ONLINE PRODUCT RECOMMENDATION WITH USER PERSONALITY ANALYSIS WITH INTERESTS MINING AND METAPATH DISCOVERY

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Abstract

In recommender systems, the cold-start problem is a critical issue. To alleviate this problem, an emerging direction adopts meta-learning frameworks and achieves success. Most existing works aim to learn globally shared prior knowledge across all users so that it can be quickly adapted to a new user with sparse interactions. However, globally shared prior knowledge may be inadequate to discern users' complicated behaviors and causes poor generalization. Therefore, we argue that prior knowledge should be locally shared by users with similar preferences who can be recognized by social relations. A recommendation system is an integral part of any modern online shopping or social network platform. The product recommendation system as a typical example of the legacy recommendation systems suffers from two major drawbacks: recommendation redundancy and unpredictability concerning new items (cold start). These limitations take place because the legacy recommendation systems rely only on the user's previous buying behavior to recommend new items. Incorporating the user's social features, such as personality traits and topical interest, might help alleviate the cold start and remove recommendation redundancy. Therefore, in this article, we propose Meta-Interest, a personality-aware product recommendation system based on user interest mining and metapath discovery. Meta-Interest predicts the user's interest and the items associated with these interests, even if the user's history does not contain these items or similar ones. This is done by analyzing the user's topical interests and, eventually, recommending the items associated with the user's interest. The proposed system is personality-aware from two aspects; it incorporates the user's personality traits to predict his/her topics of interest and to match the user's personality facets with the associated items. The proposed system was compared against recent recommendation methods, such as deep-learning-based recommendation system and session-based recommendation systems.

Keywords: *Product Recommendation, Collaborative Filtering, Content based Filtering, User Interests, Meta Path Discovery, Redundancy Reduction, Cold Start Problem.*

1. Introduction

With the widespread of personal mobile devices and the ubiquitous access to the internet, the global number of digital buyers is expected to reach 2.14 billion people within the next few years, which accounts for one fourth of the world population [1]. With such a huge number of buyers and the wide variety of available products, the efficiency of an online store is measured by their ability to match the right user with the right product, here comes the usefulness of a product recommendation systems. Generally speaking, product recommendation systems are divided into two main classes: (1) Collaborative filtering (CF), CF systems recommend new products to a given user based on his/her previous (rating/viewing/buying) history. Far from that, with the popularity of online social networks such as Face book, Twitter and Instagram [2], many users use social media to express their feeling or opinions about different topics, or even explicitly expressing their desire to buy a specific product in some cases [3]. The content based filtering and collaborative filtering is shown in Figure 1.

