FinNext: An Intelligent System for Real-Time Financial Product Recommendation Using Customer Transaction Patterns and Market Dynamics

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Abstract
This paper presents FinNext, an intelligent recommendation system for real-time financial product suggestions based on customer transaction patterns and market dynamics. Leveraging advanced machine learning techniques, FinNext aims to enhance customer satisfaction and financial service providers' offerings by providing tailored recommendations based on individual financial behaviors and current market conditions. By integrating both transaction data and external market data, the system adapts to market fluctuations, optimizing financial advice for users in a dynamic economic environment. Few researches, meanwhile, have computed the similarity between utilizing product and customer data. As a result, a confusion matrix is used in this study to produce affinity variables that mix product and consumer data. In order to improve forecasting effectiveness in massive analysis data, a variety of derived variables are also developed. A sliding-window technique is taken into consideration to build the recommendation model in this study, which applies a variety of data mining classifiers, including decision trees, neural networks, support vector machines, random forests, and rotation forests.

Keywords: Product recommendation model, Financial Product Recommendation, Real-Time Systems, Customer Transaction Patterns, Market Dynamics, Machine Learning, Personalization, Financial Technology (FinTech), Recommendation System.

1. INTRODUCTION

Financial product recommendations are essential in helping consumers navigate complex markets. With the evolution of financial technology (FinTech), personalized financial advice is becoming more achievable through data-driven approaches. Traditional recommendation systems largely rely on customer demographics and static behaviors, but real-time recommendation requires the integration of transactional data and market trends.

Every day, consumer purchasing habits shift. These shifts have a number of causes, including technological advancement, demographic issues, and economic downturns. Since the 2008 global financial crisis, customers have prioritized affordable goods. Age-specific consumption patterns are prevalent now that the population structure has reached the ageing era. Additionally, as technology has advanced and the number of SNS users has grown, the trend of combining SNS with purchasing has emerged. Customers demand reasonable usage and have a variety of traits. However, too much information makes decision-making difficult. According to psychologist Barry Schwartz, while the paradox of choice improves the choice, it also increases feelings of worry, despair, uncertainty, and discontent. Additionally, some people overconsume as a result of aggressive marketing. [2]

A. Problem Statement

There is a gap in the systems that provide real-time, dynamic, and context-aware financial product recommendations. Most systems do not incorporate market dynamics, which are crucial for providing the most relevant advice during market volatility.

B. Identification of Key Challenges

In today's fast-moving financial market, the most crucial key factor for maintaining customer satisfactions and an edge in the market is timely customized services. Data-driven financial strategies will be used to find out how to meet the needs of customers and their corporate customers who will better benefit from specific financial service or product. Such need becomes more important for such corporate customers who demand more prompt support from their bank to run their business smoothly and efficiently. This should be achieved by having information on customers to lead them with financial solutions that meet their current and future needs. Bank advisors then gather and analyze these statements and figures to better understand the financial status of the customer. A customer gets to know of products through different channels; first, there is the platform provided by the bank. Then, if he has one, through his adviser, and finally, outside of SEB. The right product has to be suggested at the right time to maximize relevance and impact. The optimal time and the most suitable products for each customer have to be understood.

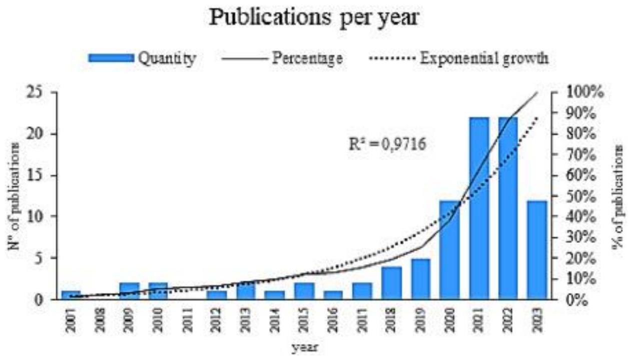

Figure 1: Identification of Key Challenges [3]

The proposed design will be a proactive personalized recommendation system that continuously updates the financial situation of its corporate customers and provides them with smart data-driven recommendations, proposals and suggestions that are customer-based. SEB is optimistic that with the technology, it will hasten its process towards digital transformation and shave significantly the time it would take to offer personalized financial services. This approach maximizes the satisfaction and engagement of the customer besides helping the bank sell more products and increase its digital sales.

C. Objectives

Develop a real-time recommendation system known as FinNext, by utilizing customer transaction patterns and market conditions to provide personalized financial product recommendations. The system main goal is to automate the processing and make the recommending product, according to the corporation special needs, easier and simpler in order to use and integrate. Advanced data analytics such as classification and clustering could now be used algorithms, this paper is aimed to assist SEB in improving its knowledge of servicing corporate customers more efficiently. The proposed system will work through various types of KPIs. Search for patterns in customer's data for recommendation evaluate and test various machine learning algorithms and then the best models will be selected for the production and development of the system and the closing of the best recommendations according to the financial performance of customers. This strategy will make the process of advisory smooth, faster, and easier for both customers and advisors.

