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RESEARCH ARTICLE

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A scientific research topic trend prediction model based on multi-LSTM and graph convolutional network

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Abstract

Predicting the development trend of future scientific research not only provides a reference for researchers to understand the development of the discipline, but also provides support for decision-making and fund allocation for decision-makers. The continuous growth of scientific publications has brought challenges to track the development trends of scientific research topics. The existing topic trend prediction methods have proved that the research topic trend of a publication is influenced by other peer publications. However, they ignore the fact that the research topics of different publications belong to different research topic space. Moreover, the existing topic prediction methods do not fully consider the interactive influence among publications that the research topic of one publication affects the topics of other publications, it is also influenced by the research topics of other publications. In line with this, this paper proposes a scientific research topic trend prediction model based on multi-long short-term memory (multi-LSTM) and Graph Convolutional Network. Specifically, multiple LSTMs are employed to map research topics of different publications into their respective topic space. Then, the graph convolutional neural network is applied to learn the scientific influence context of each publication, so that the research topic of each publication not only integrates the influence of neighbor nodes, but also considers the influence of the neighbors of the neighbor node on the research topic of the publication, so as to more accurately fuse scientific influence context of research topic of peer publications. Experiments results on the data set of scientific research papers in the field of artificial intelligence and data mining demonstrate that the model improves the prediction precision and achieves the state-of-the-art research topic trend prediction effect compared with the other baseline models.

KEYWORDS

graph convolutional networks, long short-term memory, scientific Influence modeling, time series prediction, topic trend prediction

1 | INTRODUCTION

The development and progress of computer science research has led to the development of related industries.[1] Predicting future development trend of science research not only provides decision-makers with support for decision-making and fund allocation, but also provides a reference for researchers to understand the development of the discipline in depth.[2] The discipline of computer science contains many research areas. Within a research area, there are many conferences and journals that publish the latest research results. These publications influence each other and jointly promote the development of a research area. The continuous growth of scientific publications makes it more challenging to track the development trend of scientific research in a timely and accurate manner.[3]

To capture the development trend of science and technology and promote the transfer of knowledge in key research areas, considerable effort has been made to track the topic evolution of scientific research,[4,5] aiming to analyze the history of scientific research topics over time. Chen et al. use the data sets of information retrieval publications to explore the evolution of topics by analyzing the topic trends, evolutionary dynamics, and semantic word transfer in the information retrieval field.[6] Using artificial intelligence (AI) as an example and starting from a hierarchical topic model with a multilayered topic tree, Qian et al. analyze 65,887 AI-related research papers published between 2009 and 2018. Where, a visual analysis model of the topic tree is designed to study hierarchical structure evolution[7] so as to systematically and visually study the evolution process of the topic tree over time. Using the data sets of published papers in the field of information retrieval, based on the distribution of the topic of each word over time, the transfer of semantic words is linked with the evolution of the topic, and the semantic movement of words in information retrieval field is studied from both the topic and context.[8] To reveal the future development status of research topics,[9] Wang et al. collected a set of scientific papers from 2014 to 2019 to construct a common keyword network sequence for the discipline of Computer Science. Through the self-developed network evolution analysis visualization tool NEViewer, the network topology and evolution background of the research topic are analyzed.[10]

With the increasing socioeconomic influence of scientific research, research topic trends prediction draws an increased interest[11,12] from research and development departments, academic publishing companies, and policy makers. Predicting topic trends of scientific research aims to help scientists and governments foresee future research directions, so that funding agencies can effectively allocate resources to those promising research topics.[13] Predicting emerging research topics is a step farther than identifying them, and scientific research topic prediction tasks have been carried out one after another. Prabhakaran et al. use time analysis on the historical curve to predict the rise and fall of specific research topics.[14] Several machine learning models are jointly used to detect and foresight the emerging research topics, and experimental results on gene editing data set make it clear that is feasible to detect emerging research topics with multiple machine learning models.[15] Li et al. used machine learning methods to conduct data mining (DM) on the research results of the biomedical effects of nanomaterials, and scientifically predicted the development trend of their research hotspots.[16] With the development of computer science, few studies have also begun to focus on the topic evolution trend forecasting of computer science. Abuhay et al. employ the classic time series forecasting model AutoRegressive Integrated Moving Averages (ARIMAs) to predict the trend of research topics of international conference of computer science.[17] With the development of deep neural networks,[18] long short-term memory (LSTM) is employed to capture timing sequence features,[19] and used in topic prediction tasks. Using 19,164 publications and 25 journals, Liang et al. first predict the future popularity scores of candidate topics in a time series, and then apply LSTM to predict the popularity scores of candidate topics to determine future research topics.[20] Lu et al. employ LSTM network and combine temporal feature, persistence, community size, and community development to propose author-defined keyword frequency prediction (AKFP) method to predict research topic trends of publications of computer science discipline.[21] Chen et al. propose a related influence model (Correlated Neural Influence [CONI]), which predicts the future research topics of 11 computer science conferences by fusing the scientific influence context of other peer conferences.[22] However, the research topics of different publications influence each other and are different. When expressing the research topics of different publications, they should be mapped to their respective topic space. CONI does not distinguish the research topics of different publications. And when learning the scientific influence context of peer publications, CONI does not consider the interaction among peer publications. Therefore, it is not sufficient for scientific influence context acquisition of each publication. This poses two great challenges to predict the research topics of each research field. One is how to express the research topics of different publications so that they are mapped to different topic space. The other is how to fully learn the scientific influence context of peer publications.

In fact, the scientific influence among publications is interactive. When publication *i* affects publication *j*, it is also affected by publication *k*. The association relationship among publications can be modeled as a graph structure. Graph convolutional network (GCN) is such a network which can deal with graph structure.[23] GCN can not only learn node features automatically, but also learn the associated information among nodes.[24,25] So, in this study, we model the interaction among publications as a graph structure and propose a scientific research topic trends prediction model based on multi-LSTM and graph convolutional network (MLGCN). First, we employ multiple LSTMs to capture research topic of each publication by embedding them into the hidden space. Then, GCN is applied to fuse related peer publication's research topic to capture each publication's scientific influence context. Lastly, according to the combination vector of the hidden state of the publication and its scientific influence context, the topic prediction model produces the distribution of all topical words in the next time step. Consequently, our topic prediction model can fully learn every publication's scientific influence context by modeling research topics of different research areas and considering the interaction among publications. We also present case studies on scientific research topic trend prediction to further indicate the effectiveness of the proposed method.

The contributions of this paper are as follows:

(1) Multiple different LSTM chains are used to distinguish research topic of different publications. The hidden states of each LSTM represent the accumulation of sequential historical research topic at different time steps of every publication.
(2) We apply GCN to adaptively capture the dependencies among multipublication interactions based on the learned topic representations to learn scientific influence context of each publication.
(3) We conduct experiments on two data set including conferences in DM and AI area of computer science discipline to demonstrate the effectiveness of the proposed topic prediction model. Experimental results show that the proposed model can greatly improve the precision of topic prediction. The data set can be available* to the public.

