Poetry Generation Combining Poetry Theme Labels Representations

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Abstract

Ancient Chinese poetry is the earliest literary genre that took shape in Chinese literature and has a dissemination effect, showing China's profound cultural heritage. The current work in the field of poetry generation is mainly aimed at improving the fluency and structural accuracy of words and sentences, ignoring the theme unity of poetry generation results. In order to solve this problem, this paper proposes a graph neural network poetry theme representation model based on label embedding. Based on the network representation of poetry, the topic feature representation of poetry is constructed and learned from the granularity of words. Then, the features of the poetry theme representation model are combined with the autoregressive language model to construct a theme-oriented ancient Chinese poetry generation model TLPG (Poetry Generation with Theme Label). Through experiment and evaluation by experts in related fields, the model proposed in this paper has significantly improved the topic consistency on the premise of ensuring the fluency and format accuracy of poetry.

1 Introduction

Ancient Chinese poetry is a short, vivid form of literary genre, and the depictions in ancient poetry are a living reflection of the daily life of the Chinese ancestors as well as their inner prayers and expectations. In world literature, ancient Chinese poetry is also an important means of demonstrating the power of the Chinese language. It is interesting to note that although automated machine poetry compositions fall short of human beings in terms of rhyme, mood, and feeling (Zhang et al., 2023). However automated poetry generation is still worth researching. On the one hand, machine-generated ancient poems can assist students in generating a deeper understanding of poetry (Ma et al., 2023). On the other hand, the emergence of multimodal technologies has made poetry learning not only limited to texts (Wu et al., 2021) a variety of information can be utilized in the study of poetry teaching and learning.

In terms of poetic format, poems of different genres and eras often have different formats (e.g., poetic style, rhyme, etc.), which involve grammatical, semantic, and phonological aspects. Current research tends to establish grammatical analysis as well as symbolic representation of phonology for ancient poems, which makes poetry often contain explicit thematic information (Yang et al., 2023). Themes in poetry are implicit textual information are important references for poetry appreciation and creation, so this paper focuses on the representation and integration of theme features in the process of poetry generation.

At present, the mainstream poetry generation models are mainly based on the Transformer (Zhao et al.,2022) and generate poems in the form of autoregressive language models. However, unlike general text generation tasks, poetry is a highly structured literary genre (Li,2020). In the poetry generation task, the input part of the model is designed with a special identifier to learn the specific format of the poem (Yang et al., 2022). During the learning process this special identifier learns potential formatting information in a particular type of poetry. In the poetry generation stage, such a special identifier functions accordingly in the decoding stage. Making it possible to generate text in a well-formed poetry genre. This paper focuses on proposing a label embedding-based graph neural network poetry topic representation model, while combining it with applications on poetry generation tasks. Thus, the main research work in this paper is as follows:

Firstly, a poetry text graph network is constructed based on the textual characteristics of

Proceedings of Recent Advances in Natural Language Processing, pages 1246–1255
Varna, Sep 4–6, 2023
https://doi.org/10.26615/978-954-452-092-2_132

ancient Chinese poetry, and a label embedding-based graph neural network poetry theme representation model is proposed to learn the theme feature representation of poetry based on the network representation of poetry.

Combining the features of the poetry theme representation model with the autoregressive language model, we construct the theme-oriented ancient Chinese poetry generation model TLPG (Poetry Generation with Theme Label), which integrates the attention mechanism of poetry theme features to improve the consistency of poetry generation themes.

This paper is organized as follows: Section 1 introduces the topic-controlled poetry generation task. Section 2 describes relevant work related to this paper. Section 3 demonstrates the model proposed in this paper which is the TLPG model. Section 4 describes in detail the experimental setup and the section 5 discussion related to the results. Finally, section 6 gives the conclusion of the paper.

2 Poetry generation related work

Research on automatic poetry generation started in the 1960s, and early poetry generation studies used a system architecture for generating lyrics given a melody, selecting words from a word list library, then testing and filtering them, repicking them if they are not suitable, and moving on to the next position if they are (Gervás, 2000). And then some scholars added genetic algorithms to the poetry generation task, and Zhou et al (2010) designed a coding method based on flat and oblique, introduced the coding information into the fitness function, and added elitism and roulette algorithms in genetic algorithms, but the high computational complexity of genetic algorithms and the possibility of sometimes falling into local optimal solutions made the quality of poetry generation uneven. With the advent of statistical machine learning, Wong et al (2008) used the vector space model to formulate the relationships between sentences as vectors, and then used cosine similarity to compare the relationships between sentence pairs and extract relevant statements from blog posts for generation. Yan et al (2013) used information retrieval techniques to retrieve a set of poems related to keywords from a database, and sub-phrasing, and then applied abstraction techniques to generate poems using the sub-phrasing results. However, the above method does not constrain the poetry topic and format, and the generation is not effective.

