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RECOMMENDATION SYSTEMS IN E-COMMERCE APPLICATIONS

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Nowadays, there are more and more web applications of all kinds. Each of them solves a specific problem and makes life easier for its users. Web applications come in many different types: from a platform for learning courses and watching movies to an online store selling goods. The best systems are those that make things as easy as possible for the user, behave like old friends who know the behavior and tastes of their users and can predict their next move. It would be useful to integrate such system behavior into an online store system, as nowadays, a huge number of people prefer to buy goods online, saving time and effort. Thus, recommender systems have become an important tool for improving the efficiency of e-commerce stores and ensuring customer satisfaction. This study analyzes the main approaches to the application of recommender systems for online stores, substantiates the advantages and feasibility of the selected technologies for the implementation of an online store information system using neural networks.

Key words: recommendation systems; information technology; e-commerce.

Introduction

In the modern world, web applications are becoming not only popular but also essential tools that make our lives easier. Every day, more and more diverse online platforms are emerging to address different user needs. However, among them, a special place is occupied by those that can predict and meet our needs with increased accuracy, using recommendation systems and addressing search queries and information about the preferences of each individual user. In particular, recommender systems are becoming increasingly important in online shopping, as they help users make online purchases faster and more convenient.

However, even the best systems cannot always accurately predict user preferences. This problem can be solved by using machine learning approaches. By analyzing user behavior on the site and learning their preferences, such a system can provide personalized product recommendations, making it more accurate and convenient for customers. This paves the way for the creation of an online store information system that uses neural networks to optimize the product selection process, in order to increase the convenience and efficiency of shopping for users.

Problem statement

The connection of the highlighted problem with important scientific and practical tasks is that the integration of neural networks into online store information systems is an urgent and promising task for research and implementation. The scientific tasks include analyzing literature sources to understand and assess the prospects for developing such a system, as well as studying existing analog systems and recommender system methods.

From a practical point of view, the tasks include the development and implementation of an online store information system based on neural networks for analyzing and predicting user needs. This involves selecting and using appropriate development methods and tools, developing recommendation algorithms based on neural networks, and evaluating the results of their work. The practical significance lies in the creation of an innovative information system that will improve the user experience and contribute to the growth of online store profits by increasing the likelihood of purchases.

Analysis of recent research and publications

Today, product recommendation systems can understand customers in real time and suggest the best products using several different algorithms. They typically use different types of stored data, fully personalizing category pages or search results by displaying the most relevant offers overall on the homepage. This is the so-called static approach to product recommendations[1]. The best recommendation methods should be dynamic, able to respond to user behavior, study it, analyze it, and recommend products for a particular user based on this data.

Recent research and publications on the use of recommender systems in e-commerce applications indicate that this technology continues to evolve and is becoming increasingly important for improving business efficiency and meeting consumer needs [2, 3]. The main conclusions and trends that can be identified from these studies include:

1. Personalization: Recent studies emphasize the importance of personalized recommendations for e-commerce users. Individualized recommendations based on purchase history, browsing history, and other factors can increase conversion and customer satisfaction. Researchers [4–6] explores novel AI techniques and architectures tailored for e-commerce recommendation systems, along with empirical evaluations of their performance.
2. The use of artificial intelligence: Research is focusing on the use of artificial intelligence technologies, such as neural networks, to improve the accuracy of recommendations and implement more sophisticated prediction models. The cited research [6–8] likely explores novel AI techniques and architectures tailored for e-commerce recommendation systems, along with empirical evaluations of their performance.
3. Multimodality: Recent publications indicate that recommender systems in e-commerce applications are becoming increasingly multimodal, meaning they take into account different types of data, such as textual information, images, videos, etc., to provide more accurate and relevant recommendations. The referenced publications [9–11] likely investigate methodologies for integrating multiple modalities into recommendation models and assess their impact on recommendation quality compared to unimodal approaches.
4. Ethics and transparency: Recent studies have emphasized the importance of ethical and transparent use of recommender systems, including avoiding the “filtering bubble” problem and ensuring that users have access to control over their personal data and recommendation settings [12]. Researchers are likely exploring strategies for mitigating algorithmic biases, promoting transparency in recommendation processes, and empowering users with greater control over their data and recommendations.

