

Retraction

Retracted: Research on Application Effective Evaluation of Artificial Intelligence Technology in Marketing Communication

Security and Communication Networks

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.


The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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- [1] L. Mo and L. Yang, "Research on Application Effective Evaluation of Artificial Intelligence Technology in Marketing Communication," *Security and Communication Networks*, vol. 2022, Article ID 3507353, 8 pages, 2022.

Research Article

Research on Application Effective Evaluation of Artificial Intelligence Technology in Marketing Communication

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In order to solve the current problems of ignoring individual user differences, rising marketing costs, and customer churn in the crude marketing process, we combine deep machine learning technology and the long-term operational experience of Media Network Co. deep learning. By extracting features from the network data in image format, DNSI can obtain three kinds of neighbor structure influence. The optimal graph theory approach is used to construct user intelligence graphs, and then deep machine learning techniques are used to achieve accurate marketing in combination with different scenarios. Experimental results on several real-world network data sets for tasks such as node attribute prediction, category centrality measure, and user behavior prediction show the superiority of the model in most cases.

1. Introduction

With the gradual integration of the three networks, broadcasters have entered the market competition from the traditional monopoly industry, and the operation mode has gradually started to rely on data from simply relying on licensing resources to personalization and refinement [1]. The traditional reliance on licenses for content provision lacks an understanding of the market and customers, and users are in a passive state of content reception. Moreover, the marketing strategies in many scenarios are crude and nonaccurate marketing, which do not take into account the differentiated characteristics of individual users, and therefore tend to produce a series of undesirable results such as rising marketing costs, declining marketing revenue, declining marketing efficiency, and declining user experience [2]. On the other hand, since the Internet, OTT (over the top), IPTV (interactive network TV), and other business service forms have brought a huge impact on traditional interactive TV and grabbed part of the market share. Interactive TV operators will consider how to apply the

existing big data technology to users' social attributes, on-demand behavior, payment behavior, etc. Therefore, interactive TV operators consider how to use the existing big data technology to interpret the social attributes, on-demand behavior, and payment behavior of subscribers to better sample the whole business picture of subscribers and start to introduce intelligent user mapping to provide personalized products and content to subscribers and make predictions about subscribers, so as to maintain customers more accurately [3, 4].

The evolution of the business concept needs to be supported by massive data on the one hand, and various data technologies to complete the processing of the data to extract the core from data of subscribers on the other. Therefore, the urgent issues that broadcasters need to solve at this stage are the integration of massive internal and external data, the modeling of intelligent user graphs, and the use of deep machine learning for user prediction [5].

The explosive growth of massive internet user interaction data contains huge research value and commercial value, and it has become a hot spot for many researchers to

analyze and fully explore social networks to reveal the laws behind the data [6].

Social network analysis is a technique that has been developed in recent years to study complex networks [7]. From bacteria, cells, and protein systems to family and friendship relationships in human societies, to collaborative relationships between researchers, to citation relationships between papers, to large online social networks, to hyperlinks on web pages, all of them constitute some kind of complex network systems. Social network analysis not only can analyze the characteristics of the network as a whole but also can analyze the implicit connection within the network to discover the knowledge that humans cannot discover intuitively [8]. An important piece of information in these complex end systems is the topological properties of the network itself. Link prediction between nodes in social networks, such as association structure detection, can help reveal the hierarchical structure of complex network systems and provide a comprehensive and thorough analysis of the social relationships between nodes. On the other hand, the research on social networks has also promoted the development of advertising recommendation and precision marketing, which can help alleviate the problems of data sparsity and cold start in the recommendation and marketing systems by using the social network among users for collaborative filtering. It is important to improve the performance of traditional recommendation and marketing systems by using social networks to efficiently and concisely represent the valuable information in the topology of social networks [9].

Precise marketing is a salesperson-centered approach that uses electronic media and other means to retrieve a customer database and then, through scientific analysis, divides customers into finer-grained groups, analyzes customer values, finds potential customers for specific groups, takes corresponding marketing measures, and conducts marketing activities. In the marketing process, we analyze the user's attributes, groups, and group characteristics to determine the consumers who are likely to buy, so that we can guide the sellers to change the sales strategy and convey the appropriate marketing information to the more accurate audience groups, which can make the product marketing strategy more accurate and effective [10]. User profiling technology collects information about users' social attributes, habits, and consumption preferences and abstracts a labeled user model from them. This user model can effectively improve marketers' identification and discovery of target customers, reduce unnecessary costs in the marketing process, and improve users' marketing experience. For example, in social networks such as Weibo and Facebook [11], one way is to infer the attributes of unknown users through known friends and some users with known attributes and further obtain the influence of users in different attribute categories, so as to use users with high influence in the network for efficient marketing; another way is to predict a user's future behavior, targeted for personalized marketing, and so on [12].

