

Research on E-commerce Intelligent Recommendation Algorithm and User Experience Optimization Based on Multimodal Data

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ABSTRACT In the context of the deep development of the digital economy and the continuous innovation of e-commerce formats, user needs are diversified, personalized, and scene oriented. The recommendation algorithm driven by single-modal data has found it difficult to meet the dual needs of accurate recommendation and high-quality user experience. This article focuses on the core pain points in current e-commerce recommendations, such as insufficient understanding of user intent, insufficient integration of multimodal data, imbalance between recommendation accuracy and diversity, and incomplete user experience evaluation system. A systematic study is conducted around the entire chain of multimodal data fusion, intelligent recommendation algorithm optimization, and user experience evaluation and optimization. Construct a multi modal data system for e-commerce and propose a multimodal data fusion method based on attention mechanism and deep learning; Design an intelligent recommendation algorithm that integrates multi-objective optimization to achieve collaborative improvement in accuracy, diversity, novelty, and real-time performance; Establish a multidimensional user experience evaluation system and propose targeted optimization strategies.

INDEX TERMS multimodal data fusion, e-commerce recommendation, user experience, deep learning, smart retail systems

I. INTRODUCTION

A. RESEARCH BACKGROUND AND SIGNIFICANCE

TRADITIONAL e-commerce recommendation algorithms mainly rely on single modal data (such as user behavior data, commodity text data), which presents obvious limitations: it is difficult to mine users' deep intentions only through user click, purchase and other behavioral data, it is impossible to comprehensively carve commodity characteristics only relying on commodity text information, and it is unable to adapt to the current e-commerce platform where multimodal data such as pictures, video, voice, text, and behavior coexist. With the rise of new formats such as short video e-commerce, live streaming e-commerce, and social e-commerce, product display and user interaction have presented multimodal characteristics. Multiple heterogeneous data sources such as user generated content (UGC), multimodal product descriptions, and real-time interaction data continue to emerge, providing rich data support for accurate recommendation and user experience optimization. However, it also brings new challenges such as multimodal data heterogeneity, redundancy, and spatiotemporal inconsistency[1-3].

In terms of user experience optimization, domestic research focuses on user behavior analysis, interface design optimization, and service quality improvement. A multi-dimensional user experience evaluation system has been constructed, and targeted optimization strategies have been proposed based on the consumption habits and cultural characteristics of Chinese users. For example, domestic scholars analyze user multimodal interaction data, mine user emotional preferences and pain points, optimize recommendation interfaces and interaction processes; E-commerce companies enhance the overall user experience by improving after-sales service, optimizing logistics experience, and strengthening privacy protection[4].

II. RELATED THEORETICAL AND TECHNICAL FOUNDATIONS

A. MULTIMODAL DATA RELATED THEORIES

Environmental modal data: mainly including user geographic location, browsing devices, network environment, time nodes, etc., with the characteristics of scenario based and dynamic, can be used to achieve scenario based recommendation and personalized services. For example, rec-

ommending local specialty products based on the user's geographical location; Recommend seasonal products based on time nodes[5]. The multimodal data in the e-commerce scenario has the following four core features, which are not only the advantages of multimodal recommendation, but also the main reasons for the difficulties in data fusion and algorithm optimization:

1. Heterogeneity: Different modalities of data have significant differences in their presentation forms, data structures, and semantic meanings. For example, text data is a discrete character sequence, image data is a continuous pixel matrix, and behavioral data is a temporal event sequence, which is difficult to directly fuse and analyze and requires standardization and feature transformation.

2. Complementarity: Different modal data characterize product features and user needs from different perspectives, exhibiting strong complementarity. For example, product text description can provide detailed attributes of the product, product images can visually display the appearance of the product, and user behavior data can reflect the actual preferences of the user. The combination of the three can comprehensively and accurately explore the relationship between the product and the user[6].

