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NMF-KNN: Image Annotation using Weighted Multi-view Non-negative Matrix Factorization

Mahdi M. Kalayeh, Haroon Idrees, Mubarak Shah
{mahdi| haroon| shah } @eecs.ucf.edu , *Center for Research in Computer Vision @ UCF*

IEEE 2014 Conference on Computer Vision and Pattern Recognition
CVPR 2014

Problem

- Assigning relevant tags to query images based on their visual content

Challenges

- Finding the most relevant tags among many possible ones.
- There are tags that do not occur frequently in the dataset.
- Images that share many tags may conceptually be very different.

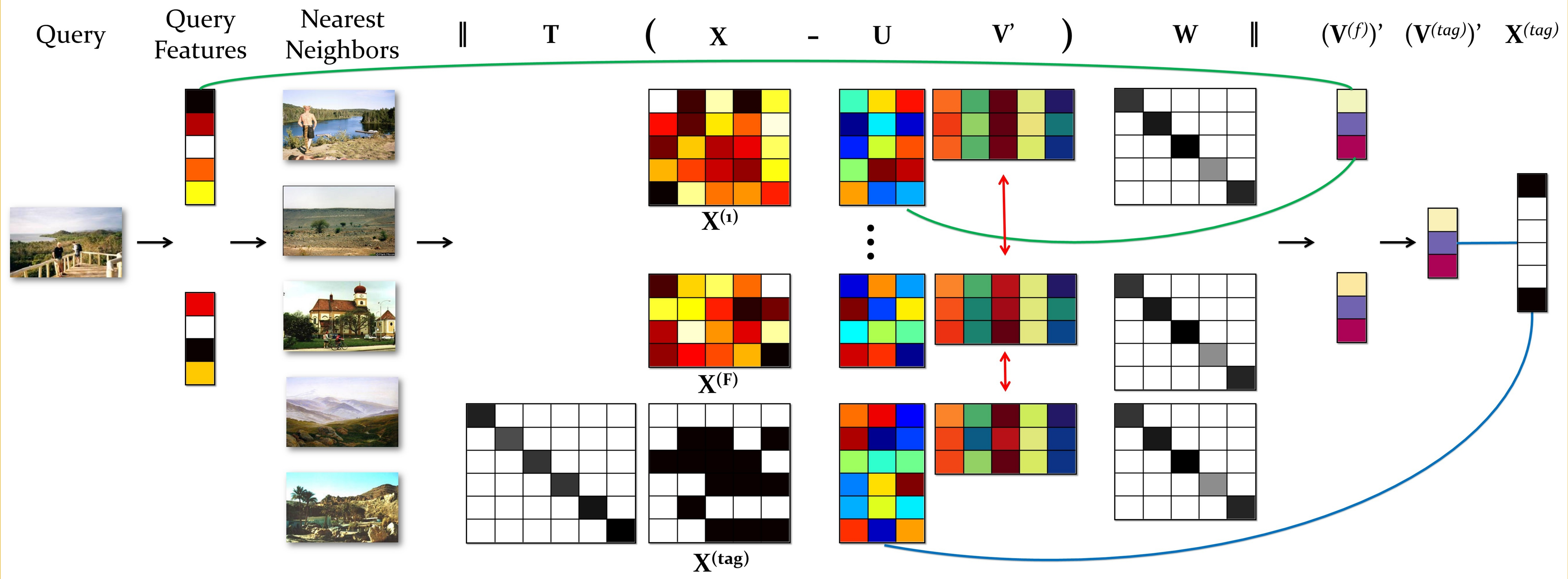
Drawbacks of Existing Methods

- Addition of images and tags requires retraining the models.
- ad-hoc feature fusion approaches are usually taken.

Our Contributions

- A query-specific model (no global training!)
- A natural solution to feature fusion
- Handling dataset imbalance through weighted NMF formulation
- $O(n)$ test-time complexity
- Straightforward extension for sub-linear test-time complexity

Proposed Approach



Query-specific Training

- Minimizing L via an iterative alternative approach (U and V are unknown)
- Training finds the optimum U that minimizes L.
- T penalizes inaccurate matrix factorization severely for rare tags.
- W is to bias the learning towards a more accurate factorization of images with rare tags.

$$L = \sum_{f=1}^{F+1} \left\| T\left(X^{(f)} - U^{(f)} V'^{(f)}\right) W \right\|_F^2 + \sum_{f=1}^{F+1} \lambda_f \left\| W'\left(V^{(f)} Q^{(f)} - V^*\right) \right\|_F^2 \quad s.t. \quad \forall\, 1 \le f \le F+1, \quad U^{(f)}, V^{(f)}, V^* \ge 0$$

$$Q^{(f)} = Diag\left(\sum_{m=1}^{M} U_{m,1}^{(f)}, \sum_{m=1}^{M} U_{m,2}^{(f)} \cdots \sum_{m=1}^{M} U_{m,K}^{(f)} \right)$$

Recovering Tags of Query (Testing)

1. Project query's feature vectors on corresponding basis matrices U
2. Approximate $V^{(tag)}$ of query by averaging over F different $V^{(visual\ features)}$
3. Predict score of different tags by computing $U^{(tag)} \times (V^{(tag)})'$
4. Select relevant tags with the highest scores

