



## PRODUCT RECOMMENDATION SYSTEM FOR PURCHASE IN E-COMMERCE

Sri. S SRINADH RAJU<sup>1\*</sup>, B. RAGHAVENDRA<sup>2</sup>, G. SAI PRAVEEN t, B. SAI MAHENDRA VARMA<sup>4</sup>, E LAVANYA<sup>5</sup>

<sup>1</sup> Associate Professor & Hod, Dept. of Computer Science Engineering, Raghu Engineering College, Visakhapatnam, Andhra Pradesh.

<sup>2,3,4,5</sup> B.Tech Students, Department of Computer Science Engineering, Raghu Engineering College, Visakhapatnam, Andhra Pradesh.

[ssraju@raghuenggcollege.in](mailto:ssraju@raghuenggcollege.in), [19981a0521@raghuenggcollege.in](mailto:19981a0521@raghuenggcollege.in),  
[19981a0551@raghuenggcollege.in](mailto:19981a0551@raghuenggcollege.in), [19981a0528@raghuenggcollege.in](mailto:19981a0528@raghuenggcollege.in),  
[19981a0545@raghuenggcollege.in](mailto:19981a0545@raghuenggcollege.in)

**Abstract :** An rising number of E-commerce sites utilize recommender systems to aid customers in finding things to buy. What was once a novelty is now a crucial commercial tool. Product knowledge, either hand-coded knowledge provided by specialists or "mined" knowledge gleaned from customer behavior, is used by recommender systems to help consumers navigate the frequently difficult chore of finding things they will like. In this post, we explain the connections between several conventional database analysis approaches and recommender systems. E-commerce is the practice of buying and selling things online, and it is becoming a vital part of daily life. In addition to social media, e-commerce is the main factor driving the increase in internet users. Making sure a quality customer experience is the main issue for e-commerce enterprises.

More and more e-commerce websites are using recommender systems to assist customers in finding things to buy. What was once a novelty has evolved into an important commercial tool. To help customers through the frequently difficult chore of finding things they will like, recommender systems leverage product information, either hand-coded knowledge provided by specialists or "mined" knowledge gleaned from consumer behavior. We explain the relationship between recommender systems and certain established database analysis techniques in this post. E-commerce refers to the buying and selling done online, a practice that is now essential to daily living. E-commerce, rather than social media, is the main driver of the increase in internet users. Providing excellent customer service is the largest difficulty for e-commerce enterprises.

**Key words :** Recommendations, accuracy, text classification, Apriori algorithm, and frequent itemset mining.

**Introduction :** Information is gathered practically everywhere in daily life. For instance, information on client purchases is kept on file at supermarket checkouts. Customer purchase behavior and personal information can be linked when payback or discount cards are utilized.

Retailers can develop more effective and improved marketing tactics by evaluating this data. [4]The vast majority of reputable organizations have gathered a tonne of data from their clients over many years. Due to the rapid expansion of e-commerce applications, organizations will have a tremendous amount of data in months rather than years. [6]Data mining, also known as knowledge discovery in databases, is the process of identifying trends, patterns, correlations, and anomalies in databases so that accurate future judgements can be made.

