new energy patent technology point generation task, we propose a method, named IGPTP, fusing the advantage of extractive and generative ways to generate patent technology points. At the same time, it uses a multi-strategies integration technique to enhance the quality of patent technology points by combining the Copy mechanism and external knowledge guidance model. The basic benefits of the method are: (1) it uses RoBERTa+CNN model to ensure the accuracy grammatical structure of the text and works UNILM to guarantee semantic coherence and readability. (2) it utilizes adversarial training to promote data robustness, external knowledge to guide word segmentation and vectorization, and Copy Mechanism to embellish the text. Substantial comparative experiments demonstrate that IGPTP can achieve better results than the traditional mainstream text generation technology. The generated text has higher readability and logic and achieves high Rouge value. Furthermore, the ablation experiments verify the effectiveness of the components in IGPTP.

As a future research direction, driven by the existing results obtained in this study, we will delve into the characters in different areas to improve our method. In addition, we will also explore the impact of text semantic information and syntactic structure on the model to improve the accuracy and readability of the generated results.

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COMPETING INTERESTS

All authors of this article declare there are no competing interest.

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ENDNOTES

[1]   http://www.soopat.com/
[2]   https://github.com/young-yhx/dataset

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