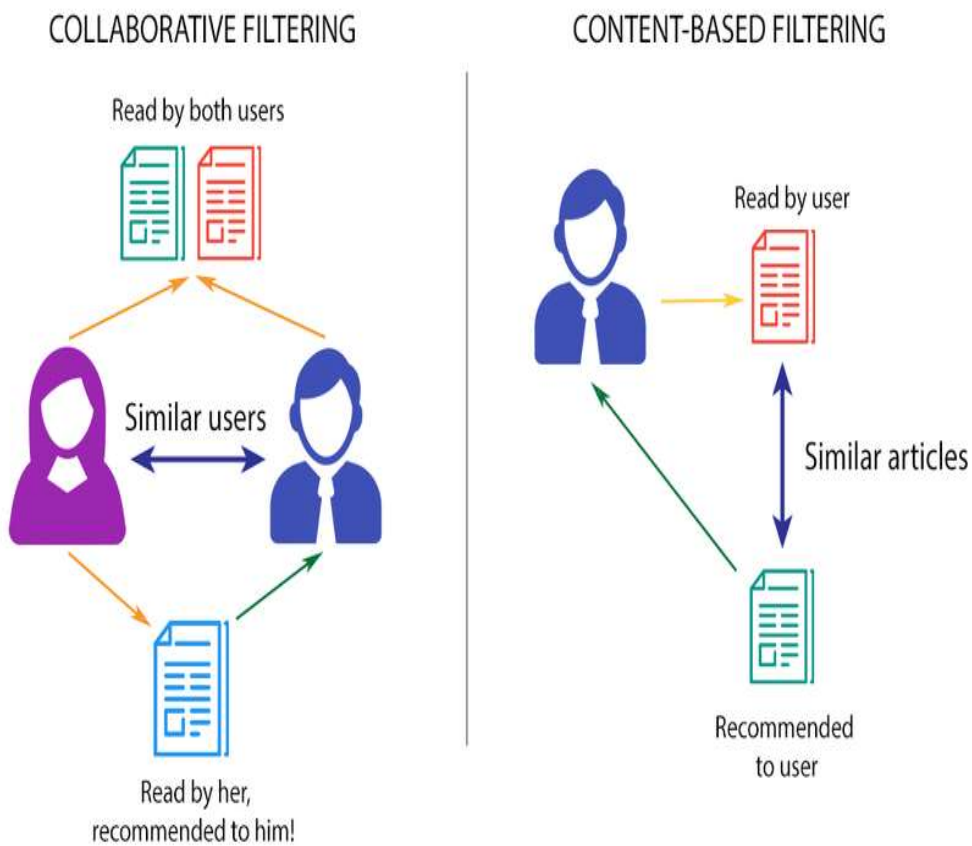

Fig 1: Content based filtering vs Collaborative filtering

A recommendation system is an integral part of any modern online shopping or social network platform. Product recommendation system as a typical example of the legacy recommendation systems suffer from two major drawbacks, recommendation redundancy and unpredictability concerning new items (cold start) [4]. These limitations take place because the legacy recommendation systems rely only on the user's previous buying behavior to recommend new items. Incorporating the user's social features such as personality traits and topical interest might help alleviate the cold start and remove recommendation redundancy [5]. Therefore, in this paper, we propose Meta-Interest, a personality-aware product recommendation system based on user interest mining and meta-path discovery [6]. Meta-Interest predicts the user's interest and the items associated with these interests, even if the user's history does not contain these items or similar ones. This is done by analyzing the user's topical interests, and eventually recommend the items associated with the user's interest [7]. The proposed system is personalityaware from two aspects; it incorporates the user's personality traits to predict his topics of interest, and to match the user's personality facets with the associated items [8]. The proposed system was compared against recent recommendation methods, such as deep-learning based recommendation system and session based recommendation systems [9]. Experimental results show that the proposed method can increase the precision and recall of the recommendation system especially in cold start settings. The Figure 2 shows the Meta-Interest suggestions process.

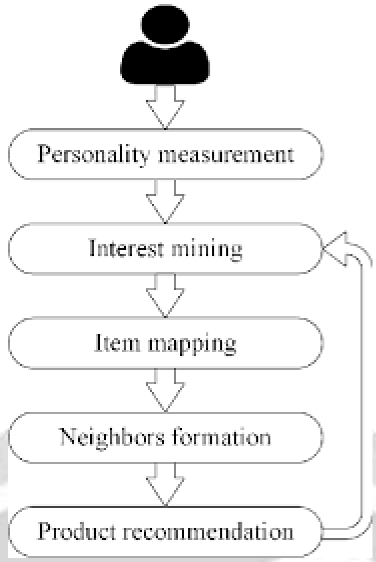

Fig 2: Meta-Interest suggestions process

On the other hand, the emerging of personality computing has offered new opportunities to improve the efficiency of user modeling in general and particularly recommendation systems by incorporating the user's personality traits in the recommendation process. In this work, we propose a product recommendation system that predicts the user's needs and the associated items, even if his history does not contain these items or similar ones [10]. This is done by analyzing the user's topical interest, and eventually recommend the items associated with the theses interest. The proposed system is personality-aware from two aspects; it incorporates the user's personality traits to predict his topics of interest, and to match the user's personality facets with the associated items.

Recently, the purchase form of consumers is gradually changing from offline or store visit to online purchase. There is data published by the Bank of Korea that demonstrates this change. According to the data, consumption in the online sector outpaced consumption in the offline sector. In the past, purchasing products online was considered to be a disadvantage because of the inconvenience of not being able to see or touch them [11]. But, recently, they are overcoming shortcomings by referencing product reviews of other consumers in their purchasing activities. In fact, research has shown that these product reviews have significant benefits for consumers. In addition, in the online shopping environment, a lot of services provided for the convenience of users are introduced, and one of them is a recommendation system [12]. The recommendation system can help users to choose from tens of thousands of products that are right for me and help them save time and effort. Therefore, research on the recommendation system is being actively conducted. A widely used technique for building a recommendation system is collaborative filtering [13]. Collaborative filtering is a technique that recommends items that are expected to be of interest to new users based on their preference information. In other words, it does not require extensive data on users and items because they recommend items based on other users‟ preference information [14]. And there is an advantage that it is free from problems caused by the limitation of the accuracy of the user profile and item characteristic information.

A product recommendation is basically a filtering system that seeks to predict and show the items that a user would like to purchase. The product recommendation system as a typical example of the legacy recommendation systems suffers from two major drawbacks: recommendation redundancy and unpredictability concerning new items (coldstart). These limitations take place because the legacy recommendation systems rely only on the users previous buying behaviour to recommend new items [15]. In personality- aware recommendation system, the similarity between the users is computing based on their personality trait similarity or using a hybrid personality-rating similarity measurement, and the resulting set of neighbors are similar in terms of personality traits to the studied user. The Personality based Recommendation Model is depicted in Figure 3.

