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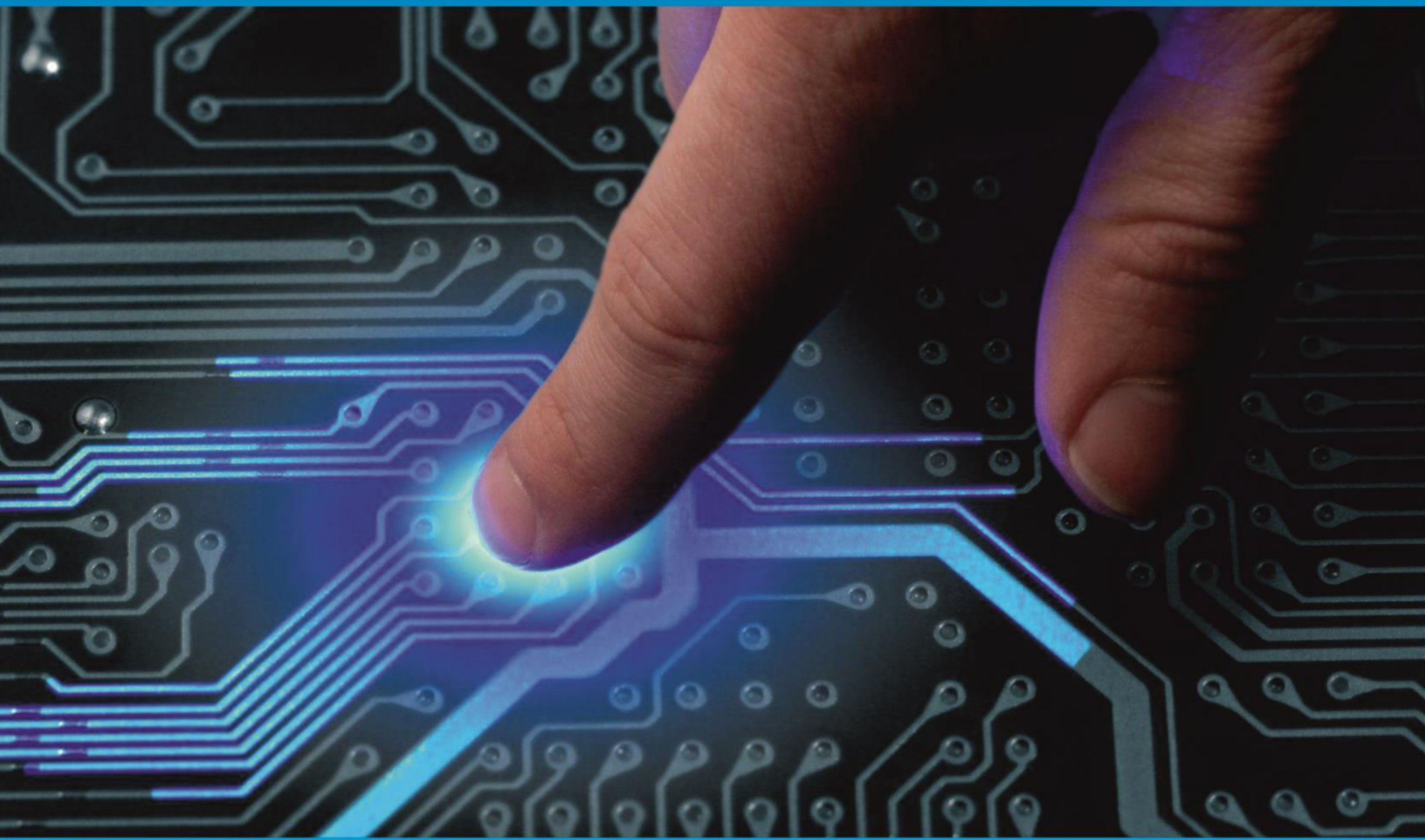

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# On Both Cold-Start and Long-Tail Recommendation with Social Data

