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Personality-aware Product Recommendation System based on User Interests Mining and Meta-path Discovery

Sahraoui Dhelim, Huansheng Ning, Nyothiri Aung, Runhe Huang and Jianhua Ma.

Abstract—**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). 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 paper, we propose Meta-Interest, a personality-aware product recommendation system based on user interest mining and meta-path 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 recommend 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 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. Experimental results show that the proposed method can increase the precision and recall of the recommendation system especially in cold start settings.**

Index Terms—**social networks, recommendation system, product recommendation, user interest mining, personality computing, big-five model, social computing, user modeling**

I. 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. 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 and his/her neighbors (similar users). For example, as shown in Figure 1 (a), most of the people of previously bought a football jersey, they have also bought a football, thus the system predicate that the user might be interested in buying a football. (2) Content filtering or content-based filtering (CBF). CBF systems recommend new items by measuring their similarity with the previously (rated/viewed/bought) products. For example, as shown in Figure 1 (b), the football is recommended because semantically similar to the football jersey.

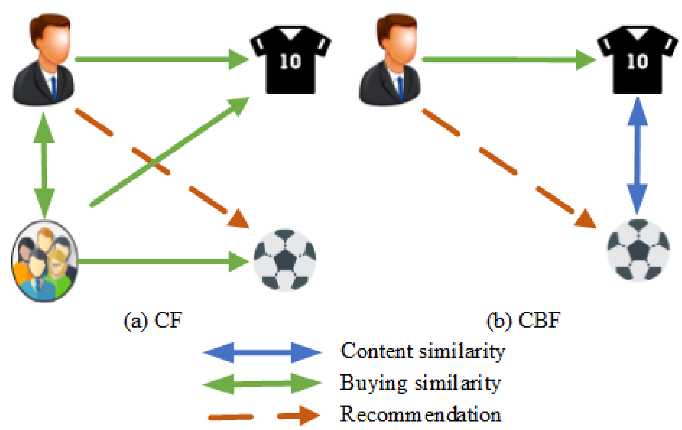

Fig. 1: Collabortive filtering and content filtering

Far from that, with the popularity of online social networks such as Facebook, Twitter and Instagram, 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. Which made social media content a rich resource to understand the users' needs and interests [1]. On the other hand, the emerging of personality computing [2] 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. 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. As shown in Figure 2 the proposed system is based on hybrid

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filtering approach (CF and CBF) and personality-aware interest mining.

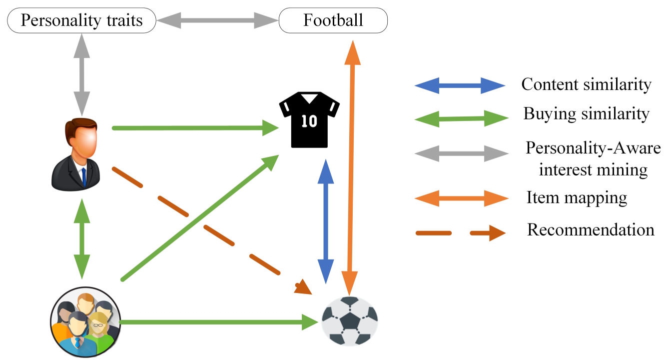


Fig. 2: Interest mining based product recommendations

Since we have multiple types of nodes (users, items and topics), the system is modeled as a heterogeneous information network (HIN), which includes multiple types of nodes and links. In our case, product recommendation could be formulated as link prediction in HIN [3]. For example, in Figure 2, 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. 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. 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.

The contributions of this work are summarized as follows:

1) Propose a product recommendation system that infers the user's needs based on her/his topical interests.
2) The proposed system incorporates the user's Big-Five personality traits to enhance the interest mining process, as well as to perform personality-aware product filtering.
3) The relationship between the users and products is predicted using a graph-based meta path discovery, therefore the system can predict implicit as well as explicit interests.

The remainder of this paper is organized as follows. In Section 2 we review the related works, while in Section 3 the system design of the proposed system is presented. In Section 4 we evaluate the proposed system. Finally, in Section 5 we conclude the work and state some of the future directions.

II. Related works

In this section, we review the recent advances of personality-aware recommendation system and interest mining schemes as well.

A. Personality and recommendation systems

Many works have discussed the importance of incorporating the user's personality traits in the recommendation systems. 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 Big-five 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 in [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 (e.g. music expertise factors and personality traits), 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).

B. Interest mining

Far from personality, many previous works have discussed user interest mining from social media content. Piao *et al.* [1] surveyed the literature of user interest mining from social networks, the authors reviewed all the previous works by emphasizing the following on four aspects, (1) data collection, (2) representation of user interest profiles, (3) construction and refinement of user interest profiles, and (4) the evaluation measures of the constructed profiles. 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. In [15], the authors discussed the usage of user's interests to customize the services offered by a cyber-enabled smart home. Faralli *et al.* [16] proposed Twixonomy, a method for modeling of Twitter users by a hierarchical representation based on their interests. Twiconomy is built by identifying topical friends (a friend represents an interest instead of social relationship) and associate each of these users with a page on Wikipedia. Dhelim *et al.* [17] used social media analysis to extract the user's topical interest. Kang *et al.* [18] proposed a user modeling framework that maps the user' posted content in social media into the associated category in the news media platforms, and based on they used Wikipedia as a knowledge base to construct a rich user profile that represents the user' interests. Liu *et al.* [19] introduced iExpand, a new collaborative filtering recommendation system based on user interest expansion via personalized ranking. iExpand uses a three-layer, user-interests-item, representation scheme, which makes the recommendation more accurate and with less computation cost and helps the understanding of the interactions among users, items, and user interests.

Table I shows a comparison between the proposed system and some of the related works presented above. Some works such as metapath2vec [20], Shi *et al.* [21] have used meta-paths embedding to represent the network information in lower dimensions for easy manipulation of heterogeneous graphs. However, in highly dynamic graphs such as the user-topic-product graph in our case, where the graph update happens very frequently, computing the meta-path embedding all over again is very expensive in terms of computation. As we will discuss in the experimental section, our method requires more computational power to compute the initial meta-paths compared with the meta-path embedding methods, but required less computing power for the update operation, which makes it favorable for highly dynamic graphs.

III. System design

In this section, we will present the theoretical framework of the proposed system.

A. Big-Five traits

There are many personality theories that have tried to explain the human personality. The most prominent personality theory is known as the Five-Factor Model (FFM) or Big-Five personality traits. The FFM is based on a common language description of personality, which makes it a compatible model for computing tasks, such as machine learning personality recognition, natural language analysis and semantic technologies to name a few. FFM is widely used for different purposes, such as mental disorders diagnosis or job recruitment. The model defines the five factors as follows: neuroticism , openness to experience, extraversion, agreeableness and conscientiousness, often denoted by the acronyms OCEAN or CANOE. The Big Five factors are shown in Table II along with their related personality facets. Many previous psychological studies have proven the relationship between user's interests and personality traits, such as the relationship between personality traits and Holland's Big Six domains of vocational interest (RIASEC) [24], and the relationship between hobby interests and personality traits [25].