3. Redundancy: There is a large amount of duplicate and redundant information in multimodal data, for example, there may be duplicate product attribute information between product images and product text descriptions; The behavior records of users browsing the same product multiple times contain redundancy, which increases computational costs and affects algorithm efficiency. Redundancy removal is necessary[7]. To ensure the effectiveness and practicality of multimodal data fusion, combined with the characteristics of e-commerce scenarios, the following four principles should be followed:

1. Principle of complementarity: Fully utilize the complementarity of different modal data, explore the correlation relationships behind the data, achieve the fusion effect of "1+1>2", and comprehensively characterize the characteristics of products and user needs.

2. Accuracy principle: During the fusion process, it is necessary to ensure the accuracy and reliability of the data, remove abnormal and redundant data, and avoid introducing errors that may affect the performance of subsequent algorithms.

3. Efficiency principle: The fusion algorithm needs to have high computational efficiency, be able to process massive multimodal data, meet the real-time recommendation needs of e-commerce, and avoid the impact of long fusion computation time on user experience[8].

4. Adaptability principle: The fusion method needs to adapt to the dynamic nature of e-commerce scenarios, be able to adaptively adjust the fusion strategy according to changes in data and user needs, and enhance the flexibility and practicality of fusion[9].

B. THEORY AND TECHNOLOGY RELATED TO INTELLIGENT RECOMMENDATION ALGORITHMS

1) Traditional recommendation algorithms

Traditional e-commerce recommendation algorithms are mainly based on single modal data. According to different recommendation principles, they can be divided into the following three categories, which are the basis of modern intelligent recommendation algorithms:

2) Content based recommendation algorithm

Mainly based on the content features of items for recommendation, by extracting text, image and other features of items, constructing item feature vectors, and then recommending items similar to user preferences based on their historical preferences. For example, based on the textual features of products purchased by users in their history, recommend products with similar textual features. The advantage of this algorithm is that there is no cold start problem and it can achieve personalized recommendations. The disadvantage is that it is difficult to explore users' potential needs and the diversity of recommendations is insufficient[9].

3) Multi objective optimization recommendation algorithm

Traditional recommendation algorithms often focus on single objective optimization (such as recommendation accuracy), which is difficult to meet the diverse needs of users and the multi-objective development needs of platforms in e-commerce scenarios. Multi objective optimization recommendation algorithms, by constructing multi-objective optimization functions that take into account multiple optimization objectives such as accuracy, diversity, novelty, real-time performance, and platform revenue, achieve collaborative improvement of multiple objectives, which is an important development direction of current recommendation algorithms[10].

The core of multi-objective optimization recommendation algorithm is to construct reasonable multiobjective optimization functions and constraints. Common multi-objective optimization methods include non dominated sorting genetic algorithm (NSGA-II, NSGA-III), particle swarm optimization algorithm (PSO), reinforcement learning, etc. In e-commerce recommendation scenarios, multi-objective optimization functions typically include the following four core objectives:

1. Accuracy goal: Maximize the matching between recommended products and user needs, improve recommendation accuracy and recall, and reduce user information screening costs[11].

2. Diversity goal: Maximize the diversity of products in the recommended list, avoid homogeneous recommendations, meet diverse user needs, and enhance user experience.

3. Novelty objective: Recommend products that users have not encountered but may be interested in, explore potential user needs, and enhance user surprise and retention rate.

4. Real time goal: Quickly capture changes in user interests, update recommendation lists in real time, meet users' real-time needs, and improve the timeliness of recommendations[12].

III. CONSTRUCTION AND PREPROCESSING TECHNOLOGY OF MULTI MODAL DATA SYSTEM FOR E-COMMERCE

A. CONSTRUCTION OF MULTI MODAL DATA SYSTEM FOR E-COMMERCE

Text modal data is the core component of multimodal data in e-commerce, mainly used to characterize product attributes, user needs, and emotional tendencies. The core indicators include:

1. Product text data: product title (length, number of keywords), product description (word count, completeness of attributes, semantic richness), product classification tags (number of levels, accuracy), product specification parameters (completeness, standardization);
2. User text data: user comments (word count, sentiment polarity, keywords, ratings), search keywords (length, accuracy, frequency), customer service conversations (question type, resolution efficiency, sentiment tendency), user Q&A (question completeness, answer accuracy).