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**ABSTRACT:** The number of "hits" has been widely regarded as the lifeblood of many web systems. One is "how to handlenew users", and the other is "how to surprise users". The former is well-known as cold-start recommendation. In this project, this show that the latter can be investigated as long-tail recommendation. This also exploit the benefits of jointly challenging both cold-start and long-tail recommendation, and propose a novel approach which can simultaneously handle both of them in a unified objective. For the cold-start problem, thus learn from side information. Then, this transfers the learned knowledge to new users. For the long-tail recommendation, this decompose the overall interesting items into two parts: a low-rank part for short-head items and a sparse part for long-tail items. The two parts are independently revealed in the training stage, and transferred into the final recommendation for new users. Furthermore, this effectively formulate the two problems into a unified objective and present an iterative optimization algorithm. A fast extension of the method is proposed to reduce the complexity, and extensive theoretical analysis are provided to proof the bounds of our approach. At last, experiments of social recommendation on various real-world datasets.

**KEYWORDS:** Hits ,Cold- Start, Long-Tail, E-Commerce

## I. INTRODUCTION

In web system number of people visiting the website like ecommerce, advertising system and multimedia consumption system are important for the website holder. Website holders has to make a note on how many people visiting their website it can be calculated to find the total hits of the visitors based on that product will be recommended. There is one problem if the website didn't show any product to the new customer user cannot able to see the product sometime new user may visit the website and some irrelevant product will be shown. Recommender system plays a important role of discovering interesting items from near-infinite inventory and exhibiting them to potential users. Yet, two problems are incapable in the recommender systems. One is "how to handle new users", and the other is "how to surprise users". The former is well-known as cold-start recommendation and latter shown as long tail recommendation.In the recent literatures reported in the community of recommender system, the most popular and effective methods are based on collaborative filtering and matrix factorization. CF methods are built on the past interactions between the user and the system. Thus, they generally cannot handle new users since there is no past interaction available. MF methods normally preserve only the principal components after the matrix factorization, so it is almost inevitable that they will lose sight of the niche items. In this paper, we investigate the two challenges and aim to jointly handle both of them in a unified objective.

## II. LITERATURE SURVEY

In 2012 Artus Krohn-Grimberghe, Lucas Drumond, Christoph Freudenthaler.This paper presents Multi-Relational Matrix Factorization using Bayesian Personalized Ranking for Social Network a key element of the social networks on the internet such as Facebook and Flickr is that they encourage users to create connections between themselves, other users and objects. One important task that has been approached in the literature that deals with such data is to use social graphs to predict user behaviour (e.g. joining a group of interest). More specially, we study the cold-start problem, where users only participate in some relations, which we will call social relations, but not in the relation on which the predictions are made, which we will refer to astarget relations. We propose a formalization of the problem and a principled approach to it based on multi- relational factorization techniques. Furthermore, we derive a

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principled feature ex- traction scheme from the social data to extract predictors for a classier on the target relation. Experiments conducted on real world datasets show that our approach outperforms current methods.

In 2010 Mohsen Jamali, Martin Ester.This paper presents A Matrix Factorization Technique with Trust Propagation for Recommendation in Social.Recommender systems are becoming tools of choice to select the online information relevant to a given user. Collaborative filtering is the most popular approach to building recommender systems and has been successfully employed in many applications. With the advent of online social networks, the social network based approach to recommendation has emerged. This approach assumes asocial network among users and makes recommendations for a user based on the ratings of the users that have direct or indirect social relations with the given user. As one of their major benefits, social network based approaches have been shown to reduce the problems with cold start users. In this paper, we explore a model- based approach for recommendation in social networks, employing matrix factorization techniques. Advancing previous work, we incorporate the mechanism of trust propagation into the model. Trust propagation has been shown to be a crucial phenomenon in the social sciences, in social network analysis and in trust-based recommendation. We have conducted experiments on two real life data sets, the public domain Epinions.com dataset and a much larger dataset that we have recently crawled from Flixster.com. Our experiments demonstrate that modelling trust propagation leads to a substantial increase in recommendation accuracy, in particular for cold start users.

