Recommender System on Text mining to recommend products based on interest of a Person

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Abstract:

Any modern e-commerce or social networking site would be incomplete without a recommender. Traditional product search systems have two key flaws: redundant recommendations and an unpredictable response to new products (cold start). Since the old recommendation algorithms rely solely on historical purchase behaviour to propose new things, these drawbacks are inevitable. It may be possible to reduce the cold start and remove redundant recommendations by including the user's social attributes such as personality traits and interests. Meta-Interest, a personality-aware product recommendation system based on user interest mining and meta-path discovery, is proposed in this study. If the user's history does not include these or comparable things, Meta-Interest can anticipate the user's interest and the objects linked with this interest. Users' subject interests are analysed, and then products related to their interests are recommended. Two components of the suggested system take into account the user's personality features: it predicts his areas of interest based on those qualities and it matches the user's personality facets with the objects that go along with those facets. Deep learning-based recommendation systems and session-based systems were used to compare the suggested system to others. Predictability and recall of the recommendation system may be improved in cold start situations, according to the results of the suggested strategy.

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Introduction

One-fourth of the world's population is anticipated to be an electronic consumer during the next few years, as smart phones and the internet are becoming more commonly accessible. Product recommender systems play a key role in assessing an online store's ability to link the right consumer with the best quality, and this is where they come into play. Recommender systems may be divided into two major categories: Collaborative filtering (CF) uses a user's prior (rating, viewing, and purchasing) history to propose new products to them. Sharing ideas and opinions about a wide range of topics has become simpler through online social networks such as Facebook and Twitter, which also allow users to express interest in a specific product in some cases. As a result, social media has become an invaluable source of information on the wishes and wants of its users. [1] Additionally, taking the user's personality traits into consideration while providing suggestions can improve the accuracy of user modelling in general and recommendation systems in particular. No matter if these or comparable goods have not been previously purchased by a user, we've created a product suggestion system that can anticipate their wishes and the associated items. When a user's preferences and interests are analysed, items that are in accordance with those preferences can be recommended. This information is used to predict what subjects the user would be interested in and to match the user's personality attributes with items that fit those themes. Fig. 2 shows the suggested system's hybrid design. Because there are so many various kinds of nodes in the system, the numerous nodes and links are referred to as a heterogeneous information network (HIN) (such as users, things, and themes). It is possible that in our case a product recommendation may be expressed using a link prediction in HIN [3]. Consider, for example, Figure 2, where the task is to predict whether or not the user and product have any kind of link, depending on the user's prior rating and thematic interest, as indicated in an HIN (the ball). Predicting connections in HIN may be difficult because of the need to balance the quantity of data needed to create a forecast with the complexity of the algorithms used to obtain it. Considering that networks might contain tens of thousands or even millions of nodes, HIN's link prediction algorithm has to be extremely efficient. Only using local information in sparse networks might lead to erroneous forecasts. It is our method's goal to construct the prediction by using meta-paths that begin at the users' nodes and end at the predicated node (in this case, a product node).

