A HIERARCHICAL ATTENTION MODEL FOR SOCIAL CONTEXTUAL IMAGE RECOMMENDATION

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ABSTRACT
Image based social networks are among the most popular social networking services in recent years. With tremendous images uploaded everyday, understanding users' preferences on user-generated images and making recommendations have becomean urgent need. In fact, many hybrid models have been proposed to fuse various kinds of side information (e.g., image visual representation, social network) and user-item historical behavior for enhancing recommendation performance. However, due to the unique characteristics of the user generated images in social image platforms, the previous studies failed to capture the complex aspects that influence users' preferences in a unified framework. Moreover, most of these hybrid models relied on predefined weights in combining different kinds of information, which usually resulted in sub-optimal recommendation performance. To this end, in this paper, we develop a hierarchical attention model for social contextual image recommendation. In addition to basic latent user interest modeling in the popular matrix factorization based recommendation, we identify three key aspects (i.e., upload history, social influence, and owner admiration) that affect each user's latent preferences, where each aspect summarizes a contextual factor from the complex relationships between users and images. After that, we design a hierarchical attention network that naturally mirrors the hierarchical relationship (elements in each aspects level, and the aspect level) of users' latent interests with the identified key aspects. Specifically, by taking embeddings from state-of-the-art deep learning models that are tailored for each kind of data, the hierarchical attention network could learn to attend differently to more or less content. Finally, extensive experimental results on real-world datasets clearlyshow the superiority of our proposed model.

INTRODUCTION
There is an old saying "a picture is worth a thousand words". When it comes to social media, it turns out that visual images are growing much more popularity to attract users [14]. Especially with the increasing adoption of smartphones, users could easily take qualified images and upload them to various social image platforms to share these visually appealing pictures with others. Many image-based social sharing services have emerged, such as Instagram1, Pinterest2, and Flickr3. With hundreds of millions of images uploaded everyday, image recommendation has become an urgent need to deal with the image overload problem. By providing personalized image suggestions to each active user in image recommender system, users gain more satisfaction for platform prosperity. E.g., as reported by Pinterest, image recommendation powers over 40% of user engagement of this social platform [30]. Naturally, the standard recommendation algorithms provide a direct solution for the image recommendation task [2]. For example, many classical latent factor based Collaborative Filtering (CF) algorithms in recommender systems could be applied to deal with user-image interaction matrix [26], [40], [26]. Successful as they are, the extreme data sparsity of the user-image interaction behavior limits the recommendation performance [2], [26]. On one hand, some recent works proposed to enhance recommendation performance with visual contents learned from a (pre-trained) deep neural network [18], [49], [5]. On the other hand, as users perform image preferences in social platforms, some social based recommendation algorithms utilized the social influence among users to alleviate data sparsity for better recommendation [33], [24], [3]. In summary,these

studies partially solved the data sparsity issue of social-based image recommendation. Nevertheless, the problem of how to better exploit the unique characteristics of the social image platforms in a holistical way to enhance recommendation performance is still under explored.
In this paper, we study the problem of understanding users' preferences for images and recommending images in social image based platforms. Fig. 1 shows an example of a typical social image application. Each image is associated with visual information. Besides showing likeness to images, users are also creators of these images with the upload behavior. In addition, users connect with others to form a social network to share their image preferences. The rich heterogeneous contextual data provides valuable clues to infer users' preferences to images. Given rich heterogeneous contextual data, the problem of how to summarize the heterogeneous social contextual aspects that influence users' preferences to these highly subjective content is still unclear. What's more, in the preference decision process, different users care about different social contextual aspects for theirpersonalized image preference. E.g. Lily likes images that are similar to her uploaded images, while Bob is easily swayed by social neighbors to present similar preference as her social friends. In other words, the unique user preference for balancing these complex social contextual aspect makes the recommendation problem more challenging.
To address the challenges mentioned above, in this paper, we design a hierarchical attention model for social image recommendation. The proposed model is built on the popular latent factor based models, which assumes users and items could be projected in a low latent space [34]. In our proposed model, for each user, in addition to basic latent user interest vector, we identify three key aspects (i.e., upload history, social influence and owner admiration) that affect each user's preference, where each aspect summarizes a contextual factor from the complex relationships between users and images. Specifically, the upload history aspect summarizes each user's uploaded images to characterize her interest. The social influence aspect characterizes the influence from the social network structure, and the owner admiration aspect depicts the influence from the uploader of the recommended image. The three key aspects are combined to form the auxiliary user latent embedding. Furthermore, since not all aspects are equally important for personalized image recommendation, we design a hierarchical attention structure that attentively weight different aspects for each user's auxiliary embedding. The proposed hierarchical structure aims at capturing the following two distinctive characteristics. First, as social contextual recommendation naturally exhibits the hierarchical structure (various elements from each aspect, and the three aspects of each user), we likewise construct user interest representation with a hierarchical structure. In the hierarchical structure, we first build auxiliary aspect representations of each user, and then aggregate the three aspect representations into an auxiliary user interest vector. Second, as different elements within each aspect, and different aspects are differentially informative for each user in the recommendation process, the hierarchical attention network builds two levels of attention mechanisms that apply at the element level and the aspect level.

