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Research on Intelligent Recommendation Algorithm Based on Deep Learning

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ABSTRACT

With the wide application of intelligent recommendation system in e-commerce shopping, video websites and social media platforms, timeliness, accuracy, scalability and interpretability have gradually become important criteria to measure the excellence of a recommendation system.The most widely used recommendation system is collaborative filtering recommendation system. Its advantages include high accuracy, good real-time performance, and strong scalability, but there are still disadvantages, including cold start, data sparsity, and vulnerability. In the current flourishing of deep learning research, adding deep learning can fundamentally solve the problem, and better use the implicit and explicit information provided by past and current new users to bring more accurate and satisfying recommendations to users. This study analyzes and introduces the model building and recommendation algorithm logic of the representative recommendation system, and studies the feasibility of combining deep learning with artificial intelligence to optimize the new recommendation system.

KEYWORDS

Intelligent recommendation; Deep learning; Algorithms

1. INTRODUCTION

Intelligent recommendation system is of great value in the field of business and social media, which can not only reduce advertising costs, but also provide users with more personalized and accurate data support based on deep learning-based data analysis technology, so that users can get the product introduction they most likely need or the news push they most want to follow.

In the field of e-commerce, SVD++ is often used for personalized product recommendation. For example, e-commerce platforms such as Amazon [1] and Taobao [2] use SVD++ algorithm to recommend products that may be of interest to users according to their purchase history and rating records. Video-on-demand platforms such as Netflix [3] use SVD++ to recommend favorite movies and TV shows; In the field of advertising recommendation, FM is widely used in click-through rate prediction and advertising targeting to improve advertising click-through rate and conversion rate; Music streaming platforms such as Spotify [4] use BPR to recommend music that users like; NCF has been applied to personalized product recommendation in the field of e-commerce. For example, JD.com [5], Tmall and other e-commerce platforms use NCF algorithm to recommend products that users may be interested in to improve shopping experience. VBPR in the field of fashion shopping is applied to personalized fashion collocation recommendation, such as clothing e-commerce platform using VBPR algorithm to recommend fashion clothing collocation according to user preferences and visual characteristics.

At the same time, the intelligent recommendation based on deep learning solves the problems of sparse, cold start and difficult scalability of the traditional machine learning recommendation system, reduces the redundant information and improves the user experience, so that the model automatically learns features to reduce the investment in manual feature engineering, and is more convenient to integrate information. The combination of deep learning technology and intelligent recommendation system helps to promote the transformation of traditional recommendation system to new recommendation system, expand the application field, and improve the efficiency of application.

In terms of practical application value, the deep learning intelligent recommendation system can provide users with personalized recommendation services in reality, and improve user experience and satisfaction. It can help e-commerce platforms, video websites, music platforms, etc., improve sales conversion rates, increase user stickiness, and improve the profitability of the platform.

At the same time, it can also provide users with more accurate and personalized information and services, and improve the efficiency of information utilization.

Based on the above, this paper studies the recommendation logic of representative algorithms widely used in the development process of recommendation systems, and presents and explores the development direction of recommendation systems based on artificial intelligence.

2. THE DEVELOPMENT PROCESS AND REPRESENTATIVE MODEL OF RECOMMENDATION SYSTEM

2.1. Traditional Recommendation System

2.1.1. Content-based recommendations

Content-based recommendation [6] was the first algorithm to be used. Recommend similar items based on what users have liked in the past.