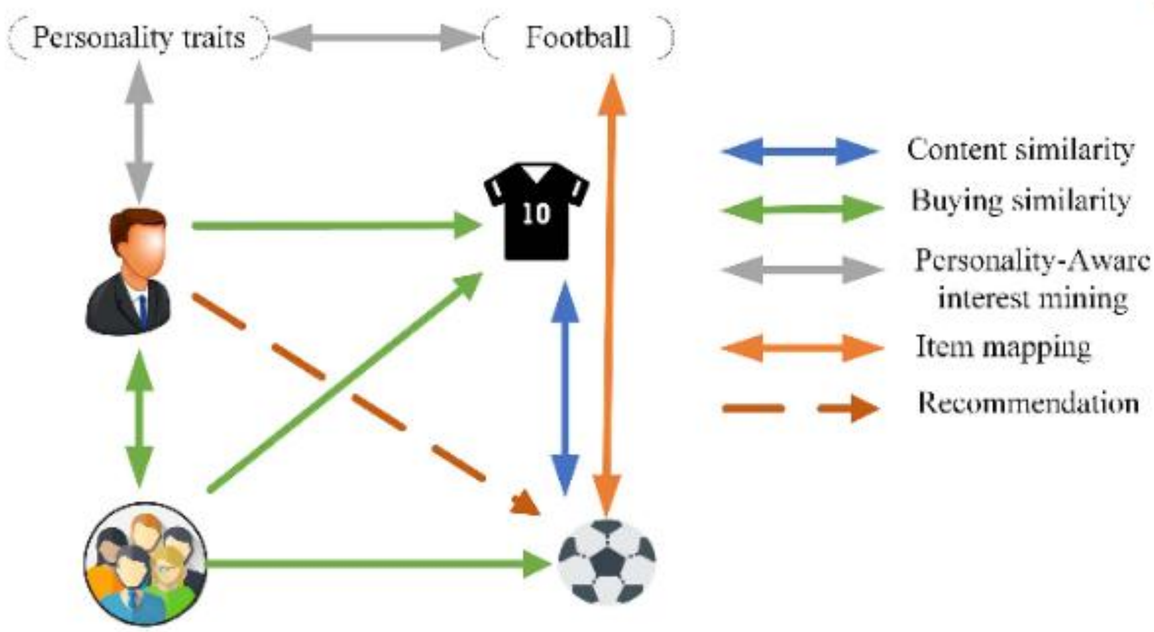

Fig 1 Recommendation System

Literature Survey

Personality-based RS RS and GRS systems that take personality into account are the subject of this section.

This is a type of RS that takes into consideration a person's personality attributes while giving a suggestion. Before discussing the impact personality plays in GRS, we'll look at few research that focus on RS for a single user. A personality profile developed from information on a person's professional activity informs the recommendations in [18]. In [19], the importance of a person's personality is discussed. This article categorises individuals based on their travel personality, which results in a certain travel style. The strategy under consideration aims to merge the characteristics of the consumers' personalities into the goods

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linked to them. We recommend [22] for a detailed summary of RS depending on personality. This article explores some of the difficulties and potential future possibilities in this field.

Recommendations from the group

Even though Internet companies like Google, Amazon, and Netflix utilise single-user recommendation systems, there aren't many studies on general recommendation systems (GRSs). When it comes to group recommendation systems, the goal is to deliver suggestions that enhance group members' happiness while minimising user inequality. It's common for GRS systems to be more complicated than single-RS systems. It has been proved that solving the GRS issue is NP-hard in several semantics, for example, by Xiao and colleagues [23]. To find a solution, they turned to Pareto optimality as the model for their multi-objective optimization issue. GRS has just seen a dramatic transformation thanks to deep learning. Multi-attention-based Group Recommendation Model (MAGRM) was suggested in 2020 by Zhenhua et al. [24], which employs deep neural network topologies for accurate group suggestions. One method of capturing social aspects inside groups was to create vector representations of the group's deep semantic characteristics in order to accomplish this aim. In the next step, a neuronal attention mechanism was used to infer the group's preferences for a particular item. Conflict management and the impact it has on individuals and groups are the basis for this assessment. When it comes to dealing with conflict, there are five basic approaches: competing; cooperating; avoiding; accommodating; and compromising.

