Deep Matrix Factorization for Social Image Tag Refinement and Assignment

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Abstract—The number of images associated with user-provided tags has increased dramatically in recent years. User-provided tags are incomplete, subjective and noisy. In this work, we focus on the problem of image tag refinement and assignment. Different from previous work, we propose a novel Deep Matrix Factorization (DMF) algorithm, which uncovers the latent image representations and tag representations embedded in the latent subspace by exploiting the weakly-supervised tagging information and visual information. Due to the well-known semantic gap, the hidden representations of images are learned by a hierarchical model, which are progressively transformed from the visual feature space. It can naturally embed new images into the subspace using the learned deep architecture. Besides, to remove the noisy or redundant visual features, a sparse model is imposed on the transformation matrix of the first layer in the deep architecture. Finally, a unified optimization problem with a well-defined objective function is developed to formulate the proposed problem. Extensive experiments on real-world social image databases are conducted on the tasks of image tag refinement and assignment. Encouraging results are achieved with comparison to the state-of-the-art algorithms, which demonstrates the effectiveness of the proposed method.

I. INTRODUCTION

In real-world applications, many photo sharing websites, such as Flickr, Picasa, Zoomr and Facebook, have been becoming popular, which facilitate millions of users to upload, share and tag their images. It leads to the dramatic increase in the number of images associated with user-provided tags. For example, the Verge reported in March 2013 that Flickr had more than 3.5 million new images uploaded daily [1]. It sheds new light on the problem of image understanding. Unfortunately, these tags are provided by amateur users and are imperfect, i.e., they are often incomplete or inaccurate in describing the visual content of images, which brings challenges to the tasks of image understanding such as tag-based image retrieval. In this work, we focus refining the user-provided tags to complement relevant tags and remove the irrelevant tags, and assigning tags to new images.

Tag refinement is to remove irrelevant tags from the initial tags associated with images and add relevant but missing tags [2], [3], [4], [5], [6], [7], [8]. By jointly utilizing the labeled and unlabeled data, a kNN-sparse graph-based semi-supervised learning method is proposed to refine tags of social images in [2]. In [3], a latent space is identified based on low rank approximation to link the visual features of images and tags. The image-tag relevance which is consistent with the original image-tag relation and the visual similarity is refined in [5]. Image-specific and tag-specific linear sparse reconstructions are introduced for automatic image tag completion in [6]. However, most of them cannot directly incorporate new images into the learned model, i.e., the out-of-sample problem. Unlike most existing studies, the proposed work simultaneously addresses the problems of image tag refinement and tag assignment assigning tags to new images. There are also few previous work [9] dealing with the image tag refinement and tag assignment simultaneously. In [8], a novel framework is proposed to learn a robust subspace for social image understanding. However, compared with the tag information, visual feature is a much lower level representation on semantics, and there exists the well-known semantic gap between visual representation and semantic meaning [10] making it challenging. It is unsuitable to directly transform the visual features to the latent representations by a flat model.
as shown in Fig. 1a and the performance is often unsatisfied.

Towards this end, in this work we propose a novel Deep Matrix Factorization (DMF) framework to refine the initial tags and assign tags to new images. Figure 2 illustrates the flowchart of the proposed framework. It learns the latent image representations and the latent tag representations in the latent subspace by jointly leveraging the weakly-supervised tagging information and visual information. To better handle the semantic gap, a deep architecture as illustrated in Fig. 1b is developed to learn the latent image representations by a progressive way, which can automatically learn the intermediate hidden representations. Besides, a sparse model with the $\ell_{2,1}$ mixed norm is imposed on the transformation matrix of the first layer to filter out the noisy or redundant visual features, since the original visual features are always correlated or redundant to each other, and sometimes noisy. The above principles are jointly formulated into a unified optimization problem. To empirically validate the effectiveness of the proposed method, extensive experiments are conducted on two widely utilized real-world datasets on the tasks of image tag refinement, image tag assignment and image retrieval. The achieved outperforming results compared with several representative methods demonstrate the superiority of the proposed method.

The main contributions of this paper are summarized as follows.

- To our best knowledge, it is the first work to propose a deep matrix factorization framework for image tag refinement and assignment.
- A Deep Matrix Factorization (WDMF) framework is proposed by leveraging the heterogenous data of social images, i.e., the weakly-supervised tagging information and the visual information.
- In the proposed framework, the problems of the imperfect tagging information and the redundant or noisy visual features are jointly addressed.

The remainder of this paper is organized as follows. In Section II, we discuss previous work on image tag refinement and matrix factorization based latent factor learning. Section III elaborate the proposed DMF framework with the optimization algorithm. The experimental evaluations and discussions are presented in Section IV. Section V concludes this paper with future research directions.

