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An overview of automatic poetry generation

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Abstract: *With the development of computer technology, the automatic generation of poetry has been gradually studied at home and abroad. The traditional poetry generation technology has defects such as requiring manual intervention, lacking generalization ability, and relying on evaluation functions.For example, rule template-based methods, genetic algorithms, etc. Although the previous work has shortcomings and defects, it continues to inspire research in this direction; With the wide application of deep learning technology, it has been applied to the automatic generation of poetry and achieved good results. This paper will introduce and discuss automatic generation methods based on traditional methods and automatic generation methods based on deep learning.*

Keywords:automatic generation of poetry ,deep learning technology,automatic writing technology

1 Introduction

Poetry has been a high-level medium for expressing human emotions since ancient times. It can express the rich emotions of human beings through concise and rhythmic language, such as love for things, singing praises to nature, and expressing people's thoughts. To a certain extent, poetry is more of a work of art, with high artistic appreciation value, and its graceful and flexible expression reflects human wisdom and unique creative ability. Poetry has developed in different styles and types all over the world. The diverse themes and genres make poetry a huge artistic treasure house in the history of human culture. Poetry is the earliest artistic work in Chinese literature and the most important part of Chinese traditional culture. The earliest poetry in my country was written in the Western Zhou Dynasty, and the earliest poetry was *The Book of Poetry* more than 2,000 years ago. Chinese traditional poetry carries the long-standing historical origin of the Chinese nation.Therefore, the inheritance of poetry culture is of great significance. However, due to the characteristics of flat rhyme, numerous genres, and regular format of traditional poetry, contemporary poetry creation has certain difficulties, and it also brings huge obstacles to the inheritance and development of poetry culture. In order to solve this problem, it has become a trend to realize the automatic generation of poetry by means of computers.

Manurung et al. [1] believe that the quality criteria for evaluating the generated poetry are: firstly, it is syntactically well-formed, that is to say, it must meet the most basic grammatical constraints; secondly, the generated verses must be meaningful, The generated poetry must be able to express and convey meaningful information and emotions; thirdly, it is poetic, and its content and format must have a certain level, not only to meet the basic requirements of flatness, rhyme and other forms, but also to meet the deep-level requirements of style, artistic conception, theme emotion and so on.This view has been widely recognized [2]. In order to realize the above poetry standards, researchers at home and abroad continue to explore in this direction. As early as the mid-20th century, foreign researchers began to study computer-generated poetry. In 1959, Theo Lutz first developed a poetry generation system[3]. Domestic research in this direction began in the 1990s[4].Although the traditional poems of different countries are different in terms of format, genre, language and expression, their research ideas and methods can be learned from each other. Throughout the development history of automatic poetry generation technology in the world, From the original rule-based and template-based form to the automatic generation of poetry using deep learning technology, it has undergone many years of development. This paper will introduce and analyze the related research situation of poetry automatic generation technology.

2 Research Status

Since the use of computer technology to automatically generate poetry in the mid-20th century, to the current automatic generation method based on deep learning, different research methods have achieved different effects. All in all, there are currently two types of research methods for automatic generation of poetry by computers, namely automatic generation based on traditional methods and automatic generation based on deep learning. This paper will analyze and discuss related researches on automatic poetry generation based on the above two methods.

2.1 Automatic Generation Method Based on Traditional Methods

2.1.1 Word Salada

Word Salada is the earliest automatic poetry generation method. In short, it just connects words into sentences in a random way. That is to say, it is just a simple list of words, ignoring syntax and grammatical rules, and it lacks practical meaning in understanding. It also lacks the poetic quality mentioned above, and does not have the rhythmic beauty of poetry. But it does open the door to an automatic generation. Its representative system is Pete Kilgannon's LYR C3205[5], and Example 0 is an example of the poem generated by this template:

judy gotta want upon somenone.
wanna sadly will go about.
sammy gotta want the thief him but the
every reason.real distance carry.

example 0.the poem generated by Word Salada

2.1.2 Automatic Generation Method Based on Rule Templates

The generation method based on rule templates refers to the use of templates, which contain fixed parts and pre-prepared blanks. The blank part is mainly used for automatic generation, because some words are randomly selected from the dictionary when generating poetry to fill in the blanks in the template. However, the words and blank spaces in these dictionaries are also based on certain rules, such as based on part of speech. Generally, only content words (such as nouns, verbs and adjectives) and a small number of adverbs can fill in the blank parts, while others Words are mostly kept unchanged in the template. The automatic generation needs to be based on certain rules, that is, according to a set of constraints, including word frequency, rhythm, tone and other conditions, and then combined with the dictionary and corpus to build poetry together. This method is mostly used in the early stage of automatic poetry generation. But it also meets the basic requirements of generating poetry under certain conditions.

The ALFRED the Agent is typical of a large number of poetry generators, and Do nald N.D. et al.[6]randomly select words from hand-crafted dictionaries to fill in gaps i n certain incomplete language structures, defining them as predefined templates or by some phrasal structure rules. Example 1 shows the output poetry of ALFRED.

Wheresoever amorphous - just barely the nightclub,
howsoever apostolic amidst a calamity,
a dragon will irrigate a Copernican currant - an emphysema.
His cowlick must have incinerated a housebroken revelry as per a melamine.
your inactive hydrocarbon could atone.

Example 1.the output poetry of ALFRED

Other such systems include ALAMO's *rimbaude-laires*, and there are similar systems on the web such as ELUAR, the Poetry Creator, and ADAM. Notable examples are RACTER and PROSE [7], whose poems were published - the collection of poems *The Policeman's Beard Is Half* consists entirely of poems constructed by RACTER. Some of these systems employ some kind of heuristic to model coherent and poetic representations, such as assigning specific emotional categories such as ethereal, philosophical, natural, love, vitality in ELUAR, and repeatedly choosing words to give a false sense of coherence , such as RACTER[8].

Template-based methods are also mostly used in Japanese haiku, a form of Japanese classical poetry that can contain a variety of imaginative expressions and can produce contextual stories[9].In 1971, Masterman first developed the h aiku system[10].

Naoko Tosa and others have developed a system to automatically generate haiku through computer technology. The user enters a word, and the system ca n automatically generate a phrase according to the input word. The user can al so choose to modify the haiku according to personal needs, so that the generat ed haiku can be more fully express emotions[11].

Most of the above methods appeared at the end of the 20th century, whic h was the early stage of automatic poetry generation.In recent years, there are still researchers who have done a lot of research in this type of method to im prove this method. Most of the research focuses on the constraints of rule template s. For example, For example, Rashel[12]and others constrain each line of a poem according to certain conditions, and finally combine them to form a poem an d evaluate it. The results show that the generated poems are better in every wa y than using loosely constrained or unconstrained methods. Similarly, Abdennad her et al. not only use constraint processing rules but also implement mandator y constraints on modules by progressively pruning custom dictionaries[13]. El Bo lock et al. made innovations in the way of implementing constraints. On the b asis of the former research, they applied advanced constraint programming lang uage to implement constraint processing rules (CHR) to satisfy the three attribu tes of poetry, grammatical, poeticand meaning[14].

Misztalradecka et al.[15] proposed a blackboard-structured poetry generation system in 2016. They named the modules commonly used in the poetry genera tion process as the blackboard, and each module was responsible for a specific task when generating poetry.The system realizes the integration of various mo dules such as input text retrieval information and user requirements. Compared with the typical methods mentioned above, it implements an extensible platfor m for poetry generation systems and promotes the development of the field of automatic poetry generation. Navarro-Colorado et al.[16] proposed an automatic prosodic analysis model to generate Spanish poetry, which combines hand-craft ed rules and probabilistic methods to extract syllable structure through a series of rules to solve prosody problems.The evaluation of this system is expected to be more than 1000 lines of text extracted from the Spanish Sonnet Collecti on of the Golden Age and achieved an accuracy of 95%, which has made rela tively great progress[16].

Poems generated by template-based methods generally have good quality as surance, and poetry publications have even accepted poems generated by the P ROSE and RACTERsystems[17].These systems generally improve the fluency of generated poems by strengthening constraints. In addition to the methods menti oned above, for example, the ELUAR system adds special emotion categories, and the RACTER system improves coherence by repeatedly selecting some wor ds[18]. However, the poems formed by this method are relatively rigid and not flexible enough. If the template design is better, the quality of the generated p oems will be higher. When the template is relatively simple, the effect of the poems will be poor.Moreover, the templates are all designed and produced man ually, so it consumes more labor time and energy, and there is no real automa tion, and the efficiency is not high.

2.1.3 Automatic pattern-based generation methods

The pattern-based method is an improvement on the template-based method. They both have a fixed template, but the flexibility of this method is far gre ater than the former, and the generated results are more poetic.

A typical system is the Spanish-language poetry generation system WASP designed by Gerv'as[19]. WASP is a rule-based forward inference system. Its in put is a set of words or a line of verse, and the output is a set of verses.Ger v'as et al. devised the initial work of a long-term project on Spanish poetry ge nerators and suggested that better heuristics should be developed to improve th e quality of generation, and that the poetry evaluation procedure still needs a l ot of improvement[20].

The cybernetic poet system[21] designed by Ray kurzweil is referred to as RKCP. The model is based on the existing poetry and uses the Markov chain algorithm to convert the learned poetry examples into outputs. Example 2 is an example of the output of this model

Crazy moon chid
Hide from your coffin
To spite your doom.

Example 2.the output of RKCP

The RKCP text in Example 2 is a haiku, which does not meet the formal requirements of a haiku, due to the fact that RKCP can relax the constraints when it cannot write a poem. Unlike the template-based system RKCP tries to follow rhyme.

