

# Image Tag Completion by Local Learning

Jingyan Wang<sup>1,2,3</sup>, Yihua Zhou<sup>4</sup>, Haoxiang Wang<sup>5</sup>, Xiaohong Yang<sup>6</sup>,  
Feng Yang<sup>6</sup>, and Austin Peterson<sup>7</sup>

<sup>1</sup> National Time Service Center, Chinese Academy of Sciences, Xi' an,  
Shaanxi 710600, China

[jingbinwang1@outlook.com](mailto:jingbinwang1@outlook.com)

<sup>2</sup> Graduate University of Chinese Academy of Sciences, Beijing 100049, China

<sup>3</sup> Provincial Key Laboratory for Computer Information Processing Technology,  
Soochow University Suzhou 215006, China

<sup>4</sup> Department of Mechanical Engineering and Mechanics, Lehigh University,  
Bethlehem, PA 18015, US

<sup>5</sup> Department of Electrical and Computer Engineering, Cornell University, Ithaca,  
NY 14850, USA

<sup>6</sup> College of Computer Science and Technology, Shandong University of Finance and  
Economics, Jinan 250014, China

<sup>7</sup> Electrical and Computer Engineering Department,  
The University of Texas at San Antonio, San Antonio, TX, 78249, USA

[austin.peterson1@outlook.com](mailto:austin.peterson1@outlook.com)

**Abstract.** The problem of tag completion is to learn the missing tags of an image. In this paper, we propose to learn a tag scoring vector for each image by local linear learning. A local linear function is used in the neighborhood of each image to predict the tag scoring vectors of its neighboring images. We construct a unified objective function for the learning of both tag scoring vectors and local linear function parameters. In the objective, we impose the learned tag scoring vectors to be consistent with the known associations to the tags of each image, and also minimize the prediction error of each local linear function, while reducing the complexity of each local function. The objective function is optimized by an alternate optimization strategy and gradient descent methods in an iterative algorithm. We compare the proposed algorithm against different state-of-the-art tag completion methods, and the results show its advantages.

**Keywords:** Image tagging, Tag completion, Local learning, Gradient descent.

## 1 Introduction

Recently, social network has been a popular tool to share images. When a social network user uploads an image, the image is usually associated with a tag/keyword which is used to describe the semantic content of this image. The tags provided by the users are usually incomplete. Zhang et al. designed and implemented a fast motion detection mechanism for multimedia data on mobile

and embedded environment [25]. Recently, the problem image tag completion is proposed in the computer vision and machine learning communities to learn the missing tags of images [22,11,10,1,23]. This problem is defined as the problem of complete the missing elements of a tag vector of a given image automatically.

In this paper, we investigate the problem of image tag completion, and proposed a novel and effective algorithm for this problem based on local linear learning. We propose a novel and effective tag completion method. Instead of completing the missing tag association elements of each image, we introduce a tag scoring vector to indicate the scores of assigning the image to the tags in a given tag set. We propose to study the tag scoring vector learning problem in the neighborhood of each image. For each image in the neighborhood, we propose to learn a linear function to predict a tag scoring vector from a visual feature vector of its corresponding image feature. We propose to minimize the perdition error measure by the squared  $\ell_2$  norm distance over each neighborhood, and also minimize the squared  $\ell_2$  norm of the linear function parameters. Besides the local linear learning, we also proposed to regularize the learning of tag scoring vectors by the available tags of each image. We construct a unified objective function to learn both the tag scoring vectors and the local linear functions. We develop an iterative algorithm to optimize the proposed problem. In each iteration of this algorithm, we update the tag scoring vectors and the local linear function parameters alternately.

This rest parts of paper are organized as follows: in section 2, we introduced the proposed method. In section 3, we evaluate the proposed methods on some benchmark data sets. In section 4, the paper is concluded with future works.