II. RELATED WORK

A. Social Image Analysis

Social image tag refinement is to remove the noisy or irrelevant tags and add the relevant tags. In [11], the group information of images from Flickr is exploited with the assumption that the images within a batch are likely to have a common style. Based on the low-rank matrix decomposition model [12], Zhu et al. [13] proposed to decompose the image-tag matrix by considering the content consistency and tag correlation. The low rank matrix recovery is combined with maximum likelihood estimation to recover the missing tags and de-emphasize the noisy tags in [14]. Tag co-occurrence is used to find the related tags with the original tags in [15].
visual similarity is learned. However, most of them cannot directly handle new images out of the learning image set. Many neighbor voting based approaches have been proposed for image tag refinement [17], [18]. However, they treat each image selected as the neighbor one either equally or simply based on its visual similarity. Some researchers focus on label propagation to refine tags of social images [2], [19]. Few previous approaches [9] are designed to address the image tag refinement and tag assignment simultaneously.

### B. The Proposed Formulation

In the deep architecture, the latent image representations in the uncovered subspace are learned in layers. Let us assume that the proposed hierarchical structure has $M$ layers. The proposed DMF model factorizes the observed image tagging matrix $F$ into $M + 1$ factor matrices, i.e., $V$, $U_M$, $U_{M-1}$, $U_2$, $U_1$. To better exploit the visual features of images and deal with new images, the output of the first layer is transformed from the visual space, i.e., $U_1 = W_1 X$. Besides, in this work, since we focus on explaining our basic idea rather than designing a complex objective function, a deep neural network is constructed to discover the hidden representations using multiple layers of linear transformations rather complex nonlinear transformations. As a consequence, the proposed factorization model is obtained as follows.

\[
F \leftarrow V U_M \\
U_M = W_M U_{M-1} \\
U_2 = W_2 U_1 \\
U_1 = W_1 X
\]

Here $W_m (m = 1, \cdots, M)$ is the transformation matrix of the $m$-th layer. $V$ is the latent tag feature matrix in the subspace and $U_m$ is the implicit representation matrix of images in the $m$-th layer. In this work, the output of the most top layer $U$ is computed as $U = U_M$. From above equations, it can be observed that the problem of learning $M + 1$ factor matrices becomes the problem of learning one factor $V$ and $M$ transformation matrices $W_M, \cdots, W_1$.

The proposed framework is formulated as the following unified objective function.

\[
\min_{V, W_M, \cdots, W_1} \frac{1}{2} \|F - VU_M\|_F^2 + \frac{\lambda_1}{2} \|V\|_F^2 + \frac{\lambda_2}{2} \|W_1\|_{2,1}
\]

However, they treat each image selected as the neighbor one either equally or simply based on its visual similarity. Some researchers focus on label propagation to refine tags of social images [2], [19]. Few previous approaches [9] are designed to address the image tag refinement and tag assignment simultaneously.

### B. Matrix Factorization Based Latent Subspace Learning

Matrix Factorization (MF) is an effective latent factor learning model. Given a data matrix $Y \in \mathbb{R}^{l \times n}$, matrix factorization tries to two low rank factors whose multiplication can well approximate it.

\[
Y \approx V U
\]

Here $V \in \mathbb{R}^{l \times r}$ and $U \in \mathbb{R}^{r \times n}$ are the latent factor matrices with $r \leq \min (l, n)$. To avoid overfitting, two regularization terms are introduced.

\[
\min_{U, V} \frac{1}{2} \|Y - VU\|_F^2 + \frac{\lambda_1}{2} \|U\|_F^2 + \frac{\lambda_2}{2} \|V\|_F^2.
\]

$\| \cdot \|_F$ denotes the Frobenius norm. $\lambda_1$ and $\lambda_2$ are two positive parameters. It has a nice probabilistic interpretation with Gaussian observation noise as detailed in Probabilistic Matrix Factorization (PMF) [20].

Different variants of MF have been proposed, such as Multi-correlation PMF (MMPMF) [21] and robust matrix factorization [22]. If each element of the latent matrices is required to be nonnegative, it leads to Nonnegative Matrix Factorization (NMF) [23]. Trigeorgis et al. [24] proposed a deep Semi-NMF method to learn hidden representations. Different from the previous work, a new deep MF method is proposed to learn a series of transformation matrices for the hidden image features and tag features in the latent subspace.

