Abstract

Image based social networks are among the most popular social networking services in recent years. With tremendous images uploaded everyday, understanding users’ preferences to the user-generated images and recommending them to users have become an urgent need. However, this is a challenging task. On one hand, we have to overcome the extremely data sparsity issue in image recommendation. On the other hand, we have to model the complex aspects that influence users’ preferences to these highly subjective content from the heterogeneous data. In this paper, we develop an explainable social contextual image recommendation model to simultaneously explain and predict users’ preferences to images. Specifically, in addition to user interest modeling in the standard recommendation, we identify three key aspects that affect each user’s preference on the social platform, where each aspect summarizes a contextual representation from the complex relationships between users and images. We design a hierarchical attention model in recommendation process given the three contextual aspects. Particularly, the bottom layered attention networks learn to select informative elements of each aspect from heterogeneous data, and the top layered attention network learns to score the aspect importance of the three identified aspects for each user. In this way, we could overcome the data sparsity issue by leveraging the social contextual aspects from heterogeneous data, and explain the underlying reasons for each user’s behavior with the learned hierarchial attention scores. Extensive experimental results on real-world datasets clearly show the superiority of our proposed model.

1 Introduction

There is an old saying “a picture is worth a thousand words”. When it comes to the social media, it turns out that visual images are growing much more popularity to attract users. Especially with the rapid increase 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 Instagram[1], Pinterest[2] and Flickr[3]. For example, in Flickr, there are over 90 million active users and over 10 billion uploaded images in November, 2017[1]. Therefore, image recommendation has become an effective approach to deal with the image overload problem by providing personalized image suggestions to each active user, thus improves user satisfaction and platform prosperity. E.g., as reported by Pinterest, image recommendation powers over 40% of user engagement on this social platform[21].

Naturally, the standard recommendation algorithms provide a naive way for the image recommendation task[2]. For example, with user-image interaction matrix, many classical Collaborative Filtering (CF) algorithms in recommender systems could be applied[2][16]. Latent factor based models are among one of the most popular techniques for CF, which provide recommendations by projecting both users and images in a latent space[28][16]. Successful as they are, the extreme data sparsity of the user-image interaction behavior limits the recommendation performance[2][16]. To solve the data sparsity problem in social image platforms, on one hand, some re-
cent works proposed to enhance recommendation performance with visual contents learned from a (pre-trained) deep neural network [10, 31]. 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 [25, 15, 3]. In summary, these works partially solved the data sparsity issue in social-based image recommendation. Nevertheless, how to better exploit the unique characteristics of the social image platforms in a holistical way to enhance recommendation performance is still under explored.

Figure 1: An overall framework of the social contextual image recommendation in a social image platform. Given the heterogeneous data from the left part, the image content is represented as visual feature from a convolutional neural network. Beside standard user interest modeling, the proposed unified framework summarizes three social contextual aspects from various heterogeneous input for recommendation.

In this paper, we study the problem of understanding users’ preferences to images and recommending images in social image based platforms. Figure 1 shows an example of a typical social image application. Each image is associated with the image content. Besides showing likeness to images, users are also creators of these images with the upload behavior. In addition, users connect to other users to form a social network to share their image preferences. These rich heterogeneous contextual data provides valuable clues to infer users’ preference to images. Nevertheless, it is non trivial to summarize the social contextual aspects that influence users’ preferences to these highly subjective content in a unified recommendation framework. Specifically, we call each factor that influence the user’s preferences for a given image from the heterogeneous social image data as a social contextual aspect. Also, different users care about different these social contextual aspects for their personalized image preference in the decision process. E.g. Lily likes images that are similar to her uploaded images, while Bob is easily swayed by social neighbors to have similar preference as her social friends. Accurately capturing these complex social contextual information in the modeling process can not only provide better recommendations, but also generate explicit recommendation that explains which social contextual aspect is important for the active user’s decision. Thus, users could trust interpretable system in making informed decisions. Also, the system becomes more active through interactions with users. However, most current solutions for explainable recommendations are based on content analysis to better describe users’ interests [37, 27]. Therefore, the problem of how to summarize and explain the complex social contextual aspects that influence users’ preferences to images in a social image platform remains pretty much open.

To address the challenge mentioned above, we design an explainable social contextual image recommendation model to simultaneously explain and predict users’ preferences to images in the social platform with a designed hierarchical attention model. Specifically, as shown in the middle part in Figure 1, we identify three key aspects that affect each user’s preference from heterogeneous data (i.e., upload coherence, social influence, and creator admiration). We design a hierarchical attention model in recommendation process given the three contextual aspects, which arranges the elements within each aspect, and the three contextual aspects in a hierarchical structure. For each contextual aspect, the bottom layered attention networks learn to select informative elements of each aspect and the top layered attention network learns to score the aspect importance for each user by taking various information sources as input (e.g., the visual representation of users and images). In this way, we could overcome the data sparsity issue by leveraging rich social contextual information, and explain the underlying reason for each user’s like behavior with the learned hierarchical attention scores. Finally, extensive experimental results on real world datasets clearly show the superiority of our proposed model.
2 Related Work and Preliminaries

2.1 Related Work

We summarize the related work in the following four categories.

