Recommendation Systems in Banking and Finance Transforming Customer Experience and Operational Efficiency

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ABSTRACT

Modern organizations rely heavily on business intelligence and data analysis due to significant advancements in information technology. Organizations can optimize their business decisions by leveraging various computer technologies to better analyze their massive amounts of data. Recommendation system plays significant role and provides an optimized decision making to leverage the large amount of data. Various recommendation system is being discussed among the massive amount of data to deliver the quality data. Based on the discussion on the recommendation methodology related to real time applications, various challenges are listed, this pave the way to determine the scalability, sparsity and cold start problem. Recommendation system with an efficient technique being considered and various practical application examples are analyzed based on the business benefits. This helps to improve overall data quality and the efficacy of personalized recommendations for real time applications.

Keywords: Machine Learning; Artificial Intelligence; Self organized, Clustering, Recommendation, banking.

1. INTRODUCTON

Providing prompt, individualized services is essential in today's fast-paced financial environment to maintain client satisfaction and a competitive advantage. The goal of data-driven financial strategies is to identify and meet consumer needs, with a particular emphasis on corporate clients who stand to gain the most from particular financial services or goods. For corporate clients that depend on their bank to provide timely assistance in order to operate their businesses profitably, these standards become even more important. In order to achieve this, these strategies need to make use of client data in order to provide them with financial solutions that address both their present and future demands. Corporate clients typically go to the bank to turn in their financial statements after realizing they need financial assistance [1].

In order to gain a deeper understanding of the customer's financial situation, bank advisors then compile and examine these documents and data. Consumers learn about products through a variety of sources, such as the bank's internal platform, advisors (should they have one), and outside resources not affiliated with SEB. To optimize relevance and impact, the right product must be suggested at the right time. Knowing when to buy and what products are best for each individual consumer can make a big difference in their experience and level of pleasure. Lack of this technology affects customer satisfaction and retention by restricting the bank's capacity to offer quick and individualized financial solutions [2]. The proposed method is a proactive, customized recommendation system that continuously evaluates the financial circumstances of corporate clients and provides astute, client-specific, data-driven proposals or recommendations. With the use of this technology, SEB intends to shorten the time needed to offer individualized financial services and quicken its journey toward digital transformation. This approach helps the bank sell more goods and improve its digital sales while also improving client satisfaction and engagement.

The financial industry's change has accelerated due to advancements in digital technologies. The term "digital transformation" refers to the integration of digital technologies into all facets of banking and financial services, drastically altering both the client's perception and the way these services are provided. The use of new technologies such as Big Data Analytics, Cloud Computing, Artificial Intelligence, and Machine Learning, which are transforming old banking models and enabling the creation of more specialized and effective financial solutions, is what defines this change. The financial services industry is experiencing a surge in the adoption of AI due to the abundance of data and its growing accessibility, together with the expected advantages of AI/ML for financial institutions. Big data, AI, and machine learning are expected to be used by financial institutions more frequently in order to get a competitive edge by raising corporate efficiency through cost reductions and enhancing the quality of financial services commodities that consumers need [3]. Improving the client experience is one of the main forces behind the digital transformation in finance. When it comes to digital technologies, banks can satisfy customers' growing need for smooth, quick, and customized services [4].