The purpose of Meta-Interest is to recommend the most relevant items by detecting the user's topical interests from its social networking data. Figure 3 shows the general system framework of Meta-Interest. The recommendation process includes five steps. Step-1 is personality traits measurement, which can be obtained by asking the user to take a personality measurement questionnaire, or using automatic personality recognition by analyzing the subject's social networks data. Personality measurement phase is the only static part of the system, that is because personality traits have been proven to be relatively stable over time. Step-2 is mining the user's topical interests, including explicit and implicit interest mining. Explicit interest mining is performed by analyzing the text shared by the user in social networks in order to detect keywords that reflect its topical interests. Implicit interest mining involves more complex analysis of the social network structure and other latent factors that may influence the user's topical interests. In Step-3 Meta-Interest match the items with the corresponding topics. The matching is in the form of many-to-many relationship, that is to say that a topic might be related to many items. Similarly, an item might be related to more than one topic. In Step-4 the set of most similar users (neighbors) to the subject user are determined. In this context, Meta-Interest uses three similarity measures, personality similarity, viewing/buying/rating similarity and common interest similarity. Finally, Step-5 is the item recommendation phase, the recommendation is refined by updating the neighbors set and the user's topical interest profile and topics-items matching.

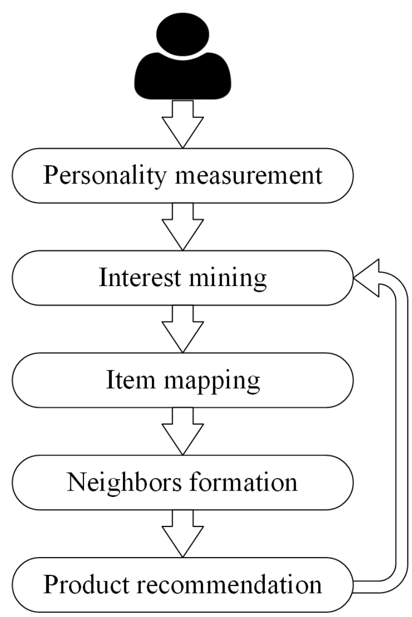


Fig. 3: Meta-Interest recommendations process

B. Notations

The notations and symbols used in the current work are explained in Table III

TABLE I: Comparison with related works

Recommendation system	Recommended content	Personality model	User interest	Representational model	Recommendation technique
Meta-Interest	products	Big-Five	Yes	HIN	personality-aware meta-paths filtering
metapath2vec [20], Shi *et al.* [21]	generic	No	No	HIN	meta-paths embedding
GNN-SEAL[22]	generic	No	No	graph neural network	heuristics from local subgraphs
Song *et al.* [23]	social	No	Yes	graph-attention neural network	session-based social recommendation
PersoNet[6]	friends	Big-Five	No	homogeneous network	collaborative filtering
Yang *et al.* [4]	games	Big-Five	No	homogeneous network	content filtering
Hafshejani *et al.* [9]	products	Big-Five	No	homogeneous network	K-means clustering

TABLE II: Big Five Traits and Associated Characters

Personality Trait	Related Characters
Openness to Experience	Artistic, Curious, Imaginative, Insightful, Original, Wide interests
Agreeableness	Trusting, Generous, Appreciative, Kind, Sympathetic, Forgiving
Conscientiousness	Efficient, Organized, Planful, Reliable, Responsible, Thorough
Extraversion	Energetic, Outgoing, Active, Assertive, Talkative
Neuroticism	Anxious, Unstable , Tense, Touchy, Worrying, Self-pitying

TABLE III: Notations and symbols

Symbol	Meaning
U	The set of all users
u_x	The user x
T	The set of all topics
t_y	The topic t
$\varphi\left(u_x,\ u_y\right)$	The similarity measure between users x and y
$\vartheta\left(P_x,\ P_y\right)$	The similarity measure between item P_x and item P_y
$\overrightarrow{P_x}$	User u_x's personality traits vector
α	User similarity weight parameter
β	Item relatedness weight parameter
Γv	Denotes the set of neighbors of node v
P_l	Meta-path length
w_p	The weight of meta-path P
l_{max}	The maximum length of a meta-path
$\delta^l_{i,j}$	The score between user u_i and item p_j with the meta-path maximum link constrain as $l_{max} = l$
ε	Link prediction score threshold

C. Representational model

Let $U = \{u_1, u_2, \cdots, u_n\}$ be the set of users, $T = \{t_1, t_2, \cdots, t_m\}$ the set of topics and $P = \{p_1, p_2, \cdots, p_k\}$ the set of all items. The system is modeled as a heterogenous graph that consists of three subgraphs $G = (G_U, G_T, G_P)$ as shown in Figure 4. $G_U = (V_u,\ E_u)$ is undirected graph where its node set V_u is the users set U, and the edges set E_u represent 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 $G_T = (V_t,\ E_t)$ and $G_P = (V_p,\ E_p)$ represent the nodes and relationship between topics, and items respectively.

1) Users representation: As mention earlier, one of the most important aspects of the proposed system is that it incorporates the user's personality traits and their related facets to detect the user's interest and eventually in product recommendations. The users' graph $G_U = (V_u,\ E_u)$ is constructed by measuring the similarity between its vertices. In this regard, we consider three types of similarities, topic interest similarity, product interest similarity and personality traits similarity, which we denote as SimT, SimI and SimP respectively. Formally, let $U = \{u_1, u_2, \cdots, u_n\}$ be the set of all users, and $P_i = \{P_O, P_C, P_E, P_A, P_N\}$ be the Big-Five personality trait vector of the user u_i, and $T_i = \{t_1, t_2, \cdots, t_m\}$ is the set of topical interest of u_i, and $I_i = \{i_1, i_2, \cdots, i_k\}$ is the set of items that were previously viewed by u_i.

$$\varphi\left(u_x,\ u_y\right) = \alpha \frac{\sum_i \left(p_x^i - \overline{p_x}\right)\left(p_y^i - \overline{p_y}\right)}{\sqrt{\sum_i \left(p_x^i - \overline{p_x}\right)^2 \sum_i \left(p_y^i - \overline{p_y}\right)^2}} + (1-\alpha)\left(\left\| \frac{2|T_x \bigcap T_y|}{|T_x| + |T_y|} \right\| \ \left\| \frac{2|I_x \bigcap I_y|}{|I_x| + |I_y|} \right\|\right) \quad (1)$$

Where $\overline{p_x}$ and $\overline{p_y}$ is the average value of the personality traits vector for user u_x and u_y respectively, p_x^i and p_y^i are the i^{th} trait in the personality traits vector of user u_x and u_y respectively. And α is the user similarity weight parameter that tunes the contribution of item-topic similarity and personality similarity in the total similarity measure.

2) Topics representation: The interests of a given user is represented form of a set of topics. The topic space is represented by the graph $G_T = (V_t,\ E_t)$, 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) [26], see Figure 5. 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.