Meanwhile, deep learning algorithms promote the implementation of automatic feature extraction, and in this

paper, the network is studied by combining CNN [13]. Since the direct input of the neighbor structure into CNN for processing will greatly reduce the operational efficiency and CNN is more adapted to process image data, the neighbor structure data can be converted to the format of images to improve the speed of CNN for data processing.

The main contributions of this paper include:

- (1) We propose a network neighbor structure influence model DNSI (neighbor structure influence based on deep learning) combined with deep learning CNN and obtain the influence size of three neighbor structures in the network by automatic feature extraction
- (2) The neighbor structure data are converted into a style that is convenient for CNN to process the network data, that is, the three neighbor structure matrix data under different categories of nodes in the network are converted into pixel values of pictures and input to CNN for batch processing
- (3) The influence of the three neighbor structures is obtained from the model DNSI, and the node attribute prediction, category centrality measure, and user behavior prediction are performed on the real-world network data set, and it is demonstrated that the model can improve the correct prediction rate in most cases

2. Related Work

An important aspect of social network analysis is to discover similar users, similar products, and so on, that is, to discover similar nodes, and network node similarity analysis has been a hot area of research and is also the basis for marketing and recommendation activities based on social network analysis [14]. Due to the importance of similarity metrics, this problem has been studied for a long time and can be roughly divided into two categories: eigenvalue-based methods and link-based methods, traditional methods of similarity metrics such as a k-nearest neighbor, Simrank, and similarity metrics based on the symmetric semantic meta-paths Path sim3, similarity metrics based on symmetric random wandering of meta-paths Hetesim [15], and other link-based methods.

In response to the situation that users in social networks will selectively provide personal information, [16] proposed the method of mapping friend relationships to Bayesian networks, and the conditional probability of predicting as each attribute can be obtained by inferring the user attributes through known prior probabilities. And [17] incorporates the user's social relationships on this basis, pointing out that different social relationships can infer different attributes. Literature [18] extended the social relations to infer user attributes by visible group information. Besides, [19] proposed an algorithm for inferring user attributes based on community discovery, which can be applied to online social networks, with the algorithmic idea that users with the same attributes are more likely to form community groups with higher aggregation.

The K-kernel decomposition algorithm proposed by [20] defines the magnitude of influence by stratifying all nodes in the network from the core to the edge. And [21] proposed through their study that the H-index (a metric for evaluating the influence of journals or authors) has a similar effect on the K-kernel in measuring the influence of nodes. The analysis of user behavior in social networks first appeared in the fields of complexity science, statistical physics, and so on, as [22] conducted a review of research on human behavior characteristics. The DeepWalk algorithm [4], inspired by natural language processing, converts a network into a series of “sentences” by randomly selecting nodes and edges in the network, where words The LINE model [23], based on DeepWalk, incorporates the neighbor structure of nodes and proposes two types of similarities in the network.

The use of user profiles to support refined marketing can reduce marketing costs, improve the success rate of sales, and provide personalized services to enhance the customer experience. The data generated by the bank’s daily business include a large amount of transaction data, and the bank’s financial product marketers need to sift through a large amount of transaction data and customer information to find out the target customers for marketing activities. Traditional screening methods based on data tables or databases do not visually show the attributes of customers and are time-consuming and difficult for marketers to develop marketing strategies for individual customers.

3. User Profiling and Precision Marketing

3.1. Precision Marketing. Precision marketing, belonging to the scope of marketing activities, emphasizes the organic unity of accurate potential target customer discovery and targeted communication methods, marketing content, and marketing conversion rate improvement.