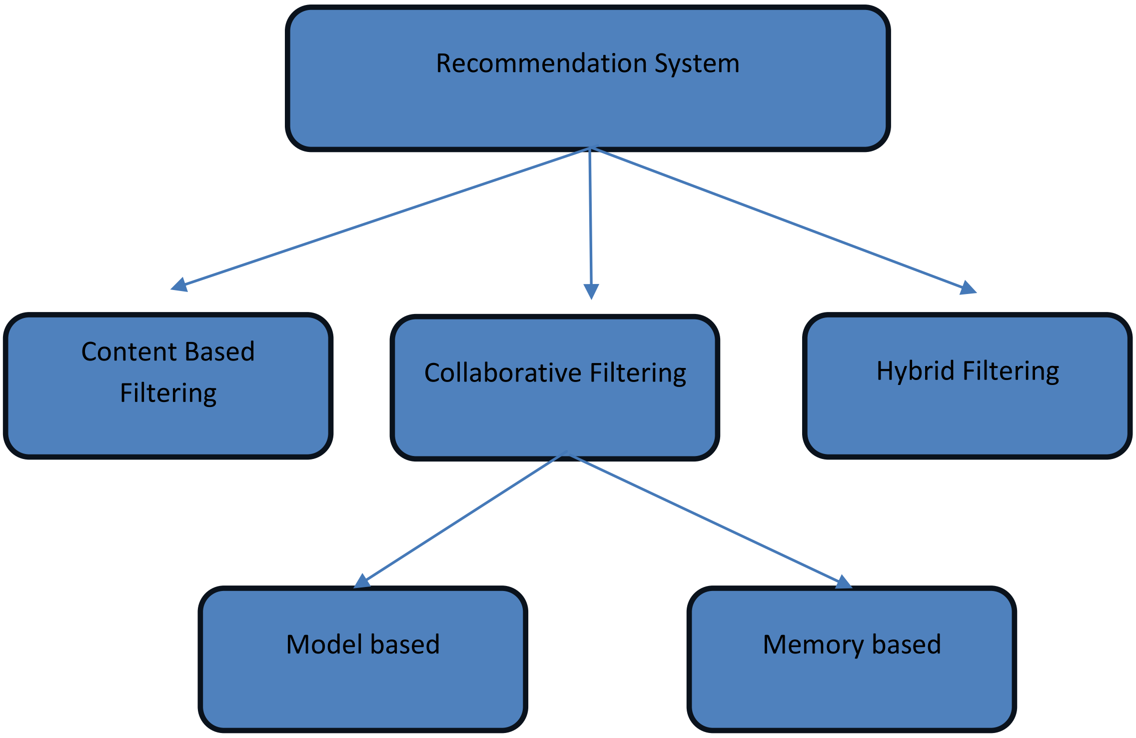

Figure 1. Recommendation System

For instance, AI and machine learning algorithms can analyze massive quantities of data to deliver personalized financial advice, identify fraud in real-time, and automate tedious tasks—all of which improve customer happiness and operational efficiency. Furthermore, banks can maximize the power of data thanks to digital transformation. Every day, financial institutions generate and collect enormous amounts of data. By utilizing contemporary data analytics, banks can gain insightful knowledge about consumer behavior, industry trends, and operational inefficiencies [5]. These insights help with informed decision-making, the creation of new goods and services, the acceleration of client growth, and, in the end, the creation of tailored recommendations. Personalized recommendation systems for online goods and services are becoming more and more crucial in an era of information and data overload. These systems help consumers find what they need quickly, saving them time. On the other hand, they enable merchants, in this case banks, to offer products that customers are likely to buy, which is advantageous to both parties. Personalized suggestions or recommendations are generated by a recommendation system, also called a recommender or recommendation engine, which is a software program or algorithm that examines user behavior, preferences, and trends [5].

Numerous techniques to enhance recommender systems that are advantageous to providers as well as users have been developed and put into practice as a result of research and innovation. Recommender systems employ a variety of strategies, some of which are shown in Figure 1. Recommender system methodology types:

A. Content-Based Filtering:

This method creates new recommendations and gives users autonomy by using tags and phrases to suggest products based on their past choices. But it isn't very creative, and it needs a lot of feature extraction, which can be computationally expensive, especially when dealing with big datasets [6].

B. Collaborative Filtering:

This method suggests things based on user interactions and comes in two flavors: memory-based and model-based

Memory-Based Collaborative Filtering: This technique looks for similarities between users and items by analyzing user-item interaction data. Using user selections as a basis, user-based filtering suggests similar

products. User B will be suggested item Y if both Users A and B enjoyed item X and User A also enjoyed item Y.
Item-Based Filtering: Makes suggestions based on items the user has previously expressed interest in. For instance, a user who prefers item X might be recommended item Y if item X and item Y are both well-liked by the same demographic.
C. Model-Based Collaborative Filtering:
This method builds prediction models using data about interactions between users and items. After then, recommendations are produced using the models. Model-based tactics anticipate user preferences for things by using machine learning and data mining. Association rules, clustering, decision trees, ANNs, Bayesian classifiers, regression, link analysis, and latent factor models—a well-studied and popular strategy—are among the techniques employed [7].
D. Hybrid Methods:
To maximize each approach's advantages, it blends collaborative and content-based filtering strategies. Cascade hybrids improve the outcomes of previous methods, feature-augmented hybrids enhance collaborative filtering with content-based features, switching hybrids utilize context-based techniques, and weighted hybrids integrate many algorithms [8] as in Figure 2.