The TKI concept was used to express the personality scores of the group members in this article. If all users are able to take part in the TKI exam, which isn't usually a possibility for big groups, our technique works well in practise. Users' information and behaviour on social media may be used without a TKI test to automatically predict personality characteristics for big groups on the platform [28]. Using the TKI metaphor, users are shown two movie characters with opposing personalities and asked to choose which character has a personality that most closely resembles their own. Some articles have combined the effect of personality and social trust in order to enhance group suggestions. According to [30], a number called Conflict Mode Weight (CMW) was produced based on personality characteristics determined from TKI. This value reflects the effect of personality on group choices. In addition, the underlying social network that connects the members of the group was mined for ties of mutual trust. The trust value is based on many network measurements, such as the number of common friends, the length of time they've known each other, and the amount of photos they've exchanged. A personality trait based on the Big-Five paradigm, agreeableness was utilised as a model for altruistic conduct in [21]. Studies on group recommendation systems often take into account the views of all members equally. While in real life, the group's final choice is heavily influenced by personality qualities. Collective dynamics cannot be accurately quantified despite certain research taking into account the influence of individual user personalities on group decisions. In addition, very few group recommendation works employ the pairwise preference. Pairwise preference approaches for recommendation systems have been demonstrated to be more accurate than individual rating methods [12, 15, 16]. Some significant works that are more pertinent to our methodology will be discussed now. The ability of group members to negotiate with one another in order to achieve a final conclusion is critical when using a group recommendation system. A coordinator may solicit input from the audience by talking to them one-on-one. [13] Wang et al. [23] built a virtual user that served as a coordinator to help the group come to a consensus on a final choice. Instead than focusing on individual differences, this decision was made based on the mutual respect and trust between the coordinator and members. In other words, the virtual coordinator's viewpoint was influenced by the trust-relationships of the users. Using the outcomes of the TKI technique in both social connections and social conduct, certain group recommendation systems, such as [14], simulate the tolerance and altruistic traits of the group members in addition to the group's preference. When Quijano et al. developed HappyMovie, they employed personality qualities in [19] to propose movies to Facebook users based on their confidence in the social network as well as a TKI metaphor, which serves as an alternative to the TKI test. When a user's rating is influenced by the opinions of others, it is inversely proportionate to their personality, according to a simple formula devised by them. The authors leverage trust instead of similarity between users in this formula, which is comparable to the memory-based technique for recommendation systems. However, this approach does not take into consideration the characteristics of other users because it only uses one person's personality at a time.

The great majority of studies that use the TKI test to account for personality traits apply some type of ad hoc method (heuristics) in order to calculate the group score, according to the literature. Rather of relying on the social influence hypothesis, we utilise it to precisely replicate the impact of other users on the final group rating. Recio-Garcia et al. [16] presented another group suggestion based on the TKI test. Using collaborative filtering approaches that take into account the different personalities in a group, they have come up with a proposal.

For example, the work of Guo et. al. [15] introduces a group recommendation model based on the TKI test, which incorporates individual personality traits such as likability, susceptibility, intimacy and expertise into the recommendation system. Although they have a method that works well for small groups, ours is better for large ones. Furthermore, no research has been done on the efficacy of paired preferences on heterogeneous data in their work. However, in order to demonstrate the model's applicability to a wide range of data, we generate random personality values using a variety of different probability distributions.

System Analysis

Recommendations based on behavioural characteristics were made by Yang and colleagues [4]. As a result, a list of games has been compiled based on the degree to which they suit the Big-Five personality characteristics of the players. Steam's gaming network provided 2040 sports and 1963 gamers to test their method. There is also an algorithm created by Wu and colleagues [5] that leverages the personality of users to determine their preferences for cultural variety and then produces a recommended list. When looking for new acquaintances, you may use a combination of the Big Five personality characteristic model and hybrid filtering to find those who are most like you.

The researchers discovered a correlation between a person's personality test results and their musical tastes after studying a sample of 1587 Last.fm users. [7] While in [8], participants were requested to utilise an application called Tune A Find to engage with a taxonomy, individual differences such as music competence (e.g. music knowledge and personality characteristics), as well as a range of user experience parameters, were examined. Collaborative filtering based on Big-Five personality traits was proposed by Hafshejani et al. [9] using the K-means approach. Clustered users are then utilised to estimate the unknown ratings in sparse user-item matrix.