The rest of this paper is organized as follows: Section 2 introduces related work, including time series prediction, scientific research trend prediction, and scientific influence modeling. Section 3 introduces the scientific research topic trends prediction model based on multi-LSTM and GCNs in detail. Section 4 reports experiments results and analysis, and we summarize this study in Section 5.

2 | RELATED WORK

Scientific research trend prediction is essentially a time series prediction problem. So our work mainly involves three lines of research: time series prediction, scientific research trend prediction, and scientific influence modeling.

2.1 | Time series prediction

In recent years, a large number of machine learning algorithms[26,27] have been widely used in time series prediction tasks and show good performance, such as the classical time series prediction model ARIMA. With the development of deep learning, some time series prediction methods based on deep learning have achieved good prediction effects, especially the neural network-based prediction method based on attention. Qin et al. propose a dual-stage attention-based Recurrent Neural Network for time series prediction (DARNN),[28] which uses an input attention mechanism to adaptively extract relevant driving series at each time step by referring to the previous encoder hidden state and introduces a temporal attention (TEMPATT) mechanism to select relevant encoder hidden states across all time steps. On the basis of the encoder–decoder network, Liu et al. only use attention mechanism on the hidden states of the encoder and the others remain unchanged to verify the validity of TEMPATT[29] prediction method. On the basis of DARNN, dual-stage two-phase (DSTP)[30] is proposed for long-term time series prediction. Specifically, DSTP-based structure is first employed to enhance the spatial correlations between exogenous series. Multiple attentions are applied on target series to boost the long-term dependency.

From the perspective of specific applications, the attention-based neural network prediction model is widely used in various prediction tasks. To accurately predict the service life of rolling bearings, a new gated recurrent unit neural network (gated dual attention unit [GDAU])[31] with dual attention gates is proposed by using the acquired life cycle vibration data of rolling bearings. This method can effectively predict the life of rolling bearings. Yuan et al. propose a spatiotemporal attention-based LSTM network for soft sensor modeling. The network can not only identify important input variables related to quality variables at each time step, but also find all time steps adaptively.[32] This model can effectively predict the initial boiling points of heavy naphtha and aviation kerosene in the process of an industrial hydrocracking process. Zhang et al. compile an analytical framework[33,34] based on multisource heterogeneous information fusion, which combines and capitalizes on all available information and applies an LSTM network equipped with attention mechanism to identify long-term temporal dependencies and adaptively highlight key features. The effectiveness of the model has been verified on several prediction tasks, including forecasting the next day's price direction and closing price and developing trading strategies.[35] In this study, research topic trend prediction is essentially time series prediction problem.

2.2 | Scientific research trend prediction

For scientific research trend prediction, people have done some exploration. Citation prediction has been widely studied. On the basis of the characteristics of highly cited papers, a regression model is deployed to study the interesting citation count prediction to test and predict the popularity of each literature in the future.[36] Li et al. establish a neural prediction model using the comprehensive semantic representation of peer-reviewed data to improve the prediction performance.[37] A GNN-based paper citation trend prediction model is proposed by using the information of cited literature (author, affiliation, and citation link), and the effectiveness of this framework is verified by a large number of experiments.[38] Prabhakaran et al. train the topic model and a rhetorical function classifier to map topic models onto their rhetorical roles which verify topic's rhetorical function is highly predictive of its eventual growth or decline.[39] Instead of topics, concepts are used to construct a model to predict ups and downs[40] taking rhetorical features into account. Balili et al. propose termball to track and predict the evolution of fine-grained topics according to the evolution types.[41] Termball constructs a weighted dynamic network of common keywords in articles through the term ball, and then finds the key topic structure and their relationships by performing community detection to predict the evolution types of topics. There are other aspects of scientific research related to the exploration of prediction. Users' actions across sessions are studied[42] to reveal correlations among various behavioral signals and build a specialized model for download prediction. A learning model was proposed[43] to predict the number of researchers' collaborators by fitting the evolution trend of the number of researchers' collaborators, the distribution of the variable and the probability of occurrence of cooperation events. Ruan et al. use a four-layer backpropagation (BP) neural network model[44] to predict the 5-year number of citations of 49,834 papers from 2000 to 2013.

The above methods predict different aspects of scientific research, but few studies are devoted to the prediction of trends of scientific research topics. This article aims to predict the topic of scientific research.

2.3 | Scientific influence modeling

Measuring the scientific influence is very important for the development of science and the allocation of resources.[45] Some scientific influence indicators, such as h-index,[12] h5-index,[46] and g-index,[47] have been proposed to evaluate the influence of scholars or journals. Zhu et al. introduced j-index[48] to model the topic level academic influence according to the novelty of each article and its contribution to the cited article. A novel method is proposed to quantify the higher-order citation influence of publications to quantify and visualize citation flows among disciplines, and to assess their degree of interdisciplinarity considering both direct and indirect citations.[49] Hu and Cao construct time-aware weighted graphs[50] to quantify the importance of links established at different times to fuse the rich information in a mutual reinforcement ranking framework to rank the future influence of multiobjects simultaneously. The above methods do not use the scientific influence to explore the topic prediction of future research trends, only a small number of studies have explored this topic. CONI model is proposed to integrate the scientific influence of the peer conferences to predict research topics of the conference. It is proved that peer conferences of a conference have an important influence on the future topic prediction of the conference. In fact, while publications affect other publications, they are also influenced by the themes of other publications. CONI does not fully consider the interaction among publications. Therefore, it is not sufficient to influence context acquisition.

3 | SCIENTIFIC RESEARCH TOPIC TREND PREDICTION BASED ON MLGCNs

In computer science discipline, the research topics of one publication will change with the development of other peer publications. The research topics of a publication in year $t+1$ should be predicted according to its own research topics and the research topics of peer publications before year $t+1$. LSTM encode publication research topics into a hidden state which is a dense and low-dimensional vector to represent the research interests of each publication. The research topics of different publications are different. When representing the research topics of each publication, we should distinguish the different publication' research topics by employing multiple LSTMs. At the same time, the research topics of the publications influence each other. When the research topics of one publication affect the topics of other publications, it is also influenced by the research topics of other publications. When modeling the scientific influence context of peer publications, the interactive influence of research topic among publications should be considered.

Thus, in this paper, we propose a scientific research topic trend prediction model based on multi-LSTM and GCNs. The research topic presentation of publications employs multiple LSTMs to differentiate the research topic of different publications. At the same time, the interaction among publications is modeled as a graph. GCN is deployed to integrate the interaction among publications to learn scientific influence context. In this way, the research topic of each publication not only integrates the influence of neighbor nodes, but also considers the influence of the neighbors of the neighbor node on the research topic of the publication, so as to more accurately integrate the scientific influence context of the research topic of peer publications. The scientific research topic trend prediction model is shown in Figure 1.