With the gradual development of the Internet, the network has stepped into the era of information overload. The Internet is filled with a large amount of. Redundant information makes it more difficult for users to find the information they want. Accordingly, the cost of marketing activities to improve the conversion rate of customers has become more and more expensive and very difficult. Therefore, personalized precision marketing is becoming one of the most important means for enterprises to effectively improve the level of marketing input and output, enhance the overall value contribution of sales business, and improve user experience [24]. In marketing activities, the most concerned customers are broadly divided into two categories:

- (1) Existing customers: From the information of existing customers, information such as the value of the user, the customer’s purchase preference for existing products, the user’s information receiving channel, and the degree of matching between the product and the customer can be extracted.
- (2) Potential customers: Potential customers are the target customers of marketing activities, and it is necessary to portray as much information as possible

about the user’s preferences, consumption habits, whether the purchase intention is strong, and so on so that marketers can easily discover potential customers and determine the marketing plan.

3.2. User Profiling. In order to further explore the potential business value of user-related data, the user profile was born. User profiling as shown in Figure 1, that is, the labeling of various user attributes, aims to abstract as comprehensively as possible the full picture of a user’s information that is important for enterprises to carry out marketing activities, providing the basis for rapid and accurate analysis of user consumption habits, describing user consumption needs and discovering important information such as the user’s potential consumption intentions [25]. First, we collect all relevant data of customers. For example, relatively stable static data such as gender, region, age, consumption level, and so on, and dynamic data such as the amount of money transferred between customers, and so on, which may change at any time. Secondly, the various attributes of customers are labeled by analyzing data. Abstract the customer’s product preference, demand level, consumption level, purchase desire, and so on from the user data. And finally, we can explore the value of users and find the core customers among existing customers and potential users with purchasing potential for different customer groups.

4. Deep Learning Based on Neighborhood Structure Influence Study

In this paper, we propose a deep-learning-based network neighbor structure influence model DNSI, which uses the CNN algorithm for feature extraction to obtain the influence of three neighbor structures, so as to perform three types of experiments: node attribute prediction, category centrality measure, and user behavior prediction. This chapter first gives the definition related to the model, then details the implementation of the model with examples, and finally discusses and analyzes the complexity of the model [12].

4.1. Related Definitions. The model first counts the number of three neighbor structures of all nodes in the network, inputs them into the CNN to build a deep network, and obtains the influence of the three neighbor structures through feature extraction, according to which the three influences can reflect the different characteristics of the nodes in different graphs [26].

Definition 1 (network graph). $G = (E, V)$ denotes a directed network graph, where E represents the energy of the network, V represents the set of nodes v , that is, $V = \{v_1, v_2, \dots, v_n\}$, and $C = \{c_1, c_2, \dots, c_n\}$ denotes the set of all categories for which $|C| \ll |V|$.

Categories of nodes have multiple interpretations in real-world data sets, for example, in biological data sets, categories can represent different populations; in user-following data sets, categories can represent different attributes of

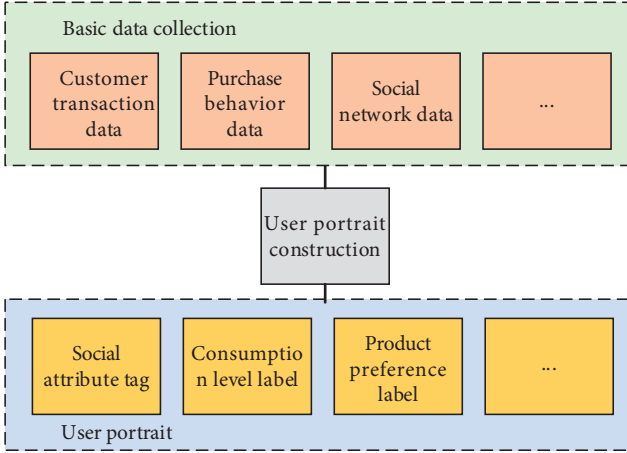


FIGURE 1: User profiling process.

users; in microbes between data sets, categories can represent different behaviors of users; and so on.

Definition 2 (one-degree neighbor structure). In the directed graph, $G = (E, V)$; the target node is v_n ; and if the direct precursor v_i of v_n does not have any precursor, then v_i constitutes a one-degree neighbor structure. In this paper, the influence of the one-degree neighbor structure on the target node is w_1 , and the number of neighbors with category c_j is $m_{j,1}$.

