Social Contextual Social Influence and Upload History Based Image Recommendation System

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ABSTRACT:

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. Most of the hybrid models relied on predefined weights in combining different kinds of information which usually resulted in sub optimal recommendation performance, 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.

Keywords: Context modelling, Data models, Task analysis, Recommender systems.

I .INTRODUCTION

Data mining is a huge amount of data available in the Information Industry. This data is of no use until it is converted into useful information. It is necessary to analyze this huge amount of data and extract useful information from it.

Extraction of information is not the only process we need to perform; data mining also involves other processes such as Data Cleaning, Data Integration, Data Transformation, Data Mining, Pattern Evaluation and Data Presentation. Once all these processes are over, we would be able to use this information in many applications such as Fraud Detection, Market Analysis, Production Control, Science Exploration.

Data Integration is a data preprocessing technique that merges the data from multiple heterogeneous data sources into a coherent data store. Data integration may involve inconsistent data and therefore needs data cleaning. Data cleaning is a technique that is applied to remove the noisy data and correct the inconsistencies in data. Data cleaning involves transformations to correct the wrong data. Data cleaning is performed as a data preprocessing step while preparing the data for a data warehouse.

Data Selection is the process where data relevant to the analysis task are retrieved from the database. Sometimes data transformation and consolidation are performed before the data selection process. Cluster refers to a group of similar kind of objects. Cluster analysis refers to forming group of objects that are very similar to each other but are highly different from the objects in other clusters. Data is transformed or consolidated into forms appropriate for mining, by performing summary or aggregation operations.

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.

Some recent works proposed to enhance recommendation performance with visual contents learned from a deep neural network . On the other hand, as users perform image preferences in social platforms.

Some 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. We study the problem of understanding users' preferences for images and recommending images in social image based platforms.

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.

In the preference of decision process, different users care about different social contextual aspects for their personalized image preference.

II. RELATED WORK

A lot of related work has been done to know the disadvantages of existing system and to have better insight of data mining models in dynamic fashion.

The unique user preference for balancing these complex social contextual aspect makes the recommendation problem more challenging. We feed embeddings from state-of-the-art deep learning models that are tailored for each kind of data into the attention networks.

We summarize the related work in the following four categories:

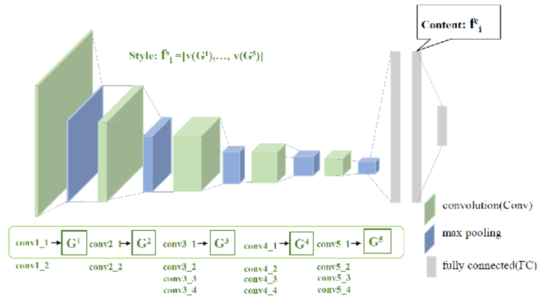
General Recommendation: These latent factor based models decomposed both users and items in a low latent space, and the preference of a user to an item could be approximated as the inner product between the corresponding user and item latent vectors. Bayesian Personalized Ranking (BPR) is such a popular latent factor based model that deals with the implicit feedback . Specifically, BPR optimized a pairwise based ranking loss, such that the observed implicit feedbacks are preferred to rank higher than that of the unobserved ones.

Image Recommendation: In many image based social networks, images are associated with rich context information. , 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. Researchers showed that many brands post images that show the philosophy and lifestyle of a brand , images posted by users also reflect users' personality.

Social Contextual Recommendation: 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. 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

Attention Mechanism: Attention mechanism is such an intuitive idea that automatically models and selects the most pertinent piece of information, which learns to assign attentive weights for a set of inputs, with higher (lower) weights indicate that the corresponding inputs are more informative to generate the output. the attention networks were proposed to learn which historical behavior is more important for the user's current temporal decision. A lot of attention based recommendation models have been developed to better exploit the auxiliary information to improve recommendation performance.