In 2018 Yu Zhu, Jinhao Lin, Shibi He, Beidou Wang, Ziyu Guan, Haifeng Liu.This paper presents Addressing the Item Cold-start Problem by Attribute-driven Active Learning recommender systems, cold-startissues are situations where no previous events, e.g. ratings, are known for certain users or items. In this paper, we focus on the item cold-start problem. Both content information (e.g. item attributes) and initial user ratings are valuable for seizing users' preferences on a new item. However, previous methods for the item cold-start problem either 1) incorporate content information into collaborative filtering to perform hybrid recommendation, or 2) actively select users to rate the new item without considering content information and then do collaborative filtering. In this paper, we propose a novel recommendation scheme for the item cold- start problem by leverage both active learning and items' attribute information. Specifically, we design useful user selection criteria based on items' attributes and users' rating history, and combine the criteria in an optimization framework for selecting users. By exploiting the feedback ratings, users' previous ratings and items' attributes, we then generate accurate rating predictions for the other unselected users. Experimental results on two real-world datasets show the superiority of our proposed method over traditional methods.

In 2018 Jongpil Lee, Kyungyun Lee, Jiyoung Park,This paper presents Deep Content-User Embedding Model for Music Recommendation. Recently deep learning based recommendation systems have been actively explored to solve the cold-start problem using a hybrid approach. However, the majority of previous studies proposed a hybrid model where collaborative filtering and content-based filtering modules are independently trained. The end-to-end approach that takes di_erent modality data as input and jointly trains the model can provide better optimization but it has not been fully explored yet. In this work, we propose deep content-user embedding model, a simple and intuitive architecture that combines the user-item interaction and music audio content. We evaluate the model on music recommendation and music auto-tagging tasks. The results show that the proposed model significantly outperforms the previous work. We also discuss various directions to improvethe proposed model further.

## III. PROPOSED METHODOLOGY

Based on the problems due to cold start and long tail, products in the ecommerce retailers getting sold out so soon. And some kind of products remains stagnant for a long duration. Thus to overcome these problems we are going to track the selling of products as well as recommending the products to the customers of same kind based on the previous purchases by using clustering and classification we achieve this First user register the details like name, password, address and registers then login with valid credentials then the large amount of transactional data collected from customer for segmentation and classification and these data are pre-processed and cluster and classify the data cold product classified based on sale and long tail is classified based product that getting sold frequently after that cold products that are available in the ecommerce site will be recommended to the user to make retailer some profit for the product and finally long tail problem solved by recommending relevant item and product that are not sold for long period gets attractive offer based on the user request. We use hadoop environment to do manipulation with the products dataset.