Overall, recent research has shown significant progress in the use of recommender systems in e-commerce applications, and also identifies new directions for further development and improvement of these technologies. There are many algorithms that use this data to recommend products, so in the following, we will review and analyze a few of these algorithms to better understand how they work [13-15].

Article purpose

Purpose – to develop an architecture for a multimodal data processing pipeline in an e-commerce recommender system.

The object of research is the processes of using recommender systems in the field of e-commerce.

The subject of research is machine learning methods used to recommend goods and services in e-commerce systems.

To achieve this goal, the following main research objectives have been identified

- to formulate the requirements and principles of developing a recommendation system using machine learning models and multimodal approaches to data processing and accumulation.
- to develop the architecture of the method of processing multimodal data in the recommender system of e-commerce;
- to propose a pipeline for processing multimodal data streams.

Methods and material

Нейронні Graph-based neural networks (GNNs) have been one of the emerging topics in the world of artificial intelligence in recent years with great potential for business applications [17] Graphs are expressive and flexible data structures that are often used due to their effectiveness in modeling and representing various complex interactions and relationships, making them ideal for processing complex and diverse data.

Due to their many useful properties, GNNs have gained popularity for use in a wide range of business tasks. They are used for fraud detection, drug detection, or social media analysis. GNNs take advantage of the fact that in many of these cases, data can be very easily represented as graphs, such as the relationships between groups of people in the case of social networks.

However, one of the most promising applications of GNNs is in recommender systems. By analyzing the relationships between products and users, GNNs can make personalized recommendations based on previous behavior and interactions [18, 19]. Due to the efficiency and business value gained from such recommendations, more and more large companies are starting to use GNNs in their re-recommendation systems, for example:

- Uber Eats used the GraphSage algorithm to suggest meals that would be most appealing to individual users;
- Pinterest used its own PinSage algorithm, which was used to create visual recommendations based on users' tastes;
- At Alibaba, GNNs were used to support a variety of business scenarios, including product recommendations and personalized search.

To determine whether or not choosing a GNN is a good approach to a particular business problem, it's first worthwhile to familiarize yourself with how they work and what data they can provide the best results [20].

I'll start with what graphs are, as this is one of the basic concepts that GNNs are based on. It is data modeled as graph structures that serve as input for these algorithms. A graph is a fairly simple data structure that is extremely flexible and can model interactions within the data well. For example, in recommender data, we typically analyze the interaction between users and items, which are shown in Fig. 1.

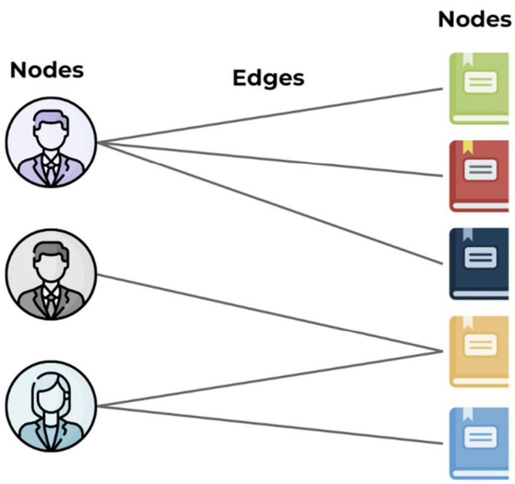

Fig. 1. Graph diagram

Graphs are basically composed of two elements: nodes, which represent some types of entities, in this case users and products, and edges, which here represent the interaction between them. This can be, for example, information about which products a user has bought or added to the cart.

But that's not all. As mentioned earlier, graphs are also very flexible and expressive data structures. It's no problem to additionally include information about interactions between users, such as users following features from Instagram or friends from Facebook. We can also add time data to our graph data representation very easily. We can also include different types of edges that indicate whether a particular user has added an item to their favorites (green dashed lines in Fig. 2). Finally, each node can additionally store classic table data that will present information about a given user or item (purple and blue tables in Fig. 2).