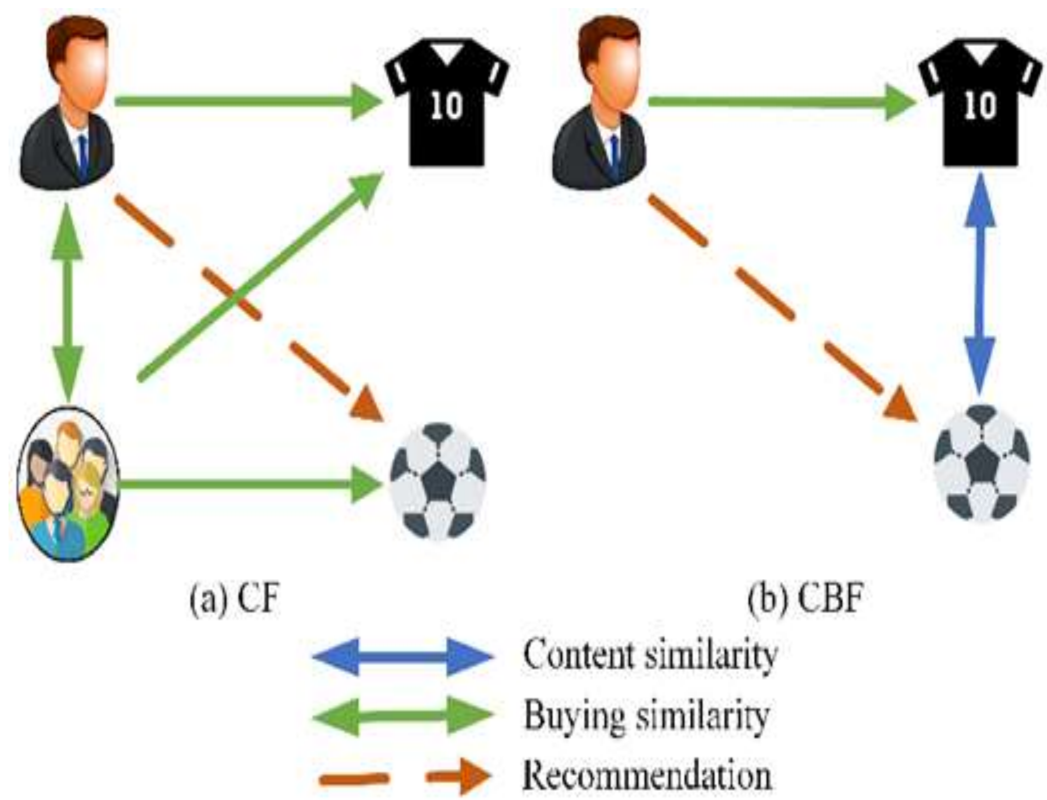

Fig 3: Personality based Recommendation Model

The Big Five Characteristics Numerous character hypotheses have been proposed in an attempt to explain human behaviour. The most well-known character theory is the five-factor model (FFM), also known as the big five character qualities. The FFM is a workable model for tasks like AI character recognition, normal language study, and semantic advancements, to mention a few. It is based on a standard language representation of character [16]. FFM is frequently employed for a number of tasks, including identifying mental health issues and applying for jobs.Neuroticism, openness to encounter, extraversion, appropriateness, and scruples are the five variables defined by the model, which are often abbreviated as OCEAN or CANOE.

2. Literature Survey

Yang et al. [4] proposed a recommendation system of computer games to players based on their personality traits. They have applied text mining techniques to measure the players' Big-five personality traits, and classified a list of games according to their matching with each dominant trait. They have tested their proposed system on 2050 games and 63 players form Steam gaming network. While Wu et al. [5] presented a personality based greedy re-ranking algorithm that generates the recommended list, where the personality is used to estimate the users' diversity preferences. Ning et al. [6] proposed a friend recommendation system that incorporates the Bigfive personality traits model and hybrid filtering, where the friend recommended process is based on personality traits and the users' harmony rating. Ferwerda et al. [7] studied the relationship between the user's personality traits and music genre preferences, they have analyzed a dataset that contains personality test scores and music listening histories of 1415 Last.fm users.

Similarly Ferwerda et al. [8] they conducted an online user survey where the participants were asked to interact with an application named Tune-A-Find, and measured taxonomy choice (i.e. activity, mood, or genre), individual differences, and different user experience factors. Similarly, Hafshejani et al. [9] proposed a collaborative filtering system that cluster the users based on their Big-Five personality traits using K-means algorithm. Following that, the unknown ratings of the sparse user-item matrix are estimated based on the clustered users. Dhelim et al. [10] discussed the benefits of capturing the user's social feature such as personality traits that are represented as a cyber entities in the cyberspace. Similarly, Khelloufi et al. [11] showed the advantages of leveraging the user's social features in the context of service recommendation in the Social Internet of Things (SIoT).

Zarrinkalam et al. [12] presented a graph-based link prediction scheme that operates over a representation model built from three categories of information: user explicit and implicit contributions to topics, relationships between users, and the similarity among topics. Trikha et al. [13] investigated the possibility of predicting the users' implicit interests based on only topic matching using frequent pattern mining without considering the semantic similarities of the topics. While Wang et al. [14] proposed a regularization framework based on the relation bipartite graph, that can be constructed from any kind of relationships, they evaluated the proposed system from social networks that were built from retweeting relationships.

Kang et al. [18] worked on mining sentiment details from social user's-reviews as proposed through their recommendation model. They also developed a new connection, called interpersonal sentiment, which reflects the effect of users' friends on the users in a sentimental manner. They assess the user's sentiment quantitatively and use the items' sentiment distribution between users to assess the item's reputation. The results of their experiments show that the 3-sentimental factors significantly contribute to the rating prediction. It also demonstrates substantial changes in existing real world dataset approaches. Liu et al [19] have worked towards designing an appropriate hybrid recommendations-system that can study, interpret the trend and predict consumer interest in the purchase of a specific product at a chosen shop from the data available for customer shopping by means of reviews. Dong et al. [20] suggested a new personalized approach for rating prediction in the product recommendation based on deep neural networks and multiview fusion, known as DeepFusion. Their model is able to integrate user-generated content and raw items in a unified space, including numeric-ratings, text-reviews and item metadata. Shi et al. [21] proposed a customized recommendation system for e-commerce products based on the representation of learning clusters. They integrated RNN and attention mechanisms to design product recommendation-systems for e-commerce.