2.1.4 Automatic generation methods based on instance-based reasoning

The generating method of Case-Based Reasoning Case-based Reasoning is base d on empirical knowledge, which combines problem solving and learning, adjusts the accumulated poems according to the target information described by the user, and gen erates new poems through appropriate modification.

Systems using CBR technology usually include four steps: 1, matching: represent ing the characteristic variables of the current problem in the system as examples. The system can find the most relevant instance in the instance library. II. Reuse: reapply th e method of the old case that can solve the problem in the new case; Correct: when th e new case is different from the old case, modify the solution to form the answer satisf ying the new case; IV. Save: After evaluating the answers to current questions, add th e new scheme to the instance library and save it for future use. Among them, the most representative poetic generation systems are ASPEAR and COLIBRI.

Among them, ASPEAR is a Spanish poetry writing system based on expert syste m designed by Gervás, which is equivalent to a semi-automatic translator from prose t o poetry. The strategy proposed in WASP is the starting point of ASPEAR generation module. Three types of input data provided by the user to ASPEAR, covering prose d escriptions of the expected poetry and related descriptions of the type of poetry requir ed, such as length, theme, emotion, etc., and providing a specific vocabulary. The syst em contains the poetic expert knowledge base, which contains the regular pattern. Fin ally, the two kinds of data can form the approximation value of the type of literary sty le that the user expects. The first draft of the poem can be generated by CRB technolo gy, and the system can be modified or verified continuously by the user. The poetic ge nerator will develop the model that meets the user's needs. The system is sufficient to perform the task of automatic poetry generation when it is in the bud and can be impr oved.

Ladrará la verdad el viento airado *en tal corazón por una planta dulce* *al arbusto que volais mudo o helado.*	The angry wind will bark the truth in such a heart for a sweet plant to the bush that volais mute or frozen.

Table 1: A three-stanza poem generated by the system, with the output Spanish poem in the left column and the English translation of the poem in the right column.

Another representative system is COLIBRI. Its input is a series of keywords with specific meanings and the desired poetic form. Figure 1 shows how COLIBRI works.

(a) *una boca ardiente pase techo y suelo*

(b) *no sólo en plata o viola truncada*
se vuelva mas tú y ello juntamente
en tierra en humo en polvo en sombra en nada

(c) *no sólo en* **boca y** *viola* **ardiente**
se **pase** *mas tú y ello juntamente*
en tierra en **techo** *en* **suelo** *en sombra en nada*

(d) *no sólo* **para* boca y** *viola* **ardiente**
se **pase** *mas tú y ello juntamente*
en **tía*** *en* **techo** *en* **suelo** *en sombra en* **serpiente***

Figure 1

Figure 1:In (a), we see keywords that represent the meaning of poetry. In (b) one cas e is a matching search from a human poetry corpus. In (c), the keyword marked in bol d in (a) has been placed in the text while maintaining a good syntax structure. Finall y, in (d), we see the result of a modification in which the word marked with * is replac ed to ensure that the beat and rhyme are defined by the strophic formula.

The system is different from the system in the previous section because, in additi on to the template-based method generated by the system pursues good syntax formatt ing and, for example, RKCP pursues prosody, its goal is to make the text almost a giv en message, even if it is quite close. However, when COLIBRI modifies a poem, rhy me and rhyme do not value meaning. Changes to the text at this stage could undermin e any meaning that had been established.

Compared with the automatic generation method based on template or pattern, ca se-based reasoning method has higher quality of generated poetry, but the common pr oblem of these three methods is that only the semantic information and expression str ucture of the most surface layer is considered, but it does not satisfy the needs of poetr y meaning and connotation. In addition, it is also a technical difficulty to realize auto matic processing in the correction step in this method.

2.1.5 Automatic generation method based on evolutionary algorithm

Evolutionary algorithm is also called evolutionary algorithm, as the name implies, is a kind of algorithm which is based on the evolution theory of nature. It includes fo ur typical methods, namely genetic algorithm, genetic programming, evolutionary pro gramming and evolutionary strategy. It is a global optimization method with high rob ustness and wide applicability. Because of the nature of the problem, we can deal with various complicated problems without the limitation of the nature of the problem, so me researchers apply evolutionary algorithm to the automatic generation of poetry, an d transform the generation of poetry into the sequence optimization problem. The mo del generally includes two parts: generating model and evaluating model, which gener ate preliminary poetry by rules, and evaluating model is responsible for grading the ge nerated poetry, and then the generating model is improved continuously by evaluating model to finally produce the poetry. The most typical systems are POEVOLVE and MCGONAGALL.

Levy POEVOLVE, which is designed and developed based on evolutionary algor ithms, can generate Limerick, and the initial population can generate words from the l exicon. Each word in the lexicon has strong and weak sound, rhyme and other inform ation. The weight of evaluation system tends to be based on subjective evaluation of tr ained neural networks. Since there are no published production examples, the experim ental results of this system are that in a 1-6.25 evaluation system, Limerick of human creation has an average score of 34 and POEVOLVE of 1.9. Although the system is n ot fully implemented, it can be seen from the possibility that the algorithm can be appl ied to poetry generation automatically.

Therefore, on this basis, a stochastic search poetry generation model McGonagall system proposed by Manurunga et al. The goal is to generate text which meets the gra mmatical, meaning and poetic requirements of poetry. The author's previous attempts to generate poetry only properly addressed a subset of these limitations. However, this method is expensive for calculation and is not robust, which means that if the system does not meet all the constraints, it will not produce a single solution. The McGonagal l model can satisfy some predefined rhythmic patterns by focusing on the grammatical ly well-structured text, and widely convey some predefined meanings, thus realizing t he three criteria of poetry. It satisfies grammatism by using lexical tree-adjacency gra mmar, and optimizes meaning and poetics by maximizing evaluation functions. However, it still has to be studied in the area of evaluation methods, especially in grammatical, meaning and poetic aspects. McGonagall is one of the most mature poetry generation systems based on evolutionary algorithms. The following is an example of its generation:

There is a young lady called bright.
She (will) travel much faster than light.
She set out one day relatively.
She is on (a) preceding night.

Example 3. An example of McGonagall

In recent years, many researchers in China have applied genetic algorithm to the automatic generation of Chinese poetry, such as Yu Wei, a model of Song word generation based on genetic algorithm, based on the characteristics of Song words, designed the coding method based on Pingyu, adaptive function based on grammar and semantic weighting value, selection strategy based on elitism and roulette algorithm, and achieved the goal of automatic generation of Song words by computer. On this basis, Zhou Changle and others have developed a computational model and implemented it systematically. The improved system can generate Song words with certain appreciative value, and its work fills up the deficiency of Chinese poetry automatic generation research in China.

Cao Weihua established a system of generating imitation Tang poetry based on evolutionary algorithm. According to the characteristics of Tang poetry, the coding method based on Pingyu law and selection strategy based on elitism and roulette gambling algorithm were adopted. The experimental results show that the system achieves the goal of automatically generating imitation Tang poetry by computer and lays a foundation for future research. Mu Zhaonan et al. studied the auto-generation system of Tang poetry based on evolutionary algorithm, designed the initial population scheme based on keywords and rhymes, fitness function based on grammatical semantic weighting, selection strategy based on tournament algorithm, evolution algorithm based on heuristic crossover operator and heuristic mutation operator, and developed the auto-generation model and system implementation of Tang poetry based on evolutionary algorithm. This system has realized the automatic generation of Tang poetry, and the generated Tang poetry has certain appreciation value after manual modification.

Yang and others, aiming at the disadvantage that most of the existing poetry automatic generation system can only generate poetry without interpersonal interaction, proposed an improved elite genetic algorithm to generate poetry that users can interact with at will, and users can specify the emotion of poetry and input the words or poems used in poetry. The improved algorithm includes an improved elite strategy to preserve user-supplied keywords or poems, and a new specific adaptation function to more accurately and effectively evaluate the quality of poetry. The algorithm can generate poetry using a given keyword or poem, and the poetry generated by the algorithm gets hi gher scores and recognition rates than the original poem written by a person.

2.1.6 Automatic generation method based on statistical machine translation

Statistical Machine Translation SMT based method is different from the above method, which neither relies on templates nor on complex and accurate algorithm design, but regards the process of generation as a translation problem.

Jiang, Zhou, etc. regard automatic generation of couplings as a machine translation process, propose a phrase based SMT method to generate the next sentence, the system uses the first sentence as input, uses the phrase based SMT decoder to generate the best list of the second sentence for output, and then uses a set of filters to remove the candidate who violates the language constraint. At last, the candidate samples were sorted by the sort support vector machine, and the results were evaluated synthetically by artificial judgment and BLEU score, which laid a foundation for automatic generation of poetry by machine translation. Jiang, Zhou and others continue to extend this method to Chinese classical poetry with quaternary poetry as an example. Given the key word describing the user's intention, the first sentence is generated by using statistical model, and then the other three sentences are generated by using the SMT model based on the phrase, and the results are good. The following is a poem automatically generated with the key words.

回舟一水香醉月 落日千山雪吟风 踏青寻花问柳春 人不在酒云梦中	Back to the boat a water fragrance drunken moon The sun sets on a thousand mountains and the snow gathers the wind Walking on the green and looking for flowers and asking for spring People are not in the wine cloud dream

Table 2. The Chinese poems generated on the left side of the table are automatically generated using the keywords *"踏青"*、*"赏花"*、*"游春"*, and the English content of the poems on the right side.