In order to better incorporate control attributes into the generation process, advanced model structures have been gradually proposed as neural networks and deep learning techniques have gradually matured. Zhang et al (2014) first introduced deep neural networks into the poetry generation task and proposed a model combining recurrent neural networks (RNN) for ancient Chinese poetry generation. Hu et al (2017) proposed the use of a Variational Auto-Encoder (VAE) with a framework overall attribute discriminator to achieve the control of generation direction by combining VAE with a discriminator. Yi et al (2020) used a semi-supervised VAE framework to generate poems with more thematic and semantic richness considering the style of the poems as a combination of multiple factors. To improve the thematic relevance of poetry generation, some scholars have proposed using a working memory model that utilizes an internal memory to store and access multiple subject terms. Sun et al (2018) used an unsupervised approach to enhance the diversity of poetry generation by maximizing the mutual information between the style distribution and the output distribution. Zhang (2020) et al. based on the Transformer structure and incorporated input identifiers to make information about the formatting and meter of the poem displayed by participating in model training to generate poems with a more standardized format. The generation model in this paper aims to ensure the quality of poetry generation while generating poems with a more uniform theme, improve the interactivity with users, and be applied in the system construction.

3 Model

3.1 Poetry theme representation

The purpose of this paper is to improve the content quality of generated poems by introducing theme information through a topic model. Based on this purpose, this paper proposes a label embedding based method for representing poetry topics in graph neural networks. Compared to the direct application of Latent Dirichlet Allocation（LDA) topic models, this paper's model first uses a dense representation vector at the word granularity in the underlying layer to ensure the representation capability of the model. Secondly, this paper uses graph neural network as a theme feature representation model to build graphs from corpus. After obtaining different topics of poems, unlike the topic vectors above, the output of the basic LDA model is a judgmental representation of the probability of different topics, which can be involved in classification.

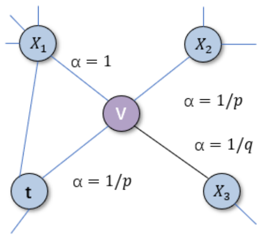

Figure 1: Structure of Node2Vec

Therefore, graph neural networks are used in this paper. Drawing on the work of Yao et al (2019) and Huang et al (2019), this paper fuses global poetry information to construct a poetry text graph. Firstly, the poetry corpus is subdivided to transform the whole poetry corpus into a graph structure, and the poems will be classified by LDA that connects the thematic category of each poem as a label to the words in the poem. Suppose a certain poem $P = \{p_1, p_2, p_3, \dots p_N\}$ containing N words in the poetry corpus D. The set of poetry topic labels can be obtained from the above as $S = \{s_1, s_2, s_3, \dots s_N\}$, then there is a text graph construction method based on the poetry corpus as shown in procedure 1 and 2.

$$E = \{\, Connect(p_i, s_j) \mid p_i \in P, s_j \in S\} \quad (1)$$

$$G = \{p_1, \dots p_n\} \cup \{s_1, \dots s_N\} \cup \{e_1 \dots e_k\} \quad (2)$$

The words in the entire poetry corpus are treated as word nodes in the text graph, and all poetry topics are treated as topic nodes. For the set of edges E is constructed as Equation 1, and all the words in the verse are connected to the corresponding topic labels as Equation 2. This results in the text graph of the complete poetry corpus, which is an undirected graph and each node has the same weight as the edge, set to 1. We combine the methods of label embedding and graph networks, and use the Node2Vec (Aditya,2016) to embed the poetry topic label nodes and poetry word nodes, and use the embedding vector of poetry topic labels as the poetry theme representation. The structure of Node2Vec structure is shown in Figure 1.

