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Research on multi-role classification task of online mall based on heterogeneous graph neural network

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Abstract. With the rapid development of e-commerce, online shopping malls have become an indispensable part of daily life. In order to better meet the needs of consumers, marketplace platforms need to accurately identify and categorize different user personas to provide personalized services and recommendations. In traditional role classification methods, basic information and behavioral data of users are typically used for classification. However, this approach often ignores the complex relationships between users and multiple heterogeneous data such as goods, reviews, social networks, and more. Therefore, we propose a new approach based on heterogeneous graphs to model different types of data in the form of graphs to better capture the connections between users and various elements in the marketplace. In this study, graph embedding technology is used to map nodes in heterogeneous graphs into low-dimensional vector spaces to capture similarities and relationships between nodes. Then, using the vector representation of these nodes, we can apply algorithms such as attention mechanisms for multi-role classification. Specifically, we use algorithms such as support vector machines to train classification models and use heterogeneous graph attention mechanisms to obtain the final feature representation of nodes. Experimental results show that our method shows significant advantages in multi-role classification tasks. Finally, the results of this study are discussed and summarized. We found that the classification model based on heterogeneous graph can effectively classify multiple roles in the online mall to provide personalized services and recommendations for the mall. At the same time, we also find that the construction of heterogeneous maps and the choice of graph embedding technology have important impacts on the classification results, which need further research and optimization. Therefore, multi-role task classification of online shopping malls based on heterogeneous graph neural networks is of great significance for improving the user experience and recommendation effect of online shopping malls, and also provides new ideas and methods for research in related fields.

Keywords: Heterogeneous Graphs, Neural Networks, Task Recommendation, Role Classification.

1. Introduction

With the rapid development of e-commerce and the diversification of consumer demand, the study of multi-role classification of mall becomes more and more important. Online shopping mall provides consumers with a convenient way to shop. Through the online mall, consumers can browse and buy a variety of goods anytime and anywhere, without being limited by time and place, which greatly improves the shopping experience of consumers. At the same time, online mall provides a broad sales platform for merchants. Traditional physical stores are limited by geographical location and size, while online malls can break through these restrictions and promote goods to consumers nationwide or even globally, which brings greater market and sales opportunities for merchants, and also reduces operating costs. Online malls also boost the economy as a whole. Through the online mall, the transaction of goods and services is more convenient and efficient, and the exchanges and cooperation between the supply and demand parties are promoted. The rise of online shopping malls has also spawned many related industries, such as logistics, payment, etc., which has injected new impetus into the development of the entire economic system.

In such a large online marketplace, it becomes especially important to accurately classify different characters. Mall multi-role classification refers to the division of consumers into different roles or groups in order to better understand their needs and behaviors and provide them with a personalized shopping experience. First of all, shopping mall multi-role classification study is helpful to understand the differences in consumer demand. Different consumers have different shopping preferences, needs and behavior patterns. By classifying consumers into multiple roles, the mall can more accurately understand the needs and preferences of different role groups, so as to provide targeted products and services. For example, for young fashion consumers, the mall can offer trendy clothes and accessories; For housewives, the mall can provide household goods and household necessities. By understanding the multi-role needs of consumers, the mall can better meet their shopping needs and increase sales and customer satisfaction. Secondly, mall multi-role classification research is helpful for personalized marketing and promotion. In a competitive business environment, personalized marketing and promotion are key to attracting and retaining consumers. Through the multi-role classification of consumers, the mall can develop personalized marketing strategies and promotion activities according to the characteristics and needs of different role groups. For example, for high-end consumers, the mall can launch limited edition products and high-end services to attract their attention; For price-sensitive consumers, the mall can offer discounts and promotions to increase their willingness to buy. Through personalized marketing and promotion, the mall can improve brand awareness and competitiveness, achieve sales growth and market share.

However, the traditional mall multi-role classification is mostly based on traditional methods, which greatly reduces the accuracy of the model to a certain extent, so this paper proposes a research on the multi-role classification task of online mall based on heterogeneous graph neural network.