3. Proposed Model

A recommendation system is an integral part of any modern online shopping or social network platform [17]. The product recommendation system as a typical example of the legacy recommendation systems suffers from two major drawbacks: recommendation redundancy and unpredictability concerning new items (cold start). These limitations take place because the legacy recommendation systems rely only on the user's previous buying behavior to recommend new items [18]. Incorporating the user's social features, such as personality traits and topical interest, might help alleviate the cold start and remove recommendation redundancy [19]. Therefore, in this article, we propose Meta-Interest, a personality-aware product recommendation system based on user interest mining and metapath discovery. Meta-Interest predicts the user's interest and the items associated with these interests, even if the user's history does not contain these items or similar ones. This is done by analyzing the user's topical interests and, eventually, recommending the items associated with the user's interest [20]. The proposed system is personalityaware from two aspects; it incorporates the user's personality traits to predict his/her topics of interest and to match the user's personality facets with the associated items [21]. The proposed system was compared against recent recommendation methods, such as deep-learning-based recommendation system and session-based recommendation systems. Experimental results show that the proposed method can increase the precision and recall of the recommendation system, especially in cold-start settings. The Figure 4 shows the Personality Aware Product Recommendation Model.

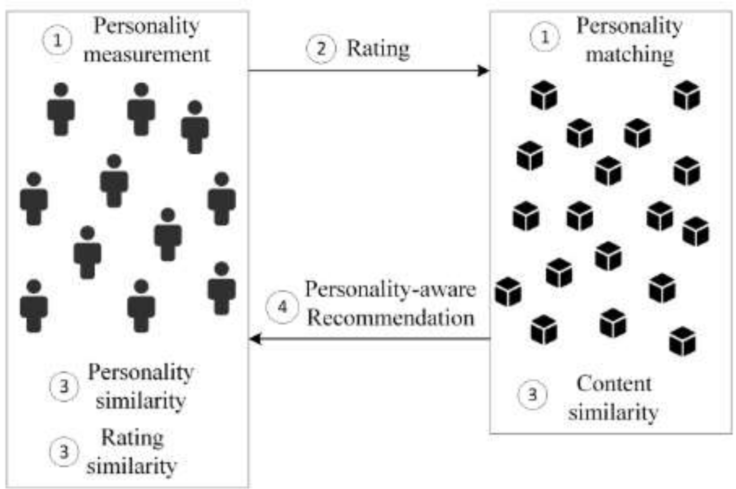

Fig 4: Personality Aware Product Recommendation Model

In the proposed system, product recommendation could be formulated as link prediction in HIN [22]. For example, in this system, given the user's previous rating and topical interest represented in a HIN, the problem is to predict whether or not a link exists between the user and the product (the ball). One of the main challenges of link prediction in HIN is how to maintain a reasonable balance between the size of information considered to make the prediction and the algorithm complexity of the techniques required to collect that information [23]. Since in practice, the networks are usually composed out of hundreds of thousands or even millions of nodes, the method used to perform link prediction in HIN must be highly efficient [24]. However, computing only local information could lead to poor predictions, especially in very sparse networks. Therefore, in our approach, we make use of meta-paths that start from user nodes and end up in the predicted node (product nodes in our case), and try to fuse the information from these meta-paths to make the prediction.

Let $U = \{u1, u2, \ldots, un\}$ be the set of users, $T = \{t1, t2, \ldots, tm\}$ the set of topics, and $P = \{p1, p2, \ldots, pk\}$ the set of all items. The system is modeled as a heterogenous graph that consists of three subgraphs $G = (GU, GT, GP)$,. $GU = (Vu, Eu)$ is undirected graph where its node set Vu is the users set U, and the edges set Eu represents the similarity relationship between users. In addition to online behaviors similarity, such as posting and follower/followee similarities, the personality traits' similarity between users is also considered to compute the overall similarity between users. Similarly, the graphs $GT = (Vt, Et)$ and $GP = (Vp, Ep)$ represent the nodes and relationship between topics and items, respectively.

The interests of a given user are represented in the form of a set of topics. The topic space is represented by the graph $GT = (Vt, Et)$, where the vertices represent the topics and the edges represent the semantic similarity relationship between these topics. To associate these topics with items graph nodes, each topic node is associated with a category of open directory project (ODP). ODP is a public open directory for web sites' classifications. Currently, it contains 3.8 million websites that have been categorized into 1 031 722 categories by 91 929 human editors. We have used the four-level subcategories to construct the topics graph; these categories are used to match the interest topics with the related items from the item graph. The Figure 5 represents the Proposed Model Framework.

