# 상호 관계 기반 자동 이미지 주석 생성
## (Correlation-based Automatic Image Captioning)

양 형 정 † Jia-yu Pan†† Pinar Duygulu††† Christos Falout††††
(Hyungjeong Yang) (Jia-Yu Pan) (Pinar Duygulu) (Christos Falout)

**요 약** 본 논문에서는 상호 관계에 기반한 자동 이미지 주석 생성 방법을 보인다. 새로운 실험 이미지를 위한 자동 주석의 생성은 훈련 데이타 내의 주석과 함께 주어진 이미지들을 이용하여 이미지의 시각적 속성과 텍스트 속성의 상호 관계를 발견해 냄으로 수행된다. 본 논문에서 제시하는 상호 관계 기반 자동 주석 생성 모델은 1) 시각적 속성의 적절한 군집화, 2) 시각적 속성과 텍스트 속성의 가중치 부여, 3) 노이즈 제거를 위한 차원 축소 등의 요소를 고려하여 설계 된다. 실험은 680 MB의 Corel 이미지 데이타를 이용하여 각 10개의 데이타 집합에 대해 수행 되었으며, 실험 결과, 시각적 속성과 텍스트 속성에 대한 가중치 부여와 시각적 속성의 적절한 군집화가 모델의 성능을 향상 시키며, 본 논문에서 제시한 상호 관계 기반 모델이 기존의 EM을 이용한 자동 주석 생성 모델에 비해 45%의 상대적 성능 향상을 보인다.

**키워드** : 이미지 주석, 상호 관계, 고유값 분해, 클러스터링

***Abstract*** This paper presents correlation-based automatic image captioning. Given a training set of annotated images, we want to discover correlations between visual features and textual features, so that we can automatically generate descriptive textual features for a new unseen image. We develop models with multiple design alternatives such as 1) adaptively clustering visual features, 2) weighting visual features and textual features, and 3) reducing dimensionality for noise sup-pression. We experiment thoroughly on 10 data sets of various content styles from the Corel image database, about 680MB. The major contributions of this work are: (a) we show that careful weighting visual and textual features, as well as clustering visual features adaptively leads to consistent performance improvements, and (b) our proposed methods achieve a relative improvement of up to 45% on annotation accuracy over the state-of-the-art, EM approach.

**Key words** : Image annotation, correlation, Singular Value Decomposition, Clustering

## 1. 서 론

Content-based image retrieval (CBIR) systems, matching images based on visual similarities, have some limitations due to missing semantic information[1-4]. Manually annotating images with words could provide such semantic information. There are some collections where images or videos are annotated with descriptive texts (e.g., the Corel data set, some museum collections, news photographs on the web with captions, etc.). Integration of the textual and visual features provided by these annotated collections improves the performance of search and retrieval[5-8]. However, manual annotation is time consuming and error-prone. Recently, automatic image annotation, which derives words from image content, has achieved promising results. Leveraging the existing text retrieval systems, automatic image annotation could be useful for the construction of content-based image retrieval systems supporting semantic information.

Several automatic image annotation methods have been proposed for better indexing and retrieval in large image databases[5,7,9-11]. Some of these approaches generate keywords for an image by

· 이 논문은 한국과학재단의 해외 Post-doc. 연구지원에 의하여 연구되었음
† 정 회 원 : 카네기멜런대학교 컴퓨터과학과 포스트닥 연구원
hjyang@cs.cmu.edu
†† 비 회 원 : 카네기멜런대학교 컴퓨터학과
jypan@cs.cmu.edu
††† 비 회 원 : 빌켄트대학교 교수
duygulu@cs.cmu.edu
†††† 비 회 원 : 카네기멜런대학교 컴퓨터학과 교수
christos@cmu.edu
논문접수 : 2004년 6월 11일
심사완료 : 2004년 8월 19일

mapping image regions to terms. In other words, captioning is conducted by finding the association between constituent regions of images and given terms for the images. Mori et al. [12] use co-occurrence statistics of image grids and words for modelling the association. Duygulu et al. [10] view the mapping as a translation of image regions to words, and learn the mapping between region groups and words by using an EM algorithm. Recently, probabilistic models such as the cross-media relevance model [7] and latent semantic analysis (LSA) based models [28] are also proposed for captioning.

In this paper, we present correlation-based automatic image captioning. Given a training set of annotated images, we want to discover the correlations between visual features and textual features, so that we can automatically generate descriptive textual features for a new unseen image. The framework of automatic image captioning consists of two parts: constructing a model for the association, and annotating new images. Images in the annotated image set are first segmented and numerical feature vectors are extracted. The segmented image feature vectors (each could be a blob or a grid) are clustered into K clusters. The K cluster centers together form a visual vocabulary for the image content.

