Research on Marxist Classics Education based on Deep Learning under e-Education

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Abstract. In the digital era, traditional Marxist education methods, which rely heavily on classroom lectures and textbook reading, lack engagement and fail to integrate modern technology, resulting in limited effectiveness and low student interest. This paper aims to address these gaps by proposing a deep learning-based model that leverages advanced natural language processing and personalized recommendation techniques to enhance the effectiveness of Marxist classical education. The advent of deep learning technology has opened up new avenues for the delivery of personalised and intelligent educational content. This paper puts forth an innovative proposal for a Marxist classical education model based on deep learning. The model employs natural language processing technology to conduct comprehensive analysis of Marxist classic texts, construct knowledge graphs, and extract pivotal concepts and themes. By training a language model based on the Transformer architecture, the system is capable of automatically generating text summaries, answering students' questions, and providing personalised learning suggestions. Additionally, an intelligent recommendation system is integrated to enable the dynamic customisation of learning paths according to students' learning behaviours and interests, thereby enhancing the efficiency and effectiveness of the learning process. The proposed deep learning-based model not only improves student engagement and comprehension but also provides valuable insights for educators and policymakers in modernizing the curriculum of Marxist education. By integrating intelligent recommendation systems, the model facilitates a personalized and dynamic learning experience, which could lead to a paradigm shift in teaching strategies and curriculum design, making Marxist education more relevant and accessible in the digital era.

Keywords: Deep Learning, Marxist Classical Education, E-Education, Natural Language Processing.

1 Introduction

In the era of rapid development of information technology and the Internet, e-education has become an indispensable part of the modern education system. With the help of digital platforms, cloud computing, big data and multimedia resources, the presentation of teaching content has become more diverse and interactive. Students can not only

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acquire knowledge through advanced technologies such as online courses, virtual reality (VR), and augmented reality (AR), but also participate in online discussions, collaborative learning, and other activities to achieve personalized and flexible learning [1]. However, despite these advancements, traditional Marxist education methods still rely heavily on classroom lectures and textbook reading, lacking effective integration with modern technological tools. This gap makes it challenging to fully engage students in the learning process and hinders the achievement of deep understanding and practical application of Marxist theories [2]. Under the impact of the information explosion and diverse value systems, it has become increasingly difficult to maintain students' interest and active participation, which has resulted in suboptimal teaching outcomes. Therefore, there is an urgent need to explore new methods that can modernize Marxist classical education by leveraging technological advancements.

At the same time, deep learning, as a cutting-edge technology in the field of artificial intelligence, has attracted widespread attention due to its excellent ability to process massive data and complex pattern recognition[3]. Especially in the fields of natural language processing, speech recognition, image recognition, and intelligent recommendation systems, deep learning technology has shown great potential and application value. In the field of education, deep learning can support functions such as personalized learning path planning, intelligent tutoring, and evaluation, so as to achieve intelligent and accurate education[4].

The application of deep learning technology to Marxist classical education can conduct in-depth semantic analysis of classic texts, excavate knowledge structures, and refine core ideas. At the same time, based on the data of students' learning behavior, personalized learning resources and suggestions are provided to promote students' deep understanding and application of classical theories[5]. This kind of integration not only helps to enrich the teaching methods of Marxist classical education, improve teaching efficiency and effectiveness, but also meets the learning needs of students in the new era and opens up a new path for the innovative development of ideological and political education[6].

This paper aims to address this gap by proposing a deep learning-based model that enhances the efficiency and effectiveness of Marxist classical education. Deep learning, as a cutting-edge technology in the field of artificial intelligence, has shown great potential in various educational applications due to its powerful capabilities in processing massive amounts of data and recognizing complex patterns. Through the use of natural language processing (NLP) techniques, the proposed model conducts in-depth semantic analysis of Marxist classical texts, constructs knowledge graphs, and refines core ideas.

2 Related Work

Initially, Zhang et al. [7] made a comprehensive and in-depth discussion on the application of deep learning in recommendation systems, and provided new ideas and methods for personalized learning. The advantages of deep learning in processing large-scale, high-dimensional, and sparse data are highlighted, which is of great significance for personalized learning in the field of education. By leveraging deep learning models, recommender systems can more effectively analyze students' learning behaviors, interest preferences, and knowledge levels to provide tailored learning resources and pathways. In addition, they discussed ways to fuse contextual information, multimodal data, and time series data in recommender systems, which are essential for building a more intelligent and dynamic personalized learning environment.

Subsequently, the Bidirectional Encoder Representations from Transformers (BERT) proposed by Devlin et al. [8] has triggered a major revolution in the field of natural language processing. Through the pre-trained bidirectional Transformer architecture, BERT can understand the text context from left to right and right to left at the same time, and achieve a comprehensive capture of the deep semantics of the language. This model made breakthroughs in several NLP tasks, such as question answering systems, reading comprehension, text classification, and named entity recognition, all of which reached the state-of-the-art level at the time. This has led to a significant improvement in the ability of machines to understand human language, ushering in a new era of natural language processing.

