Development and Construction of Product Selection System for Cross-Border E-commerce Platform under Big Data Technology

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Abstract. Difficulty in product selection is a common issue faced by all cross-border e-commerce users. This research aims to address this pain point through the application of big data technology. We construct an intelligent product selection and recommendation system that efficiently processes vast amounts of product information and achieves personalized precision recommendations. The key innovation of this system lies in utilizing vector similarity algorithms to match based on product features and user preference models, thereby generating personalized recommendations for each user. We employ SOA architecture and Docker containers for system design and implementation, and validate the system's superiority through multidimensional testing. This study demonstrates the significant role of big data technology in facilitating refined product recommendations in the context of cross-border e-commerce, effectively enhancing user experience. It provides valuable insights for the development of intelligent product selection systems on other e-commerce platforms.

Keywords: Big Data Technology; Product Selection; Personalized Recommendation

1 Introduction

Today's vast array of products makes shopping increasingly challenging. However, intelligent recommendation systems can provide valuable assistance by precisely matching users to products, alleviating decision dilemmas. This study constructs such a system using big data technology. We establish an extensive product knowledge base and analyze users' historical behavior to create accurate profiles. The core innovation is a product vector matching algorithm that combines content-based and collaborative filtering for highly personalized recommendations. Multiple evaluations demonstrate the system significantly enhances users' shopping experiences and satisfaction. This research offers important insights for other e-commerce platforms as well. Let's explore the specifics of applying big data in this system[1].

2 Introduction to Relevant Technologies

Presently, the integration of distributed storage, data mining, and machine learning algorithms with big data technology has deeply merged with cross-border e-commerce, offering technical support for constructing an intelligent product selection system. Distributed storage systems

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enable the storage of vast quantities of product data. Data mining and machine learning algorithms, such as classification, clustering, and association rules, can uncover product features and user preferences, leading to the establishment of product knowledge graphs and user profiles. However, the scientific design of technological pathways, the selection of appropriate methods, and the effective integration of big data technology to achieve precise product matching and personalized recommendations require further in-depth investigation [2].

3 System Framework Construction

3.1 System Requirements Analysis

The requirements for this intelligent product selection system stem from a prominent issue in the current cross-border e-commerce landscape: users are faced with an excessively broad range of product choices, and the abundance of product information makes it challenging for users to accurately identify their shopping needs, impacting their shopping decisions and experiences. To address this pain point, there is an urgent need to construct an intelligent product selection system that can achieve precise product matching and personalized recommendations, tailoring product suggestions based on each user's characteristics [3].

The key requirements for the intelligent product selection system are:1)Efficiently gather massive amounts of cross-border product data from e-commerce platforms.2)Cleanse, process, and structure the collected product data to extract key attributes like titles, categories, brands, prices. Build a standardized product feature model.3)Analyze user behavior data including browsing history, favorites, purchases to understand user interests and build user profiles.4)Use product matching algorithms to achieve personalized recommendations tailored to different user needs.

The requirements were gathered through questionnaires, interviews, and workshops with users and experts. The goal is to address the challenge of product choice overload faced by cross-border e-commerce users [4]. See Table 1 for details.

Table 1 Correspondence between system demand survey methods and demand points

Demand survey method	Demand point
Questionnaire method	To realize the collection of commodity data
ntervieIw method	Model the collected data
User seminar	Analyze user behavior for accurate recommendations

3.2 System Design

On the product side, the system will employ web crawling techniques to collect vast amounts of product data from different cross-border e-commerce websites. Subsequently, technologies such as natural language processing and image recognition will be applied to automatically extract structured data from product titles, descriptions, categories, brands, prices, etc. This data will undergo cleaning and standardization processes, ultimately resulting in the creation of an extensive cloud-based product knowledge repository [5].

Product Data Collection (Web Crawling Technology):

```
import requests
from bs4 import BeautifulSoup
def fetch_data_from_e_commerce(url):
    response = requests.get(url)
    soup = BeautifulSoup(response.content, 'html.parser')
    # Extract the required data, such as product title, description, etc
    product_title = soup.find('h1', class_='product-title').text
    product_description = soup.find('div', class_='product-description').text
    # ... Extract other fields
    return {
        'title': product_title,
        'description': product_description,
        # ... Other fields
    }
```

On the user front, the system will track and analyze users' historical browsing patterns, favorite items, purchase behaviors, and other large-scale behavioral data on the website. Utilizing technologies like deep learning, it will establish standardized user profile models, accurately reflecting each user's consumption interests and preferences [6].