## 2 Proposed Method

We assume that we have a data set of  $n$  images, and their visual feature vectors are  $\mathbf{x}_i|_{i=1}^n$ , where  $\mathbf{x}_i \in \mathbb{R}^d$  is the  $d$ -dimensional feature vector of the  $i$ -th image. We also assume that we have a set of  $m$  unique tags, and a tag vector  $\hat{\mathbf{t}}_i = [\hat{t}_{i1}, \dots, \hat{t}_{im}]^\top \in \{+1, -1\}^m$  for the  $i$ -th image  $\mathbf{x}_i$ , where  $\hat{t}_{ij} = +1$  if the  $j$ -th tag is assigned to the  $i$ -th image, and  $-1$ , otherwise. In real-world applications, the tag vector of an image  $\mathbf{x}_i$  is usually incomplete, i.e., some elements of  $\hat{\mathbf{t}}_i$  are missing. We define a vector  $\mathbf{v}_i = [v_{i1}, \dots, v_{im}] \in \{1, 0\}^m$ , where  $v_{ij} = 1$  if  $\hat{t}_{ij}$  is available, and 0 if  $\hat{t}_{ij}$  is missing. We propose to learn a tag scoring vector  $\mathbf{t}_i = [t_{i1}, \dots, t_{im}] \in \mathbb{R}^m$ , where  $t_{ij}$  is the score of assigning the  $j$ -th tag to the  $i$ -th image.

The set of the  $\kappa$  nearest neighbor of each image  $\mathbf{x}_i$  is denoted as  $\mathcal{N}_i$ , and we assume that the tag scoring vector  $\mathbf{t}_j$  of a image  $\mathbf{x}_j \in \mathcal{N}_i$  can be predicted from its visual feature vector  $\mathbf{x}_j$  using a local linear function  $f_i(\mathbf{x}_j)$ ,

$$\mathbf{t}_j \leftarrow f_i(\mathbf{x}_j) = W_i \mathbf{x}_j, \quad \forall j : \mathbf{x}_j \in \mathcal{N}_i, \quad (1)$$

where  $W_i \in \mathbb{R}^{m \times d}$  is the parameter of the local linear function. To learn the tag scoring vector and the local function parameters, we propose the following minimization problem,

$$\min_{\mathbf{t}_i|_{i=1}^n, W_i|_{i=1}^n} \left\{ g(\mathbf{t}_i|_{i=1}^n, W_i|_{i=1}^n) = \sum_{i=1}^n \left( \sum_{j:\mathbf{x}_j \in \mathcal{N}_i} \|\mathbf{t}_j - W_i \mathbf{x}_j\|_2^2 + \alpha \|W_i\|_2^2 + \beta (\mathbf{t}_i - \hat{\mathbf{t}}_i)^\top \text{diag}(\mathbf{v}_i) (\mathbf{t}_i - \hat{\mathbf{t}}_i) \right) \right\} \quad (2)$$

where  $\alpha$  and  $\beta$  are tradeoff parameters. The objective function  $g(\mathbf{t}_i|_{i=1}^n, W_i|_{i=1}^n)$  in (2) is a summarization of three terms over all the images in the data set. The first term,  $\sum_{j:\mathbf{x}_j \in \mathcal{N}_i} \|\mathbf{t}_j - W_i \mathbf{x}_j\|_2^2$ , is the prediction error term of the local linear predictor over the neighborhood of each image. The second,  $\|W_i\|_2^2$ , is to reduce the complexity of the local linear predictor. The last term,  $(\mathbf{t}_i - \hat{\mathbf{t}}_i)^\top \text{diag}(\mathbf{v}_i) (\mathbf{t}_i - \hat{\mathbf{t}}_i)$ , is a regularization term to regularize the learning of tag scoring vectors by the incomplete tag vectors, so that the available tags are respected. To optimize the minimization problem in (2), we propose to use the alternate optimization strategy [4,12] in an iterative algorithm.

- **Optimization of  $\mathbf{t}_i|_{i=1}^n$**  In each iteration, we optimize  $\mathbf{t}_i|_{i=1}^n$  one by one, and the minimization of (2) with respect to  $\mathbf{t}_i$  can be achieved with the following gradient descent update rule,

$$\mathbf{t}_i^{new} = \mathbf{t}_i^{old} - \eta \nabla_{\mathbf{t}_i} g(\mathbf{t}_j|_{j=1}^n, W_i|_{i=1}^n)|_{\mathbf{t}_i = \mathbf{t}_i^{old}}, \quad (3)$$