3 Methodologies

3.1 Semantic Analysis

Initially, collect and organize the digitized texts of Marxist classics to build a special corpus $D = \{d_1, d_2, \dots, d_N\}$, where d_i represents the i document. In order to ensure the accuracy and validity of the subsequent analysis, the text is carefully pre-processed. For the preprocessed word sequence, the BERT model is used to obtain the context vector representation of each word and represented as Equation 1.

$$H = BERT([w_1, w_2, \dots, w_L]) = (h_1, h_2, \dots, h_L) \tag{1}$$

where $h_i \in \mathbb{R}^d$, d is the vector dimension, which represents the semantic vector of the word w_i. Further, the word vector of BERT was used to calculate the importance weight of each word by combining the attention mechanism, denoted as Equation 2.

$$\alpha_i = \frac{exp\,(v^\top \tanh\,(Wh_i))}{\sum_{j=1}^{L} exp(v^\top \tanh\,(Wh_i))} \tag{2}$$

where W and $v^\top$ are learnable parameters. Based on the weight α_i, the word with the higher weight is selected as the key concept.

Knowledge representation learning uses the TransE model to embed entities and relationships into the same vector space, so that the vectors corresponding to the relations meet $h + r \approx\ t$. Loss function is represented as Equation 3.

$$\mathcal{L} = \sum_{(h,r,t)\in S} \sum_{(h',r,t')\in S'} [\gamma + \left||h + r - t|\right| - ||h' + r - t'||] \tag{3}$$

where S is the correct triplet set, S' is the wrong triplet set from negative sampling, and γ is the marginal hyperparameter.

3.2 Learning Recommendations Model

Initially, the Transformer-based sequence-to-sequence (Seq2Seq) model is used to generate questions from students to answers. The model structure includes an encoder and a decoder: the encoder encodes the student's question into a context vector to capture the semantic information of the question; The decoder generates the response text based on these context vectors. The core of the Transformer model is the multi-head self-attention mechanism, which can capture the dependencies between different positions in the sequence, and enhance the model's understanding of the problem and the accuracy of the answer, denoted as Equation 4.

$$Attention(Q,K,V) = softmax\left(\frac{QK^{\mathrm{T}}}{\sqrt{d_k}}\right)V \tag{4}$$

Note that, the Q, K, and V are query, key, and value matrices, respectively. Subsequently, model maps students' behavior data to the eigenvector u, and learning resources to the eigenvector i. Multilayer perceptron was used for nonlinear mapping to predict students' interest in learning resources, represented as Equation 5.

$$\hat{y}_{ui} = \sigma(h^{\mathrm{T}}W[u{:}\,i] + b) \tag{5}$$

where $\sigma(\cdot)$ is the activation function, W and b are the learnable parameters, and h^{T} is the hidden layer representation. The proposed model utilized binary cross-entropy loss, combined with L_2 regularization, denoted as Equation 6.

$$L = -\sum_{(u,i)\in y}[y_{ui} log\hat{y}_{ui} + (1 - y_{ui})\log(1 - \hat{y}_{ui})] + \lambda||\Theta||^2 \tag{6}$$

where y_{ui} is the actual feedback and Θ is the collection of model parameters.

4 Experiments

4.1 Experimental Setups

In order to address the absence of suitable public datasets, we employed the use of simulated datasets in the experiment, with the objective of accurately reflecting the authentic Marxist educational scenarios and students' learning behaviours. The initial step involved the construction of a simulated corpus comprising Marxist classic texts. Secondly, the learning behaviour data of 800 students was simulated, comprising approximately two million learning logs and 100,000 question-and-answer records and discussion records. These cover the duration of the learning process, completion of individual chapters, interactive behaviour and other relevant information. The Chinese BERT-Base pre-trained model was fine-tuned, with an initial learning rate of 2e-5, using the AdamW optimiser and batch size and number of training rounds as variables for optimisation.

4.2 Experimental Analysis

The experiment was compared with the LSTM-based sequence-to-sequence (Seq2Seq) model, the Word2vec word vector model, singular value factorisation (SVD) and probability matrix factorisation (PMF) on the basis of the data used.

The Recall-Oriented Understudy for Gisting Evaluation (ROUGE) metric is an important evaluation criterion for evaluating automatic text summarization and natural language generation tasks. It focuses primarily on recall by comparing the degree of overlap between a machine-generated summary and one or more reference summaries. Above Figure 1 compares the ROUGE scores of Seq2Seq, Word2Vec, SVD, PMF, and our model (Ours) with different data volumes.

