

Enhanced Experiences: Benefits of AI-powered Recommendation Systems.

Kouayep Sonia Carole*, Tagne Poupi Theodore Armand**, Hee Cheol Kim*

* Institute of Digital Anti-Aging Healthcare, Inje University, Gimhae 50834, Republic of Korea

** Institute of Digital Anti-Aging Healthcare, Inje University, Gimhae 50834, Republic of Korea
 carolesonia39@gmail.com, poupiarmand2@gmail.com, heeki@inje.ac.kr

Abstract— Today, information technology has brought various innovations and developments in almost every field of advancement. Recommendation Systems (RS) have achieved a significant milestone in the service business during the information systems era. Regarding online services, RS has been crucial in enhancing product availability and offering prospective customers a wider range of luxurious options. Conversely, online retailers face increasing their sales volume and achieving greater product prices than their rivals. One solution is to use recommendation systems that leverage artificial intelligence (AI) to provide personalized recommendations to users. These systems employ machine learning algorithms to examine user data, including search history, purchasing patterns, and preferences, to anticipate the products that consumers are most likely to be interested in. AI-powered recommendation systems have demonstrated their immense value as tools for decision-making, enhancing user experience, and fostering corporate success. This comprehensive review explores the multifaceted world of recommendation systems, delving into their mechanisms, applications, and transformative impact across diverse domains. From e-commerce to content streaming and beyond, these systems have redefined how we discover, choose, and engage with products, content, and services.

Keywords— Artificial Intelligence (AI) collaborative filtering (CB), content-based recommendation, hybrid recommendation system, Recommendation System (RS), user-based recommendation

I. INTRODUCTION

Recommendation systems emerged soon after the development of the World Wide Web, and related technologies were thoroughly studied and applied in both academic and corporate contexts. Recommendation systems are powerful web programs that provide daily suggestions for many types of material, such as news feeds, videos, e-commerce products, music, movies, books, games, friends, and work. They are offering services to an immense multitude of individuals, amounting to billions. Recommendation systems are artificial intelligence (AI) technologies that suggest items and services to users based on their interests and decisions. It assists users in discovering neglected products, provides personalized recommendations based on user preferences, and ultimately improves the efficiency and enjoyment of the shopping experience. This technology can significantly improve customer satisfaction and increase revenue by automating the search process and saving clients

time. Recommendation systems utilize machine learning algorithms to offer personalized products, services, or information recommendations, considering users' behavior, interests, and history. According to statistics, 80% of customers are more likely to buy from a brand that provides a personalized experience.

Additionally, businesses that utilize recommendation engines experience a 150% surge in click-through rates, boosting sales and revenue. Netflix is an excellent example of a company that has harnessed the power of recommendation engines to revolutionize streaming. Netflix reduced its churn rate and annual savings of almost \$1 billion by delivering customized content to its viewers.

AI-powered recommendation systems have become indispensable in the digital landscape as they facilitate customized experiences and shape user behavior. These systems use artificial intelligence to examine extensive datasets, detect user preferences, and provide customized recommendations. This paper provides an in-depth analysis of the fundamental elements of recommendation systems, elucidating their mechanisms and the various applications that derive advantages from their capabilities.

II. TYPES OF RECOMMENDATION SYSTEMS

Recommender systems can be constructed using several methods, ranging from algorithmic and formulaic approaches to model-centric ones. The methodologies encompass page rank, collaborative filtering, content-based, and link prediction. However, it is important to note that complexity does not necessarily translate to better performance, and simple solutions and implementations often produce the best results. Establishing clear criteria for "good" recommendations is essential for assessing the effectiveness of the recommender system that has been constructed. The efficacy of a recommendation can be evaluated using diverse strategies that gauge its comprehensiveness and precision. Accuracy refers to the ratio of the right recommendations to the total number of possible recommendations.

In contrast, coverage quantifies the fraction of items in the search area that the system can provide recommendations for. The evaluation of suggestions is contingent exclusively upon the dataset and the methodology employed to generate these recommendations. Figure1 illustrates two distinct recommendation system approaches: one is a content-based

strategy, while the other is a collaborative filtering method. A hybrid recommendation system is a modern recommendation [9].