where  $\nabla_{\mathbf{t}_i} g(\mathbf{t}_j|_{j=1}^n, W_i|_{i=1}^n)$  is the sub-gradient function of  $g(\mathbf{t}_j|_{j=1}^n, W_i|_{i=1}^n)$ , with respect to  $\mathbf{t}_i$ ,

$$\nabla_{\mathbf{t}_i} g(\mathbf{t}_j|_{j=1}^n, W_i|_{i=1}^n) = 2 \sum_{k:\mathbf{x}_i \in \mathcal{N}_k} (\mathbf{t}_i - W_k \mathbf{x}_i) + 2\beta \text{diag}(\mathbf{v}_i) (\mathbf{t}_i - \hat{\mathbf{t}}_i), \quad (4)$$

and  $\eta$  is the descent step.

- **Optimization of  $W_i|_{i=1}^n$**  In each iteration, we also optimized  $W_i|_{i=1}^n$  one by one. When  $W_i$  is optimized,  $W_j|_{j \neq i}$  are fixed. Gradient descent method is also employed to update  $W_i$  to minimize the objective in (2),

$$W_i^{new} = W_i^{old} - \eta \nabla_{W_i} g(\mathbf{t}_i|_{i=1}^n, W_i|_{i=1}^n)|_{W_i = W_i^{old}}, \quad (5)$$

where  $\nabla_{W_i} g(\mathbf{t}_i|_{i=1}^n, W_i|_{i=1}^n)$  is the sub-gradient function with respect to  $W_i$ ,

$$\nabla_{W_i} g(\mathbf{t}_i|_{i=1}^n, W_i|_{i=1}^n) = 2 \sum_{j:\mathbf{x}_j \in \mathcal{N}_i} (\mathbf{t}_j - W_i \mathbf{x}_j) \mathbf{x}_j^\top + 2\beta W_i. \quad (6)$$

## 3 Experiments

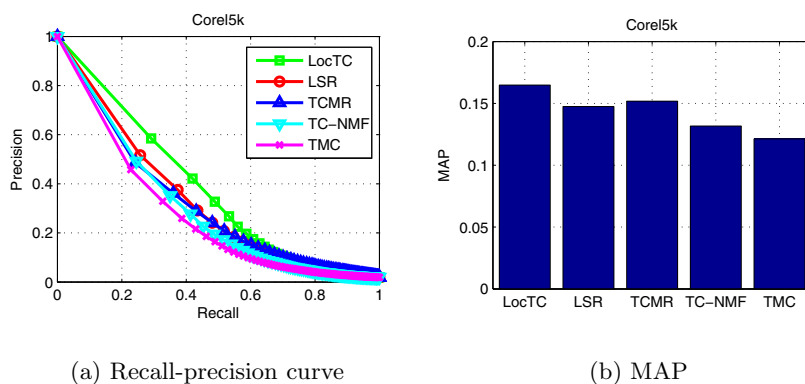
### 3.1 Setup

In the experiments, we used two publicly accessed image-tag data sets, which are Corel5k data set [30,5,14] and IAPR TC12 data set [31,9,30]. In the Corel5k data

set, there are 4,918 images, and 260 tags. We extract density feature, Harris shift feature, Harris Hue feature, RGB color feature, and HSV color feature as visual features for each image. Moreover, we remove 40% of the elements of the tag vectors to make the incomplete image tag vectors. In the IAPR TC12 data set, there are 19,062 images, and 291 tags. We also remove 40% elements of the tag elements to construct the incomplete tag vectors. To evaluate the tag completion performances, we used the recall-precision curve as performance measure. We also use mean average precision (MAP) as a single performance measure.

### 3.2 Results

We compared the proposed method to several state-of-the-art tag completion methods, including tag matrix completion (TMC) [22], linear sparse reconstructions (LSR) [10], tag completion by noisy matrix recovery (TCMR)[1], and tag completion via NMF (TC-NMF) [23]. The experimental result on two data sets are given in Fig. 1 and Fig. 2. From these figures, we can see that the proposed method LocTC performs best. Its recall-precision curve is closer to the top-right corner than any other methods, and its MAP is also higher than MAPs of other methods.



