Product Recommender System

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Abstract- *The Product Recommender System in Online marketing which uses potential variables such as age, gender, type of interest and other authentic records during social login profile update that can be measured and analyzed to predict likely behaviour of individuals and other entities. Multiple variables are combined into a predictive model is capable of assessing future probabilities with an acceptable level of reliability. This software relies heavily on advanced algorithms and methodologies such as a modified gradient boosting trees method to transform users' social networking features into user embeddings.*

Keywords- predictive model, social login, embeddings, cross site recommendation.

I. INTRODUCTION

The new trend of conducting e-commerce activities on social networking sites is important to leverage knowledge extracted from social networking sites for the development of product recommender systems. The Product Recommender includes real-time status updates and interactions between its buyers and sellers. An interesting problem of recommending products from e-commerce websites to users at social networking sites who do not have historical purchase records i.e cross-site product recommendation.

The main strategic goal for social media interaction is to provide users with a more engaging and social experience, thus increasing user retention and adoption. More importantly, social media is often seen as a means to rejuvenate the user base and attract younger users. Typical features unlocked by social media include the possibility of sharing purchase activities with friends, and tools such as friends gifting applications and chats.

When users connect from an e-commerce site to social media for the first time, they often agree to share with the e-commerce company basic information such as their demographics and personal interests. However, e-commerce companies have not fully developed technologies to leverage this information to improve important features such as purchase behavior prediction and product recommendation. Social media information could also help solve the cold start problem, i.e., providing an engaging and personalized experience to brand new users.

When a new user comes, traditional prediction and recommendation algorithms cannot in fact be applied, as no past information about the user is available. This research predicts in specific both users' and products' feature representations from data collected from ecommerce websites using recurrent neural networks and then modified gradient boosting trees method to transform users' social networking features into user embeddings.

The major contributions are listed below:

- Formulates a novel problem of recommending products from an e-commerce website to social networking users in situations where historical purchase records are not present.
- The recurrent neural networks is applied for learning correlated feature representations for both users and products from data collected from ecommerce website.
- A modified gradient boosting trees method is used to transform users' micro blogging attributes to latent feature representation which can be easily incorporated for product recommendation.

II. RELATED WORKS

[1].Yongzheng Zhang et al(2006) proposed "collaborative and content based filtering and mapping methods" to predict purchase behaviors from social media. The Specific aim is understanding if the user's profile information in a social network can be leveraged to predict what categories of products the user will buy from. It deals with the problem of predicting the purchase behaviours of social media users who have unknown history on an e-commerce website by collaborative and content based filtering and mapping methods.

[2]. M. Giering et al(2008) proposed "a straight forward method to deal with this multiplicity of models to build a rolled-up model that is a linear combination of all the submodels" to predict retail sales and item recommendations

using customer demographics at store level : A major challenge for large retailers to address the needs of the consumers more effectively on a local level, while maintaining the efficiencies of central distribution is mentioned. The problem then is to determine the mixing weights of the submodels, where each sub-model corresponds to a different partition.

[3]. Andrew I. Schein et al(2002) proposed “Methods and Metrics for Cold-Start Recommendations” for Recommender systems that suggest items of interest to users based on their explicit and implicit preferences, the preferences of other users, and user and item attributes. The performance of two machine learning algorithms on cold start prediction were evaluated by Implicit Rating Prediction, Rating Prediction and Rating Imputation.

[4]. Bernd Hollerit,et al(2013) proposed a system in which the Potential buyers and sellers can be contacted directly thereby opening up novel perspectives and economic possibilities, Since more and more people use the micro-blogging platform Twitter to convey their needs and desires, they also provide characteristics of tweets exhibiting commercial intent.

[5].Reza Zafaraniand Huan Liu,(2009) proposed a system that provide insights into the nature and characteristics of tweets exhibiting commercial intent thereby contributing to the understanding of how people express commercial activities on Twitter.

The work is built upon these studies, especially in the areas of cross-domain and cold-start recommendation. The most relevant studies are from [1], [3]. However, they only focus on brand- or category-level purchase preference based on a trained classifier, which cannot be directly applied to the cross-site cold-start product recommendation task. In addition, their features only include gender, age and Facebook likes, as opposed to a wide range of features explored in our approach. Lastly, they do not consider how to transfer heterogeneous information from social media websites into a form that is ready for use on the e-commerce side, which is the key to address the cross-site recommendation problem.