2. RECOMMENDATION

General Recommendation. Recommender systems could be classified into three categories: content based methods, Collaborative Filtering (CF) and the hybrid models [2]. Among all models for building recommender systems, latent factor based models from the CF category are among the most popular techniques due to their relatively high performance in practice [40], [34], [39]. These latent factor based models decomposed both users and items in a low latent space, and the preference of a user to an item could be approximated as the inner product between the corresponding user and item latent vectors. In the real-world applications, instead of the explicit ratings, users usually implicitly express their opinions through action or inaction. Bayesian Personalized Ranking (BPR) is such a popular latent factor based model that deals with the implicit feedback [40]. Specifically, BPR optimized a pair wise based ranking loss, such that the observed implicit feedbacks are preferred to rank higher than that of the unobserved ones. As users may simultaneously express their opinions with several kinds of feedbacks (e.g., click behavior, consumption behavior). SVD++ is proposed to incorporate users' different feedbacks by extending the classical latent factor based models, assuming each user's latent factor is composed of a base latent factor, and an auxiliary latent factor that can be derived from other kinds of feedbacks [26]. Due to the performance improvement and extensibility of SVD++, it is widely studied to incorporate different kinds of information, e.g., item text [58], multi-class preference of users [36].

Image Recommendation. In many image based social networks, images are associated with rich context information, e.g., the text in the image, the hashtags. Researchers proposed to apply factorization machines for image recommendation by considering the rich context information [6]. Recently, deep Convolutional Neural Networks(CNNs) have been successfully applied to analyzing visual imagery by automatic image representation in the modeling process [27]. Thus, it is a natural idea to leverage visual features of CNNs to enhance image recommendation performance [18], [28], [17], [5]. E.g., VBPR is an extension of BPR for image recommendation, on top of which it learned an additional visual dimension from CNN that modeled users' visual preferences [18]. There are some other image recommendation models that tackled the temporal dynamics of users' preferences to images over time [17], or users' location preferences for image recommendation [35], [49], [35]. As well studied in the computer vision community, in parallel to the visual content information from deep CNNs, images convey rich style information. Researchers showed that many brands post images that show the philosophy and lifestyle of a brand [14], images posted by users also reflect users' personality [13]. Recently, Gatys et al. proposed a new model of extracting image styles based on the feature maps of convolutional neural networks [10]. The proposed model showed high perceptual quality for extracting image style, and has been successfully applied to related tasks, such as image style transfer [11], and high-resolution image stylisation [12]. We argue that the visual image style also plays a vital role for evaluating users' visual experience in recommender systems. Thus, we leverage both the image content and the image style for recommendation.

Social Contextual Recommendation. Social scientists have long converged that a user's preference is similar to or influenced by her social connections, with the social
theories of homophily and social influence [3]. With the prevalence of social networks, a popular research direction is to leverage the social data to improve recommendation performance [33], [23], [24], [51]. E.g., Ma et al. proposed a latent factor based model with social regularization terms for recommendation [33]. Since most of these social recommendation tasks are formulated as non-convex optimizing problems, researchers have designed an unsupervised deep learning model to initialize model parameters for better performance [9]. Besides, ContextMF is proposed to fuse the individual preference and interpersonal influence with auxiliary text content information from social networks [24]. As the implicit influence of trusts and ratings are valuable for recommendation, TrustSVD is proposed to incorporate
the influence of trusted users on the prediction of items for an active user [16]. The proposed technique extended the SVD++ with social trust information. Social recommendation has also been considered with social circle [38], online social recommendation [59], social network evolution [50], and so on.

PROBLEM STATEMENT

In the existing work,the latent factor based models decomposed both users and items in a low latent space, and the preference of a user to an item could be approximated as the inner product between the corresponding user and item latent vectors.The system is less effective due to lack of content based recommendations.