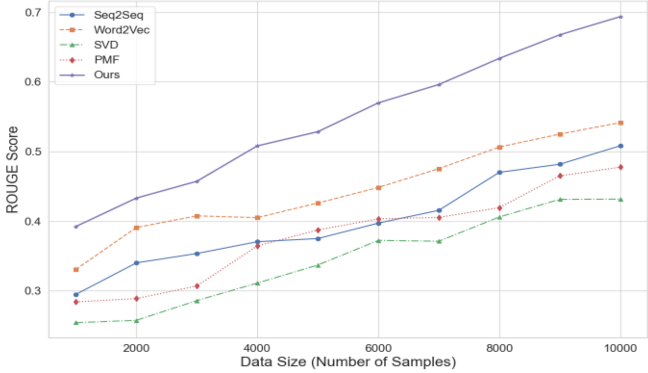

Fig. 1. ROUGE Score Comparison.

Normalized Discounted Cumulative Gain (NDCG) is an evaluation standard used to evaluate the performance of recommender systems and information retrieval systems. NDCG takes into account the relevance and ranking position of the recommendation results, and measures the model's ability to recommend highly relevant items at a given position by calculating cumulative gain and reducing and normalizing position. Figure 2 compares the NDCG scores of Seq2Seq, Word2Vec, SVD, PMF, and our method for different data volumes.

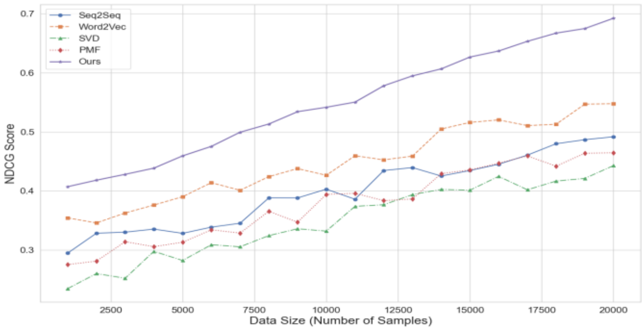

Fig. 2. NDCG Score Comparison.

Finally, system response time is an important measure of the performance of a computer system or application, referring to the time it takes from when a user makes a request to when the system returns a response. Figure 3 illustrates the distribution of system response time for different models.

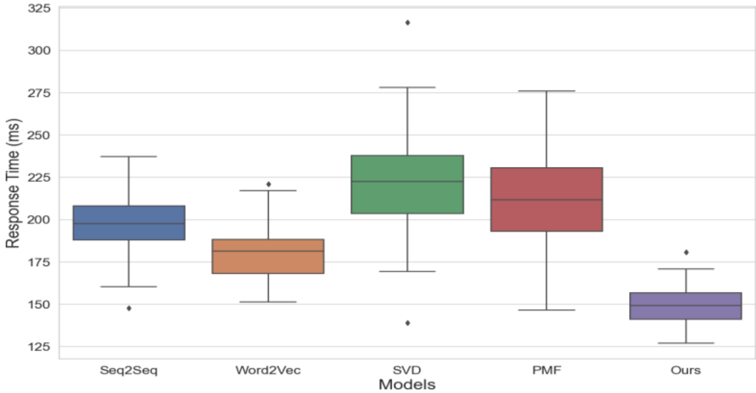

Fig. 3. System Response Time Comparison.

5 Conclusion

In conclusion, this work utilized natural language processing technology to conduct in-depth analysis of classic texts, construct knowledge graphs, realize text summary generation and intelligent Q&A, and provide students with efficient learning support. Through the neural collaborative filtering model, a personalized recommendation system was constructed, and the learning path was dynamically customized, which significantly improved the learning effect. As for future improvements, we can expand the scale of data, and deeply explore application of deep learning in ideological education.

References

1. Liu, Zongxu. "Based on the Classical" Basic Principles of Marxism" Class Teaching and Learning." The Educational Review, USA 7.10 (2023): 1476-1479.
2. Zang, Peng. "Evaluation Method of Classroom Teaching Quality of Marxist Theory Course Based on Deep Learning." International Conference on E-Learning, E-Education, and Online Training. Cham: Springer Nature Switzerland, (2022).
3. Jiang, Xiaoming. "[Retracted] Analysis of the Relevance Environment between Marxist Philosophy and System Theory Based on Deep Learning." Journal of Environmental and Public Health 2022.1 (2022): 6322272.
4. Popa, Bogdan. "Marxism in Education." The Palgrave International Handbook of Marxism and Education (2023): 381.
5. Hall, Richard, Inny Accioly, and Krystian Szadkowski. "Introduction: The Relevance of Marxism to Education." The Palgrave International Handbook of Marxism and Education. Cham: Springer International Publishing, (2023): 3-24.

6. Ardill, Allan. "Deep critique: critical pedagogy, Marxism, and feminist standpoint theory in the corporate classroom." Teaching Marx & Critical Theory in the 21st century. Brill, (2019): 143-163.
7. Zhang, Shuai, et al. "Deep learning based recommender system: A survey and new perspectives." ACM computing surveys (CSUR) 52.1 (2019): 1-38.
8. Devlin, Jacob. "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805 (2018).