In the directed graph, $G = (E, V)$; the target node is v_n ; and if the direct precursor v_i of v_n also has precursor v_j pointing to v_n , then v_i and the precursor v_j pointing to v_i form a strengthened second-degree neighbor structure. In this paper, the influence of the strengthened second-degree neighbor structure on the target node is w_3 , and the number of strengthened second-degree neighbor structures formed by the neighbors of category c_j is $m_{j,3}$.

4.2. Model Description. Let the target node that needs to predict the category be v_n , its true category be c_k , and the total number of categories in the whole network graph G , then the objective of the model is to learn the most appropriate w_1, w_2, w_3 such that the probability of v_n being predicted as its own category c_k is maximized, that is, the overall optimization objective function of this model is as follows:

$$f = \max P(c(v) = c_k | w_1, w_2, w_3), \quad (1)$$

where $m_{k,i}$ refers to the number of neighbors belonging to the c_k and class forming the i -th structure and similarly $m_{q,i}$ refers to the number of neighbors belonging to the c_q class forming the i -th structure so that the probability of a node being predicted as its true class is maximized [27].

The whole model is mainly divided into two parts, after the first two algorithms can get three influences, the third algorithm is to predict the node attributes, and the fourth algorithm is to perform the category centrality metric on the nodes.

4.3. Experimental Results. This section first introduces the parameter settings of the model and the comparison algorithm, followed by the introduction of evaluation metrics and data sets [6], and finally the analytical experiments on several real network data sets with parameter sensitivity analysis.

4.4. Experimental Setup. By experimenting on the real network data set, it is found that the learning rate size and patch size should be relatively reduced when the number of nodes is less than 1,000, and the way of weight initialization should be changed. The optimal parameter settings in Table 1 are obtained after several experiments [25]. The second row of the table refers to the set of parameters used when the number of nodes in the network is greater than or equal to 1,000, and the third row refers to the set of parameters used when the number of nodes is less than 1,000.

For the three types of tasks that the model will handle, they will be compared with different algorithms, which mainly include the following ones:

- (1) KNN algorithm: this method is a machine learning algorithm, which determines the category of the target node based on the k closest neighbors of the target node, and predicts the category of the target node to be the category of neighbors with the largest proportion.
- (2) ExDegree algorithm: the expansion degree algorithm that different propagation probabilities need to calculate the number of neighbors of nodes of different layers will be counted separately for different categories of neighbors. The parameters in the original paper will be used in this experiment; the propagation probability is between 0.01 and 0.15; the maximum expansion degree is 8; 30 independent experiments to take the average result; and the node will be predicted as the highest probability of the category.
- (3) StructInf algorithm: neighborhood structure influences algorithm, using the source code published by the authors, according to the sampling parameters in the original paper, $q = 0.9$, $p_x = 0.6$, $p_y = 0.1$, first to obtain the influence degree of 20 neighbor structures and then to predict the behavior of unknown users.

4.5. Evaluation Indicators and Data Description. This experiment consists of three parts, each using different evaluation metrics.

4.5.1. Node Attribute Prediction. The task uses accuracy and mean average precision (MAP) as evaluation metrics, which are defined as follows:

$$\text{accuracy} = \frac{|\{v_j | v_j \in E, D(v_j) = c_j f(v_j) = c_j\}|}{|E|}, \quad (2)$$

TABLE 1: Parameter setting in algorithm 2.

$ v $	Batce_sich	Epoch	Kernelinitialisation	Num_of_dense	Learning_rate
$ v \geq 1000$	300	500	Truncated	3	0010
$ v < 1000$	45	480	Random	3	0001

where $f(v_j)$ is the attribute for which v_j is predicted. The correct rate is expressed as the ratio of the number of correctly predicted nodes to the number of all nodes in the network.

$$\text{MAP} = \frac{|\sum_{i=1}^{|C|} \text{Precision}_i|}{|C|}, \quad (3)$$

$$\text{precision} = \frac{|\{v_j | v_j \in E, D(v_j) = c_j, f(v_j) = c_j\}|}{|\{v_j | v_j \in E, f(v_j) = c_j\}|}$$

where Precision_i denotes the ratio of the number of nodes where an attribute is predicted correctly to the number of all nodes predicted to be that attribute and then MAP denotes the ratio of the sum of the accuracy of all attributes to the total number of attribute classes in the network. The MAP metric is intended to compensate for the low correctness of many nodes in the network due to the lack of precursor nodes.