While the above models perform the standard vanilla attention to learn to attend on a specific piece of information, the co-attention mechanism is concerned to learn attention weights from two sequences , the hash tag recommendation with both text and image information, the co-attention network is designed to learn which part of the text is distinctive for images, and simultaneously the important visual features for the text.



The problem of how to design sophisticated network embedding techniques, and the visual image features are well researched. Since the focus of this paper is not to advance these topics, we adopt state-of-the-art models and put emphasis on enhancing the recommendation performance with the rich social contextual information.

III. EXISTING SYSTEM

General Recommendation. Recommender systems could be classified into three categories: content based methods, Collaborative Filtering (CF) and the hybrid models . 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. 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.

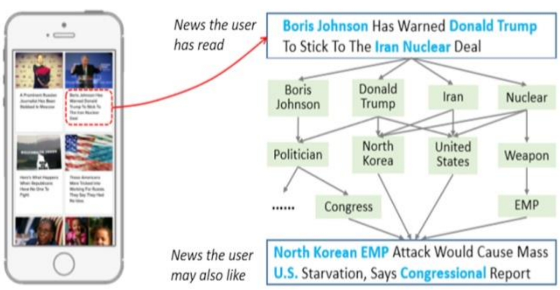
In many image based social networks, images are associated with rich context information, e.g., the text in the image, the hash tags.

Researchers proposed to apply factorization machines for image recommendation by considering the rich context information . Recently, deep Convolutional Neural Networks. CNN have been successfully applied to analyzing visual imagery by automatic image representation in the modeling process .

IV. PROPOSED MODEL

A hierarchical neural network that models users' preferences for to unknown images from two attention levels with social contextual modeling. The top layered attention network depicts the importance of the three contextual aspects (i.e., upload history, social influence and creator admiration) for users' decision, which is derived from the bottom layered attention networks that aggregate the complex elements within each aspect.

A large attentive degree denotes the current user cares more about this aspect in image recommendation process. Besides, as there are various elements within the upload history context la and social influence context.



Objective Prediction Function: As many latent factor based models [40], [26], we also take the inputs of the three social contextual aspects: sa, la, and Ci. To model the complex contextual aspects, we extend the classical latent factor models and assume each user and each item has two embeddings. Specifically, each user a is associated with a base embedding pa from the base embedding matrix P to denote her base latent interest in the standard latent factor based models, and an auxiliary embedding vector qa from the auxiliary embedding matrix Q .

Thus, by combining the attention mechanism with the embeddings, we model each user a's predicted preference to image i as a hierarchical attention:

$$r\hat{}ai = wTi\ (pa + \gamma a1xea + \gamma a2qea + \gamma a3qCi)$$

where

$$xea = XN\ j{=}1\ lja\alpha ajxj$$

$$qea = XM\ b{=}1\ sba\beta abqb.$$

We leave the details of how to model these three attention networks in the following subsections. Next, we show the soundness of the objective predicted function.

In the above prediction function, the representations of three contextual aspects are seamlessly incorporated in a holistic way. Specifically, the first line is a top layer attention network that aggregates the three contextual aspects for user embedding.

As each image is uploaded by a creator, the last term models the creator admiration aspect. This is quite natural in the real-world, as we always like to follow some specific creators' updates.

Upload History Attention: The goal of the upload history attention is to select the images from each user a's upload history that are representative to a's preferences, and then aggregate this upload history contextual information to characterize each user.

Social Influence Attention: The social influence attention module tries to select the influential social neighbours from each user a's social connections, and then summarizes these social neighbors' influences into a social contextual vector.

Aspect Importance Attention Network: The aspect importance attention network takes the contextual representation of each aspect from the bottom layered attention networks as input, and models the importance of each aspect in the user's decision process.

IV.CONCLUSION

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.

HASC could better learn each user's preference from various social contextual aspects. Thus, it shows the the best performance for the users in the first three rows. In the fourth row, we present a case that all the models do not perform well expect than the simplified C model from HASC that leverages the single creator admiration aspect into consideration.

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