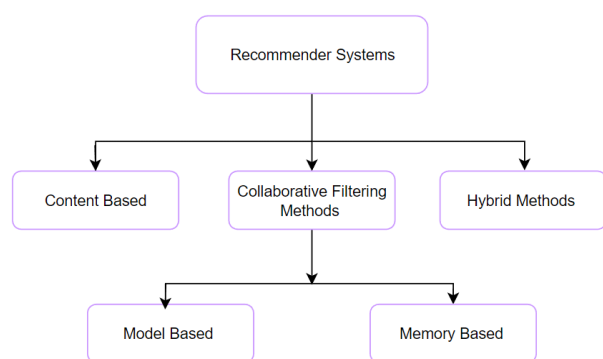


Figure 1. Different recommendation techniques.

A. Collaborative filtering

Collaborative filtering is a technique used in recommendation systems to predict user interests and preferences based on data and patterns from many users. The basic principle of collaborative filtering is that two users with similar preferences in one product are likely to have similar preferences in other products. The two primary categories of collaborative filtering methods are memory-based, which involves neighborhood computation, and model-based, which utilizes data mining techniques such as Bayesian networks, clustering, and semantic analysis

B. Content-based

The content-based approach suggests recommending an item to a user by considering their previous interactions with related items. A content recommender system generally consists of three main steps: user-profile generation, item-profile generation, and model-building. These steps are used to provide personalized recommendations for an active user. A content-based recommender system utilizes the characteristics or attributes of objects and user profiles to suggest items to users. Both the user and item qualities hold equal significance in creating a prediction. Let's take the example of a news recommender. To determine the similarity between news articles, it is necessary to consider features such as categories (Finance et al., Entertainment, etc.) and Location (local, national, or international).

C. Hybrid recommendation

In modern times, organizations employ a combination of many recommendation approaches, known as a hybrid recommendation technique [1]. The hybrid approach [2, 3] leverages the benefits of both content-based and collaborative filtering techniques, combining their efforts to develop a system that maximizes their individual strengths. The system employs accuracy metric methodologies to provide user-centered evaluation and give recommendations. It enhances the overall efficacy of the recommendation.

III. AI-POWERED RECOMMENDED SYSTEMS

Recommendation systems use AI techniques to analyse data and make suggestions

A. AI methods used in recommender systems

Machine learning and deep learning techniques play the main role in recommender systems that help with prediction and recommendation. The primary determinant in recommender systems is the combination of information security and privacy [6]. The recommender system employs machine learning techniques, including Matrix factorization, singular value decomposition, and variable-weighted singular value decompositions.

1) Matrix Factorization

This method correlated both user and item to latent factors which help to hide the internal information behind the data [12]. Matrix factorization algorithms can be used to make predictions about user preferences by mapping users and items to these latent factors and using the relationships between the factors to make recommendations

2) Singular Value Decomposition

This fancy math method makes the big table from Matrix factorization easier to work with. It helps the computer to find pattern in the data even faster [13,14].

3) Variable Weighted

This method is the improved version of the Singular Decomposition method. The variable weight plays a main role in the method [10]

B. Deep learning method used in recommender system

Deep learning is the subset of machine learning field where different models of deep learning approach can be used in prediction and recommendation of recommender system such as Multilayer Perceptron (MLP), Restricted Boltzmann Machine (RBM), Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) [6,7,8]

a. MLP with auto-encoder

MLP is based on a feed forward neural network that uses multiple hidden layers. Each layer uses a different transfer function as activation function arbitrarily. Auto-encoder is a deep learning model, i.e., based in back propagation technique that finds the gradient of the error function w.r.t. the weights of the neural network

b. Convolution neural network

CNN is a deep learning model that based on feed-forward network. This neural network used a different convolution layer which finds the local and global features of the input data.

c. Restricted Boltzmann Machine

This model is usually working on probability distribution over the inputs, which consists of two layers such as visible and hidden layer [11]. No layer is communicated among the visible and hidden layer. A matrix of weights W represents the strength of the connections among hidden and visible units.

Performance of the model mainly depends on the number of hidden units

d. Adversarial networks

Adversarial Network is a kind of neural network, which is generative in nature and this network has two parts such as discriminator and generator.