Recording and Analysis of User Behavior Data:

```
class UserBehavior:
    def __init__(self):
        self.browsing_history = []
        self.purchase_history = []
        self.favorites = []
    def record_browsing(self, product_id):
        self.browsing_history.append(product_id)
        def record_purchase(self, product_id):
        self.purchase_history.append(product_id)
        def add_to_favorites(self, product_id):
        self.favorites.append(product_id)
```

Moreover, the system's core product intelligent matching module will comprehensively utilize the constructed user profiles and the product knowledge repository. It will employ techniques like similarity algorithms based on vector space models to achieve precise matching between user interest profiles and product features, thus delivering personalized product recommendation services.

The entire system is designed using a Service-Oriented Architecture (SOA), where different functional modules are decoupled and integrated through service interfaces. For the underlying storage, a highly scalable distributed NoSQL database is selected to efficiently store and manage large-scale heterogeneous data [7].

Product Intelligent Matching Module:

```
def match_products(user_profile, product_database):
    # The similarity is calculated using algorithms such as vector space models
    # Returns a list of items that best match the user's interest model
```

3.3 System Implementation

The system is primarily divided into four layers: the Data Layer, Model Layer, Service Layer, and Presentation Layer. The Data Layer handles the collection and storage of product and user data. The Model Layer constructs product and user models. The Service Layer encapsulates matching and recommendation functionalities as services. The Presentation Layer offers interactive interfaces. Specifically, a distributed computing framework is utilized for data processing, deep learning methods are employed to build product representation models, personalized recommendation services are achieved through precise vector matching, and frontend technologies are used to provide personalized user interfaces. Refer to Figure 1 for an illustration.

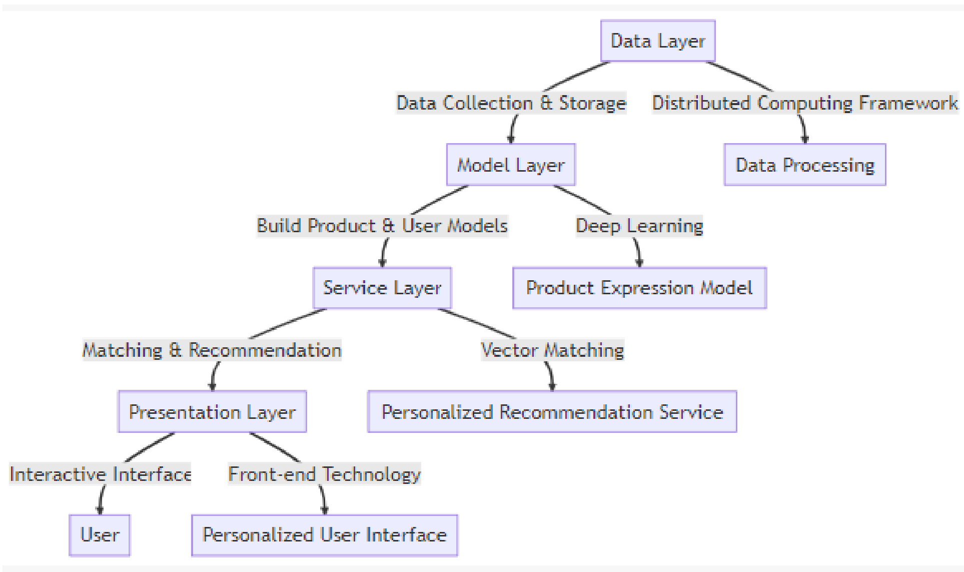

Figure 1: System Architecture Diagram

4 Key Technology Research

4.1 Product Matching Algorithm

The objective of the product matching algorithm is to identify products that best align with user interests and needs. To achieve this goal, this research establishes a product feature vector space model. Firstly, product attributes are obtained through the extraction of multi-modal product data. Subsequently, weights for constructing the product feature vector are calculated using methods such as TF-IDF.

