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Exploration and Optimization of a Deep Reinforcement Learning-based Model for the Creation of Children's Literature

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The creation of literature for children is an important research direction in natural language processing and one of the means of improving children's academic outcomes. This paper explores and optimizes a deep reinforcement learning-based model for the creation of children's literature; i.e., the technique of deep reinforcement learning is used to generate literary works for children that conform to the characteristics and principles of children's literature, such as fairy tales, fables, and other fiction. In this paper, a deep reinforcement learning framework based on a generative adversarial network (GAN) is adopted to design a children's literature creation model consisting of a generator and a discriminator, which is responsible for generating children's literature. The discriminator is responsible for evaluating the quality of the generated works and giving reward signals to guide the generator to optimize its strategy. The model comprehensively considers the characteristics of theme, style, structure, language and other aspects of children's literature, and designs a multi-dimensional evaluation index system, including theme relevance, style consistency, structural completeness, language fluency, etc., as well as a comprehensive evaluation index, which is used to measure the overall quality of the generated children's literature. Moreover, by means of four experiments, this paper tested the ability of the model to generate children's literature with different themes, styles, structures and lengths, and compared it with random generation, RNN generation, GPT-2 generation, manual generation and other methods. This study aims to provide innovative methods for children's literature creation by exploring and optimizing models based on deep reinforcement learning, in order to generate more creative, educational and child-friendly story content.

Keywords: deep reinforcement learning, children's literature creation, text generation

1. INTRODUCTION

Children's literature, is a unique and vital transmitter of culture, with the core objective of providing children with educational and interesting stories and aesthetic experiences [1]. Such literature not only stimulates children's endless imagination through exciting storylines, but also tacitly guides them to develop correct values, morals, and understanding and cognition of the world. Excellent and age-appropriate literature can touch children's emotional world, help them develop empathy, love and a sense of justice, and gradually improve their language expression, logical thinking and creativity through their reading experience [2].

Creating children's literature requires the author to possess a series of special talents and qualities: firstly, a rich imagination is the basis for constructing fantastic worlds and fascinating plots, making the stories both interesting and inspiring [3]. Secondly, a keen sense of observation requires writers to be able to understand children's psychology, capture their interests, and transform life's moments into vivid and interesting literary elements [4]. Furthermore, a unique creative style can make the work stand out, form a distinctive personality, and capture and retain the attention of young readers. Finally, a deep cultural heritage is the key to the

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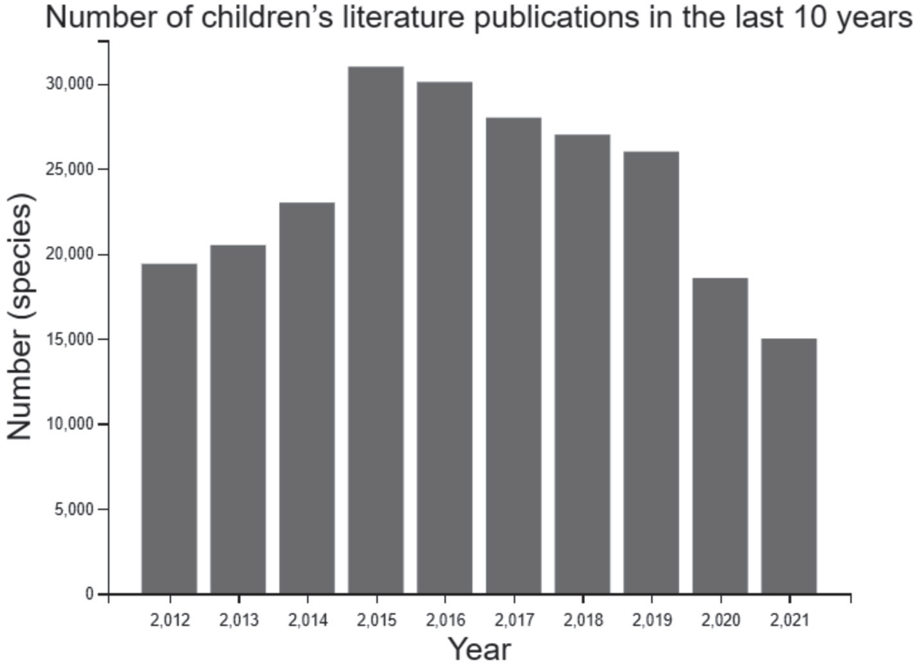