IV. BENEFITS OF USING AI-POWERED RECOMMENDED SYSTEMS

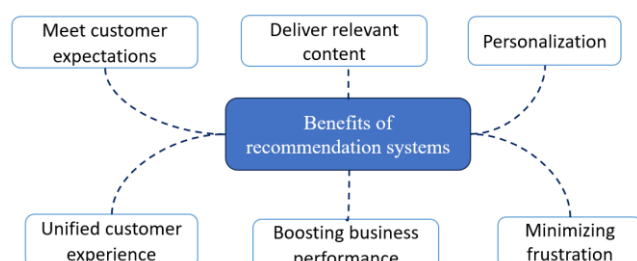


Figure 2. Benefits of Recommendation systems

1. PERSONALIZATION

In today's world of information overload, customers are inundated with choices and information, making it challenging to capture their attention. Personalization enables businesses to differentiate themselves by offering clients customized recommendations that align with their distinct requirements and preferences. Consequently, this can increase engagement, drive sales, and foster long-term customer loyalty. A recommendation engine is a very efficient tool for providing customized consumer experiences. A recommendation engine utilizes consumer data on prior behavior and preferences to propose products or services that are highly likely to interest the individual. This results in a smoother and more pleasant customer experience where customers feel understood, valued, and appreciated.

2. UNIFIED CUSTOMER EXPERIENCE ACROSS CHANNELS

An AI-driven recommendation engine has the potential to revolutionize the delivery of a uniform experience across diverse channels such as social media, websites, and mobile apps. This engine ensures uniformity by collecting and utilizing client interaction data from several channels. When a consumer searches for a product on your website, the recommendation engine can use this information to provide individualized product recommendations via email or other channels, creating a smooth and consistent user experience.

3. DELIVER RELEVANT CONTENT

In today's digital age, the delivery of pertinent content is paramount for engaging customers. Brands that provide customized content have a greater likelihood of attracting and retaining their client base. Recommendation engines are

crucial in helping organizations achieve this goal by providing customized and relevant material to their target audience.

4. MINIMIZING FRUSTRATION IN THE CUSTOMER EXPERIENCE

An AI recommendation engine can reduce user frustration by offering customized and relevant content. The engine employs consumer behavior and preferences analysis to deliver tailored recommendations that effectively capture customer attention. This not only enhances the overall consumer experience but also results in increased sales and profitability for enterprises. By employing an AI recommendation engine, enterprises may prevent consumer dissatisfaction by delivering a tailored and engaging experience.

5. MEET CUSTOMER EXPERIENCE EXPECTATIONS

Providing personalized and seamless experiences is now more crucial than ever, emerging as a pivotal factor in building brand loyalty. By examining client behavior and preferences, these engines provide customized product recommendations that anticipate individual wants and aspirations. This tailored approach enhances the strength of customer connections and fosters enduring dedication. Furthermore, recommendation engines contribute to maintaining consistency across several touchpoints, ensuring a uniform experience from the website to social media and other channels. By offering customized and relevant content, businesses can engage customers on their preferred platforms, ensuring a seamless and uninterrupted experience throughout their whole contact.

6. BOOSTING BUSINESS PERFORMANCE WITH RECOMMENDATIONS ENGINES

In order to enhance the likelihood of a purchase, offering personalized product recommendations to your customers is recommended. Utilizing an AI-powered recommendation engine can optimize the efficiency of your up-selling and cross-selling strategies, simplifying the buying process and improving customer convenience.

V. AI-POWERED RECOMMENDATIONS SYSTEMS: ONLINE RESERVATION HEALTH-CARE: STUDY CASE

A recommendation engine utilizes machine learning and data analysis to generate customized recommendations. Data is the fundamental basis of a recommendation engine, as it supplies the essential information required for extracting patterns. This technique can potentially transform how people receive medical treatments by simplifying the procedure according to their symptoms and preferences. Here is a potential implementation of the concept:

1. **Data Collection:** AI-powered recommendation systems acquire user data through explicit methods, such as user ratings and comments, and implicit

ways, such as examining order history, return history, and search logs. After gathering substantial data, the system offers more relevant recommendations, enhancing the probability of attracting consumer interest. Individuals can enroll themselves to access the functionalities offered by the health interface.