3) Item representation: Similar to the users and interest topics, the items are represented as a graph data structure $G_P = (V_p,\ E_p)$, where the nodes represent the items, and edges represent the similarity between 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 $C_x : \{c_0, c_1, \ldots, c_n\}$ and $C_y : \{c_0, c_1, \ldots, c_m\}$ denote the content tags of item P_x and P_y respectively, V_x and V_y represent the sets of their viewing/buying users. The similarly between P_x

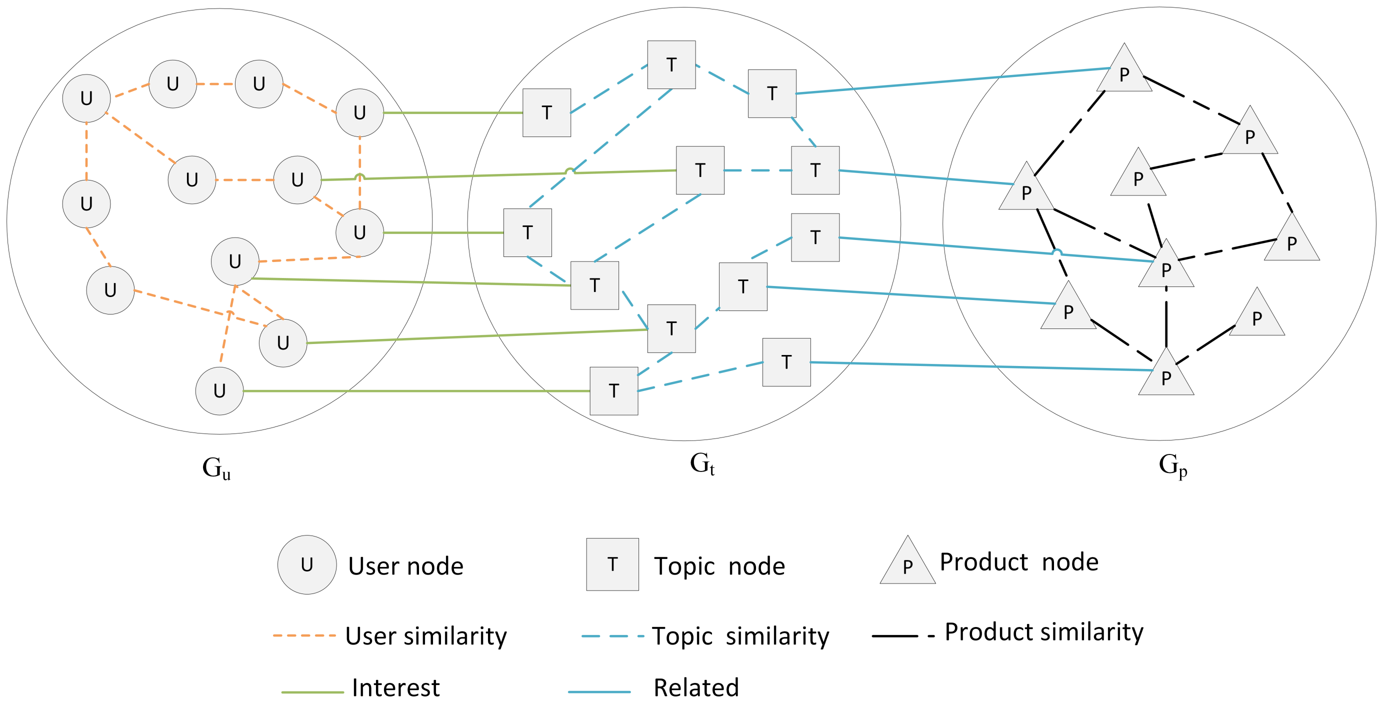


Fig. 4: User-Topic-Item heterogeneous information network

Fig. 5: OPD root categories

and P_y is computed using the function ϑ as shown in (2), where β is the item similarity threshold and it is used to tune the contribution of content similarity and collaborative similarity to the overall similarity measure, $\beta = 0$ when the item has no views and never been bought before (item cold start).

$$\vartheta\left(P_x,\ P_y\right) = \beta \left\| \frac{2|C_x \bigcap C_y|}{|C_x|+|C_y|} \right\| + (1-\beta)\left(\left\| \frac{2|V_x \bigcap V_y|}{|V_x|+|V_y|} \right\| \right) \quad (2)$$

D. Interest mining

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 her topical interests. The task can be achieved by applying automatic topic extraction techniques such as Latent Dirichlet Allocation (LDA) [27] or frequency-inverse category frequency (TFICF) [28]. However, such techniques are supposed to be applied on long articles, and they do not yield good results if applied on the user's short sparse noisy posts like tweets [29]. 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 in [18]. Algorithm 1 shows the pseudocode of interest mining steps. When the user is during the cold start phase or completely did not view any articles (lines 1-4), Meta-Interest estimates the topical interest based on the interests of users with similar personality facets. Otherwise, it crawled the viewed news articles and extracts the labels of each news article to serve as the topical interest of the user as we will see in the experimental section.

Algorithm 1 Interest_mining

Input u_x, s_x, F_x
Output I_x

1: **if** $(s_x > CS)$ **then**
2: Semantic_Annotation(s_x)
3: Topics_Extraction(s_x)
4: **else**
5: **for** $f \in F_x$ **do**
6: $I_x \leftarrow I_x \cup \{Personality\_facet\_topics(f)\}$
7: **end for**
8: **end if**

E. Item mapping

After populating the topics public space using ODP ontology categories, the items are matched with these topics. Each item is associated with one or more topics, and subsequently recommended for users that have these topics within their topical interests. Algorithm 2 shows the pseudocode of item interest mapping process. With newly added items that have not been viewed by any user, the item is directly associated with the corresponding topic category in ODP ontology. Whereas items that have passed the cold start phase are associated with interest of that are related to the personality facets that are shared among the users who bought this item.

Algorithm 2 Item_mapping

Input p_z, U_{p_z}
Output I_{p_z}

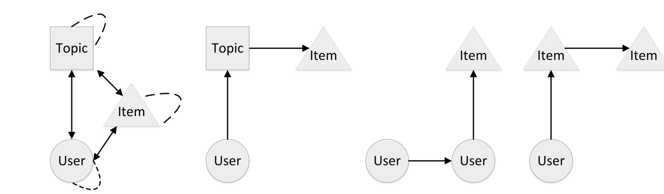
if $(views(p_z) > CS)$ **then**
  $I_{p_z} \leftarrow OPD\_Topics(p_z)$
else
  for $f \in F_x$ and $u_x \in U_{p_z}$ **do**
    if $(|u_y, f \in F_y| > \frac{|U_{p_z}|}{2})$ **then**
      $I_{p_z} \leftarrow I_{p_z} \cup \{Personality\_facet\_topics(f)\}$
    end if
  end for
end if

F. Meta path discovery

After building the users-topics-items heterogeneous graph $G = (G_U, G_T, G_P)$ that incorporates the users, topics and items subgraphs and their inter-relationships. 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, such as Adamic/Adar [30], Katz [31] and Jaccard [32]. However, these schemes are supposed to work on homogeneous graphs where all nodes represent the same type of entities and all the edges connecting these entities, which is not the case with our heterogeneous graph. Since in our representation model $G = (G_U, G_T, G_P)$ 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 meta-paths [21] to predict the matching score between a given user node in G_U and an item node in G_P.

A meta-path 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 meta-paths that start from a user node and end with an item node $P : \{u \rightarrow x \rightarrow \cdots \rightarrow x \rightarrow i\}$. Each meta-path is characterized by the number of links between the source and destination nodes and it is called the path length P_l. For example, the possible meta-path with path length P_2 from a user node to an item node are presented in Figure 6. For a given meta-path $P : \{s \rightarrow x \rightarrow \cdots \rightarrow x \rightarrow d\}$, any path in the network that connect node s and d following the same intermediate node types as defined by P is called a path instance of P. For a given meta-path P path count is the number of all path instances $P_c = |\{p : p \in P\}|$. In our case, we consider all meta-paths that start with a user node and ends with an item node with maximum meta-path length to $l_{max} = 2$. We have made the maximum length to 3 because short meta-paths 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 meta-path, because the path count increase exponentially with the increase of the path length P_l [33].