2. LITERATURE REVIEW

It is a profile-based studies, the product recommends customers. A recommender, or simply, recommendation system, is a method of designing tools to support decision-making processes in users performing specific tasks. Normally, before filtering through the available choices, systems consider prior information about usage to the behavioral, or product segmentation becomes a requirement for research when determining the target customer of the product. It is possible to profile the customer based on size and behavior. Programs are executed based on customers' usage habits of their products- how customers use ATMs or digital channels, or credit use characteristics. After being identified through profiling studies, the product recommendation system will be activated for the target customer group. The lending is segmented based on customers applying for loans and, subsequent from product usage behavior analysis that reveals preferences, institutions make offerings recommendations to both new-loan applicants and existing-customers. [3] The ML methodology features in intense application along with profiling and product recommending procedures. Among them, artificial neural networks, classification methods, and SVM algorithms usage is impressive since it appears to be the complementing methods in literature. These methods can be used making use of data available at the institution itself, also by using analysis on news related to economic, analysis on comments coming through user's social media, and general product suggestions can be designed.

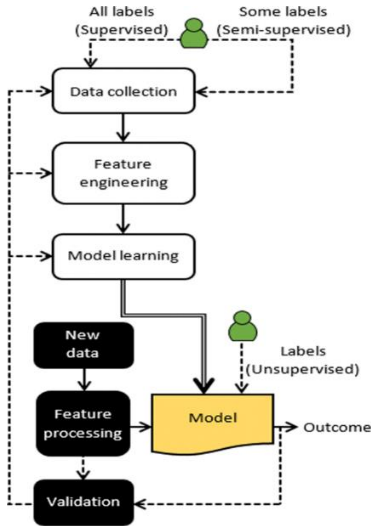

Figure 2: Machine Learning [5]

Product recommendation systems can often be combined with supervised, unsupervised, or ensemble methods. These systems are typically grouped into two main categories. The first is collaborative filtering (CF), which recommends items based on the similarities between users. The recommended items are those preferred by the users. The second involves content-based systems, matching user and product profiles. Users are recommended items that have the greatest overlap with their profile. Different ML approaches have been analyzed by the researchers, for example, deep learning of credit card scoring by SME customers and deep learning of credit card scores.

3. METHODOLOGY

This research will guide us on the evolution that recommender systems and AI techniques have undergone, as well as what they are employed for in the e-commerce field. Therefore, it will give us a chance to know what has been achieved and what remains to be accomplished. By proper usage of a good method, we can portray what is known about this evolving area.

A. Eligibility Criteria

This bibliometric review centers on recommender systems in e-commerce and AI. In determining sources, titles and keywords are used based on record relevance to a subject matter. Excluding process has three stages: the first is regarding the stripping up of records with an indexing error, a document with missing text for SR in the third stage, and stripping up incomplete records; whereas last and third phase will consider as inclusion-exclusion process concerning documentation with incomplete indexing, but this will ensure all validity and consistency of source undergoing the bibliometric study. [4]

B. Search Strategy

Two search equations were developed to be used for searching in the Scopus and Web of Science databases. The criteria considered by those equations relate to the structure chosen for the databases and are related to bibliometrics. To be able to detect studies on recommender systems in e-commerce and AI, specific database search equations are required.

- Knowing the company procedures: The first step in identifying the real issue.
- Data preprocessing step: This stage involves making decisions about the data prep reprocessing procedures.
- Model phase: Based on the data sources and the enduring issue, a statistical or machine learning model is created.
- Evaluation phase: This step involves a broad review and assessment of the earlier stages. To find out if it satisfies the success criteria established in the first step (the problem description phase), the overall performance is evaluated.
- Product phase: In certain situations, the results of every step in the study can be packaged as a solution that is ready for manufacturing.

Table 1: Bibliometric Analysis

Stage 1	Planning	Identify the relevance topic
Stage 2	Search	Define the search strategy
Stage 3	Data Analysis	Import the data in tools
Stage 4	Description of results	Presentation of tables and graphs

C. Analysis of Exploratory Data (EDA)

EDA is a technique used to examine data in order to find unclear patterns. To make sure that assumptions and hypotheses are sound inside statistical frameworks with graphical representations, EDA is also utilized to gain a deeper understanding of the data.

4. REAL-TIME RECOMMENDATION AND ADJUSTMENT

FinNext differs from competitors in the fact that it provides real-time recommendations based on individualized patterns of transactions and on the current conditions of the markets.

A. Customer Transaction Patterns

The system uses customer transaction patterns to categorize spending behavior into different segments such as savings, investments, and loans. With the knowledge of a customer's financial priorities, the system can suggest products that align with the customer's current and future financial goals. For instance, a customer who regularly saves might be offered high-yield savings accounts, while a customer with a high discretionary spend might be offered personal loans or investment products.