3.1 | Problem definition

For a certain research field, the research topics are the words that can fully reflect the research hotspot of the field. In this study, research topics are the words that are representative noun or adjective that appears frequently in papers of this field. For example, for research field i at year t, we collect the titles of all the papers of this study area and remove the stop words, and then use words with word frequency greater than one as research topics. For the collection of papers of n publications $P = \{p_1, p_2, ..., p_n\}$, p_i stands for a collection of papers of a publication. The definition of topic word set in this publication is $\{w_1, w_2, ..., w_j, ..., w_v\}$. One-hot embedding $p_i^t \in R^v$ is applied to represent the topic of publication p_i at year t $p_i^t = \{p_1^t, p_2^t, ..., p_j^t, p_v^t\}$, p_j^t represents the normalized word frequency of the topic word w_j, v is the vocabulary appearing in P. The calculation of p_i^t is as follows:

$$p_i^t = \frac{tf(w_j)}{\sum_{i=1}^{num} tf(w_i)}, \tag{1}$$

$tf(w_j)$ is the word frequency of topic word w_j in publication p_i, and num is the number of all the topic words of publication p_i.

Research topic prediction is to forecast future research topics based on historical observations. This can be formulated as a time series prediction problem as follows:

Given one-hot vector $f_i^t \in R^v$ and $f_i^{t+1} \in R^v$ which represent the research topic of f_i field at year t and year $t+1$. The topic prediction model is optimized by approximating the predicted topic distribution $\bar{f}_i^{t+1}$ to the target topic distribution f_i^{t+1}.

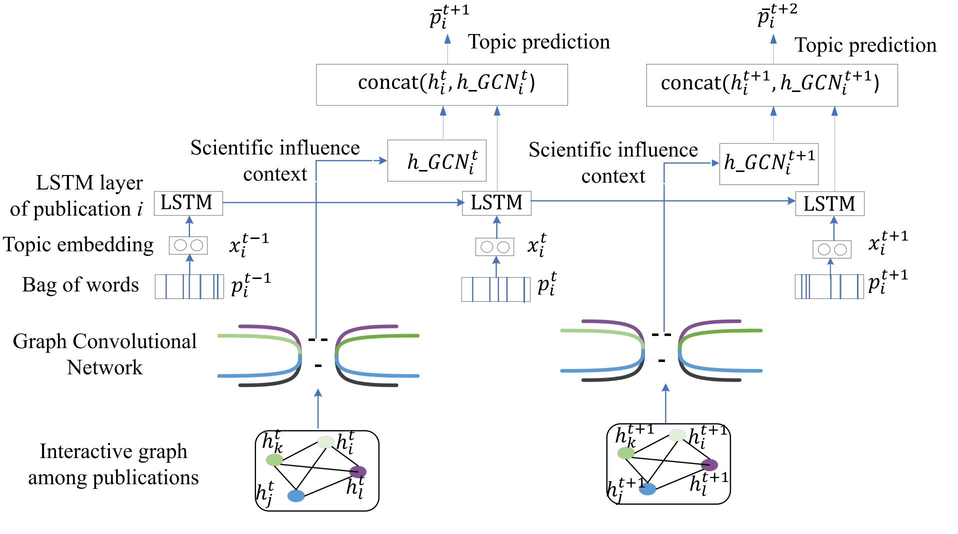

FIGURE 1 Scientific research topic trend prediction based on multi-LSTM and GCN. GCN, graph convolutional network; LSTM, long short-term memory [Color figure can be viewed at wileyonlinelibrary.com]

3.2 | Multi-LSTM-based sequential model of different publication's research topic

To track the research progress of each publication and differentiate the research topics' representation of different publications, multiple LSTMs are deployed to model the research topic sequence of different publications. It takes the research topics of the current time step as the input, iteratively encodes the research topics into a hidden state to capture the research topics of different publications. The sequences of all publications are modeled by multiple LSTMs chains sharing different parameters.

Suppose there are four publications: i, j, k, and l, taking i as an example. This paper introduces how our model updates research topics of different publications according to historical research topics. Given the research topics of publication i $p_i = \{p_i^1, p_i^2, ..., p_i^T\}$, p_i^t is the research topics of the tth year of publication i, $p_i^t \in R^v$. The word embedding matrix $\varnothing$ is employed to transform p_i^t into a dense low-dimensional vector to avoid the curse of dimensionality when the vocabulary size increases, where $\varnothing \in R_{d_w \times v}$. Research topics of the tth year of publication i is represented by x_i^t.

$$x_i^t = \Phi p_i^t, \tag{2}$$

where Φ is the word embedding matrix, $\Phi \in R^{d_w \times v}$, $x_i^t \epsilon R^{d_w}$.

Taking the research topics embedding x_i^t as the input, use standard Recurrent Neural Network (RNN) or other complex transformation functions like gated recurring unit (GRU)[51] and LSTM[52] to model research topic representation h_i^t of publication i at year t. In this paper, we choose LSTM because of its effectiveness.

$$h_i^t = LSTM\left(h_i^{t-1}, x_i^t\right). \tag{3}$$

The updating formula of the research topics is as follows:

$$h_i^t = \sigma\left(W_O\left[h_i^{t-1}, x_i^t\right] + b_o\right) * tanh\left(C_i^t\right), \tag{4}$$

$$C_i^t = f_i^t * C_i^{t-1} + r_i^t * \tilde{C}_i^t, \tag{5}$$

$$\tilde{C}_i^t = tanh\left(W_C \cdot \left[h_i^{t-1}, x_i^t\right] + b_c\right), \tag{6}$$

$$r_i^t = \sigma\left(W_r \cdot \left[h_i^{t-1}, x_i^t\right] + b_r\right), \tag{7}$$

$$f_i^t = \sigma\left(W_f \cdot \left[h_i^{t-1}, x_i^t\right] + b_f\right). \tag{8}$$

3.3 | Scientific influence context learning based on GCN

For a certain publication, its research topics will change with the influence of other peer publications' topics. Therefore, in addition to tracking research topics within publications, it is also necessary to calculate the scientific influence context of other peer publications on the evolution of the publication's topics. In this paper, the interactive influence of topics among publications is modeled as a graph, and the scientific influence context of peer publications is aggregated by deploying GCN. Given research topic representation of all publications at year th_i^t, h_j^t, h_k^t, h_l^t. We model it as a graph $G = (V, E)$, where V represents the vertex, that is, h_i^t, h_j^t, h_k^t, h_l^t, E stands for edge, which represents the interaction between publications' research topic.