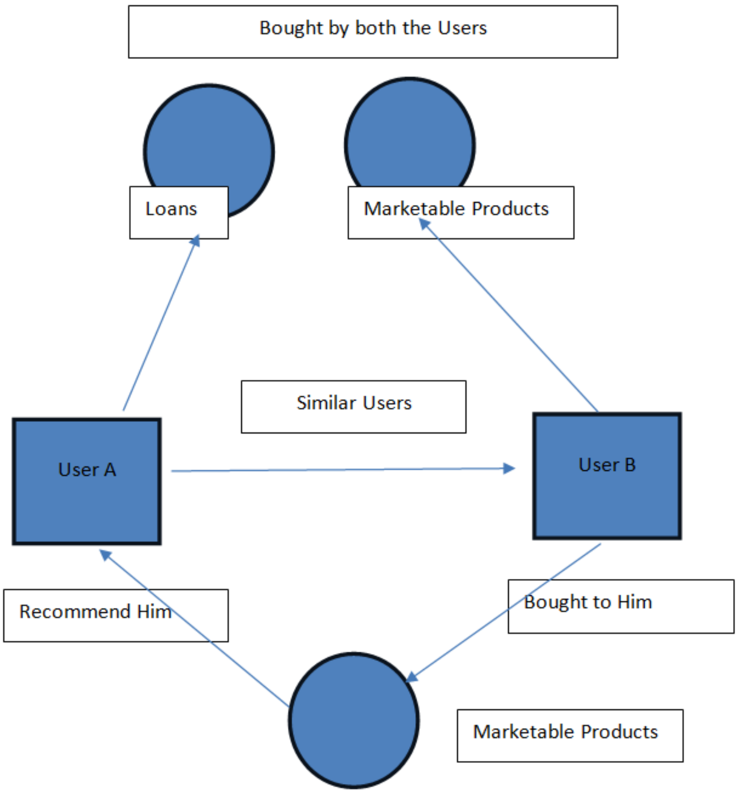

Figure 2. User Based Recommendation System

Helping customers locate relevant products or content that meet their needs, interests, or preferences is the primary goal of a recommendation system. Numerous industries, such as social media, streaming services, e-commerce, and many more, leverage these technologies [9-11]. Recommendation systems are essential in today's environment of data-driven decision-making, especially in the financial industry. By evaluating and interpreting consumer data to offer tailored recommendations, these systems seek to increase customer satisfaction and engagement. Considering SEB's goals, developing a customized recommendation system is essential to tailoring financial product suggestions to corporate clients' unique requirements.
This suggests creating a proactive digital recommendation system that makes use of artificial intelligence (AI) and machine learning (ML) technologies in order to address these issues. The main objective is to automate and optimize the process of making customized product suggestions based on each corporate client's distinct financial requirements. Through the application of sophisticated data analytics methods, like clustering and classification algorithms, the paper seeks to improve SEB's capacity to comprehend and better assist its business clientele. In order to provide customized recommendations, the proposed

system will examine a variety of Key Performance Indicators (KPIs) and find trends in client data. The best models will be chosen to develop and construct the system, concluding that the client will receive better recommendations based on their financial success, after a variety of machine learning techniques have been investigated and tested. This strategy seeks to revolutionize the consulting process by making it quick, easy, and seamless for advisers and clients alike. The main goal is to examine client financial data, spot trends, and combine findings with information from other bank data sources [12].

SEB may boost client happiness and engagement by drastically cutting down on the time needed to deliver individualized financial advice by implementing a proactive recommendation system. Advisors will be able to concentrate on more strategic duties as a result of this system's reduction of the manual workload. In the end, the initiative aims to strengthen SEB's standing as a dependable financial partner committed to offering cutting-edge and creative solutions in a fiercely competitive financial industry.

2. Challenges Related To Recommendation System In Banking Sector

With the evolution of the internet and modern web services over the last few decades, everyone now has access to a wealth of information. Users may have difficulty sorting through all of this data and extracting the most critical bits. With millions of products available on a single platform, many online e-commerce companies recommend products to their clients. The vast number of alternatives available to the ordinary user can be overwhelming, resulting in information overload. By providing users with exact, individualised recommendations of items or products based on their preferences, recommender systems attempt to address the issue of information overload while also personalising the user experience. A recommendation system (RS) uses the information offered to decide if a product is valuable to a user. Retail and e-commerce enterprises such as eBay and Amazon use these systems, as do other sectors including as agriculture, event management, transportation, education, healthcare, and insurance [26], and their use has grown dramatically in recent years. These companies collect a large amount of user data and tailor the recommendation system to meet both user and company needs [13].

High-quality recommendation systems improve user experiences as well as organisational decision-making and income. In recent years, many academics have focused their attention on recommendation systems, and multiple literature reviews have been conducted to investigate the features, challenges, and algorithms of various recommendation systems[1].However, none of these reviews thoroughly examined every facet of the recommendation system. The authors focused on classifying the recommendation system based on the data they used. In addition to the location-based recommendation system that uses social networks, there is also a review of recommendation systems that only use social networks. Recommendation systems are evaluated based on their applicability. A review focused on recommendation system algorithms and summarised their properties [14].

This article provides an in-depth introduction to recommendation systems, describes several different types of recommendation systems, and examines challenges with existing recommendation systems such as cold start, data sparsity, scalability, and diversity. Furthermore, we demonstrate how to evaluate the recommendation system's effectiveness using a variety of metrics including as recall, precision, accuracy, the Receiver Operating Characteristic curve, and F-measures. We also discuss the extensive use of recommendation systems in numerous professions and industries. Therecommender does not support raw profile data.

Creating a meta-level hybrid from any pair of recommenders is not always simple. Because the contributing recommender must create a model that will be used as input by the real recommender, not all recommendation algorithms can accomplish this. The trained model provides a concise representation of the user's desire, which is a benefit of this approach. Dealing with this reduced form is simpler than working with raw rating data in a collaborative manner [15], A system that generates personalised recommendations as output or has the effect of leading the user to interesting objects in a greater range of potential possibilities. Recommender systems will become a vital component of the Media and Entertainment sector in the near future, and it has become a beautiful background for any industrial power.