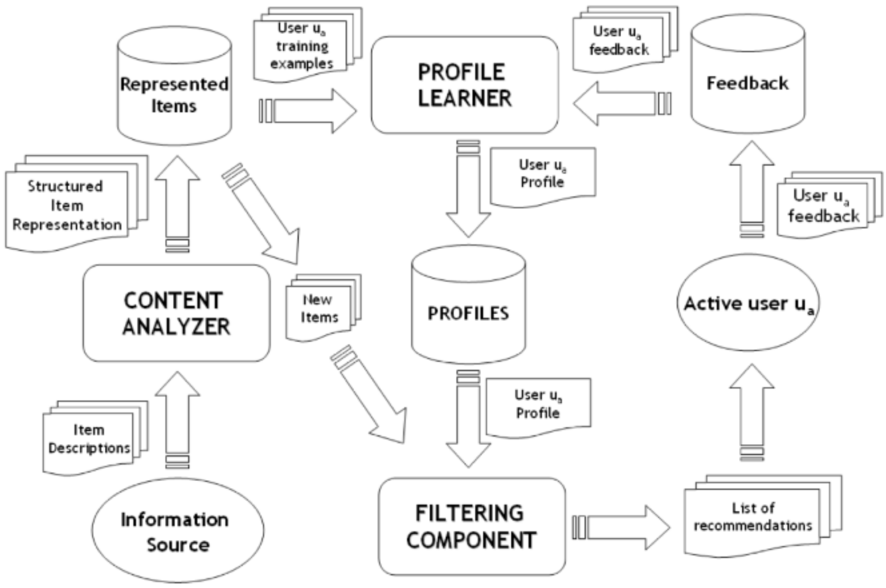

Figure 1. Content-based recommendation architecture

The main process in Figure 1 is as follows:

(1) Item Representation: Extracting features from an item;

(2) Profile Learning: Learning characteristics preferred by users according to their previous preferences;

(3) Recommendation Generation: Comparing features of users' preferences with the features of items, and recommend a set of items that are most relevant to users.

2.1.2. Recommendations based on collaborative filtering

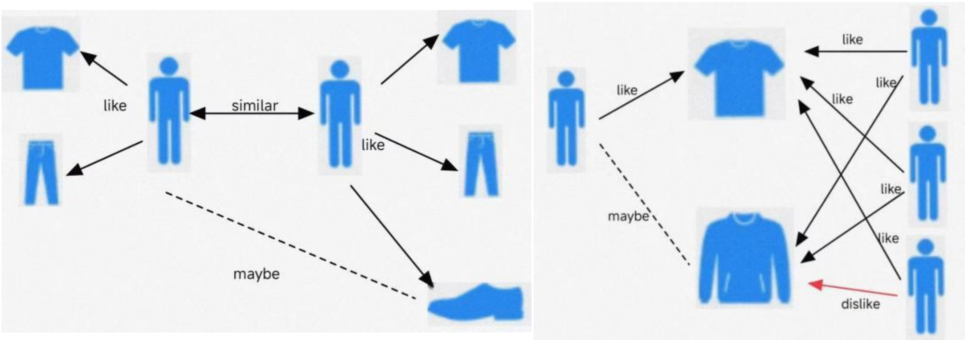

Figure 2. Collaborative filtering schemes based on users and items, respectively

The logic of the algorithm [7] is as follows:

(1) User-based: Recommend items that users with similar preferences like.

(2) Item-based: Recommend items that are similar to your favorite items.

The algorithm flow is as follows:

(1) Build an inverted index of items

In general, user-based collaborative filtering algorithms need to calculate the similarity between two users. In fact, in many cases, two users do not have many items in the intersection. The inverted index is categorized by item, and each item corresponds to a list of users. If two users appear in the user list for a certain type of item at the same time, they have similar preferences. Building an inverted index of items can speed up the calculation of User-CF molecules.

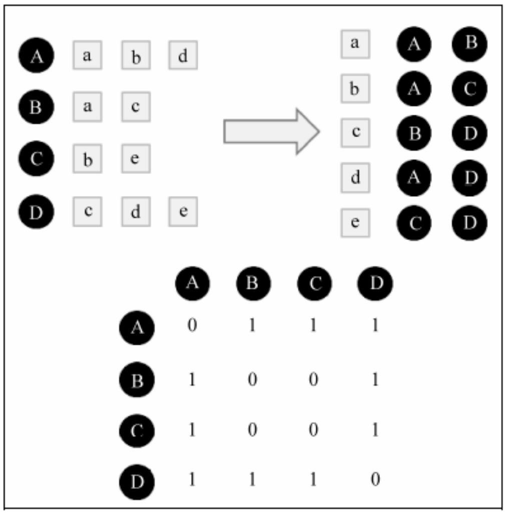

Figure 3. Inverted index scheme

(2) Similarity calculation

When the user attitude is Boolean, Jaccard similarity or cosine similarity is used;

When the user attitude is numerical, cosine similarity or Pearson similarity is used.