Genzel et al made the first attempt to deal with poetry by machine translation, which restricted the length, rhythm and rhyme, and obtained certain results, but its quality still needs to be strengthened, and the problem of characteristic function needs to be solved. In addition, the system is too slow to run, and it needs to be adjusted later.

Jing He et al. designed a statistical machine translation SMT system and proposed a new poetry automatic evaluation system, which receives a set of key words representing the intention of writing, and then generates it in a single sentence to form a complete poem. Using statistical machine translation (SMT) system, new sentences are generated based on the previous generated sentences. For each line of sentences, use a specially trained model, rather than a model for all sentences. In order to improve the consistency of each line of sentences, the candidates with better consistency with the previous sentence are selected by using the consistency model of mutual information[40].

双眸剪秋水, 一手弹春风。 歌尽琵琶怨, 醉来入梦中。	With two eyes,watching the autumn river With one hand,playing the springtime lute With song done and lute exhausted I drunkenly fall into a dream

Table 3:The Chinese poems generated on the left side of the table are automatically generated using the keywords"春"(spring)、"琵琶"(lute)、"醉"(drunk), and the English content of the poems on the right side.

Based on statistical machine translation theory, Jiang Ruizhao and others have studied the automatic generation of rhythmic poetry, mapped the relationship between the upper sentence and the lower sentence into the relationship between the source language and the target language in the statistical translation model, designed a statistical machine translation model integrating the knowledge of the poetry field, and strengthened the theme and artistic conception of poetry. This study has formed a complete evaluation system of poetry by means of automatic evaluation method based on BLEU and artificial evaluation criteria.

The poetry generation system based on Statistical Machine Translation SMT does not need to design the evaluation function artificially, but considers the semantic and rhythmic information of the upper sentence. Therefore, the system generated by this method has strong semantic relation, the implementation method is simple and clear, but at the same time, it will appear corresponding problems, such as it is relatively dependent on corpus, because the generation of the next sentence is only based on the first sentence, so the correlation degree may become lower with the increase of the length of poetry, that is, the subject drift may occur. In addition, in order to ensure the semantic balance between sentences, the result overemphasizes the formal counterpoint, neglects the syntactic and meaning correlation, the comprehension of sentence combination may be problematic. The researchers of this approach also focus their future work on how to make the content of a poem more logical and consistent.

2.2 Automatic Generation Method Based on Deep Learning

The above automatic generation model based on traditional methods depends on the rules of manual design and the restriction of constraint conditions or strict algorithms to be designed, but most of the results can only meet the formal requirements, and it is still difficult to satisfy the consistency and logic of upper sentence and lower sentence as well as the poetic characteristic.

In recent years, deep learning has promoted the development of various fields and promoted the rapid development of AI. The field of natural language processing has also achieved great achievements under the development of deep learning technology. More researchers have applied deep learning technology to the direction of automatic generation of poetry, such as Chinese poetry is typical of Tang poetry and Song poetry, Japanese haiku[42] and other traditional poetry, etc.

The cyclic neural network RNN is a neural network with "memory", which is a sequence language model, which can input the output of the hidden layer at T-1 time and the word vector at the current time into the hidden layer at t time to get the feature representation at t time, and then predict y with this feature. Circulating neural networks can store any length of context information in a hidden state. Therefore, it is the most suitable neural network for processing serial-class data. In recent years, RNN has been widely used in natural language processing. How can it be used in poetry automatic generation? It can guarantee the correlation of poetry content to some extent.

2.2.1 RNNPG

Zhang et al. proposed a model of Chinese poetry generation based on circular neural network, which is suitable for capturing the content and form of poetry[43]. The model generator realizes the combination of content and form by learning the representation of single characters, how they are combined into one line or more lines, and how the characters reinforce and restrict each other. and each line of its poem is determined by the whole above, rather than by the limited range applied by the previous line or n-gram, as the machine translation method, and two cyclic neural networks, the cyclic context model and the cyclic generation model, are introduced, which can capture multiple sentences.

In detail, first, all the related phrases are retrieved according to the keywords given by the user and all candidate combinations are obtained under the constraints of poetic peace, and the candidate combinations are scored by language model, and the highest score combination is used as the first sentence. This method is similar to the method based on SMT to generate poetry automatically. The most characteristic is that the second sentence is generated according to the first sentence, the third sentence is generated according to the first sentence and the second sentence, and the poem is repeated until it meets the length requirement. The model mainly includes the following three parts:

I. Convolutional Sentence Model (CSM): This part is a convolutional sentence model proposed by Kalchbrenner and Blunsom[44]because it is based on n-gram and does not use parsing, pos-marking or segmentation tools not available in any Chinese poetry. In principle, any model that produces a vector based phrase or sentence representation can be used[45]. Thus, CSM converts a line of poetry into a vector.

II. Recurrent Context Model (RCM): This section can take the vectors of each sentence generated before as input and compress them into row compression vectors (hidden layers), and then decode the compression vectors at different character positions in the current row. Thus, the output layer is connected by several vectors (one per position). In this way, different contexts can produce different sentences.

III. Recurrent Generation Model (RGM): This section estimates the probability distribution of the next character (in the entire vocabulary) by considering the context vector provided by RCM and the 1-n encoding of the previous character. RGM is essentially a cyclic neural network language model with an auxiliary input layer[46], i.e. cont ext vectors from RCM. Similar strategies for encoding additional information are used in related language modeling and machine translation[47].

The model uses five and seven words quaternary sentences as training corpus and cross entropy as training target. In the model evaluation, the puzzlement, BLEU and manual evaluation are used, and the results are good. However, the limitation lies in that the method of statistical machine translation is still used when producing the first line of verse, and the keywords entered by the user are only related to the first line of verse, which is still prone to subject drift. The following is an example of the output of the RNNPG system:

白鹭窥鱼立， 青山照水开。 夜来风不动， 明月见楼台。	Egrets stood,peeping fishes. Water was still,reflecting mountains. The wind went down by nightfall, As the moon came up by the tower.
满怀风月一枝春， 未见梅花亦可人。 不为东风无此客， 世间何处是前身。	Budding branches are full of romance. Plum blossoms are invisible but adorable. With the east wind comes Spring. Where on earth do I come from?

Table 4:The Chinese poems in this table are examples of the output of the RNNPG system, and the English translations of the poems are shown on the right.

2.2.2 ANMT

Neural machine translation is an emerging machine translation method proposed in recent years by Kalchbrenner and Blunsom[48], Sutskever et al.[49], and Cho et al.[50]. Unlike traditional phrase-based translation systems[51] that consist of many individually tuned small components, neural machine translation attempts to build and train a single, large neural network to read a sentence and output correct translation. Most of the proposed neural machine translation models belong to an encoder-decoder[52][53], or apply a language-specific encoder to each sentence and then compare its outputs[54].The encoder neural network reads the source sentence and encodes it into a fixed-length vector.The decoder then outputs the translation of the encoded vector. The entire encoder-decoder system consists of a pair of language encoders and decoders that are jointly trained to maximize the probability of correct translation given a source sentence.A potential problem with this encoder-decoder approach is that neural networks need to be able to compress all the necessary information of the source sentence into a fixed-length vector. This may make it difficult for neural networks to cope with long sentences. Cho et al.[55] show that the performance of the basic encoder-decoder does drop rapidly as the length of the input sentence increases. To solve this problem, the model introduces an extension of the encoder-decoder model, learning joint alignment and translation. Whenever the model generates a word in the translation, it searches for a set of positions in the most relevant information set in the source sentence. The model then predicts the target words based on t he context vectors associated with these source locations and all previously generate d target words[56].

The ANMT model is the application of the neural network machine translation model based on attention mechanism in Song Ci, which is a famous Chinese traditional poetry type with variable length and strict rhythm pattern. This method follows the RNN based-idea, with differential improvements based on the research of Zhang and Lapata[57]. First, the ANMT model uses LSTM instead of the traditional RNN to obtain long-distance storage; Second, the model uses the attention mechanism to enhance the consistency of themes;Third, the model is a simple sequence-to-sequence structure, much simpler than the model proposed in [57], and it is easier to expand and generate poetry with various styles. Yi et al.[58] have established a quaternary poetry generation system based on RNN encoder decoder, and proved that RNN encoder decoder is also suitable for learning tasks of semantic correlation sequences, attention mechanism can capture character association, gate unit can roughly recognize word boundary, etc. In particular, the model is used to generate more complex Song words. Up to now, the research on automatic generation of Song words has not been successful.

The research method used the LSTM model, Shimul et al. took 350 poems of Tagore as samples.This study trained a recurrent neural network model based on LSTM to test whether the recurrent neural network can learn to generate poetry, and obtained good results. It is the first time to use this model to automatically generate Bengali poetry works[59].

The specific research method of this model is to use a bidirectional LSTM model as the encoder, which consists of two LSTMs, which encode the input sequence in forward and reverse directions respectively. LSTMs are able to learn longer histories, and the use of a bidirectional structure further improves this ability and then predicts information about the entire Song Ci. Every tune of Song Ci has its own rules. This means that the dynamic properties of each tune are unique and should therefore be modeled with different models, such as LSTM in attention model. However, training data for most tunes is very limited, meaning it is almost impossible to train a separate model for each tune, except for a handful of popular tunes. Therefore, the model adopts a mixed tuning training method to solve this problem. Basically, all tunes share the same attention model, and a "tune indicator" is extended to the context vector C1 to inform the model to adjust the training or generative processing. Specifically, it is the first hidden state added to the LSTM decoder by linear transformation. Tuning metrics are derived as eigenvectors of a 200 × 200-dimensional random matrix, which are fixed during model training and inference.