The organization's changing requirements for using and deploying a recommendation system make it difficult to assess their success. User happiness is frequently the most representative metric. Even if a heuristic method cannot be used to determine user satisfaction, we may still evaluate how well recommendation systems function by examining how successfully they handle common difficulties. This section of the review article outlines how measurements are used to determine how effectively a recommendation system works with respect to the following important problems

- Diversity
- Accuracy
- Scalability

- Data scarcity
- Potential for attack
- Cold start issue
- Habituation effect

A. Scalability

Scalability issues have become more prevalent as e-commerce websites have grown in popularity. For complicated applications, sophisticated recommendation system approaches are required to give speedy results. Recommendation systems can search for a large number of potential neighbours in real time, but the requirements of modern e-commerce sites push them to look for even more neighbours. Algorithms have performance issues when dealing with large amounts of data from information consumers. Finding a relevant neighbour for a certain neighbour, for example, might be difficult and time-consuming if a site has tens of thousands of datapoints for a single user. The exponential growth in users or items needs an increase in computation capacity for nearest-neighbor-based filtering methods [16].

Scalability is a critical issue for a platform with millions of users and products. One-dimensionality reduction is a common strategy for addressing scalability issues. Scalability issues can be mitigated by employing clustering techniques. Their primary responsibility is to apply a clustering approach to divide up the user base into neighbourhoods. The neighbourhood of any active user is then determined by peering within the partition that serves as the user's neighbourhood. After selecting a neighbourhood, normal filtering processes can be used to provide a forecast. The employment of clustering techniques provides two significant benefits. First and foremost, it reduces the data set's sparsity. Second, it divides the data into smaller bits, significantly slowing the rate of prediction development. Scalability has also been addressed through the use of Singular Value Decomposition (SVD). For dimensionality reduction, SVD is used. SVD generates a set of uncorrelated eigenvectors or latent vectors.

Each eigenvector represents either a consumer or a product. Using this strategy, the same eigenvectors can map users who have rated comparable but not identical goods. Predictions may be produced by computing the cosine similarity (dot product) between n-pseudo customers and n-pseudo products after the n rating matrix is broken down into SVD component matrices [17]. DATA

B. Sparsity

Many recommender systems are being used more frequently these days. Several commercial recommender systems take advantage of enormous datasets. Because the user-item matrix utilised for filtering is excessively large and sparse, the recommendation process's performance could suffer. The primary reason of the cold start problem is data scarcity. Because consumers only plan to rate a small number of objects, data is sparse. Although most recommendation systems integrate similar user evaluations, the reported user-item matrix contains empty or unknown ratings due to a lack of incentives or user awareness to assess things. Because they do not submit comments or ratings, recommendation systems may provide illogical suggestions to such users. Assume, for example, that an online retailer has a huge number of consumers and sells one million individual films, each of which can be rated (active) or notrated/liked and considered cold [18].

In this case, each client is characterized by a feature matrix with one million integer elements, where each element's value represents the customer's rating of a particular movie.The consumer-product interaction matrix is what is known as this matrix. The bulk of large-scale applications have huge numbers of both users and things; the matrix components will be greater than 99%, while the average will be zero. At the time of comparison, it is likely that both entries will be zero for all two users, resulting in a sparse matrix. Several techniques, such as matrix factorisation [19], try to address data sparsity by modelling users' decisions based on their behaviour and trustworthy social connectedness. The broad use of trust has significantly improved the durability of the recommendation system. Trust is defined as faith in another person's ability to provide reliable explicit or implicit ratings. The trust value can be calculated by counting the number of arcs between the users. This provides a trust-aware recommendation system that uses a trusted webnetwork to determine how a user can trust another user.

A trust network is formed by integrating each trust declaration. In a trust network, nodes represent users, whereas directed edges represent trust claims. Because of these measures, the mean error of projected accuracy has been greatly reduced. The merge strategy has attracted attention among the numerous trust-based solutions that have been presented. To increase the overall forecast accuracy of the recommendation engine, the merge adds active users' trusted neighbours. According to the similarity between the activeuser and trusted neighbor, the ratings of a trusted neighbor of an active user are specifically combined by averagingon frequently rated items.

C. Cold Start Problem

A recommendation system does not operate at its best when there is inadequate information or metadataprovided. Product cold starts and user cold starts are two distinct types of cold starts. There are no reviews since there is no customer participation when a new product is first introduced on an e-commerce website, as it goes through the product cold start. If there are insufficient user interactions, the recommendation algorithm will not know when to show the ad for that product. When a person establishes an account for the first time without any prior productpreferences or purchase history on which to base suggestions, this behavior is known as "cold-start." Both new andseasoned users experience the cold start issue. What should the recommendation system display if, for example, John searches for new refrigerators on an e-commerce site, buys one within a week, and then decides he no longer wants to purchase a refrigerator [20]

Users will always be drawn to fresh and novel ideas. When measuring and analyzing cold-startsuggestions, we discover that the Bayes classifier is most frequently applied. Graphical models known as Bayesianmodels are utilized in artificial intelligence and probability.Whether it is collaborative or content-based, Bayesian reasoning is likely to be used in model-basedrecommendation system. The naive Bayes model is the most often used application of Bayesian models. Even thought is straightforward, it has shown out to be the most accurate. Different attributes are thought to represent mutuallyindependent properties of the objects in the naive Bayes classification [21]. By using a set of qualities not included inthe training data, one may estimate the properties of a new object using this method.