Experimental Results

- Datasets: Corel5K and ESP Game
- Evaluation metrics: Precision, Recall and N+

Method	P	R	F_1	$N+$
CRM[17]	16	19	17.3	107
InfNet[23]	17	24	19.9	112
NPDE[37]	18	21	19.3	114
SML[2]	23	29	25.6	137
MBRM[7]	24	25	24.4	122
TGLM[20]	25	29	26.8	131
JEC[22]	27	32	29.2	139
TagProp-ML[15]	31	37	33.7	146
TagProp-σML[15]	33	42	36.9	160
Group Sparsity[38]	30	33	31.4	146
FastTag[3]	32	43	36.7	166
NMF-KNN	38	56	45.2	150

Table 1. Performance evaluation on Corel5k dataset

Method	P	R	F_1	$N+$
MBRM[7]	18	19	18.4	209
JEC[22]	22	25	23.4	224
TagProp-σSD[15]	39	24	29.7	232
TagProp-ML[15]	49	20	28.4	213
TagProp-σML[15]	39	27	31.9	239
FastTag[3]	46	22	29.7	247
NMF-KNN	33	26	29.0	238

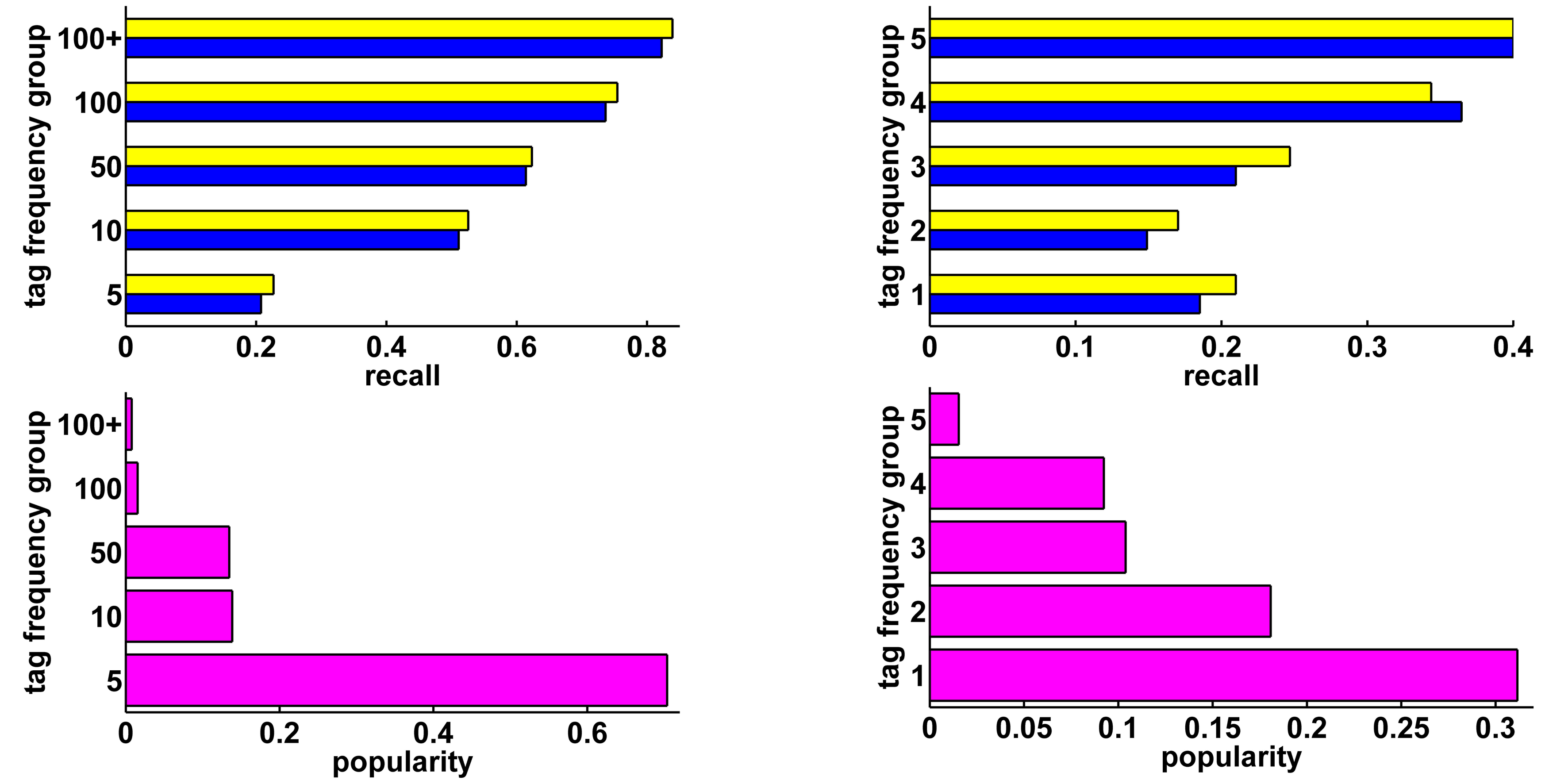
Table 2. Performance evaluation on ESP Game dataset

Qualitative Results

Predicted tags in **green** appear in the ground truth while **red** ones do not.

Effect of Weight Matrices (W and T)

with weights
without weights



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