4.5.2. Category Centrality Metric. The task uses the total algorithm runtime and the average first k recall $M_Recall@k$ as evaluation metrics, and the average first k recall is defined as follows:

$$\text{Recall}@k = |\{v_j | v_j \in E, D(v_j) = c_j, \text{index}(v_j) \leq k\}|, \quad (4)$$

$$M_{\text{Recall}@k} = \frac{|\sum_{i=1}^{|C|} \text{Recall}@k|}{\text{num}_g}$$

4.5.3. User Behavior Prediction. This task uses accuracy, mean accuracy MAP, time, and maximum acceleration ratio MRa as evaluation metrics [14], where MRa refers to the maximum value of the ratio of other algorithms to the model running time in this experiment.

The data used in this experiment are real-world data sets, including both public data sets and crawled microbial data, as shown in Table 2, where “1” in the “Experiment” column indicates node attribute prediction, “2” indicates category centrality, and “3” indicates user behavior prediction. The number “2” denotes the category centrality measure, and “3” denotes the user behavior prediction. Biological_tim [21] is a US biology data set; Bcspwer10 [25] is a US power grid data; Fpga_dcop1220 [21] is a circuit simulation network; Facebook_4039 [21] is a social network data set; Cite (<http://www.nber.org/patents/>) is a subgraph of the US patent citation network; Weibo is a crawled network of Sina Weibo users following each other, and the tweets and retreats of these users within 10 days (all tweets belong to “you at the same table,” “house prices,” “haze,” and “house prices”). If

users do not post or between these four topics, the category is “0,” so there are five (categories).

4.6. Experimental Results and Analysis. For each data set in the node attribute prediction experiments, 80% of the data are selected as training data and the rest as test data. The results of the correctness and MAP metrics are shown in Table 3, and for the Biological_tim small data set, the parameters are referred to row 3 in Table 1. For other data sets, the parameters refer to row 2 in Table 1. Among them, the KNN algorithm uses $k=2$ and $k=5$ to do experiments, respectively, which is more comprehensive and representative.

We can see that the DNSI model works better than the other models except for the MAP on the Biological_tim data set and the Fpga_dcop1220 data set where the correct rate is slightly lower than the other models. In the Biological_tim small data set, the correct rates of several algorithms are relatively low, and the analysis of the original data reveals that many nodes lack precursor nodes, so there will be a situation that they cannot be predicted. Results of the Fpga_dcop1220 data set are generally higher, especially the highest correct rate is obtained when KNN, which indicates that the correlation between the attributes of the data itself and the attributes of neighboring nodes is very high. In contrast, the results for $k=5$ in the algorithm KNN are often not as good as those for $k=2$. The analysis suggests that the neighbor expansion is too large and the error is caused by the mixing of the number of neighbors with different attributes.

The category centrality metric experiment uses the US patent citation data set, which can better reflect the superior performance of DNSI on large data sets. In order to efficiently recall nodes with high centrality, this experiment only takes the subgraphs composed of nodes with entry degree greater than 100 as the data set.

The technical field of the patent is taken as the category, and the first 800 patents with the highest number of citations from 1963 are taken as the true high centrality nodes, that is, $\text{num}_g = 800$ in (1).

The results of the comparison with KNN, ExDegree, betweenness centrality, and closeness centrality are shown in Table 4, which shows that the DNSI algorithm can achieve the highest recall in most cases except for $k=40$. In particular, for $k=10$, the DNSI algorithm can achieve 10% recall rate, which indicates that DNSI can recall the nodes with the highest centrality more accurately than the other four algorithms, and the DNSI algorithm has the shortest running time, which is stable and superior compared to the other algorithms.

The user behavior prediction experiment uses crawled Weibo data. Since Weibo is time-sensitive, in order to analyze the accuracy of the prediction of the three algorithms,

TABLE 2: Statistical information of the data set.

Data set	$ V $	$ E $	$ C $	Experiment
Biological_tim	170	184	5	1
B_cspwerl0	5,300	8,271	8	1
Fpga_dc op1220	1,220	4,725	16	1
Facebook_4039	4,039	88,234	18	1
Cite	53,650	102,726	6	2
Weibo	29,495	445,219	5	3

TABLE 3: Prediction results of node attributes.