Heuristics and the projectionin Weighted Alternating Least Squares are employed to some extent to alleviate the cold-start issue. If there is a newitem for the projection in the Weighted Alternating Least Squares technique that was not encountered in training butthe system has a limited number of user interactions, it is simple to compute the user's embedding for this item withouthaving to retrain the entire model. Weighted Alternating Least Squares technique, where the system solves for the embedding of the new itemwhile maintaining the accuracy of the user's embedding. This procedure may be repeated for a new user to keepthe model current. If the system has no interactions, the embedding produced by heuristic approaches for fresh objectscan be approximated. By averaging the item's embedding in the same category, this is finished.

DeepFM is a hybrid of FM and deep neural networks that use the same input embedding layer. Raw features are changed so that continuous fields are represented independently, and categorical fields are encoded once. The FM component, as a Factorization Machine, represents the strong importance of both order 1 and order 2 interactions, which are directly added to the Deep component output and fed into the sigmoid activation in the final layer as in Figure 3.

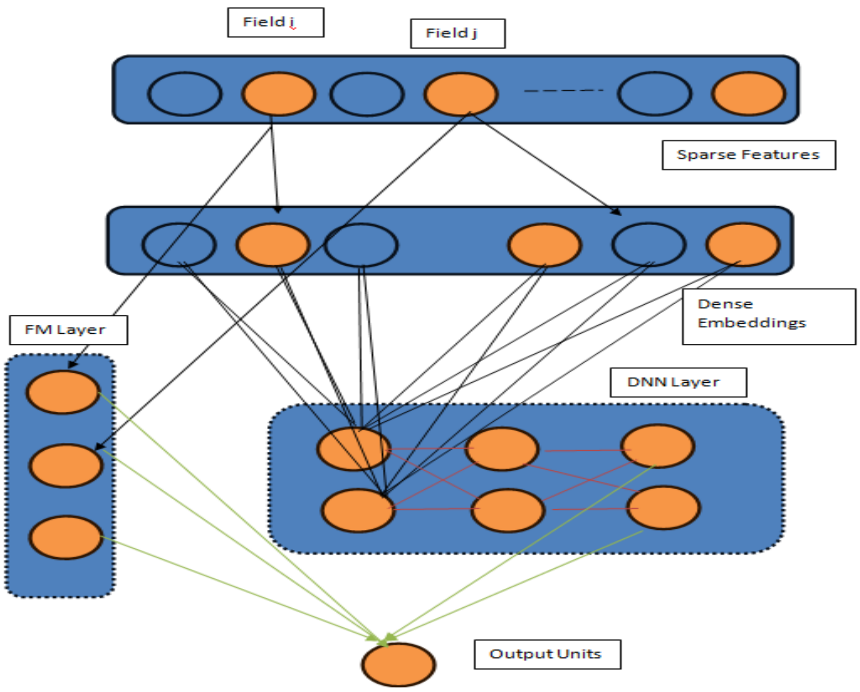

Figure 3. Deep FM Model

GNN has been widely adopted in recommender systems. Another reason is that, unlike traditional methods that only implicitly capture collaborative signals (by using user-item interactions as supervised signals), GNN can naturally and explicitly encode the critical collaborative signal (i.e., topological structure) to improve user and item representations in Figure 4. In reality, utilizing collaborative signals to improve representation learning in recommender systems is not a novel concept, having originated from GNN. Early initiatives, such as SVD++ and FISM, have shown that interacted objects are useful for user representation learning. In terms of the user-item interaction graph, these earlier efforts can be interpreted as utilizing one-hop neighbours to improve user representation learning. The advantage of GNN is that it gives powerful and systematic techniques for investigating multi-hop correlations, which have been shown to benefit recommender systems.
With these benefits, GNN has had amazing success in recommender systems during the last few years. In academic research, many studies show that GNN-based models outperform previous approaches and produce new state-of-the-art outcomes on public benchmark datasets. Meanwhile, several of their versions have been developed and applied to various recommendation tasks, including session-based recommendation, point-of-interest (POI) recommendation, group recommendation, multimedia recommendation, and bundle recommendation. In industry, GNN has been used in web-scale recommender systems to deliver high-quality recommendation results. Pinterest, for example, created and deployed PinSage, a random-walk-based Graph Convolutional Network (GCN) algorithm model, on a graph with 3 billion nodes and 18 billion edges, resulting in significant increases in user engagement in an online A/B test.
A more efficient solution is to use recommendation systems. In fact, recommendation systems are designed to provide personalized recommendations based on user specific data and interactions. This personalization ensures that the recommended cloud services are tailored to each user's unique needs, leading to higher user satisfaction and a more efficient selection process. In general, recommendation systems adopt three main techniques:

(i) Content based approaches [16] recommend services that are similar to the cloud services previously used by the active user,