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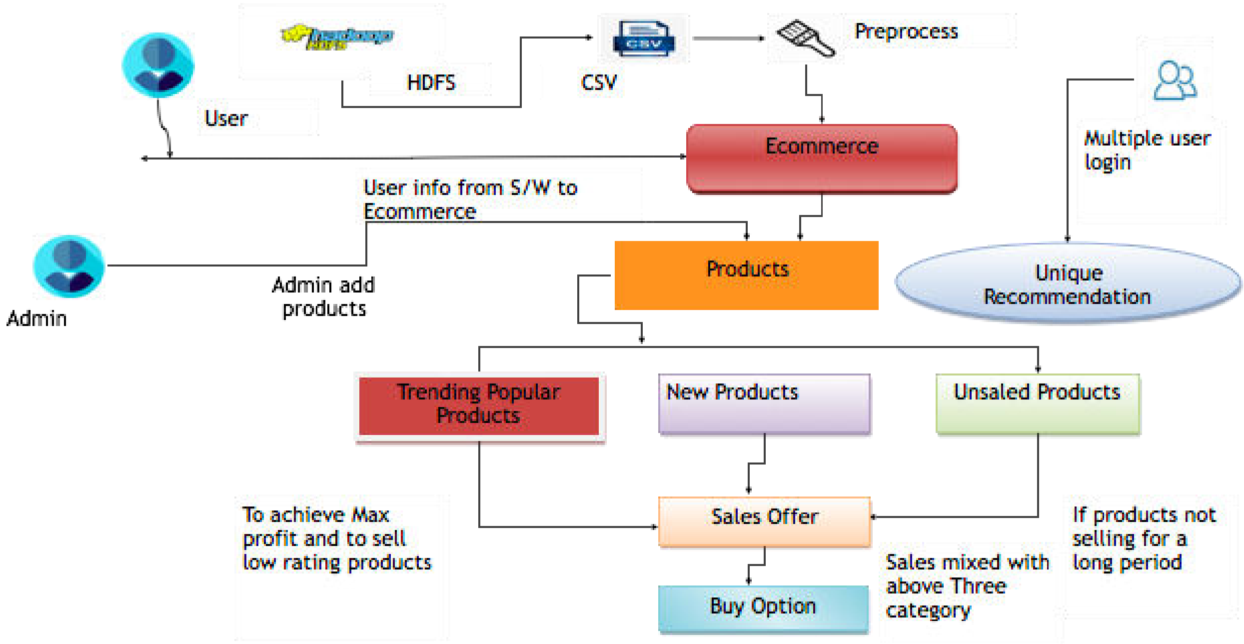


FIG.1 ARCHITECTURE DIAGRAM

## IV. MODULES

### USER AUTHENTICATION

- Initially user need to create their own account and register their basic detail in the server.
- Here whereas the Database server will maintain the user personal detail and all the transaction detail which are processed by the user.
- By the way user need to register into the blank application. A new user account number will be generated where user can deposit initial amount.

### DATA PREPROCESSING

- A huge amount of transactional data has to be collected for customer segmentation and products classification.
- From the collected dataset the long tail products and cold products will be clustered and classified based on the sales data.
- Here the most popular products which are getting sold in the online markets is classified which comes under long tail group.
- Whereas some products which are popular once in trend but was not sold for recent days , these criteria are considered and data preprocess will be done.

### COLD PRODUCT RECOMMENDATION

- For a group of customers who came into ecommerce application their previous transactions will be obviously null.
- For this new customers our recommendation system will provide some valuable products recommendation to attain margin for the retailers. In retailers perspective some cold products will be pushed to recommender platform for the new customers.
- Thus we can solve the cold start problem by recommending the users some products from cold product category.

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**COMBO PRODUCTS RECOMMENDATION**

- In-order to solve the long tail problem from the categorized group of products, most selling products has to be collected and some product descriptions will be compared and based on the matching patterns these relevant products will be recommended to the customer.
- In-order to push the unsold products for a long period based on the customer's request some attractive offers should be promoted.
- So we implement a product combo offer logic to make the sale possible. Thus long tail and cold start problem has been handled.

## V. EXPERIMENTAL RESULTS

- Both cold-start recommendation and long-tail recommendation are challenging problems in the community. To the best of our knowledge, this work is the first one which challenges both cold-start recommendation and long-tail recommendation in a unified optimization problem. Extensive experiments on four real-world datasets verify the effectiveness of the proposed method. This project shows that one can use side information to warm-up the recommender system when there is no available historical recorders. This also find that considering long-tail items in the process of cold-start can be beneficial. In fact, our ideas of independently handling the short-head items and long-tail items can also be used in regular recommendations (relative to cold-start recommendation). It is one of the work we will study in the future.
- In our experiments, the side formation is mainly from social data. However, side information can be collected from many other sources, e.g., cross domain platforms, questionnaires by active learning, and each source can reinforce the others. As a result, in our future work, we are going to study the multi- source side information assisted cold-start recommendation.