(3) Predict ratings and generate recommendations

To utilize formula $p_{ui} = \sum_{v \in S(u,k) \bigcap N(i)} w_{uv} \cdot r_{vi}$, selecting k similar users for user u and recommend to u the ones that they have purchased and that u has not purchased.

2.1.3. Recommendations based on matrix factorization

(1) SVD++

SVD++ [8] introduces implicit feedback (such as clicks, favorites, adding to shopping cart, etc.) and user attribute information, which is equivalent to introducing additional information sources to reflect user preferences from the side, and can solve the cold start problem caused by less explicit scoring behavior. Add the implicit factor vectors to express the user's preferences. The predicted value composition of SVD++ is:

$$\hat{r}_{ui} = \mu + b_u + b_i + q_i^T \left(p_u + |N_u|^{-0.5} \sum_{j \in N(u)} x_j + \sum_{a \in A(u)} y_a \right)$$

The number of users u and the number of goods i form a matrix, which is multiplied to obtain the first score. μ is the total average score, b_u is the attribute of user u, and b_i is the attribute of item i. N(u) is the set of items for which user u generates an action; x_j is a hidden, implicit item vector for item j, and the sum is the user's preference for these hidden factors; y_a is similar to x_j in that each attribute corresponds to a user implicit factor vector.

Combined with implicit feedback, better user characteristics are obtained and over-fitting is avoided. Fewer items and more users to avoid overfitting caused by inadequate p_u.

(2) FM

FM [9] is a common algorithm for feature combination, aiming to solve the feature combination problem under large-scale sparse data.

$$\hat{y}(x) := w_0 + \sum_{i=1}^{n} w_i x_i + \sum_{i=1}^{n} \sum_{j=i+1}^{n} w_{i,j} x_i x_j$$

The predicted value consists of linear regression (the first two terms) + cross terms: linear regression is the initial value and the weighted sum of all features, cross terms represent the influence of different features superposition on the result, and the weight is represented by the implicit vector inner product $<v_i, v_j>$.

Advantages of FM:

a. The problem of inadequate learning of feature combination terms is reduced;

b. Improved prediction ability: It can learn single-feature implicit vectors and predict feature combinations that do not appear in the training set;

c. Improved the efficiency of parameter learning: the number of parameters was reduced from (n^2+n+1) to (n*k+n+1), greatly reducing the complexity of the model.

Through feature transformation, FM can simulate SVM, MF, SVD++ and other models. FM performs well when dealing with sparse data, improves learning efficiency and prediction ability by learning the combination relationship between features, and is used very much in the industry.

(3) BPR

BPR [10] relies on implicit feedback from users and uses Bayesian method to calculate the maximum posterior probability for sorting.

According to the evaluation, only a few positive samples can be obtained, while the matrix decomposition takes the missing value as the negative sample, and then approaches the sample with the prediction error as the evaluation standard, which cannot deeply distinguish the importance and is not conducive to sorting.

In this regard, BPR combines items that do not explicitly express user preferences with positive examples to build a partial order relationship. The core assumption is that users prefer items with implicit feedback over those without. Based on this, BPR builds a complete partial order relationship for each user, represented by $>_u$.

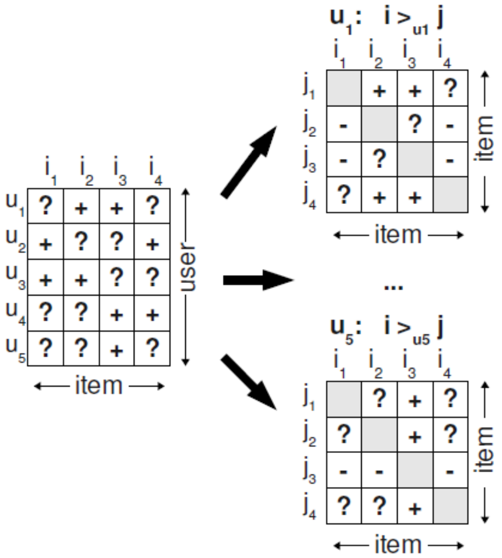

Figure 4. Total order relationship construction schematic

The matrix on the left of Figure 4 is the feedback data set, "+" means there is feedback, "?" means no feedback;

The small matrix on the right of Figure 4 is the partial order relation matrix of each user, "+" represents the preference i over j, which is a positive example. -" Indicates preference for j over i, negative example;" ?" It means that a partial order relationship cannot be determined for homogeneous data.