In Node2Vec, some random wandering sequences are first generated, and then the training paradigm Skip-gram of Word2Vec is borrowed to transform the words into a high-dimensional space vector representation. In the training process, a negative sampling method is used, and the final word vector representation can be obtained through multiple iterations of training. The training objectives are shown in Equation 3 and Equation 4:

$$max \sum_{u \in V} \log Pr(N_s(u) \mid f(u)) \quad (3)$$

$$Pr(p_i) = f(p_i)^{3/4} / \sum_{j=0}^{n} \left(f(p_j)^{3/4}\right) \quad (4)$$

The process of poetry theme and word representation based on label embedding graph network is shown in Figure 2, where T_i is the theme node of the poem, which relates to the words in the poem to generate a random wandering sequence, and the word representation and theme representation are finally obtained through training.

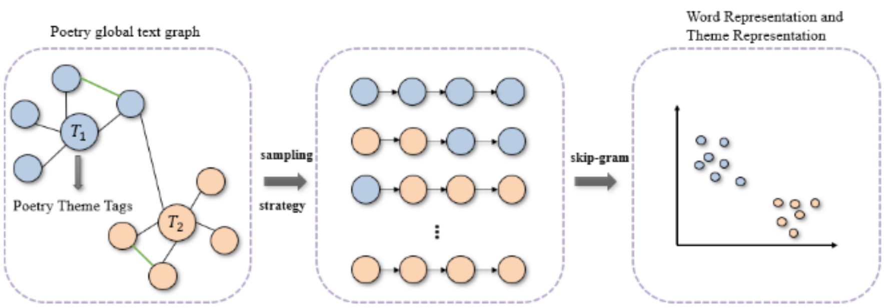

Figure 2: The Generation Process of Poetry Theme and Word Representation

3.2 A poetry generation model combining poetry theme representation

The model proposed in this paper is based on the Transformer framework, and the input of the model is $x = (< bos >, p_1, p_2, p_3, \ldots, p_n)$, where n is the number of sample words and $< bos >$ denotes the input starting symbol. The output of the model is $y = (p_1, p_2, p_3, \ldots, p_n, < eos >)$, where $< eos >$ denotes the ending symbols, and the model diagram is shown in Figure 3. In order to improve the model's ability to learn a series of writing rules for poetry, a series of extensions to the input information are made in this paper. The model input identifier part refers to the research idea of Li（2020）, in addition, combined with the section on poetry theme representation based on label embedding and graph network in Section 3.1, this paper adds the theme label representation into the model input, and then incorporates the poetry topic label representation into the generative model. Regarding the design of the input identifiers, "银烛秋光冷画屏，轻罗小扇扑流萤。"（The painted screen is chilled in silver candlelight, She uses silken fan to catch passing fireflies） is presented as an example for the sake of understanding.

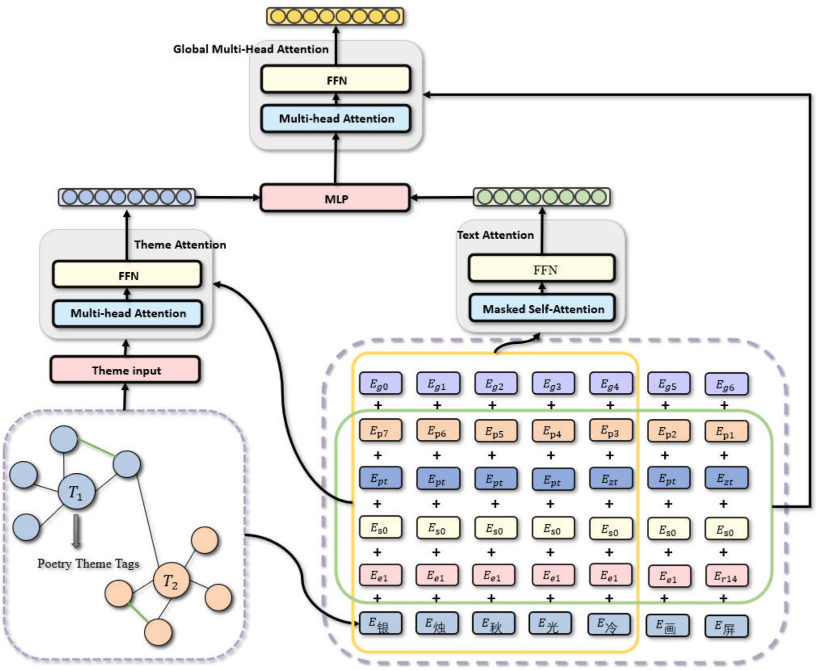

Figure 3: The generative model of Poetry Combined with Poetry Theme Representation