A user's social characteristics, such as personality traits, can be depicted as a cyber entity in the virtual world, according to Dhelim and coworkers. [10] Another research [11] has showed the advantages of using a user's social characteristics. Zarrinkalam et al. [12] suggested a graph-based link prediction approach based on three categories of information: user explicit and implicit contributions to subjects, relationships between users, and similarity across topics. Frequent pattern mining can be used to predict users' implicit interests based solely on topic matching, without taking into account the semantic similarity of the subjects. Wang et al. [14] utilised social networks produced via retweeting linkages rather than the related bipartite graph Wang et al. [14] proposed for evaluating the suggested regularisation approach.

Disadvantages

1. User interest mining and personality computing are not implemented in the system, making it less effective.
2. Collaborative filtering (CF) is not implemented in the system.

Proposed System

Product recommendations might be expressed as HIN link predictions in the proposed system [3]. If the user's prior rating and topical interest are stored in an HIN, for example, determining whether or not there is a connection between them and the product becomes more difficult in this system (the ball). For link prediction to be successful in HIN, it must be possible to maintain a suitable equilibrium in data quantity and algorithm complexity while still collecting enough data to generate accurate predictions. For HIN to operate, the mechanism used to conduct link prediction must be extremely efficient, due to the large number of nodes in practise. Even in sparse networks, relying solely on local knowledge might lead to inaccurate predictions. Meta-paths that begin with user nodes and terminate at the projected target (product nodes in our instance) are used to fuse information from these nodes.

Advantages

1. Develop a product suggestion system based on the user's subject interests to infer his or her wants.
2. This approach includes the user's Big-Five personality characteristics as well as personality-aware product filtering into the interest mining process.
3. It is possible for the system to anticipate both implicit and explicit interests by employing a graph-based meta route discovery to forecast the user-product connection.

Implementation

Implementation is the phase of the project in which the theoretical design is put into practise. So it's fair to say that this is the most crucial stage in implementing a new system successfully and instilling trust in its users about its functionality and effectiveness.

During the implementation stage, rigorous planning, research of the present system and its implementation restrictions, design of techniques to achieve switchover, and assessment of switchover methods are all required.

1. Network Credentials Module that Requires Registration
2. Authentication module
3. Attribute based module.
4. MAM (multiple authority).

Network Credentials Module that Requires Registration

In this step, the system prepares the trustees for a user named Alice. An authenticator like password is first used to verify Alice's identity. Then, a few of Alice's friends, who also have accounts in the system, are selected by Alice herself or the service provider and designated as Alice's Registration. This is done either by the service provider or by the service provider themselves.

Authentication module

In order to protect your account and prevent faked communications from harming your online reputation, you must authenticate your account. Imagine a phishing email being sent from your email account because someone had faked your personal data. In order to restore your good name, you'll have to deal with the fallout, including angry customers and spam complaints. Systems based on trustees allow users to choose their own trustees freely. To provide stronger security, we demonstrate in our experiments (i.e. Section VII) that the service provider can confine trustee selections by requiring that no users be picked as trustees by an excessive number of other users.

Attribute based module.

Each node's data storage is encrypted using an attribute-based encryption module. Data that has been encrypted and then re-encrypted is being used for a fine-grain notion based on user data that has been uploaded. Cloud storage may be made more secure by using attribute-based encryption. Encryption using Attribute-Based Methods (ABE). Identity is considered as a collection of descriptive properties in this encryption system, and decryption is achievable if the identity of the decrypter matches the identity indicated in the ciphertext.

MAM

Users can communicate with various key generators (authorities) by using different pseudonyms in a system with many authorities, each of which has its own id. Our ultimate aim is to create a multi-authority CP-ABE that accomplishes the above-described levels of security, protects the privacy of Data Consumers' personal information, and is tolerant of authority compromises or collusion assaults. Multi-authority attribute-based encryption has finally been put into practise for the first time.