If the user has seen item i_2 but not i_1, assume that the user likes i_2 better than i_1: that is, $i_2 >_u i_1$.

The maximum a posteriori estimation function is:

$$\ln P(\theta|>_u) \propto \ln P(>_u|\theta)P(\theta) = \ln \prod_{(u,i,j)\in D} \sigma(\bar{x}_{ui} - \bar{x}_{uj}) + \ln P(\theta) = \sum_{(u,i,j)\in D} \ln \sigma(\bar{x}_{ui} - \bar{x}_{uj}) + \lambda \|\theta\|^2$$

The latter term is the regularization term, which is the view of Bayes school.

Compared with the matrix decomposition of single point method, BPR based on pairing method has advantages in selecting a very small amount of data from the massive data.

2.1.4. VBPR

VBPR [11] proposes a scalable factorization model that incorporates visual signals into predictors of people's views. Visual features from product images not only help to obtain a more accurate personalized ranking, but also help to alleviate the cold start problem.

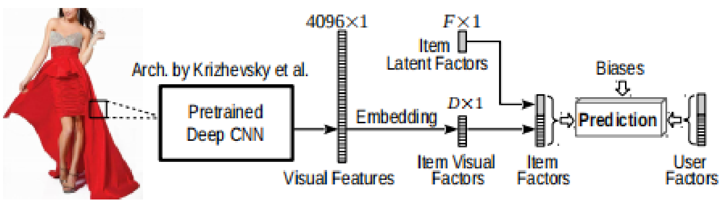

Figure 5. Simulate visual interaction

Visual decision factors influence many of the choices people make, from the clothes they wear to how they interact with each other. In this paper, we investigate the usefulness of visual features for personalized sorting tasks on instant-feedback datasets. We propose a scalable approach to incorporate visual features extracted from product images into a matrix decomposition to reveal the "visual dimensions" that most influence people's behavior.

$$\widehat{x}_{u,i} = \alpha + \beta_u + \beta_i + \gamma_u^T \gamma_i + \theta_u^T (\mathbf{E} f_i) + \beta'^T f_i$$

α is the global offset, β_u and β_i are the deviation terms of user u and item i respectively, γ_u and γ_i are K-dimensional vectors describing the potential factors of user and item respectively, $\gamma_u^T\gamma_i$ inner product represents the preference degree of user and item, θ_u and θ_i are D-dimensional visual factors, inner product simulated the visual interaction of u and i, that is, the degree to which u is attracted by each D-dimensional visual dimension. E is the D×F matrix where the DCNN feature space (f-dimension) is embedded into the visual space (D-dimension), and f_i is the original visual feature quantity of the i term.

The model was trained using stochastic gradient ascending Bayesian personalized ordering (BPR). VBPR maps projects to a low-dimensional "visual space" so that projects with similar styles (in terms of how users evaluate them) are mapped to similar locations. Not only does it help to learn hidden categories, but more importantly, it also finds the most relevant potential visual dimensions and maps projects and users into undiscovered Spaces, thus effectively solving the cold start problem.

2.2. New Recommendation System With Deep Learning --NCF

NCF [12] is a neural network-based algorithm that combines the advantages of collaborative filtering and neural networks. The algorithm uses neural network to learn the association between users and items, which can better capture the complex relationship between users and items, and improve the accuracy and personalized degree of recommendation through deep learning technology. The core idea of NCF algorithm is to take the characteristics of users and items as input, and learn the interaction characteristics between them through multi-layer neural network, so as to predict the user's preference for unknown items. NCF unifies the linear modeling advantages of matrix decomposition MF with the nonlinear advantages of multi-layer perceptron MLP.