3. PROPOSED SYSTEM

The proposed model is built on the popular latent factor based models, which assumes users and items could be projected in a low latent space [34]. In our proposed model, for each user, in addition to basic latent user interest vector, we identify three key aspects (i.e., upload history, social influence and owner admiration) that affect each user's preference, where each aspect summarizes a contextual factor from the complex relationships between users and images. Specifically, the upload history aspect summarizes each user's uploaded images to characterize her interest. The social influence aspect characterizes the influence from the social network structure, and the owner admiration aspect depicts the influence from the uploader of the recommended image. The three key aspects are combined to form the auxiliary user latent embedding. Furthermore, since not all aspects are equally important for personalized image recommendation, we design a hierarchical attention structure that attentively weight different aspects for each user's auxiliary embedding. The proposed hierarchical structure aims at capturing the following two distinctive characteristics. First, as social contextual recommendation naturally exhibits the hierarchical structure (various elements from each aspect, and the three aspects of each user), we likewise construct user interest representation with a hierarchical structure. In the hierarchical structure, we first build auxiliary aspect representations of each user, and then aggregate the three aspect representations into an auxiliary user interest vector. Second, as different elements within each aspect, and different aspects are differentially informative for each user in the recommendation process, the hierarchical attention network builds two levels of attention mechanisms that apply at the element level and the aspect level.The system studies the problem of image recommendation in social image based platforms. By considering the uniqueness of these platforms, we identify three social contextual aspects that affect users' preferences from heterogeneous data sources.The system designs a hierarchical attention network to model the hierarchical structure of social contextual recommendation. In the attention networks, we feed embeddings from state-of-the-art deep learning models that are tailored for each kind of data into the attention networks. Thus, the attention networks could learn to attend differently based on the rich contextual information for user interest modeling.The system conducts extensive experiments on real-world datasets. The experimental results clearly show the effectiveness of our proposed model.

BENFITS OF SYSTEM

The system is more effective since the proposed model is built on the popular latent factor based models, which assumes users and items could be projected in a low latent space.
For each user, in addition to basic latent user interest vector, we identify three key aspects (i.e., upload history, social influence and owner admiration) that affect each user's preference, where each aspect summarizes a contextual factor from the complex relationships between users and images.

4. IMPLEMENTATION

4.1 Admin

In this module, the Admin has to login by using valid user name and password. After login successful he can perform some operations such as View All Users and Authorize, Add Category, Add Images, View All Heterogeneous Images with Rate, View Social Influence Attention Image, View Recommendations By Category, View All Reviewed Behavior Images, View All Searched History, View All Friend Req and Res,View Results

4.2 Friend Request & Response

In this module, the admin can view all the friend requests and responses. Here all the requests and responses will be displayed with their tags such as Id, requested user photo, requested user name, user name request to, status and time & date. If the user accepts the request then the status will be changed to accepted or else the status will remains as waiting.

4.3 Social Network Friends
In this module, the admin can see all the friends who are all belongs to the same site. The details such as, Request From, Requested user's site, Request To Name, Request To user's site.

4.4 All Recommended Images
In this module, the admin can see all the images which are shared among the friends in same and other network sites. The details such as post image, title, description, recommend by name and recommend to name.

4.5 Adding Images
In this module, the admin adds images details such as title, description and the image of the post. The post details such as title and description will be encrypted and stores into the database.

4.6 User
In this module, there are n numbers of users are present. User should register before performing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user can perform some operations like Search Friends, View Friend Requests, each Images and Recommend, View My Search History, View All Recommended Images, View Other User Recommended Images, View Top K Recommendation.

4.7 Searching Users
In this module, the user searches for users in Same Site and in Different Sites and sends friend requests to them. The user can search for users in other sites to make friends only if they have permission.

5. CONCLUSIONS
In this paper, we have proposed a hierarchical attentive social contextual model of HASC for social contextual image recommendation. Specifically, in addition to user interest modeling, we have identified three social contextual aspects that influence a user's preference to an image from heterogeneous data: the upload history aspect, the social influence aspect, and the owner admiration aspect. We designed a hierarchical attention network that naturally mirrored the hierarchical relationship of users' interest given the three identified aspects. In the meantime, by feeding the data embedding from rich heterogeneous data sources, the hierarchical attention networks could learn to attend differently to more or less important content. Extensive experiments on real-world datasets clearly demonstrated that our proposed HASC model consistently outperforms various state-of-the art baselines for image recommendation.

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