In the existing system user purchase history records were used to recommend products. The users who don’t have historical records cannot get product recommendation in the existing system. The social network information of users cannot be used for ecommerce system in the existing system. Purchase history of users’ records are used to recommend products. The users who don’t have historical records cannot get product recommendation in the existing system. The social network information of users cannot be used for ecommerce system in the existing system. This focuses on brand or category level purchase preference based on a trained classifier, which cannot be directly applied to the cross-site cold start product recommendation task.

Only includes gender, age and the other attributes got during profile update is explored in the approach. In existing, No consideration in how to transfer heterogeneous information from social media websites into a form that is ready for use on the e-commerce side, which is the key to address the cross-site recommendation problem. One extreme hypothesis is that a user is completely unfocused, i.e., the user likes to buy randomly across categories. On the other end, the user may have a few favorite categories from which majority purchases are made. The former hypothesis depicts a chaotic world where it is impossible to predict user behaviors and provide recommendations. There is no interesting problem of recommending products from e-commerce websites to users at social networking sites who do not have historical purchase records, i.e., in “coldstart” situations.

In the existing e-commerce websites, users and products cannot be represented in the same latent feature space through feature learning with the recurrent neural networks. There are no features such as linking users across both e-commerce websites and social networking sites so that feature mapping functions can be learned, which maps users’ attributes extracted from social networking sites onto feature representations learned from e-commerce websites. Only the users social networking information is available and it is a challenging task to transform the social networking information into latent user features which can be effectively used for product recommendation.

III. PROPOSED SYSTEM

The objective of the proposed system is cross site product recommendation and to transform social networking information to latent user features which can be used for product recommendation.

In this system on the e-commerce websites, users and products can be represented in the same latent feature space through feature learning with the recurrent neural networks. Using a set of linked users across both e-commerce websites and social networking sites as a bridge, feature mapping functions can be learned, which maps users’ attributes extracted from social networking sites onto feature representations learned from e-commerce websites.

3.1 Formulating the problem:

Given an e-commerce website, let U denote a set of its users, P a set of products .Each user u ∈ U can be linked to their micro blogging accounts (or other social network accounts), denoted as UL. Each user u ∈ UL is also associated with their respective micro blogging attribute information. Let A denote the set of micro blogging features, and each micro blogging user has a |A|-dimensional micro blogging feature vector au, in which each entry au, i is the attribute value for the i-th micro blogging attribute feature.

Considering a micro blogging user u0 /∈U is new to the e-commerce website, who has no historical purchase records. It is easy to see u0 /∈UL, since UL ⊂ U. The aim is to generate a personalised ranking of recommended products for u0 based on the micro blogging attributes au0. On the whole it extracts micro blogging features and transforms them into a distributed feature representation for product recommendation.

3.2.Data Extraction and Representation:

- A list of potentially useful micro blogging attributes are prepared.
- Construct the micro blogging feature vector au for each linked user u ∈UL;
- Distributed feature representations {vu} u∈U using the information from all the users U on the e-commerce website is generated;
- The mapping function, f(au) → vu, which transforms the micro blogging attribute information au to the distributed feature representations vu. It utilises the feature representation pairs {au, vu} of all the linked users u ∈UL as training data.

3.2.1.Feature selection:

3.2.1.1 Demographic Attributes:

A demographic profile of a user such as sex, age and education can be used by e-commerce companies to provide better personalised services. The users demographic attributes are extracted from their public profiles on Social Login. Six major demographic attributes are identified: gender, age, marital status, education, career and interests.

3.2.1.2 Text Attributes:

Recent studies have revealed that micro blogs contain rich commercial intents of users .Also, users' micro blogs often reflect their opinions and interests towards certain topics. On expecting a potential correlation is established between text attributes and users' purchase preferences.

3.2.1.3 Network Attributes:

In the online social media space, it is often observed that users connected with each other (e.g., through following links) are likely to share similar interests. As such, parse out latent user groups by the users' following patterns assuming that users in the same group share similar purchase preferences.

3.3.METHODS:

3.3.1 Recurrent Neural Networks:

However, it is not straightforward to establish connections between users and products. Intuitively, users and products should be represented in the same feature space so that a user is closer to the products that she has purchased compared to those she has not. Inspired by the recently proposed methods in learning word embeddings using recurrent neutral networks to learn user embeddings.