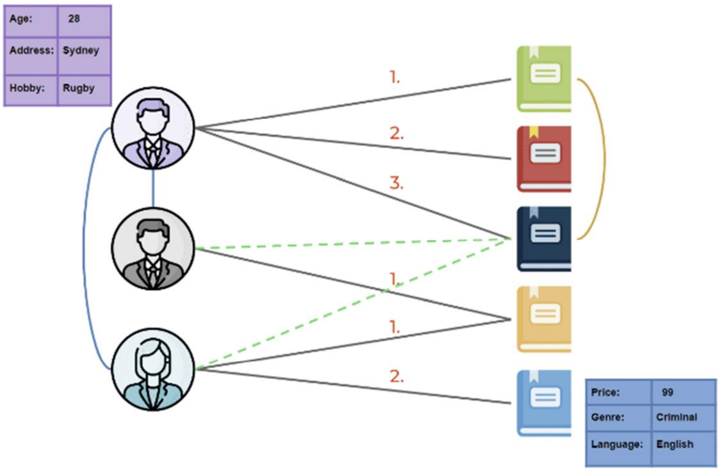

Fig. 2. Graph diagram

So with graphs, we can really model a lot of complex interactions in a fairly simple way. However, what makes these data structures very useful is how GNNs can use them.

Now that we know what graphs are, we can focus on how GNNs use them to solve a specific problem, namely product recommendation. Suppose we want to predict which product we should recommend to a user to increase the chances that the user will buy it. Let's assume that we have already defined the characteristics of users and items for each node, which are depicted by colored bars in Fig. 3.

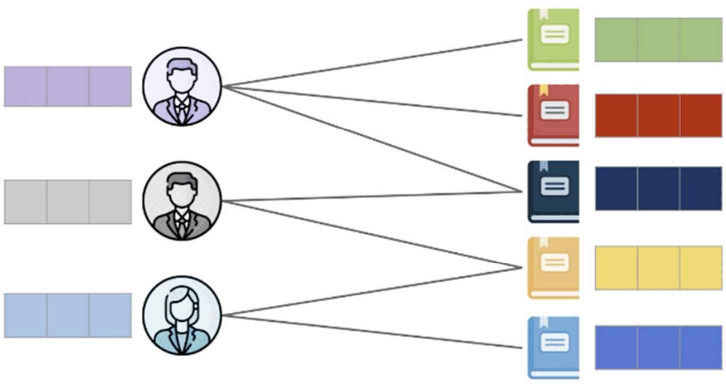

Fig. 3. Graph diagram

A vector representation of a characteristic is simply a numerical representation of it, which is easier to use by many different algorithms because it is a fairly universal format. In this form, we can represent categories, images, or entire texts that can be descriptions of our products. As mentioned, the task will be to predict which product a particular user is likely to buy next, so we just need to find a new edge/connection between the user and the product. This prediction will help us create a useful recommendation. The idea of how we do this is to update the node characteristic values so that by comparing the vector representation of the user characteristic with the vector representation of the item characteristic so that based on their similarity we can calculate the probability that this user will buy this particular item. So, how is this done? First, let's define what are the neighbors of a node in the graph – they are simply nodes connected by an edge. Okay, moving on, like any other deep neural network, graph neural networks also have layers. In each layer, for each node, we collect information from each of its neighbors. Using this information, we update the vector representation of the target node's characteristics.

For this example, let's focus on the gray user in Fig. 3 above. We can see that he has two neighbors: a dark blue object and a yellow object. At the first level of our GNN, we take the vector representation of the characteristics of these two items, combine them, and update the vector value of the gray user's characteristic with this. This process is called graph propagation. If we were to add a second layer to our network, we would first perform the above steps for the gray user's neighbors as target nodes, and only then update the gray user's state. An example of the scheme is shown in Fig. 4 below. The more layers our network has, the more neighbors will be considered during a single pass through the network. Each of these passes consists of steps of updating the node view and is performed sequentially according to the order of the layers – from the last to the first. Aggregation and update functions can take many different formats and may vary depending on the network architecture.