HIN’s Algorithm

(1) Find the common neighbor set .common_neighbor of the node pair.
(2) Extract the sub-graph which contains the tested node pair and their common neighbors.
(3) While (the common neighbor ser is not null){
(4) Calculate the degree of node , and get .degree. Node is one node of the common neighbor set.
(5) Calculate the degree of node in the sub-graph extracted in the Step 2, get

.common_degree.

(6) Calculate the guidance capability of node , Guidance

(7) The similarity of node and node is Similarity.+ = Guidance ()}

Results

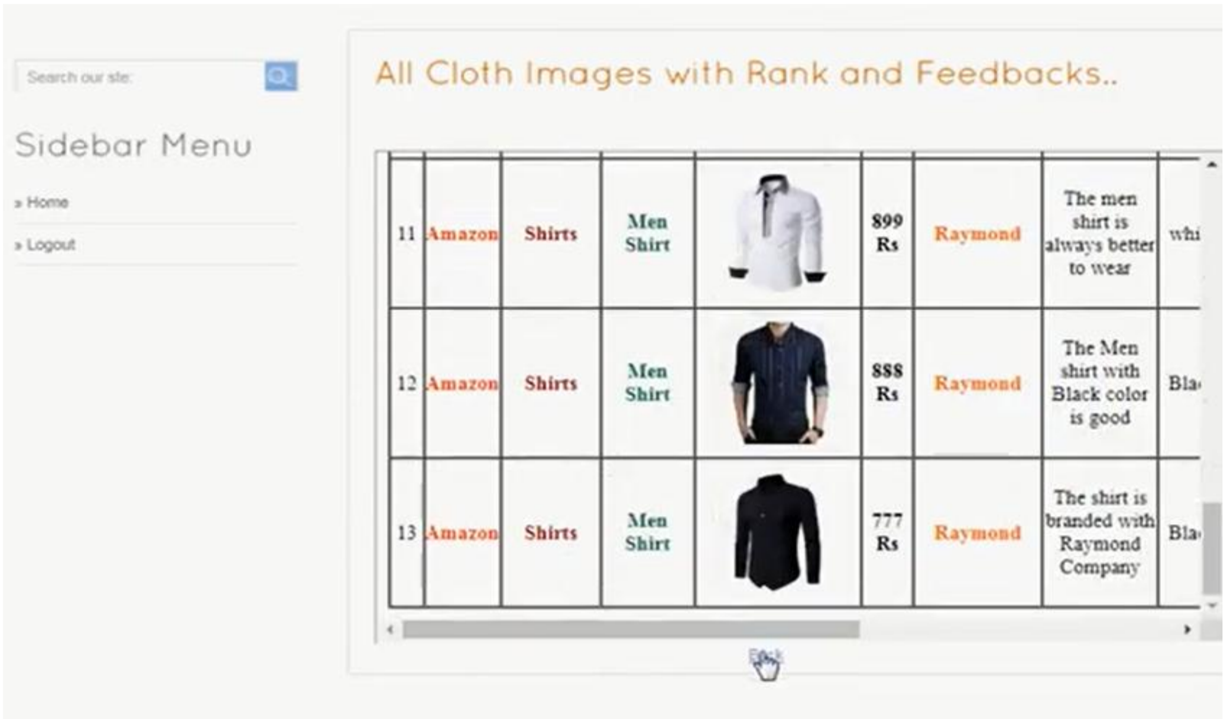

Fig 2: Recommendation table

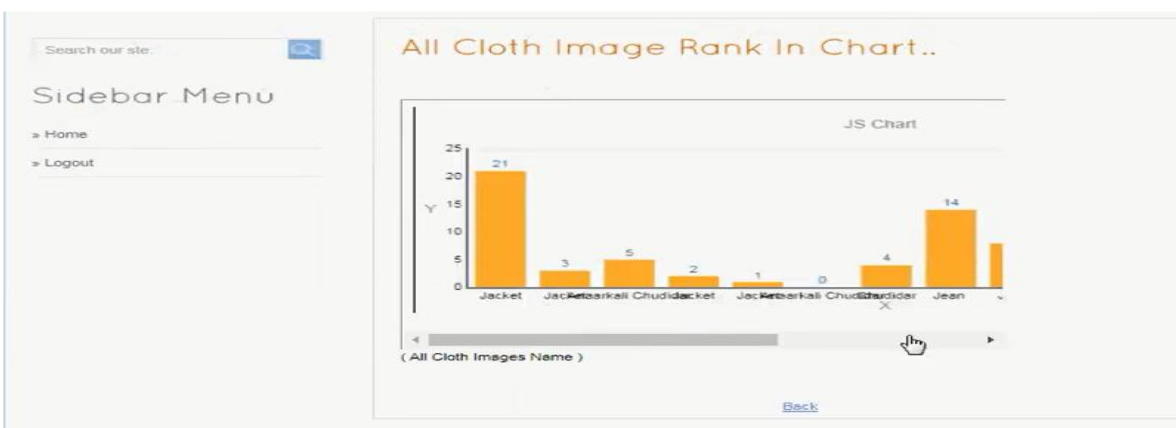

Fig 3: Comparision Graph

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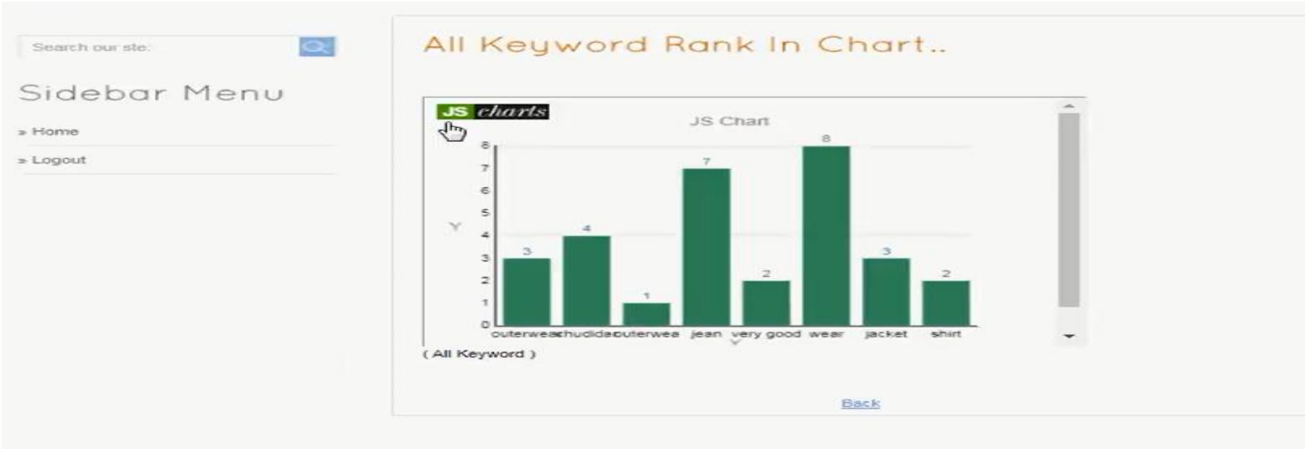

Fig 4: Keyword based search results

Conclusion

As outlined in this work, we have developed an interest mining and meta route discovery based product recommendation system that anticipates user wants and connected objects. Users' interests are taken into account to determine what products are most likely to be of interest to them. Two elements of the suggested method take into use the user's personality features to anticipate his or her preferred areas of interest. Secondly, the user's personality traits are matched with the corresponding goods. Predictive precision and recall are superior in the cold start phase for new products and users when using the suggested approach as compared to existing state-of-the-art systems.

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