General Recommendation. Recommender systems could be classified into three categories: content based methods, collaborative filtering 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 [28, 24]. In the real-world applications, instead of the explicit ratings, users usually implicitly express their opinions through action or inaction. E.g., in a social image platform, users express their likeness to images through the “Like” or “Thumbsup” button in this platform. BPR is such a popular latent factor based model that deals with the implicit feedback [28]. While most recommendation algorithms focused on improving recommendation accuracy with black-box models, recently some researchers argued that building explainable recommendations are beneficial for both users and the platform. Most explainable recommendations utilized the reviews posted by users to discover the detailed aspect a user cares about [37, 11, 27]. Instead of the review information, our work focuses on discovering the social contextual aspects that explain each user’s preference.

Image Recommendation. Recently, deep Convolutional Neural Networks (CNNs) have been successfully applied to analyzing visual imagery by automatic image representation in the modeling process [17]. Thus, it is a natural idea to borrow visual features of CNNs to enhance image recommendation performance [10, 18, 9, 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 preference [10]. He et al. proposed an attentive collaborative filtering model for multimedia recommendation [5]. They designed a component level attention module to extract informative components of images and an item-level attention to learn item preference. There are some other image recommendation models that tackled the temporal dynamics of users’ preferences to images over time [9], or users’ location preferences for image recommendation [25]. Image visual features are also exploited for the POI recommendation task, where each user is associated with the uploaded images and each POI also contains multiple images [31, 25]. Different from these works, as users usually share images in social platforms, our model directly models the social contextual aspects in the image recommendation process.

Social Contextual Recommendation. Social scientists have long converged that a user’s preference is similar to or influenced by the 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 [23, 14, 15]. E.g., Ma et al. proposed a latent factor based model with social regularization terms for recommendation [23]. 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 [8]. Besides, ContextMF is proposed to fuse the individual preference and interpersonal influence with auxiliary text content information from social networks [15]. Specifically, the individual preference and interpersonal influence are fused in the latent factor model, and the item text-based topic similarity is enforced as regularization terms in this model. Social recommendation has also been considered with social circle [26], online social recommendation [38], and so on. We distinguish from these works as we focus on image-based social networks, which has rarely been studied before. Besides, the proposed model could also explain the various social contextual aspects that influence a user’s preference with a designed hierarchical attention model.

Attention Mechanism. Neural science studies have shown that people focus on specific parts of the input rather than using all available information [13]. 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. Attention mechanism is widely used in many neural network based tasks, such as machine translation [4] and image captioning [33]. Besides, the idea of attention can be easily adapted to other real-world applications, such
as health-care learning [6], question answering [19, 22], and image recommendation [5]. In some real-world applications, there exists hierarchical structure among the data, several pioneering works have been proposed to deal with this kind of relationship [34, 20]. E.g., a hierarchical attention model is proposed to model the hierarchical relationships of word, sentence and document for document classification [34]. Our work borrows ideas from attention model is proposed to model the hierarchical relationships of word, sentence and document for document classification [34, 20]. E.g., a hierarchical attention model is proposed to model the hierarchical relationships of word, sentence and document for document classification [34].

2.2 Preliminaries

In a recommender system, let \( \mathbf{R}^{M \times N} \) denote the user-item interaction matrix, where \( M \) is the number of users and \( N \) the number of items. Each element \( R_{ai} \) represents the detailed preference of user \( a \) to item \( i \). The core idea of latent factor based models is to map both users and items in a same low latent space. We use \( \mathbf{W}^{D \times M} = [W_1, W_2, ..., W_1, ..., W_M] \) and \( \mathbf{D}^{D \times M} = [P_1, P_2, ..., P_a, ..., P_N] \) to denote the user and item latent matrix in the low latent space. Then, the predicted preference \( \hat{R}_{ai} \) could be estimated as the linear product between the corresponding user latent vector \( P_a \) and item latent vector \( W_i \):

\[
\hat{R}_{ai} = W_i^T \times P_a. \tag{1}
\]