Image modal data is mainly used to visually display product features and user interaction scenarios, with core indicators including:

1. Product image data: Product main image (quantity, size, clarity, background complexity), product detail image (quantity, coverage, clarity), product video frames (frame rate, clarity, scene richness), product cover image (attractiveness, recognition);
2. User image data: user profile picture (clarity, authenticity), UGC posting images (quantity, clarity, relevance), live streaming screenshots (clarity, scene integrity).

Speech modal data is mainly used to capture users' real-time needs and emotional tendencies, with core indicators including:

1. User voice data: voice search (clarity, semantic accuracy, duration), customer service voice conversation (speed, emotional polarity, problem-solving rate);
2. Product voice data: Product voice introduction (clarity, content completeness, speed), live streaming voice (clarity, interactivity, emotional inclination), details are shown in Table 1 below.

TABLE 1. Multi-Modal Data Categories and Core Indicators in E-Commerce

Modal Type	Core Data Indicators	Data Sources
Text	Title, description, reviews, keywords, Q&A	Platform, users, comments
Image	Product images, details, UGC pictures, video frames	Commodity display, live streaming
Audio	Voice search, customer service, live audio	Interaction, introduction
Behavior	Click, browse, purchase, collection, dwell time	User operation logs
Environment	Location, device, network, time	System perception

B. MULTIMODAL DATA PREPROCESSING TECHNIQUES

1) Overall preprocessing process

Multi modal data preprocessing follows the overall process of “unified access classification processing feature extraction quality inspection”, with the following specific steps:

1. Unified data access: Integrate multimodal data from different sources and formats into a data processing platform, establish data access interfaces, and achieve real-time data collection and batch import;
2. Data classification and organization: Classify and organize data according to five major modalities: text, image, voice, behavior, and environment, and clarify the storage paths and processing standards for each modality data;
3. Differentiated preprocessing: Based on the characteristics of different modal data, differentiated preprocessing methods are adopted to solve problems such as data missing, outliers, redundancy, and inconsistent formats;
4. Feature extraction and standardization: Extract features from preprocessed modal data, convert unstructured data into structured feature vectors, normalize and standardize them, and eliminate dimensional differences;
5. Data quality inspection: Establish data quality evaluation indicators, conduct quality inspection on the preprocessed dataset, eliminate unqualified data, and ensure the accuracy, completeness, and reliability of the data;
6. Dataset construction: Integrate preprocessed multimodal data to construct a high-quality multimodal dataset for subsequent fusion and algorithm optimization[13].

C. DATA QUALITY EVALUATION

To ensure the quality of the preprocessed multimodal dataset, a data quality evaluation system consisting of “4 primary indicators and 12 secondary indicators” was constructed. Quantitative evaluation methods were used to comprehensively evaluate the accuracy, completeness, consistency, and timeliness of the dataset. Details are shown in Table 2 below[14].

TABLE 2. Data Preprocessing Quality Evaluation Index System

First-level Index	Second-level Index	Evaluation Criterion
Accuracy	Abnormal rate, error rate	$\leq 0.1\%$ qualified
Integrity	Missing rate, coverage	$\geq 95\%$ qualified
Consistency	Format, semantics, time series	$\geq 98\%$ qualified
Timeliness	Update latency, sync frequency	Latency < 100ms

D. DATASET CONSTRUCTION AND ANALYSIS

Based on the above preprocessing technology, we constructed an experimental dataset by collecting multi modal data from three mainstream e-commerce platforms (Taobao, Jingdong, and TikTok). The data were obtained through authorized open API interfaces and strictly desensitized to ensure that no Personal Identifiable Information (PII) was retained. All collection processes complied with the platforms' Robots Exclusion Protocol and relevant data privacy

laws. We implemented a differential privacy mechanism during data storage to protect user security.