Data set	Accuracy (%)				MAP (%)			
	DNSI	KNN ($k=2$)	KNN ($k=5$)	ExDegree	DNSI	KNN ($k=2$)	KNN ($k=5$)	ExDegree
Biological_tim	66.47	56.47	51.76	52.94	98.05	98.28	91.97	93.23
B_cspwerl0	95.86	82.43	82.23	82.28	98.95	98.43	98.20	98.26
Fpga_dc op1220	98.03	98.27	97.88	98.44	98.78	97.88	91.76	97.73
Facebook_4039	95.20	93.69	92.68	93.14	92.35	81.36	92.45	85.68

TABLE 4: Category centrality metric results.

Algorithm	M Recall(@10)	M Recall(@40)	M Recall(@70)	M Recall(@100)	M Recall(@130)	Time (s)
DNSI	0.100	0.183	0.329	0.420	0.540	805.12
KNN($k=2$)	0.067	0.175	0.290	0.297	0.306	8,393.30
ExDegree	0.050	0.192	0.310	0.354	0.395	14,064.09
Betweenness	0.067	0.167	0.230	0.300	0.387	3,789.60
Closeness	0.033	0.175	0.226	0.233	0.235	857.67

TABLE 5: Predicted results of user behavior in the microblogging data set.

Algorithm	K	Accuracy (%)	MAP (%)	Time (s)	MRa
DNSI4	2	68.58	78.56	54.63	1.83
	3	70.56	81.01	58.13	1.93
	4	72.39	85.40	62.78	2.39
	5	72.40	93.42	62.78	3.31
	6	72.45	93.48	71.66	3.50
	7	76.38	95.11	74.15	4.10
	8	76.32	95.40	79.87	5.13
	9	78.39	96.45	86.23	6.43
	StructInf	2	53.19	63.04	100.22
3		69.32	79.88	112.34	—
4		76.010	82.14	15.038	—
5		70.55	90.14	220.54	—
6		71.55	91.40	25.97	—
7		76.99	94.89	3.03.85	—
8		77.83	92.45	410.63	—
9		80.19	95.50	554.63	—
DeepWalk		2	51.67	61.24	60.90
	3	52.60	61.58	66.28	—
	4	52.69	72.18	69.89	—
	5	53.01	73.19	70.39	—
	6	53.35	74.80	85.10	—
	7	60.19	83.41	91.60	—
	8	61.19	83.41	91.60	—
	9	63.50	85.10	92.79	—

the user retrieves from day $k + 1$ to day 10 are predicted by following the network and retrieving the first k days (where $2 \leq k < 10$).

The DNSI model uses the parameters in row 2 of Table 1. StructInf, and DeepWalk models use the parameters in the original paper and adapt the data format specifically for the algorithm so that the user relationship data and user behavior category data are adapted to the input format of the algorithm, and the impact probabilities of 20 structures are obtained from the data of the first k days, so as to calculate the probability of users retreating on days $k + 1$ to 10 of different categories of tweets and take the largest one as the predicted value.

From the results in Table 5, we can see that the time of all three algorithms keeps growing as k increases, but the StructInf algorithm generally runs longer, with the highest speedup ratio of DNSI to StructInf algorithm up to 6.43. The highest correct rate of the three algorithms is up to about 80% and the gap with MAP is relatively large, also due to the lack of precursor nodes in the nodes.

In order to make the influence of the neighbor structure of different data sets comparable with each other, w_1, w_2, w_3 is scaled to be between 0 and 1, and $w_1 + w_2 + w_3 = 1$. It can be found that except for the Facebook data set where the influence of the enhanced second-degree neighbor structure is relatively low, all other data sets have the highest influence of the enhanced second-degree neighbor structure, indicating that the neighbor composition that is closely related and performs more frequent interaction behavior will have more influence on the target node.

5. Conclusions

In this paper, we propose DNSI, a deep learning-based influence model for network neighbor structures, which can obtain the influence of three neighbor structures by automatically extracting features and perform node attribute prediction, category centrality measure, and user behavior prediction based on these three influences. Through experiments conducted on several real network data sets, it is demonstrated that DNSI can have excellent performance in different application scenarios. And it is found that the influence of strengthening the second-degree neighbor structure is the highest in general, which also indirectly indicates that the more closely connected nodes in the network and the more frequent interaction behaviors, the greater the influence on the target nodes.

Data Availability

The data sets used in this paper are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

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