In the real-world applications (e.g., in a social image application), as users usually implicitly express their rating opinions on items through action or inaction (e.g., the “like” action), research attention on recommendation has shifted towards this scenario with implicit feedback. As to the implicit feedback, \( R_{ai} \) equals 1 if \( a \) interacts with \( i \), otherwise it equals 0. Bayesian Personalized Ranking (BPR) is an advanced latent factor based model for dealing with implicit feedback [28]. Instead of modeling users’ predicted preference in a point wise setting, BPR is based on the pairwise ranking loss of items, such that the observed implicit feedbacks are ranked higher than that of the unobserved ones. In particular, by applying the latent factor based prediction function in Eq.(1), a widely used loss function in BPR is defined as:

\[
\min \mathcal{L} = \sum_{a=1}^{M} \sum_{(i,j) \in \mathcal{D}_a} \sigma(\hat{R}_{ai} - \hat{R}_{aj}) + \lambda ||\Theta||^2 \tag{2}
\]

with \( \sigma(x) \) is a logistic function. The training data for user \( a \) is \( \mathcal{D}_a = \{(i,j) | i \in R_a \land j \in V - R_a\} \), where \( R_a \) denotes the set of implicit positive feedbacks of \( a \) (i.e., \( R_{ai} = 1 \)), and \( j \in V - R_a \) is an unobserved feedback. Thus, the first part of the above loss function defines the training loss, and the second part is a regularization parameter with \( \lambda \) denotes the balance parameter that needs to be tuned.

3 The Proposed Model

In an online social image platform, there are a set of users \( U (|U| = M) \) and a set of images \( V (|V| = N) \). As shown in Figure 1, each image is associated with a deep visual feature vector \( \mathbf{F}_i \), which can be pre-trained from a Convolutional Neural Network (CNN) [17, 29]. In fact, representing images with pre-trained visual features from CNNs is a common practice in many recommendation tasks with image information [10, 31, 35]. As to users’ behaviors, besides rating images as standard recommender systems, users also perform another two kinds of behaviors on this social image platform: uploading images and building social links. We represent users’ three kinds of behaviors with three matrices: a rating matrix \( \mathbf{R} \in \mathbb{R}^{M \times N} \), an upload matrix \( \mathbf{L} \in \mathbb{R}^{M \times N} \), and a social link matrix \( \mathbf{S} \in \mathbb{R}^{M \times M} \). As we focus on implicit feedback, each element \( R_{ai} \) in the rating matrix \( \mathbf{R} \) represents the implicit rating preference of user \( a \) to image \( i \), with \( R_{ai} = 1 \) denotes user \( a \) likes image \( i \), otherwise it equals 0. \( S_{ab} = 1 \) if user \( a \) follows (connects to) user \( b \), otherwise it equals 0. If the social platform is undirected, a connects to \( b \) means \( S_{ab} = 1 \) and \( S_{ba} = 1 \). We use \( S_a \) to denote the userset that \( a \) connects. Please note that different from traditional social networking platforms (e.g., the social movie sharing platform), users in these platforms are both image consumers (i.e., reflected in the rating behavior) and image creators (reflected in the upload behavior). Each element \( L_{ai} \) in the upload matrix \( \mathbf{L} \) denotes whether the image \( i \) is uploaded (created) by user \( a \). In other words, if \( a \) is the creator of image \( i \), then \( L_{ai} = 1 \), otherwise it equals 0. Since each image can be uploaded by only one user, we have \( \sum_{a=1}^{M} L_{ai} = 1 \). For ease of explanation, we use \( C_i \)
to denote the creator of image $i$. And the images that are uploaded by user $a$ is denoted as a set $L_a = [i : L_{ai} = 1]$. Without confusion, we use $a, b, c, u$ to represent users and $i, j, k, v$ to denote items.

With heterogeneous data introduced as above, our goal is to predict each user’s unknown preference to image $i$ based on various social contextual information from social matrix $S$ and upload matrix $L$. Specifically, the social influence aspect from each user $a$’s social network structure $S_a$ is well recognized as an important factor in the recommendation process. The social influence states that, each active user is influenced by her social connections, leading to the similar preferences between social connections. Besides, for each user-item pair $(a, i)$, we could get an upload history list $L_a$ of user $a$, and the creator $C_i$ of image $i$ from the upload matrix $L$. Based on this observation, we design another two contextual aspects in users’ preference decision process: an upload coherence aspect that explains the consistency between her upload history $L_a$ and her preference for images, and the creator admiration aspect that shows the admiration from the creator $C_i$. These three contextual aspects characterise each user’s implicit feedback to images in various contextual situations from the heterogeneous social image data. Since each user may has her own uniqueness for these contextual aspects, understanding the underlying reasons for their like behavior benefit both transparent and accurate recommendation. In the following of this section, we detail how to model these three social contextual aspects in the image recommendation process. Now, we define the social contextual image recommendation problem as:

**Definition 1** [PROBLEM DEFINITION] Given the user rating matrix $R$, the upload matrix $L$, and the social network $S$, the social contextual recommendation task aims at: (1) Predict each user $a$’s unknown preference to image $i$ with various social contextual inputs as $g(a, i, L_a, S_a, C_i, F_i)$; (2) quantify the importance of three contextual aspects (i.e., $S_a$, $L_a$, and $C_i$) that explain each user $a$’s decision to a particular image $i$.