Heterogeneous graph neural network (HGNN) is a graph neural network specially designed for heterogeneous graphs, in processing heterogeneous graphs with complex heterogeneous semantics, in general, heterogeneous graph neural networks can be superior to the general-purpose graph neural networks designed for homogeneous graphs. Different from homogeneous graph neural networks, heterogeneous graph neural networks need to overcome the heterogeneity of nodes and design appropriate fusion methods to integrate different types of neighbors. In order to capture and interpret the semantics in heterogeneous maps, metapaths [1-4] are proposed for processing heterogeneous maps, and the choice of metapaths can rely on expert knowledge [5] or automatic model selection [6]. Part of the research work [7-9] proposes that different types of nodes allocate different attention, which can help the model solve heterogeneity. One of the main applications of heterogeneous maps is recommender systems [10-12], that is, modeling the relationship between users and items into heterogeneous graphs, and designing HGNN to capture user intent for recommendation. In addition, DyHATAR studies dynamic heterogeneous maps to capture temporal information in heterogeneous maps. For the first time, HeCo incorporated the idea of contrastive learning into the design of HGNN [13], capturing the high and low order structures of heterogeneous maps simultaneously through a cross-perspective contrast mechanism.

The existing heterogeneous graph contrast learning algorithm based on metapath only considers the local neighbor information of nodes when capturing metapath view information, and ignores the high-order neighbor information of nodes [14-16], resulting in insufficient captured metapath view information, which affects the representation quality of nodes. To solve this problem, we use algorithms such as support vector machines to train classification models, and use the heterogeneous graph attention mechanism to obtain the final feature representation of nodes. Finally, the effectiveness and necessity of the model are proved by experiments [17].

2. Model

2.1. Heterogeneous map

Definition 1: Heterogeneous map. A heterogeneous graph can be represented as $\mathcal{G} = \{\mathcal{V}\ \ ,\mathcal{E}\}$, consisting of the object set $\mathcal{V}$ and the edge set $\mathcal{E}$. Heterogeneous graphs are also associated with object mapping functions $\emptyset : \mathcal{V} \to \mathcal{A}$ and edge mapping functions $\varphi: \mathcal{E} \to \mathcal{R}$. $\mathcal{A}$ and $\mathcal{R}$ represent predefined sets of object types and edge types, and $|\mathcal{A}| + |\mathcal{R}| > 2$。

As an example of the ACM dataset in Figure 1, the ACM heterogeneous graph includes three types of nodes: actors, films, and directors; There is an acting relationship between the actor and the film, and there is a shooting relationship between the director and the film, and there are two kinds of relationship. At this point there is $|\mathcal{A}|$=3,$|\mathcal{R}|$ =2, then $|\mathcal{A}| + |\mathcal{R}|$ = >5, satisfies the definition of heterogeneous graphs.

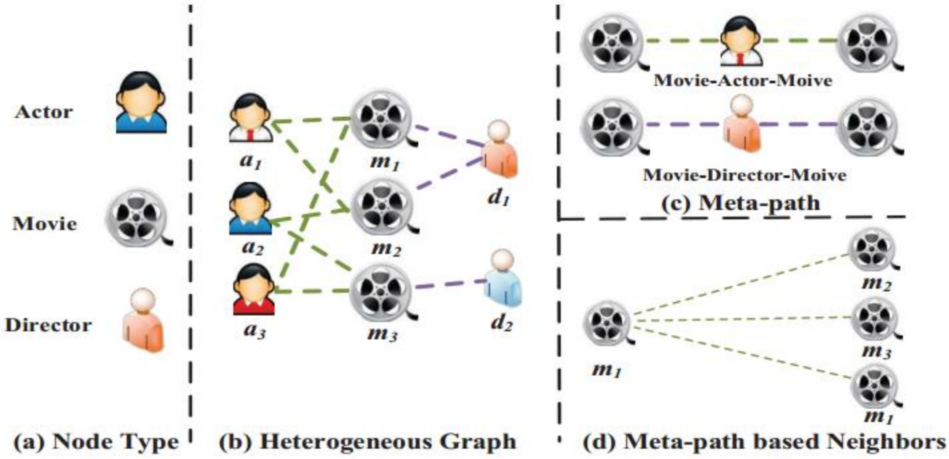

Figure 1. Heterogeneous graph example.