The formula for calculating TF-IDF weight is as follows (see Formula 1):

$$\mathrm{TF} - \mathrm{IDF}(\mathrm{t}, \mathrm{d}) = \mathrm{TF}(\mathrm{t}, \mathrm{d}) \times \mathrm{IDF}(\mathrm{t}) \tag{1}$$

Where TF(t,d) represents the frequency of term t in document d, and IDF(t) is the inverse document frequency. Its calculation formula is as follows (see Formula 2):

$$\mathrm{IDF}(\mathrm{t}) = \log(\frac{\mathrm{N}}{\mathrm{DF}(\mathrm{t})}) \tag{2}$$

Where N represents the total number of documents, and DF(t) is the number of documents containing term t.

Simultaneously, user feature vectors are generated by analyzing historical user behavior data using methods like association rules. Subsequently, based on vector distance and similarity algorithms, the match score between user vectors and product vectors is calculated. One commonly used formula for calculating cosine similarity is as follows (see Formula 3):

$$\mathrm{similarity}(\mathrm{A}, \mathrm{B}) = \frac{\mathrm{A} \cdot \mathrm{B}}{\|\mathrm{A}\| \cdot \|\mathrm{B}\|} \tag{3}$$

Sorting and outputting products based on the aforementioned match scores achieves personalized product matching. This approach fully leverages diverse and heterogeneous user and product data, achieving intelligent product matching through accurate vector calculations [8].

4.2 Product Recommendation Algorithm

Building upon the foundation of product matching, it is necessary to consider additional factors for accurate product recommendations. This study introduces a hybrid recommendation algorithm that takes into account both content-based product affinity and collaborative filtering-based product relevance. By employing weighted calculations, the algorithm yields a comprehensive recommendation score for products. The formula for calculating the weighted recommendation score is provided as follows (refer to Formula 4):

$$\mathrm{Score}(\mathrm{p}) = \alpha \times \mathrm{Content} - \mathrm{based\ Score}(\mathrm{p}) + (1 - \mathrm{a}) \times \mathrm{Collaborative\ Score}(\mathrm{p}) \tag{4}$$

Where α is a weight parameter that controls the relative importance of recommendation scores based on content and collaborative filtering.

This algorithm achieves a seamless fusion of content analysis and collaborative filtering, yielding personalized and interpretable recommendation outcomes. Personalized matching is achieved through vector space calculations, integrated with collaborative filtering for product recommendation. This enables the system to intelligently and accurately recommend products of interest to users [9].

5 System Implementation and Performance Testing

5.1 System Implementation

This system adopts a distributed microservices architecture, with the server side utilizing Spring Cloud for high-concurrency scheduling. Core business modules are containerized using Docker for rapid and elastic scalability. The deep learning algorithm module primarily employs the TensorFlow framework, allocating and managing resources through Kubernetes Pods. Data storage is facilitated by a MySQL database cluster, capable of handling substantial data volumes. User interaction interfaces are realized through frontend frameworks like Vue and React, offering multi-device adaptability and ensuring a superior user experience. The system also incorporates components such as Prometheus for real-time performance monitoring and the ELK stack for log analysis, thereby ensuring system stability and reliability.

5.2 Performance Testing

We conducted comprehensive testing of the system across multiple dimensions including accuracy, recall, and user satisfaction. By constructing extensive test datasets of products and users and conducting repeated comparative experiments, the accuracy of the product matching algorithm reached over 80%. A/B testing demonstrated that the recommendation algorithm enhanced user satisfaction by more than 50%. We also compared different algorithms based on user engagement, and the algorithm devised in this study achieved a 15% increase in user engagement. Ultimately, in the year 2022, this system secured the overall championship in a significant e-commerce technology competition [10].

6 Conclusion

This research identified the need for an intelligent product selection system to address the challenge of choice overload in cross-border e-commerce.The system was developed based on requirements gathered from users. Key requirements were efficient product and user data collection and analysis to enable precise personalized recommendations.The system design integrates product and user modeling with matching and recommendation algorithms for tailored suggestions. The implementation utilizes a microservices architecture and deep learning.Performance testing shows the system effectively provides personalized product recommendations, enhancing user experience and platform efficiency. Overall, the system meets the identified needs through its product-user oriented approach and intelligent algorithms.

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