By exploring all meta-paths with length constraint, we could holistically extract all relationships between nodes with different filtering combinations. We are interested in three types of meta-paths: Firstly, the interest meta-paths (IP) of the format <U-T-P> (Figure 6 (b)) which represent meta-paths that are based on interest mining and item matching. Secondly, the friendship meta-paths (FP) of the format <U-U-P> (Figure 6 (c)) which represent meta-paths that are based on collaborative filtering (users' similarity). Finally, content meta-paths (CP) of the format <U-P-P> (Figure 6 (d)))) which represent meta-paths that are based on the content filtering (items similarity). Similarly, by exploring longer meta-path we get more hybrid filtering paths (based on both CF and CBF, in addition to interest mining and item mapping), for example meta-paths of length $P_l = 3$ could be based on CBF (i.e. <U-P-P-P>), CF (i.e. <U-U-U-P>) or hybrid filtering (i.e. <U-U-P-P>), or a combination of filtering and interest mining (i.e. <U-T-T-P>, <U-T-P-P>,<U-U-T-P>).



(a) Network Scheme (b) Meta-Path U-T-P (c) Meta-Path U-U-P (d) Meta-Path U-P-P

Fig. 6: Network scheme and length 2 meta-path samples

The importance of each meta-path is characterized by its weight w_p. The path weight is computed by the sum of its edges' weight over its length P_l. Formally, let $P^n : \{v_1, v_1, \ldots, v_n\}$ be a meta-path with a length of $P_l = n$, the path weight of P is denoted as w_p, which is the sum of all the links' weights within P as shown in (3), where $w_{v_i,v_{i+1}}$ represent the weight of link that connect the nodes v_i and v_{i+1}.

$$w_p = \frac{\sum_{i=1}^{n} w_{v_i,v_{i+1}}}{P_l} \quad (3)$$

In order to predict a possible recommendation for a given user node, we explore all the instances of meta-path with a maximum path length $l_{max} = 3$. Because short meta-paths are more semantically significant compared to longer meta-paths. Therefore, we prioritize shorter meta-path by considering that the contribution of a path weight to the overall link prediction score is inversely proportional to the meta-path length P_l. The link prediction score between user u_i and item p_j with the meta-path maximum link constrain as $l_{max} = l$ is computed using (4). To predict the N-most recommended items for a given user, we extract all meta-paths by exploring the interest graph with a fixed length and link prediction score constraints.

$$\delta^l_{i,j} = \sum_{k=2}^{l} \frac{\sum_{r \in P_{i,j}(k)} w_r}{k-1} \tag{4}$$

Algorithm 3 DiscoverMetaPaths

Input $u_s, l_{max}, \varepsilon$
Output FNL
1: $VIST \leftarrow \emptyset$
2: $P \leftarrow \emptyset$
3: $FNL \leftarrow \emptyset$
4: **for** $i = 1$ to l_{max} **do**
5: **if** $(i = 1)$ **then**
6: $VIST \leftarrow VIST \cup \{u_s\}$
7: **for** $NGB \in \Gamma u_s$ **do**
8: $P \leftarrow P \cup \{u_s \rightarrow NGB\}$
9: $VIST \leftarrow VIST \cup \{NGB\}$
10: **end for**
11: **else**
12: $TEMP \leftarrow \emptyset$
13: **for** $CURN \in P$ **do**
14: $NODE \leftarrow p_c[i]$
15: **if** $(NODE = item)$ **and** $(w_{p_c} > \varepsilon)$ **then**
16: $FNL \leftarrow FNL \cup \{p_c\}$
17: **end if**
18: **if** $(\Gamma NODE - VIST \neq \emptyset)$ **then**
19: **for** $NGB \in \Gamma NODE - VIST$ **do**
20: $TEMP \leftarrow TEMP \cup \{CURN \rightarrow NGB\}$
21: $VIST \leftarrow VIST \cup \{NGB\}$
22: **end for**
23: **end if**
24: $P \leftarrow P - CURN$
25: **end for**
26: $P \leftarrow TEMP$
27: **end if**
28: **end for**

To compute the recommended items for a given user, we extract all meta-paths instances between the user and potential recommended items by exploring the user-interest-item graph with a fixed length and link prediction score constraints. The pseudocode shown in Algorithm 3 presents the steps of meta-path discovery. The algorithm takes as input the user source node u_s, the maximum meta-path length to explore l_{max} and the link prediction score threshold ε. We denote P as the set of the temporarily explored meta-paths, P is updated by adding new explored paths or removing dead paths (paths that have no neighbors or paths that do not end with a item node), and FNL is the set of the final meta-paths. The set of visited nodes is denoted as $VIST$, and Γv denotes the set of neighbors of node v. $NODE$ and $CURN$ are temporary variables used to denote the current node and current path respectively in each iteration. In Lines 5-11 a path from the source node u_s to every neighbor node is created and inserted into the set of meta-paths P, node u_s and its neighbors are marked as visited nodes $VIST$. Lines 13-25, for each path $CURN$ from P, the last node of these paths is visited and and added to the final meta-paths if it is a item node, and recursively all the nodes that have not been visited before are added as a potential meta-paths. Algorithm 4 shows the pseudocode of recommendation process. Initially if the user is still in cold start phase (Lines 2-7) the recommended items with be filtered based on the topical interests that were extracted from the user's social media data, and by associating these topics with the related items according to their OPD categories. Otherwise, the meta-paths starting from the source user u_s are discovered and grouped according to the meta-path types (interest meta-path, friendship meta-path and content meta-path), the items that are in the intersection of these meta-paths sets are given propriety in the recommended items set.

Lines 7-10 that enumerates all the neighbors of the source node and lines 13-25 (and eventually lines 19-22) are the primary computational blocks in Algorithm 3. If we study the worst-case graph structure, which is a complete graph (fully connected graph), where every user is similar to all other users and interested in all topics, and also connected to all the available products (even though in this case, we do not have to run Algorithm 3, as there is no unknown link that we need to predict). Algorithm 3 still run in linear time complexity. Let G be a complete graph (fully connected) with n nodes and $n = x + y + z$ (x user nodes and y topic nodes and z product node). The run time of the block (lines 7-10) is $O(x + y + z - 1)$ to add all the graph nodes to the visited nodes group $VIST$ and their generated paths to P. The block (12-25) also runs in linear time of $O(x + y + z - 1)$ as well, even it includes a nested loop (lines 19-22) that could result a quadratic time, however lines 19-22 will never be reached, due to the if condition block in lines 18-23 (as the studied graph is a complete graph, $VIST$ will contain all the graph nodes (added in block (7-10)), therefore $\Gamma NODE - VIST = \emptyset$). Hence, the overall time complexity of Algorithm 3 is $O(n)$.