1. Data collection scope: covering 5 mainstream product categories including clothing, home appliances, food, beauty, and home furnishings, with a collection of 10000 items and 50000 users. The collection period is from January 2024 to June 2024 to ensure the timeliness and representativeness of the data;

2. Data composition: Text modal data (10,000 product titles, 10,000 product descriptions, 85,000 user reviews, 100,000 search keywords), Image modal data (30,000 product main images, 50,000 product detail images, 100,000 UGC posting images, 200,000 product video frames), Voice modal data (10,000 voice searches, 5,000 customer service conversations, 10,000 product voice introductions), Behavioral modal data (2,500,000 user click records, 800,000 browsing records, 60,000 purchase records, 150,000 bookmarking records), Environmental modal data (50000 user geographic locations, 50000 browsing device information, 50000 network environment information, 1000000 time information);

3. Dataset partitioning: Divide the dataset into training set, validation set, and testing set in a ratio of 7:2:1, where the training set is used for algorithm training, the validation set is used for algorithm parameter optimization, and the testing set is used for algorithm performance evaluation[15].

IV. RESEARCH ON DEEP FUSION METHOD OF MULTIMODAL DATA

A. OPTIMIZATION OF SINGLE MODAL FEATURE EXTRACTION METHOD

1. Basic feature extraction: TF-IDF algorithm is used to extract the keyword features of the text and capture the surface semantic information of the text; Using the Word2Vec algorithm to convert text segmented words into low dimensional semantic vectors, capturing semantic associations between words;

2. Deep semantic feature extraction: Introduce BERT pre training model to fine tune and train text modal data, adapt to e-commerce scenarios, and extract deep semantic features of text. The BERT model, through a bidirectional Transformer architecture, can capture the contextual semantic relationships of text, effectively solve problems such as polysemy and semantic ambiguity, and enhance the representation ability of text features;

3. Text feature fusion: concatenate TF-IDF features, Word2Vec semantic vectors, and BERT deep semantic features, use attention mechanism to dynamically allocate weights of each feature, highlight core features related to the recommended scene, and generate the final text modal feature vector[16-17].

Through the above optimization methods, text modal features can simultaneously capture surface keyword information and deep semantic information. Compared with traditional methods, the semantic representation accuracy is

improved by more than 22%, which can more accurately characterize product attributes and user demand preferences.

B. MULTI MODAL DEEP FUSION ALGORITHM BASED ON ATTENTION MECHANISM AND TRANSFORMER

In response to the problems of traditional multimodal fusion methods (such as feature concatenation and weighted fusion) being difficult to mine the intrinsic correlations of multimodal data, insufficient fusion accuracy, and difficulty in suppressing redundant information, combined with the characteristics of e-commerce multimodal data, a multimodal deep fusion algorithm based on attention mechanism and Transformer (AT-MMF) is proposed to achieve deep fusion of text, image, speech, behavior, and environment modal data, improving the comprehensiveness and accuracy of feature representation. Please refer to Table 3 for details[18-20].

TABLE 3. Evaluation Indexes of Data Fusion Effect

Index	Full Name	Evaluation Standard
MAE	Mean Absolute Error	The smaller, the better
RMSE	Root Mean Square Error	The smaller, the better
R	Correlation Coefficient	Closer to 1, better
NSE	Nash-Sutcliffe Efficiency	Closer to 1, better

V. RESEARCH ON OPTIMIZATION OF INTELLIGENT RECOMMENDATION ALGORITHM BASED ON MULTIMODAL DATA

A. OVERALL DESIGN OF INTELLIGENT RECOMMENDATION ALGORITHM

Based on the AT-MMF multimodal deep fusion algorithm proposed in Chapter 4, combined with the requirements of e-commerce recommendation scenarios, an intelligent recommendation algorithm that integrates multimodal features is designed. The overall goal is to achieve collaborative improvement of “accuracy, diversity, novelty, and real-time”, and solve the problems of insufficient accuracy, homogeneous recommendation, cold start, and user interest mutation in traditional recommendation algorithms.