A model is constructed to capture the association between terms and the visual vocabulary. Model parameters are trained using the given annotated image set. When a new image arrives, the new image is segmented. Each segmented region is labeled by a token in the visual vocabulary, based on some similarity function. Captioning terms for the new image will most likely describe the content of the image. The likelihood of each term is determined by the model trained in the first step, given the visual tokens of the new image. We develop models with multiple design alternatives such as 1) adaptively clustering visual features, 2) weighting visual features and textual features, and 3) reducing dimensionality for noise suppression, for the better association model. We experiment thoroughly on 10 data sets of various content styles from the Corel image database, about 680MB. The major contributions of this work are: (a) we show that careful weighting on visual and textual features, as well as adaptive visual feature clustering, leads to consistent performance improvements, and (b) our proposed methods achieve a relative improvement of up to 45% on annotation accuracy over the state-of-the-art, EM approach.

The rest of the paper is organized as follows: Section 2 gives the related work, followed by section 3 where an adaptive method for obtaining image region groups is explained. The proposed uniqueness weighting scheme and correlation-based image annotation methods are given in Section 4. Section 5 shows the experimental results on the Corel data set. Several discussions are given in Section 6. Section 7 concludes the paper.

## 2. Related Work

There have been several attempts at captioning images automatically. Basically, the essential question is how we associate the visual content of an image with its semantics (expressed by the annotated terms). Previous approaches differ in how the image's visual content is represented (e.g., in blobs or regions) and in the particular models which are used to capture the association (e.g., language translation model or conditional random field).

**Image captioning** In this study, we are interested in linking the visual and textual features for annotating the images automatically. Automatic image captioning is useful since manual annotation of these collections is subjective and requires a huge amount of human effort.

Maron et al. [13] use multiple-instance learning to train classifiers to identify particular keywords from image data using labeled bags of examples. In their approach, an image is a "positive" if it contains an object (e.g. tiger) in the image but "negative" if it doesn't. Wenyin et al. [14] propose a semi-automatic strategy for annotating images utilizing users' feedback of the retrieval system. The query keywords which receive positive feedback are collected as possible annotation words to the retrieved images. Li and Wang [11] model image concepts with a 2-D multiresolution Hidden Markov Model and label images with the concepts

that best fit the content.

Recently, probabilistic models are proposed to capture the joint statistics between image regions and caption terms. Mori et al. [12] use co-occurrence statistics collected for words and image areas which are defined by a fixed grid. Duygulu et.al [10] utilize machine translation approach proposed by Brown et al. [15] to find the correspondences between words and types of image regions. Jeon et al. [7] propose a cross-media relevance model for words and types of image regions, which takes the advantage that an image can be described both using image features and words. Monay et al. [28] use latent semantic analysis (LSA) to find the association. These methods quantize or cluster the image features into discrete tokens and find correlations between these tokens and captioning terms. The quality of tokenization could effect the captioning accuracy.

Other works model directly the association between words and the numerical features of the regions. Barnard et al. [6,9,16] propose a generative hierarchical model, inspired by Hofmann's aspect model for text [17], for integrating the semantic information provided by the text and visual information provided by image features. Blei and Jordan [5] propose correspondence Latent Dirichlet Allocation (Corr-LDA) model that finds conditional relationships between latent variable representations of sets of image regions and sets of words. The continuous-space relevance model (CRM) [18], and the contextual model which models spatial consistency by Markov random field [19] are also proposed to find the actual association between image regions and terms for image annotation and a greater goal of object recognition.

While most previous approaches are complex and delicate, we want to explore simpler yet superior methods, motivated by some approaches employed for efficient document retrievals.

**Clustering:** One important preprocessing step is the construction of the visual and textual vocabularies. The model is then constructed to link the visual and textual tokens in the vocabularies. Many clustering algorithms can be used for the vocabulary construction [20], where mostly used ones are K-means, K-Harmonic means [21], OPTICS [22] and [23]. However, all these algorithms need the user to specify the number of desirable clusters K.

There are works which try to adaptively determine the number of clusters K. X-means [24] and G-means [25] determine the optimal K for the K-means algorithm by evaluating the quality of clusters using different criteria, namely BIC and normality statistical test. They start with small K, and split the clusters of poor quality (effectively increases K) until the criteria are met. Among all these algorithms, we choose the G-means algorithm in this paper.

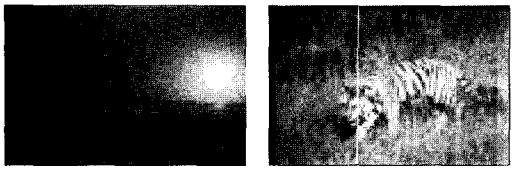
## 3. Adaptive Visual Vocabulary Generation

The common approach for automatic image captioning is to find the association between the visual elements and the caption terms of an image. At first, two sets of vocabularies, namely the vocabulary of visual information (visual vocabulary) and that for the content semantics (content vocabulary), are constructed. Usually, a set of terms are used as the vocabulary for content semantics. The visual vocabulary consists of tokens representing visual information on either a sub-region (a grid or an image segment) or the entire image. Then, a model is used to capture the association between tokens from the two vocabularies. In this work, we follow the work in [10] and use a term set as the content vocabulary, and a blob-token set as the visual vocabulary. Let us begin with the definition of an annotated image set.