Definition 2: Network pattern [2]. Given A heterogeneous graph $G = \{\mathcal{V}, \mathcal{E}\}$, the network pattern defined on the heterogeneous graph $\mathcal{G}$ is A directed graph defined on object type $\mathcal{A}$, with edge relations from $\mathcal{R}$, denoted $\mathcal{T} = (\mathcal{A}, \mathcal{R})$.

In fact, the network pattern is an abstraction for better understanding and analysis of heterogeneous graphs, focusing on the local structure of the graph.

Definition 3: Metapath. A metapath is defined as a sequence of specific node types on a heterogeneous graph A1 → A2 → A3 ⋯→ An (abbreviated A1A2... An), which describes a specific combination of relationships between A1 and An.

Figure 1 (c) shows the combination of two meta-paths, revealing the relationship between film actors and film directors. Meta-paths can be used to model the rich semantic information of heterogeneous graphs, which may be one of the reasons why meta-path-based methods have become the mainstream of representation learning methods for heterogeneous graphs.

2.2. Metapath view enhancement module

Recent research on self-supervised visual representation learning has shown that comparing consistent and inconsistent image views allows encoders to learn rich representations. For image view enhancement, human visual perception can be used as a reference, such as horizontal flipping, color transformation and random cropping of the image, etc. These enhancement operations will not change the core meaning of the image. Unlike image view enhancement, it is not so intuitive to define a new view on the graph data, but you can refer to the idea of image enhancement. Just as image enhancement processes the pixels that make up the image in different forms, the enhancement of graph data is actually a disturbance to the basic components of the graph, such as nodes and edges, or to the node characteristics and graph structure, and reasonable disturbance should not affect the result of graph representation learning. For the metapath view graph in this paper, it is also a homogeneous graph in essence. Generally speaking, perturbations of nodes and edges are also considered, such as perturbations of node features, masking of initial node features or adding Gaussian noise. Or perturbations to the graph structure, such as by adding or removing edges, subgraph sampling, using the shortest distance or diffusion matrix to generate a global view.

Each metapath view can be viewed as a homogeneous graph. In order to encode the initial feature X of nodes in the metapath view and the information of the graph structure, so as to obtain the node representation corresponding to the metapath view, the node-level encoder can be defined by the following formula (1):

$$H^{\emptyset_i} = a\left(X, A^{\emptyset_i}\right) \tag{1}$$

The framework of this paper has no restrictions on the choice of encoders. Here, the simple and commonly used graph Convolutional network (GCN) is chosen as the meta-path view encoder, and a view-specific encoder is used for each meta-path view. The meta-path view or the adjacency matrix and the corresponding diffusion matrix based on the meta-path can be considered as two consistent structural perspectives. The GCN layers are defined respectively, such as equations (2) and (3), to learn the node representation of the same meta-path from different perspectives.

$$H^{\emptyset_i} = \sigma(AXW) \tag{2}$$

$$H^{\emptyset_i} = \sigma(SXW) \tag{3}$$

Where A is the adjacency matrix, S is the diffusion matrix, X is the initial feature of a node, W is a learnable network parameter, and σ is a nonlinear activation function. We choose ReLu so that for the primitive heterograph H and the enhanced heterography $H^{'}$, we can express them as $\left\{H^{\emptyset'_1}, H^{\emptyset'_2} \ldots H^{\emptyset'_l}\right\}$ and $\left\{H^{\emptyset'_1}, H^{\emptyset'_2} \ldots H^{\emptyset'_l}\right\}$, and the next step uses attention to merge the meta-paths inside H or $H^{'}$.