Figure 3: Customer Patterns [9]

B. Market Dynamics

Market dynamics play an important role in suggesting products. The system assimilates information in real time about stock market fluctuations, commodity prices, interest rates, and economic trends. For example, if interest rates are expected to increase, the system could suggest fixed-rate investment products or long-term savings plans. However, if stock markets are rising, the system could suggest equity-based investment products.

C. Dynamic Updates

As the transaction patterns of customers change and market conditions change, FinNext continuously updates its recommendations. This dynamic nature ensures that the recommendations are always relevant and timely, providing customers with up-to-date financial products that align with both personal financial goals and external market conditions. [6]

5. RESULTS

This paper discusses some of the important research trends, which indicates a massive increase in scientific production, underpinning the growing interest in the relationship between recommender systems and artificial intelligence strategies within the context of electronic commerce. Various approaches and strategies through the main authors in recommender systems and AI techniques in e-commerce can be identified, showing how it has proven that to be productive is essential and you can do big if you concentrate your work. This past year has seen numerous researches on topics such as sentiment analysis, convolutional neural networks, collaborative filtering, session-based recommendation, and implicit feedback. That is much more complete a view of the field.

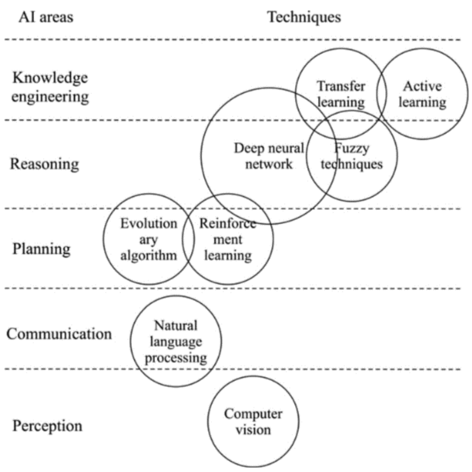

Figure 4: AI techniques [11]

The results come out according to a systematic approach to adhering to the guidelines of PRISMA-2020. This methodology provides a structured framework toward a comprehensive bibliometric study by enabling the identification and synthesis of relevant information in a transparent and reproducible manner. The methodology ensures proper search, selection, and analyses of data, which makes the results more valid and reliable.

6. FUTURE DIRECTIONS

Future advancements in **FinNext** can focus on integrating even more advanced artificial intelligence techniques, such as deep learning, to enhance the recommendation engine's accuracy. Additionally, expanding the system to include a wider array of financial services, such as insurance and retirement planning, can provide a more comprehensive solution for customers.

Further research can also explore the integration of **FinNext** with smart financial assistants, enabling a seamless, hands-free experience for customers to manage their finances. In the specific case of our study, customers who can use the CAD product are identified, and CAD is recommended to these target customers in the recommendation system. While product diversity in SME banking benefits customers in terms of finding appropriate and fast solutions to their financial problems, from a banking perspective, it also increases customer profitability and loyalty. Our model can be adapted to any of the existing product groups in SME banking. In future studies, the study can be expanded with new algorithms, and recommendation systems for the sale of new products in line with banking strategies and goals are thought to provide positive effects on the system in determining the target audience for all product groups and increasing sales.

7. CONCLUSIONS

FinNext is a revolutionary advancement in the evolution of recommendation systems for financial products. It combines real-time customer transaction analysis with dynamic market data and presents personalized and contextually relevant recommendations that help customers make better-informed financial decisions. Its evolution will continue to revolutionize the financial services industry, offering smarter and more adaptive solutions to both consumers and financial institutions.

While the primary internal stakeholders for customer engagement in the banking and finance sector, as in any other business organization, are marketing, sales, and customer service teams, CRM strategies encourage company-wide collaboration as they collect (often dispersed) customer data to improve customer interactions. From this perspective, one of the biggest components of CRM strategies is product recommendation systems. Effective CRM strategies equip the entire organization to leverage customer data in feedback loops to inform product and service offerings, including data from sales, customer service interactions, and marketing campaigns. All this is made possible by CRM strategies and the software tools that help to achieve them.

This study can contribute to the automated prediction and evaluation of customer product recommendations in both banking and retail business applications. Moreover, the research is automatically repeatable over time to keep the algorithm performances high. Instead of updating the ML algorithms or addressing the combined algorithm selection and hyperparameter optimization, banks, and financial institutes can benefit from the research outcomes by deploying automated ML in the study that is being conducted in the United States, the researchers wrote in a blog post on Monday. [7] According to the conducted analysis, customers' behavior has a significant impact with recommendation product. This finding has a considerable impact on designing effective client relationship management strategies in the future because the higher the rate of accuracy in detecting and identifying potential customer need for products, the higher the rates of success for more effective and efficient retention strategies.

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