**Fig. 1.** Results of comparison to state-of-the-art methods on Corel5k data set

In this section, we will study the sensitivity of the proposed algorithm to the two parameters,  $\alpha$  and  $\beta$ . The curves of  $\alpha$  and  $\beta$  on different data sets are given in Fig. 3 and Fig. 4. From these figures, we can see that the performances are stable to different value of both  $\alpha$  and  $\beta$ .

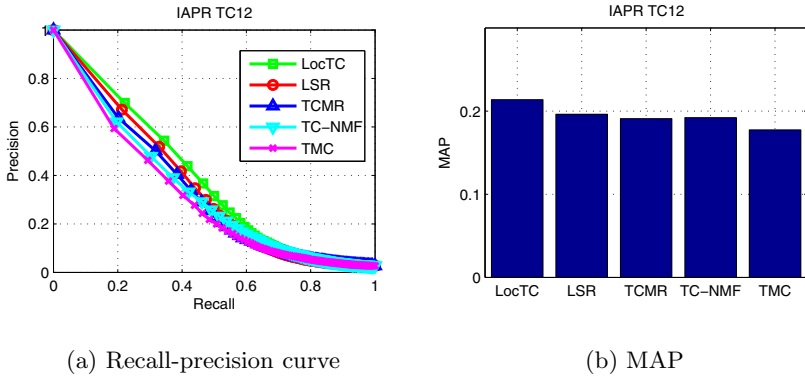


Fig. 2. Results of comparison to state-of-the-art methods on IAPR TC12 data set

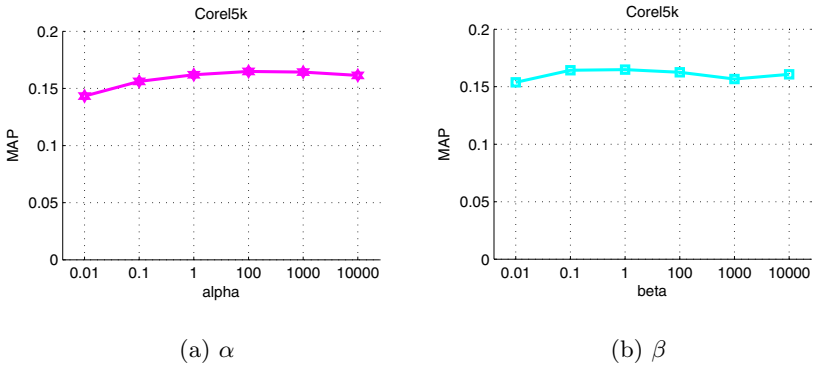


Fig. 3. Parameter sensitivity curve on Corel5k data set.

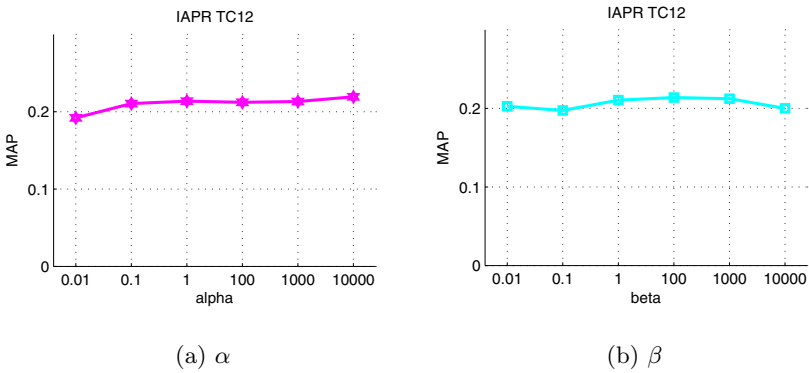


Fig. 4. Parameter sensitivity curve on IAPR TC12 data set.

## 4 Conclusion and Future Works

In this paper, we study the problem of tag completion, and proposed a novel algorithm for this problem. We proposed to learn the tags of images in the neighborhood of each image. A local linear function is designed to predict the tag scoring vectors of images in each neighborhood, and the prediction function parameter is learned jointly with the tag scoring vectors. The proposed method is compared to state-of-the-art tag completion algorithms, and the results show that the proposed algorithm outperforms the compared methods. In the future, we will study how to incorporate these connections into our model and learn more effective tags. In this paper, we used one single local function for each neighborhood, and in the future, we will use more than than regularization to regularized the learning of tags [15,16], such as usage of wavelet functions to construct the local function [13]. Moreover, correntropy can also be considered as a alternative loss function to construct the local learning problem [17,24,6,34]. In the future, we also plan to extend the proposed algorithm for completion of tags of large scale image data set by using high performance computing technology [36,21,28,29,32,33,2,25,8,35,7,18,20,19], and completion of tags of gene/protein functions of bioinformatics problems [3,26,27,3].