Algorithm 4 RecommendProducts

Input u_s, l_s
Output R
1: $R \leftarrow \emptyset$
2: **if** $(CS(u_s))$ **then**
3: **for** $t \in I_s$ **do**
4: $PR \leftarrow Product\_interest(t)$
5: $R \leftarrow R \cup PR$
6: **end for**
7: **else**
8: $P = DiscoverMetaPath(u_s)$
9: $IP = InterestPaths(P)$
10: $FP = FriendPaths(P)$
11: $CP = ContentPaths(P)$
12: $RecPaths = TopNPaths(IP \cap FP \cap CP, FP \cap CP, CP \cap IP)$
13: **for** $Path \in RecPaths$ **do**
14: $PR \leftarrow Path[last_node]$
15: $R \leftarrow R \cup PR$
16: **end for**
17: **end if**

IV. System evaluation

In this section, we present the details of the collected dataset, evaluation metrics and baselines, and the analysis of the obtained results.

A. Baselines

To evaluate the performance of the proposed product recommendation system, we have compared it with different baselines that uses various recommendation techniques such as deep-learning, meta-path analysis, network embedding and session-based. The proposed system is compared to the following baselines:

GNN-SEAL (Graph Neural Networks)[22]: GNN-SEAL is a link prediction framework that formulates link prediction problem as a subgraph classification problem. For every predicted link (user-item link in our case), GNN-SEAL determine its h-hop enclosing subgraph A and computes its node information matrix X (which contains structural labels, latent embeddings, as well as the explicit attributes of nodes). After that, the framework feeds (A,X) into a graph neural network (GNN) to classify the link existence, so that it can learn from both graph structure features (from A) and latent/explicit features (from X) simultaneously for link prediction. The framework is open source and the code is available on GitHub [1].

metapath2vec (Meta-Path, Network embedding)[20]: metapath2vec formalizes meta-path-based random walks to build the heterogeneous neighborhood of a node and then uses heterogeneous skip-gram model to perform node embeddings, and subsequently user-item link prediction. metapath2vec is open source and its implementation code is available on Github [2].

DGRec (session-based) [23]: DGRec is a session-based recommendations framework that employs dynamic-graph-attention neural network to model the context dependent social influence and recurrent neural network to model dynamic user interest. Finally, DGRec gives the recommendation by merging the user's interests and preferences and her social influence. DGRec is open source and its implementation code is available on Github [3].

LightFM (Cold Start) [34]: LightFM is cold-start alleviation framework that uses a hybrid matrix factorization model to represent items (products in our case) and users as linear combinations of their content features' latent factors. LightFM is parameterized in terms of d-dimensional user and item feature embeddings e U f and e I f for each feature f. Every feature is also modeled by a scalar bias term (b U f for user and b I f for item features). The model's prediction for user u and item i is then given by the dot product of user and item representations, adjusted by user and item feature biases. LightFM is open source and the implementation code is available on GitHub [4].

CF-CBF: hybrid filtering system, in which combine the users' viewing similarity and product similarity to determines the neighborhood set and recommends new items.

[1]github.com/muhanzhang/SEAL

[2]ericdongyx.github.io/metapath2vec/m2v.html

[3]github.com/DeepGraphLearning/RecommenderSystems/tree/master/socialRec

[4]github.com/lyst/lightfm

B. Evaluation metrics

Any product recommendation system is evaluated by measuring the accuracy and coverage of its recommended items. To test the efficiency of Meta-Interest and compare it to the afore-mentioned baselines, we determine the recommended items by each baseline and displayed it in the user's feed along with other irrelevant items, and measure the accuracy rate of the relevant items. Formally, Let $F = R \cup I$ be the set that represents all items in user u's feeds, where $R = \{p_1, p_2, \ldots, p_r\}$ is the set relevant items, and $I = \{p_1, p_2, \ldots, p_i\}$ is the set of irrelevant items. After showing F in user u's feeds, we denote $V = \{p_1, p_2, \ldots, p_v\}$ as the set of viewed items. In this context we are interested in the following values: (1) true positives: the group of relevant items that have been viewed by the user $TP = \{x \ / \ x \in R \bigcap V\}$, (2) false positives: the group of irrelevant items that have been viewed by the user $FP = \{x \ / \ x \in I \bigcap V\}$ and (3) false negatives: the group of relevant items that have not been viewed by the user $FN = \{x \ / \ x \in R, \ x \notin V\}$. We have used the following metrics:

Precision: the portion of relevant viewed items in the total viewed items, and it is computing using (5)

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

Recall: the portion of relevant viewed items in the total relevant items, and it is computing using (6)

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

F-Measure: also called the balanced F-Score, it is the harmonic average of the precision and recall, and it is computing using (7)

$$F = \frac{2 \ P \ R}{P + R} \tag{7}$$

C. Dataset description

We have integrated Meta-Interest product recommendation system with a social network platform called Newsfulness[5] that we have implemented earlier for automatic personality recognition project. Newsfulness enables the user to view, and share news articles from various news publishers. During registration, the users go through TIPI Big-Five personality questionnaire [35] to capture their personality traits. Newsfullness collects published articles from different English-speaking news websites, the collected articles are from the following outlets (BBC, CNN, Aljazeera, France24, Russia-Today, Reuters, The Guardian and The NY 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 statistical details of the used dataset are presented in Table IV.

[5]www.newsfullness.live/dataset

TABLE IV: Dataset statistics

Parameter	Value
Number of users	2228
Number of articles	25873
Number of items	6230
Cold start users	575
Cold start items	1520

D. Result discussion

To tune the optimal value of the users similarity parameter α and products similarity parameter β, we observe the optimal value of α and β that maximizes the F-Measure of the proposed system. Figure 7 and Figure 8 shows the optimal value of α and β in different topic of interest count and viewed items count respectively. As we can observe from Figure 7, during the cold start phase with no topic of interest at all, $\alpha = 1$ and at this point the users similarity is based only on personality similarity measurement. With the increase of previously detected topics of interest, the value of α gradually decreases, and finally stabilize with $\alpha = 0.2$ when the user passes the cold start phase and had enough topical interest and previously viewed items. Similarly, the optimal value of β during the cold start phase for the new item with no views is $\beta = 1$, and with the increase of number of views the value of β decrease to finally stabilize with $\beta = 0.5$ as shown in Figure 8. For the size of Top-N recommended products, in our experiment we set N=20, as choosing larger value, will lead to uncertainty of whether the users did not view the products feed because they are not interested in them, or they did not view them because there are too many items in the products' feed. And if we ignore this uncertainty and just consider that the user did not view the product out of his disinterest, this will lead to the increase of false positives and false negatives as well, hence the decrease of the overall system performance. As we can observe from Figure 9, the F-Measure of proposed system as well as all the studied baselines have decrease dramatically when the value of N is over 22.