Specifically, in the above definition, $S_a$, $L_a$, $C_i$ denotes the inputs of the three social contextual aspects, i.e., upload coherence aspect, social influence aspect and the creator admiration aspect. And $F_i$ is the visual feature of image $i$, which would be incorporated in the modeling process.

In the following of this section, we present our proposed Hierarchical Attentive Social Contextual recommendation (HASC) model for the above problem in detail. We start with the overall framework of HASC, followed by the detailed social contextual formulations of each part in the proposed framework. We then give the optimization goal in the end of this section.

![Figure 2: The overall architecture of the proposed HASC model.](image)

### 3.1 The Overall Framework

As shown in Figure 2, HASC is a hierarchical neural network that models users’ preference scores to unknown im-
ages from two hierarchical levels with social contextual modeling. The top layered network depicts the importance of the three contextual aspects (i.e., upload coherence, social influence and creator admiration) for users’ decision, which is derived from the bottom layered network that aggregates the complex elements within each aspect. Given a user $a$ and image $i$ with three social contextual aspects, we use $\gamma_{al}$ ($l = 1, 2, 3$) to denote $a$’s attentive degree for aspect $l$ on the top layer (denoted as the aspect importance attention with orange part in the figure). A large attentive degree denotes the current user cares more about this aspect in image recommendation process. Specifically, there are various elements within the upload coherence context $L_a$ and social influence context $S_a$. We use $\alpha_{aj}$ to denote $a$’s preference degree for image $j$ in the upload coherence context $L_a$ ($j \in L_a$), with a larger value of $\alpha_{aj}$ indicates that $a$’s current interest is more coherent with uploaded image $j$ by user $a$. Similarly, we use $\beta_{ab}$ to denote the influence strength of the $b$ to $a$ in social neighbor context $S_a$ ($b \in S_a$), with a larger value of $\beta_{ab}$ indicates that $a$ is more likely to be influenced by $b$. Please note that, for each user $a$ and image $i$, different from the upload coherence aspect and the social influence aspect, the creator admiration aspect is composed of one element $C_i$ (the creator). Thus, this aspect does not have any sub layers and it is directly sent to the top layer. We use three attention sub-networks to learn these attentive scores in a unified model. Specifically, we employ the upload coherence attention network to obtain each user’s representation from her upload history (the blue part in Figure 2), and the social influence attention network to generate the social neighbors’ aggregated representations (the blue part in Figure 2). The output of these two bottom layer representations, associated with the creator admiration, are sent to the top layer of the aspect importance attention subnetwork to get each user’s final representation. The learned attentive scores in each layer explain the contribution of elements of this layer for the recommendation.

Objective Prediction Function. In addition to parameterize each user $a$ with a base embedding $P_a$ and each item $i$ with a base embedding $W_i$ as many latent factor based models [28, 16], we also take the inputs of the three social contextual aspects: the set of items $L_a$ that is uploaded by $a$, the set of users $S_a$ that $a$ follows, and the corresponding creator $C_i$. 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 $P_a$ to denote her base latent interest in the standard latent factor based models, and an auxiliary embedding vector $Q_a$. This auxiliary user embedding vector characterizes each user’s preference from the social contextual aspects that could not be detected by standard user-item rating behavior. Similarly, each image $i$ is also associated with two embeddings: a base embedding $W_i$ to denote the basic image latent vector, and an auxiliary vector $X_i$ to characterize each image from the social contextual inputs. Thus, by combining the attention mechanism with the embeddings, we model each user $a$’s predicted preference to image $i$ as a hierarchical attention:

$$
\hat{R}_{ai} = W^T_i \times (P_a + \gamma_{a1}X_a + \gamma_{a2}Q_a + \gamma_{a3}Q_{C_i})
$$

where $X_a = \sum_{j \in L_a} \alpha_{aj}X_j$, $Q_a = \sum_{b \in S_a} \beta_{ab}Q_b$. (3)

In the above predicted function, the representations of three contextual aspects are seamlessly incorporated in the predicted function. Specifically, the first line of Eq.(3) is a top layer attention network that aggregates the three contextual aspects for user embedding. The detailed attention subnetworks of the upload coherence attention and the social influence attention are listed in the second row. In fact, the attentive weights ($\gamma_{al}, \alpha_{aj},$ and $\beta_{ab}$) relies on our designed attention networks that takes user embeddings, image embeddings, and the image visual representations as input. We leave the details of how to model these three attention based networks and learn the model parameters in the following subsections. Next, we show the soundness of the predicted preference score in Eq 3.