Figure Considering two simple recurrent neutral architectures proposed in to train product embeddings, namely, the Continuous Bag-Of-Words model (CBOW) and the Skip-gram model. The major difference between these two architectures lies in the direction of prediction:

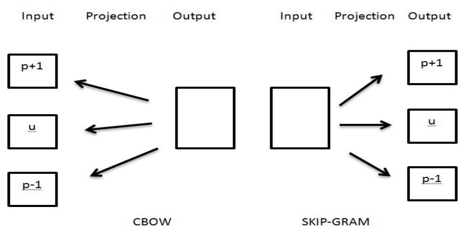

Figure 3.3.1.1

In Figure 3.3.1.1 CBOW predicts the current product using the surrounding context, i.e., Pr(pt|context), while Skip-gram predicts the context with the current product, i.e., Pr(context|pt).

The attribute information of a user can be considered as a "sentence" consisting of a sequence of attributes as word tokens. A user ID is placed at the beginning of each sentence, and both user IDs and product IDs based on feature representation mapping are treated as word tokens in a vocabulary in the learning process.

3.3.2 Modified Gradient Boosting Trees:

A micro blogging feature vector au from a micro blogging site and learn a distributed representation vu from an e-commerce website respectively. a product recommendation to a user u who has never purchased any products from an ecommerce website. The micro blogging feature vector au for user u can only be obtained. The key idea is to use a small number of linked users across sites as a bridge to learn a function which maps the original feature representation au to the distributed representation vu. Specifically, a training set can be constructed consisting of feature vector pairs, {au,vu} u∈UL and cast the feature mapping problem as a supervised regression task: the input is a micro blogging feature vector au and the output is a distributed feature vector vu. In equation no.3.3.2.1 assume that vu contains K dimensions, a set of K functions need to be learned{f(i)}K i=1, and the i-th function f(i) takes the original feature vector of a user u as the input and returns the corresponding i-th transformed feature value vu,i, i.e.,

vu,i = f(i)(a(u)) - 3.3.2.1

On extending the Multiple Additive Regression Tree (MART) method to learn feature mapping functions since it is powerful to capture higher-order transformation relationship between input and output.

A brief Introduction of MART Gradient boosting algorithms aim to produce an ensemble of weak models that together form a strong model in a stage-wise process. Typically, a weak model is a J-terminal node Classification And Regression Tree (CART) and the resulting gradient boosting algorithm is called Multiple Additive Regression Tree (MART) . An input feature vector $x \in Rd$ is mapped to a score $F(x) \in R$. The final model is built in a stage-wise process by performing gradient descent in the function space.

Completeness-Based Feature Sampling An issue about the gradient boosting algorithm is that it tends to overfit the training data. It has been previously shown that the incorporation of randomized feature sampling improves the tree based ensemble methods in Random Forest .The idea is to use an attribute-level importance sampling method where each attribute is assigned with an importance score and at each node split in building the MART trees which sample a fraction of attributes (empirically set to 2 3) based on each attribute's importance score instead of enumerating all the attributes. Once an attribute is sampled, its corresponding attribute value features will be selected subsequently.

The importance score of each attribute is set to the proportion of the attribute values that can be extracted from the users' public profiles on social networking site during Social Login. Another benefit of completeness-based sampling is that attributes with a larger proportion of missing values will be more likely to be pushed to the leaf nodes, which alleviates the missing value problem in regression trees.

Fitting Refinement Here two methods have been proposed to refine the fitted values. First, the fitting quality relies on the number of available linked users since insufficient training data would hurt the performance of the regression method. Recall that the user embeddings for all the users can be learned on an e-commerce website. A super user embedding vector v(sup) is created by averaging all available user embeddings. When the training data is limited, requirement is that the fitted vector should not deviate from v(sup) too much. Secondly, fit each dimension separately with an individual MART model. Based on the data analysis, it is found that the values of some dimensions from the same user might be correlated .

On building a single learner for each dimension in the transformed feature representation vu using a modified gradient boosting trees model. The reason for choosing MART is that its components are regression trees, and trees are shown to be effective to generate high-order and interpretable knowledge using simple plain features . Note other tree-based ensemble methods can apply here, such as Random Forest (RF). In the experiments, it is found MART is slightly better than RF, and therefore MART is adopted as the fitting model.