The first one is the sentence identifier, and the sentence identifier can guide and enhance the learning process of the model in the learning of sentences in different positions in the poem text. Where $</s>$ is the separator number between sentences, s_i in the above equation indicates the i-th sentence of the word in the poem, and the sentence identifier is expressed as $SEN = \{s_0, s_0, s_0, s_0, s_0, s_0, s_0, s_0, </s>, s_1, s_1, s_1, s_1, s_1, s_1, s_1, s_1, </s>, < eos >\}$. The second is the internal order identifier, where p_i is the penultimate i-th character in each verse. The reason for this decreasing approach is to let the model notice that the generation has proceeded to the end position of the verse. Where the last character of each verse is denoted as p_1 and the punctuation position is denoted as p_0. The internal order identifier is denoted as $POS = p_7, p_6, p_5, p_4, p_3, p_2, p_1, p_0, </s>, p_7, p_6, p_5, p_4, p_3, p_2, p_1, p_0, </s>, < eos >$. The third one is the tone identifier, which aims to allow the model to learn the tone information corresponding to the word, and to be able to produce more compliant verses under the specific tone format requirements. The tones of poetry are mainly divided into a total of two types: "平"(level tones) and "仄"(oblique tones). In terms of formal representation, the "平" is represented by pt, while the "仄" is represented by zt, and the punctuation is represented by n. In this paper, the labeling rules of data refer to "中华新韵" (Zhao,2019). The tone identifier is represented as

$TONE = \{pt, pt, pt, pt, zt, zt, pt, n, </s>, pt, pt, zt, zt, pt, pt, pt, n, </s>, <eos>\}$. The fourth type is the metrical identifier. In the example verse of this article, "屏" and "萤" at the end of the sentence rhyme, and the two characters belong to "十四英"(a set of rhyme pattern) according to "中华新韵" (Zhao,2019), so denoted as $<rhyme\text{-}14>$. Use e_0 for punctuation and e_1 for ordinary words in the verse. The purpose of the metrical identifiers is to allow the model to display the rhyme writing techniques used in the learned poems and to make the generated poems more beautiful. The metrical identifiers are represented as $RHY = \{e_1, e_1, e_1, e_1, e_1, e_1, <rhyme\text{-}14>, e_0, </s>, e_1, e_1, e_1, e_1, e_1, e_1, <rhyme\text{-}14>, e_0, </s>, <eos>\}$. The last input is a poetry theme label representation vector, which identifier is the final poetry topic label representation derived from the LDA trained in the previous section after text graph construction by global poetry text. The example verse in this paper belongs to the poetry theme category $<theme\text{-}48>$. It's one of the predefined 50 categories given by the LDA topic model, which is automatically learned from corpus. This theme label is further incorporated into the theme model to enable the generative model to learn the theme information of the poem.

In the input layer of the model, the different types of identifier representations are accumulated, E is a vector of different identifier representations, and t is the current position of the word or identifier, where E_{W_t} and $<theme\text{-}48>$are from the poetry graph network introduced in Section 3.1. Here, combined with the identifier representation introduced above, E_{G_t} is the global position, and the final input is shown in Equation 5:

$$H_t^0 = E_{W_t} + E_{SEN_t} + E_{POS_t} + E_{TONE_t} + E_{RHY_t} + E_{G_t} \tag{5}$$

In addition, in order to better generate the canonical content, the model needs to know the structural information of the sentence to be generated next in the state of time t. Therefore, the variable F^0 is introduced, as shown in Equation 6:

$$F_t^0 = E_{SEN_t} + E_{POS_t} + E_{TONE} + E_{FMT_t} \tag{6}$$

Also, in order to make the results generated by the model notice the theme information, where E_{SEN_t} and E_{POS_t} are placeholders. Theme identifiers are introduced in the input layer, as shown in Equation 7:

$$M_t^0 = E_{<theme\text{-}48>_t} + E_{SEN_t} + E_{POS_t} \tag{7}$$

In order to make the three vectors of global information, poetry text representation information of fusion generation rules and poetry theme representation information to fuse the information effectively. In this paper, we design a two-layer attention for fusing poetry theme features. The first step is to obtain the poetry text representation input with Masked Multi-head attention layer, which is calculated as shown in 8, where $SLF-ATT$ stands for self-attention mechanism in the model:

$$C_t^l = LN\,(FFN\,(C_t^l) + C_t^l)$$

$$C_t^l = LN\,(SLF-ATT\,(Q_t^l, K_{\le t}^l, V_{\le t}^l) + H_t^l)$$

$$Q^l, K^l, V^l = H^l\boldsymbol{W^Q}, H^l\boldsymbol{W^K}, H^l\boldsymbol{W^V} \tag{8}$$

where $\boldsymbol{W^Q}$, $\boldsymbol{W^K}$ and $\boldsymbol{W^V}$ are learnable weight matrices. The Transformer mask mechanism makes the restriction that the current position in the model used to handle the self-attention can only see the previous part of the position, So the model cannot notice what comes after t when $\le t$. The output of the masked self-attention layer with the topic label representation vector is fed into the topic multiheaded attention, and the theme attention formula incorporating the poetry theme features is shown in 9:

$$S_t^l = LN\,(FFN\,(S_t^l) + S_t^l)$$

$$S_t^l = LN(ATT(Q_t^l, K^l, V^l) + H_t^l)$$

$$Q^l, K^l, V^l = H^l\boldsymbol{W^Q}, M^0\boldsymbol{W^K}, M^0\boldsymbol{W^V} \tag{9}$$

The representation obtained from the above two attention modules is combined and then the vector dimension is changed through the fully connected layer as shown in Equations 10:

$$K_t^l = [C_t^l : S_t^l]$$

$$K_t^l = MLP(K_t^l + H_t^l) \tag{10}$$

Finally, the global information is input so that the generative model can know the poetry rules to be generated later, from the l layer representation H^l obtains the $l+1$ implicit representation H^{l+1} shown in Equation 11, where $GLO-ATT$ means the global attention mechanism in the model:

$$H_t^{l+1} = LN\,(FFN(H_t^{l+1}) + H_t^{l+1})$$

$$H_t^{l+1} = LN(GLO-ATT(Q_t^l, K^l, V^l) + K_t^l)$$

$$Q^l, K^l, V^l = K^l\boldsymbol{W^Q}, F^0\boldsymbol{W^K}, F^0\boldsymbol{W^V} \tag{11}$$

In this paper, negative log-likelihood is chosen as the loss function of this model, as shown in Equation 12:

$$\mathcal{L} = -\sum_{t=1}^{n} log\ P(\boldsymbol{y}_t \mid \boldsymbol{y} < t) \quad (12)$$

4 Data set and experimental setup

4.1 Data set and parameters

The dataset in this paper comes from the open-source database called Chinese-poetry on GitHub mentioned above, and draws on the work of Zhang et al (2014) and Luo et al (2021) to select more structured poems from the library. In this paper, four types of modern poetry were chosen to test the correctness of the model described in this chapter. The data of each type are shown in Table 1.

Poetry genre	Number of poems
Five-character quatrain	2268
Seven-character quatrain	9377
Five-character regulated poem	7105
Seven-character regulated poem	7299

Table 1: Statistics of Poetry Information in Corpus.

In this paper, the training set, validation set and test set are divided in the ratio of 80:10:10, and the same poetry genre in each set is proportionally distributed. p of the hyperparameter of the Node2Vec algorithm is set to 1.2, and the hyperparameter q is set to 0.5. In the SkipGram algorithm, the window size is set to 5, and the negative sampling technique is used to improve the computational efficiency.

Model	PPL↓		Theme consistency↑ (%)
	val	test	
GPT	17.71	18.01	8.61
SongNet	12.86	13.11	15.77
MCPG	11.47	11.59	38.37
TLPG	9.98	10.01	61.74

Table 2: PPL& Theme consistency.

The number of layers of the model is set to 12, and in the multi-headed attention mechanism module, the number of heads is set to 12. In the training phase, dropout controls the randomness in the process of fitting the model to the data, and this parameter is set to 0.2. In the model training optimizer section, Adam is selected to train the model, and the learning rate is also dynamically adjusted during the training process by the Noam learning rate decay strategy (Kingma and Ba, 2014).

The analysis is performed for the parameter of number of topics. The topic model uses LDA, the topic model is constructed on the whole poetry corpus combined with the LDA model, and the co-occurrence scores are calculated using the UMass (2012) metrics as shown in Equations 13:

$$coherence\ (V) = \sum_{(v_i, v_j) \in V} score\ (v_i, v_j, \epsilon)$$

$$score\ (v_i, v_j, \epsilon) = log\ \frac{D(v_i, v_j) + \epsilon}{D(v_j)} \quad (13)$$

Where V is a set of topic words, ϵ denotes the smoothing factor $D(x, y)$ counts the number of documents containing words x and y, and counts the number of documents containing $D(x)$. and set different number of topics from 10 to 500, the best co-occurrence score index can be achieved when the number of topics is 50, so this paper uses 50 as the number of topics parameter in the process of building the model.