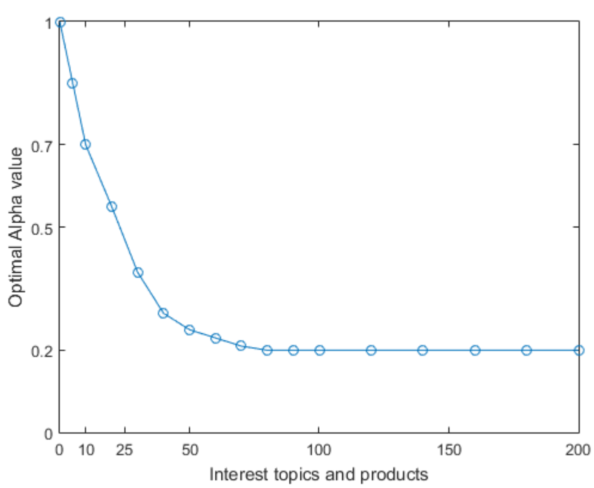


Fig. 7: Users similarity parameter tuning

The precision, recall and F-measure of Meta-Interest compared to the baseline schemes are shown in Figure 10. As

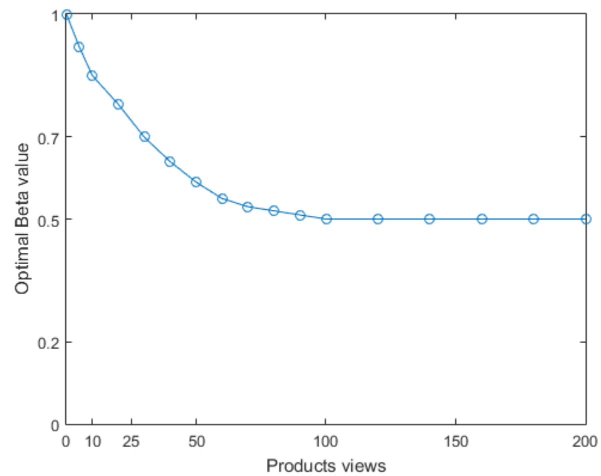


Fig. 8: Products similarity parameter tuning

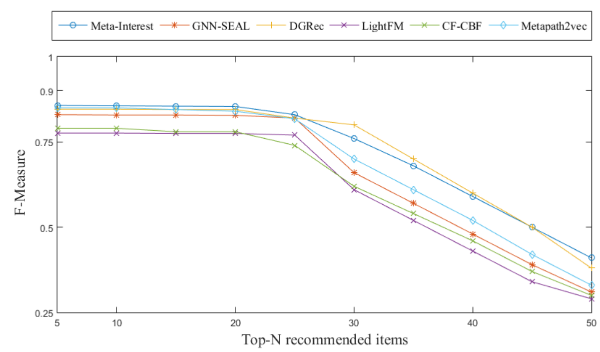


Fig. 9: Top-N recommendation parameter tuning

we can observe, the proposed system Meta-Interest as well as the session-based system DGRec clearly have the highest precision (0.854 and 0.845) and recall (0.868 and 0.855) respectively. The superiority of the proposed system is because of the personality biased approach that filters the relevant items that are related to the personality facets of the user. While other approaches views the user's personality traits just as an additional information that helps find the similarity and construct the network embeddings or features. The second reason of the superiority of Meta-Interest (and also DGRec compared to other baselines), is the ability of Meta-Interest and DGRec to alleviate the cold start effects, hence maintain a stable precision, and recall values all over the phases. Unlike the network representation method metapath2vec and the deep-learning method GNN-SEAL that comes third and fourth with 0.84 and 0.828 of precision value and 0.835 and 0.825 of recall value respectively. LightFM performs quite well in the cold start phase (as we will see later in other figures), however it fails to cope with a large amount of diverse data in later stages, which leads to a drop in its precision and recall values.

One of the main reasons for incorporating the user' personality in the product recommendation systems and interest mining schemes is to alleviate the effects of the cold-start problem [6]. In this regard, we have tested the performance

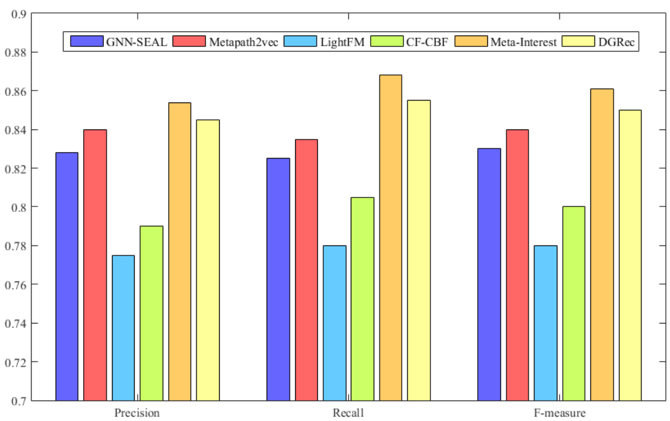


Fig. 10: Overall system evaluation

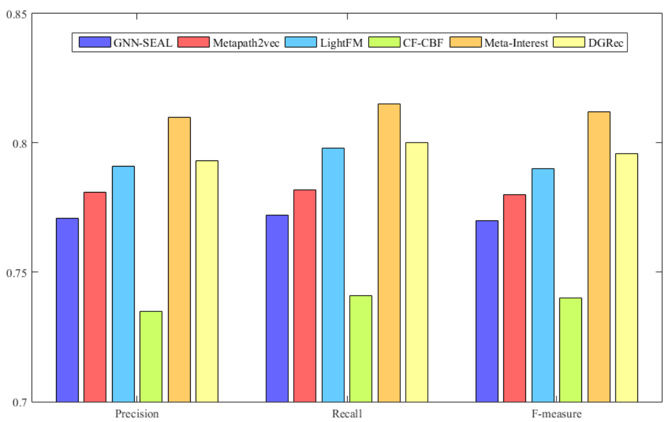


Fig. 11: System evaluation under cold start (new users)

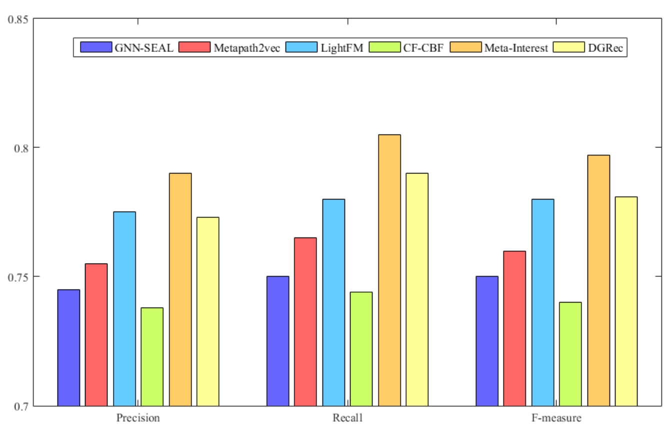


Fig. 12: System evaluation under cold start (new items)

of Meta-Interest and the studied baselines under the cold start settings. The cold start settings include two tests, (1) cold start users test, in which only the new users are considered in the precision and recall measurements. In our experiment, a user is considered in cold-start phase if the number of viewed articles and items is less than 20. And (2) cold start items test, in which we consider only the new items that have not been viewed or rated by any user. Figure 11 and Figure 12 shows the results of the cold start users test and cold start items test respectively. As we can observe, the proposed system and

TABLE V: Speed comparison (Sec)