Relations to Other Models. By rewriting the predicted preference score in Eq 3, we have:

$$
\hat{R}_{ai} = \frac{P_a^T \times W_i}{\gamma_{a1} \sum_{j \in L_a} \alpha_{aj}X_j^T W_i} + \underbrace{\gamma_{a2} \sum_{b \in S_a} \beta_{ab}Q_b^T \times W_i}_{\text{Social Neighborhood Model}} + \underbrace{\gamma_{a3}Q_{C_i}^T \times W_i}_{\text{Owner Admiration Bias}},
$$

Item Neighborhood Model
where the first part is a basic latent factor model, and the following three parts are extracted from the three contextual aspects. In the last three terms, \( X_i^j W_i \) can be seen as the similarity function between image \( i \) and the user's uploaded image \( j \) in the neighborhood-based collaborative filtering from the upload coherence aspect \([16]\). \( Q_j^i W_i \) represents the social neighbor's preference to image \( i \) with the social influence aspect. In fact, social scientists have long converged the social correlation of users’ interests for items, thus the social neighbor could well complement each user’s sparse action data to alleviate the data sparsity and enhance accuracy of the predicted preference \([3]\). 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.

Please note that, if we replace all the attention scores to the equal weights (i.e., \( \alpha_{ai} = \frac{1}{|L_{ai}|} \), \( \beta_{ab} = \frac{1}{|N_{ab}|} \), and \( \gamma_{al} = \frac{1}{L} \), our model turns to an enhanced SVD++ model with rich social contextual information modeling \([16, 36]\). However, this fixed weight assignment treats each user, each aspect, and the elements in each aspect equally. In fact, each user has different considerations for these three contextual aspects. By using hierarchical attention networks, we could learn each user’s attentive weights from their historical behaviors.

3.2 Hierarchical Attention Network Modeling

In this subsection, we would follow the bottom-up step to introduce the above mentioned hierarchical attention networks. Specifically, we would first introduce the two low layered attention networks: the upload coherence attention network and the social influence attention network, followed by the top layered aspect importance attention network that is based on the above two low layered attention networks.

Upload Coherence Attention. The goal of the upload coherence attention is to select the images from each user \( a \)'s upload history that are representative to \( a \)'s preference, and then aggregates this upload coherence contextual information to characterize each user. Given each image \( j \) that is uploaded by \( a \), we model the upload coherence attentive score \( \alpha_{aj} \) as:

\[
\alpha_{aj} = \sigma(w_2 \times (W_1 \times [P_a, Q_a, X_j, W_j, F_i, F_a]))
\]

where \( \sigma(x) \) is a sigmoid function. \( \Theta_a = [W_1, w_2] \) is the parameter set in this attention network, with \( W_1 \) denotes the matrix parameter and \( w_2 \) denotes the parameters of the sigmoid function. \( P_a \) and \( Q_a \) are the basic and auxiliary embeddings of user \( a \). Similarly, \( X_j \) and \( W_j \) are the basic and auxiliary embeddings of item \( j \). Besides, \( F_i \) and \( F_a \) are the visual representations of the user and image in the visual space. As illustrated before, it is easy to get the visual representation \( F_i \) of each image \( i \) from pre-trained CNNs. With the pre-trained image visual representations, each user \( a \)'s visual representation \( F_a \) is represented in the same visual space as images, which can be summarized from the implicit rating feedbacks of user \( a \) as:

\[
F_a = \frac{\sum_{j=1}^{N} R_{aj} F_j}{\sum_{j=1}^{N} R_{aj}}.
\]

In the above equation, we use an average pooling operation that aggregates each user’s visual representation into a fixed-length vector from \( a \)'s preference history. In fact, the pooling technique is an effective operation in neural networks and empirically shows better results with much lower storage cost \([17, 29]\). Commonly used pooling techniques include max pooling and average pooling. As the focus of our paper is not to design more sophisticated visual representation of users, we adopt this average pooling for user visual feature construction, and leave the exploration of different pooling techniques in the future work. Then, the final attentive upload coherence score \( \alpha_{aj} \) is obtained by normalized the above attention scores as:

\[
\alpha_{aj} = \frac{\exp(\alpha_{aj})}{\sum_{k \in L_a} \exp(\alpha_{ak})}.
\]

After we obtain the attentive upload coherence score \( \alpha_{aj} \), the upload coherence context of user \( a \), denoted as \( \tilde{X}_a \), is calculated as the a weighted combination as:

\[
\tilde{X}_a = \sum_{j \in L_a} \alpha_{aj} X_j.
\]