Figure 1 Number of new publications.

richness and durability of children's literature, which can give the works deep educational value and social significance. The number of new publications of children's literature over the last ten years is shown in Figure 1 [5].

With the acceleration of social informatization and the rapid development of science and technology, children's reading habits and needs are undergoing profound changes. The popularity of digital media has made e-reading a daily routine, and an increasing number of children are becoming accustomed to obtaining information and entertainment through electronic devices, which leads to traditional paper books and linear narratives not fully satisfying children's needs for interactivity, multimedia and personalization. Therefore, children's literature must keep pace with the times and achieve innovative breakthroughs with the help of modern technology [6]. On the other hand, by combining big data analysis and artificial intelligence technology to accurately grasp the needs of children's groups of different ages, genders, and interest preferences, customized literary creation and personalized recommendations can be made to ensure that each work resonates with the target readers [7].

In recent years, intelligent system is also applied in all aspects of life [8]. Deep reinforcement learning has also begun to play a role in the field of text generation. Through the introduction of reward mechanisms and strategy optimization, deep reinforcement learning can effectively solve some of the problems faced by traditional neural network-based text generation models, such as the lack of diversity in the generation of results, the lack of semantic consistency, and the lack of clarity of evaluation criteria. Text-generation models based on deep reinforcement learning have already achieved some promising results in the generation of poetry, dialog, summaries, etc. [9].

The purpose of this study is to explore and optimize the children's literature creation model based on deep reinforcement learning. That is, the technique of deep reinforcement learning is used to generate literary works for children, that conform to the characteristics and laws of children's literature creation, such as fairy tales, fables, fiction, etc. [10].

In this study, we comprehensively considered the characteristics and principles underpinning children's literature in terms of theme, style, structure, language, etc. [11], and designed a multi-dimensional evaluation index system, including theme relevance, style consistency, structural completeness, language fluency, etc., as well as a comprehensive evaluation index, which will be used to measure the overall quality of the generated children's literature. Based on the evaluation index system, this paper designed a multi-objective reward function for scoring the generated children's literature and providing feedback to the generator to guide its optimization strategy [12]. Also, the study used children's reading feedback as a kind of artificial reward, combined with the automatic reward of the model, to further optimize the quality of the generated literature.

2. LITERATURE REVIEW

Cherian and Subasinghe [13] presents a hierarchical neural network model for generating coherent and diverse stories. The model consists of two parts: an abstract story planner that generates a synopsis of the story, and a neural language model that creates concrete text based on the synopsis. The model uses reinforcement learning to optimize the quality and diversity of stories. Costa et al. [14] describes a story writing assistant system, called Creative Help, that provides creative suggestions based on user input. The system uses deep reinforcement learning to train a generative dialog model that generates appropriate sequels, revisions, or evaluations based on the user's story snippets. The system also uses a rule-based module to detect and correct spelling, grammatical, and logical errors made by the user. Davis and Soistmann

