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Enhancing User Experience through Machine Learning-Based Personalized Recommendation Systems: Behavior Data-Driven UI Design

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Abstract: The application of artificial intelligence (AI) continues to expand across various industries, especially in enhancing user experience and optimizing business processes. Through deep learning and machine learning algorithms, companies are able to analyze user behavior data and provide personalized recommendations, which effectively improve customer satisfaction and loyalty. This data-driven approach enables businesses to stand out in a highly competitive market. This paper explores the key role of machine learning-based personalized recommendation systems in improving user experience and highlights the importance of behavioral data-driven UI design for business success. Research shows that successful recommendation systems not only rely on advanced technology applications, but also need to deeply understand user needs to optimize user interface design and promote effective user interaction. As technology continues to advance, personalized recommendation systems will become more intelligent, and companies should actively explore these innovative ways to increase user engagement and brand loyalty to achieve sustainable business growth.

Keywords: Personalized recommendation systems, User experience, machine learning, behavioral data, UI design.

1. Introduction

As a UI design and front-end development practitioner, ACE Vision has always believed that in today's competitive Business environment, the design of B-side (business-to-business) systems is no longer just a functional piling, but more and more attention to user experience and personalized customization. [1]An excellent B-end system UI design can not only enhance the corporate image, but also enhance user satisfaction and loyalty, so as to occupy a place in the market.

Recommendation system is a field of engineering application. In order to introduce recommendation system into commercial products and use recommendation system to help users filter information, in addition to building accurate and efficient recommendation algorithm, it is also necessary to design a recommendation product form that is suitable for specific scenes, has aesthetic

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feeling and is easy to interact. Users get recommendation services in the process of interacting with recommended products and complete a user experience of recommended products through UI interaction[2]. Users are more willing to continue using products with better experience. The form of the recommended product can be perceived by the user visually, and the user can judge whether the recommended object is his favorite through the perceptible visual elements, so as to decide whether to proceed to the next step. Through reasonable UI design, the recommendation system can not only improve the user's satisfaction and use intention, but also encourage users to explore the recommended content more deeply and achieve a better user experience.

2. Machine Learning and Personalized Recommendation Systems

2.1. Personalized recommendation system algorithm

Machine Learning ML is a specialized branch of artificial intelligence (AI) that focuses on developing algorithms that can learn and make predictions or decisions based on patterns in data. Compared to traditional programming paradigms, machine learning algorithms have a unique ability to derive knowledge from the data they analyze, which improves their accuracy and effectiveness over time. This is the final step in filtering the data to access the relevant information needed to make recommendations to the user. To enable this feature, you need to choose an algorithm that is suitable for the recommendation system.

2.2. The role of AI personalized recommendation system

Personalization drives the digital age. It has become essential to build a recommendation system tailored to individual preferences. Artificial intelligence is playing an important role in this transformation. [3]This paper focuses on building an AI-driven recommendation system. This process will be explored in detail, providing a systematic guide. A practical case study involving Python and MovieLens datasets will also be presented. These systems are powered by artificial intelligence, predicting and suggesting items that align with user preferences. You encounter these systems every day.

In the recommendation process of various user data, machine learning algorithms are used in the recommendation system, including collaborative filtering algorithm, content-based filtering algorithm and hybrid method[4]. Statistics to date show that up to 80% of the content on the Netflix platform comes from personalized recommendations based on collaborative filtering technology, which will affect and measure the content balance of the system. Because one of the many attractions of video streaming services is that you can watch shows and movies almost anywhere as long as you have an Internet connection.

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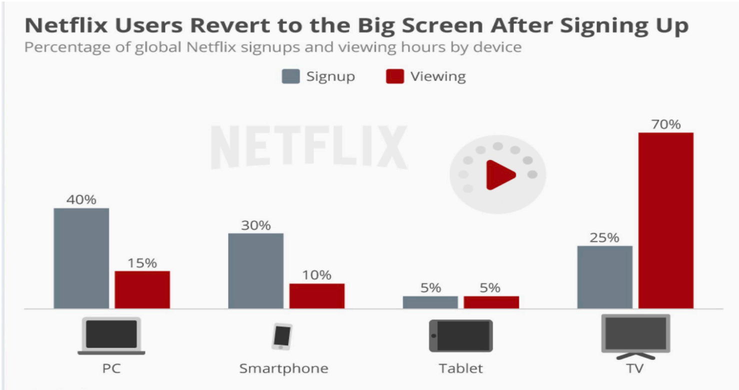

Figure 1: Statistics show that up to 80% of watches on Netflix come from recommendations, and the impact of these systems is both profound and measurable.

