© JETIR.ORG | ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Recommendation system For E-Commerce website

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***Abstract*—Recommendation systems are changing novelties used by a few E-commerce sites, to serious business tools that are re-shaping the world of E-commerce. Most of the reputed and large MNCs are already using these technology to increase their sales and mass customization all over the world. A system which will take inputs from customer and will provide best and fast service to its clients. This paper aims to research the requirements which will help recommendation AI to become more precise and valuable. In this paper we try to explain a taxonomy of recommender system based on the existing technology, including call to upgrade on system accuracy rate, instant troubleshoot and its interface(extended). Secondly this paper is also useful for academics purposes such as study of multiple recommendation approaches , techniques and its working. The detailed explanation is included about its types, benefits, problems faced during implementation and various aspects on which recommendation system model is evaluated.**

Keywords—Recommendation system, instant troubleshoot, mass troubleshoot, interface, Explainable AI, accuracy rate

I. Introduction

Joe Pine highlights the wake-up call in his book Mass Customization (Pine, 1993)[8] for companies. In his book he argues that companies need to shift from the old technology where production are managed by the process of "standardization and manually labour, homogeneous markets with one product life cycle were in use " to the new world where everywhere is a huge demand of products and which can hold customer interest and loyalty. Pine argues that building one product is generally not adequate anymore. Companies should move to generation of multiple and variety of products. The movement towards E-commerce has given many advantages to the companies[8]. Recommendation system help companies in their market growth and on other hand ensures customer satisfaction by providing them best deals and offers on a budget friendly note.

However, in expansion to the new level has to face many obstacles and challenges which are need to be tackled for the smooth performance in business. Amount of information is too large and vast which is must to be processed before giving it to the customers so that they can't find any problem in selecting their products which meets their need. One solution to this information overload problem is the use of recommendation systems.

Recommendation systems are used by E-commerce websites to suggest products to their customers with similar other products. The products are recommended based on top over all sellers in the websites, customer behaviour and interest or on the principles of different algorithms like Hybrid, Content- Based, Collaborative filtering etc. In simple words it can be said that recommendation system train E-commerce sites to adapt itself as per its each customer area of interest. This is the process of automate personalization on a site, enabling to deal with each and every customer. Thus, Pine would probably be agree with Jeff Bezos, CEO of Amazon.com statement " If I have a 2 million customers on the site, I should have 2 million stores on the web."[8]

Benefits of using Recommendation system

Recommendations provide many benefits to e-commerce platforms and their customers. Here's a breakdown of the key benefits:

For customers:

1.Better discovery: Recommendations help customers review products Great job by showing relevant products they might n ot otherwise see.[7] This can lead to exciting discoveries and t he desire to buy.

2.Reduce Decision Making: With so many options, the search can become endless. Recommendations simplify the process b y providing products that align with your customers' interests and past behavior, saving them valuable time and reducing str ess.

3.Personalization:[10] By analyzing purchasing history, viewi ng behavior, and even demographic information, recommenda tions can be customized based on personal preferences.[7] Thi s improves the sense of connection with the platform and allo ws customers to find products they are truly interested in.

4.Satisfaction: When customers continue to receive positive fe edback, they are more likely to find what they are looking for and complete the purchase[9]. This leads to a better shopping experience and increased customer satisfaction.

For e-commerce:

1.More sales and income: Suggestions can be made to increase sales turnover and average order value by directing customers to buy the products they like. This means immediate growth in business sales and gross profit.

2.Higher customer engagement: Personalized recommendation allow users to engage with the platform for longer periods of time. They can view more catalog items[9], increasing their chances of discovery and purchase.

3.Better product management: Recommendations may address bad products or suggest returns for frequently purchased items.[10] This valuable information allows businesses to imp rove their inventory management and sales strategies.

4.Comparison and molding time: Deals can encourage custom ers to spend more with each purchase by recommending additi onal products or upgrades[1]. This means increasing commerc ial profitability.

5.Deeper understanding of customers: Data collected from cus tomer feedback provides insight into customer behavior and pr eferences. [9]This allows companies to develop marketing stra tegies and products that will increase customer satisfaction.[10]

This table displays average E-commerce digital sales and purchasing habits of the target audience

Industry	Average
Grocery	6.80%
Pharmaceuticals	6.80%
Health & Beauty	3.90%
Travel & Hospitality	3.90%
Fashion	3.30%
Home Goods & Furnishings	3.30%
Consumer Electronics	1.40%
Luxury	1.10%
Automotive	0.70%
B2B	0.70%

Fig. 1 Conversion rate of various E-commerce

Types of Recommendation System Algorithms

There are several different recommendation systems, each with their own strengths and weaknesses. The most common types of recommender systems are:

1. Collaborative Filtering:[10] This type of recommender system looks at what users like you have liked in the past and recommends things that they have liked. Collaborative filtering can be further divided into two subgroups.[3][6][7]

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2. User-Based Collaborative Filtering[3][7]: This type of collaborative filtering focuses on finding users with similar interests to your target users and recommending items that those similar users like.