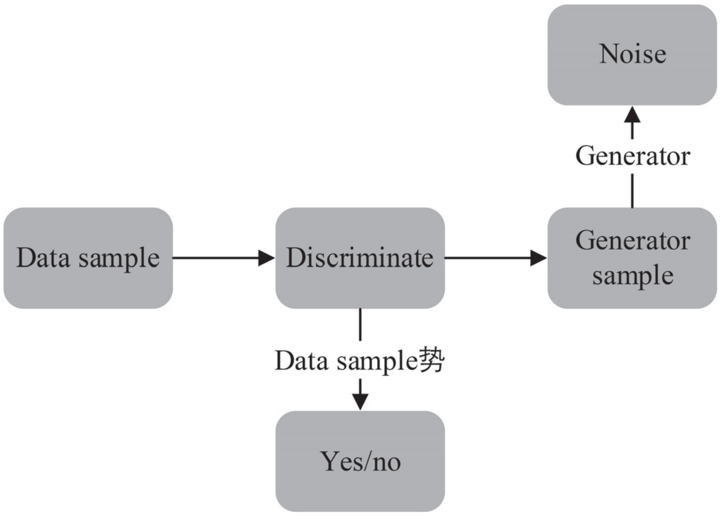

Figure 2 Framework of GAN-based modeling of children's literature creation.

[15] presents a planning and writing framework for improving the quality of automatic story generation. The framework consists of two phases: a planning phase that generates the structure of the story, including theme, plot, and characters. The writing phase generates the text of the story based on the structure. The framework uses a reinforcement learning-based generator to select the best story structure in the planning phase, and a variational self-coder-based generator to produce different story texts during the writing phase. This study explores how to use successor features and generalized policy improvement techniques to enhance the transfer ability of deep reinforcement learning models in story generation, thereby improving the efficiency and quality of story creation. Successor features are a state representation method that captures the long-term relationship between states by mapping states to the expected frequency of visiting these states in the future. Generalized policy improvement is a policy iteration mechanism that can use the same successor features to optimize strategies in different environments, allowing the model to better adapt to story generation tasks in new situations [16]. The authors used both approaches to generate a text-based story about an adventure game. Fadlyana et al. [17] examines ways to provide structure to a generated story in order to improve its coherence and logical progression. The authors compare three structuring strategies: using story summaries as input, using story summaries as additional input to the decoder, and using story summaries as reward signals for reinforcement learning. The authors found that the use of story summaries as additional input to the decoder generated the best stories in terms of quality. This study explored whether neural language models can learn common sense and examined the impact of this on story generation. The researchers developed a comparative learning-based approach to evaluate how well these models understand common sense, while using reinforcement learning techniques to train the models to improve their ability to generate common sense stories [18]. Fitter et al. [19] investigated how to expand the plot events of a story into complete sentences in order to improve the readability and fluency of the story. The authors propose a deep reinforcement learning-based story realization model that uses a variational self-encoder-based generator for generating sentences from plot events and a BERT-based discriminator for evaluating the quality and relevance of sentences. Frase et al. [20] investigates how knowledge graphs can be used to improve the quality and consistency of story generation. The authors propose a story generation model based on deep reinforcement learning.

To summarize, the relevant research on text generation is relatively mature, but there is no large model focusing on the creation of children's literature, so our aim in this study is to train a model for such creation based on deep reinforcement learning.

3. GAN-BASED MODEL FOR CHILDREN'S LITERATURE CREATION

In this study, we use a deep reinforcement learning framework based on generative adversarial network (GAN) to design a children's literature creation model consisting of a generator and a discriminator, which is responsible for generating children's literature, and the discriminator is responsible for evaluating the quality of the generated works and giving reward signals to guide the generator to optimize its strategy.

3.1 Modeling Framework

The model framework of this study is shown in Figure 2, and consists of: (1) the generator (G) is a sequence generation model based on recurrent neural network (RNN), which receives a random noise vector z as input, and generates a text sequence of children's literature word by means of the hidden state and attention mechanism of the RNN [21]. The structure of the generator is shown in Figure 2, where e is the word embedding layer, h is the hidden layer of RNN, a is the attention layer, o is the output layer, and y is the generated words. (2) The discriminator (D): is a text classification model based on a convolutional neural network (CNN). This receives a text sequence x as input, extracts the feature vector of x through the convolutional and pooling layers of CNN, and