**Definition 1** (Annotated image set) An annotated image set is a set of images $I = \{I_1, ..., I_N\}$, where each image $I_i$ is annotated with a set of $W_i$ terms $\{w_{i,1}, ..., w_{i,W_i}\}$, where $W_i$ is the number of annotated terms.

Figure 1 gives two examples of annotated images along with their captioning terms. Let the two images be $I_1$, $I_2$, then $W_1=4$ and $W_2=4$.

In this paper, we use different font styles for different types of symbols, namely: bold and italic symbols for sets (e.g., the image annotation set $I$ ); bold, uppercase symbols for matrices (e.g., D); bold, lowercase symbols for vectors (e.g., **q**); italic symbols for set sizes (e.g., $W$).



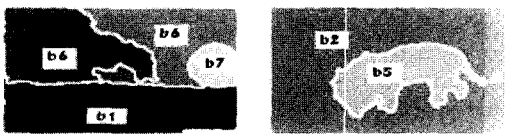
(a) sea, snu, sky (b) cat, forest, grass, tiger

Figure 1 Annotated images

**Definition 2** (Term set of an annotated image set) The term set of an annotated image set $I$ ={$I_1$, ..., $I_N$}, denoted as $W$ ={$w_1$, ..., $w_W$}, is defined as the collection of all $W$ terms used as annotating terms for the images in $I$.

**Definition 3** (Blob) A blob of an image is a contiguous, homogeneous region of the image, given by an image segmentation algorithm.

A blob is usually represented as a continuous-valued vector of features describing the characteristic of the region. Figure 2 illustrates the blobs of the two example images in Figure 1, along with their captioning terms. We use the normalized cuts algorithm in [26] to break an image into regions, and then map each region into a 30-d feature vector. We used features such as the mean and standard deviation of its RGB values, average responses to various texture filters, its position in the entire image layout, and some shape descriptors (e.g., major orientation and the area ratio of the bounding region to the real region). All features are normalized to have zero-mean and unit-variance. For a given image $I_i$, the number of blobs $B_i$ is not necessarily equal to the number of captioning terms $W_i$. For example, in Figure 2, the numbers of blobs in each image are $B_1$=5 and $B_2$=2 while the numbers of words are $W_1$ = 4 and $W_2$ = 4, respectively.




(a) $W_6$,$W_7$,$W_8$,$W_1$ (b) $W_2$,$W_9$,$W_{10}$,$W_{11}$

Figire 2 The blobs of two annotated images in Figure 1

**Definition 4** (Blob-token) A set of continuous-valued blobs represented as feature vectors can be clustered. Each cluster is labeled as a blob-token.

**Definition 5** (Blob-token set of an annotated image set) The blob-token set of an annotated image set $I$, denoted as $B$ ={$b_1$, ..., $b_B$}, is defined as the collection of all $B$ blob-tokens which appear in the individual images of $I$.

Figure 3 shows three examples of the blob-tokens. For presentation purpose, these blob-tokens are semantically labeled as "cat", "sky" and "sun", however, the actual labels to the blob-tokens are not crucial. The consistency among the member blobs of a blob-token is more important for applications. In other words, we would like to have all blobs of a blob-token similar to each other, and dissimilar to those not belong to this blob-token.

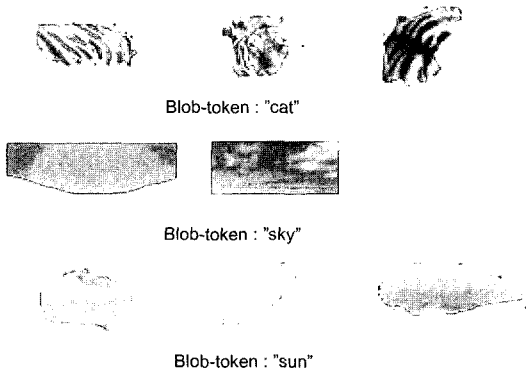



Figure 3 Three blob-tokens "cat", "sky" and "sun", along with examples of their member blobs

The quality of blob-tokens would affect the accuracy of image captioning. In [10], the blob-tokens are generated by applying K-means algorithm on all the raw blobs in an annotated image set, with the number of blob-tokens, $B$, set at 500. However, the choice of $B$=500 is by no means optimal. Intuitively, if the optimal $B^*$=625, then setting $B$=500 would inevitable mixing red blobs with blue blobs together (i.e., cluster them as the same blob-token). On the other hand, if $B^*$=325, then setting $B$=500 would generate clusters which are too fine and hurts the algorithm's ability on generalization.

In this study, we determine the number of blob tokens $B$ adaptively using the idea of G-means

[26]. Essentially, G-means is a wrapper around the K-means algorithm, it runs K-means starting from a small number of $B$, and split clusters (thus, increases $B$) which are not gaussian. The gaussianity of a cluster is checked by a statistical test (e.g., Kolmogorov-Smirov test) on the distribution of the data points in that cluster. In our work, the blob-tokens adaptively found by G-means are the labels of the clusters. The number of blob-tokens generated for the training set are all less than 500, ranging from 339 to 495, mostly around 400. We refer the reader to [25] for the details.