3. Item-based engagement filtering: This type of engagement filtering focuses on finding similar items to items your target users have liked in the past and recommending those similar items.

4. Content-based filtering: This type of recommender system recommends items similar to items the user has liked in the past. Content-based filtering[3][6] works by building a profile of a user's interests based on things the user has interacted with in the past. This profile can include the genres of movies the user has watched, the type of music the user has listened to, the articles the user has read, and more. Once a user's profile is created, a recommender system can recommend items that share similar characteristics with items the user has liked in the past.[6]

5. Hybrid recommender system[7]: This type of recommender system combines collaborative filtering[3] and content-based filtering to provide more accurate recommendations. Hybrid recommender systems can leverage the strengths of collaborative filtering and content-based filtering to provide additional benefits.[6]

6. Demographic Recommender Systems: This type of recommender system recommends items that are popular with users who have similar demographics to the target user. [7]Demographics can include things like age, gender, location, and income.

7. Knowledge-based recommender systems: This type of recommender system uses knowledge about the relationships between different items to recommend items that are likely to be of interest to users.[5] Knowledge-based recommender systems can be used to recommend items[7] that complement each other or to recommend items that are based on the user's current task.

8. Content-enhanced collaborative filtering: This type of recommender system[1] uses the power of collaborative filtering, but also includes information about the content of items[7].This can help improve the accuracy of recommendations, especially for new or unseen items.

9. Matrix Factorization: This is a technique that can be used to implement both collaborative and content-based filtering. Matrix decomposition works by decomposing the user-item interaction matrix into two lower dimensional matrices. The first matrix represents the latent factors underlying user preferences, and the second matrix represents the latent factors underlying item properties.[12][11] By multiplying these two matrices together, the recommender system can predict how much the user is likely to like.

Proposed Requirements for improvement

1.Advanced data integration and understanding:

A. Multi-modal data integration: Not only your purchase history, but also the reviews you write (positive words can indicate a preference for eco-friendly products) and the time you spend reviewing them.[5] Imagine a system that takes into account specific types of clothing (indicating potential style preferences) and even your local climate (recommended during the rainy season). Combining these different data points makes recommendations more nuanced and relevant.

b. Understanding User Intent: Going beyond what users buy and considering why they buy it requires a deeper analysis of behavior. An example is shown below[1]. Customers often buy sportswear. Standard recommendation systems may recommend more sportswear. However, using sentiment analysis, the system may identify reviews that need more stylish sportswear. Understanding the "why" behind a purchase enables more targeted recommendations that address specific needs.

2.Personalization and user control:

c. Explainable AI: Imagine a recommendation system[11] that not only says "I recommend this product" but also explains why. Factors such as past similar purchases, positive reviews mentioning features they liked about other products, or consistency with your browsing history can be highlighted. This transparency builds trust and allows users to understand the logic behind the offers.

d. Detailed personalization: Allows users to personalize their recommendation experience[8].This may include filtering recommendations by brand (sustainable brands only), price range (excluding luxury goods) and even ethical certifications. Imagine selecting "prefer organic cotton clothing" and being presented with recommendations that prioritize those materials.[1]

3. Dealing with challenges and biases:

e. Cold start problem: New users find recommendation systems challenging due to their limited purchase history[1]. Here the system can (and suggests) use data such as demographics (recommendations for products that are popular in certain age groups) or implicit user signals (dwell time in certain product categories).[7][5] For example, if a new user spends a lot of time on a particular brand's page, the system may recommend other products from that brand.

f. Addressing bias: Recommender systems can reflect bias in the data they are trained on. To mitigate this, equity metrics can be incorporated during development to ensure that all demographics have an equal opportunity to recommend relevant products. Additionally, using diverse datasets to train the system can reduce bias against certain types of products or users.

4. Novelty and randomness:

g. Balance exploration and exploitation: A good system should strike a balance between recommending popular items that users are already familiar with and introducing them to new and exciting products[7]. This could include combining the "Best Selling" and "Currently Trending" sections to display personalized recommendations.

h. Trend Discovery: Real-time trend analysis allows the system to identify upcoming products and styles. Imagine a recommendation system[1] that suggests new types of phone cases based on recent spikes in searches for specific colors or designs. This allows users to find new favorites before they become mainstream.