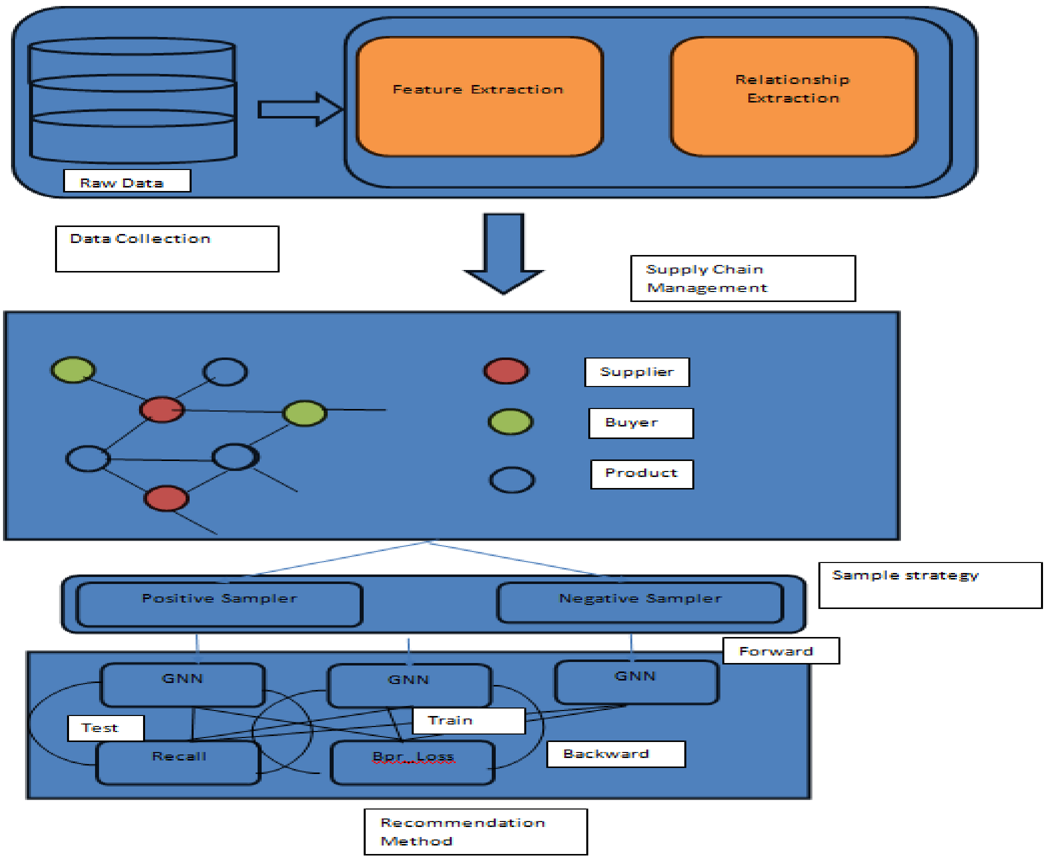

Figure 4. GNN Model

(ii) Collaborative filtering-based approaches [17] identify the active user's neighbours and predict the missing values of the user-service matrix based on similar users' previous behaviour,
(iii) Hybrid approaches [18] that are a combination of content and collaborative methods. The collaborative filtering-based technique is the most popular and commonly used technique for recommender systems [22] and [23]. Most collaborative filtering-based approaches, on the other hand, rely on users' rating (or feedback) to find the user's neighbours, predict missing ratings, and rank the recommended services. However, users' rating histories allow for the detection of three key issues: cold start, data sparsity, and malicious attack. The cold start problem arises when the system is unable to establish any relations between users and services for which it lacks sufficient data. In other terms, the cold start problem occurs when a new user has not rated a sufficient number of services (user's cold start problem), or when a new service has not been rated by a significant number of users (service's cold start problem) [24].

In this instance, the recommendation algorithm will be unable to provide accurate recommendations since it will be unable to locate an appropriate neighbourhood for the user or the service in order to properly predict the missing data. The data sparsity problem occurs when a small subset of available services are rated. Hence, the rating matrix used for recommendation is rather sparse. As a result of this, identifying similar users or services becomes difficult. Consequently, the similarity between two users or services cannot be calculated and eventually, the accuracy of prediction becomes extremely low [21]. The malicious attack problem arises when users create malicious profiles that contain biased and deceptive feedback in order to sway the active user's decision and influence the ranking of recommendations in their Favor [22]. As a result, user satisfaction declines and recommendation accuracy falls to low levels.

To cope with the above-mentioned problems, we present, in this paper, "HRPCS", a hybrid recommendation of personalized cloud services approach. The novelty of our research lies in the development of an enhanced clustering based hybrid recommendation approach that effectively addresses the challenge of providing personalized cloud services to users. By combining clustering techniques with recommendation algorithms, our proposal leverages the advantages of both approaches to deliver accurate and personalized recommendations. Indeed, our proposed approach is based on user and service clustering. A key factor in accurate clustering is the proper determination of similar users and services. As a result, we presented a novel similarity measure for users based on their QoS preferences, location, and usage traces, as well as a similarity measure for services based on their location and usage traces [25].