The scientific influence context $h\_GCN_i^t$ of publication i which has aggregated research topic from other peer publications is calculated as follows:

$$H^{t(l+1)} = tanh\left(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}H^{t(l)}W\right), \tag{9}$$

$$h\_GCN_i^t = H_i^{t(l+1)}, \tag{10}$$

where l is the number of layers of GCN. At the beginning, $l = 0$. $H^{t(l)}$ is the network initialization matrix, which represents the research topic of all publications at year t, $H^{t(l)} \in R^{n*m}$, n represents the number of publications and m represents the dimension of the topic of each publication. The number of layers of GCN determines how far a node should fuse information from the network. When the number of layers of GCN is 1, each node can only fuse the information of neighbor nodes. When the number of layers of GCN increases by one, the neighbor nodes have fused their own neighbor information, which makes the representation of nodes more informative. $\tilde{A} = A + I$. A is the adjacency matrix represented by the research topic of different publications, $A \in R^{n \times n}$. A_{ij} represents the similarity between topic words of different publications, which is measured by the cosine similarity between topic words. If topic word i is similar to topic word j, $A_{ij} = 1$, otherwise $A_{ij} = 0$. $\tilde{D}$ is diagonal matrix. $\tilde{D}_{ii} = \sum_j \tilde{A}_{ij}$.

3.4 | Model training

The softmax function is employed to output the predicted distribution of research topic words $\bar{p}_i^{t+1}$ for publication i at the next time step $t + 1$. The hidden state h_i^t and the scientific influence context vector $h\_GCN_i^t$ are concatenated and fed to the softmax predictor as follows:

$$\bar{p}_i^{t+1} = softmax\left(W_O\left[h_i^t; h\_GCN_i^t\right] + b_o\right). \tag{11}$$

We use the generalization of multinomial logistic loss as the loss function, which minimizes the Kullback–Leibler divergence[53] between the predicted topic word distribution $\bar{p}_i^{t+1}$ and the target word distribution p_i^{t+1}.

$$loss = \sum_{s \in \{i,j,k,l\}} \sum_{t=1}^{T} KL\left(\bar{p}_s^{t+1} \| p_s^{t+1}\right), \tag{12}$$

$$KL\left(\bar{p}_s^{t+1} \| p_s^{t+1}\right) = \sum_j \bar{p}_{s,j}^{t+1} log \frac{\bar{p}_{s,j}^{t+1}}{p_{s,j}^{t+1}}. \tag{13}$$

The model is trained by minimizing the loss of research topic sequences of all publications. We use BP algorithm to optimize the parameters.

4 | EXPERIMENTS AND RESULTS ANALYSIS

4.1 | Data preprocessing and experiments settings

We collect two data sets including AI area and DM area of computer science from DBLP.[†] The publication year of both data sets is from 2007 to 2020. We select six top conferences, including AAAI, ACL, CVPR, SIGIR, WWW, and ICML, with a total of 55,064 papers in AI area. Five top conferences in DM area including ICDM, SDM, KDD, ICDE, and CIKM are selected, with a total of 23,016 papers. Each paper contains the title, publication time, and venue. To further process the data, we crawl the abstract of each paper as a collection of candidate papers.

The title of a paper can best reflect the topic of a paper. So, we only use the title of each paper as the text to extract topic words to train the topic prediction model. Specifically, stopwords removal is applied on the candidate papers. Then, the frequency of every word appearing in each publication is counted. For conference i at year t, we treat the title word which occurs more than once in conference i of this year as the research topic word. For conference i at year t, we treat the title word which occurs more than once in conference i of this year as the research topic word.

The word embeddings are pretrained based on the candidate papers. The implementation of word2vec[‡] is employed. In particular, we employ skip-gram with the dimension set to be 100, window size to be 5, minimum count to be 5, and a subsampling threshold of 10^{-2}. The skip-gram model is trained for five iterations on the target corpus.

We treat the data of the first 2007–2019 as training set and the 2020 years' papers as testing set. In the process of training the model, we use the conference's research topics from 2007 to 2018 to predict the conference's research topics of 2019 to train the research topic prediction model MLGCN. The proposed network is implemented based on PyTorch framework. Adam optimizer is used to train the network. We adopt dropout technology to prevent overfitting. The other parameters are set for their best performances in experiments.

4.2 | Baseline methods

We compare our method with classical time series prediction method ARIMA,[54] research topic prediction method based on RNN LSTM, GRU, research topic prediction method based on encoder–decoder ENDE,[55] TEMPATT,[29] DARNN,[28] DSTP,[30] research topic prediction method based on CONI modeling.[22]

ARIMA: ARIMA is a widely used time series prediction method. For each research area, the frequency dynamics of each topic word at each year is regarded as the time series and the ARIMA individually predicts the frequency of each word at the next year.

LSTM: The topic prediction model based on LSTM models the research topic of every year of each area into time series and uses gated units to capture long-term dependencies in the process of topic prediction.

GRU: The topic prediction model based on GRU merges different gated units of LSTM, and also combines the cell state and the hidden state, which leads to fewer parameters and easy convergence and is suitable for scenarios with smaller amounts of data.

ENDE: This method is originally used for machine translation, and we deploy it to predict research topic of different areas. It encodes area research topics into fixed-length vectors, and the decoder is responsible for predicting future research topic.

TEMPATT: On the basis of the encoder–decoder method, temporal attention mechanism is employed on the hidden states of the encoder to learn more robust temporal relationships.

DARNN: DARNN is a dual-stage attention-based RNN encoder–decoder for single-step time series prediction. It employs multilayer perceptron as attention to capture spatial correlations and long-term dependencies.

DSTP: The basic structure of DSTP is similar to DARNN, but it involves an additional phase of attention so as to process the exogenous series and the target series separately.

CONI: CONI modeling that can integrate the scientific influence of the peer publications and jointly model the topic evolution of all peer publications in a unified RNN framework. In the implementation of CONI, we also use LSTM to model the topic time series of different publications.

4.3 | Evaluation metrics

To evaluate the prediction performance of the proposed model MLGCN, we use the following metrics:

(1) Root Mean-Squared Error (RMSE)[56]: RMSE is the root mean-squared error on the test set.

$$RMSE = \sum_{i=1}^{m}\sum_{t=1}^{T} p_i^t - p_i^t. \tag{14}$$

(2) Precision@n (abbreviated as P@n): In the predicted n topic words, the correct probability of prediction. Where, tr is the number of topic words predicted correctly and fr is the number of topic words predicted incorrectly.

$$P@n = tr/tr + fr. \tag{15}$$

4.4 | Experiment results and analysis

4.4.1 | Comparison of different prediction models

In this section, we give the precision of topic prediction of MLGCN and baseline methods in AI area and DM area (Precison@10, Precison@20, Precison@40, Precison@60, Precison@80, and Precison@100) which is the average precision of all the conferences in the area. At the same time, the average RMSE of MLGCN and baseline methods in both areas are also reported which is the average RMSE of all the conferences in the area. The topic prediction precision and RMSE of the two areas are shown in Tables 1 and 2.