5. Integration with other technologies:

i. Conversational commerce: Imagine using a chatbot to chat about your fitness goals and get personalized recommendations for exercise equipment.[5] Integrating recommendations with chatbots and virtual assistants can create a more engaging and interactive shopping experience.

j. Augmented Reality (AR): AR has the potential to revolutionize e-commerce. Imagine trying on clothes virtually to ensure fit or arranging furniture in your home to see how it looks before you buy. This integration increases the confidence of users to buy and increase sales.

Techniques used in Recommendation

1.Neural networks for recommendations:

Neural networks are inspired by the structure and function of the human brain and are particularly adept at processing complex,[5] non-linear relationships in data. This makes them well suited for recommender systems where user preferences may be multifaceted and influenced by various factors.

Here are some common neural network architectures used in recommender systems:

a)Auto-encoders: These networks are trained to reconstruct user interaction data with an item.[5][4] By learning a compressed representation of this data, they can identify hidden patterns and user preferences that can be used to make recommendations.

b) Restricted Boltzmann Machines (RBMs): Similar to autoencoders, RBMs learn a compressed representation of the user's interactions with an item. They can be particularly useful for collaborative filtering[13] tasks where user-item relationships are emphasized.

c) Convolutional Neural Networks (CNNs): If you're dealing with recommender systems for items with visual content (eg product images), CNNs[4] excel at extracting features from those images.[12] These features can then be used to recommend visually similar items.

d) Recurrent Neural Networks (RNN): These networks are adept at processing sequential data. In recommendations, they can be used to model user behavior over time, taking into account the order in which users interact with items. This can be beneficial for capturing evolving preferences and recommending items based on recent interactions.[13]

2. Deep learning for recommendations:

Deep learning refers to a class of neural networks with multiple layers that enable them to learn complex relationships in data. Deep learning techniques can be particularly effective for recommender systems,[9][8] especially when working with large and diverse datasets.

Here are some benefits of deep learning for recommendations:

a) Improved accuracy: Deep learning models can capture complex user preferences and item characteristics, leading to more accurate recommendations.

b) Scalability: Deep learning algorithms can efficiently process massive data sets, making them suitable for large e-commerce platforms.[7]

c) Modeling complexity: Deep learning can model non-linear relationships and hidden patterns in data, leading to more accurate recommendations.

Beyond Neural Networks[13]: More Advanced Techniques

Several other advanced techniques are being explored for building recommender systems:

3. Matrix Factorization with Neural Networks: This approach combines matrix factorization (a dimensionality reduction technique)[12][13] with neural networks to learn more complex latent factors that influence user preferences.

4. Reinforcement Learning: This technique can be used to build recommender systems that learn through trial and error. By interacting with the simulated environment (e.g. recommending items and monitoring user feedback), the system can learn optimal recommendation strategies.

5. K-Nearest Neighbors (KNN):

a) Simple and interpretable: KNN is a relatively simple technique that identifies k nearest neighbors[5] (most similar users) for a target user based on their purchase history or interaction data. It then recommends items that neighbors liked.

Strengths: KNN is easy to implement and understand. It can be effective for smaller data sets and situations where interpretability is important [5](eg when you want to understand why a particular item is recommended).

Weaknesses: KNN can be computationally expensive for large datasets. Additionally, it may have problems recommending new or unseen items that are not contained in the training data.[5]

6.Text mining:

Extracting insights from text data: Text mining techniques can be used to analyze user reviews[4], product descriptions and other text data to gain valuable insights for recommendations.

Applications: Text mining can be used for:

Content-based filtering: Analyzing product descriptions or user reviews to identify relevant keywords and recommend items with similar characteristics.

Understanding user preferences: Analyzing user reviews to identify sentiment and preferences not directly captured in purchase history.

Neural Networks for Advanced Needs[4][5][13]: When you have a large dataset and complex user behavior, neural networks can be a powerful tool for uncovering hidden patterns and generating more accurate recommendations.

By carefully evaluating your data, goals, and resources, you can choose the most appropriate technique to build a powerful and effective recommendation system.

In the upcoming table there is given a brief comparison between approaches with their merits and demerits and in second table there has shown frequency of system using recommendation techniques.