**Acknowledgements.** This works was supported by an open research funding of the Provincial Key Laboratory for Computer Information Processing Technology, Soochow University, China, Grant No. KJS1324.

## References

1. Feng, Z., Feng, S., Jin, R., Jain, A.K.: Image tag completion by noisy matrix recovery. In: Fleet, D., Pajdla, T., Schiele, B., Tuytelaars, T. (eds.) ECCV 2014, Part VII. LNCS, vol. 8695, pp. 424–438. Springer, Heidelberg (2014)
2. Gao, Y., Zhang, F., Bakos, J.D.: Sparse matrix-vector multiply on the keystone ii digital signal processor. In: 2014 IEEE High Performance Extreme Computing Conference (HPEC), pp. 1–6 (2014)
3. Hu, J., Zhang, F.: Improving protein localization prediction using amino acid group based physichemical encoding. In: Rajasekaran, S. (ed.) BICoB 2009. LNCS, vol. 5462, pp. 248–258. Springer, Heidelberg (2009)
4. Huang, S., Ma, Z., Wang, F.: A multi-objective design optimization strategy for vertical ground heat exchangers. *Energy and Buildings* 87, 233–242 (2015)
5. Huang, Y., Liu, Q., Zhang, S., Metaxas, D.: Image retrieval via probabilistic hypergraph ranking. In: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 3376–3383 (2010)
6. Li, L., Yang, J., Xu, Y., Qin, Z., Zhang, H.: Documents clustering based on max-correntropy nonnegative matrix factorization, pp. 850–855 (2015)
7. Li, T., Zhou, X., Brandstatter, K., Raicu, I.: Distributed key-value store on HPC and cloud systems. In: 2nd Greater Chicago Area System Research Workshop (GCASR) (2013)

8. Li, T., Zhou, X., Brandstatter, K., Zhao, D., Wang, K., Rajendran, A., Zhang, Z., Raicu, I.: Zht: A light-weight reliable persistent dynamic scalable zero-hop distributed hash table. In: 2013 IEEE 27th International Symposium on Parallel & Distributed Processing (IPDPS), pp. 775–787 (2013)
9. Li, Z., Liu, J., Xu, C., Lu, H.: Mlrank: Multi-correlation learning to rank for image annotation. *Pattern Recognition* 46(10), 2700–2710 (2013)
10. Lin, Z., Ding, G., Hu, M., Lin, Y., Sam Ge, S.: Image tag completion via dual-view linear sparse reconstructions. *Computer Vision and Image Understanding* 124, 42–60 (2014)
11. Lin, Z., Ding, G., Hu, M., Wang, J., Ye, X.: Image tag completion via image-specific and tag-specific linear sparse reconstructions. In: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 1618–1625 (2013)
12. Liu, L., Li, H., Xue, Y., Liu, W.: Reactive power compensation and optimization strategy for grid-interactive cascaded photovoltaic systems. *IEEE Transactions on Power Electronics* 30(1), 188–202 (2015)
13. Liu, Z., Abbas, A., Jing, B.Y., Gao, X.: Wavpeak: picking nmr peaks through wavelet-based smoothing and volume-based filtering. *Bioinformatics* 28(7), 914–920 (2012)
14. Wang, C., Yan, S., Zhang, L., Zhang, H.J.: Multi-label sparse coding for automatic image annotation, pp. 1643–1650 (2009)
15. Wang, J.J.Y., Bensmail, H., Gao, X.: Multiple graph regularized protein domain ranking. *BMC Bioinformatics* 13(1), 307 (2012)
16. Wang, J.J.Y., Bensmail, H., Gao, X.: Multiple graph regularized nonnegative matrix factorization. *Pattern Recognition* 46(10), 2840–2847 (2013)
17. Wang, J.J.Y., Wang, X., Gao, X.: Non-negative matrix factorization by maximizing correntropy for cancer clustering. *BMC Bioinformatics* 14(1), 107 (2013)
18. Wang, K., Kulkarni, A., Zhou, X., Lang, M., Raicu, I.: Using simulation to explore distributed key-value stores for exascale system services. In: 2nd Greater Chicago Area System Research Workshop (GCASR) (2013)
19. Wang, K., Zhou, X., Chen, H., Lang, M., Raicu, I.: Next generation job management systems for extreme-scale ensemble computing. In: Proceedings of the 23rd International Symposium on High-Performance Parallel and Distributed Computing, pp. 111–114 (2014)
20. Wang, K., Zhou, X., Li, T., Zhao, D., Lang, M., Raicu, I.: Optimizing load balancing and data-locality with data-aware scheduling. In: 2014 IEEE International Conference on Big Data (Big Data), pp. 119–128 (2014)
21. Wang, K., Zhou, X., Qiao, K., Lang, M., McClelland, B., Raicu, I.: Towards scalable distributed workload manager with monitoring-based weakly consistent resource stealing. In: Proceedings of the 24rd International Symposium on High-Performance Parallel and Distributed Computing, pp. 219–222 (2015)
22. Wu, L., Jin, R., Jain, A.: Tag completion for image retrieval. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 35(3), 716–727 (2013)
23. Xia, Z., Feng, X., Peng, J., Wu, J., Fan, J.: A regularized optimization framework for tag completion and image retrieval. *Neurocomputing* (2014)
24. Xing, H.J., Ren, H.R.: Regularized correntropy criterion based feature extraction for novelty detection. *Neurocomputing* 133, 483–490 (2014)
25. Zhang, F., Gao, Y., Bakos, J.D.: Lucas-kanade optical flow estimation on the ti c66x digital signal processor. In: 2014 IEEE High Performance Extreme Computing Conference (HPEC), pp. 1–6 (2014)