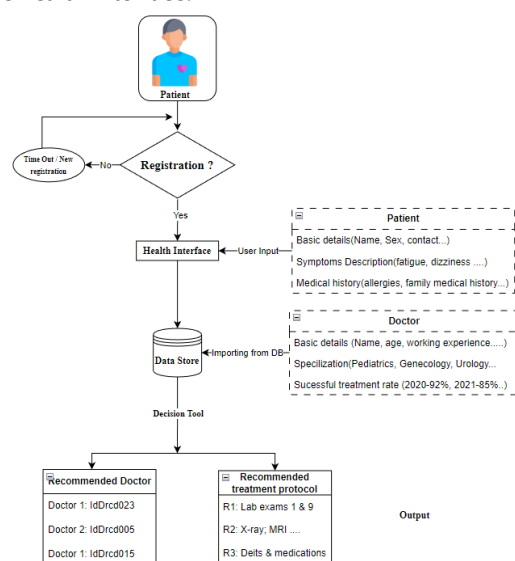


Figure 3. Online reservation recommender system for health-care

2. **Data storage:** After a successful registration, individuals are given access to the health interface, where they can input their personal information, symptoms, and other pertinent details.
3. **Data Analysis:** The patient's specific information is stored in a data repository. Decision logic refers to making decisions based on various methods such as classification, fuzzy logic, IF-THEN rules, and decision trees. The system employs AI algorithms to analyze the symptoms the user provides, categorizing and evaluating them based on a database of medical conditions and their corresponding departments.
4. **Data filtration:** Once the system has accumulated and analyzed sufficient data to generate pertinent recommendations, the final stage involves filtering the data. Data can be filtered using various techniques, such as content-based, cluster-based, or collaborative filtering. The system utilizes symptom analysis to recommend the most suitable department(s) where the patient should seek medical care.

VI. CHALLENGE IN RECOMMENDATION SYSTEMS

Cold start problem: occurs when a system is used by a new client or when new items are introduced into the system.

Synonym: two or more different words which represents same object or meaning is known as synonym. Recommendation algorithms cannot distinguish between these words. For instance, "comedy movies" and "comedy films" are perceived as distinct by a memory-based system—collaborative filtering technique.

Privacy: Sharing personal data with recommender systems might enhance system performance, but it poses risks to data privacy and security. Privacy concerns require Users to be more confident in data to recommendation systems. Hence, content-based and collaborative filtering recommender systems must establish trust among users. However, collaborative filtering recommender systems are particularly susceptible to privacy concerns. In collaborative filtering systems, user data, including reviews, is maintained in a central repository, which might be compromised and lead to data misuse.

Sparsity: occurs when a user-item metric becomes sparse due to a very big item set. It results in subpar recommendations for certain things. The recommendation of new things relies on the evaluation provided by previous users. The absence of a record of user preferences results in subpar recommendations for new users.

Latency problem: Collaborative filtering-based recommendation systems encounter latency problems when the knowledge base is often updated with new items. In such cases, the system promotes previously scored products, while newly added products have not yet been ranked. Using the CB filtering approach might decrease the waiting time for goods, while it may result in excessive specialization.

VII. CONCLUSIONS

In today's ever-changing business environment, companies face intense competition and must do everything they can to stay ahead of their competitors. Recommendation systems are a way to stay ahead of the curve and achieve larger business goals like increasing sales, ad revenue, and user engagement. However, to be successful with a recommendation system, you must carefully consider its need and agility. Agility is also essential for recommendation systems. Recommendation systems must adapt to remain relevant and effective as user behaviors, preferences, and needs change. Agile recommendation systems evolve, considering what works and what doesn't and additional data sources that help improve recommendations. By continually evaluating and enhancing AI-powered recommendation systems, businesses can achieve their goals while providing their users with the best possible experience.

ACKNOWLEDGMENT

This research was supported by the MSIT (Ministry of Science ICT), Korea, under the National Program for Excellence in SW, supervised by the IITP (Institute of Information & Communications Technology Planning & Evaluation) in 2022 (2022-0-01091, 1711175863).