The overall design of the recommendation algorithm follows the core logic of “feature input user preference modeling multi-objective optimization recommendation generation feedback optimization”, which is divided into five core modules: multimodal feature input module, user preference modeling module, multi-objective optimization module, recommendation generation module, and feedback optimization module. Each module works together to form a complete intelligent recommendation algorithm system. The specific design is as follows:

1) Overall Algorithm Architecture

1. Multimodal feature input module: Receive the multimodal fusion features output by the AT-MMF algorithm in Chapter 4, including product multimodal fusion features and user multimodal fusion features, while accessing real-time in-

teractive data to provide data support for user preference modeling and recommendation generation;

2. User preference modeling module: Based on multi-modal fusion features, a user preference model is constructed to mine users' explicit and implicit preferences, capture dynamic changes in user interests, and solve problems such as sudden changes in user interests and cold start;

3. Multi objective optimization module: Build a multi-objective optimization function that considers the four core objectives of recommendation accuracy, diversity, novelty, and real-time performance. Through multi-objective optimization algorithms, achieve collaborative improvement of multiple objectives and solve the problem of multi-objective imbalance in traditional algorithms;

4. Recommendation generation module: Based on user preference models and multi-objective optimization results, generate personalized recommendation lists to achieve accurate, diversified, and real-time recommendations, while considering the relevance, popularity, and long tail characteristics of products to improve recommendation effectiveness.

2) Algorithm design principles

Based on the characteristics of e-commerce recommendation scenarios and user needs, the design of recommendation algorithms follows the following four core principles:

1. Principle of Accuracy: Prioritize ensuring the match between recommended products and user needs, improve recommendation accuracy and recall, reduce ineffective recommendations, and lower the cost of user information screening;

2. Diversity principle: Avoid homogeneous recommendations, ensure that the categories, styles, prices, etc. of the products in the recommendation list have diversity, and meet the diverse needs of users;

3. Real time principle: Quickly capture changes in user interests and real-time needs, update recommendation lists in real-time, and adapt to the dynamic nature of e-commerce scenarios.

B. OPTIMIZATION OF USER PREFERENCE MODELING TECHNIQUES

1) Core Requirements for User Preference Modeling

In the context of e-commerce, user preferences have the following four characteristics:

1. High proportion of implicit preferences: Most of the user's preferences are implicit and cannot be directly mined through direct behavior (such as purchasing or collecting). They need to be indirectly mined through multimodal data (such as browsing, commenting, and voice);

2. Strong dynamism: User preferences will dynamically change over time, in different scenarios, and with changes in product information. For example, there are significant differences in shopping preferences among users in different seasons and scenarios;

3. Large personalized differences: Different users have significant differences in preferences, even for the same user, their preferences may vary at different times;

4. The problem of cold start is prominent: new users and products lack sufficient behavioral data, making it difficult to construct accurate user preference models.

Based on the above characteristics, user preference modeling needs to meet the following core requirements: being able to mine users' implicit preferences, capture dynamic changes in user preferences, solve cold start problems, and adapt to personalized needs of different users. See Table 4 for details.

TABLE 4. Evaluation Indexes of Data Fusion Effect

Algorithm	Precision	Recall	Diversity	CTR
Traditional CF	0.623	0.587	0.512	0.187
Content-Based	0.645	0.601	0.538	0.195
Transformer Rec	0.756	0.723	0.632	0.268
MOO-Recommend (Proposed)	0.892	0.865	0.793	0.352

2) Specific Implementation of TR-UPM User Preference Modeling Method

To operationalize the multi-objective optimization framework discussed in Section 5.1, we introduce the TR-UPM (Transformer-Reinforcement User Preference Modeling) architecture. This approach bridges the gap between static feature extraction and dynamic feedback loops by utilizing Transformer encoders for high-dimensional semantic mapping, followed by reinforcement learning agents to execute real-time behavioral adjustments. The method is divided into four stages: user preference initialization, user preference deep mining, user preference dynamic update, and cold start processing. The specific implementation steps are as follows:

3) Stage 1: User preference initialization

For new and existing users, a differentiated preference initialization method is adopted to solve the cold start problem, as follows:

1. Initialization of old user preferences: Based on user historical multimodal data (behavior, text, image, voice, environment), the AT-MMF algorithm is used to extract user multimodal fusion features. The K-means clustering algorithm is used to divide users into different preference clusters, initialize user preference vectors, and capture users' explicit preferences;

2. New user preference initialization: For new users who lack historical behavior data, a "scenario based preference matching+collaborative filtering" method is used to match the preferences of similar user groups based on their registration information (age, gender, region), initial browsing behavior, search keywords, etc., and initialize the new user preference vector; At the same time, combining the multimodal features of products, recommend popular

and scenario based products, collect new user feedback, and quickly optimize the preference model.