These equations are also valid for new users and new services where we can maintain the users' QoS preferences and location and the services' location, and therefore solve the user and service cold start problems. In addition, we adopted the clustering method to reduce the computational complexity and address the data sparsity issue. Furthermore, integrating the elimination of users' feedback into recommender systems offers a promising approach to tackling the pressing issue of malicious attacks. By removing users' feedback, particularly from unverified or suspicious sources, the system can significantly reduce the impact of certain types of attacks. Notably, shilling attacks, profile injection attacks, and data poisoning attacks, which heavily rely on manipulating feedback to promote certain items and influence recommendations, can be mitigated. The absence of maliciously crafted feedback prevents the infiltration of misleading data into the training process, thus fostering a more secure and trustworthy recommendation environment.

Indeed, the absence of user-generated feedback helps to neutralize the influence of fake positive ratings and manipulated preferences, preventing attackers from distorting the system's recommendations. Moreover, by minimizing its reliance on user data, the recommender system can reduce its vulnerability to privacy breaches and user-targeted exploits. Additionally, we focus on ranking the services based on their prices and credibility. The credibility of each service is calculated based on the expected QoS parameter values (declared by the service provider) and observable QoS parameter values (specific measurements related to the performance of a service that can be easily observed, monitored, and quantified). Finally, our approach is founded on the concept of diversity. This diversity allows for less redundancy in the list of recommendations while also taking into account the diverse interests of users[26].

3. Practical Application And Examples

Netflix, which was nine years old at the time, introduced "The Netflix Prize" in 2006, with the goal of improving the firm's recommendation engine's accuracy by 10%. The competition quickly spread throughout the world. This issue was so important that Netflix offered a $1 million reward. It is vital to note that the majority of the attention was focused on the data set under consideration. Indeed, the data set included 100 million ratings for 17,770 films from 480,189 customers, a staggering figure at the time.

We'd all like to know how firms like Netflix, which is valued at $216.38 billion, have achieved such high levels of success and can accurately recommend films to their viewers - more than 75% of viewer activity is based on Netflix recommendations [27].

Netflix currently knows practically everything about its users, including their favourite movie genre, frequency of visits, and whether they like Spanish TV dramas like "Casa de Papel" ("Money Heist") or American comedy films like "21 Jump Street". One may question where this success comes from, and the solution is simple: a sophisticated recommender system based on a massive user database of over 193 million users globally!

TikTok (ByteDance), a popular Chinese social media for millennials, recognised that recommender systems would pave the road for its success. TikTok employs personalisation primarily to identify and leverage patterns in its users' behaviour. Given that the movies on this platform are so short (approximately 15 seconds), the 800 million+ visitors generate a massive amount of training data! In fact, TikTok employs reinforcement learning to maximise time spent on the platform, with the action space containing the films to be recommended.

To put it simply, the recommendation engine gathers, sorts, and analyses data. Then, it will "play" with the data to forecast its users' future tastes. The results will be used to provide personalised recommendations for users when they click on a webpage while exploring a certain website. Let's try to grasp the general idea of a recommender system. For example, if someone buys a $500 aeroplane ticket, the recommender system will immediately recognise that they are heading abroad and recommend that they also purchase a travel insurance bundle. A more applicable example in these pandemic times would be health-related ideas, such as masks [28].

Recommender systems use transaction data to help banks make decisions on how to tailor college loans or invest in real estate. This is a significant advantage because it will increase bank revenues due to the personalised activity delivered to clients. Banks can use recommender systems to enhance adherence to savings regulations (for example, Ubank). The recommendation is based on transaction data, which allows for tailored personalisation to the client. A generic example could include: Customer 1 has "A B C" transactions, whilst Customer 2 has "D E F" transactions. Recommender systems basically learn that sequential patterns linked with "A B C" are more likely to require banking service "X" than another service, "Y".

Banks stand to benefit more from increased savings rates. Thus, banks enhance their income directly through digital sales resulting from successful suggestions, as well as indirectly through increases in customer savings, which may subsequently be used to sell more financial products, invest in other assets, and so on. Finally, a recommender system can be considered as a commercial tool capable of increasing a company's revenue by up to 30%. Nowadays, a user does not want to see things advertised on the Internet that they have previously purchased or that do not interest them. That is why recommender systems strive to understand user behaviour, so making users' lives easier and the site or application gaining their confidence [29].

Given that selling to existing customers is easier than selling to new consumers, recommender systems provide for cost savings. Selling to existing customers is much easier because the probability of converting an existing client is 60% to 70%, whereas converting a new prospect is only 5% to 20% [30].

Finally, a recommendation engine enhances the general client experience. Customer experience is an important lever in highly competitive industries such as banking. With plenty of options, an unsatisfied consumer can easily switch providers. The importance of customer experience is even more apparent today, as traditional market players face competition from pure digital businesses who rely solely on the customer experience and a 100% self-caring client connection. Faced with internet competition available outside of regular agency hours, incumbent players must reconsider their client interactions. Customers' demands for immediacy and autonomy also prompt businesses to reconsider user experience and customer relationships.

Personalisation of recommendations is providing the consumer with the correct product at the right time, depending on their personal profile data and, most importantly, on the items with which the customer has interacted or expressed an interest. Recommendations enable banks to react to client expectations, simplify their offerings, build loyalty, and, ultimately, increase purchase and consumption frequency.