The image below shows a Song poem generated by the model with the theme of a poet standing by a river thinking about the past.

菩萨蛮 哀筝一弄湘江曲， 风流水上人家绿。 小艇子规啼，	Pusaman A sad melody flows with the wave, But still everything seems to thrive. A cuckoo sings over my little boat,

不堪春去时。 花前杨柳下， 红叶满庭洒。 月落尽成秋， 愁思欲寄留。	Hard to let spring go. Blossoms and green willows we found, Soon will be maple leaves red on the ground. The moon is setting,the fall is coming, But my longing for the past lingers around.

Table 5:This is a Song poem generated by the model, the theme of the poem is the poet standing by the river and reminiscing about the past, the title of the poem is"菩萨蛮".

Compared with the popular poetry generation methods at that time, the mo del has the advantages of simple structure, flexible learning with variable sente nce length, and strong learning ability of complex rules. And under the large-sc ale hybrid training, the attention model can well generate poetry text, which so lves the problem of topic drift to a certain extent, and the model can also be applied to the generation of other texts[60].

2.2.3 iPOET

The model is based on the research results of Yan et al.[43]. The model is the first t ime to propose a poetry generation model based on the iterative optimization model o f circular neural network, which makes written poetry more coherent and meets th e requirements of poetry. This generative model generates poetry more like a re al human poetry creation, rethinking and rephrasing it.Assimilate human writing intentions in the system framework and output the created poetry. The writing intent is encoded and then decoded through a hierarchical structure of recurre nt neural networks, i.e. two-level representations of "word" and "line". The syst em works in an encode-decode fashion, representing the user's intent as a singl e vector, which is then decoded into the entire poem. The diagram below sho ws the architecture of the iPoet system.

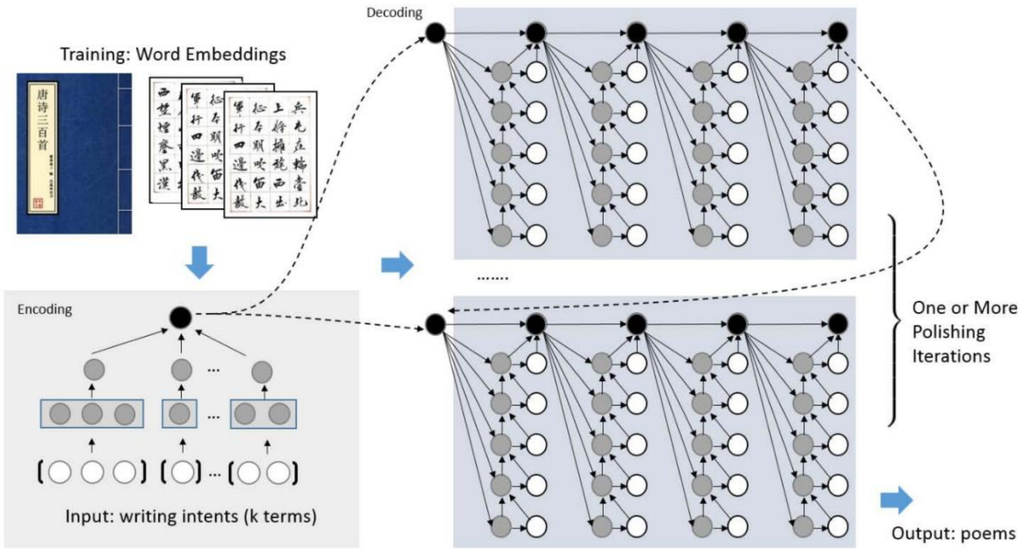

Figure 2

Figure 2:Diagrammatic representation of the iPoet system framework, including encoding and decoding neural networks. The system takes the user's writing intentions as queries and encodes these intentions as implicit vectors. The system has two strategies for encoding intentions. Using the hidden vectors as trigger states, a poem is "composed" by a recurrent neural network in a continuous decoding process using the learned embeddings as well as a poetic language model. The model is based on an iterative polished generative model. The white circles indicate the generated characters that are observable. The shaded circles (gray and black) represent hidden vectors in the local and global hierarchy, which are the hidden states of the generated characters.

It mainly includes three parts: the first part is the keyword input. The system accepts a set of user-specified keywords as input, and uses convolutional neural network (CNN) or cyclic neural network (RNN) to capture the meaning of specific keyword terms.The information of different terms is then integrated through a pooling layer. This results in a vector representing the user's intentions. The second part is: poetry generation. Conditioned on the vector representation of user intent, RNN is used to generate characters word by word. Note that poetry contains multiple lines, each of which contains multiple characters, using hierarchical structures to generate poetry. Specifically, there is an RNN that represents the global information of each row, and the global information vector affects all character generation in this row. On top of the global RNN, there is another RNN representing local information, which directs the generation of a single character in a row. Details are shown in Figure 1. The third part is polishing poetry. In order to imitate a human poet, his works may be reorganized many times, so the poetry is perfected by an iterative polishing schema and a generation. This process is basically the same as the sequential generation, the difference is that the information representation of the previous draft is used as input, as the additional information of the user's intention, to promote the overall semantic coherence of the whole poem[61].

The iPoet neural model has undergone a hierarchical polishing mechanism, and can produce quite good poetry, and is superior to other models. In addition, both optimization scheme and hierarchy can help improve the performance of the method. However, since it represents the historical content as a fixed vector, the model may ”forget” the historical content in the process of generating, thereby weakening the semantic coherence and possibly causing the subject drift problem[18]. If the model incorporates more poetic features such as alignment and emotion in the creation process, the effect will be better.

2.2.4 Hafez

The algorithm can generate any number of poems on a user-provided topic. The generator can select a specific and large number of words according to the subject words input by the user, and calculate the stress mode of each word, and generate any line number of poems meeting the requirements of rhythm.

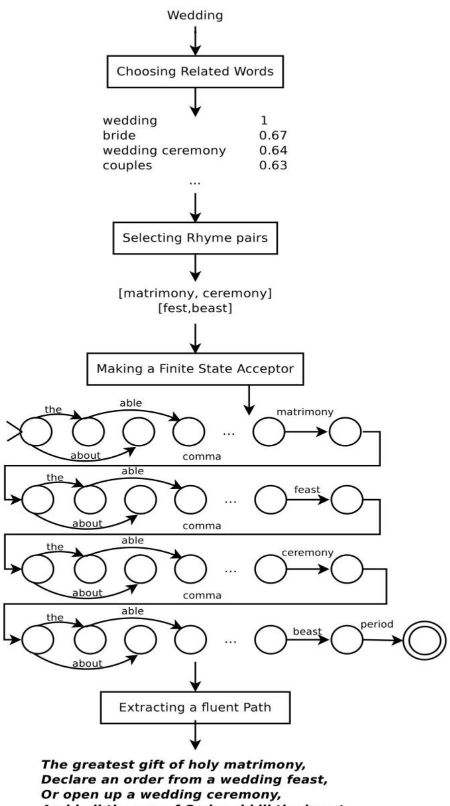

Figure 3

Figure 3:This figure shows a systematic overview of the four-line iambic pentameter stanzas generated with the theme word as the wedding.

The specific steps are as follows: 1. finding relevant vocabulary. The user provides a topic and counts a large number of related words.Choose rhyming words. 2. Choose words that rhyme. From the set of related words, choose the words that rhyme as the last word; 3. Finite State Receptor (FSA). An FSA is built for every conceivable lexical sequence that obeys formal rhythm constraints and rhyming words are chosen where appropriate; 4.Select the path. A fluent path is selected via FSA and scored using a Recurrent neural network (RNN)[62]. The following are sample verses generated from different topic phrases.

Love at First Sight

An early morning on a rainy night,
Relax and make the other people happy,
Or maybe get a little out of sight,
And wander down the streets of Cincinnati.

Girlfriend

Another party started getting heavy.
And never had a little bit of Bobby,
Or something going by the name of Eddie,
And got a finger on the trigger sloppy.

Noodles

The people wanna drink spaghetti alla,
And maybe eat a lot of other crackers,
Or sit around and talk about the salsa,
A little bit of nothing really matters.

Civil War

Creating new entire revolution,
An endless nation on eternal war,
United as a peaceful resolution,
Or not exist together any more.

Figure 4

Figure 4:These are sample stanzas generated from different thematic phrases, the thematic phrases are”Love at First Sight”、”Girlfriend”、”Noodles”、”Civil War”.

The Hafez system controls the subject and the last word of each line, so the subject drift problem is alleviated to some extent, but the coherence of the content is weakened because its form and content are fixed.

2.2.5 SeqGAN

Generative Adversarial Nets (GAN),as a new training method of generating model, uses discriminant model to guide the training of generating model, and has achieved considerable success in generating real-valued data. However, when the target is to generate discrete marker sequence, it has limitations.The main reason is that the discrete output makes it difficult to pass the gradient update of the discriminative model to the generative model. In addition, the discriminant model can only evaluate a complete sequence. The sequence generation framework SeqGAN can solve this problem, SeqGAN models data generators as stochastic policies in reinforcement learning (RL), and bypassing the generator differentiation problem by directly performing gradient policy updates. The RL reward signal comes from the GAN discriminator based on the complete sequence judgment, returning to intermediate state-action steps via Monte Carlo search.