26. Zhang, F., Hu, J.: Bayesian classifier for anchored protein sorting discovery. In: IEEE International Conference on Bioinformatics and Biomedicine, BIBM 2009, pp. 424–428 (2009)
27. Zhang, F., Hu, J.: Bioinformatics analysis of physicochemical properties of protein sorting signals (2010)
28. Zhang, F., Zhang, Y., Bakos, J.: Gpaprriori: Gpu-accelerated frequent itemset mining. In: 2011 IEEE International Conference on Cluster Computing (CLUSTER), pp. 590–594 (2011)
29. Zhang, F., Zhang, Y., Bakos, J.D.: Accelerating frequent itemset mining on graphics processing units. *The Journal of Supercomputing* 66(1), 94–117 (2013)
30. Zhang, S., Huang, J., Li, H., Metaxas, D.: Automatic image annotation and retrieval using group sparsity. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics* 42(3), 838–849 (2012)
31. Zhang, X., Liu, C.: Image annotation based on feature fusion and semantic similarity. *Neurocomputing* 149(PC), 1658–1671 (2015)
32. Zhang, Y., Zhang, F., Bakos, J.: Frequent itemset mining on large-scale shared memory machines. In: 2011 IEEE International Conference on Cluster Computing (CLUSTER), pp. 585–589 (2011)
33. Zhang, Y., Zhang, F., Jin, Z., Bakos, J.D.: An fpga-based accelerator for frequent itemset mining. *ACM Transactions on Reconfigurable Technology and Systems (TRETTS)* 6(1), 2 (2013)
34. Zhang, Z., Chen, J.: Correntropy based data reconciliation and gross error detection and identification for nonlinear dynamic processes. *Computers and Chemical Engineering* 75, 120–134 (2015)
35. Zhao, D., Zhang, Z., Zhou, X., Li, T., Wang, K., Kimpe, D., Carns, P., Ross, R., Raicu, I.: Fusionfs: Toward supporting data-intensive scientific applications on extreme-scale high-performance computing systems. In: 2014 IEEE International Conference on Big Data (Big Data), pp. 61–70 (2014)
36. Zhou, X., Chen, H., Wang, K., Lang, M., Raicu, I.: Exploring distributed resource allocation techniques in the slurm job management system. Illinois Institute of Technology, Department of Computer Science, Technical Report (2013)