## 4. Correlation-based Image Captioning

In this section, we propose correlation-based methods with proper weighting assignments on the terms and blob-tokens and dimension reduction for noise suppression. The common goal among the proposed methods is to have an estimate for $p(w_i|b_j)$, the conditional probability of a term wi given a blob-token $b_j$. Since the number of terms and blob-tokens are fixed and finite, the goal is to estimate an table whose (i, j) item is the desired $p(w_i|b_j)$, which we called the association table. In this section, we propose 4 methods to obtain such estimates, namely, method **Corr, Cos, SvdCorr,** and **SvdCos**.

Table 1 shows the symbols and terminology we used in the paper.

Table 1 Summary of symbols used in the paper

| Symbol | Description |
|---|---|
| Sets | |
| $I$ | annotated image set of $N$ images $\{I_1, ..., I_N\}$ |
| $W$ | term set of $W$ terms $\{w_1, ..., w_W\}$ |
| $B$ | blob-token set of $B$ tokens $\{b_1, ..., b_B\}$ |
| Sizes | |
| $W_i$ | the number of captioning terms for image $I_i$ |
| $B_i$ | the number of blob-tokens in image $I_i$ |
| Matrix / Table | |
| D | data matrix, $[D_W\|D_B]$ |
| $D_W$ | image-to-term data matrix |
| $D_B$ | image-to-blob-token data matrix |
| $T_{Corr}$ | correlation-based association table |
| $T_{Cos}$ | cosine-similarity association table |
| Vectors | |
| $d_{Wi}$ | the $i$-th column of the matrix $D_W$ |
| $d_{Bi}$ | the $i$-th column of the matrix $D_B$ |

The correlation between terms and blob-tokens is computed based on their co-occurrence relation in the given annotated image set. Recall that each image in the annotated image set has a set of blob-tokens, as well as a set of annotated terms. We can represent each image by a vector of counts on terms and blob-tokens. If there are $W$ possible terms and $B$ possible blob-tokens, the entire annotated image set of $N$ images can be represented by a data matrix $D_{[N\text{-by-}(W+B)]}$. We now define two matrices: one is unweighted, the other is uniqueness-weighted as initial data representation.

**Definition 6** (Unweighted data matrix) Given an annotated image set $I = \{I_1, ..., I_N\}$ with the term set $W$ and the blob-token set $B$, the unweighted data matrix $D_{UW} = [D_{UW\_W}|D_{UW\_B}]$ is a $N$-by-$(W+B)$ matrix, where the (i, j)-element of the $N$-by-$W$ matrix $D_{UW\_W}$ is the count of term $w_j$ in image $I_i$, and the (i, j)-element of the $N$-by-$B$ matrix $D_{UW\_B}$ is the count of blob-token $b_j$ in image $I_i$.

The data matrix D is weighted according to the "uniqueness" of each term(blob-token). If a term appears only once in the image set, say with image $I_1$, the term is only associated with the blob-tokens of $I_1$. The more common a term is associated with the more blob-tokens. The uncertainty of finding the correct term-and-blob-token association goes up. In other words, common terms are "noisy". Similarly, these arguments hold for blob-tokens. The idea is to give higher weight to terms (blob-tokens) which are more "unique" in the training set, and low weights to noisy, common terms (blob-tokens).

**Definition 7** (Uniqueness weighting and weighted data matrix) Given a unweighted data matrix $D_{UW} = [D_{UW\_W}|D_{UW\_B}]$. Let $z_j$ ($y_j$) be the number of images which contain the term $w_j$ (the blob-token $b_j$). The weighted data matrix $D=[D_W|D_B]$ is constructed from $D_{UW}$, where the (i, j)-element of $D_W$ ($D_B$), $d_{W(i,j)}$ ($d_{B(i,j)}$), is

$$d_{W(i,j)} = d_{UW\_W(i,j)} \times \log N/z_j,\ d_{B(i,j)} = d_{UW\_B(i,j)} \times \log N/y_j, \quad (1)$$

where $N$ is the total number of images in the set.

In the following, whenever we mention the data matrix **D**, it will be always the weighted data

matrix.