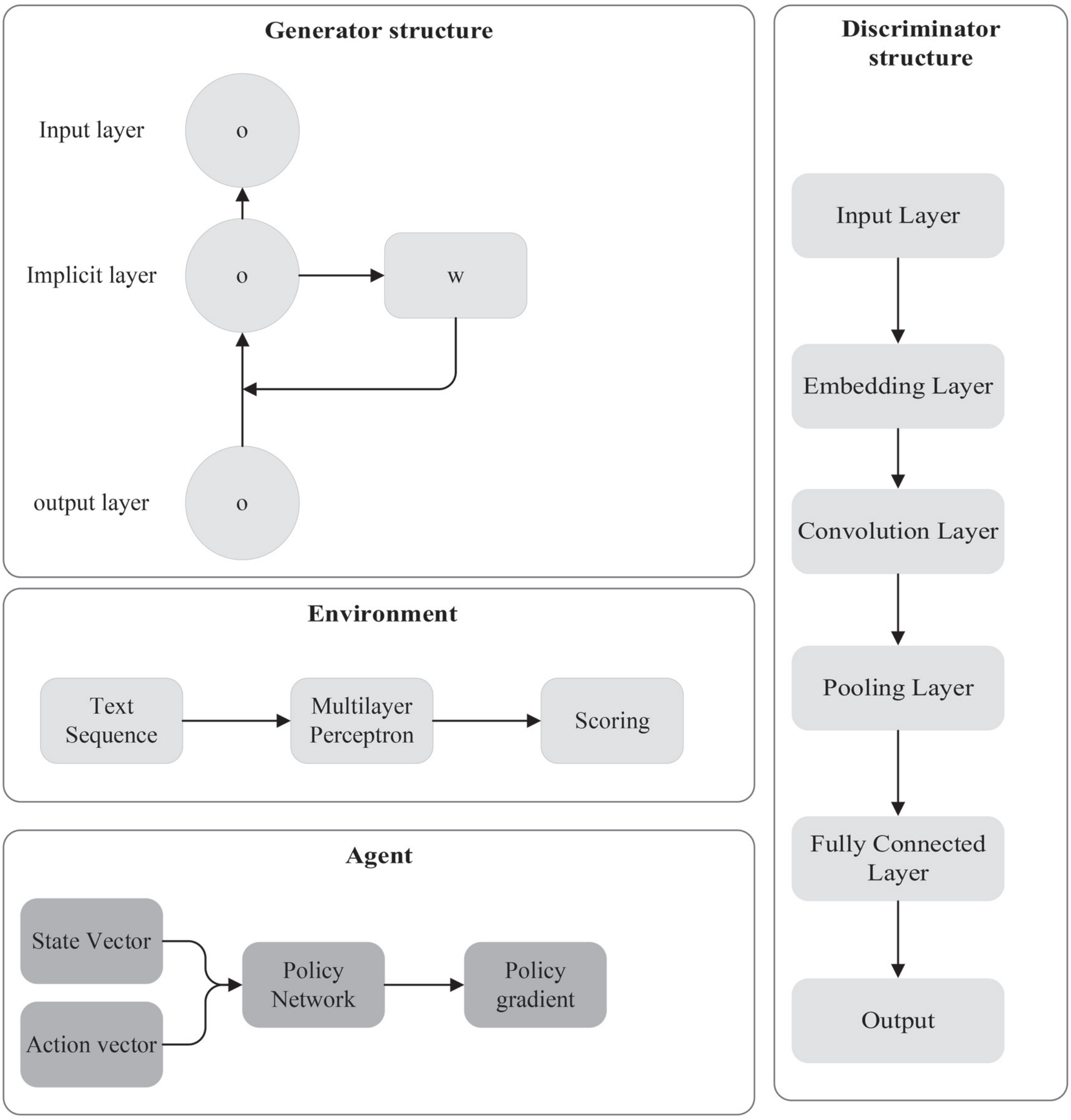

Figure 3 Model structure.