Algorithm 1 Interest_mining
Input ux,sx, Fx
Output Ix
1: if (sx > CS) then
2: Semantic_Annotation(sx)
3: Topics_Extraction(sx)
4: else
5: for f ∈ Fx do

6: Ix ← Ix ∪{Personality_facet_topics(f)}
7: end for
8: end if

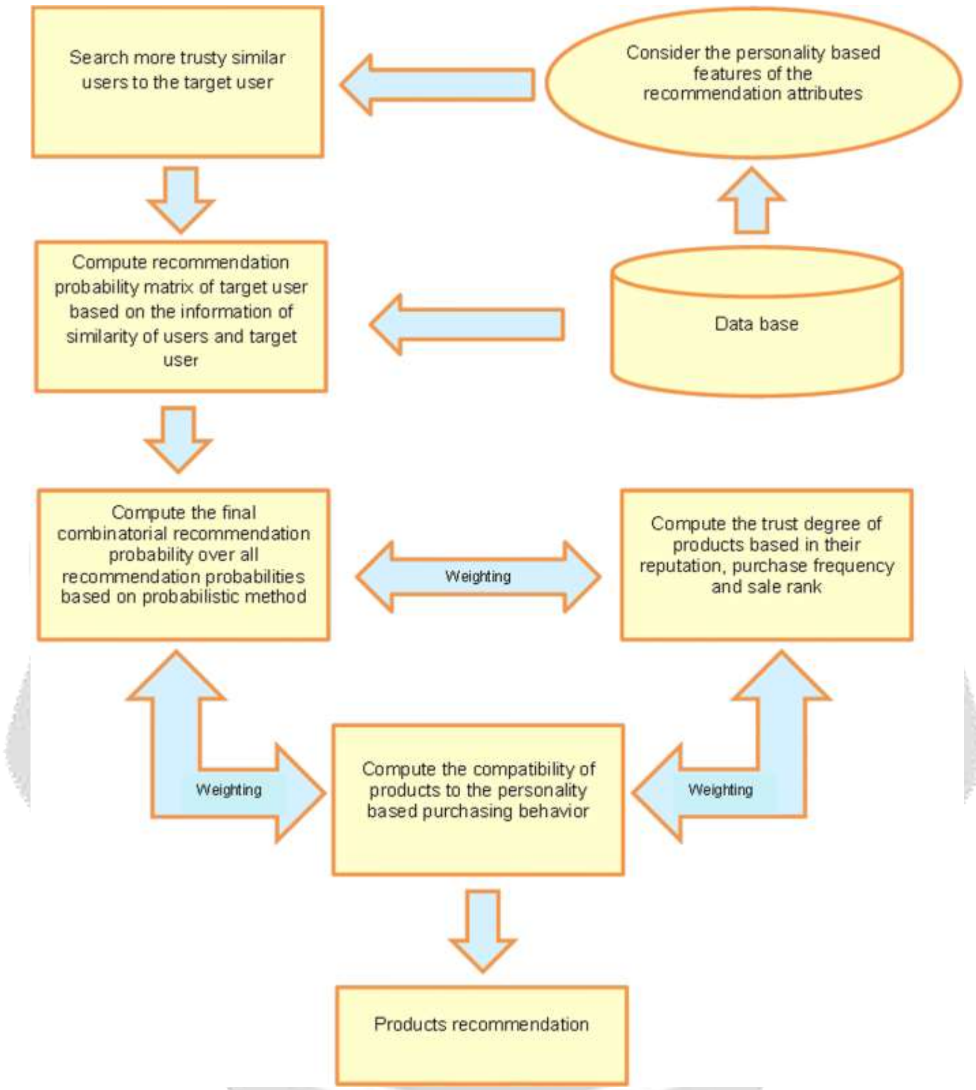

Fig 5: Proposed Model Framework

Similar to the users and interest topics, the items are represented as a graph data structure *GP = (Vp, Ep)*, where the nodes represent the items and the edges represent the similarity between the items. The similarity between items is computed from two similarity measures, content similarity and collaborative similarity. The content similarity is measured by common item's metadata tags, while the collaborative similarity is calculated by measuring the ratio of common buyers/viewers between the two items to the total buyers/viewers of each item. Formally, let Cx : {$c0$, $c1$, . . . , cn} and Cy : {$c0$, $c1$, . . . , cm} denote the content tags of item Px and Py , respectively, and Vx and Vy represent the sets of their viewing/buying users. The similarly between Px and Py is computed using the function _, as shown in (2), where _ is the item similarity threshold, and it is used to tune the contribution of content similarity and collaborative similarity to the overall similarity measure, _ = 0, when the item has no views and never been bought before (item cold start)

Algorithm 2 Item_mapping
Input pz,Upz Output Ipz
1: if (views(pz)>CS) then
2: Ipz ← OPD_Topics(pz)
3: else
4: for f ∈ Fx and ux ∈Upz do
5: if (|uy, f ∈ Fy|> |Upz| 2) then
6: Ipz ← Ipz ∪{Personality_facet_topics(f)}
7: end if
8: end for
9: end if

The main advantage of our approach is that the proposed system makes use of the user's interests along with the user's personality information to optimize the accuracy of system recommendations and alleviate the cold-start effects. By analyzing the user's social network posted data, we can infer his/her topical interests. The task can be achieved by applying automatic topic extraction techniques, such as latent Dirichlet allocation (LDA) or frequency-inverse category frequency (TFICF). However, such techniques are supposed to be applied to long articles, and they do not yield good results if applied on the user's short sparse noisy posts, such as tweets. Therefore, to overcome this problem, we have enriched each post from the user's data using semantic annotators, which could help to reduce the noise and alleviate ambiguity of the post and increase the topic detection accuracy, as shown in the proposed framework.

