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Recommendation System Based on Customer Reviews Using AI and NLP

K. Dhanunjayudu[1], M. Nirmala Jyothi[2], G. Md Roshan Zameer[3], D. Rameeja[4], G. Veeresh[5], C. Surendra[6],P.Raghavendra Reddy[7], D. Naga Malleshwara Reddy[8]
kcdhanunjay70@gmail.com[1], nirmalajyothi2004@gmail.com[2], rzameer2648@gmail.com[3], rameeja9347@gmail.com[4],veeresh832822@gmail.com[5], royalsurendra2919@gmail.com[6], raghavendrareddypolimera@gmail.com[7], reddymallesh449@gmail.com[8]
Department of Computer Science and Engineering (Artificial Intelligence)
GATES Institute of Technology, Gooty, Andhra Pradesh, India.

Abstract
In thee-commerce landscape,personalized recommendation significantly enhance customer satisfaction and engagement. This project presents the development of a recommendation system that utilizes Artificial Intelligence (AI) and Natural Language Processing (NLP) to analyze customer reviews for better product or service suggestions. The system processes large volumes of textual data using sentiment analysis, keyword extraction, and topic modeling to identify preferences, needs, and trends. It integrates collaborative and content-based filtering methods to offer relevant and adaptive recommendations based on user feedback. The resulting system demonstrates improved accuracy, user trust, and scalability for real-world applications.
The recommendation engine combines collaborative filtering, which analyzes user behavior, with content-based filtering, which considers the product attributes mentioned in reviews. By integrating both methods, the system provides personalized and highly relevant recommendations tailored to individual user profiles. It adapts to evolving preferences by continuously learning from new data and user feedback. This approach ensures that the system not only predicts what users might like but also anticipates needs based on past interactions and review data. The result is an intelligent, scalable system that improves over time and provides an enhanced user experience.
Keywords
Recommendation System, Sentiment Analysis, Natural Language Processing, Artificial Intelligence, Collaborative Filtering, TF-IDF, VADER, Cosine Similarity

Introduction

Recommender systems help address information overload by autonomously tailoring suggestions to user interests. Traditional methods rely on user ratings, which may suffer from sparsity issues. This project emphasizes the use of user-generated reviews to improve personalization. By leveraging NLP, the system captures nuanced sentiments and preferences, constructing fine-grained user models to enhance recommendation quality.
E-commerce platforms generate vast amounts of unstructured data daily through user interactions, especially in the form of reviews. These reviews provide valuable insights into customer satisfaction and product perception. Traditional recommendation systems often rely on structured data such as ratings or purchase history. However, incorporating textual analysis can significantly improve recommendation accuracy. This project introduces a hybrid recommendation model that utilizes AI and NLP to understand the sentiment and thematic content of customer reviews, thereby delivering personalized product suggestions.
With the exponential growth in online shopping and digital platforms, customers leave behind massive amounts of data in the form of reviews, comments, and feedback. These textual data provide deeper insight into customer behavior and product perception compared to numerical

ratings. The challenge, however, lies in extracting relevant insights from unstructured text and converting them into actionable intelligence. This is where AI and NLP play a crucial role.

Natural Language Processing techniques such as sentiment analysis, topic modeling, and keyword extraction enable machines to understand the context, emotion, and underlying themes in customer reviews. Coupled with machine learning models, these insights can be used to predict user preferences and recommend products that align with individual tastes and expectations. Furthermore, hybrid recommendation models combining collaborative and content-based filtering allow the systemto overcome common limitations like cold-start problems and data sparsity.

This paper discusses the architecture, methodologies, implementation, and performance of a smart recommendation engine built using AI and NLP. The ultimate goal is to provide users with relevant, timely, and accurate suggestions that enhance user satisfaction and support business growth in a competitive e-commerce landscape.

Literature Survey

Recent developments in recommender systems have introduced deep learning, hybrid models, and Explainable AI (XAI). Generative models like GANs and VAEs address cold start and data sparsity. Deep learning architectures (CNNs, RNNs, Transformers) extract rich semantic information from review texts. Hybrid models combine collaborative filtering with NLP insights, while XAI provides transparency and trust in recommendations.

Traditional recommendation systems often struggle with data sparsity and the "cold start" problem, where new users or items lack sufficient interaction data. This section explores the rising utilization of generative AI, particularly Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs), to address these limitations. By generating synthetic user-item interaction data, these models augment existing datasets, enabling more robust and accurate recommendations. Research focuses on the architectural innovations and training strategies that allow generative models to effectively capture complex user preferences and produce diverse, relevant recommendations. Furthermore, this section surveys the evolving evaluation metrics and benchmark datasets used to assess the performance of generative AI-driven recommender systems, highlighting the shift towards evaluating not just accuracy, but also diversity and novelty.