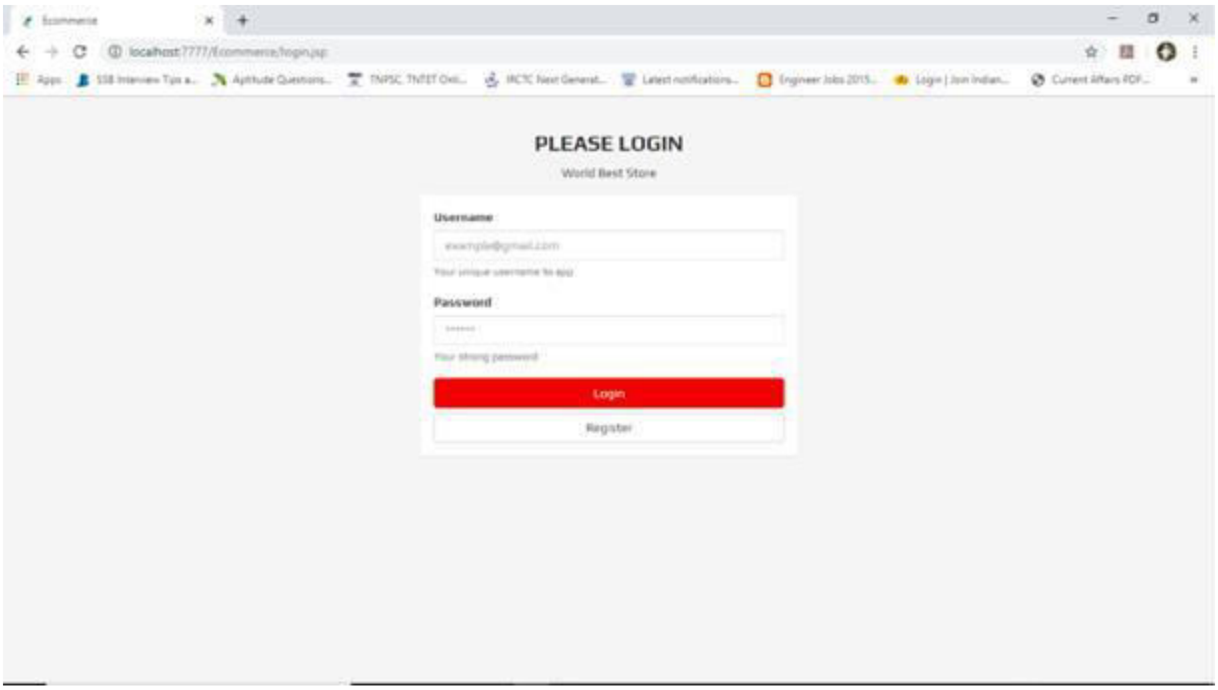


FIG.2 LOGIN PAGE

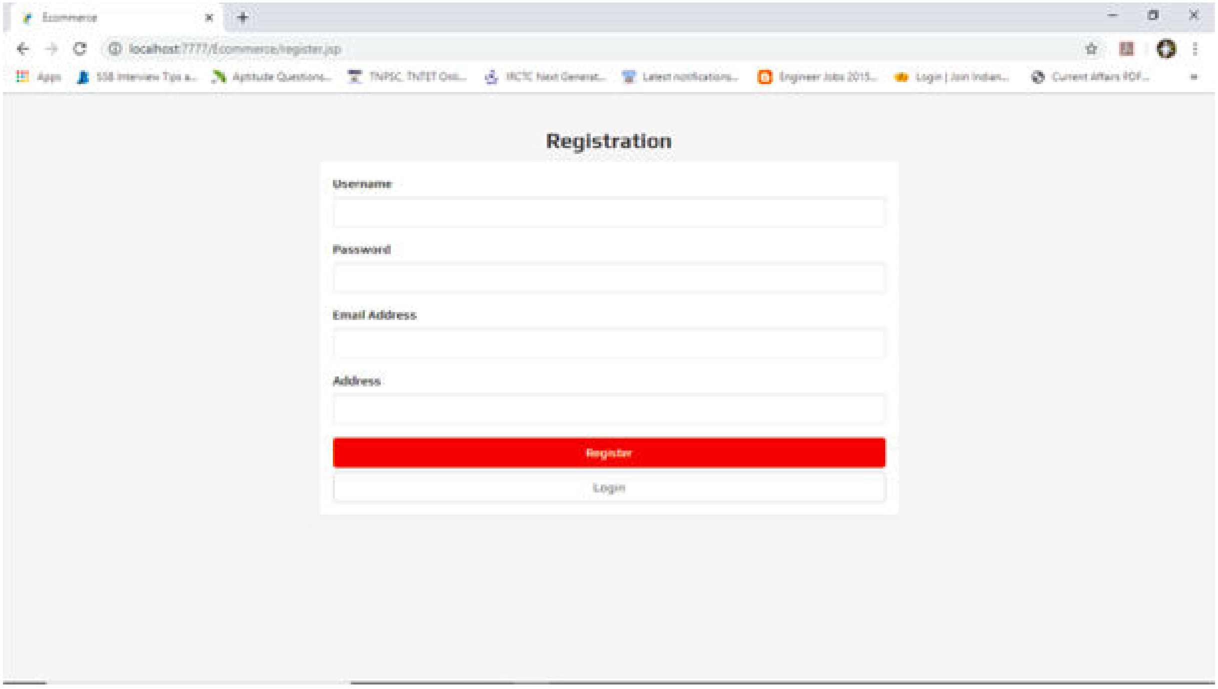


FIG.3 REGISTRATION PAGE

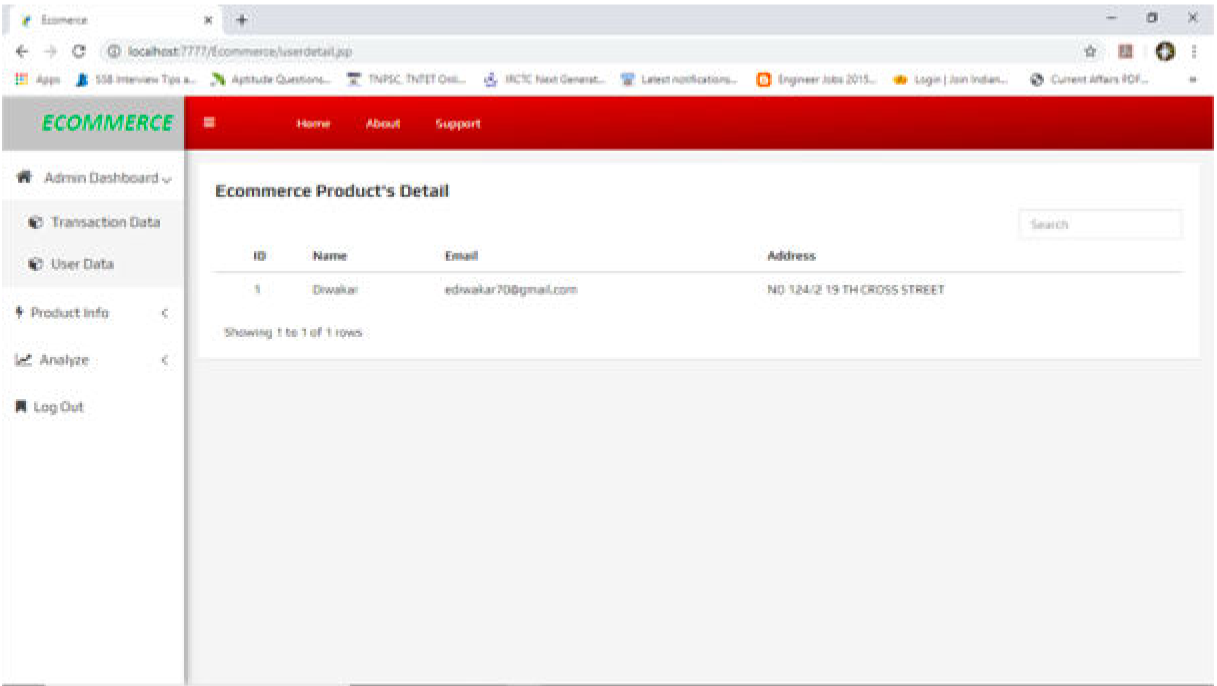


FIG.4 PRODUCT DETAILS

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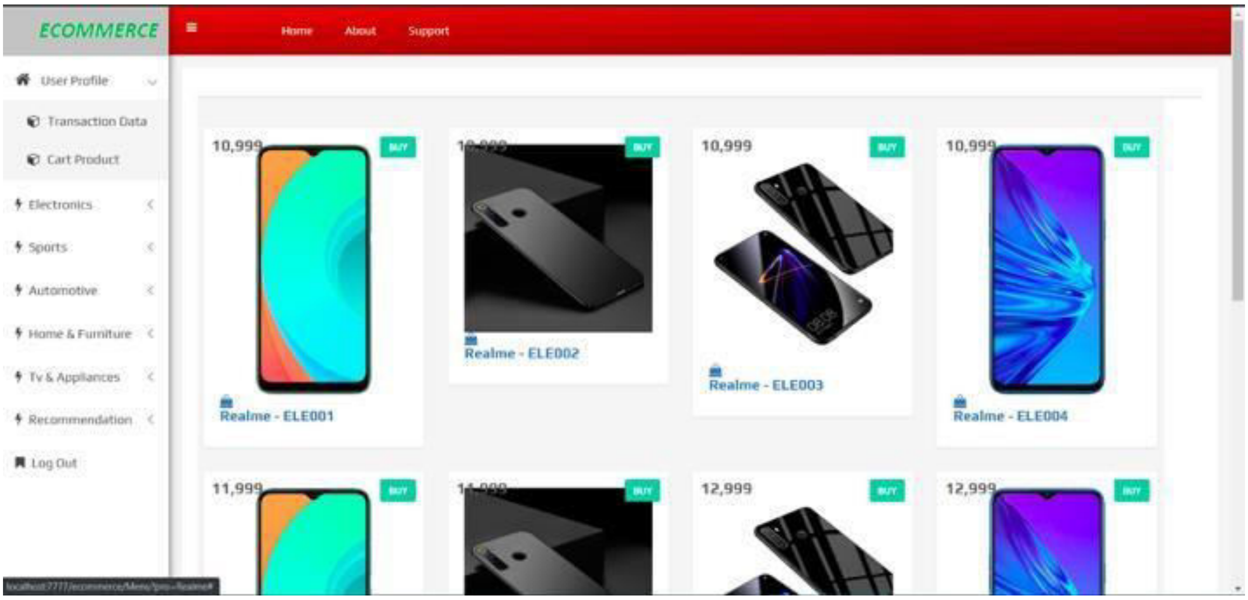


FIG.6 HOME PAGE


FIG.7 PAYMENT GATEWAY

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## V. CONCLUSION AND FUTURE ENHANCEMENTS

- Both cold-start recommendation and long-tail recommendation are challenging problems in the community. To the best of our knowledge, this work is the first one which challenges both cold-start recommendation and long-tail recommendation in a unified optimization problem. Extensive experiments on four real-world datasets verify the effectiveness of the proposed method. This project shows that one can use side information to warm-up the recommender system when there is no available historical recorders. This also find that considering long-tail items in the process of cold-start can be beneficial. In fact, our ideas of independently handling the short-head items and long-tail items can also be used in regular recommendations (relative to cold-start recommendation). It is one of the work we will study in the future.
- In our experiments, the side formation is mainly from social data. However, side information can be collected from many other sources, e.g., cross domain platforms, questionnaires by active learning, and each source can reinforce the others. As a result, in our future work, we are going to study the multi-source side information assisted cold-start recommendation.

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