After building the users–topics–items heterogeneous graph $G = (GU , GT , GP)$ that incorporates the users, topics, and items subgraphs and their interrelationships. At this stage, the objective is to predict for a given user the N-most recommended items that match his/her topical interests and previous buying/viewing behaviors. Predicting the users' recommended items is formulated as a graph-based link prediction problem. Link prediction problem has been investigated in many works before, and many schemes have been proven to achieve high accuracy in their predictions. However, these schemes are supposed to work on homogeneous graphs where all nodes represent the same type of entities and all the edges are connecting these entities, which is not the case with our heterogeneous graph. Since, in our representation model $G = (GU, GT , GP)$, nodes can represent different entities (users, topics, and items) and the links can connect different nodes (user–user, user–topic, user–item, topic–item, item–item, and topic–topic). We use metapaths to predict the matching score between a given user node in *GU* and an item node in *GP* .

A metapath is a sequence of relations between nodes defined over a heterogeneous network, which can be used to define a topological structure with various semantics. In our case, we investigate the metapaths that start from a user node and end with an item node $P : \{u \rightarrow x, \ldots, u \rightarrow i \}$. Each metapath is characterized by the number of links between the source and destination nodes, and it is called the path length *Pl* . For example, the possible metapath with path length *P*2 from a user node to an item node is presented. For a given metapath $P : \{ s \rightarrow x, \ldots, s \rightarrow d \}$, any path in the network that connects nodes *s* and *d* following the same intermediate node types as defined by *P* is called a path instance of *P*. For a given metapath *P*, the path count is the number of all path instances $Pc = |\{p : p \_ P\}|$. In our case, we consider all metapaths that start with a user node and end with an item node with maximum metapath length to *l*max = 2. We have made the maximum length to 3 because short metapaths are semantically more important than long ones, and they are good enough for capturing the structure of the network. Besides that, it is computationally expensive to explore longer metapath because the path count increases exponentially with the increase in the path length *Pl*.

Algorithm 3 DiscoverMetaPaths
Input us,lmax,ε Output FNL
1: VIST←Ø
2: P ←Ø
3: FNL←Ø
4: for i =1 tolmax do
5: if (i =1) then
6: VIST← VIST∪{us}
7: for NGB∈ us do

P ← P ∪{us → NGB}
VIST← VIST∪{NGB}
end for
else
TEMP←Ø
for CURN ∈ P do
NODE← pc[i]
if (NODE=item) and (wpc >ε) then
FNL← FNL∪{pc}
end if
if (NODE−VIST =Ø) then
for NGB∈ NODE−VIST do
TEMP← TEMP∪{CURN → NGB}
VIST← VIST∪{NGB}
end for
end if
P ← P −CURN
end for
P ← TEMP
end if
end for

4. Results

We have integrated the Meta-Interest product recommendation system with a social network platform called Newsfulness5 that we have implemented earlier for automatic personality recognition projects. Newsfulness enables the user to view and shares news articles from various news publishers. During registration, the users go through the TIPI Big-Five personality questionnaire to capture their personality traits. Newsfullness collects published articles from different English-speaking news websites, and the collected articles are from the following outlets (BBC, CNN, Aljazeera, France24, Russia-Today, Reuters, The Guardian, and The New York Times). The gathered articles are from all the news classes (politics, business, sports, health, travel, education, entertainment, art, science, and technology) from different geographic regions categories. The products' recommendation system was implemented by fetching products from different online stores (mainly JD, Banggood, and Amazon). The products considered and their rating representation is shown in Figure 6.

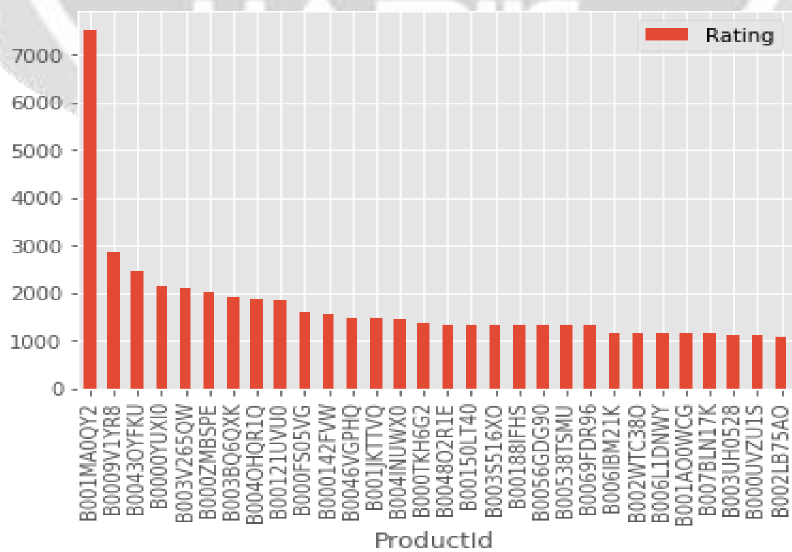

Fig 6: Product ID Rating Representations

A Product Rating is a forecast, an expert opinion about a product's capacity to meet its obligations to consumers over time. Product ratings inform consumers — enhancing transparency and enabling them to focus on considerations that are most critical to their organizations. The product rating levels are shown in Figure 7.