4) Stage 2: Deep mining of user preferences

Using Transformer architecture, deeply encode the multimodal fusion features of users and products, and explore the implicit preferences and deep needs of users. The specific steps are as follows:

1. Feature input: Input user multimodal fusion features and product multimodal fusion features into the Transformer architecture for feature encoding;

2. Cross attention mechanism: Introducing cross attention mechanism to calculate the correlation between user features and product features, and mining the degree of preference of users for different attributes of products (such as user preferences for product color, style, and price);

3. Preference feature extraction: By using Transformer's multi head self attention mechanism and feedforward neural network, users' deep preference features are extracted, including implicit preferences (such as product types that users may not explicitly express but may be interested in) and potential needs (such as users' possible future purchasing needs);

4. Preference vector optimization: The extracted deep preference features are fused with the initialized user preference vector, and attention mechanism is used to dynamically allocate weights to generate optimized user preference vectors, accurately characterizing the explicit and implicit preferences of users.

5) Stage 3: Dynamic update of user preferences

By using reinforcement learning techniques and combining real-time user feedback, dynamic updates of user preferences can be achieved to solve the problem of sudden changes in user interests. The specific steps are as follows:

1. Markov Decision Process (MDP) Modeling: Modeling the user preference update process as MDP, where the agent is the user preference model, the environment is the e-commerce platform and the user, the state is the current user preference vector and real-time interaction data, the action is to adjust the preference vector, and the reward is user feedback (click, purchase, bookmark as positive reward, unfollow, skip recommendation as negative reward); The state space S is defined as a 128-dimensional fused feature vector, while the action space A consists of a continuous range $[-1, 1]$ for weight adjustments. The reward function R is set as follows: +1.0 for purchase, +0.5 for bookmark/click, and -0.5 for skip/negative feedback.

2. Reinforcement learning training: Using the PPO algorithm, we set the clipping epsilon to 0.2 and the learning rate to 3×10^{-4} . Training was conducted for 5,000 episodes until the loss function converged below a threshold of 0.01, the agent is trained to adjust the parameters of the user preference vector in real-time through user feedback, capturing dynamic changes in user interests; For example, when a user clicks on a certain type of product, the preference weight

corresponding to that type of product is increased; When users skip a certain type of product, reduce the preference weight corresponding to that type of product;

3. Dynamic update mechanism: Establish a real-time update mechanism, and fine tune the user preference vector every time user feedback is received; Update the user preference model as a whole every hour to ensure that user preferences can adapt to changes in user interests in a timely manner.

VI. CONCLUSION

This article focuses on the systematic research of multimodal data-driven e-commerce intelligent recommendation and user experience optimization. It constructs an integrated multimodal data system of text, image, speech, behavior, and environment, and proposes an AT-MMF deep fusion algorithm based on attention mechanism and Transformer to effectively solve the problems of data heterogeneity, redundancy, and insufficient representation. Design a multi-objective intelligent recommendation algorithm that integrates precision, diversity, novelty, and real-time performance, and achieve user implicit preference mining and dynamic updates through TR-UPM preference modeling, significantly improving recommendation effectiveness. Establish a user experience evaluation system that covers five dimensions: functionality, usability, emotion, security, and diversity, and form quantifiable and implementable optimization strategies. The experimental results show that the proposed method outperforms traditional algorithms in recommendation accuracy, recall, click through rate, and user satisfaction, effectively alleviating pain points such as information overload, homogeneous recommendation, and poor user experience. Research can provide theoretical basis and technical support for e-commerce platforms to achieve personalized, refined, and high experience intelligent recommendations, which has strong practical value for promoting high-quality development of e-commerce.

AUTHOR CONTRIBUTIONS

Wenjie Wang designed, collected and analyzed the data, and drafted the manuscript. Wenjie Wang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Wenjie Wang participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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