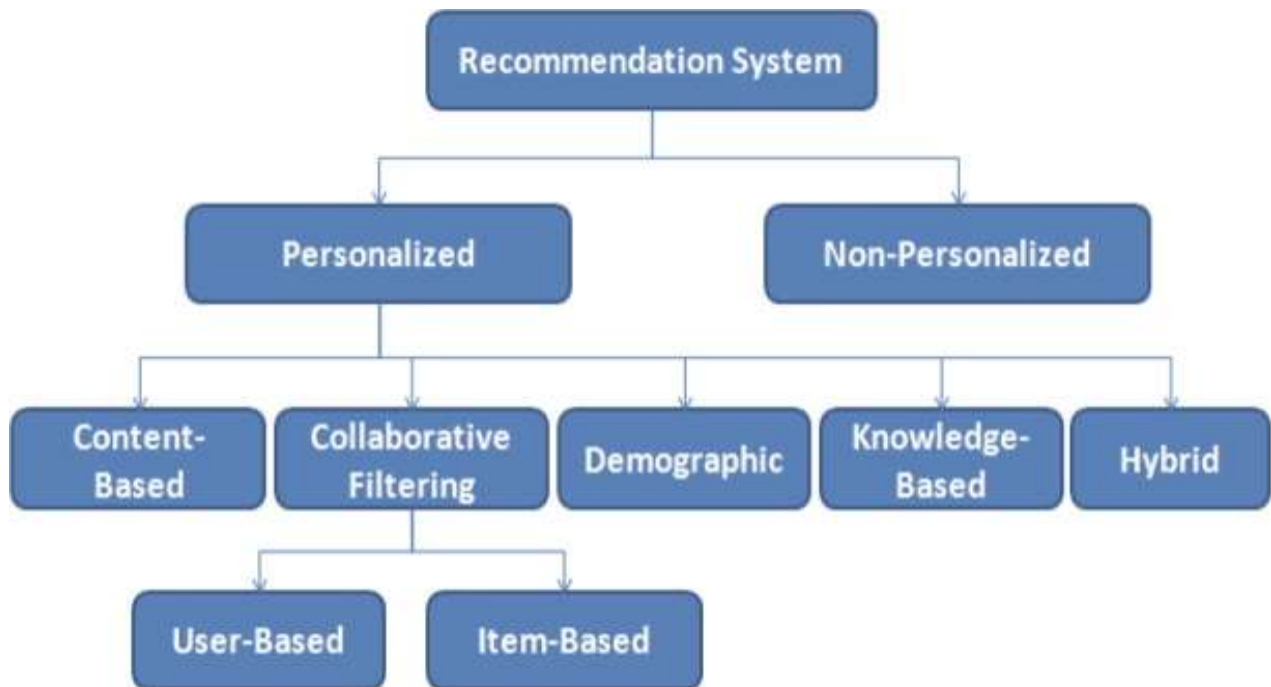


Fig. 1

### Literature Review :

Nearest neighbor algorithms calculate the distance between consumers using six different factors. their history of preferences. [1]The weighted average of the opinions of a group of closest neighbors for a certain product is used to predict how much a consumer will enjoy it. Neighbors who haven't voiced an opinion on the subject are ignored. Scaling opinions is necessary to account for user variances in rating inclinations (Herlocker et al., 1999).

Numerous machine-learning techniques, such as rule induction, neural networks, and Bayesian networks, can be used to create classifiers. [5]Each time, a training set with available ground truth classifications is used to train the classifier. The classification of novel items for which there are no ground truths can then be done using it. The classifier may eventually need to be retrained if new ground facts become available in the future. The identification of fraud and credit risks in financial transactions, medical diagnosis, and intrusion detection have all seen significant success with classifiers. [8]Using an induction-learning classifier, Basu et al. (1998) created a hybrid recommender system that combines collaboration and content filtering.

Induction-learned feature vector classification of films was used by Good et al. (1999), and the classification was compared to nearest-neighbor recommendation. This study found that while the classifiers did not perform as well as nearest neighbor, combining the two improved upon nearest neighbor alone. Association rules have been used in marketing for a long time to study consumer preference trends across items and to make product recommendations to customers based on the products they have already chosen.

Collaborative recommendation that is content-based. The tools that readers of the World Wide Web need to can aid people in navigating the enormous amount of information available online. The selection of books is made easier for readers by traditional media. [11]Explicit support services like movie reviews and restaurant guides are examples of this kind of assistance, as is editorial monitoring. In the digital age, there is a new opportunity to create recommendation systems that could change over time to reflect the preferences of its users. Fab is an excellent example of a recommendation system. A hybrid system combines the best of both worlds while also



having their own shortcomings. putting together a hybrid recommendation system. The authors first talk about two methods: cooperative. The implementation of such a system is then described in content-based detail.