Tables 1 and 2, respectively, show the precision and RMSE of baseline methods and MLGCN in AI and DM areas. Experimental results show that for AI area, MLGCN achieves the best topic prediction performance. The prediction precision of the prediction method based on RNN and the prediction method based on encoder–decoder is not as good as the classic topic

TABLE 1 Topic prediction precision in AI area

Model	P@10	P@20	P@40	P@60	P@80	P@100	RMSE
ARIMA	0.5333	0.5833	0.6083	0.6306	0.6271	0.6333	0.6430e−3
GRU	0.5167	0.5083	0.5333	0.5444	0.5250	0.5450	0.4546e−3
LSTM	0.5500	0.5250	0.5625	0.5667	0.5958	0.5817	0.4033e−3
ENDE	0.5000	0.5250	0.5500	0.5694	0.5875	0.5933	0.4124e−3
TEMPATT	0.5333	0.5167	0.5250	0.5278	0.5521	0.5650	0.4534e−3
DARNN	0.5000	0.5250	0.5917	0.5472	0.5396	0.5750	0.4254e−3
DSTP	0.5167	0.5667	0.5750	0.5944	0.6125	0.6250	0.3818e−3
CONI	0.5000	0.5417	0.5417	0.5361	0.5500	0.5767	0.4701e−3
MLGCN	0.7500	0.7500	0.7417	0.7472	0.7375	0.7467	0.3002e−3

Abbreviations: AI, artificial intelligence; ARIMA, AutoRegressive Integrated Moving Average; CONI, Correlated Neural Influence; DARNN, dual-stage attention-based Recurrent Neural Network; DSTP, dual-stage two-phase; ENDE, encoder–decoder; GRU, gated recurring unit; LSTM, long short-term memory; MLGCN, multi-LSTM and graph convolutional network; P@10, Precison@10; RMSE, root mean-squared error; TEMPATT, temporal attention.

TABLE 2 Topic prediction precision in DM area

Model	P@10	P@20	P@40	P@60	P@80	P@100	RMSE
ARIMA	0.4333	0.4583	0.5333	0.5195	0.5104	0.4817	0.6584e−3
GRU	0.5200	0.5700	0.6600	0.6367	0.5750	0.5460	0.4331e−3
LSTM	0.5800	0.5800	0.5950	0.6133	0.6050	0.5680	0.3649e−3
ENDE	0.5000	0.5500	0.6150	0.6100	0.5875	0.5820	0.4606e−3
TEMPATT	0.5800	0.5700	0.5850	0.6000	0.5450	0.5160	0.5632e−3
DARNN	0.5600	0.5800	0.5850	0.5967	0.5575	0.5400	0.6144e−3
DSTP	0.5000	0.5500	0.6000	0.6100	0.5900	0.5640	0.4594e−3
CONI	0.5200	0.5500	0.6100	0.5967	0.5750	0.5560	0.4685e−3
MLGCN	0.7800	0.7100	0.7050	0.7100	0.6675	0.6580	0.3430e−3

Abbreviations: ARIMA, AutoRegressive Integrated Moving Average; CONI, Correlated Neural Influence; DARNN, dual-stage attention-based Recurrent Neural Network; DM, data mining; DSTP, dual-stage two-phase; ENDE, encoder–decoder; GRU, gated recurring unit; LSTM, long short-term memory; MLGCN, multi-LSTM and graph convolutional network; P@10, Precison@10; RMSE, root mean-squared error; TEMPATT, temporal attention.

prediction method ARIMA. For DM area, the prediction precision of the method based on RNN and the method based on encoder–decoder exceeds ARIMA. The topic prediction model MLGCN still obtains the best prediction effect. It shows that our topic prediction method MLGCN is robust.

Next, we report the change curve of precision (Precison@10, Precison@20, Precison@40, Precison@60, Precison@80, and Precison@100) of baseline methods and MLGCN in AI and DM areas with the increasing number of iterations. For each research area, the topic prediction precision is the average value of the topic prediction precision of all conferences in the area.

The change curve of precision (Precison@10, Precison@20, Precison@40, Precison@60, Precison@80, and Precison@100) of AI and DM areas with the increasing number of iterations is shown in Figures 2 and 3. At the same time, as the number of iterations increases, the average RMSE of baseline methods and MLGCN of AI and DM areas are also reported. The change curve of RMSE of AI and DM areas with the increasing number of iterations is shown in Figure 4.

Figures 2 and 3 show the change curve of precision of AI and DM areas with the increasing number of iterations. As can be seen from Figures 2 and 3, at the beginning of model training, the topic prediction precision of each model shows a trend of rapid improvement. When the number of iterations reaches a certain number, the topic prediction precision of MLGCN is still improving, while the precision of other prediction models is stable. It can be concluded that MLGCN has higher prediction precision compared with baseline methods.

Figure 4 shows the change of the average RMSE of each topic prediction model in AI and DM areas with the increase of the number of iterations. It can be seen from Figure 4 that with the increase of the number of iterations, the average RMSE of each model of both areas shows a downward trend, and the RMSE of MLGCN decreases the fastest. It shows that MLGCN has a good performance in topic prediction.

4.4.2 | Comparison of MLGCN with two of its variants

In this section, to further validate the effectiveness of MLGCN, we compare MLGCN with its two variants as follows.

(1) *MLGCN-ML*: To evaluate the impact of GCN on model performance, we evaluated MLGCN-ML, a variant of MLGCN, which uses only one LSTM to model the topic

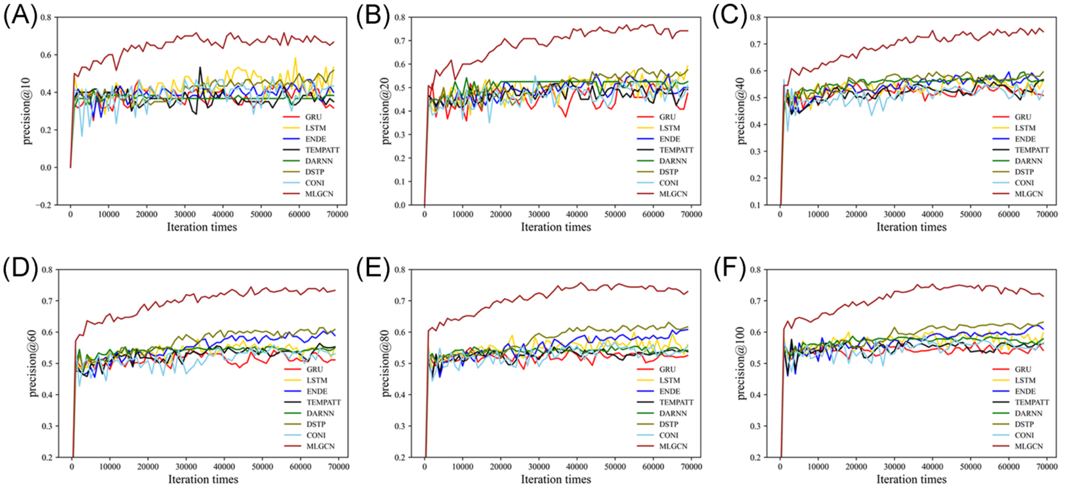

FIGURE 2 The change curse of precision of different prediction models in AI area. (A) Precision@10, (B) Precision@20, (C) Precision@40, (D) Precision@60, (E) Precision@80, and (F) Precision@100. AI, artificial intelligence; CONI, Correlated Neural Influence; DARNN, dual-stage attention-based Recurrent Neural Network; DSTP, dual-stage two-phase; ENDE, encoder–decoder; GRU, gated recurring unit; LSTM, long short-term memory; MLGCN, multi-LSTM and graph convolutional network; TEMPATT, temporal attention [Color figure can be viewed at wileyonlinelibrary.com]