**Example 1** Let the annotated image set $I$ ={$I_1$, $I_2$}, with term set $W$={$w_1$, $w_2$, $w_3$} (e.g., {"boat", "sea", "sky"}) and blob-token set $B$={$b_1$, $b_2$, $b_3$, $b_4$} (e.g., {"wood-like-token", "sea-token", "sky-token", "blue-token"}). Let image $I_1$ has annotated words $w_1$, $w_2$ and blob-tokens $b_1$, $b_2$; Then, the corresponding data matrix.

$$D_{UW} = [D_{UW\_W}|D_{UW\_B}] = \begin{pmatrix} 1 & 1 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 & 1 \end{pmatrix}$$

The weighted data matrix

$D=[D_W|D_B]$

$$= \begin{pmatrix} \log(2) & \log(2) & 0 & \log(2) & 0 & 0 & 0 \\ 0 & 0 & \log(2) & 0 & 0 & \log(2) & \log(2) \end{pmatrix}$$

**Definition 8** (Method Corr: correlation-based association table) Let table $T_{UN\_Corr} = D_W{}^T D_B$. The *correlation-based association table* $T_{Corr}$ is defined by normalizing each column of $T_{UN\_Corr}$ such that each column sum up to 1. Note that the (i, j)-element of $T_{Corr(i,j)}$ can be viewed as an estimate to $p(w_i|b_j)$, the conditional probability of term $w_i$ given blob-token $b_j$.

**Example 2** The table TUN_Corr of the data matrix in Example 1 is

$D_W{}^T D_B$

$$= \begin{pmatrix} \log(2) & \log(2) & 0 \\ 0 & 0 & \log(2) \end{pmatrix}^T \begin{pmatrix} \log(2) & 0 & 0 & 0 \\ 0 & 0 & \log(2) & \log(2) \end{pmatrix}$$

$$= \begin{pmatrix} (\log(2))^2 & 0 & 0 & 0 \\ (\log(2))^2 & 0 & 0 & 0 \\ 0 & 0 & (\log(2))^2 & (\log(2))^2 \end{pmatrix}$$

The correlation-based association table $T_{Corr}$ by normalizing each column of $T_{UN\_Corr}$ is $\begin{pmatrix} 0.5 & 0 & 0 & 0 \\ 0.5 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 \end{pmatrix}$.

**Example 3** (Without doing weighting on D) Continue from Example 2, if we define a correlation table $F_{UN\_Corr}$ with the unweighted $D_0$, i.e., we define $F_{UW\_Corr}=D_{UW\_W}{}^T D_{UW\_B}$ and let $F_{Corr}$ be $F_{UN\_Corr}$, with columns normalized which each sums to 1. We have $F_{Corr} = \begin{pmatrix} 0.5 & 0.33 & 0 & 0 \\ 0.5 & 0.33 & 0 & 0 \\ 0 & 0.33 & 1 & 1 \end{pmatrix}$.

Notice that TCorr is not confused by the "noisy" blob-token "$b_2$" and would not annotate terms $w_1$ and $w_2$ for the image $I_2$. On the other hand, $F_{Corr}$ will have probability of 0.66 of annotating the wrong terms ($w_1$ or $w_2$) for the image $I_2$.

$T_{Corr}$ measures the association between a term and a blob-token by the co-occurrence counts. Another possible measurement could be to see how similar the overall occurrence pattern(over the training images) of a term and a blob-token is. Such occurrence patterns are in fact the columns of $D_W$ or $D_B$, and the similarity can be taken as the cosine value between pairs of column vectors.

**Definition 9** (Method **Cos**: cosine-similarity association table) Let the $i$-th column of the matrix $D_W(D_B)$ be $d_{Wi}$ ($d_{Bi}$). Let $Cos_{i,j}$ be the cosine similarity between column vectors $d_{Wi}$ and $d_{Bj}$, which is

$$Cos_{i,j} = \frac{d_{Wi} \cdot d_{Bj}}{|d_{Wi}| \, |d_{Bj}|}$$

Let the table $T_{UN\_Cos}$ be a $W$-by-$B$ matrix whose (i, j)-element $T_{UN\_Cos}(i,j) = Cos_{i,j}$. Normalize the columns of $T_{UN\_Cos}$ such that each column sums up to 1, and we get the cosine-similarity association table $T_{Cos}$.

Note that the cosine-similarity table $T_{Cos}= \hat{D}_W{}^T \hat{D}_B$, where $\hat{D}_W(\hat{D}_B)$ is the matrix $D_W$ ($D_B$) with each column normalized to unit length. Like the correlation-based association table, the (i, j)-element of $T_{Cos}(i,j)$ can also be viewed as an estimate to the conditional probability of term $w_i$ given blob-token $b_j$, $p(w_i|b_j)$.

**Example 4** Continue from Example 1, we have the column-normalized matrix $[\hat{D}_W|\hat{D}_B] = \begin{pmatrix} 1 & 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 1 \end{pmatrix}$. Hence, the table $T_{UN\_Cos}$ is $\begin{pmatrix} 1 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}^T \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 \end{pmatrix}$, and the cosine-similarity table $T_{Cos}$ is $\begin{pmatrix} 0.5 & 0 & 0 & 0 \\ 0.5 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 \end{pmatrix}$

The low rank representation by Singular Value Decomposition (SVD) reveals latent semantics in a given matrix [27]. Specifically, SVD is used to clean up the observed (noisy) term-document matrix. They showed that estimating the term-term correlation after SVD gives better retrieval performance than the one of the observed (noisy) term-document matrix. In this paper, we propose to use SVD to suppress the noise in the data matrix before learning the association.

