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Book recommendation system using artificial intelligence

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Abstract—Recommendation systems are designed to help online platform users manage large volumes of information and provide them with a personalized experience. This is achieved by suggesting items of interest to users based on their explicit and implicit preferences. There have been growing interests in the area of recommendation systems using machine learning algorithms. Because there is a large number of explicit and implicit characteristics. Which can be used to estimate user preferences, requires scalable and precise algorithms with a system with High availability and scalability? Apache Spark is an open source distributed platform. To process big data, obtaining good speed and scalability and Suitable for iterative self-learning algorithms.

Keywords—Collaborative Filtering, Machine Learning, Recommedation.

I. INTRODUCTION

As we think about the title of this paper is related to Recommender System which is part of the Data mining technique. Recommendation systems use different technologies, but they can be classified into two categories: collaborative and content-based filtering systems. Content-based systems examine the properties of articles and recommend articles similar to those that the user has preferred in the past. They model the taste of a user by building a user profile based on the properties of the elements that users like and using the profile to calculate the similarity with the new elements. We recommend items that are more similar to the user's profile. Recommender systems, on the other hand, ignore the properties of the articles and base their recommendations on community preferences. They recommend the elements that users with similar tastes and preferences have liked in the past. Two users are considered similar if they have many elements in common.

II. RELATED WORK

They propose various matrix factorization (MF) based techniques. Second, a neighbor correction method for MF is outlined, which alloys the global perspective of MF and the localized property of neighbor based approaches efficiently. In the experimentation section, we first report on some implementation issues, and we suggest on how parameter optimization can be performed efficiently for MFs. We then show that the proposed scalable approaches compare favorably with existing ones in terms of prediction accuracy and/or required training time. Finally, we report on some experiments performed on Movie Lens and Jester data sets [1].

In this work we identify unique properties of implicit feedback datasets. We propose treating the data as indication of positive and negative preference associated with vastly varying confidence levels. This leads to a factor model which is especially tailored for implicit feedback recommenders. We also suggest a scalable optimization procedure, which scales linearly with the data size. The algorithms used successfully within a recommender system for television shows. It compares favorably with well-tuned implementations of other known methods. In addition, we offer a novel way to give explanations to recommendations given by this factor model [2].

Recommender systems rely on different types of input data, which are often placed in a matrix with one dimension representing users and the other dimension representing items of interest. The most convenient data is high-quality explicit feedback, which includes explicit input by users regarding their interest in products. For example, Netflix collects star ratings for movies, and TiVousers indicate their preferences for TV shows by pressing thumbs-up and thumbs-down buttons. We refer to explicit user feedback as ratings. Usually, explicit feedback comprises a sparse matrix, since any single user is likely to have rated only a small percentage of possible items [3].

Humans inevitably develop a sense of the relationships between objects, some of which are based on their appearance. Some pairs of objects might be seen as being alternatives to each other (such as two pairs of jeans), while others may be seen as being complementary (such as a pair of jeans and a matching shirt). This information guides many of the choices that people make, from buying clothes to their interactions with each other. We seek here to model this human sense of the relationships between objects based on their appearance. Our approach is not based grained modeling of user annotations but rather on capturing the largest dataset possible and developing a scalable method for uncovering human notions of the visual relationships within. We cast this as a network inference problem defined on graphs of related images, and provide a large-scale dataset for the training and evaluation of the same. The system we develop is capable of recommending which clothes and accessories will go well together (and which will not), amongst a host of other applications [4].

Here we develop a method to infer networks of substitutable and complementary products. We formulate this as a supervised link prediction task, where we learn the semantics of substitutes and complements from data associated with products. The primary source of data we use is the text of product reviews, though our method also makes use of features such as ratings, specifications, prices, and brands. Methodologically, we build topic models thatare trained to automatically discover topics from text that are successful at predicting and explaining such relationships. Experimentally, we evaluate our system on the Amazon product catalog, a large dataset consisting of 9 million products, 237 million links, and 144 million reviews [5].

III. PROPOSED SYSTEM

- As I studied then I want to propose Book recommendation system using collaborative filtering is propose the integration of content based recommendation and collaborative filtering
- firstly find users point of interest then to recommend to user based on implicit and explicit feedback and achieve the high accuracy and also remove cold-start problem in recommendation system.
- In this system, particular Recommendation of books for new users.
- A general solution is to integrate collaborative filtering with content based filtering from this point of view of research, some popular.
- Content-based collaboration filtering frameworks, have been recently Proposed, but designed on the basis of explicit feedback with favorite samples both positively and negatively.
- Such as Only the preferred samples are implicitly provided in a positive way. Feedback data while it is not practical to treat all unvisited books as negative, feeding the data on mobility together. With user information and books in these explicit comments Frames require pseudo-negative drawings.

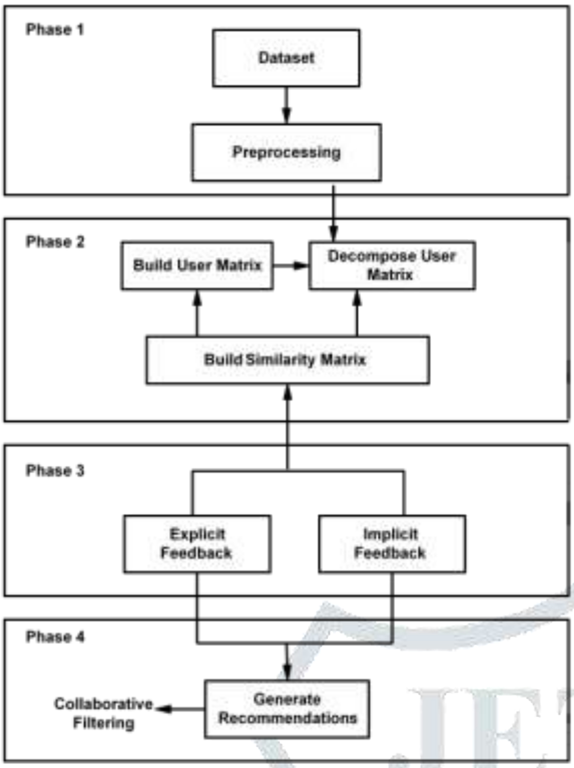
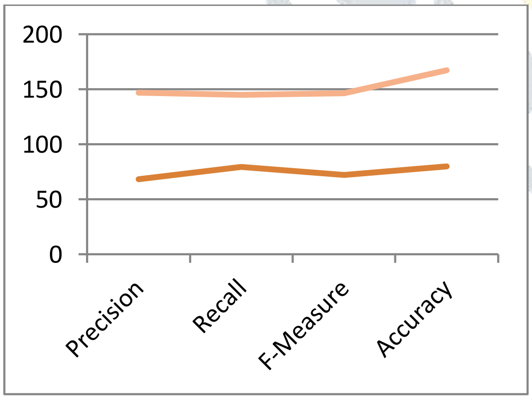


Figure 1. System Architecture

IV. Result and Discussion

We compared the proposed book recommendation accuracy on number of samples and show the result graphically. Let see the following graph and table shows the book recommendation accuracy result based on machine learning technique.



	Existing system	Proposed System
Precision	69.75	79.88
Recall	82.45	64.99
Accuracy	78.99	90.91

Conclusion

In this work, we develop a book recommendation using collaborative filtering algorithm. In order To improve the accuracy of the algorithm, we have developed the System in the spark framework. We also compare its performance using different configurations. The experiment the results showed a decent average quadratic error as output of the recommendation model with efficient execution times. The experiment also showed that it is performed on a cluster it also exceeds at a reasonable cost for the data set that used

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