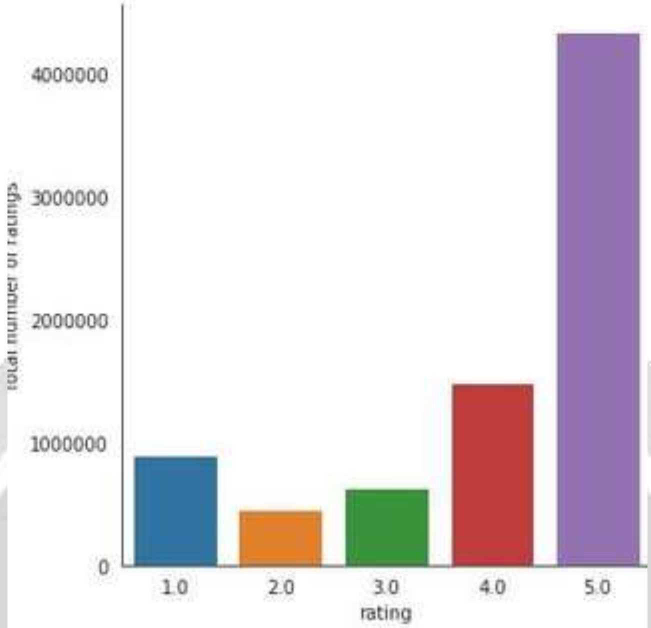

Fig 7: Product Rating Levels

A product recommendation is basically a filtering system that seeks to predict and show the items that a user would like to purchase. It may not be entirely accurate, but if it shows you what you like then it is doing its job right. The purpose of product recommendations is twofold: first, to improve the shopping experience, and second to increase revenues. Product recommendation systems do this by presenting shoppers offers they are most likely to want. The Figure 8 represents the Recommendation Levels.

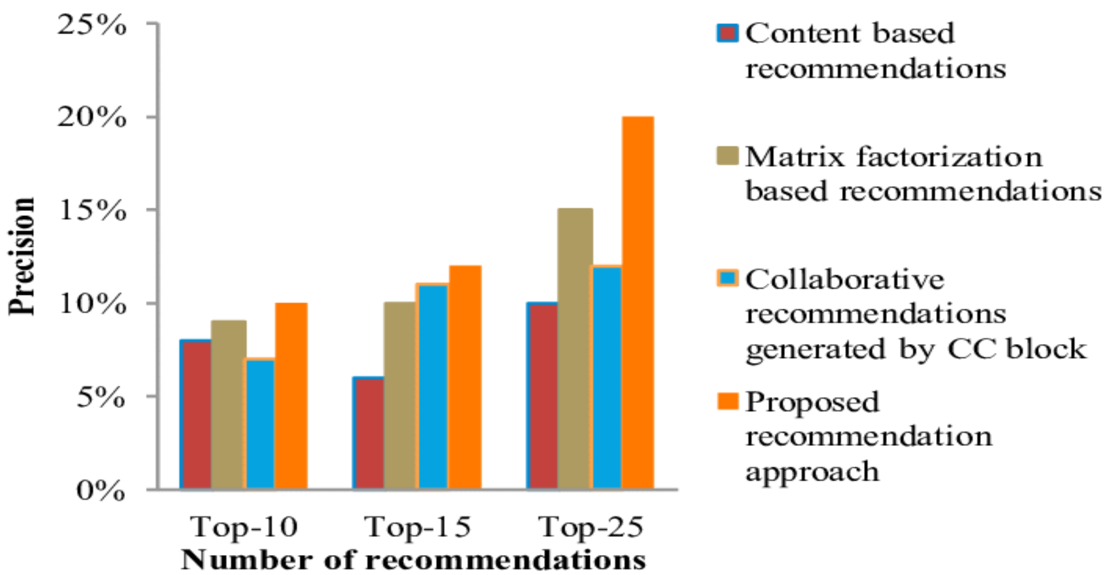

Fig 8: Recommendation Levels

The user could manually give some basic profile information during the registration, such as name, age, sex, location, and other essential information. Additional information are acquired by analyzing the user's data, such as behaviors, habits, preferences and other contextual information. User interests are one of the most critical information in user profile. The process of automatically acquiring the user's interests is known as user interest mining. The User Interest Mining accuracy levels are represented in Figure 9.