### III. DEEP MATRIX FACTORIZATION

#### A. Preliminary

Throughout this work, bold uppercase characters and bold lowercase characters are utilized to denote matrices and vectors, respectively. For any matrix $A$, $a_i$ means the $i$-th column vector of $A$, $a_i$ means the $i$-th row vector of $A$. $A_{ij}$ denotes the $(i, j)$-element of $A$ and $\text{Tr}[A]$ is the trace of $A$ if $A$ is square. $A^T$ denotes the transposed matrix of $A$. The Frobenius norm of a matrix $A \in \mathbb{R}^{m \times n}$ is defined as $\|A\|_F = \sum_{i=1}^m \sum_{j=1}^n A^2_{ij} = \text{Tr}[A^T A]$. The $\ell_{2,1}$-norm for $A$ is defined as

\[
\|A\|_{2,1} = \sum_{i=1}^n \|a_i\|_2.
\]

Consider a social image set consisting of $n$ images $\{x_i\}_{i=1}^n$ assigned with $l$ user-provided tags $C = \{t_1, t_2, \cdots, t_l\}$. For each image $x_i$, the observed relationships between this image and tags can be represented as a $l$-dimensional binary-valued vector $\{y_i^t\}$. The visual feature matrix is denoted as $X = [x^1, \cdots, x^n]$, in which $x^j \in \mathbb{R}^d$ is the feature vector of the $i$-th image while $F = [f^1, \cdots, f^n] \in \mathbb{R}^{l \times n}$ is the tagging matrix, in which $F_{ji} = 1$ indicates that $x^i$ is associated with the $j$-th tag, and $F_{ji} = 0$ otherwise. $I_m \in \mathbb{R}^{m \times m}$ denotes the identity matrix.

#### B. The Proposed Formulation

In the deep architecture, the latent image representations in the uncovered subspace are learned in layers. Let us assume that the proposed hierarchical structure has $M$ layers. The proposed DMF model factorizes the observed image tagging matrix $F$ into $M + 1$ factor matrices, i.e., $V$, $U_M$, $U_{M-1}$, $U_2$, $U_1$. To better exploit the visual features of images and deal with new images, the output of the first layer is transformed from the visual space, i.e., $U_1 = W_1 X$. Besides, in this work, since we focus on explaining our basic idea rather than designing a complex objective function, a deep neural network is constructed to discover the hidden representations using multiple layers of linear transformations rather complex nonlinear transformations. As a consequence, the proposed factorization model is obtained as follows.
Here $U = W_M \cdots W_1 X$, $\alpha$, $\beta$ and $\mu$ are three positive trade-off parameters. $\lambda_1$ is a regularization parameter to avoid fitting, and $\lambda_2$ is a regularization parameter to control the sparsity in columns of $W_1$. For the regularization penalty on the transformation of the first layer, it can be seen as matrix-counterpart of the so-called “elastic net” penalty for vectors [25]. Since the visual features are often correlated or redundant to each other, and sometimes noisy, the sparse model in columns with $\ell_{2,1}$ mixed norm is introduced, which ensures $W_1$ sparse in columns. It can compress the redundant or noisy features.

C. Optimization

The joint optimization problem in Eq. 5 is not convex over all the variables $V$ and $W_m$ ($1 \leq m \leq M$) simultaneously. Thus, we propose an iterative optimization algorithm using the sub-gradient descent scheme. For ease of representation, we use notation $\mathcal{O}$ to denote the objective function in Eq. 5. The variables $V$ and $W_m$ ($1 \leq m \leq M$) are alternately updated by fixing other variables.

First, $V$ is solved with $W_m$ ($1 \leq m \leq M$) fixed. The derivative of $\mathcal{O}$ with respect to $V$ is calculated as follows.

$$\frac{\partial \mathcal{O}}{\partial V} = (VU - F)U^T + \beta LV + \lambda_1 V \quad (6)$$

Then, we solve $W_m$ by fixing $V$. The derivatives of $\mathcal{O}$ with respect to $W_m$ are obtained.

$$\frac{\partial \mathcal{O}}{\partial W_1} = \prod_{i=2}^{M} W_i^T V^T (VU - F)X^T + \lambda_1 W_1 + \lambda_2 W_1 D \quad (7)$$

$$\frac{\partial \mathcal{O}}{\partial W_m} = \prod_{i=m+1}^{M} W_i^T V^T (VU - F)U_{m-1}^T + \lambda_1 W_m \quad (8)$$

$$\frac{\partial \mathcal{O}}{\partial W_M} = V^T (VU - F)U_{M-1}^T + \lambda_1 W_M \quad (9)$$

Here $D \in \mathbb{R}^{d \times d}$ is a diagonal matrix with $D_{ii} = \frac{1}{2\|w_i\|_2}$. It is worth noting that in practice, $\|w_i\|_2$ could be close to zero but not zero. Theoretically, it could be zero. For this case, we can regularize $D_{ii} = \frac{1}{2\|w_i\|_2 + \epsilon}$, where $\epsilon$ is a very small constant.