A. Business Benefits

There are numerous ways that B&FS organisations can use advanced recommendation engines to gain a competitive advantage. Using these tools, banks may not only provide tailored recommendations that respond to the specific requirements and preferences of individual clients, but they can also do much more to develop a strong customer-centred business model. Let's look at some of the most important applications of recommender systems in this context: banking-recommendation-systems

1. Providing relevant product recommendations

As banking users, we all receive alerts from our credit card/debit card companies about discount deals on flights, movies, pizzas, salons and anything else that will entice us to spend money. However, banks today have realised that it is pointless to constantly push all items to all consumers. Instead, they must adapt into customer-centric businesses that personalise their product and service offerings. New-age personalised product recommendation systems are intended to provide intelligent insights that allow banks to propose the correct items or services to the right clients at the right time [31].

Using a recommender system, a bank can recognise patterns in a customer's spending habits and tailor offers to these transactions. This automatically results in higher sales and money.

Let's use Jane's example again. Jane's purchasing habits reveal that she frequently uses her XYZ Bank credit card at a specific taco restaurant, followed by another transaction at a neighbouring ice cream shop. XYZ Bank discovers that Jane enjoys eating ice cream after her taco dinner. This information is used by the Bank to discover partnering ice cream parlours, customise discount offerings based on profit margins, and notify Jane instantly.

2. Anticipating customer needs

Again, Jane and her daughter Jessica frequently utilise Bank XYZ's mobile banking app for their daily transactions. For Jessica, a student with typical Gen Z tastes, the app prominently displays her account balance with quick-access capabilities for checking credit ratings, budgeting, and bill splitting. This personalised layout is consistent with Jessica's anticipated interests and preferences. However, when Jessica's mother Jane login into the same app, she encounters a different setting. Her initial screen displays not just her account balance, but also her loan balances, investment opportunities, and useful stock information [32].

When Jessica, who represents the Gen Z demographic, and her mother Jane, who belongs to a different cohort, log in, they both get a personalised UI. This is all down to the bank's personalised recommendation system, which intelligently prioritises and highlights the financial tools and features that each customer is most likely to use. This dynamic adaption increases user happiness dramatically.

3. Strengthening Product Portfolio

A recommendation system, which leverages data science and cognitive automation, helps B&FS organisations to establish a robust product portfolio for long-term success. By rigorously analysing customer behaviours, preferences, and transactional patterns, the bank receives vital information that may be used to make strategic business decisions. The data can be utilised to improve their present product range by proactively adding or modifying items to meet client wants and expectations. Furthermore, the significance of a sophisticated recommendation system extends beyond simple product suggestions by providing a comprehensive understanding of consumer propensity, allowing the bank to adapt its offerings on an individual basis. This level of personalisation increases client satisfaction and fosters a stronger bond between the bank and its customers.

4. Improving data quality

According to Gartner's research, poor data quality costs organisations an average of $9.7 million per year, while IBM claims an annual loss of $3.1 trillion in the United States alone as a result of this difficulty. The consequences of poor data quality, such as slower business growth and lost prospective consumers, highlight the significance of preserving data quality for effective data commercialisation [33].

Recognising the importance of data quality in recommendation systems, firms must guarantee that only high-quality data is provided into the recommender system, reducing the danger of inaccurate and incomplete inferences. Thus, a strong recommendation system not only serves as a catalyst for personalised client experiences, but also protects against the significant financial consequences of poor data quality.

5. Enriching Data Continuously

Financial institutions today understand the need of aggregating data from many internal and external source systems. The goal is to create a comprehensive and valuable data asset that will aid in the never-ending quest for higher data quality. When data enrichment is implemented as a continuous process, it makes data more current and useful, allowing users to serve customers more effectively. This requires B&FS organisations to engage in a constant data discovery process. Personalised recommendation systems drive data enrichment in banks by leveraging user data, feedback, and behavioural analysis. The continual learning and adaption capabilities of recommender systems help to improve overall data quality and the efficacy of personalised recommendations in the banking industry[34-36].

CONCLUSION

Based on the utilization of large amount of data among the real time applications, recommendation system provides major impact such as, increased accuracy, efficiency, and data-driven insights, issues such as data quality, model interpretability, regulatory compliance, and ethical considerations must be addressed carefully. As the various recommendation systems are discussed as it results in creating a comprehensive and valuable data asset that will aid in the never-ending quest for higher data quality. As this methodology can be implemented in different real time applications, it provides huge impact in the business sector in terms of relevant products, fulfilling the customer needs, effective product portfolio, enhancing the data quality and enriching the data. As in this article, the various methodologies are considered as it gives a wide view on the data quality in various applications regarding the customer experience and efficiency on the operational data.

Financial institutions can achieve faster, more accurate assessments based on data-driven insights by resolving the challenges and responsibly leveraging their potential. In future, Automated processes is required to reduce manual workload. Reduced risk, earlier detection of potential defaults, and improved portfolio management tactics. Responsible AI deployment leads to a stronger financial ecosystem, more stability, and sustainability.

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