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**Upload Coherence Attention.** The goal of the upload coherence attention is to select the images from each user a’s upload history that are representative to a’s preference, and then aggregates this upload coherence contextual information to characterize each user. Given each image j that is uploaded by a, we model the upload coherence attentive score \( \alpha_{aj} \) as:

\[
\alpha_{aj} = \sigma(w_2 \times (W_1 \times [P_a, Q_a, X_j, W_j, F_j, F_a]))
\]

where \( \sigma(x) \) is a sigmoid function. \( \Theta_a = [W_1, w_2] \) is the parameter set in this attention network, with \( W_1 \) denotes the matrix parameter and \( w_2 \) denotes the parameters of the sigmoid function. \( P_a \) and \( Q_a \) are the basic and auxiliary embeddings of user a. Similarly, \( X_j \) and \( W_j \) are the basic and auxiliary embeddings of item j. Besides, \( F_i \) and \( F_a \) are the visual representations of the user and image in the visual space. As illustrated before, it is easy to get the visual representation \( F_i \) of each image i from pre-trained CNNs. With the pre-trained image visual representations, each user a’s visual representation \( F_a \) is represented in the same visual space as images, which can be summarized from the implicit rating feedbacks of user a as:

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\]

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\[
\tilde{X}_a = \sum_{j \in E_a} \alpha_{aj} X_j.
\]

### 3.4 Model Learning

Since we focus on implicit feedbacks of users, similar as the widely used ranking based loss function in BPR [28], we also design a ranking based loss function to optimize the overall performance as:

\[
\min_{\Theta} L = \sum_{a=1}^{M} \sum_{(i,j) \in D_a} \sigma(\hat{R}_{ai} - \hat{R}_{aj}) + \lambda||\Theta||^2
\]

where \( \Theta = [\Theta_1, \Theta_2] \), with \( \Theta_1 = [P, Q, W, X] \) denotes the embedding matrices and \( \Theta_2 = [\Theta_u, \Theta_v, \Theta_a] \) denotes the parameters in each attention network. \( \lambda \) is a regularization term that regularizes the user and image embeddings. \( D_a = \{(i,j)|i \in R_a \wedge j \in V - R_a\} \) is the training data for a with \( R_a \) the imageset that a positively shows feedback.

Since all the parameters in the above loss function are differentiable, in practice, we implement HASC with TensorFlow to train model parameters with mini-batch Adam. The detailed training algorithm is shown in Algorithm 1. As we only observe positive feedbacks of users with huge missing unobserved values, similar as many implicit feedback works, for each positive feedback, we randomly sample 5 missing unobserved feedbacks as pseudo negative feedbacks at each iteration in the training process [12] [31] [5]. As each iteration the pseudo negative samples change, each missing value gives very weak negative signal.

### 4 Experiments

In this section, we would show the effectiveness of our proposed model from the following directions: 1) How does our proposed model perform compared to the baselines (Sec.4.2)? 2) How does the model perform under different sparsity (Sec.4.3)? 3) How does the proposed social contextual aspects and the hierachical attention perform (Sec.4.4)? and 4) Can our proposed attention network learn personalized attention scores for explanation (Sec.4.5)?
4.1 Experimental Settings

Dataset. To the best of our knowledge, there is no public available dataset that contains heterogeneous data sources in a social image based network as described in Figure 1. To show the effectiveness of our proposed model, we crawl a large dataset from one of the largest social image sharing platform Flickr, which is extended from the widely used NUS-WIDE dataset [7, 30]. NUS-WIDE contains nearly 270,000 images with 81 human defined categories from Flickr. Based on this initial data, we get the uploader information according to the image IDs provided in NUS-WIDE dataset from the public APIs of Flickr. We treat all the uploaders as the initial user set, and the associated images and the image set. We then crawl the social network of the user set, and the implicit feedbacks of the user set to the image set.

After data collection, in data preprocessing process, we filter out users that have less than 2 rating records and 2 social links. We also filter out images that have less than 2 records. We call the filtered dataset as $F_L$. As shown in Table 2, this dataset is very sparse with about 0.15% density. Besides, we further filter $F_L$ dataset to ensure each user and each image have at least 10 rating records. This leads to a smaller but denser dataset as $F_S$, denoting it is a smaller dataset compared to $F_L$. Table 2 shows the statistics of the two datasets after pruning. Please note that the number of images is much higher than that of the users. This is consistent with the observation that the images far exceed the users on the social image platform [1], as each user could be a creator to upload multiple images. In data splitting process, we follow the leave-one-out procedure in many research works [5, 12]. Specifically, for each user, we select the last rating record as the test data, and the remaining data are used as the training data. To tune model parameters, we randomly select 5% of the training data to constitute the validation dataset.