This section focuses on the use of social and content based information in recommending products and services to users. from recommendation systems on various objects, When it comes to movie recommendations, for example, they can forecast whether a user is interested in seeing a certain film[7]. In order to offer suggestions to a user about new artifacts, social recommendation algorithms collect ratings from a large number of people and employ nearest-neighbor approaches.[3] These methods, however, do not make advantage of the wealth of other data that may be found about a given artifact. Such as cast or critic lists. Here, we present an inductive learning recommendation approach able to use ratings and other information about each artifact to predict user preferences. On a dataset of over 45.000 movie reviews collected from over 250 individuals, we show that our method beats an existing social filtering algorithm in the domain of movie recommendations. Predictive algorithms for collaborative filtering are studied empirically in this section.

**Methods :** A well-known technique for figuring out how things fit together is the apriori algorithm. For use with transactional databases, Apriori was designed. Apriori examines the frequency of candidate item sets, which are created by combining frequently occurring sub-item sets, when doing database searches.

In other words, all users of the system fall under the UI layer Administrators, Point of Sale staff, and market analysts categories. [9]The administrators can use this approach to add or remove transactional objects from the database. The POS officers have the ability to enter the transactions into the database. The market analyst can identify patterns by examining the transactional database. Due to the system's user-friendly interface, even a new analyst can sift through vast data vaults to uncover insightful information. It is common practice in Logic for Business Itemset mining to count the number of supporters, generate candidate item sets, and then trim the sets of candidates produced by the counting. The business logic module implements the aforementioned steps.

A crucial step in the RS process is the computation of inter- and intra-personal similarity values as well as similarity values based on products. [2]The system argued that the RS model would be more successful when individual preferences, interpersonal impact, and intrapersonal influence were taken into account. The technology takes into account the users' independent interest in the e-commerce area. That is to say, it can, to some extent, make product recommendations based on user preferences. Additionally, it can exploit user associations with product characteristics in boosting algorithms, particularly for current and more awaited users. The system also makes use of the interest circle inference technique. The boosting approach separates the social network into a variety of sub-networks, each of which is associated with a certain item collection. By incorporating user reviews.

**Collaborative Filtering :** The collaborative filtering method, which enables the prediction of a user's interests based on the preferences and data gathered from several users, forms the basis of recommendation systems. Collaborative filtering is essentially a kind of data analysis used to generate predictions about a user's interests.

**Decision Tree :** The decision tree is a guided learning technique used in machine learning. A decision tree is a type of tree-structured classifier that uses internal nodes to represent a data set's attributes, branches to represent the decision rules, and leaf nodes to reflect the decision's outcomes. Based on a certain decision condition, the decision tree offers a visual depiction of all possible solutions to a problem.

**Apriori algorithm :** The Apriori algorithm is a popular algorithm for mining frequent itemsets in a dataset. The algorithm is based on the principle of association rule mining, which involves discovering relationships between different items in a dataset. [10]The algorithm was introduced by Agrawal et al. in 1994 and has been widely used in various applications such as market basket analysis, web usage mining, and social network analysis.

Candidate creation and candidate trimming are the two stages of operation for the Apriori algorithm. The



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algorithm creates every itemset of length  $k$ , where  $k$  is an integer higher than or equal to 1, in the first phase. The algorithm then looks over the dataset to determine how frequently each itemset occurs. The method eliminates the candidate itemsets in the second step if they fall short of the minimal support level.



### Proposed System

The Fast Items Miner method (FIM) prevents the generation of too many candidates as well as any additional candidate validation steps. The picture below shows the inputs, operations, and results of the FIM algorithm.