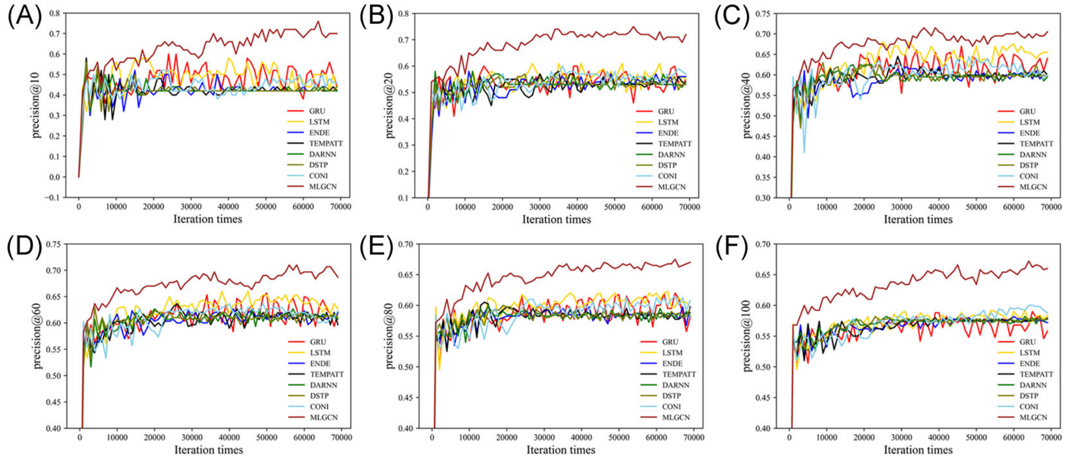

FIGURE 3 The change curse of precision of different prediction models in DM area. (A) Precision@10, (B) Precision@20, (C) Precision@40, (D) Precision@60, (E) Precision@80, and (F) Precision@100. CONI, Correlated Neural Influence; DARNN, dual-stage attention-based Recurrent Neural Network; DM, data mining; DSTP, dual-stage two-phase; ENDE, encoder–decoder; GRU, gated recurring unit; LSTM, long short-term memory; MLGCN, multi-LSTM and graph convolutional network; TEMPATT, temporal attention [Color figure can be viewed at wileyonlinelibrary.com]

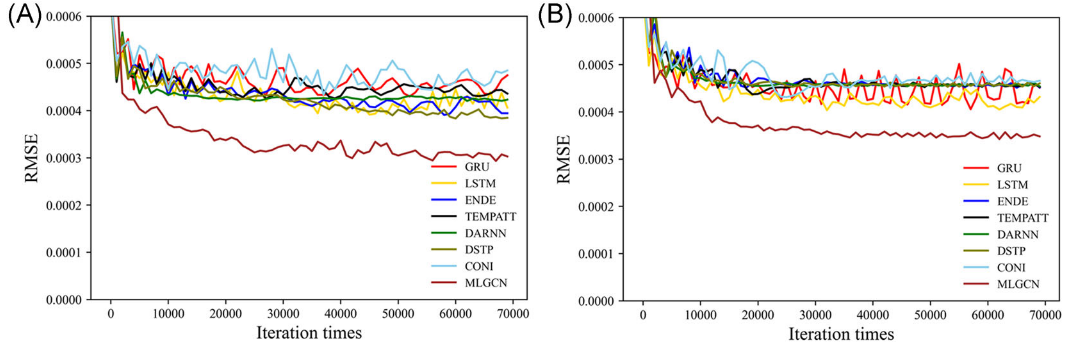

FIGURE 4 The change curse of RMSE of different prediction models. (A) AI area and (B) DM area. AI, artificial intelligence; CONI, Correlated Neural Influence; DARNN, dual-stage attention-based Recurrent Neural Network; DM, data mining; DSTP, dual-stage two-phase; ENDE, encoder–decoder; GRU, gated recurring unit; LSTM, long short-term memory; MLGCN, multi-LSTM and graph convolutional network; RMSE, root mean-squared error; TEMPATT, temporal attention [Color figure can be viewed at wileyonlinelibrary.com]

representation of multiple conferences which share the same parameters, and uses GCN to integrate the research topic of each conference to model science influence context.

(2) *MLGCN-GCN*: To evaluate the impact of multiple LSTMs on model performance, we designed a variant of MLGCN named MLGCN-GCN, which uses multiple different LSTMs to model the research topic of different conferences. The method of scientific influence context learning is similar to CONI.[22]

We give the precision of topic prediction (Precison@10, Precison@20, Precison@40, Precison@60, Precison@80, and Precison@100) of MLGCN and two of its variants (MLGCN-ML and MLGCN-GCN) in AI and DM areas. The precision is the average precision of all the conferences in the area. At the same time, the average RMSE of MLGCN and two of its variants in both areas are also reported which is the average RMSE of all the conferences in the area. The topic prediction precision and RMSE of the two areas are shown in Tables 3 and 4.

Tables 3 and 4, respectively, show the precision and RMSE of MLGCN and two of its variants in AI and DM areas. Experimental results show that the performance of both MLGCN-GCN and MLGCN-ML is worse than that of MLGCN. MLGCN-ML applies GCN to fuse peer conferences' research topic to capture each conference's scientific influence context. But it does not consider that the presentation of research topics of different conferences is different. MLGCN-GCN employs multiple LSTMs to distinguish research topics of different conferences by embedding them into the hidden space. MLGCN not only uses multiple LSTMs to distinguish the research topic of different conferences, but also models different conferences' topic representation as graphs, which better captures the influence context of different conferences' topics. Therefore, MLGCN obtained the best prediction effect. Furthermore, the experimental results show that the precision of MLGCN-GCN's research topic prediction is better than that of MLGCN-ML. This shows that deploying different LSTMs to model different research topic representations is more important for research topic prediction effects.

Furthermore, we found that the prediction precision of MLGCN-GCN in AI area is higher than that of MLGCN-ML, while the prediction precision of MLGCN-GCN in DM area is lower than that of MLGCN-ML. It shows that whether it is MLGCN-GCN or MLGCN-ML, its predictive effect is unstable. However, MLGCN reaches the best topic prediction effect in both areas. It shows that MLGCN has stable topic prediction ability. MLGCN first employs multiple LSTMs to capture research topic for each publication by embedding them into the hidden space. Then, GCN is applied to learn the scientific influence context of each conference, so that the research topic of each conference not only integrates the influence of neighbor nodes, but

TABLE 3 Performance comparison of MLGCN with two of its variants in AI area

Model	p@10	p@20	p@40	p@60	p@80	p@100	RMSE
MLGCN-GCN	0.7000	0.6417	0.6625	0.6750	0.6896	0.6917	0.3192e−3
MLGCN-ML	0.5500	0.6333	0.6375	0.6444	0.6479	0.6633	0.3573e−3
MLGCN	0.7500	0.7500	0.7417	0.7472	0.7375	0.7467	0.3002e−3

Abbreviations: AI, artificial intelligence; GCN, graph convolutional network; LSTM, long short-term memory; ML, machine learning; MLGCN, multi-LSTM and graph convolutional network; P@10, Precison@10; RMSE, root mean-squared error.