### Table 2: The statistics of the two datasets.

|       | Users | Images | Ratings | Social Links | Rating Density |
|-------|-------|--------|---------|--------------|---------------|
| $F_S$ | 4,418 | 31,460 | 761,812 | 184,991      | 0.55%         |
| $F_L$ | 8,358 | 105,648| 1,323,963| 378,713      | 0.15%         |

Evaluation Metrics. Since we focus on recommending images to users, we use two widely adopted ranking metric for top-K recommendation evaluation: the Hit Ratio (HR) and Normalized Discounted Cumulative
Algorithm 1 The learning algorithm of the proposed HASC model

**Input:** Rating matrix $R$, social matrix $S$, Uploader matrix $L$;

**Output:** Latent embedding matrix $\Theta_1 = [P, Q, W, X]$ and parameters in the attention networks $\Theta_2$;

1: Initialize model parameter set $\Theta$ with small random values;
2: while Not converged do
3: for Each user-item pair $< a, i >$ in the training data do
4: Compute the upload influence (Eq. (9));
5: Compute the social influence (Eq. (10));
6: Compute the factor importance (Eq. (11));
7: Compute the predicted rating $\hat{R}_{ai}$ (Eq. (12));
8: for Each parameter $\theta$ in $[\Theta_1, \Theta_2]$ do
9: Update $\theta = \theta - \eta \frac{\partial L}{\partial \theta} \frac{\partial \hat{R}_{ai}}{\partial \theta}$ (Eq. (13));
end for
end for
end while
13: Return $\Theta_1 = [P, Q, W, X]$ and parameters in the attention $\Theta_2$.

Gain (NDCG) [10, 5]. HR measures the percentage of images that are liked by users in the top-K list, and NDCG gives a higher score to the hit images that are ranked higher in the ranking list. As the image size is huge, it is inefficient to take all images as candidates to generate recommendations. For each user, we randomly select 1000 unrated images as candidates, and then mix them with the records in the validation and test data to select the top-K results. This process is repeated for 10 times and we average the results [10, 5]. For both metrics, the larger value, the better the ranking performance.

**Baselines.** We compare our proposed HASC model with the following baselines:

- **BPR:** it is a classical ranking based latent factor based model for recommendation with competing performance. This method has been well recognized as a strong baseline for recommendation [28].

- **SR:** it is a social based recommendation model that encodes the social influence among users with social regularization in classical latent factor based models [23].

- **ContextMF:** this method models various social contextual factors, including item content topic, user personal interest, and inter-personal influence in a unified social contextual recommendation framework [15].

- **VBPR:** it extends BPR by modeling both the visual and latent dimensions of users’ preferences in a unified framework, where the visual dimension is derived from a pre-trained convolutional neural network [10].

- **ACF:** it models the item level implicit feedback in image recommendation with an item level attention module models the item preference. For fair comparison, we enrich this baseline by leveraging the upload history as users’ additional feedback in this model [5].

- **VPOI:** it is a visual based POI recommendation algorithm that considers the associated images with each POI and the uploaded image of each user. To adapt the POI recommendation to image recommendation task, we treat the associated images of each user as the uploaded images by her. [31]

**Visual Feature Extraction.** In our proposed model, we need to get each image $i$’s visual feature $F_i$. We choose VGG16 model for visual feature extraction as it is a state-of-the-art convolutional neural network architecture, and has shown powerful performance for extracting high-level visual features [29]. Given any input image, we have a ground truth classification of this image from 81 concepts. The concepts of these images are derived from the NUS-WIDE dataset and are empirically labelled by experts [7]. As commonly adopted by many works, we use the 4096 dimensional representation in the last connected layer in VGG16 as the visual representation of the image, i.e., each image visual feature $F_i$ has 4096 dimensions [10, 35].

**Parameter setting.** There are two important parameters in our proposed model: the dimension $D$ of the user and image embeddings, and the regularization parameter $\lambda$ in the objective function (Eq. (13)). We choose $D$ in $[10, 15, 20, 30]$ and $\lambda$ in $[0.001, 0.01, 0.1]$, and perform grid search to find the best parameters. The best setting is $D = 15$ and $\lambda = 0.01$. We find the dimension of the attention networks does not impact the results much, we empirically set the dimensions of the parameters in the attention networks as 20 (i.e., parameters in $\Theta_2$). To initialize the model, we randomly set the weights in the attention network with small random values. Since the objective function of HASC is non-convex, we initialize $P$ and $W$ from the basic BPR model, and $Q$ and $X$ with small random values to speed up convergence. We use
mini-batch gradient descent to optimize the model, where the batch size is 512. There are several parameters in the baselines, for fair comparison, all the parameters in the baselines are also tuned to have the best performance.