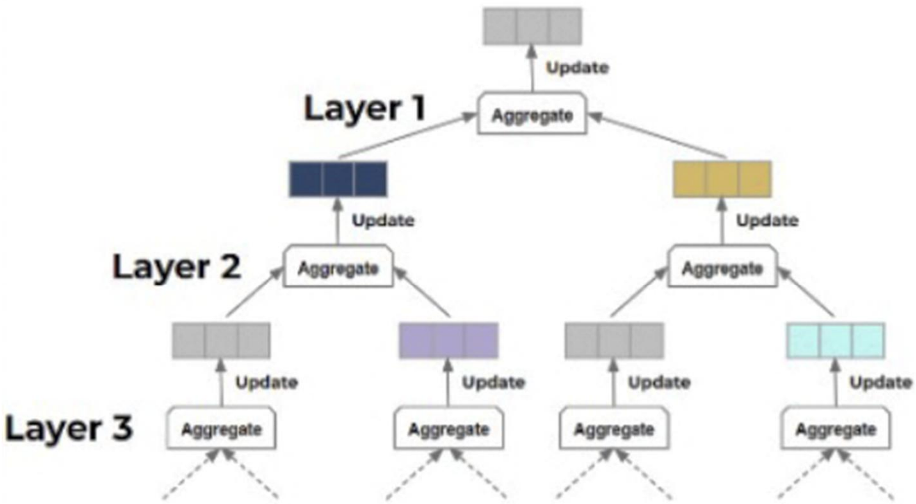

Fig. 4. Graph diagram

At the end of this process, we can compare the user's vector values with each of the elements and recommend the element whose vector value is closest to the user's vector value. For example, the gray user and the red element shown in Fig. 5 below. Through the process of message propagation, the generated user vector values take into account the characteristics of the items that users have previously interacted with, as well as the characteristics of users who have similar tastes to our target user.

This ensures that the final vector value captures well the interaction between users and items, as well as their characteristics, allowing for accurate and personalized recommendations.

The information system under development uses an algorithm based on Graph Neural Networks (GNN). This approach allows modeling the interaction between users and products, as well as other additional information such as ratings, reviews, and product categories. The main stages of a GNN-based information system for product recommendations can be described as follows and are shown in Fig. 6:

1. Processing of input data: A graph is created based on the interactions between users and products. Each user and product are represented as nodes in the graph, and the edges of the graph represent their interactions, such as purchases or reviews.

2. Vectorization: For each node in the graph (user or product), a vector representation is defined. This representation can be obtained using a GNN that processes information about interactions with neighboring nodes.
3. Prediction: The resulting vector representations of users and products are used to predict product ratings for users or to make recommendations.
4. Training the GNN model: The GNN model is trained using training data that contains interactions between users and products. During training, the GNN optimizes the parameters for better vector representation and recommendations. Initially, all the data is represented in graph form using an adjacency matrix, and then the GNN model optimizes the parameters for the max-margin loss function.
5. Evaluation of recommendations: The generated recommendations can be used to display to users on a website or in an application. The key metric for evaluating the quality of the proposed recommendation is the hit rate, i.e. whether the user chose the proposed recommendation, determined as a percentage of the total number of recommendations received from the system.