**Definition 10** (Singular Value Decomposition) SVD decomposes a given matrix into a product of

three matrices U, Λ, $V^T$. That is, $X = UAV^T$, where $U=[u_1, ..., u_n]$ and $V = [v_1, ..., v_m]$ are orthonormal, and Λ is a diagonal matrix. Note that $u_i$ ($v_i$) are columns of the matrix U(V). Let $A=diag(\sigma_1, ..., \sigma_{min(n,m)})$, then $\sigma_j > 0$, for $j \leq rank(X)$, $\sigma_j=0$, for $j > rank(X)$.

Note that the SVD of a matrix X can also be written as

$$X = \sum_{i=1}^{rank(X)} \sigma_i u_i v_i^T \quad (2)$$

The latter terms in the summation contribute less to X, as the corresponding $\sigma_i$'s become smaller and smaller.

The following example shows that SVD is used to clean up noise and reveals informative structure in a matrix, by omitting the smallest terms in the summation (equation 2).

**Example 5** Let X be $\begin{pmatrix} 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.5 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.5 & 0 \end{pmatrix}$. Let SVD give matrices U, Λ, V such that $X = UAV^T$. Cleaning up X by representing it using only the first two σ's, we get the clean up version $\hat{X}$ $\begin{pmatrix} 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$. The cleaned up version $\hat{X}$ shows the structure of the original $X$ which is hidden by the noise before applying SVD.

We kept only the first r terms of Equation (2) to preserve the 90% variance of the distribution. More specifically, let $S90=0.9 \times \sum_{i=1}^{rank(X)} \sigma_i^2 > S_{90}$, then $r$ is determined as $r = \underset{j}{argmin}(\sum_{i=1}^{j} \sigma_i^2 > S_{90})$. In other words, $r$ is determined capturing 90% of the total variance.

In the following, we denote the data matrix after SVD as $D_{svd}=[D_{W,svd}|D_{B,svd}]$. Now, Let us define correlation-based association tables with SVD.

**Definition 11** (Method **SvdCorr** :correlation-based association table with SVD) Method **SvdCorr** generates the correlation-based association table $T_{SvdCorr}$ following the procedure outlined in Definition 8, but instead of starting with the weighted data matrix D, here the matrix $D_{svd}$ is used.

**Definition 12** (Method **SvdCos** : cosine-similarity association table with SVD) Method **SvdCos** generates the cosine-similarity association table $T_{SvdCos}$ following the procedure outlined in Definition 9, but instead of starting with the weighted data matrix D, here the matrix $D_{svd}$ is used.

Given an association table by the proposed methods, an image is annotated by the following algorithm.

**Algorithm 1** (Association table based annotation) Given an association table $T_{[W\times B]}$ ($W$: total number of terms; $B$: total number of blob-tokens), and also the number of captioning terms needed k, an image with l blob-tokens set $B' = \{b'_1, ..., b'_l\}$, can be captioned through the following steps:

1. Form a query vector $\mathbf{q} = [q_1, ..., q_B]$, where $q_i$ is the count of the blob-token b$i$ in the set $B'$.
2. Compute the term-likelihood vector $\mathbf{p} = \mathbf{Tq}$, where $p=[p_1, ..., p_W]^T$, and $p_i$ is the predicted likelihood of the term $w_i$.
3. If k captioning terms are to be generated, select the terms corresponding to the top k $p_i$'s in the **p** vector.

## 5. Experimental Result

The experiments are performed on 10 Corel image data sets. Each data set contains about 5200 training images and 1750 testing images. The sets cover a variety of themes ranging from urban scene to natural scene, and from artificial objects like jet/plane to animals. Each image has in average 3 annotated terms and 9 blobs.

We apply G-means and uniqueness weighting to show the effects of clustering and weighting. We compare our proposed methods, namely **Corr, Cos, SvdCorr** and **SvdCos**, with the state-of-the-art machine translation approach [10], namely **EM** approach as the comparison baseline. Each method constructs an association table as an estimated conditional probability of a term $w_i$ given a blob-token $b_j$, ($p(w_i|b_j)$). These association tables are then used in Algorithm 1 for annotation. Particularly, we would like to answer the following questions:

1. How important is the clustering algorithm?
2. How does the proposed "uniqueness" weighting

effect the performance?

3. Which proposed method is best?

We measure the annotation accuracy on each test image as the percentage of correctly predicted words as a measurement of the quality of the association table [10]. Given an image with m true annotated terms (given by human annotators), we also predicted m terms for this image using Algorithm 1. The accuracy of the annotation is defined as $S=m_{correct}/m$ where $m_{correct}$ is the number of correct terms annotated for the new image. The overall performance is expressed by the average accuracy over all images in a (test) set.