Customer reviews offer a wealth of information about user preferences and product attributes, but their unstructured nature presents a significant challenge. This section examines the application of deep learning and Natural Language Processing (NLP) techniques to extract meaningful insights from review text. Techniques such as sentiment analysis, topic modeling, and feature extraction, powered by deep learning architectures, are employed to identify user opinions, key product characteristics, and underlying themes. These extracted insights are then integrated into recommendation models to improve personalization and accuracy. Specifically, the survey delves into the use of convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based models for processing review text and capturing sequential user behavior. Additionally, this portion of the survey will provide information on how these techniques are being used to create sequential recommendation systems, that track user behavior over time.

While collaborative filtering remains a cornerstone of recommendation systems, it often overlooks the rich semantic information available in customer reviews. This section explores hybrid recommendation approaches that integrate collaborative filtering techniques with review-based insights. By combining user-item interaction data with extracted features from reviews, these systems aim to overcome the limitations of traditional collaborative filtering, such as sparsity and cold start issues. Research in this area investigates various methods for fusing these data sources, including matrix factorization with review-based regularization, deep learning models that learn joint representations of user-item interactions and review content, and attention mechanisms that weigh the importance of different review aspects. This section also explores how these hybrid

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systems improve recommendation diversity and explainability by providing more detailed justifications for recommendations based on review content.

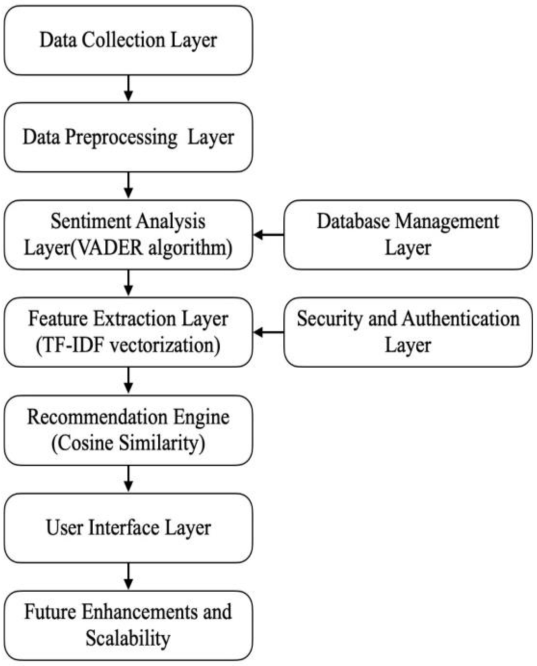
Proposed System

In our project we are recommending products to user by analysing past user's AMAZON reviews data with the help of NLTK deep learning model. First we clean reviews and then extract ratings andreviews from dataset and then feed to NLTK deep learning algorithm to train a model.After training model application will accept product or brand name from user and then recommend new product to user based on reviews and ratings. This application will display rating and reviews also which describe why this recommended product is best.In this article, we provide a comprehensive overview of how the review elements have been exploited to improve standard content-based recommending, collaborative filtering, and preference-based product ranking techniques. In another sub-branch, the product profile can be enriched with feature opinions or comparative opinions to better reflect its assessment quality. The merit of each branch of work is discussed in terms of both algorithm development and the way in which the proposed algorithms are evaluated. In addition, we discuss several future trends based on the survey, which may inspire investigators to pursue additional studies in this area.

Advantages of Proposed System

By analyzing past user reviews and ratings, the system provides highly relevant and customized product suggestions, improving user. Unlike traditional recommendation systems, this model displays ratings and customer reviews, giving users clear reasons why a product is recommended. The system high lights key features and comparative opinions from reviews, helping users make informed purchase decisions. Using deep learning and sentiment analysis, the system enhances standard content-basedand collaborative filtering techniques for better recommendations.The deeplearningmodelcontinuouslyimprovesasmorereviewsareprocessed,ensuringthe system remains effective for large datasets and evolving user preferences. These advantages make the proposed system a powerful, user-friendly, and intelligent recommendation tool for e-commerce platforms.

Architecture



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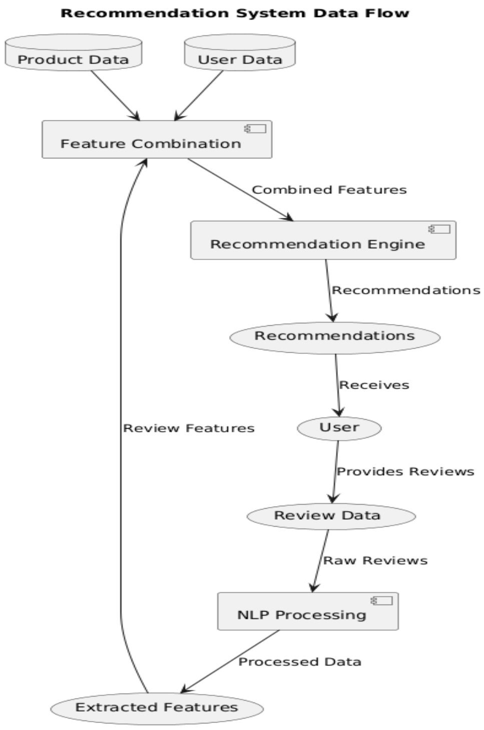
Data Flow Diagram