Class/Approach		Techniques and Algorithms Used	Advantages	Drawbacks
Content-based [3]		– Content similarity analysis (TF/IDF) [18] – Clustering [3] – Decision tree	– Improvement of the quality of recommendation [42] – Reduction of data sparsity [42]	– Lack of recommendation diversity – Content indexation (extraction of representative attributes) – Problems of indexing multimedia documents
Collaborative-based [24]	CF Model-based [14]	– Clustering [3] – Dimensionality reduction (SVD, PCA) [42] – Association rule learning, sequential pattern, Markov models: Web Usage Mining (WUM) [18]	– Improvement of the quality of recommendation – Prediction of future behavior	– Costly model construction – Loss risk of pertinent information due to dimensionality reduction – Problem of calculating pattern rules when the system lacks sufficient data/relevance due to dimensionality reduction – Does not take into account the user profile for WUM models
	CF Memory-based [36]	– CF using KNN[1] (user-based, item-based) [43]	– Simple implementation – Easy integration of new data – Great accuracy of recommendation	– Dependency on grade data – Deterioration of recommendation quality due to sparsity – Scalability problem
Demographic-based [12]		– Collaborative recommendation techniques [12] – Considering three main components: – K-means[2] clustering [43] – Matrix-factorization [42] – Singular value decomposition (SVD) [29]	– The demographic data used – Classify users	– Requires a database of homogeneous users to classify users – Low performance
Knowledge-based [21]		– Always inspired by the explicit knowledge of users [36] – Rule-based systems make it easier to represent knowledge [72]	– Production of new preference results – Relationships between the selected preferences – No cold start problem	– Knowledge depiction of users is considered – Problem with the accuracy of predictions – Users with unrestricted reasoning
Utility-based [22]		– Classification of item data based on a core attribute of the items – Genetic algorithm (GA) used for the weight value of certain attributes – Multi-attribute utility (MAU) as a function to measure the usefulness of each item, including the value of the user's preferred attribute – Top-N utility element [22]	– Same functionality as content-based recommendation	– Evolution issue – Full re-computation for each new one – Users with unrestricted reasoning

Fig. 2 Table of comparison

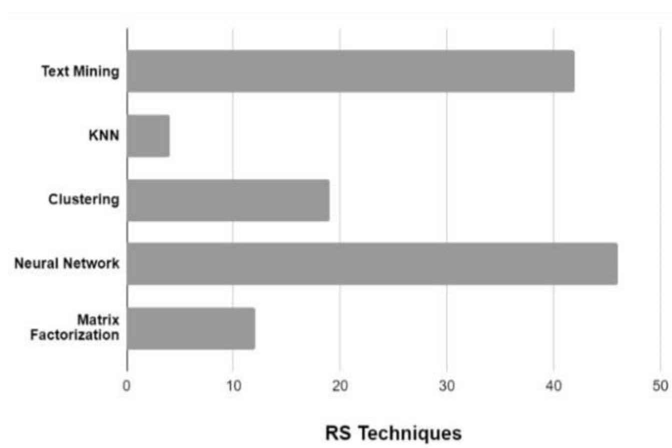

Fig.3 RS Techniques

A. *Challenges*

Although recommendation systems are a powerful tool for e-commerce, they face several challenges that can hinder their effectiveness. Here are some of the most common:

1. Data fragmentation and cold start problems:

A) Data Scattering: Occurs when there is not enough information about a user or item to make accurate recommendations. For example, new users with limited purchase history or new items with little user interaction present challenges to the system.[1][7]

B) Cold Start Problem: This is a specific example of data fragmentation related to new users or items[1]. Due to the lack of user behavior data, the system has difficulty recommending relevant items.

2. Excess and accuracy[7]:

A) Overfitting: When a recommender system is too focused on specific training data to generalize to new users or cases. This may result in irrelevant or duplicate recommendations.

B)Accuracy and Serendipity: It can be difficult to strike a balance between what users are already familiar with (accuracy) and introducing new and exciting products (serendipity).

3. Prejudice and impartiality:

A) Data Bias and Algorithms: Recommender systems can reflect biases that exist in the data they are trained on. For example,[5] if past purchases favor certain demographics, recommendations can perpetuate these biases.

B)Fairness of recommendations:It is important to ensure that all users have an equal opportunity to receive relevant product recommendations regardless of factors such as race, gender or region.

4. Transparency and explainability:

A) The Black Box Problem: Some recommender systems can be like a "black box", [11]making recommendations without explaining why a particular item is recommended. This can lead to a lack of trust among users.

B) Explainable recommendations: Ideally, the system should be able to explain the reason behind its recommendations[11]. This builds trust and allows users to understand the logic behind your offers.

5. Other issues:

Scalability: Recommender systems must efficiently handle large data sets of users, items, and interactions, [7]especially for platforms with huge user bases.

CONCLUSION

Recommendations are a powerful tool that can improve customer experience on e-commerce websites. Leveraging user data and complex algorithms, these systems can recommend products that suit each buyer's preferences and needs. This provides many benefits, including increased sales and conversion rates increased customer satisfaction and engagement discover new products customers won't see fewer buyers feel decision-making fatigue E- As trading continues, recommendations for improvement will become more important for businesses looking to get ahead of the competition. By providing a personalized and interactive shopping experience, these systems can help convert website visitors into loyal customers.

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