Finally, $V$ and $W_m$ are updated by using the following gradient descent algorithm until convergence.

$$V = V - \eta \frac{\partial \mathcal{O}}{\partial V} \quad (10)$$

$$W_m = W_m - \eta \frac{\partial \mathcal{O}}{\partial W_m} \quad (11)$$

Here $\eta$ is the learning rate.

**Algorithm 1** summarizes the detailed procedure of the proposed WDMF approach. The utilized convergence criterion is that the number of iterations is more than $N_t$ or $|O_t - O_{t-1}| / O_{t-1} < \xi$, where $O_t$ is the value of the objective function in the $t$-th iteration.

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**Algorithm 1 The Proposed DMF Algorithm**

**Input:**

Visual feature matrix $X$, the tagging matrix $F$, the number of network layers $M$, learning rate $\eta$, iterative number $N_t$, and convergence error $\xi$.

1: Initialize $V$ and $W_m$ ($1 \leq m \leq M$); Set $D$ as an identity matrix;
2: **repeat**
3: //Forward propagation
4: for $m = 1, 2, \ldots, M$
5: Do forward propagation to get $U_m$;
6: **end**
7: //Computing gradient
8: Compute gradient according to Eq. 6;
9: for $m = M, M-1, \ldots, 1$
10: Obtain gradient $\partial \mathcal{O} / \partial W_m$ according to Eq. 7-9;
11: **end**
12: //Back propagation
13: Update $V$ according to Eq. 10;
14: for $m = 1, 2, \ldots, M$
15: Update $W_m$ according to Eq. 11;
16: **end**
17: Update the diagonal matrix $D$ as
18: **until** Convergence criterion satisfied

**Output:**

The latent tag matrix $V$, and transformation matrices $W_m$ ($1 \leq m \leq M$).

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D. Implementation

To expedite the proposed method and obtain better approximation of the latent factors, the designed deep architecture is first pre-trained, which can obtain initial matrices of $V$ and $W_m$. It has been widely implemented on deep networks, which can shorten the learning time. For the pre-training, we first utilize the regress model to learn $V_1$: $\min_{V_1} \|F - V_1 X\|_F^2 + \lambda_1 \|V_1\|_F^2$. With the learned $V_1$, we then decompose it: $V_1 \leftarrow V_2 W_1$. Now, we obtain $W_1$ and $V_2$, and then further decompose $V_2$. Following this, we have $V_M \leftarrow W M$. By now, all the layers have been pre-trained. Afterwards, each layer is fine-tuned by the proposed optimization algorithm in **Algorithm 1**. For new images, they can be directly embedded in the underlying subspace using the transformation matrices and tagged by the nearest tags in the hidden subspace.

IV. Experiments

A. Datasets

In this work, we conduct extensive experiments on two widely utilized social image datasets: MIRFlickr [26] and NUS-WIDE [27]. Table I summarizes some statistics of these data sets.
TABLE I: Statistics of the used datasets with image and tag counts in the format mean / maximum.

<table>
<thead>
<tr>
<th></th>
<th>MIRFlickr</th>
<th>NUS-WIDE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tag size</td>
<td>457</td>
<td>3,137</td>
</tr>
<tr>
<td>Concept size</td>
<td>18</td>
<td>81</td>
</tr>
<tr>
<td>Image size</td>
<td>25,000</td>
<td>269,648</td>
</tr>
<tr>
<td>Tags per image</td>
<td>2.7 / 45</td>
<td>7.9 / 201</td>
</tr>
<tr>
<td>Concepts per image</td>
<td>4.7 / 17</td>
<td>1.9 / 13</td>
</tr>
<tr>
<td>Images per tag</td>
<td>145.4 / 1,483</td>
<td>677.1 / 20,140</td>
</tr>
<tr>
<td>Images per concept</td>
<td>3.102.8 / 10,375</td>
<td>6,220.3 / 74,190</td>
</tr>
</tbody>
</table>

Data are randomly partitioned into two groups in our experiments: the learning data for image tag refinement and the testing data for image tag assignment. $n$ images are randomly chosen as the learning data while the rest ones are used as the testing data. The learning data is utilized to learn the proposed model and evaluate the performance of image tag refinement. The testing images are utilized to validate the effectiveness of image tag assignment. In our experiments, we set $n = 20,000$ and $n = 50,000$ for the MIRFlickr and NUS-WIDE datasets, respectively. To alleviate the instability introduced by the randomly partition, experiments are independently repeated 5 times to generate different learning and testing data, and report the average values of all the results. The experimental results on the learning data and the testing data are both reported.