### 4.2 Overall Performance

Figure 3 shows the overall performance of all models on HR@K and NDCG@K on the two datasets with varying sizes of $K$, where the left two subfigures depict the results on F$_S$ dataset and the right two subfigures depict the results on F$_L$ dataset. As shown in this figure, our proposed HASC model always performs the best. With the increase of the top-K list size, the performance of all models increase. The performance trend is consistent over different top-K values and different metrics. We find that considering either the social network or the visual image information could alleviate the data sparsity problem and improve recommendation performance. E.g., VBPR improves over BPR about 3% by incorporating the visual information in the modeling process. ACF further improves VBPR by assigning the attentive weights to different images the user rated and uploaded in the past. SR also has better performance as it leverages the social network information, and ContextMF further improves the performance with content modeling. On average, our proposed model more than 15% on NDCG@K on F$_L$ over BPR baseline of NDCG@5. Last but not the least, by comparing the results of F$_S$ and F$_L$, we observe that for each method, the results on F$_L$ always outperform F$_S$. We guess a possible reason is that, though F$_S$ is denser than F$_L$, the larger F$_L$ has nearly two times as many records as F$_S$ for training. As the overall trend is similar on the two metric with different values of $K$, in the following of the subsections, for page limit, we only show the top-5 results.

### 4.3 Performance under Different Data Sparsity

A key characteristic of our proposed model is that it alleviates the data sparsity issue with various social contextual aspects modeling. In this subsection, we investigate the performance of various models under different data sparsity. We mainly focus on the F$_L$ dataset as it is more challenging with sparser user rating records compared to the denser F$_S$ dataset. Specifically, we bin users into different groups based on the number of the observed feedbacks in the training data, and then show the performance under different groups. Figure 4 shows the results, where the left part summarizes the user group distribution of the training data, and the right part depicts the performance with different data sparsity. As shown in the left part, more than 5% users have less than 8 ratings, and 20% users have less than 16 ratings with more than 1.3 million images on the F$_L$ dataset. When the rating scale is very sparse, the BPR baseline that only relies on the rating matrix, can not work well on this situation. The improvement is significant for all models over BPR as these models utilized different auxiliary data for recommendation. E.g., when users have less than 8 ratings, our proposed HASC model improves over BPR by more than 25%. As user rating scale increases, the performance of all models increase quickly as we have more rating records for training, and HASC still consistently outperforms the baselines.

### 4.4 Attention Analysis

In this part, we conduct experiments based on different combinations of the designed three contextual aspects in HASC. Particularly, if we simply set the attentive scores with the average pooling (i.e., $\alpha_{ai} = \frac{1}{|L_a|}$, $\beta_{ab} = \frac{1}{|S_a|}$, $\gamma_{al} = \frac{1}{2}$), our model degenerates to an enhanced SVD++ with social contextual modeling but without any attentive modeling. If we do not contain any social contextual modeling, our model degenerates to the BPR model \cite{28}. As shown in Table 3, each aspect improves the performance, with the upload coherence aspect shows the best improvement. And the attention modeling always performs better results than its corresponding part with the average attention score. When we combine all social contextual aspects with hierarchical attention, the model reaches the best performance.

Besides, as shown in Eq. (9), Eq.(?), and Eq.(?), we also learn the attention weights with different kinds of input information. For each attention layer, it consists three kinds of inputs: the base embeddings (i.e., $P_a$ and $W_i$), the auxiliary embeddings (i.e., $Q_a$ and $X_i$), and the visual representations (i.e., $F_a$ and $F_i$). Table 4 shows the performance of HASC with different attention input information. This table clearly shows that, by combining the three different kinds of inputs for attention modeling,
the proposed HASC could achieve the best performance.

4.5 Hierarchical Attention Visualization

By learning the hierarchical attention score of each aspect, and the attentive score of each element within each aspect, HASC provides a quantitative evaluation that explains each user’s preference. We provide several examples in Figure 5, where the left part shows the test image record that is accurately predicted by HASC. The middle part shows the learned attentive weights for the three social contextual aspects, and the right part depicts the detailed attentive weights of the elements in the aspect that have the largest attention scores. As can be seen from this figure, each user has her unique preference for balancing these three contextual aspects. E.g., for user 1, she has a large attentive score of 0.83 for the upload coherence aspect. In the upload coherence aspect, we list the learned $\alpha_{1i}$ values of several images she upload. As can be seen from the right part, each uploaded image that is similar to the test image has a large upload coherence score. For example, the first upload image is similar to the test image with desserts, thus the learned coherence score is high. For user 2, she prefers the social influence aspect from the three contextual aspects. Also, the learned social influence strength from each connected user is different.
5 Conclusions

In this paper, we have proposed a hierarchical attentive social contextual model for social 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 coherence aspect, the social influence aspect, and the owner admiration aspect. By leveraging the image and user visual features learned from convolutional neural networks, we have designed a hierarchical attention network that automatically learns users’ personalized weights for these contextual aspects. Thus, our model can not only solve the data sparsity issue in recommendation with social contextual modeling, but also explain the underlying reasons for each user’s behavior with the learned hierarchical attention scores. 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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