4.2 Evaluation Indicators

In this paper, machine evaluation uses PPL, theme consistency, Format, Tone and Rhyme. Theme consistency is used to judge whether the overall themes expressed in the generated poems are consistent. The formula is shown in 14:

$$\text{Theme consistency} = \frac{1}{|Y|} \sum_{y \in Y} \text{OL}\ (P(T|y), P(T|\bar{y}))$$

$$\text{OL}\ (P(T), Q(T)) = \sum_{t \in I} \min(P(T), Q(T)) \quad (14)$$

The format accuracy rate indicates whether the generated samples match the four poem formats in the dataset. Tone accuracy rate is the percentage of correctly predicted tones among all generated samples. Rhyming accuracy rate is the average percentage of a poem that rhymes correctly.

Model	Format(%)	Tone(%)	Rhyme(%)
GPT	45.09	48.66	63.21
SongNet	99.80	65.33	77.61
MCPG	99.98	98.58	97.19
TLPG	98.41	96.54	98.79

Table 3: Format Tone & Rhyme.

Model	PPL↓		Theme consistency↑ (%)
	val	test	
TLPG w/o TL	11.70	11.91	56.83
TLPG w/o theme	12.53	12.75	20.08
TLPG	9.98	10.01	61.74

Table 4: Results of ablation experiment.

When evaluating a poetry generation model or system, the results of human evaluation are also an important reference. The human evaluation will invite some people who know about poetry or have experience in poetry writing (e.g., Chinese language scholars) to conduct the evaluation. The order of the poems produced by the different models is disordered and the evaluator must rate each poem from 0 to 3 on each assessment index (minimum 0, maximum 3 and scored using 0, 1, 2 or 3). In this paper, 60 poems (15 poems in each of the four genres) were randomly selected for evaluation. In this paper, 10 raters were invited to rate the generated collection of poems, and multiple raters usually rate a poem in order to reduce the subjectivity of the evaluation. The manual evaluation metrics include Rhyming tone, Unity of theme and Expression fluency.

Model	Rhyming tone	Unity of theme
SongNet	**2.31**	2.26
MCPG	2.15	2.23
TLPG	2.30	**2.58**
	Expression fluency	**Avg**
SongNet	**2.38**	2.32
MCPG	2.32	2.23
TLPG	2.36	**2.41**

Table 5: Manual evaluation results.

4.3 Contrast and ablation experiments

In this paper, the more advanced existing models and systems are selected for comparison experiments, along with ablation analysis of the models, to demonstrate the effectiveness of using graph neural network modeling labels and their introduction into the generative model for controlling poetry generation themes. The comparative experimental setup is shown below:

GPT (2018): GPT is a natural language generation model. Its core structure is Transformer

SongNet (2020): SongNet is a format-controlled and autoregressive language-model-based text generation framework, which is designed with a series of input identifiers displayed at the input layer.

MCPG (2021): this model also formulates the poetry generation task as a constrained text generation problem and gives certain keywords to participate in poetry generation, and differs from the model in this paper in the design of Encoder and Decoder.

The ablation experiment setup is shown as follows:

TLPG w/o TL: The poetry theme label representation obtained from the graph neural network is not used, and the output of the LDA model is used directly with the same frame structure.

TLPG w/o Theme: remove the theme feature input and the attention module associated with it.

5 Experimental results and analysis

The experimental results are shown in Table 2 and Table 3. From the results, we can see that the perplexity and theme consistency metrics on both the validation and test sets of this paper's model are optimal, which highlights the effectiveness of introducing theme tags into the poetry generation task to improve the theme consistency of poetry, because both SongNet model and MCPG introduce input operators to regulate the poetry generation format, tone and rhyme, so the experimental results are similar in terms of format accuracy, tone accuracy, and rhyme accuracy.

The results also demonstrate that TLPG improves thematic consistency while also ensuring the regularity of its generated format. When using the GTP model for top-k sampling, it is easy to lose control over the regularity of the generated poems due to its random nature, and significantly lower than the other models in terms of format accuracy, tone accuracy and rhyme accuracy, and perplexity and theme consistency.