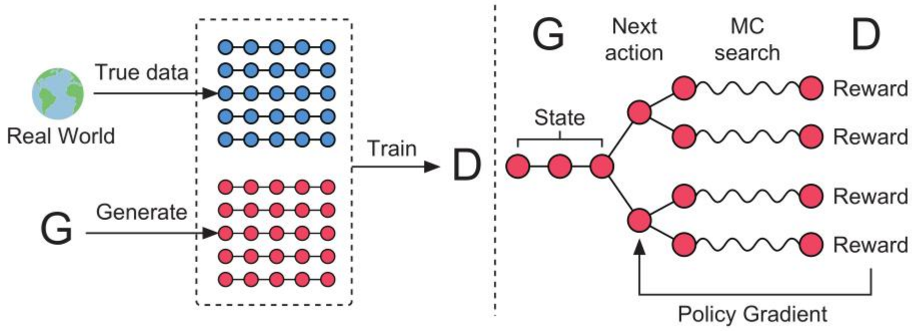

Figure 5:

Figure 5 The process diagram of SeqGAN. Left: D is trained by real data and data ge nerated by G, right: G is trained by a policy gradient, where the final reward signal i s provided by D and returned to the intermediate action values by Monte Carlo search [63].

SeqGAN effectively trains to generate adversarial net through a strategy gradien t to generate structured sequences. This is the first extension of GANs to generate disc rete marker sequence. For the three real scenes of poetry, phonetics and music gener ation, SeqGAN excels at generating creative sequences. However, text is discrete, i t is more difficult than other models, and because the generated part is random variabl e, the user's requirements cannot be reflected.

To address the above limitations, WU et al.[64] redefined the loss function. The tru th-guided method was added to bring the generated text closer to the real data. The net work structure of discriminant model is improved, and the semantic information of w hole sentence is fused by self-attention mechanism. The SeqGAN based on true-guide d improves the convergence speed of the text generation model, and the quality of th e text generated by the network is also improved.

2.2.6 PPG

PPG is a new two-stage poetic generation method proposed by Wang et al.[18] Firs tly, according to the user's intention of writing, it can be a set of key words, a sentenc e or even a document, and the poetry planning model is used to determine the subthe me of poetry, each line is represented by a subtheme.The system improves on the Recurrent Neural Network Encoder-Decoder framework (RNN enc-dec). The im proved RNN encl-dec model has two encoders that encode subtopics and prea mbles, and then generate poems line by line. The following is a frame for generati ng the model.

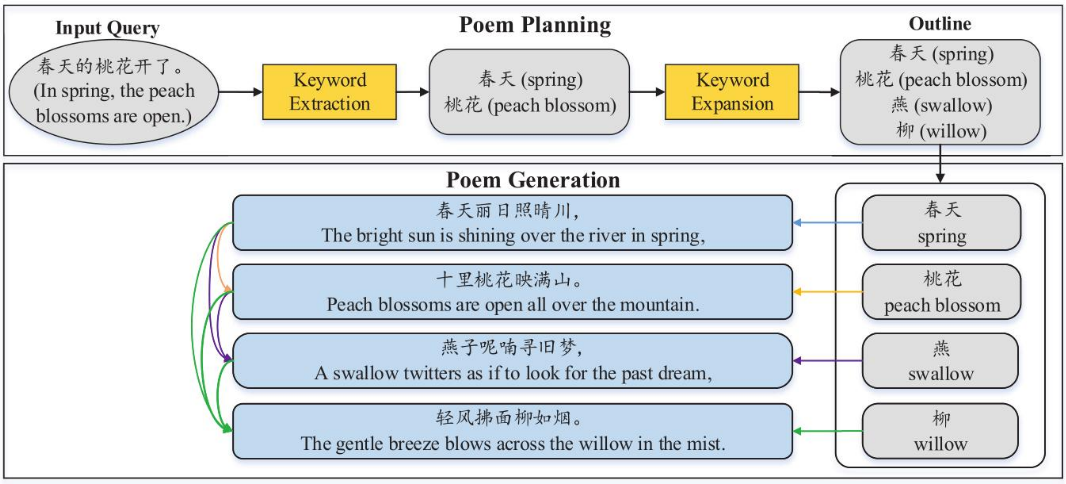

Figure 6

Figure 6:This is the poetry generation framework of the PPG model, which takes the example of "春天的桃花开了 "(In spring, the peach blossoms are open.),and extracts the keyword "春天" (spring)、"桃花"(peach blossom)、"燕"(swallow)、"柳 "(willow).The above words were used to generate the poems,the generated poems are shown in the figure.

Compared with previous methods, this model has two advantages. First, each line of the generated poem is more closely related to the user's writing intent. Second, poetry planning models can be learned from additional sources of knowledge beyond poetry data, such as large-scale web data or knowledge extracted from encyclopedias. Therefore, it can bridge the modern concept and the words covered by ancient poetry. Taking the term "Barack Obama" as an example: Using the knowledge of encyclopedia, the poetry planning model can extend the user's query “Barack Obama” to a series of sub-themes such as “outstanding”, “power”, etc., thereby ensuring the consistency of the generated poetry semantics. Figure 1 shows two poems selected at random. On the left is a machine-generated poem, on the right is a poem by Ge Shaotti, a poet of the Song Dynasty. The following is an example of poetry produced by the title of modern concepts.

秋夕湖上 一夜秋凉雨湿衣， 西窗独坐对夕晖。 湖波荡漾千山色， 山鸟徘徊万籁微。	By a Lake at Autumn Sunset A cold autumn rain wetted my clothes last night, And I sit alone by the window and enjoy the sunset. With mountain scenery mirrored on the rippling lake, A silence prevails over all except the hovering birds.
秋夕湖上 狄花风里桂花浮， 恨竹生云翠欲流。 谁拂半湖新镜面， 飞来烟雨暮天愁。	By a Lake at Autumn Sunset The wind blows with osmanthus flying, And the bamboos under clouds are so green as if to flow down. The misty rain ripples the smooth surface of lake, And I feel blue at sunset.

Table 6:Two poems selected from the blind test.The titles of both poems are "秋夕湖上
",The first one is a machine-generated poem, and the one on the right is a po em by Shaoti Ge, a poet of the Song Dynasty.

啤酒 今宵啤酒两三缸， 杯底香醇琥珀光。 清爽金风凉透骨， 醉看明月挂西窗。	Beer I drink glasses of beer tonight, With the bottom of the glass full of aroma and amber light. Feeling cold as the autumn wind blows, I get drunk and enjoy the moon in sight by the west window.
冰心 一片冰心向月明， 千山春水共潮生。 繁星闪烁天涯路， 往事萦怀梦里行。	Xin Bing I open up my pure heart to the moon, With the spring river flowing past mountains. Although my future is illuminated by stars, The past still lingers in my dream.

Table 7:These two poems are examples of poems that arise from the title of a modern concept, with the titles "啤酒" and "冰心".

However, there are still some problems in this model. At present, only the poetr y planning part can introduce external knowledge, and the training of poetry generatio n model can only be based on given poetry corpus. In the current field of poetry re search, there is a lack of automatic evaluation methods and can only rely on manual evaluation. In addition, the method of generating with the results of the planning model can be used not only in poetry generation, but also in other natural language generation fields, such as machine translation, dialogue system s, etc. For example, in the dialogue system, the subject word of the next sente nce is obtained from the previous sentence, and then the subject word obtained by planning and the content of the previous sentence are used to generate the text of the next sentence, thereby improving the diversity of the generated res ults.

2.2.7 TCPG

The method is a theme controlled poetic generation model (Topic Controlled of P oetry Generation Model TCPG) based on seq2seq framework, which regards This me thod regards poetry generation as the process of one sequence generating anoth er sequence, and it introduces the process that poets need to conceive and then write when writing. Before generating the poem, plan a writing outline for th e poem to guide the theme of the poem. Considering the limited expression abi lity, the potential thematic information in the ancient poem is deeply mined as the thematic reference knowledge of the poem through the LDA thematic mo del, which is used to dynamically expand the relevant thematic information in the process of generating the poem.Ultimately, the outline information and relat ed thematic information are dynamically applied to the process of poetry gener ation, so that the whole poetry theme is shared and the poem is generated wit h clear meaning in the sentences and connections between the sentences.Ultimately, the outline information and related thematic information are dynamically integrated into the poem generation process. The poem is made thematically clear and closely linked between sentences.The differences between the approach used in this model and other previous approaches are as follows. Firstly, the word separation task is based on a modern context-based word separation tool, while this method is based on a word list constructed in the context of ancient poetry. Secondly, the additional input of relevant thematic knowledge embedded in a priori knowledge is dynamically applied to the poetry generation process through an attention mechanism. Most importantly, the method encodes thematic information at the granularity of both characters and words based on the self-attentive mechanism to maximize the retention of thematic information.The model structure is shown in the figure below.

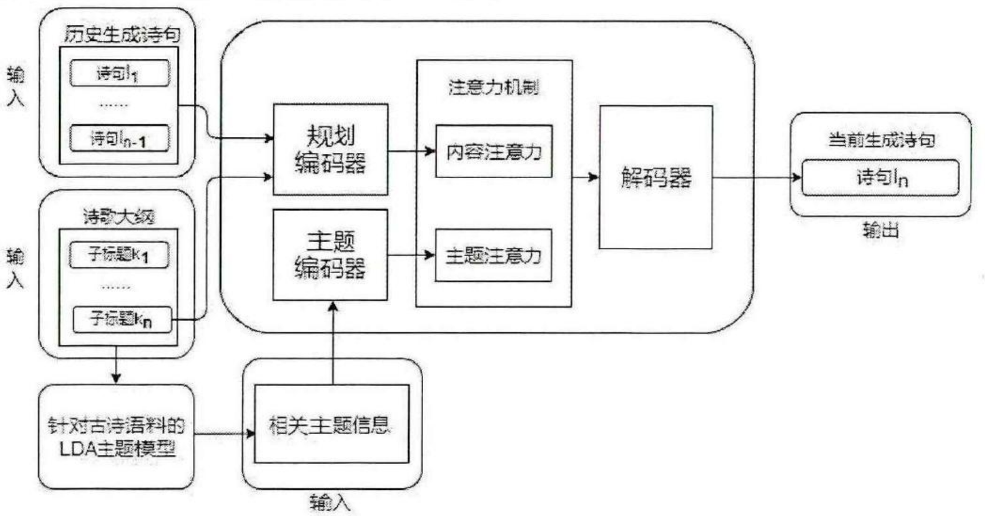

Figure 7

Figure 7:This figure shows the overall structure of the model.