System	Total computational time	Update computational time
Meta-Interest	16.05	3.56
metapath2vec	14.6	14.6
GNN-SEAL	15.5	15.5
DGRec	16.2	4.66
LightFM	19.04	5.92
CF-CBF	16.15	5.41

the session-based system DGRec still have the upper hand even in the cold start phase as both system are robust in cold start settings as explained early. However, we can notice the LightFM is ranked third and obviously outperform metapath2vec and GNN-SEAL because LightFM was originally designed to mitigate the cold start effects, and as mentioned early, LightFM has a poor performance when the amount of the data increases. To further study the relationship between the amount of available data and the performance of the proposed system compared to the baselines, we measure the performance of Meta-Interest and the other baseline systems while changing the percentage of training set size from 10% to 100%. Figure 13 shows the precision, recall and F-measure values of the studied systems with different training set size. We can clearly observe that Meta-Interest outperforms the other baselines with only small training set size, with only 10% of the training set, Meta-Interest scores 0.768, 0.765 in precision and recall respectively. With the increase of training set size, Meta-Interest steadily improves to reach 0.854, 0.868 in precision and recall using 100% of the training set (around 10.07% improvement compared with 10% training). LightFM ranks second in terms of precision and recall with 10% of the training set, however, it ends in the fifth place (better only than the conventional CF-CBF) with full training set 100%. Whereas deep-learning-based schemes (GNN-SEAL) and network embeddings approach (metapath2vec) have a low performance with small training data. When trained with 10% of the dataset, GNN-SEAL scores 0.63, 0.64, in precision and recall respectively. However, GNN-SEAL and metapath2vec performance increase dramatically with the increase of the training data size. For instance, when trained with the full training data, metapath2vec scores 0.84, 0.835 (around 23% improvement compared with 10% training). That is because metapath2vec uses network embedding, which requires the presence of dense node links to capture the network structure.

In practical situation with a large graph of millions nodes and links that requires intensive computational power, the speed of the recommendation system is crucial to keep a reasonable response time. Therefore, it is important to analyze the speed and time complexity of the proposed system compared to the compared baselines. Table V shows the time complexity of the proposed system compared to the studied baselines. The shown values in Table V are the average of 100 times testing. The time complexity of Meta-Interest and all the baselines were tested on Dell Inspiron 17 3000 Laptop, with 10th Generation Intel Core i7-1065G7 Processor (8 MB Cache, up to 3.9 GHz), and 16 GB ram (2x8 GB,

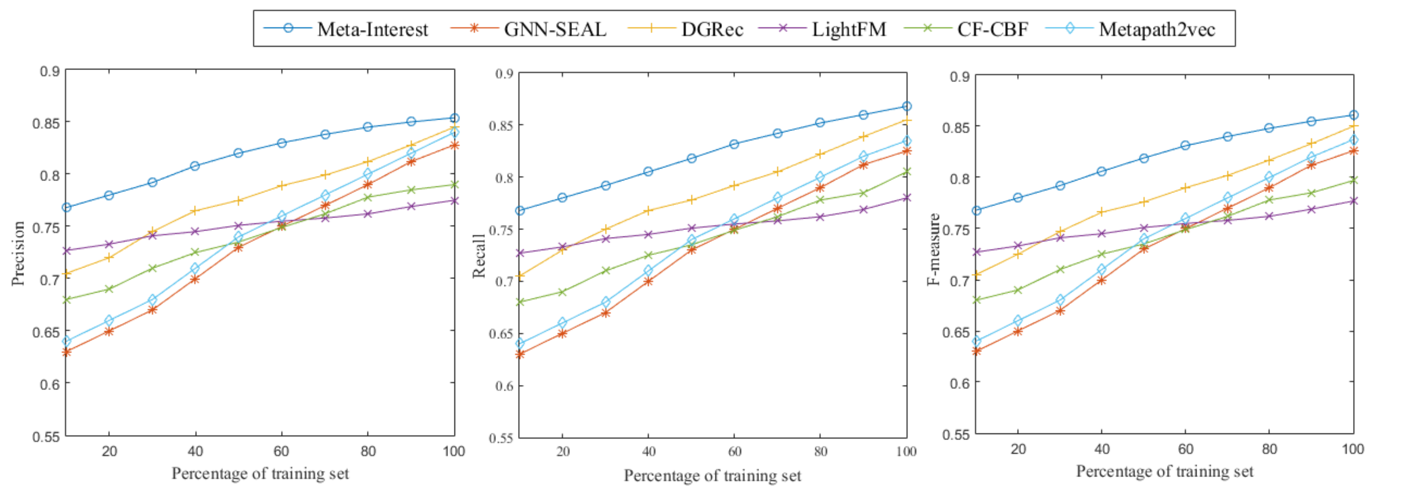


Fig. 13: System evaluation with different sizes of the training set

DDR4, 2666 MHz), running Ubuntu 19.04 operating system. As we can observe from Table V, when it comes to the total computational time required for the system to compute the recommendation for all users, Meta-Interest is not the fastest system, metapath2vec has the lowest computational time of 14.6 seconds, and GNN-SEAL ranks second with 15.5. However, for the update operation where we add a new block of users and items and compute the time required for the system to compute the recommendation of these new users, metapath2vec needs to recalculate the network embeddings in lower dimensional space all over again, which cost as high as the initial time required to compute all the recommendations. Which is not the case with Meta-Interest, as we just need to recalculate the weights of the newly added meta-paths.

V. Conclusion

In this paper, we have proposed a personality-aware product recommendation system based on interest mining and meta-path discovery, the system predicts the user's needs and the associated items. Products recommendation is computed by analyzing the user's topical interest, and eventually recommend the items associated with the those interests. The proposed system is personality-aware from two aspects, firstly because it incorporates the user's personality traits to predict his topics of interest. Secondly, 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.

However, Meta-Interest could be improved in different aspects:

1) In this work, the users' personality traits measurement was conducted through questionnaires. Integrating automatic personality recognition system, that can detect the users' personality traits based on their shared data, into Meta-Interest is one of our future directions.
2) The proposed system uses Big-Five to model the user' personality. Extending Meta-Interest to include other personality traits models such as the Myers–Briggs type indicator is a future direction.
3) The proposed system could be further improved by integrating a knowledge graph and infer topic-item association using semantic reasoning.

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References

[1] G. Piao and J. G. Breslin, "Inferring user interests in microblogging social networks: a survey," *User Modeling and User-Adapted Interaction*, vol. 28, no. 3, pp. 277–329, aug 2018. [Online]. Available: http://link.springer.com/10.1007/s11257-018-9207-8

[2] A. Vinciarelli and G. Mohammadi, "A Survey of Personality Computing," *IEEE Transactions on Affective Computing*, vol. 5, no. 3, pp. 273–291, jul 2014. [Online]. Available: http://ieeexplore.ieee.org/document/6834774/

[3] V. Martínez, F. Berzal, and J.-C. Cubero, "A Survey of Link Prediction in Complex Networks," *ACM Computing Surveys*, vol. 49, no. 4, pp. 1–33, feb 2017.

[4] H.-C. Yang and Z.-R. Huang, "Mining personality traits from social messages for game recommender systems," *Knowledge-Based Systems*, vol. 165, pp. 157–168, feb 2019. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S095070511830577X

[5] W. Wu, L. Chen, and Y. Zhao, "Personalizing recommendation diversity based on user personality," *User Modeling and User-Adapted Interaction*, vol. 28, no. 3, pp. 237–276, 2018.