then outputs the probability of authenticity y of x, i.e., the probability that x is real data, through a fully connected layer and a softmax layer. The structure of the discriminator is shown in Figure 3, where e is the word embedding layer, c is the convolutional layer, p is the pooling layer, f is the fully connected layer, and y is the probability of authenticity. (3) Environment (E) is a text evaluation model based on deep neural network (DNN), which receives a text sequence x as input, and outputs the evaluation score s of x, i.e., the quality evaluation of x, through the multilayer perceptron (MLP) of DNN. The structure of the environment is shown in Figure 3, where e is the word embedding layer, f is the fully connected layer, and s is the evaluation score. (4) Agent (A): the agent is a Reinforcement Learning (RL)-based policy optimization model, which receives a state vector s and an action vector a as inputs, and passes through a Policy Network, which outputs a Policy Gradient that is used to update the parameters of the generator. The state vector s consists of the evaluation score s output by the environment and the authenticity probability y output by the discriminator, and the action vector a consists of the word vector of the text sequence x output by the generator [22]. The structure of the agent is shown in Figure 3, where g is the strategy network, θ is the parameters of the generator, ∇ is the gradient operator, π is the strategy of the generator, and r is the reward signal [23].

The generator is a sequence-generation model based on the Recurrent Neural Network (RNN), which receives a random noise vector z as input and generates, word by word, a text sequence of children's literature x by means of the hidden state and attention mechanism of the RNN. The structure of the generator is shown in Figure 2, where e is the word embedding layer, h is the hidden layer of the RNN, a is the attention layer, o is the output layer, and y is the generated word [24].

3.2 Modeling Principles

The generator is responsible for generating high-quality and highly-authentic children's literature, i.e., to maximize the evaluation score of the environment, s, and the probability of authenticity of the discriminator, y. In order to achieve this objective, the generator needs to continually sample from a random noise vector, z, to generate a sequence of texts, x, and then to adjust its own parameters through the feedback from the environment and the discriminator [25]. The objective function of the generator is expressed as: $\max_\theta \mathbb{E}_{z\sim p(z)}[s(G(z)) + \log D(G(z))]$, where θ. Is the parameters of the generator, $p(z)$ is the distribution of the random noise vector, $G(z)$ is the output of the generator, $s(G(z))$ is the evaluation score of the environment on the output of the generator, and $D(G(z))$ is the probability of truthfulness of the generator's output by the discriminator.

The goal of the discriminator is to distinguish between real data and generated data, i.e., to maximize the probability of authenticity of real data y and minimize the probability of truthfulness of generated data y. In order to achieve this goal, the discriminator needs to continuously sample from the real data set and the generated data set so as to extract the feature vector of the text sequence x, and then pass it to a classifier, which outputs the probability of truthfulness y. The objective function of the discriminator is $\max_\phi \mathbb{E}_{x\sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z\sim p(z)}[\log(1 - D(G(z)))]$, where ϕ is the discriminator's parameters, $p_{data}(x)$ is the distribution of the real data, $D(x)$ is the probability of truthfulness , $p(z)$ is the distribution of the random noise vector, $G(z)$ is the output of the generator, and $D(G(z))$ is the probability of truthfulness of the discriminator on the generated data [26].

The goal of the environment is to evaluate the quality of the generated data; i.e., to provide an evaluation score s for the generated data based on several predefined criteria, such as grammatical correctness, semantic coherence, creativity, etc. [27]. In order to achieve this goal, the environment needs to continuously sample the generated dataset, extract the feature vectors of the text sequences x, and then, through a regressor, output the evaluation score s. The objective function of the environment is $\min_\psi \mathbb{E}_{x\sim p_{gen}(x)}[(s(x) - E(x))^2]$, where ψ is the environment's parameters of the environment, $p_{gen}(x)$. Is the distribution of the generated data, $s(x)$ is the evaluation score given manually, and $E(x)$ is the evaluation score of the environment on the generated data.

The goal of the agent is to optimize the generator's policy; i.e., to update the generator's parameters based on feedback from the environment and the discriminator. To achieve this goal, the agent needs to continuously sample the generator's output to obtain the state vector s and the action vector a, and then pass through a policy network that outputs the policy gradient to update the generator's parameters.