Many people enjoy watching sitcoms on their evening commute, while others enjoy finishing a feature-length film on their tablet in bed or watching a documentary at the airport to pass the time. While it's possible to watch almost anything anywhere you want, the majority of video streaming still happens on the big screen[5]. As the company reported in a press release this week, at least for Netflix. According to the company, 70 percent of the world's viewing time takes place on connected TVS, not mobile devices or personal computers.

Given the sometimes-clunky user interface of smart TVS, it's perhaps no surprise that most Netflix users sign up for the service using a PC or smartphone, however, they tend to revert to the big screen once binge watching begins.

3. Methodology

Personalization through AI is becoming increasingly common in enhancing the customer experience. By leveraging data such as browsing history, social media activity, and previous interactions with companies, AI algorithms can generate tailored recommendations based on customers' interests and needs and provide a seamless and efficient shopping experience. This leads to increased customer satisfaction and brand loyalty, which ultimately leads to increased revenue for the company.

In addition, AI can also help improve customer service by providing timely, relevant support and reducing response times. However, it is important for companies to strike a balance between personalization and data privacy, ensuring that customers' data is ethically consistent with their consent[6]. This part of the experiment is based on the e-commerce platform BI/DA online purchase intention as the core, and the analysis and recommendation system can push customers' needs more accurately with the assistance of artificial intelligence. Enhancing User Experience through Machine Learning-Based Personalized Recommendation Systems: Behavior Data-Driven UI Design.

3.1. Dataset

The dataset for this experiment consists of feature vectors belonging to 12,330 sessions. The dataset is formed so that each session will belong to other users within 1 year, to avoid any particular activity, special day, user preference profile, or period. The dataset consists of 10 numeric attributes and 8 categorical attributes.

The Income property can be used as a class label. As shown in Table 1

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Table 1: Dataset of BI/DA Online Purchase Intention - recommendations

	Administrative	Administrative_ Duration	Product Related	BounceRates	ExitRates	PageValues	SpecialDay	Month
0	0	0	1	0.2	0.2	0	0	Feb
1	0	0	2	0	0.1	0	0	Feb
2	0	0	1	0.2	0.2	0	0	Feb
3	0	0	2	0.05	0.14	0	0	Feb
4	0	0	10	0.02	0.05	0	0	Feb

The dataset includes various features that capture user interaction on an e-commerce site. Key features like "Administration," "Information," "Product Related," and their respective durations represent the number of pages visited and the time spent on each category during a session. The dataset also encompasses details about the user's operating system, browser, region, traffic type, and whether the visitor is new or returning, along with Boolean indicators for weekends and the month of the year.

3.2. Construction and evaluation of machine learning models

This section explains how to prepare the data and build a decision tree model to predict a user's purchase intentions. First, the data is cleaned and preprocessed, missing values and duplicates are processed, and Boolean-type features are converted to integer types[7]. Next, a label encoder is used to convert the categorical variables into numerical ones so that they can be used for model training. At the same time, SMOTE and random downsampling (RUS) techniques were used to balance positive and negative samples in the training set to solve the problem of data imbalance.

A decision tree classifier is selected to construct the model, and cost-sensitive learning is applied to deal with class unbalance in the training stage. In the end, the decision tree model had an accuracy of about 62% on the test set, showing a good recall rate (about 73%), but a low accuracy rate (about 25%), suggesting the need to further optimize the model or consider other algorithms to improve overall performance. Through these steps, we not only completed the construction and evaluation of the model, but also provided a clear basis for the subsequent improvement direction.

3.3. Experimental discussion

By constructing a decision tree model, this experiment reveals the key characteristics that affect users' purchase intentions, among which "page value" is identified as the most important driver. While the overall accuracy of the model was 62 percent, the F1 score was only 37 percent, indicating poor performance in predicting a small number of classes (i.e., users who generate revenue)[8]. Ultimately, by optimizing landing page design, ensuring smooth technology, and implementing personalized email redirection strategies, the goal is to improve the overall user experience, which in turn drives sales growth. These measures will help better meet user needs, strengthen brand loyalty, and further optimize UI design based on behavioral data.

4. Conclusion

Through in-depth analysis of the widespread use of personalized recommendation systems on digital platforms, especially from industry leaders such as Netflix and Amazon, we can clearly see the profound impact of machine learning technology in enhancing user experience and business value. Netflix tracks users' viewing behavior, ratings and preferences to provide accurate movie recommendations for each user[9-10]; Amazon, on the other hand, analyzes users' browsing and

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purchase history and adjusts its home page content in real time to ensure that users always see the products that are most relevant to their interests. With the continuous progress of technology, the personalized recommendation system will be more intelligent and precise in the future, and enterprises should actively explore and apply these innovative methods to enhance user stickiness, enhance brand loyalty, and achieve sustainable business growth. Therefore, in this data-driven era, understanding user behavior and needs will be the key to business success.

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