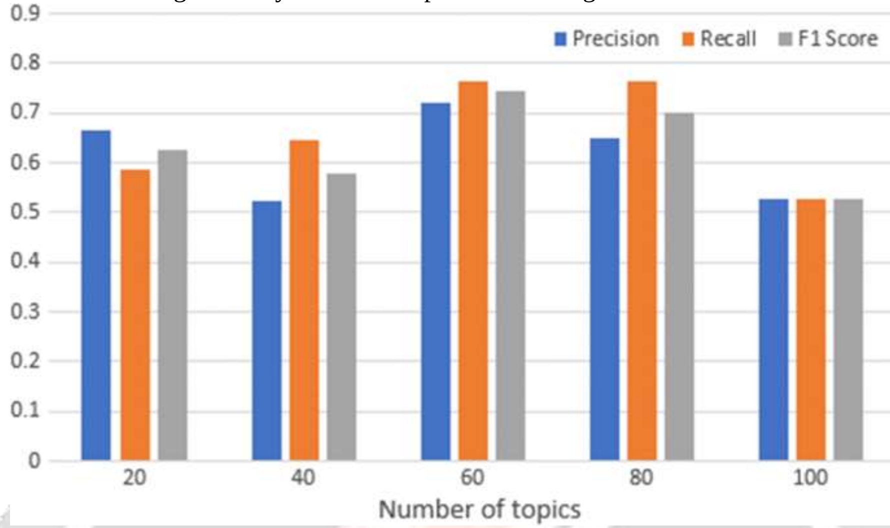

Fig 9: User Interest Mining Accuracy Levels

The training and testing loss levels represent that the loss levels is very minimum. The accuracy of product recommendation is high in the proposed model based on user interests. The training and testing loss levels are shown in Figure 10.

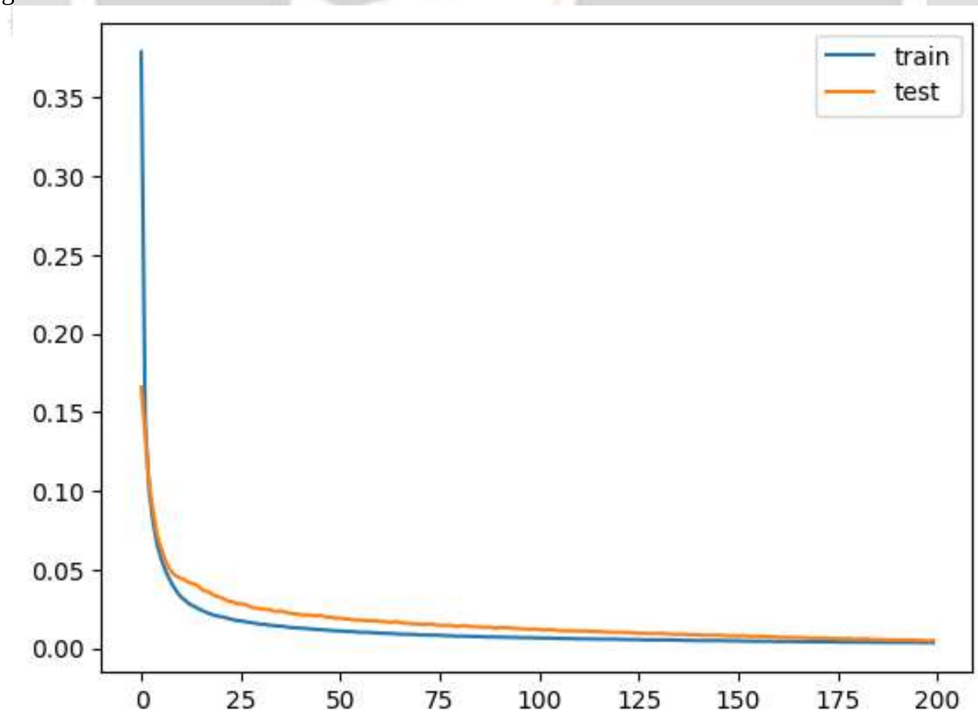

Fig 10: Training and Testing Loss Levels

5. Conclusion

Consumers are moving beyond product promotion and marketing to product development as well as simply purchasing products. Recently, more and more companies are analyzing various opinions of customers on their products and services, focusing on their needs, and reflecting them in their management activities. And There is a research showing that customer reviews written by real consumers have a positive effect on the performance of a company. Accordingly, research is being conducted to reflect customer reviews in the recommendation system. Existing recommendation systems, however, provide a consistent and unified list of products, despite different criteria for selecting products. Therefore, there is a limit to acting as a recommendation system without understanding the user‟s purchase intention. Therefore, the proposed system utilizes detailed and reliable product reviews rather than ratings based on collaborative filtering techniques. In this article, we have proposed a personality-aware product recommendation system based on interest mining and metapath discovery, and the system predicts the user's needs and the associated items. Products' recommendation is computed by analyzing the user's topical interest and, eventually, recommending the items associated with those interests. The proposed system is personality-aware from two aspects: first, because it incorporates the user's personality traits to predict his topics of interest; second, it matches the user's personality facets with the associated items. Experimental results show that the proposed system outperforms the state-of-art schemes in terms of precision and recall especially in the cold-start phase for new items and users. The proposed model achieves 98% accuracy in recommending products based on user interests. In future, optimization models can be integrated for better performance levels.

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