In the rest of the paper, we denote an experiment result by the design alternatives chosen along the process which generates the result. That is, each process is denoted with a string in the following format: **"[method]-[nTokens]-[weighted]"** with 3 fields to fill in the specific choices made at the 3 stages of the process. The choices for each stages are:

- field [method]: the 5 methods, **EM, Corr, Cos, SvdCorr**, and **SvdCos**. We also use All to denote all proposed methods (i.e., all except **EM**).
- field [nTokens]: **B500**, where the number of blob-tokens fixed at 500; **AdaptB**, where the number of blob-tokens is determined adaptively.
- field [weighted]: **W**, if the data matrix is weighted; **UW**, otherwise.

We first evaluate the performance of the proposed 4 methods with unweighted 500 blob-token data sets. Table 2 shows the annotation accuracy of the proposed methods and the baseline algorithm [10] denoted as **EM-B500-UW** (which means **EM** is applied to an unweighted matrix, denoted as UW, in which the number of blob tokens is 500, denoted as B500). With fixed 500 blob tokens, method **Cos-B500-UW** achieves an improvement around 2% in absolute accuracy over **EM-B500-UW**.

The adaptive blob-token generation improves the annotation accuracy shown, in Table 3. **Cos-AdaptB-UW** shows 9.4% absolute accuracy improvement over **EM-B500-UW**, the baseline method. Using the G-means algorithm (Section 3), the numbers of blob-tokens found for the 10 training set are all less than 500, ranging from 339 to 495, mostly around 400. In fact, we found that the improvement is not only on **EM** method, but also on our proposed methods. The annotation accuracy of All-B500-UW as well as **EM-B500-UW** are improved around 7% with adaptively generated blob-tokens.

Figure 4(a) illustrates the improvement of all proposed methods over the **EM-B500-UW**. Figure 4(b) compares the average annotation accuracy of fixed number of blob-tokens of 10 data sets versus the one of adaptively generated number of blob-tokens.

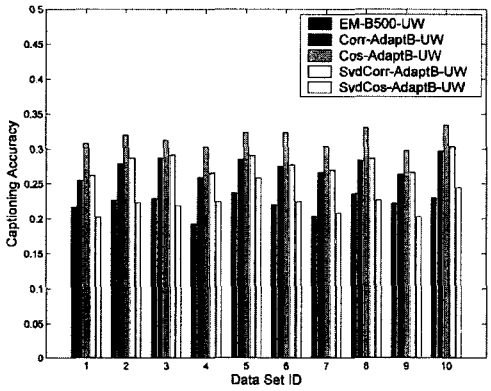
Table 4 and Table 5 illustrate the annotation accuracy with "uniquness" on **B500** and **AdaptB** data sets, respectably. After applying the "uniqueness" weighting, the 4 proposed methods on the fixed number of blob-token data perform about 2% better and the performances on the adaptive number of blob-token data gives about 9% improve-

Table 2 Annotation accuracy on "B500-UW" data sets

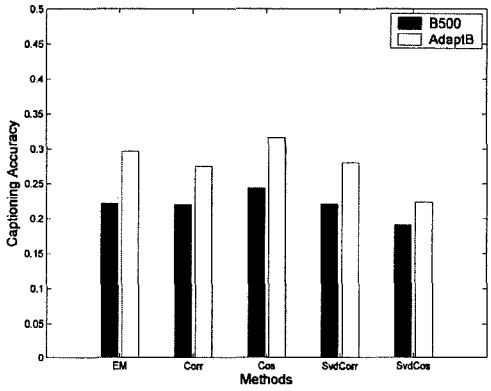
| Dataset ID | EM | Corr | Cos | SvdCorr | SvdCos |
|---|---|---|---|---|---|
| 001 | 0.2199 | 0.2196 | 0.2445 | 0.2216 | 0.1810 |
| 002 | 0.2177 | 0.2183 | 0.2464 | 0.2212 | 0.1989 |
| 003 | 0.2279 | 0.2282 | 0.2423 | 0.2278 | 0.1881 |
| 004 | 0.1925 | 0.1941 | 0.2118 | 0.1950 | 0.1621 |
| 005 | 0.2280 | 0.2299 | 0.2594 | 0.2326 | 0.2126 |
| 006 | 0.2065 | 0.2072 | 0.2410 | 0.2085 | 0.1920 |
| 007 | 0.2095 | 0.2085 | 0.2312 | 0.2118 | 0.1714 |
| 008 | 0.2290 | 0.2308 | 0.2555 | 0.2314 | 0.1961 |
| 009 | 0.2223 | 0.2233 | 0.2414 | 0.2236 | 0.1916 |
| 010 | 0.2324 | 0.2332 | 0.2586 | 0.2327 | 0.2078 |
| Average | 0.2213 | 0.2193 | 0.2432 | 0.2206 | 0.1902 |