The algorithm partitions the transactions in D into n intervals. For each time, all frequently occurring item sets in the partition are located. You could make: candidate things are categorized globally depending on Any group of objects that are most likely to be shared in terms of D must exist in at least one of the partitions as a group of often occurring objects. The most popular item sets globally are now determined using the support count for each contender. Frequently can be used to perform market basket analysis.

### Results

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[ ] df.shape
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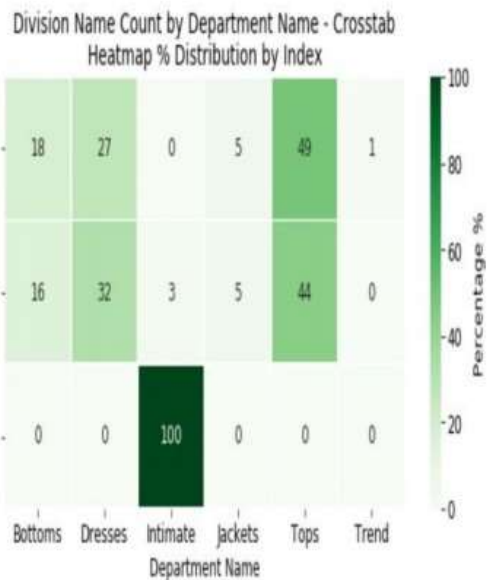
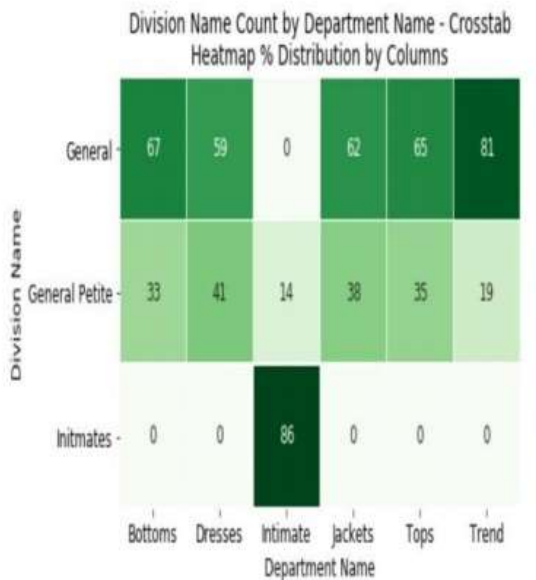
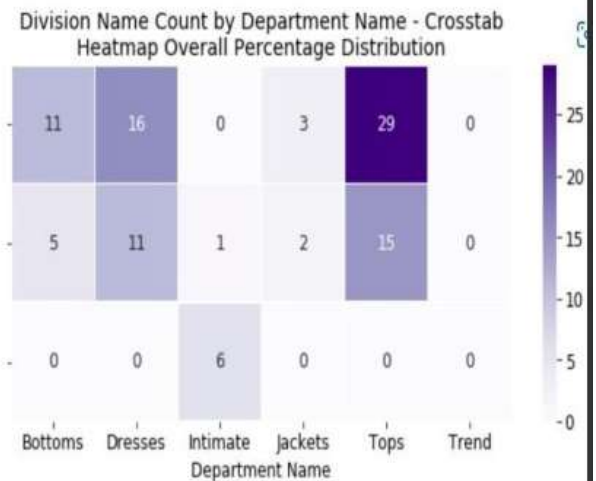
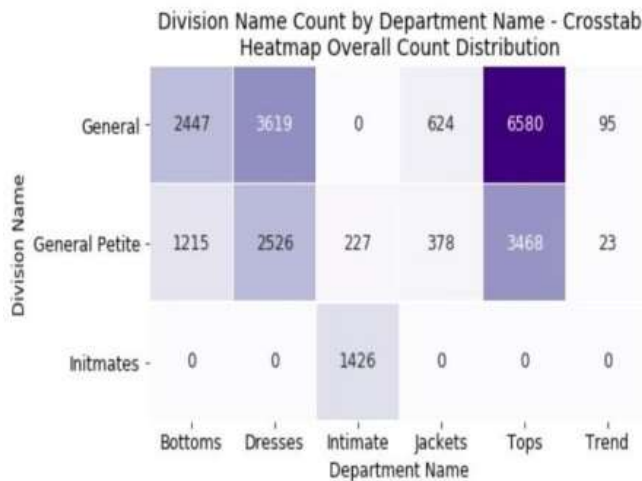
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(22628, 10)
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	Clothing ID	Age	Title	Review Text	Rating	Recommended IND	Positive Feedback Count	Division Name	Department Name	Class Name	Label	Word Count
4975	927	40	Better in person than the photos	Like another reviewer, I was in the store look...	4	1	1	General	Tops	Sweaters	1	97
19423	873	41	Great top!	I wore this for the first time this weekend an...	5	1	1	General	Tops	Knits	1	54
2776	868	42	Love it!	I tried this (black motif) on yesterday in my ...	5	1	3	General	Tops	Knits	1	94
20774	1110	68	You will feel so elegant!	As part of the over 60 crowd, I rarely wear dr...	5	1	0	General	Dresses	Dresses	1	75
1177	1094	53	Beautiful summer dress	I was unsure about this dress when I first tri...	4	1	0	General Petite	Dresses	Dresses	1	82