Meanwhile, this paper conducted ablation experiments on the model, and the results of these three indicators are not discussed here because there is no variable control on format, tone and rhyme aspects, and the final results of the ablation experiments are shown in Table 4, where TLPG w/o TL does not use the poetry theme label representation obtained in Section 4.2, but directly uses the output of the LDA model.

With the overall experimental framework structure unchanged, there is a decrease in theme consistency, which also indicates that adding the vector obtained by training the theme representation again after establishing the connection with the verse to the generative model is more effective than simply using the LDA model output vector representation of the theme labels for input.

<table>
<tr><th colspan="2">Poetry generation samples in Chinese</th></tr>
<tr><td>Theme：14</td><td>Theme：20</td></tr>
<tr><td>秋山万壑云飞乱，明月当空照江河。
北风吹彻楼台上，龙城千古高楼多。
东海波涛浩无垠，西湖烟波渺茫多。
南楼一曲千古恨，汉水万里泪空流。</td><td>寒夜乌飞叫声哀，霜风凛冽雁归来。
明月高挂空悬浸，寒霜落尽叶翩跹。
风过寒衣冷又惊，耿耿长夜未成眠。
声音渐远难寻觅，风雪之中有谁家。</td></tr>
<tr><td>Theme-14:山 天 海 万 风 云 江 河 楼 龙 千 城 里 白 月 南 西 东 汉 水 马</td><td>Theme-20:飞 寒 霜 雁 空 鸿 夜 衣 晓 影 声 乌 高 雪 差 不 惊 微 耿 参</td></tr>
<tr><th colspan="2">Translation</th></tr>
<tr><td>Autumn mountains and ravines, clouds flying chaotic, bright moon in the sky shining river.
The north wind blows through the building on the platform, thousands of ancient buildings high-rise in Dragon city.
The waves of the East China Sea are vast and boundless, and the smoke and waves of the West Lake are remote.
The southern building has a song of a thousand hates, and the Han River has ten thousand miles of empty tears.</td><td>The cold night crows fly and scream, the frosty wind is cold and the geese return.
The moon hangs high in the sky, and the leaves are dancing in the frost.
The wind is cold and frightening, and the night is long and sleepless.
The voices are far away and hard to find, whose home is there in the snow and wind.</td></tr>
<tr><td>Theme-14：The mountains, sky, sea, wind, clouds, river, building, dragon, thousand cities, white moon, south, west, east, Han, water, horses.</td><td>Theme-20：Flying, cold, frosty geese, empty skies, dark clouds, night clothes, dawn shadows, voices, high snow, no surprise.</td></tr>
</table>

Table 6: Example of TLPG results on different theme.

The TLPG w/o theme representation removes the theme identifier and the attention module associated with it, and the experimental results show that the generated poems lose the involvement of the theme identifier and are significantly less consistent in theme than the model with the theme identifier involved. In summary, the experimental metrics of the machine evaluation index prove the advanced and scientific nature of the experiment. Table 5 shows the results of the manual evaluation metrics, as the input tone identifiers, metrical identifiers, and internal position identifiers are the same, there is no big difference between the three in terms of rhyme, SongNet is better in terms of expressive fluency and rhyming tone, while TLPG, the model of this paper, performs the best in terms of theme consistency. Finally, Table 6 shows the generated poetry samples under different poetry theme labels.

6 Conclusion

In this paper, we propose a method for constructing a graph network of poetry texts, based on which a tag embedding method is combined with the graph network to obtain a poetry theme style modeling and representation, which is finally applied to the task of generating ancient Chinese poetry on a specific theme. The model is firstly based on the existing autoregressive language model framework and constructs a poetry generation model TLPG incorporating poetry theme tags by setting specific identifiers in the input layer, the model in this paper can ensure that the generated poems are formatted as required, and at the same time, combined with the poetry theme representation, can guide the model to generate poems that are more in line with the user's desired theme style. After the evaluation of real datasets and the results of manual evaluation by experts in related fields, the method proposed in this paper can not only improve the accuracy and quality of poetry generation, but also meet the personalized needs of users.

In addition, this paper will further investigate the introduction of more types of texts such as Song lyrics and Yuan songs into the TLPG model to improve the generalization ability and application scenarios of the model. In the future, with the continuous development and improvement of natural language processing technology, the ancient poetry generation technology will also be more widely and deeply applied.

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