[6] H. Ning, S. Dhelim, and N. Aung, "PersoNet: Friend Recommendation System Based on Big-Five Personality Traits and Hybrid Filtering," *IEEE Transactions on Computational Social Systems*, pp. 1–9, 2019. [Online]. Available: https://ieeexplore.ieee.org/document/8675299/

[7] B. Ferwerda, M. Tkalcic, and M. Schedl, "Personality Traits and Music Genres: What Do People Prefer to Listen To?" in *Proceedings of the 25th Conference on User Modeling, Adaptation and Personalization*. ACM, 2017, pp. 285–288.

[8] B. Ferwerda, E. Yang, M. Schedl, and M. Tkalcic, "Personality and taxonomy preferences, and the influence of category choice on the user experience for music streaming services," *Multimedia Tools and Applications*, pp. 1–34, 2019.

[9] Z. Yusefi Hafshejani, M. Kaedi, and A. Fatemi, "Improving sparsity and new user problems in collaborative filtering by clustering the personality factors," *Electronic Commerce Research*, vol. 18, no. 4, pp. 813–836, dec 2018. [Online]. Available: http://link.springer.com/10.1007/s10660-018-9287-x

[10] S. Dhelim, N. Huansheng, S. Cui, M. Jianhua, R. Huang, and K. I.-K. Wang, "Cyberentity and its consistency in the cyber-physical-social-thinking hyperspace," *Computers & Electrical Engineering*, vol. 81, p. 106506, jan 2020. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0045790618334839

[11] A. Khelloufi, H. Ning, S. Dhelim, T. Qiu, J. Ma, R. Huang, and L. Atzori, "A Social Relationships Based Service Recommendation System For SIoT Devices," *IEEE Internet of Things Journal*, pp. 1–1, 2020. [Online]. Available: https://ieeexplore.ieee.org/document/9167284/

[12] F. Zarrinkalam, M. Kahani, and E. Bagheri, "Mining user interests over active topics on social networks," *Information Processing & Management*, vol. 54, no. 2, pp. 339–357, 2018.

[13] A. K. Trikha, F. Zarrinkalam, and E. Bagheri, "Topic-Association Mining for User Interest Detection," in *European Conference on Information Retrieval*. Springer, 2018, pp. 665–671.

[14] J. Wang, W. X. Zhao, Y. He, and X. Li, "Infer user interests via link structure regularization," *ACM Transactions on Intelligent Systems and Technology (TIST)*, vol. 5, no. 2, p. 23, 2014.

[15] S. Dhelim, H. Ning, M. A. Bouras, and J. Ma, "Cyber-Enabled Human-Centric Smart Home Architecture," in *2018 IEEE SmartWorld)*. IEEE, oct 2018, pp. 1880–1886. [Online]. Available: https://ieeexplore.ieee.org/document/8560294/

[16] S. Faralli, G. Stilo, and P. Velardi, "Automatic acquisition of a taxonomy of microblogs users' interests," *Web Semantics: Science, Services and Agents on the World Wide Web*, vol. 45, pp. 23–40, 2017.

[17] S. Dhelim, N. Aung, and H. Ning, "Mining user interest based on personality-aware hybrid filtering in social networks," *Knowledge-Based Systems*, p. 106227, jul 2020. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0950705120304354

[18] J. Kang and H. Lee, "Modeling user interest in social media using news media and wikipedia," *Information Systems*, vol. 65, pp. 52–64, 2017.

[19] Qi Liu, Enhong Chen, Hui Xiong, C. H. Q. Ding, and Jian Chen, "Enhancing Collaborative Filtering by User Interest Expansion via Personalized Ranking," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 42, no. 1, pp. 218–233, feb 2012. [Online]. Available: http://ieeexplore.ieee.org/document/6006538/

[20] Y. Dong, N. V. Chawla, and A. Swami, "metapath2vec: Scalable Representation Learning for Heterogeneous Networks," in *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. New York, NY, USA: ACM, aug 2017, pp. 135–144. [Online]. Available: https://dl.acm.org/doi/10.1145/3097983.3098036

[21] C. Shi, B. Hu, W. X. Zhao, and P. S. Yu, "Heterogeneous Information Network Embedding for Recommendation," *IEEE Transactions on Knowledge and Data Engineering*, vol. 31, no. 2, pp. 357–370, feb 2019. [Online]. Available: https://ieeexplore.ieee.org/document/8355676/

[22] M. Zhang and Y. Chen, "Link prediction based on graph neural networks," in *Advances in Neural Information Processing Systems*, 2018, pp. 5165–5175.

[23] W. Song, Z. Xiao, Y. Wang, L. Charlin, M. Zhang, and J. Tang, "Session-Based Social Recommendation via Dynamic Graph Attention Networks," in *Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining*. New York, NY, USA: ACM, jan 2019, pp. 555–563. [Online]. Available: https://dl.acm.org/doi/10.1145/3289600.3290989

[24] P. I. Armstrong and S. F. Anthoney, "Personality facets and RIASEC interests: An integrated model," *Journal of Vocational Behavior*, vol. 75, no. 3, pp. 346–359, dec 2009. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0001879109000657

[25] U. Wolfradt and J. E. Pretz, "Individual differences in creativity: Personality, story writing, and hobbies," *European Journal of Personality*, 2001.

[26] J.-H. Lee, J. Ha, J.-Y. Jung, and S. Lee, "Semantic contextual advertising based on the open directory project," *ACM Transactions on the Web (TWEB)*, vol. 7, no. 4, p. 24, 2013.

[27] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent dirichlet allocation," *Journal of machine Learning research*, vol. 3, no. Jan, pp. 993–1022, 2003.

[28] J. Han and H. Lee, "Characterizing user interest using heterogeneous media," in *Proceedings of the 23rd International Conference on World Wide Web*, 2014, pp. 289–290.

[29] N. Naveed, T. Gottron, J. Kunegis, and A. C. Alhadi, "Searching microblogs: coping with sparsity and document quality," in *Proceedings of the 20th ACM international conference on Information and knowledge management*. ACM, 2011, pp. 183–188.

[30] L. A. Adamic and E. Adar, "Friends and neighbors on the web," *Social networks*, vol. 25, no. 3, pp. 211–230, 2003.

[31] L. Katz, "A new status index derived from sociometric analysis," *Psychometrika*, vol. 18, no. 1, pp. 39–43, 1953.

[32] S. Dhelim, N. Aung, and H. Ning, "ComPath: User Interest Mining in Heterogeneous Signed Social Networks for Internet of People," *IEEE Internet of Things Journal*, vol. 7, 2020.

[33] Y. Sun, J. Han, X. Yan, P. S. Yu, and T. Wu, "Pathsim: Meta path-based top-k similarity search in heterogeneous information networks," *Proceedings of the VLDB Endowment*, vol. 4, no. 11, pp. 992–1003, 2011.

[34] M. Kula, "Metadata embeddings for user and item cold-start recommendations," in *Proceedings of the 2nd Workshop on New Trends on Content-Based Recommender Systems co-located with 9th ACM Conference on Recommender Systems (RecSys 2015), Vienna, Austria, September 16-20, 2015.*, vol. 1448. CEUR-WS.org, 2015, pp. 14–21. [Online]. Available: http://ceur-ws.org/Vol-1448/paper4.pdf

[35] S. D. Gosling, P. J. Rentfrow, and W. B. Swann Jr, "A very brief measure of the Big-Five personality domains," *Journal of Research in personality*, vol. 37, no. 6, pp. 504–528, 2003.

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