	mean	std	min	25%	50%	75%	max
<b>Clothing ID</b>	919.695908	201.683804	1.0	861.0	936.0	1078.0	1205.0
<b>Age</b>	43.282880	12.328176	18.0	34.0	41.0	52.0	99.0
<b>Rating</b>	4.183092	1.115911	1.0	4.0	5.0	5.0	5.0
<b>Recommended IND</b>	0.818764	0.385222	0.0	1.0	1.0	1.0	1.0
<b>Positive Feedback Count</b>	2.631784	5.787520	0.0	0.0	1.0	3.0	122.0
<b>Label</b>	0.895263	0.306222	0.0	1.0	1.0	1.0	1.0
<b>Word Count</b>	60.211950	28.533053	2.0	36.0	59.0	88.0	115.0



	unique	top	freq
<b>Title</b>	13983	Love it!	136
<b>Division Name</b>	3	General	13365
<b>Department Name</b>	6	Tops	10048
<b>Class Name</b>	20	Dresses	6145



**Discussion**

One of the main benefits of a product recommendation system is that it can assist users to save time and effort when searching for products that are specific to their needs which can lead to a saving in time and effort. Instead



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of manually searching through lists of products, users can receive tailored recommendations based on their interests and preferences. In online e-commerce sites, where a larger number of products are available and it can be overwhelming for consumers to choose from, product recommendation systems are especially valuable. With targeted recommendations, these systems can assist users in staying engaged and motivated, enabling them to



progress toward purchasing products or goods. This project provides an application with an user friendly graphical user interface (GUI). Where the system will make suggestions after the user enters the product name. The suggested system focuses on using a collaborative filtering technique with knowledge-based recommendations to point students in the direction of the most suitable product. The suggested system will use the Appropri algorithm to map all similar products based on the data set that is currently available. The knowledge-based trained model suggests appropriate products for consumers after the collaborator filtering method. Additionally, the system's design uses few resources.

### Conclusion

The planned work will increase customer satisfaction. considering that the recommendation algorithm incorporates a variety of techniques to find comparable products after a buyer chooses one to buy. Customers are happier because the issue of "out-of-stock" items is no longer a problem. This is a more successful marketing tactic that also increases customer satisfaction. This assesses the novelty of rating items based on the perceptions of seasoned users and a number of other factors. Interpersonal relations and user reviews are taken into account in the current literature on personalized recommendation models. The proposed system will be able to offer customers more pertinent and timely suggestions by merging location data and other elements.

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