2.3. Attention module

The representation learned under a specific metapath view only contains specific semantic information, so it is necessary to merge the semantic information of each metapath to obtain a final representation of better quality. The key to realize semantic information fusion is to determine how much each metapath view contributes to the final representation learned. In order to learn the contribution of each metapath view, this paper uses a semantic attention layer to learn the weight of the corresponding metapath. For the original heterograph H and the enhanced heterograph $H^{'}$, there are formulas (4) and (5) respectively:

$$\beta^{\emptyset'_1}, \beta^{\emptyset'_2}, \ldots \beta^{\emptyset'_l} = L_{att}\left(H^{\emptyset'_1}, H^{\emptyset'_2} \ldots H^{\emptyset'_l}\right) \tag{4}$$

$$\beta^{\emptyset_1}, \beta^{\emptyset_2}, \ldots \beta^{\emptyset_l} = L_{att}\left(H^{\emptyset_1}, H^{\emptyset_2} \ldots H^{\emptyset_l}\right) \tag{5}$$

Taking the original heterogeneous graph H as an example, the weight calculation and fusion of different meta paths are introduced. The meta-path $\emptyset_i$ necessity is calculated as follows

$$a^{\emptyset_i} = \frac{1}{N}\sum_{n=1}^{N} q^T \tanh\left(Wh_n^{\emptyset_i} + b\right) \tag{6}$$

Where W is a linear transformation parameter matrix, b is an offset vector, and q is an attention vector, that is, semantic attention is calculated by nonlinear transformation of metapath view nodes into semantic attention space. The metapath weight β is obtained by using the normalized exponential function softmax for metapath importance $a^{\emptyset_i}$:

$$\beta^i = softmax\left(a^{\emptyset_i}\right) \tag{7}$$

Then the linear combination of the final representation of the original heterograph H can be obtained by attention calculation:

$$H = \sum_{i=1}^{P} \beta^i \cdot H^{\emptyset_i} \tag{8}$$

Where P represents the number of meta paths, and $H^{\emptyset_i}$ is the characteristic representation of the meta path enhancement module. With an embedded representation of the node, we can act on it for downstream tasks.

3. Experiment

3.1. Data set

Three real heterogeneous graph data were used in the experiment of this paper. The statistical information of the data set is shown in Table I, which is described as follows:

Table 1. Data set information.

Dataset	Target Node	Training	Validation	Test	Node Type	Link Type
ACM	4019	400	400	3219	Paper(P) Author(A) Subject(S)	P-P P-A P-S
DBLP	4057	400	400	3257	Author(A) Paper(P) Term(T) Venue(V)	A-P P-T P-V
IMDB	4278	400	400	3878	Movie(M) Director(D) Actor(A)	M-D M-A

1) ACM: This dataset contains 4019 papers, and 5,835 authors on 56 topics related to them. In addition, according to the research field of the paper, it can be divided into three categories: database, data mining and wireless communication. The initial node feature of the paper is the word bag encoding of the corresponding paper abstract.

2) DBLP: This dataset contains 14,328 papers, 4,057 authors, 8,789 keywords, and 20 conferences. The target node is the author, which can be divided into four categories according to the author's research field: data mining, data library, information retrieval and machine learning. The author's initial node feature is the word bag coding based on his personal introduction.

3) IMDB: This dataset contains 4,278 films, 2,082 directors, 5,431 actors and 7,313 keywords. According to the film type, it can be divided into comedy, opera and action movies, and the initial node feature of the film is the word bag coding of the film plot.

3.2. Baselines

(1) GCN: A semi-supervised learning method on homogeneous graphs is a well-known graph convolution model, which treats the neighborhood nodes of each node equally, aggregates them as the representation of the central node, and uses the label information of some nodes to guide the optimization of the model. Since GCN is a homogeneous graph method, the heterogeneous graph is transformed into

multiple homogeneous graphs through the meta path, and then the best effect of GCN on each homogeneous graph is taken.

(2) RGCN: a knowledge graph method that can learn the representation of all entity type nodes in heterogeneous graphs by performing GCN aggregation in the same class for each type of neighbor, and then adding the results of different types.