Since the method is based on the theme to achieve automatic generation and encodes the theme information from both character and theme granularity based on the self-attentive mechanism, the theme offset problem is greatly alleviated, while the method tends to generate poems with better coherence and meaningfulness compared with other methods. However, the method still has bottlenecks in recognizing the word lists based on the context of the ancient poems, as well as the probability distribution of individual characters in the knowledge corpus that the model learns, but not the complex emotions, so the generated poems still need much improvement in terms of emotional expression. The following figure shows the results of the five-syllable poem and seven-syllable poems generated by this system[29].

草木	grass and trees
绿草入花木,	Green grass into flowers and trees.
红杏万千株。	Thousands of red almond plants.
白杨绿新树,	Poplar green new trees.
春风潋荻出。	Spring breeze brimming with dilly out.

山水	Landscape
高山流水自西东,	High mountains and flowing water from the west to the east.
烟波万里目不通。	There's no way to see through the waves。
扁舟一叶归来晚,	A leaf of a flat boat returns late.
冷风飘入万山中。	The cold wind drifts into the ten thousand mountains.

Table 8 :This is a display of the results of the five- and seven-line poems generated by the TCPG system[29]. The titles are "草木" and "山水" respectively.

2.2.8 Automatic Poetry Generation Based on Image

Most of the automatic poetry generation methods and systems so far have used keywords to generate poems, however, images have richer visual content i nformation as well as richer semantic content to express the user's writing inte ntion more conveniently, so automatic poetry generation based on images is a meaningful and challenging research direction.

Liang Jiang et al[66] designed a memory-based deep neural network that ca n generate Chinese poems based on pictures, and the model can mine the visu al and semantic information in pictures very effectively. This is the first model that automatically generates ancient Chinese poems based on pictures. The mo del mainly uses memory neural networks to solve the problems of topic drift a nd only a small number of keywords input in the existing work. In the proces s of generating ancient poems, it effectively combines the semantic and visual information in the pictures.

The core of its model framework is: MIPG to generate the next ancient p oem, which includes a picture-based encoder (I-Enc) and a memory-based deco der (M-Dec). I-Enc encodes the picture visual features into a visual feature vec tor and encodes the preceding text into a semantic representation vector. m-De c decodes the next ancient poem word by word based on the encoding result of I-Enc.M-Dec decodes the next ancient poem word by word based on the en coding result of I-Enc.The external knowledge base is constructed in M-Dec by using the extracted keywords as memory entities of the Topic Memory Netwo rk (TMN), and this operation achieves the dynamic planning of a potential topi c vector for each word of the decoding, which solves the problem of needing to artificially assign a topic to each ancient poem in the existing work and im proves the correlation between ancient poems and pictures.At the same time, T MN is used to extract as many keywords as possible from the images in order to cover as many topics as possible in the images, and then TMN dynamicall y selects the important keywords for planning the topics.Finally, TE-Softmax is used to achieve further enhancement of the high thematic relevance between t he poem and the image by encouraging the words in the keywords to appear i n the generated poem[66].

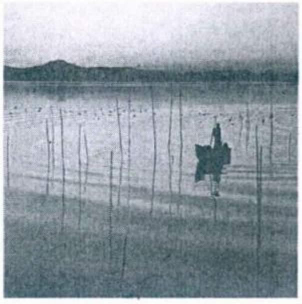	
霞天、晓筹、水湛、寒洲、照影、海浪、映、渔舟、嘌、淀、海客、金影、西湖、暗影、光景、河堤、秋静、喷、远海、棹	仙院、小院、栊、怀亲、青草、家定、花枝、圃、门风、群木、树、楼上、孟夏、门唯、青草、风姿
The sky, the dawn, the water, the cold island, the shadow, the waves, the reflection, the fishing boat, the sunset, the precipice seafarer, golden shadow, west lake, dark shadow, light scene, river bank, autumn quiet, spray, distant sea, hawking	Immortal courtyard, small courtyard, bar, wai-jin, green grass, home set, flowering branch, garden, door wind, group of trees, tree, upstairs, Meng Xia, door only, green grass, wind posture
扁舟一曲水平堤, 一棹渔舟日向西。 长忆西湖水中月, 东风吹过武陵溪。	春风庭院养花姿, 春入帘栊叶满枝。 堪笑门前青草树, 谁家芳节几多时。
A flat boat with a horizontal dike. A fisherman's boat is rowing to the west. I always remember the moon in the West Lake. The east wind blows across the Wuling River.	Spring breeze courtyard nurturing flower posture. Spring into the curtain leaves full of branches. I laugh at the green grass trees in front of the door. Who has a lot of time for the festival.

Table 9 :This is an example of a story generated based on images, with the first row losing the original image, the second row the keywords, the third row the English representation of the keywords, the fourth row the generated ancient poem, and the last row the English translation of the ancient poem.

However, the model needs further research on the emotion of introducing pictures in the process of generating stories. The emotion expressed in the pictures can currently only come from the emotion of the ancient poem that matches the theme, but not directly from the pictures, such as using the hue of the pictures to express it.In addition, the thematic consistency of pictures and ancient poems mainly relies on human evaluation, but the efficiency of this method is relatively low, and there are problems of subjectivity and variability, which will affect the accuracy of the experiment, if we want to get better test resu lts we should also design an automatic scoring system with high efficiency and accuracy.

Wang Xiaoyu[67] et al. address the above issues, especially the imagery inf ormation in images to generate good literary effect ancient poems, and, unlike Jiang Liang[66], it uses an evaluation index that is a combination of both confu sion and manual scoring.The researchers proposed two approaches for different image inputs and optimized them for semantic incoherence.The system proposes two methods for different types of image input, the first method is applicable to single-target images, and it establishes an I-AG model for generating ancie nt poems based on single-target images. The model extracts the image keyword s, obtains the target information of the image through the image feature extract or, then uses it as the outline of the ancient poem, and finally generates the a ncient poem line by line based on the character-level recurrent neural network. The model performs better on pentameter poems than on heptameter poems.The second method is applicable to complex images, and it establishes a scene-bas ed image generation method I-PG model. Similarly, the model obtains the targe t and scene information of the image by two image feature extractors, and exp ands based on these information to generate four theme words for guiding the subsequent generation of ancient poems.In the ancient poem generation module, an attention-based encoding-decoding model is used to generate ancient poems line by line, and the subject words are used as external inputs, and finally ea ch subject word corresponds to a line of poetry.Meanwhile, in response to the weak coherence of ancient poems in existing studies, the output of the current line of the model is only related to the information of the first two lines of t he poem.The results show that the I-AG model works better when the informat ion of the input image is relatively single, and when the amount of image inf ormation increases, the ancient poems generated by I-PG via two image feature extractors fit the image content expression better.The following figures show i mages with single content and images with complex content, and the ancient p oems generated by the two models, respectively.

<table>
<tr><td></td><td></td></tr>
<tr><td>I-AG
仓山长灯遥相忆，雨花云殿水阳城。
鼠映浦枝粉雪开，水鸣河凭海潮生。</td><td>I-AG
江黄西堤半不终，海亭浮席无人声。
水招将晚望归京，菩歌寂寞又长安。</td></tr>
<tr><td>I-AG
The long light of Kurama is remembered fro m afar.</td><td>I-AG
Half of the river yellow west dike is not fi nished.</td></tr>
</table>

The city of Yangtze, the temple of rain and clouds. The mouse reflecting the snow on the branch es of the river. The tide of the sea is born by the sound of t heriver.	The floating seats in the sea pavilion have no sound. It is late to return to the capital. The bodhisattva song is lonely and long.
I-PG 把酒频年三十春，多贫贫更知主人。 悲歌不是行人去，世事安知有几人。	I-PG 渔舟去在河水边，故人下山流水烟。 水光浓淡半山色，且问北湖沽酒船。
I-PG The wine is frequently drunk for 30 years. The poor and the impoverished know more a bout the master. The lamentation is not for the pedestrians to go. The world knows how many people.	I-PG The fishing boat goes by the river. The old man descends from the mountain a nd the smoke of running water. The light of the water is thick and light, an d the color of the mountain is half. And ask the boat selling wine in the northe rn lake.

Table 10 :These are the images with single content and the images with complex content, respectively, and the ancient poems generated by the two models of I-AG and I-PG. The first row is for the images with single content and complex content, respectively, and the second and fourth rows are for the ancient Chinese poems generated by these two models, respectively.

Similarly, the model still has the problem of image emotion feature extract ion, which is mainly used to obtain scene information by image feature extract or, but lacks emotion representation.And from the above examples, we can see that the rhythm of the ancient poems generated by the model is not good, an d the rhyming rules and polishing mechanism are not added to the model.