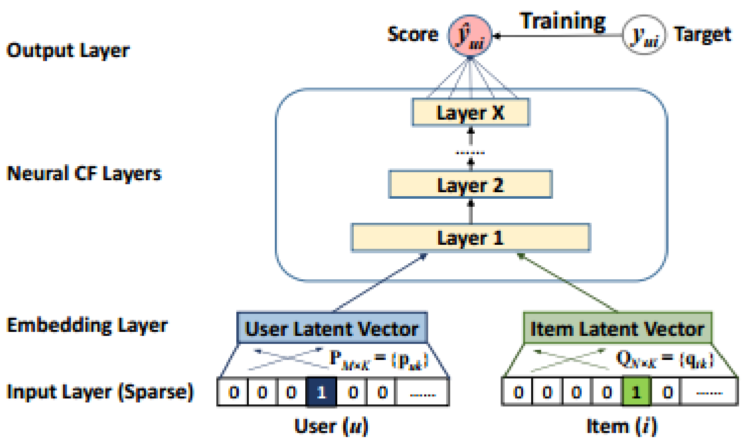

Figure 6. NCF universal framework

The embedding layer above the input layer maps the sparse representation of the input layer to a dense vector. It is fed into a multi-layer neural network to map the potential vector to a prediction score. The dimension of the last hidden layer X determines the capability of the model, and the final output layer is the prediction fraction $y^{\wedge}_{ui}$, which is trained by minimizing the point-by-point loss between $y^{\wedge}_{ui}$ and its target value y_{ui}.

$$L = -\sum_{(u,i)\in\mathcal{Y}} \log \hat{y}_{ui} - \sum_{(u,j)\in\mathcal{Y}^-} \log(1 - \hat{y}_{uj})$$
$$= -\sum_{(u,i)\in\mathcal{Y}\cup\mathcal{Y}^-} y_{ui} \log \hat{y}_{ui} + (1 - y_{ui}) \log(1 - \hat{y}_{ui})$$

2.2.1. Generalized Matrix Factorization --GMF

The output layer result is:

$$\hat{y}_{ui} = a_{out}(h^T(p_u \odot q_i))$$

$\odot$ represents the element-by-element product of user potential vector p_u and project potential vector q_i, and a_{out} and h represent the activation function and connection weight of the output layer, respectively. To generalize MF to nonlinearity, the Sigmoid function is used as the activation function to form GMF.

2.2.2. Multilayer perceptron --MLP

The input of NCF includes two types of users and items. Simple connection vector is not enough to discover the potential features between users and items. NCF proposes to add a hidden layer on the vector connection, and use MLP to learn the interaction between users and potential features of items, so as to give the model high flexibility and nonlinear modeling ability.

$$\mathbf{z}_1 = \phi_1(\mathbf{p}_u, \mathbf{q}_i) = \begin{bmatrix} \mathbf{p}_u \\ \mathbf{q}_i \end{bmatrix},$$
$$\phi_2(\mathbf{z}_1) = a_2(\mathbf{W}_2^T \mathbf{z}_1 + \mathbf{b}_2),$$
$$\ldots\ldots$$
$$\phi_L(\mathbf{z}_{L-1}) = a_L(\mathbf{W}_L^T \mathbf{z}_{L-1} + \mathbf{b}_L),$$
$$\hat{y}_{ui} = \sigma(\mathbf{h}^T \phi_L(\mathbf{z}_{L-1})),$$

W_x, b_x, and α_x represent the weight matrix, bias vector, and activation function of the X-layer perceptron, respectively.

2.2.3. Integrating GMF and MLP

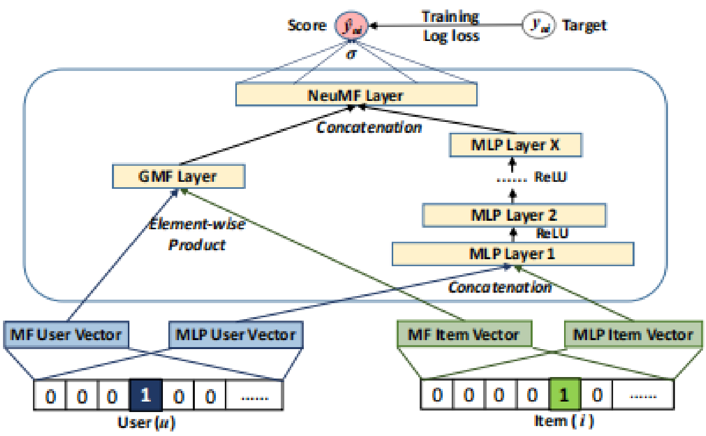

Figure 7. GMF and MLP learn independent embeddings

In order to improve the flexibility of the fusion model, NCF allows GMF and MLP to be embedded independently, and combines the two models by connecting the final hidden layer output, the formula is as follows:

$$\phi^{GMF} = \mathbf{p}_u^G \odot \mathbf{q}_i^G,$$
$$\phi^{MLP} = a_L(W_L^T(a_{L-1}(\dots a_2(W_2^T \begin{bmatrix} \mathbf{p}_u^M \\ \mathbf{q}_i^M \end{bmatrix} + \mathbf{b}_2)\dots)) + \mathbf{b}_L),$$
$$\hat{y}_{ui} = \sigma(\mathbf{h}^T \begin{bmatrix} \phi^{GMF} \\ \phi^{MLP} \end{bmatrix}), \quad (12)$$

P^G_u and P^M_u stand for user embedment of GMF and MLP, respectively, and q^G_i and q^M_i stand for embedment of projects, respectively, using ReLU as the activation function of the MLP layer.

GMF linearly simulates underlying feature interactions, and MLP nonlinearly learns interaction functions from the data. GMF and MLP are integrated under the NCF framework to reinforce each other and better deal with complex modeling.

3. DISCUSSION: JOIN CHATGPT FOR SMART RECOMMENDATIONS

To solve the three problems of the traditional recommendation system: cold start, sparsity and vulnerability, the recommendation system with ChatGPT can be effectively solved.

According to the study of Lin and Zhang[13], artificial intelligence comprehensive recommendation (hereinafter referred to as AGR) should include conversational, that is, human-computer interaction; And universality, that is, perform a large number of tasks and complete personalized recommendations for different areas.

3.1. For Cold Start Problems

The cold start problem refers to the lack of sufficient historical data or personalized information at the beginning of the system operation or new content, resulting in the system can not effectively recommend or predict.

AGR needs to do the following four things:

(1) Hybrid drive: The system should talk to the user rather than the user unilaterally demand; If the user has misunderstanding, the system should request the user to provide more information;

(2) Acquisition strategy: The system should ask questions that can best obtain information and improve the effectiveness of suggestions;

(3) Context memory: The system should be associated with context and combined with previous interaction records;

(4) Personal recommendation: According to some characteristics of the user himself, contact the recommendation project, the user himself and the context.

AGR has semantic understanding and context awareness. ChatGPT understands and generates natural language with semantic understanding of user input. This allows it to better understand the user's intentions and needs, allowing for more precise personalized recommendations. In the cold start phase, even without a large amount of historical data, ChatGPT can infer the preferences and needs of users through semantic analysis of user input, so as to make initial personalized recommendations.

3.2. For Sparsity Problems

Data sparsity refers to the limited or uneven distribution of interaction information between users and items in the data set, which makes it difficult for the recommendation system to accurately capture user preferences and behaviors.

AGR needs to do two things:

(1) Entity reasoning: When the user's memory is vague and only remembers some attributes or details, the system still has to give guesses and write reasons at the same time;

(2) Contradiction detection: In case of inconsistency with user interaction history, failure to realize user expectations or inconsistency with objective facts, the contradiction should be pointed out and reasons given.

AGR has comprehensive knowledge and cross-domain recommendation ability to solve. ChatGPT training is based on a large number of multi-domain text data, and can synthesize knowledge and information in various fields. This cross-domain understanding allows it to deal with data sparsity and make recommendations based on related knowledge even when there is limited information on certain fields or items.

In the case of high data sparsity, ChatGPT can leverage its extensive language model training experience, combined with domain knowledge and context, to provide more comprehensive and accurate recommendations.

3.3. For Vulnerability Problems

Vulnerability refers to the fact that the recommendation system is very sensitive to small changes or anomalies in the input data, which may lead to unreasonable or unstable recommendation results.