(3) GAT: - A semi-supervised graph neural network that considers the attention mechanism to learn the neighbor weights. Unlike GCN, which treats each node's neighborhood nodes indiscriminately, GAT can adaptively learn the importance of nodes in the neighborhood. Like GCN, GAT takes its best effect on each homogeneous graph

3.3. Experimental result

In node classification experiments, the representation of unsupervised method learning needs to be provided to the downstream classifier to obtain classification results, while the semi-supervised method is an end-to-end model that can directly obtain its classification results. In order to ensure comparability, the relevant evaluation methods were set in line with HDGI [3]. For example, in order to reduce the randomness of the node classification experiment, the experiment was repeated 10 times under the same conditions, and then the average scores of Micro-f1 and Macro-f1 were reported. In addition, the data set partitioning is also consistent, with the training set size (that is, the given training label) being 20% or 80% of the complete data set, and the validation and test set sizes being fixed at 10% of the complete data. The downstream classifier is the logistic regression classifier, which uses Adam [12] for optimization, the learning rate is 0.001, and the early-stopping strategy is used according to the accuracy on the verification set.

As shown in Table II, on the three data sets, the MAGNN algorithm in this paper achieves the best results, and generally improves by one to two points over the second best. The heterogeneous graph representation learning algorithm can effectively deal with the heterogeneity of the graph, so the result is better than the homogeneous graph representation learning algorithm. Graph neural networks (such as GCN and GAT) are superior to traditional random walk class graph representation learning algorithms which only consider graph structure information because they comprehensively consider graph structure information and node attribute information.

Table 2. Experimental results of classification on different data sets.

Datasets	Metrics	R-GCN	GCN	GAT	OUR
ACM	Ma-F1	87.53	91.91	91.01	91.75
	Mi-F1	87.73	91.76	90.93	92.13
DBLP	Ma-F1	75.36	92.87	92.16	92.98
	Mi-F1	77.18	93.69	93.05	94.11
IMDB	Ma-F1	49.99	53.56	51.62	54.26
	Mi-F1	49.99	53.58	52.85	54.17

In order to further evaluate the quality of node representation, node clustering experiments are also carried out in this paper. The node representation can be obtained by forward propagation after the training of MAGNN algorithm. The node clustering experiment adopts Kmeans, in which the number of node classes is taken as the cluster number of Kmeans, and NMI and ARI are used as evaluation indicators. In order to reduce the influence of randomness in Kmeans algorithm and modeling training, the experiment was repeated 10 times, and their average results were reported in Table III.

Table 3. Experimental results of classification on different data sets.

	ACM		DBLP		IMDB	
	NMI	ARI	NMI	ARI	NMI	ARI
R-GCN	0.7016	0.7234	0.7467	0.8202	0.1308	0.1276
GCN	0.4947	0.3489	0.3233	0.2721	0.1308	0.1304
GAT	0.7025	0.7425	0.7763	0.8247	0.0624	0.0878
OUR	0.7183	0.7448	0.7884	0.8526	0.1439	0.1489

As can be seen from Table III, in terms of clustering performance, the MAGNN algorithm in this paper also achieved competitive results. Compared with the method that only considers the homogenous graph structure, the graph neural network algorithm performs better because it also considers the heterogeneous information of the graph structure.

To sum up, the MAGNN algorithm in this paper performs well in node classification and node clustering on all data sets. Node classification has surpassed traditional classical methods such as GAT and performed better than other graph representation learning methods. The node clustering effect has also achieved competitive performance, so it is more suitable for multi-role classification tasks.

4. Conclusion

In this paper, we propose a method based on heterogeneous graph neural network to classify multiple user roles in an online mall. This method models different types of data by constructing heterogeneous graphs, and uses graph embedding technology to map nodes into low-dimensional vector Spaces to capture the similarities and relationships between nodes. Then, the multi-role classification task is trained and predicted by deep learning algorithm. The experimental results show that the classification model based on heterogeneous maps has significant advantages in multi-role classification tasks, and can provide personalized services and recommendations for shopping malls. Therefore, the multi-role task classification of online mall based on heterogeneous graph neural network is of great significance to improve the user experience and recommendation effect of online mall, and also provides new ideas and methods for the research in related fields.

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