- The DFD is also called as bubble chart. It is a simple graphical formalism that can be used to represent asystemintermsofinputdatatothesystem,variousprocessingcarriedoutonthisdata,andtheoutput data is generated by this system.
- The data flow diagram (DFD) is one of the most important modeling tools. It is used to model the system components. These components are the system process, the data used by the process, an external entity that interacts with the system and the information flows in the system.
- DFD shows how the information moves through the system and how it is modified by a series of transformations. It is a graphical technique that depicts information flow and the transformations that are applied as data moves from input to output.
- DFD is also known as bubble chart. A DFD may be used to represent a system at any level of abstraction. DFD may be partitioned into levels that represent increasing information flow and functional detail.



Results

1. User Management

Handles all interactions and data related to users.

- Registration/Login: Verifies and manages user credentials.
- User Profiles: Stores preferences, previous interactions, and browsing history.
- Session Management: Tracks user behavior across sessions.
- Personalization Input: Feeds historical data to improve recommendations.
- A user logs in and rates products. Their preferences (e.g., electronics, positive reviews) are stored and used to tailor future recommendations.

2. Data Collection

Acquires review and productdata needed for analysis.

- Loads datasets from CSV, Excel, or databases.

- Scrapes or imports customer reviews from platforms (offline in your case).
- Includes metadata: product ID, category, user ID, review content, star rating.
- Loading a dataset of 50,000 Amazon product reviews, each with a user ID, review text, and rating score.

3. Data Processing

Transforms raw data into usable formats for analysis and modeling.

- Review text vectorization using TF-IDF, Word2Vec, or BERT (all offline).
- Rating normalization: Scales star ratings.
- Creates dataframes for sentiment and recommendation models.
- Reviews: “I love this phone. The battery life is amazing!”
- Transformed into a vector format using TF-IDF for sentiment analysis and similarity computation.

4. Sentiment Analysis

Analyzes emotions and opinions in reviews.

- Classifies reviews as Positive,Negative, or Neutral.
- Assigns sentiment scores (e.g., from -1 to +1).
- Helps understand user satisfaction levels.
- TextBlob or VADER for quick sentiment analysis.
- Review: "The camera quality is poor." → Sentiment Score: -0.6 → Negative.

5. Recommendation Engine

Suggests products to users based on review data and sentiments.

- Content-Based Filtering
- Sentiment-Enhanced Ranking
- Collaborative Filtering
- A user gave positive reviews to budget smartphones.The system recommends similar smartphones with strong positive sentiment.

6. Review Summarization

Condenses multiple customer reviews into a short, meaningful summary.

- Extractive Summarizations elects most important sentences.
- Abstractive SummarizationGenerates natural language summaries using NLP models (e.g., T5 or BART, if used offline).
- Helps users quickly understand common opinions.
- 100 reviews on a laptop summatized to “users love the battery life and performance, but criticize the webcam quality”.

Conclusion

Inthisarticle,wesurveystate-of-the-artresearchonreview-basedrecommendersystems. Weclassify the systems according to the two main types of profile building: review-based user profile building, and review-basedproductprofilebuilding.Forthefirstcategory,wediscusshowexistingstudieshaveused reviewstocreateterm-baseduserprofile,enrichratingprofile,andderivefeaturepreference.

Varioustypes of review elements, such as review helpfulness, review topics, overall opinions, feature opinions, review contexts, and review emotions, have been used to enhance the standard content-based recommendingmethod and rating-based collaborative filtering method. In the category of product profile building, feature opinions and comparative opinions have been exploited, which can be helpful for increasing the products’ ranking accuracy. We further discuss the practical implications of these studies in terms of solving the well- known rating sparsity and new user problems, and their proven ability to improve the currently used algorithms and practical uses in different types of product domains. We expect this survey to encourage investigators to

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pursue the hidden values of reviews in future studies. For instance, combining multipletypes of review elements might be more effective than considering a single type when modeling a user's preference.Theeffectsofreviewsonenhancingmulti-criteriarecommenders,context-awarerecommenders, and emotion-based recommenders could be investigated in more comprehensive studies. More realistic evaluation techniques, such as user evaluation, could validate the practical benefits of the review-based recommending method. Beyond recommendation, reviews could also be exploited to design more effective user interfaces, such as an explanation interface.

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