Neither of the above two approaches constructed an image-poetry dataset, while Lijian He[68] built a dataset, used an end-to-end model, and designed thre e evaluation models for testing.The model framework is based on an encoder-d ecoder, using a full convolutional network FCN for the encoder and a long sh ort-term memory network LSTM for the decoder.Spatial visual features and se mantic representations are extracted from pixel-level images using FCN encoder s.An FCN-LSTM-based encoder-decoder model framework employed in image-i nspired work on generating poetry.The model introduces an attention mechanis m through fine-grained and semantically guided attention to aggregate feature i nformation of all outputs of the FCN encoder into a joint contextual aggregatio n layer to provide the decoder LSTM with more favorable information for poet ry generation.The introduction of the memory model in the LSTM decoder, wh ich makes the poems output by this model more diverse and creative.An image -poetry dataset is constructed to prepare for end-to-end model training of image -generated poetry. And three model evaluation experiments were designed:model structure analysis, poetry Turing test analysis, and multi-model comparison ana lysis.

Although the model is automatically learned from the image-poetry data set, it can directly input poetry to output poetry end-to-end, but the model also does not introduce the rhythm constraint model, and the rhyme problem of generated poetry remains unresolved. Its image-poetry dataset is also underdeveloped, so the style of the generated poems is not obvious, due to the model's dependence on the dataset, which however is still not comprehensive at the moment.

Unlike the image-poetry dataset in the model, Yusen Liu[69] constructed a special image dataset and a poetry dataset, respectively. In addition, his proposed poetry generation system is based on deep learning techniques and can accept a variety of modal inputs, not only image based generation but also textual input or poetic imagery input. At the same time, it also adds the function of assisted poetry writing, users can collaborate with the system to create poems, and the system acts as an assistant tool to help users to complete the creation. For ease of use, the poetry generation system is deployed on WeChat small program platform to support users using the system on mobile devices.

The model populates each line of the poem with keywords of specific information in an explicit manner, thus ensuring that the keywords extracted from the image must appear in the generated poem, and thus solving the problem of topic shifting.The system proposes an abstract information fusion method based on word embedding to fuse abstract information into the generated poems by means of word embedding, which solves the problem that abstract information in images cannot be accurately expressed.The researchers of the model used a special training method to align image and poetry information, using non-parallel data in the training process, rather than a paired dataset of images and poems. To train the model, special image datasets and poetry datasets were constructed separately.The following figure shows the framework of the system.

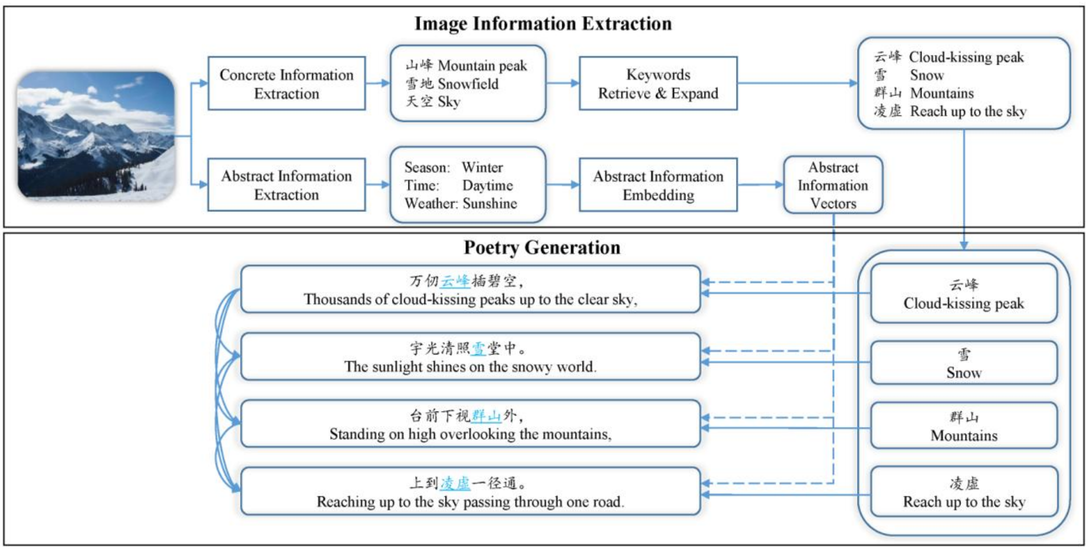

Figure 8

Figure 8:This system extracts the keywords "山峰"(Mountain peak), "雪地"(Snowfield)and "天空"(Sky) from the input image, and expands the keywords t

o "云峰"(Cloud-Mountain peak), "雪"(Snow)、"群山"(Mountain) and "凌虚"(Rea ch up to the sky), and finally generates the poem in the picture.

The system is capable of human-computer interaction, not only accepting multimodal input, but also allowing the user to participate in the process of writing the poem, allowing the system to assist the user in composing the poem.In addition, the system is deployed in the WeChat applet to include other functions such as work wall, poetry card making and word puzzle games, which can effectively stimulate the public's interest in traditional poetry culture.Since the model is built with image dataset and poetry dataset, the training set is relatively large, so the problem of semantic inconsistency is improved, but the problem of rhyme constraints and emotion expression in poetry remains unresolved.

3 Summary

This paper summarizes and discusses the domestic and foreign automatic poetry generation methods. Throughout the history of development, we can see the stages from the beginning of combining words into poems, to meeting the formal requirements of poetry, from meeting the semantic requirements of poetry to generating poetry according to the theme and meaning. Nowadays, many researchers are still studying how to achieve the goal of expressing emotion. In addition to inputting text to generate poetry, there are now researchers who have conducted cross-modal automatic poetry generation.

Based on traditional automatic generation methods, poems can be generated that meet the basic requirements of poetry formatting and keyword-based poetry according to the user's intention. In particular, automatic generation methods based on evolutionary algorithms and statistical learning are not only satisfied with formatting requirements, but also have higher requirements for grammaticality, rhythm and coherence of poems.With the rapid development of deep learning technology and its wide application, researchers have designed a large number of automatic poetry generation techniques based on deep learning technology, which are based on the content and form of poetry and generate poems with more flexibility than those generated by traditional methods. In addition, a lot of research has been conducted on the theme and meaning of poetry, and many of these models are based on the theme of automatic generation, focusing more on the emotional expression and meaningfulness of poetry.The current models still suffer from the dilemma of inability to express emotion, and the generated poems are incomplete in terms of meaning expression. Although there are models whose technical route is designed to imitate the poet's writing process to design the framework, the generated poems do not have the same high level of fluency and abundant emotion expression as the poems made by real poets, and many researchers are still working on this direction.In addition, cross-modal automatic poetry generation is mainly based on image generation poetry, and the implementation of the system is also based on deep learning technology. Researchers in this direction have combined visual information technology and semantic information technology, and there have been breakthrough results, but there are still generated poems that are not obvious enough in style compared with the meaning to be expressed by the pictures, and the emotions are not prominent enough, or the emotional information to be conveyed by the pictures cannot be fully expressed in the form of poetry.All in all, the common problem of the above models is the lack of emotional expression and style of poetry, which is a major bottleneck in the current field.

References

[1] Zhang X, Lapata M. Chinese poetry generation with recurrent neural networks[C]//Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP). 2014: 670-680.

[2] 孙茂松.诗歌自动写作刍议[J].数字人文,2020(00):32-38.

[3] Tosa N, Obara H, Minoh M. Hitch haiku: An interactive supporting system for composing haiku poem[C]//International Conference on Entertainment Computing. Springer, Berlin, Heidelberg, 2008: 209-216.

[4] Oh A, Rudnicky A. Stochastic language generation for spoken dialogue systems[C]//ANLP-NAACL 2000 Workshop: Conversational Systems. 2000.

[5] Ernst J. Computer poetry: An act of disinterested communication[J]. New Literary History, 1992, 23(2): 451-465.

[6] Falkenhainer B, Forbus K D, Gentner D. The structure-mapping engine: Algorithm and examples[J]. Artificial intelligence, 1989, 41(1): 1-63.

[7] HartmanC. O.Virtual Muse: Experiments in Computer Poetry[M]. Wesleyan University Press.1996

[8] Manurunga R , Ritchieb G , Thompsonc H . Using genetic algorithms to create meaningful poetic text[J]. Journal of Experimental & Theoretical Artificial Intelligence, 2012, 24(1):43-64.

[9] Tosa N,Obara HMinoh M.Hitch haiku: An interactive supporting system for composing haiku poem[C]//International Conference on Entertainment Comput ing.Springer,Berlin,Heidelberg , 2008:209-216.

[10] Masterman, M.: Computerrized Haiku. In: Cybernetics, pp. 175 – 183 (1971).

[11] Tosa N, Obara H, Minoh M. Hitch haiku: An interactive supporting system for composing haiku poem[C]//International Conference on Entertainment Computing. Springer, Berlin, Heidelberg, 2008: 209-216.

[12] Rashel F, Manurung R. Poetry generation for Bahasa Indonesia using a constraint satisfaction approach[C]//2013 International Conference on Advanced Computer Science and Information Systems (ICACSIS). IEEE, 2013: 219-224.

[13] El Bolock A, Abdennadher S. Towards automatic poetry generation using constraint handling rules[C]//Proceedings of the 30th annual ACM symposium on applied computing. 2015: 1868-1873.

[14] Bolock A E, Abdennadher S. Satisfying Poetry Properties Using Constraint Handling Rules[C]//International Conference on Intelligent Text Processing and Computational Linguistics. Springer, Cham, 2015: 335-347.