AGR needs to do the following four things:

(1) Repair mechanism: In the process of dialogue, when the user modifies/ supplements/deletes some relevant information, the system should discard/reason.

(2) Feedback mechanism: In response to users' implicit dissatisfaction (implicit feedback), the system needs to request users to provide more information and re-recommend;

(3) Behavior analysis: Users use the recommendation system many times, during which their preferences may change regularly. The system should have the ability to detect and summarize changes in user preferences;

(4) External factors: Some important external factors can also affect the user's desired decision, such as weather, time, certain deadlines, and so on. The system should capture such factors and make reasonable recommendations accordingly.

AGR has the ability to learn in real time and can be gradually improved and adjusted to solve the problem. ChatGPT can continuously learn and adjust the model in its interaction with the user, thereby gradually improving the personalization effect during the recommendation process. Its flexibility and instant learning capabilities make the system more adaptable and responsive. For vulnerability problems, ChatGPT can adjust recommendation policies and model parameters in real time through continuous interaction with users to cope with changes in user behavior and unexpected situations, thus improving the stability and robustness of the recommendation system.

3.4. Sum Up

The above research not only solves the three problems, but also clarifies the standard of future intelligent recommendation system based on ChatGPT. After learning more effective user and product information, improving learning, forecasting and comprehensive processing capabilities, the timeliness and effectiveness of recommendations will be further improved.

However, while ChatGPT has many benefits, it also has some disadvantages:

(1) Difficulty in understanding complex professional fields in semantic processing;

(2) The understanding of context is limited, and it is difficult to carry out overly complex reasoning;

(3) Training data may lack some specific demand data;

(4) Timeliness still needs to be improved;

(5) The information used for training has the risk of security attacks and information disclosure;

(6) The diversity, novelty and effectiveness of the questions raised when the system requests information from users still needs to be improved.

4. CONCLUSION

Based on deep learning and intelligent recommendation system, this paper reviews relevant literature, focuses on the technical methods of machine learning and deep learning in intelligent recommendation system, summarizes the development history of algorithms, and analyzes the progress of different algorithms.

In summary, the advantages and disadvantages of the recommendation algorithm and its application scenarios are as follows:

Because content-based recommendation is based on item characteristics, it has the advantage of strong interpretability, but the disadvantage is that it is difficult to capture complex changes in users' interests. It is suitable for scenes with rich content and information and can clearly describe item characteristics, such as music and video recommendation;

The advantage of collaborative filtering based recommendation is that it can discover hidden user interests and communities, but the disadvantage is the problem of cold start and sparsity, so it is suitable for large-scale user and commodity data;

SVD++ uses implicit feedback to process sparse data and improve accuracy. However, it has the disadvantage of complex calculation, large computing resource requirements and careful parameter tuning. It is used for scenes requiring high precision, such as movie and music recommendation;

The advantage of FM learning the interactive relationship between features is that it can process high-dimensional sparse data, but the disadvantage is that it has limited nonlinear modeling ability and high parameter optimization requirements, which is used to deal with multi-dimensional feature goods and advertising recommendation;

BPR uses the missing value hypothesis, which has the advantage of better processing of implicit feedback and directly optimizing ranking objectives, but has the disadvantage of large demand for training data and computing resources, and cold start problem, which is used for music recommendation;

NCF is combined with deep learning to learn complex user-item relationships. The advantage is that it can handle various types of recommendation tasks, such as score prediction and ranking recommendation. The disadvantage is that it has high computational complexity, large demand for training data and computing resources, and overfitting of small data sets, which is used in scenarios with complex data and large user data scale, such as e-commerce and video streaming platforms.

Intelligent recommendation system has been widely used in important links of business and social media [14], including data processing, information extraction and information sorting, etc., effectively improving the efficiency and accuracy of recommendation. For example, commodity-based accurate recommendation is conducive to reducing advertising costs [15], and social-media information based accurate recommendation is conducive to improving user adhesion [16].

In addition, whether it is engine search or machine learning or deep learning, all search or learn recommendations based on known databases, and artificial intelligence has another important ability in addition to learning and understanding: generation [17]. Especially in the field of e-commerce, according to the needs and descriptions of customers, while searching for goods, real-time generation of goods wearing or placing simulation is also a major direction of e-commerce applications.