IV. EXPERIMENTS

The task requires data from both an e-commerce website and an online social networking site.

4.1 E-commerce data:

An E-Commerce website is created which serves as a admin module wherein it includes a unique login, category and products addition, views customer details, lists their recommendation histories. Product details are the main data here which includes productID, productName, productPrice, productSpecification.

4.2 Micro blogging data:

The main focus is to filter out users attribute information on their public profiles. Next is to divide users appropriately based on mapping feature.

4.3 User Linkage:

The recommended products to the other users are inclusive of its own details.

4.4 Methods to Compare:

4.4.1 Semantic Similarity:

Search via search box with proper keywords.

4.4.2 User attributes:

Based on the user profile information updated during the social login.

4.4.3 Embeddings:

The proposed approach which uses the fitted user embedding features and product embedding features .

4.4.4 Demographic+Embeddings:

The proposed approach which uses the micro blogging features, the product embedding features and the fitted user embedding features . Especially, the demographic attributes are only used here, since they have been shown important to product recommendation.

V. CONCLUSION AND FUTURE WORK

A novel problem of cross-site product recommendation, i.e., recommending products from e-commerce websites to micro blogging users without historical purchase records . Feature mapping functions can be learned using a modified gradient boosting trees method, which maps users' attributes extracted from social networking sites onto feature representations learned from e-commerce websites.

The mapped user features can be effectively incorporated into a feature-based matrix factorisation approach for cold start product recommendation. An ecommerce and social networking website is constructed. The results show that the proposed framework is indeed effective in addressing the cross-site product recommendation problem without purchase histories. Currently, only a simple neutral network architecture has been employed for user and product embeddings learning. In the future, more advanced deep learning models such as Convolutional Neural Networks can be explored for feature learning.

REFERENCES

[1] Yongzheng Zhang,Marco Pennacchiotti, "Predicting Purchase Behaviors from Social Media" In WI'06 Conference Proceedings, pages 719–723, 2006.

[2] M. Giering, "Retail sales prediction and item recommendations using customer demographics at store level," SIGKDD Explor. Newsl., vol. 10, no. 2, Dec. 2008.

[3] Andrew I. Schein, Alexandrin Popescul, and Lyle H. Ungar, David M. Pennock, "Methods and Metrics for Cold-Start Recommendations", Appeared in Proceedings of the 25'th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2002), pp. 253260. Tampere, Finland. August, 2002.

[4] Bernd Hollerit, Mark Kröll, Markus Strohmaier, "Towards Linking Buyers and Sellers: Detecting Commercial Intent on Twitter " May 13–17, 2013, Rio de Janeiro, Brazil. ACM 978-1-4503-2038-2/13/05.

[5] Reza Zafaraniand Huan Liu, "Connecting Corresponding Identities across Communities", Appeared in the Proceedings of the Third International ICWSM Conference (2009).

[6] J.Wang and Y. Zhang, "Opportunity model for e-commerce recommendation: Right product; right time," in SIGIR, 2013.

[7] G. Linden, B. Smith, and J. York, "Amazon.com recommendations: Item-toitem collaborative filtering," IEEE Internet Computing, vol. 7, no. 1, Jan. 2003.

[8] V. A. Zeithaml, "The new demographics and market fragmentation," Journal of Marketing, vol. 49, pp. 64–75, 1985.

[9] W. X. Zhao, Y. Guo, Y. He, H. Jiang, Y. Wu, and X. Li, "predict what people buy": a demographic-based system for product recommendation on micro blogs," in SIGKDD, 2014.

[10] J. Wang, W. X. Zhao, Y. He, and X. Li, "Leveraging product adopter information from online reviews for product recommendation," in ICWSM, 2015.

[11] Y. Seroussi, F. Bohnert, and I. Zukerman, "Personalised rating prediction for new users using latent factor models," in ACM HH, 2011.

[12] Q. V. Le and T. Mikolov, "Distributed representations of sentences and documents," CoRR, vol. abs/1405.4053, 2014.

[13] J. Lin, K. Sugiyama, M. Kan, and T. Chua, "Addressing cold start in app recommendation: latent user models constructed from twitter followers," in SIGIR, 2013