Fig. 5. Graph diagram

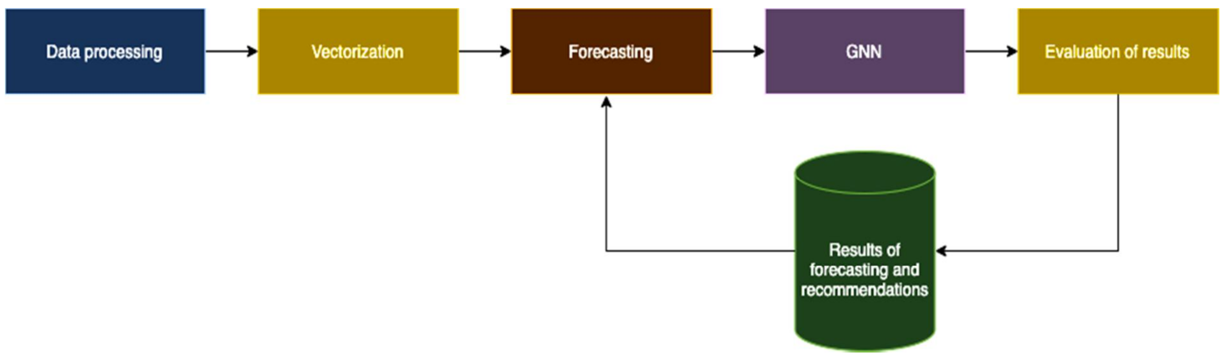

Fig. 6. Proposed architecture of the recommender system

Conclusion

This study analyzes the literature related to recommendation algorithms, in particular, product recommendations using GNN-based neural networks. It is determined that the introduction of recommender systems based on artificial intelligence can affect sales performance, increase customer loyalty, conversion and the average number of orders. The purpose, subject, object and tasks of this study are formulated. The methods of solving the problem, their advantages and feasibility of further implementation are described. An architectural solution for a recommender system based on GNN is developed and demonstrated. As a result, the use of GNNs for recommendations allows modeling complex interactions between users and goods and services, taking into account the history of their interactions and other contextual factors. This can improve the quality of recommendations and provide users with a more personalized experience when shopping in e-commerce applications.

References

1. Kulkarni, A., Shivananda, A., Krishnan, V. A. (2022). Applied Recommender Systems with Python: Build Recommender Systems with Deep Learning, NLP and Graph-Based Techniques, pp. 264, Publisher Apress.

2. Izonin, I., Tkachenko, R., Vitynskyi, P., Zub, K., Tkachenko, P., Dronyuk, I. (2020). Stacking-based GRNN-SGTM Ensemble Model for Prediction Tasks. International Conference on Decision Aid Sciences and Application (DASA), 326–330.

3. Shakhovska, N., Basystiuk, O., & Shakhovska, K. (2019). Development of the Speech-to-Text Chatbot Interface Based on Google API. In MoMLeT, 212–221.

4. Falk, K. (2019). Practical Recommender Systems. Manning Publications. https://www.perlego.com/book/1469487/practical-recommender-systems-pdf

5. Genovese, A. (2020, October 6). *Recommendation algorithms in e-commerce industry*. Alexgenovese. https://alexgenovese.it/blog/recommendation-algorithms-in-e-commerce-industry-how-they-works

6. Masolo, C. (2023, January 18). EBay New Recommendations Model with Three Billion Item Titles. Infoq. https://www.infoq.com/news/2023/01/ebay-recommendations-odel/

7. Krysik, A. (2021, October 14). Amazon's Product Recommendation System In 2021: How Does The Algorithm Of The eCommerce Giant Work? Recostream. https://recostream.com/blog/amazon-recommendation-system

8. Faggella, D. (2022, May 10). Artificial Intelligence at Alibaba – Two Current Use-Cases. Emerj. https://emerj.com/ai-sector-overviews/artificial-intelligence-at-alibaba/

9. Marr, B. (2022, May 10). *The Amazing Ways Retail Giant Zalando Is Using Artificial Intelligence*. Bernard Marr & Co. https://bernardmarr.com/the-amazing-ways-retail-giant-zalando-is-using-artificial-intelligence/

10. Rybchak, Z., & Basystiuk, O. (2017). Analysis of methods and means of text mining. ECONTECHMOD. AN INTERNATIONAL QUARTERLY JOURNAL., 6(2), 73–78.

11. Shakhovska, N., Vovk, O., Kryvenchuk, Y. ((2018). Uncertainty reduction in Big data catalogue for information product quality evaluation. Eastern-European Journal of Enterprise Technologies., 1(2), 12–20.