REFERENCES

- [1] Erion, C. and Maurizio, M., Hybrid Recommender Systems: A Systematic Literature Review. *Intell. Data Anal.*, 21, 6, 1487–1524, 2017.
- [2] J. Breckling, Ed., *The Analysis of Directional Time Series: Applications to Wind Speed and Direction*, ser. Lecture Notes in Statistics. Berlin, Germany: Springer, 1989, vol. 61.
- [3] S. Zhang, C. Zhu, J. K. O. Sin, and P. K. T. Mok, “A novel ultrathin elevated channel low-temperature poly-Si TFT,” *IEEE Electron Device Lett.*, vol. 20, pp. 569–571, Nov. 1999.
- [4] M. Wegmuller, J. P. von der Weid, P. Oberson, and N. Gisin, “High resolution fiber distributed measurements with coherent OFDR,” in *Proc. ECOC’00*, 2000, paper 11.3.4, p. 109.
- [5] R. E. Sorace, V. S. Reinhardt, and S. A. Vaughn, “High-speed digital-to-RF converter,” U.S. Patent 5 668 842, Sept. 16, 1997.
- [6] Cheng, H.T., Koc, L., Harmsen, J., Shaked, T., Chandra, T., Aradhye, H., Anderson, G., Corrado, G., Chai, W., Isipir, M., Anil, R., Wide & deep learning for recommender systems, in: *Proceedings of the 1st Workshop on Deep Learning for Recommender Systems*, ACM, pp. 7–10, September, 2016.
- [7] Portugal, I., Alencar, P., Cowan, D., *The use of machine learning algorithms in recommender systems: A systematic review. Expert Syst. “PDCA12-70 data sheet,”* Opto Speed SA, Mezzovico, Switzerland *Appl.*, 97, 205–227, 2018.
- [8] Mu, R., A survey of recommender systems based on deep learning. *IEEE Access*, 6, 69009–69022, 2018 J. Padhye, V. Firoiu, and D. Towsley, “A stochastic model of TCP Reno congestion avoidance and control,” *Univ. of Massachusetts, Amherst, MA, CMPSCI Tech. Rep.* 99-02, 1999.
- [9] Zhong, Z. and Li, Y., A Recommender System for Healthcare Based on Human-Centric Modeling, in: 2016 IEEE 13th International Conference on e-Business Engineering (ICEBE), IEEE, pp. 282–286, 2, November, 2016.
- [10] Wu, J., Yang, L., Li, Z., Variable weighted BSVD-based privacy-preserving collaborative filtering, in: *10th International Conference on Intelligent Systems and Knowledge Engineering (ISKE)*, IEEE, pp. 144–148, November, 2015.
- [11] Yedder, H.B., Zakia, U., Ahmed, A., Trajković, L., Modeling prediction in recommender systems using restricted Boltzmann machine, in: 2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC), IEEE, pp. 2063–2068, October, 2017.
- [12] Ortega, F., Hernando, A., Bobadilla, J., Kang, J.H., Recommending items to group of users using matrix factorization based collaborative filtering. *Inform. Sci.*, 345, 313–324, 2016
- [13] Ponnamp, L.T., Punyasamudram, S.D., Nallagulla, S.N., Yellamati, S., Movie recommender system using item based collaborative filtering technique, in: 2016 International Conference on Emerging Trends in Engineering, Technology and Science (ICETETS), IEEE, 1–5, 2016
- [14] Sahoo, A.K., Pradhan, C., Mishra, B.S.P., SVD based Privacy Preserving Recommendation Model using Optimized Hybrid Item-based Collaborative Filtering, in: 2019 International Conference on Communication and Signal Processing (ICCSP), IEEE, pp. 0294–0298, April, 2019



Kouayep Sonia Carole is Ph.D. candidate in digital anti-aging and healthcare at Inje University, South Korea. She received her Master at the Department of Information Technology (IT) and applications Engineering at Pukyong University in Busan, South Korea.

Previously, she earned her B.S degree in Computer Science from Dschang in Cameroon. Her research interests include image processing, computer vision, Artificial intelligence and Business intelligence



Metaverse.

Tagne Poupi Theodore Armand is a Ph.D. research scholar at the Institute of Digital Anti-aging and healthcare at Inje University. He received his M.Sc. in information System and Networking at ICT University USA, Cameroon Campus. His research interest field includes Artificial Intelligence in healthcare; image processing with a focus on medical image analysis, Deep Learning, Machine Learning, and



Hee-Cheol Kim received his BSc at the Department of Mathematics, MSc at the Department of Computer Science at SoGang University in Korea, and Ph.D. in Numerical Analysis and Computing Science at Stockholm

University in Sweden in 2001. He is a professor at the Department of Computer Engineering and Head of the Institute of Digital Anti-aging Healthcare Inje University in Korea. His research interests include machine learning, deep learning, Computer vision, and medical informatics.