TABLE 4 Performance comparison of MLGCN with two of its variants in DM area

Model	p@10	p@20	p@40	p@60	p@80	p@100	RMSE
MLGCN-GCN	0.6600	0.6700	0.6300	0.6333	0.6250	0.5960	0.4214e−3
MLGCN-ML	0.6400	0.6700	0.6850	0.6500	0.6400	0.6120	0.3981e−3
MLGCN	0.7800	0.7100	0.7050	0.7100	0.6675	0.6580	0.3420e−3

Abbreviations: DM, data mining; GCN, graph convolutional network; LSTM, long short-term memory; ML, machine learning; MLGCN, multi-LSTM and graph convolutional network; P@10, Precison@10; RMSE, root mean-squared error.

also considers the influence of the neighbors of the neighbor node on the research topic of the conference. Lastly, according to the combination vector of the hidden state of the conference and the scientific influence context, the topic prediction model produces the distribution of all topic words in the next time step. Therefore, our topic prediction model not only models research topic of different research areas, but also considers the interactive influence among publications to model one publication's scientific influence context.

Next, we report the change curve of precision of MLGCN and two of its variants in AI and DM areas with the increasing number of iterations. For each research area, the topic prediction precision is the average value of the topic prediction precision of all conferences in the area. The change curve of precision in AI and DM areas with the increasing number of iterations is shown in Figures 5 and 6. At the same time, as the number of iterations increases, the average RMSE of MLGCN and two of its variants in AI and DM areas are also reported. The change curve of RMSE of AI and DM areas with the increasing number of iterations is shown in Figure 7.

Figures 5 and 6 show the change curve of precision of MLGCN and two of its variants in AI and DM areas with the increasing number of iterations. As can be seen from Figures 5 and 6, the topic prediction precision of MLGCN has higher prediction precision compared with two of its variants.

Figure 7 shows the change of the average RMSE of MLGCN and two of its variants in AI and DM areas with the increase of the number of iterations. It can be seen from Figure 7 that the average RMSE of MLGCN is lower compared with two of its variants. This further illustrates the effectiveness of our topic prediction method.

4.4.3 | Influence of GCN layers on topic prediction results

GCN can obtain the topic influence context of peer publications of graph using the convolution operation. The number of convolutional layers determines the quality of the scientific influence

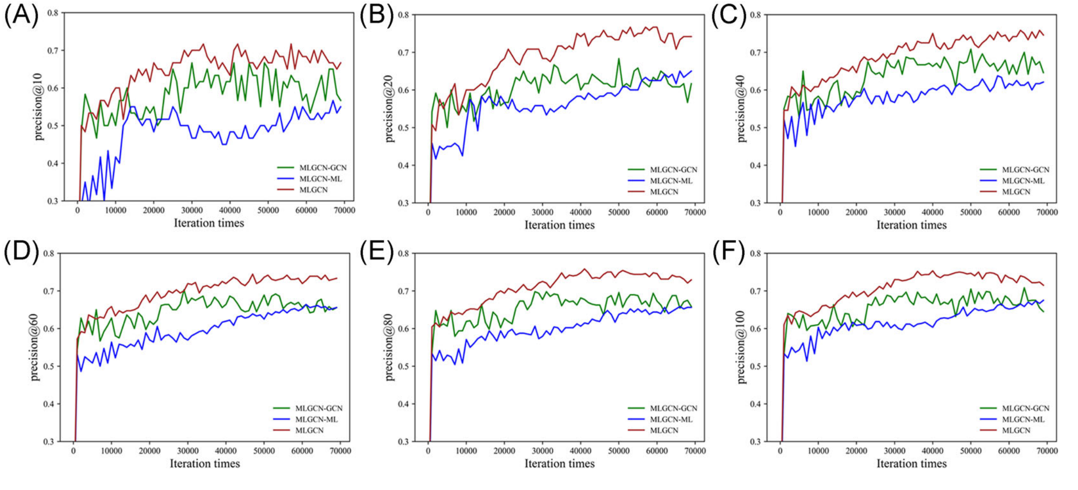

FIGURE 5 The change curse of precision of our model with two of its variants in AI area. (A) Precision@10, (B) Precision@20, (C) Precision@40, (D) Precision@60, (E) Precision@80, and (F) Precision@100. AI, artificial intelligence; GCN, graph convolutional network; LSTM, long short-term memory; ML, machine learning; MLGCN, multi-LSTM and graph convolutional network [Color figure can be viewed at wileyonlinelibrary.com]

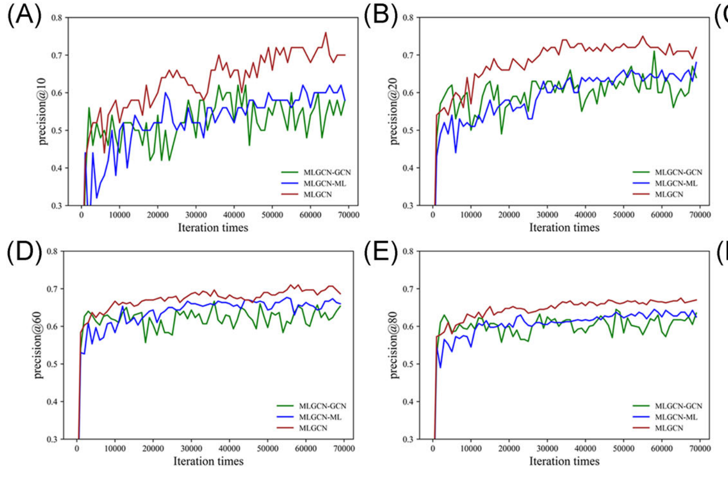

FIGURE 6 The change curse of precision of MLGCN and two of its variants in DM area. (A) Precision@10, (B) Precision@20, (C) Precision@40, (D) Precision@60, (E) Precision@80, and (F) Precision@100. DM, data mining; GCN, graph convolutional network; LSTM, long short-term memory; ML, machine learning; MLGCN, multi-LSTM and graph convolutional network [Color figure can be viewed at wileyonlinelibrary.com]