[15] Misztalradecka J , Indurkhya B . A Blackboard System for Generating Poetry[J]. Computer Science, 2016, 17(2):265.

[16] Navarro-Colorado B. A metrical scansion system for fixed-metre Spanish poetry[J]. Digital Scholarship in the Humanities, 2018, 33(1): 112-127.

[17] Hartman Co.Virtual Muse: Experiments in Cor mputer Poetry[M].[S.1.]:Wes-leyan University Press. 1996.

[18] 王哲. 基于深度学习技术的中国传统诗歌生成方法研究[D].中国科学技术大学,2017.

[19] Gervás P.Wasp: Evaluation of different strategies for the automatic generation of spanish verse[C]//Proceedings of the AlSB-00 symposium on creative & cultural aspects of AI.

[S.1.],2000: 93-100.
[20] Gervás P.Wasp: Evaluation of different strategies for the automatic generation of spanish verse[C]//Proceedings of the AlSB-00 symposium on creative & cultural aspects of AI. [S.1.],2000: 93-100.
[21] Kurzweil R. Ray kurzwe's cybernetic poet[J]. Kurzweil CyberArt Technologies.(http://www. kurzweilcyberart. com/), 2001.
[22] Carslisle J P. Comments on Kurzweil's Cybernetic Poet[J]. 2000.
[23] Aamodt A. Foundational issues, methodological variations, and system approaches[J]. AI communications, 1994, 7(1): 39-59.
[24] Pablo Gervás, An Expert System for the Composition of Formal Spanish Poetry, London: Springer, 2001,pp. 181–188.
[25] Modeling literary style for semi-automatic generation of poetry[C]//International Conference on User Modeling. Springer, Berlin, Heidelberg, 2001: 231-233.
[26] Díaz-Agudo B, González-Calero P A, Recio-García J A, et al. Building CBR systems with jCOLIBRI[J]. Science of Computer Programming, 2007, 69(1-3): 68-75.
[27] Aamodt A, Plaza E. Case-based reasoning: Foundational issues, methodological variations, and system approaches[J]. AI communications, 1994, 7(1): 39-59.
[28] Díaz-Agudo B, Gervás P, González-Calero P A. Adaptation guided retrieval based on formal concept analysis[C]//International Conference on Case-Based Reasoning. Springer, Berlin, Heidelberg, 2003: 131-145.
[29] 陈宾. 基于主题控制的中国古代诗歌生成方法研究与应用[D].陕西师范大学,2020.DOI:10.27292/d.cnki.gsxfu.2020.000808.
[30] Manurung R, Ritchie G, Thompson H. Using genetic algorithms to create meaningful poetic text[J]. Journal of Experimental & Theoretical Artificial Intelligence, 2012, 24(1): 43-64.
[31] 游维. 基于遗传算法的宋词自动生成研究[D].厦门大学,2007.
[32] Manurung H M. A chart generator for rhythm patterned text[C]//Proceedings of the First International Workshop on Literature in Cognition and Computer. 1999: 15-19.
[33] 周昌乐,游维,丁晓君.一种宋词自动生成的遗传算法及其机器实现[J].软件学报,2010,21(03):427-437.
[34] 曹卫华. 基于进化策略的仿唐诗自动生成系统[D].广东工业大学,2011.
[35] 穆肇南,刘梦珠,孙界平,等. 基于演化算法的唐诗自动生成系统研究[J]. 华东师范大学学报（自然科学版）,2020(6):129-139. DOI:10.3969/j.issn.1000-5641.201921017.
[36] Yang W, Weng W, Chen G, et al. Elitist Strategy of Genetic Algorithms for Writing Tang Poetry[J]. INTERNATIONAL ARAB JOURNAL OF INFORMATION TECHNOLOGY, 2021, 18(4): 604-610.
[37] Jiang L,Zhou M.Generating Chinese Couplets using a Statistical MT Approach[C]//Proceedings of the 22nd International Conference on Computational Linguistics(Coling 2008). 2008: 377-384.
[38] Zhou M, Jiang L, He J. Generating Chinese couplets and quatrain using a statistical approach[C]//Proceedings of the 23rd Pacific Asia Conference on Language, Information and Computation, Volume 1. 2009: 43-52.
[39] Genzel D, Uszkoreit J,Och F J, et al."Poetic" Statistical Machine Translation: Rhyme and Meter[C].Empirical Methods in Natural Language Processing, 2010: 158-166.
[40] He J, Zhou M, Jiang L. Generating chinese classical poems with statistical machine

translation models[C]//Twenty-Sixth AAAI Conference on Artificial Intelligence. 2012.
[41] 蒋锐滢,崔磊,何晶,周明,潘志庚.基于主题模型和统计机器翻译方法的中文格律诗自动生成[J].计算机学报,2015,38(12):2426-2436.
[42] Shao G, Kobayashi Y, Kishigami J. Traditional japanese haiku generator using rnn language model[C]//2018 IEEE 7th Global Conference on Consumer Electronics (GCCE). IEEE, 2018: 263-264.
[43] Zhang X, Lapata M. Chinese poetry generation with recurrent neural networks[C]//Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP). 2014: 670-680.
[44] Nal Kalchbrenner and Phil Blunsom. 2013. Recurrent Continuous Translation Models. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, pages 1700–1709, Seattle, Washington.
[45] Jeff Mitchell and Mirella Lapata. 2010. Composition in Distributional Models of Semantics. Cognitive Science, 34(8):1388–1439.
[46] Mikolov T, Karafiát M, Burget L, et al. Recurrent neural network based language model[C]//Interspeech. 2010, 2(3): 1045-1048.
[47] Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013. Distributed Representations of Words and Phrases and their Compositionality. In Advances in Neural Information Processing Systems, pages 3111–3119, Lake Tahoe, Nevada, United States.
[48] Kalchbrenner, N. and Blunsom, P. (2013). Recurrent continuous translation models. In Proceedings of the ACL Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1700–1709. Association for Computational Linguistics.
[49] Sutskever, I., Vinyals, O., and Le, Q. (2014). Sequence to sequence learning with neural networks. In Advances in Neural Information Processing Systems (NIPS 2014).
[50] Cho, K., van Merrienboer, B., Bahdanau, D., and Bengio, Y. (2014b). On the properties of neural ¨ machine translation: Encoder–Decoder approaches. In Eighth Workshop on Syntax, Semantics and Structure in Statistical Translation. to appear.
[51] Koehn, P., Och, F. J., and Marcu, D. (2003). Statistical phrase-based translation. In Proceedings of the 2003 Conference of the North American Chapter of the Association for Computational Linguistics on Human Language Technology - Volume 1, NAACL '03, pages 48–54, Stroudsburg, PA, USA. Association for Computational Linguistics.
[52] Sutskever I, Vinyals O, Le Q V. Sequence to sequence learning with neural networks[J]. Advances in neural information processing systems, 2014, 27.
[53] Cho K, Van Merriënboer B, Gulcehre C, et al. Learning phrase representations using RNN encoder-decoder for statistical machine translation[J]. arXiv preprint arXiv:1406.1078, 2014.
[54] Blunsom P, Hermann K M. Multilingual distributed representations without word alignment[J]. 2014.
[55] Cho K, Van Merriënboer B, Bahdanau D, et al. On the properties of neural machine translation: Encoder-decoder approaches[J]. arXiv preprint arXiv:1409.1259, 2014.
[56] Bahdanau D, Cho K, Bengio Y. Neural machine translation by jointly learning to align and translate[J]. arXiv preprint arXiv:1409.0473, 2014.
[57] Xingxing Zhang and Mirella Lap-ata. Chinese poetry generation with recurrent neural net-works. In Proceedings of the 2014 Conference on Empir-ical Methods in Natural Language Processing (EMNLP),pages 670–680, 2014.

[58] Yi X, Li R, Sun M. Generating chinese classical poems with rnn encoder-decoder[M]//Chinese Computational Linguistics and Natural Language Processing Based on Naturally Annotated Big Data. Springer, Cham, 2017: 211-223.
[59] Hassan S, Mohammed N, Momen S. Learning from tagore[C]//2016 International Workshop on Computational Intelligence (IWCI). IEEE, 2016: 79-84.
[60] Wang Q, Luo T, Wang D, et al. Chinese song iambics generation with neural attention-based model[J]. arXiv preprint arXiv:1604.06274, 2016.
[61] Yan R. i, Poet: Automatic Poetry Composition through Recurrent Neural Networks with Iterative Polishing Schema[C]//IJCAI. 2016, 2238: 2244.
[62] Ghazvininejad M, Shi X, Choi Y, et al. Generating topical poetry[C]//Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing. 2016: 1183-1191.
[63] Yu L, Zhang W, Wang J, et al. Sequence generative adversarial nets with policy gradient. arxiv e-prints, page[J]. arXiv preprint arXiv:1609.05473, 2016.
[64] Wu Y, Wang J. Text generation service model based on truth-guided SEQGAN[J]. IEEE Access, 2020, 8: 11880-11886.
[65] Wang Z, He W, Wu H, et al. Chinese poetry generation with planning based neural network[J]. arXiv preprint arXiv:1610.09889, 2016.
[66] 蒋亮. 深度神经网络在基于图片生成中国古诗问题中的研究与应用[D].中国科学技术大学,2018.
[67] 王小宇. 基于深度学习的图像生成古诗方法研究[D].武汉理工大学,2019.
[68] 何立健. 图像生成诗歌的端到端模型研究[D].广东工业大学,2019.
[69] 刘雨森. 基于深度学习的图像生成诗歌方法与系统[D].四川大学,2021.