12. Basystiuk, O., Melnykova, N. (2022). Multimodal Approaches for Natural Language Processing in Medical Data. 5th International Conference on Informatics & Data-Driven Medicine, 246–252.

13. Havryliuk, M., Dumyn, I., Vovk, O. (2023). Extraction of Structural Elements of the Text Using Pragmatic Features for the Nomenclature of Cases Verification. Advances in Intelligent Systems, Computer Science and Digital Economics IV. CSDEIS 2022. Lecture Notes on Data Engineering and Communications Technologies., 158. https://doi.org/10.1007/978-3-031-24475-9_57

14. Shakhovska, N., Zherebetskyi, O., Lupenko, S. Model for Determining the Psycho-Emotional State of a Person Based on Multimodal Data Analysis. Applied Sciences. 2024; 14(5):1920. https://doi.org/10.3390/app14051920

15. Basystiuk, O., Shakhovska, N., Bilynska, V., Syvokon, O., Shamuratov, O., & Kuchkovskiy, V. (2021). The Developing of the System for Automatic Audio to Text Conversion. Symposium on Information Technologies & Applied Sciences.

16. Chukhray, N., Mrykhina, O., Izonin, I. Holistic Approach to R&D Products' Evaluation for Commercialization under Open Innovations. Journal of Open Innovation: Technology, Market, and Complexity. 2022; 8(1):9. https://doi.org/10.3390/joitmc8010009

17. Boyko, N., Mochurad, L., Parpan, U., & Basystiuk, O. (2021). Usage of Machine-based Translation Methods for Analyzing Open Data in Legal Cases. Cyber Hygiene and Conflict Management in Global Information Networks (CyberConf 2019), 328–338.

18. Gunawardana, A., Shani, G. (2015). Evaluating Recommender Systems. In: Ricci, F., Rokach, L., Shapira, B. (eds) Recommender Systems Handbook. Springer, Boston, MA. https://doi.org/10.1007/978-1-4899-7637-6_8

19. Zheliznyak, I., Rybchak, Z., Zavuschak, I. (2017). Analysis of clustering algorithms. Advances in Intelligent Systems and Computing, 305–314.

20. Havryliuk, M., Kaminskyy, R., Yemets, K., Lisovych, T. (2023). Interactive Information System for Automated Identification of Operator Personnel by Schulte Tables Based on Individual Time Series. Advances in Artificial Systems for Logistics Engineering III. ICAILE 2023. Lecture Notes on Data Engineering and Communications Technologies, vol 180. Springer, Cham. https://doi.org/10.1007/978-3-031-36115-9_34

ЗАСТОСУВАННЯ РЕКОМЕНДАЦІЙНИХ СИСТЕМ В ЕЛЕКТРОННІЙ КОМЕРЦІЇ

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У наш час з'являється усе більше і більше найрізноманітніших вебдодатків. Кожен з них вирішує якусь конкретну проблему, все більше і більше спрощує життя своїм користувачам. Веб-додатки бувають найрізноманітніших типів: від платформи навчальних курсів та перегляду фільмів до інтернет-магазину з продажу товарів. Найкращі системи – це ті системи які максимально спрощують роботу для користувача, поводять себе наче старі друзі, які чудово знають поведінку та смаки користувачів та можуть передбачати їх наступний крок. Таку поведінку системи було б корисно інтегрувати в систему інтернет-магазину, оскільки зараз надзвичайно багато людей купують товари онлайн, економлячи час та сили. Отже, рекомендаційні системи стали важливим інструментом для підвищення ефективності магазинів електронної комерції і забезпечення задоволення споживачів. В межах дослідження було проаналізовано основні підходи до застосування рекомендаційних системи для інтернет магазинів, обґрунтовано переваги та доцільність вибраних технологій для реалізації інформаційної системи інтернет-магазину з використанням нейронних мереж

Ключові слова: рекомендаційні системи; інформаційні технології; e-commerce.