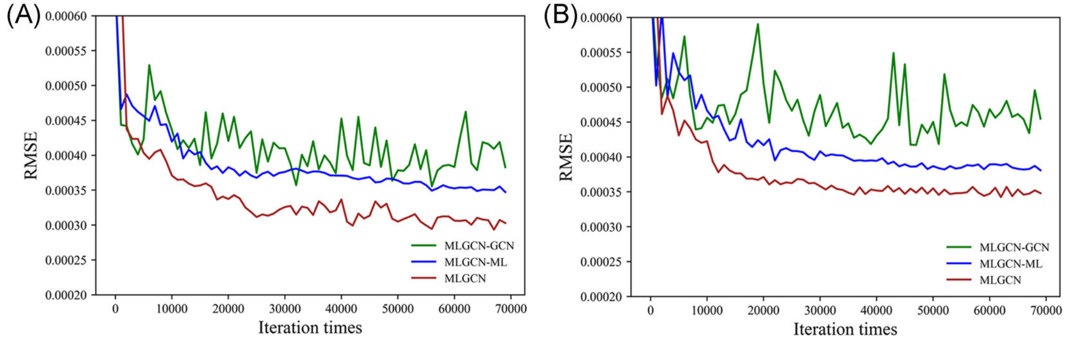

FIGURE 7 The change curse of RMSE of MLGCN and two of its variants. (A) AI area and (B) DM area. AI, artificial intelligence; DM, data mining; GCN, graph convolutional network; LSTM, long short-term memory; ML, machine learning; MLGCN, multi-LSTM and graph convolutional network; RMSE, root mean-squared error [Color figure can be viewed at wileyonlinelibrary.com]

context of a publication obtains. In the experiments, we set the number of GCN layers to be 1, 2, 3 and give the prediction precision of the model. The experimental results are shown in Tables 5 and 6.

The experimental results show that when the number of GCN layers is 2, the topic prediction effect is the best. When the number of GCN layers is 2, it shows that the scientific influence context of a publication not only integrates the topic information of neighbor nodes, but also the topic information of neighbors' neighbors. These experimental results are consistent with the discussion of the number of layers of GCN[50,57] that the number of GCN layers is best setted to be 2–3 and too deep GCN will cause the precision to drop due to excessive smoothing.[51,58]

TABLE 5 The experimental results of different layer numbers of GCN in AI area

Num. of GCN layers	p@10	p@20	p@40	p@60	p@80	p@100	RMSE
1	0.6833	0.6500	0.6917	0.7000	0.7000	0.7067	0.0003324
2	0.7500	0.7500	0.7417	0.7472	0.7375	0.7467	0.0003002
3	0.7500	0.7333	0.7417	0.7167	0.7313	0.7267	0.0003109

Abbreviations: AI, artificial intelligence; GCN, graph convolutional network; P@10, Precison@10; RMSE, root mean-squared error.

TABLE 6 The experimental results of different layer numbers of GCN in DM area

Num. of GCN layers	p@10	p@20	p@40	p@60	p@80	p@100	RMSE
1	0.6800	0.6800	0.6950	0.6833	0.6375	0.6240	0.0003590
2	0.7800	0.7100	0.7050	0.7100	0.6675	0.6580	0.0003420
3	0.7600	0.7100	0.7000	0.7033	0.6650	0.6580	0.0003796

Abbreviations: DM, data mining; GCN, graph convolutional network; P@10, Precison@10; RMSE, root mean-squared error.

TABLE 7 Predicted top 10 research topics of AI area in 2020

Conference	Predicted research topic	True research topic
AAAI	Learning, neural, deep, detection, network, image, generation, attention, data, reinforcement	Learning, generation, detection, network, neural, image, deep, abstract, graph, attention
ACL	Neural, learning, data, language, word, embeddings, generation, text, machine, semantic	Neural, language, learning, translation, generation, machine, text, model, knowledge, graph
CVPR	Learning, deep, image, adversarial, network, neural, detection, attention, video, object	Learning, image, detection, network, deep, video, object, recognition, segmentation, semantic
ICML	Learning, graph, deep, detection, neural, network, data, attention, gradient, optimization	Learning, neural, network, deep, graph, detection, data, gradient, optimization, reinforcement
SIGIR	Search, information, retrieval, recommendation, learning, neural, cross, text, data, query	Recommendation, learning, search, cross, retrieval, graph, information, ranking, neural, network
WWW	Data, social, web, learning, neural, search, network, query, online, recommendation	Learning, graph, search, generation, neural, data, network, social, recommendation, web

Abbreviations: AAAI, Association for the Advancement of Artificial Intelligence; ACL, Association for Computational Linguistics; AI, artificial intelligence; CVPR, Computer Vision and Pattern Recognition; ICML, International Conference on Machine Learning; SIGIR, Special Interest Group on Information Retrieval; WWW, World Wide Web.

TABLE 8 Predicted top 10 research topics of DM area in 2020

Conference	Predicted research topic	True research topic
CIKM	Learning, network, neural, deep, graph, data, embedding, recommendation, prediction, knowledge	Learning, graph, network, knowledge, data, embedding, neural, prediction, search, detection
ICDE	Data, efficient, attention, network, search, query, graph, learning, processing, approach	Data, efficient, network, graph, learning, approach, query, processing, online, spatial
ICDM	Learning, data, mining, deep, detection, mining, time, series, network, prediction	Learning, graph, data, network, detection, deep, series, neural, time, mining
KDD	Learning, data, machine, search, prediction, knowledge, deep, detection, network, graph	Learning, data, graph, machine, deep, neural, network, knowledge, model, search
SDM	Dynamic, spatial, learning, data, mining, detection, optical, system, classification, network	Dynamic, spatial, network, learning, deep, data, time, series, optical, system

Abbreviations: CIKM, Conference on Information and Knowledge Management; DM, data mining; ICDE, International Council for Distance Education; ICDM, International Conference on Data Mining; KDD, Knowledge Discovery in Databases; SDM, SIAM International Conference on Data Mining.

4.5 | Case STUDY: Topic trend prediction of each conference

In this section, we use the topic prediction model MLGCN to predict the research topic of AI area including six top conferences and DM area including five top conferences in 2020 and gives the true topic words in 2020. As shown in Tables 7 and 8, it can be seen that MLGCN has high precision in topic prediction compared with the real topic in eleven top conferences in 2020.

5 | CONCLUSIONS

Aiming at the problem of predicting the trend of research topic in computer science discipline, this paper proposes a scientific research topic trend prediction model based on multi-LSTM and GCN. On the basis of the LSTM topic sequence modeling method, we employed multi-LSTM to map the research topic of different publications to their respective topic space to distinguish the research topic of different publications. Taking into the interactive scientific influence among publications account, a scientific influence context learning method based on graph convolutional neural network is proposed. The topic of different publications is modeled as graph, and GCN is deployed to obtain the scientific influence context of peer publications. Finally, combine the research topic representation and the scientific influence context vector to predict future research topic trend of publications. The experimental results on AI and DM area of compauter science discipline including 11 top conferences demonstrate the effectiveness of our proposed model MLGCN. A case study based on research topic of AI area including six top conferences and DM area including five top conferences in 2020 is used to show that MLGCN has high topic prediction precision and robust topic prediction ability compared with the real topics of the conferences.[57,58]

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ENDNOTES

* https://github.com/xumingying0612?tab=repositories.

† https://dblp.org/.

‡ https://code.google.com/p/word2vec/.

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