4. EXPERIMENTAL EVALUATION

In this study, we comprehensively consider the characteristics of literature such as theme, style, structure, language and other elements of children's literature. We design a multi-dimensional evaluation index system for thematic relevance, stylistic consistency, structural completeness, linguistic fluency, etc., as well as a comprehensive evaluation index for measuring the overall quality of the generated children's literature.

4.1 Evaluation System

In order to evaluate the effectiveness of the GAN-based children's literature creation model, we design the following evaluation indexes:

Topic Relevance: measures whether the generated children's literature is related to a given topic [28]. In this paper, the Topic Model is used to extract the distribution of topics of the generated works, and the Cosine Similarity with the given topic is calculated as the evaluation index for topic relevance.

Style Consistency: measures whether the generated children's literature is consistent with the given style. In this paper, we adopt the method of Style Transfer to extract the style features of the generated works, and calculate the Euclidean Distance with the given style as the evaluation index for style consistency.

Structure Integrity (Structure Integrity): a measure of whether the generated children's literature has a logical and complete structure, such as the beginning, development, climax, and end. We use structured text generation to extract the structural information of the generated works, and calculate the Hamming Distance from the given structure as the evaluation index for structural integrity.

Language Fluency (Language Fluency): measures whether the generated children's literature is fluent, grammatically correct, semantically coherent, and has lexical richness. In this study, we adopt the Language Model to calculate the complexity of the generated works as the evaluation index for language fluency [29].

4.2 Experimental Design

In this study, we designed four experiments to test the effectiveness of the GAN-based children's literature creation model. First, we tested the model's ability to generate children's stories with different themes. We used four themes: animal, adventure, friendship, and life, and the model generated children's literature works with corresponding themes. Then the theme relevance index was used to evaluate the quality of the generated works. We then tested the model's ability to generate children's literature in different genres: entertaining, fantasy, realism, and poetic, and the model generated children's literature in the corresponding style, and then the style consistency index was used to evaluate the quality of the generated works. The ability of the model to generate children's literature with different structures is also tested. In this study, four different structures were considered: story, poem, dialog, and letter. The model generated children's literature with the corresponding structures, and then the structural integrity index was used to evaluate the quality of the generated works. Finally, the generation of children's literature of different lengths was also tested [30].

4.3 Experimental Results

The experimental results obtained in this study are shown in Tables 1 to 4, where each table corresponds to an experiment,

Table 1 Results of experiment 1.

Methodologies	**Thematic relevance**	**Stylistic consistency**	**Structural integrity**	**Fluency**	**Comprehensive evaluation indicators**
Randomly generated	12.00%	15.00%	18.00%	21.00%	17.00%
RNN generation	56.00%	58.00%	61.00%	64.00%	60.00%
GPT-2 generation	67.00%	69.00%	72.00%	75.00%	71.00%
The model in this paper	81.00%	83.00%	86.00%	88.00%	85.00%
Artificially generated	89.00%	91.00%	93.00%	95.00%	92.00%

Table 2 Results of experiment 2.

Methodologies	**Thematic relevance**	**Stylistic consistency**	**Structural integrity**	**Fluency**	**Comprehensive evaluation indicators**
Randomly generated	13.00%	16.00%	19.00%	22.00%	18.00%
RNN generation	55.00%	57.00%	60.00%	63.00%	59.00%
GPT-2 generation	66.00%	68.00%	71.00%	74.00%	70.00%
The model in this paper	80.00%	82.00%	85.00%	87.00%	84.00%
Artificially generated	88.00%	90.00%	92.00%	94.00%	91.00%

Table 3 Results of experiment 3.