B. Evaluation Metrics

To compare the effectiveness of methods, in our experiments we adopt the area under the receiver operating characteristic (ROC) curve, known as the AUC, as evaluation metric. AUC is currently considered to be the standard method for model comparison and a more faithful criterion used in many applications. Both the microaveraging and macroaveraging measures are utilized to evaluate both the global performance across multiple concepts and the average performance of all the concepts. Besides, the performance is also evaluated by using F1 measure. The mean F1 over concepts is presented.

C. Experimental Setting

To validate the performance of our method, we compare the proposed DMF method with one baseline and a number of related state-of-the-art algorithms. The compared methods are OT (The original user-provided tags from Flickr as the baseline.), PMF [20], NMF [23], LR [12] and DNMF [24]. For all the compared methods except the baseline method, there are some parameters to be set in advance. All the parameters corresponding to the overfitting regularization terms in the compared algorithms are set to 0.005. For the other hyperparameters, we adopt the same parameter configuration as described in their original reports. For the proposed DMF method, we set $\lambda_1 = 0.005$, $\lambda_2 = 0.01$ and empirically set the learning rate to 0.001. A deep network with three layers ($M = 3$) are learned. For all the matrix factorization methods, the dimension of the latent subspace $r$ is empirically set to 50.

D. Experimental Results

In the first set of experiments, different algorithms are evaluated for the task of image tag refinement and tag assignment. The corresponding experimental results for tag refinement in terms of the mean MicroAUC and mean MacroAUC on the MIRFlickr and NUS-WIDE datasets are presented in Table II. The compared performance for tag assignment is shown in Table III. It is worth noting that new images can be directly tagged by the proposed method while they are tagging using the neighbor voting scheme for the compared methods.

From the above experimental results, the following interesting observations are revealed. First, the proposed method achieves the best performance for image tag refinement and tag assignment, which well demonstrates the effectiveness of the proposed method. The proposed method can well address the out-of-sample problem while achieve good performance for tag refinement simultaneously. Second, compared with the original tags, the latent factor models achieve better results. It demonstrates that the latent factor models enable to complete the image tagging matrix. Third, by comparing the flat model and the deep model, i.e., NMF VS. DNMF and MF VS. DMF, the deep models achieve better results for both tag refinement and tag assignment, which can well demonstrate the advantage of the deep framework for social image analysis. Forth, for the tag assignment problem of new images, the proposed method obtains significant improvement over other methods. It verifies the effectiveness of the proposed scheme to tag new images. In a word, the proposed method can well address the problems of social image tag refinement and tag assignment simultaneously.

V. Conclusion

In this work, we proposed a deep matrix factorization method to find the latent image representations and tag representations embedded in the latent subspace. The hidden representations of images are progressively transformed from the visual feature space to handle the semantic gap. A sparse model is imposed on the transformation matrix of the first layer in the deep architecture to compress the noisy or redundant visual features. Extensive experiments are conducted to verify the effectiveness of the proposed method on two real-world social image databases. In future, the latent structures will be considered to be uncovered and incorporated into the deep framework.

Acknowledgment

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TABLE II: Experimental results (mean micro-auc ± standard deviation, mean macro-auc± standard deviation and mean F1 ± standard deviation) on the MIRFlickr and NUS-WIDE datasets for tag refinement. The best results are highlighted in bold.

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<td>MicroAUC</td>
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<tr>
<td>OT</td>
<td>0.587 ± 0.001</td>
<td>0.568 ± 0.001</td>
</tr>
<tr>
<td>PMF</td>
<td>0.617 ± 0.005</td>
<td>0.588 ± 0.006</td>
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<tr>
<td>NMF</td>
<td>0.623 ± 0.003</td>
<td>0.592 ± 0.005</td>
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<tr>
<td>LR</td>
<td>0.634 ± 0.005</td>
<td>0.603 ± 0.004</td>
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<tr>
<td>DNMF</td>
<td>0.639 ± 0.007</td>
<td>0.623 ± 0.005</td>
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<td>DMF</td>
<td>0.647 ± 0.006</td>
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TABLE III: Experimental results (mean micro-auc ± standard deviation, mean macro-auc± standard deviation and mean F1 ± standard deviation) on the MIRFlickr and NUS-WIDE datasets for tag assignment. The best results are highlighted in bold.

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