At present, generative AI technology has shown great potential in various information technology industries. In the future, with the accumulation of more data for learning and the realization of more advanced algorithm logic, the application of deep learning technology in intelligent recommendation system will be further expanded and deepened. On the basis of solving the three problems of traditional algorithms, Greater improvement in timeliness, convenience and accuracy.

REFERENCES

[1] Li Ke and Chen Guangping, Amazon product recommendation based on deep semantic features of text [J]. Computer science, 2020, 47(02):65-71.

[2] Li Anran, Research on Taobao product recommendation method based on reinforcement learning [D]. Capital University of Economics and Business,2023.DOI:10.27338/d.cnki.gsjmu.2021.001292.

[3] Harald Steck; Linas Baltrunas; Ehtsham Elahi; Dawen Liang Yves Raimond;Justin Basilico. Deep learning for recommender systems: A Netflix case study [J]. AI Magazine. Volume 42, Issue 3. 2021. PP 7-18

[4] Lu Yao, Qiao Zhi, Zhang Peng and Guo Li. (2016, June). Ranking-based music recommendation in online music radios [C]. In 2016 IEEE first international conference on data science in cyberspace (DSC) (pp. 614-619). IEEE.

[5] Hong liang, Ren Qiuyuan and Liang Shuxian, S. X. Comparative study on information service quality of domestic e-commerce website recommendation system -- taking Taobao, Jingdong and Amazon as examples [J]. Library and information work, 2016, 60(23): 97-110. DOI:10.13266/j.issn.0252-3116.2016.23.013.

[6] Zheng Zhijun, Research on the application of content-based recommendation algorithm in thematic database [J]. Information and Computers (Theory), 2023, 35(15):116-119.

[7] Wang Z. A content-based collaborative filtering algorithm for movies and TVS recommendation [C]//Faculty of Medical and Health Sciences and Bioengineering Institute, University of Auckland, ITM Department, Illinois Institute of Technology, USA. Proceedings of the 5th International Conference on Computing and Data Science (part2), 2023:10. DOI:10.26914/c.cnkihy.2023.108612.

[8] Koren, Y. (2008, August). Factorization meets the neighborhood: a multifaceted collaborative filtering model [C]. In Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 426-434).

[9] Rendle S. Factorization Machines with libFM [J]. ACM Transactions on Intelligent Systems and Technology (TIST), 2012, 3(3):1-22.

[10] Rendle S, Freudenthaler C, Gantner Z, et al. BPR: Bayesian Personalized Ranking from Implicit Feedback [J]. CoRR, 2012, abs/1205.2618

[11] He R, McAuley J. VBPR: Visual Bayesian Personalized Ranking from Implicit Feedback [J]. CoRR, 2015, abs/1510.01784

[12] He Xiangnan, Liao Lizi, Zhang Hanwang, Nie Ligiang, Hu Xia and Chua Tat-Seng. (2017, April). Neural collaborative filtering [C]. In Proceedings of the 26th international conference on world wide web (pp. 173-182).

[13] Lin Guo and Zhang Yongfeng. (2023). Sparks of artificial general recommender (agr): Experiments with chatgpt [J]. Algorithms, 16(9), 432.

[14] Bai Huawei, Research on recommendation system based on deep network factorization model [D]. Shanghai Jiao Tong University, 2022. DOI:10.27307/d.cnki.gsjtu.2020.001601.

[15] Zhu Jiaxing, Design and Implementation of a News Recommendation System Based on Deep Learning [D]. Beijing University Of Posts and Telecommunications, 2022. DOI:10.26969/d.cnki.gbydu.2021.001473.

[16] Sun Lanchang, Research and Implementation of Recommendation System Based on Deep Learning [D]. Beijing University Of Posts and Telecommunications, 2024. DOI:10.26969/d.cnki.gbydu.2022.000600.

[17] Bao Junxian and Hong Hong, Research on the Application Status and Risks of Generative Artificial Intelligence in the E-commerce Industry [J]. Marketing of time-honored brands, 2024(07):55-57.