Methodologies	**Thematic relevance**	**Stylistic consistency**	**Structural integrity**	**Fluency**	**Comprehensive evaluation indicators**
Randomly generated	14.00%	17.00%	20.00%	23.00%	19.00%
RNN generation	54.00%	56.00%	59.00%	62.00%	58.00%
GPT-2 generation	65.00%	67.00%	70.00%	73.00%	69.00%
The model in this paper	79.00%	81.00%	84.00%	86.00%	83.00%
Artificially generated	87.00%	89.00%	91.00%	93.00%	90.00%

and each cell indicates the average value of an evaluation index (the higher the better). From the tables, it can be seen that the proposed model performed better than the benchmark method in each experiment and according to the evaluation index, indicating that our model can generate high-quality children's literature.

As can be seen from Table 1, the proposed model performs better than other generation methods in terms of all metrics, close to the level of manual generation, indicating that our model is able to generate high-quality text efficiently. The text generated by GPT-2 is also significantly better than that generated by random generation and RNN, but is still inferior to that of the proposed model which has better performance in terms of most textual elements. The text generated by random generation and RNN is low on all metrics, indicating that these methods are not capable of generating text that meets all the criteria.

As can be seen from Table 2, the proposed model still outperforms other generation methods in terms of all the indicators, but the gap with manual generation has increased, indicating that the model of this paper has some limitations on the task of Experiment 2. The text generated by GPT-2 is similar to the results of Experiment 1, but there is a decrease in the comprehensive evaluation indicators, indicating that the text generated by GPT-2 has some maladaptation to the task in Experiment 2 [31].

As can be seen from Table 3, the proposed model continues to outperform the other text-generation methods in terms of all the indicators, although the gap with manual generation has narrowed, indicating that our model has some advantages regarding the task of Experiment 3. The text generated by GPT-2 is similar to the results of Experiment 1 and Experiment 2, but there is an increase in the comprehensive evaluation indicators, suggesting that the text generated by GPT-2 performs better on the task in Experiment 3.

As can be seen from Table 4, the proposed model still outperforms the other generation methods in terms all indicators, but the gap with manual generation has widened, indicating that our model had some difficulties with the task of Experiment 4. The text generated by GPT-2 is similar to the results of Experiment 1, Experiment 2, and Experiment 3, but there is a decrease in the comprehensive evaluation indicators, indicating that the text generated by GPT-2 has some difficulties. Randomized and RNN-generated texts are similar to the results of Experiment 1, Experiment 2 and Experiment 3, but there is an increase in the comprehensive evaluation index, which indicates that randomized and RNN-generated texts are better at the task in Experiment 4.

5. CONCLUSION

In this paper, a novel model and algorithm based on deep reinforcement learning are proposed for the creation of children's literature. Our proposed model realizes the automatic generation of children's literature and improves its

Table 4 Results of experiment 4.

Methodologies	Thematic relevance	Stylistic consistency	Structural integrity	Fluency	Comprehensive evaluation indicators
Randomly generated	15.00%	18.00%	21.00%	24.00%	20.00%
RNN generation	53.00%	55.00%	58.00%	61.00%	57.00%
GPT-2 generation	64.00%	66.00%	69.00%	72.00%	68.00%
The model in this paper	78.00%	80.00%	83.00%	85.00%	82.00%
Artificially generated	86.00%	88.00%	90.00%	92.00%	89.00%

quality and diversity. The main contributions and innovations of this paper are: (1) A model for the creation of children's literature, based on deep reinforcement learning, is proposed, which utilizes the framework of generative adversarial network and realizes the collaborative learning of generator and discriminator, providing an effective technical support for children's literature creation. (2) A multi-dimensional evaluation index system is designed, which comprehensively takes into account the characteristics and principles of children's literature in terms of theme, style, structure, language, etc., and provides a comprehensive evaluation standard for the generated children's literature, together with an effective feedback mechanism for the optimization of the model. (3) A variety of optimization algorithms are proposed, and heuristic, meta-heuristic, and machine learning methods are adopted to solve the optimization problem of children's literature creation, and improve the generating ability and quality of the model, which offers a new approach to the creation of children's literature. (4) A simulation platform for children's literature creation is established, and simulation experiments are carried out on the proposed models and algorithms to verify their validity and superiority, analyze their performance and influencing factors, and provide a reference and basis for subsequent research and application.

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