Table 3 Annotation accuracy on "AdaptB-UW" data sets

| DataSet ID | # of BT | EM | Corr | Cos | SvdCorr | SvdCos |
|---|---|---|---|---|---|---|
| 001 | 339 | 0.2786 | 0.2548 | 0.3076 | 0.2622 | 0.2021 |
| 002 | 416 | 0.3000 | 0.2791 | 0.3204 | 0.2875 | 0.2227 |
| 003 | 392 | 0.3045 | 0.2872 | 0.3121 | 0.2917 | 0.2183 |
| 004 | 438 | 0.2779 | 0.2593 | 0.3031 | 0.2659 | 0.2242 |
| 005 | 495 | 0.2945 | 0.2854 | 0.3232 | 0.2905 | 0.2581 |
| 006 | 353 | 0.3055 | 0.2751 | 0.3239 | 0.2775 | 0.2243 |
| 007 | 433 | 0.2873 | 0.2665 | 0.3041 | 0.2698 | 0.2078 |
| 008 | 384 | 0.3073 | 0.2833 | 0.3306 | 0.2870 | 0.2271 |
| 009 | 388 | 0.2808 | 0.2630 | 0.2978 | 0.2667 | 0.2028 |
| 010 | 386 | 0.3261 | 0.2970 | 0.3346 | 0.3037 | 0.2445 |
| Average | 402 | 0.2963 | 0.2751 | 0.3157 | 0.2802 | 0.2232 |




(a) EM-B500-UW vs. ALL-AdaptB-UW




(b) All(EM)-B500-UW vs. All(EM)-AdaptB-UW

Figure 4 Comparison of annotation accuracy on AdaptB vs. B500 data sets

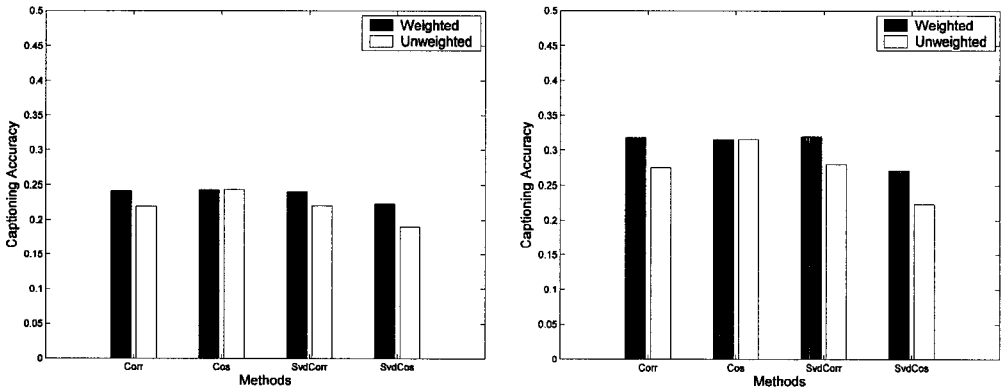
Table 4 Annotation accuracy on "B500-W" data sets

| Dataset ID | Corr | Cos | SvdCorr | SvdCos |
|---|---|---|---|---|
| 001 | 0.2439 | 0.2445 | 0.2366 | 0.2219 |
| 002 | 0.2446 | 0.2464 | 0.2433 | 0.2274 |
| 003 | 0.2466 | 0.2423 | 0.2499 | 0.2202 |
| 004 | 0.2137 | 0.2118 | 0.2103 | 0.1935 |
| 005 | 0.2567 | 0.2594 | 0.2559 | 0.2406 |
| 006 | 0.2358 | 0.2410 | 0.2364 | 0.2266 |
| 007 | 0.2273 | 0.2312 | 0.2304 | 0.2062 |
| 008 | 0.2517 | 0.2555 | 0.2520 | 0.2318 |
| 009 | 0.2392 | 0.2414 | 0.2400 | 0.2239 |
| 010 | 0.2576 | 0.2586 | 0.2543 | 0.2376 |
| Average | 0.2417 | 0.2432 | 0.2409 | 0.2230 |

ment. As in case of the **B500** data set, applying uniqueness weighting on the **AdaptB** data set also raises the performance of methods **Corr, SvdCorr** and **SvdCos** to the level of **Cos**. Method **Corr** and **SvdCorr** even outperform **Cos**. The uniqueness weighting improves the performance of all proposed methods except **Cos** (Figure 4(b)). Note that the method **Cos** always perform better than the baseline method. Intuitively, the uniqueness weighting multiplies each column $d_{wi}$ or $d_{bi}$ by some constant, which effectively changes the lengths of each column. However, the angles between them remain unchanged, so do the cosine values which are measured by the **Cos** method.

Table 5 Annotation accuracy on "AdaptB-W" data sets

| Dataset ID | Corr | Cos | SvdCorr | SvdCos |
|---|---|---|---|---|
| 001 | 0.3092 | 0.3076 | 0.3076 | 0.2618 |
| 002 | 0.3171 | 0.3204 | 0.3184 | 0.2695 |
| 003 | 0.3176 | 0.3121 | 0.3202 | 0.2585 |
| 004 | 0.3081 | 0.3031 | 0.3071 | 0.2616 |
| 005 | 0.3218 | 0.3232 | 0.3224 | 0.2901 |
| 006 | 0.3248 | 0.3239 | 0.3295 | 0.2833 |
| 007 | 0.3170 | 0.3041 | 0.3158 | 0.2636 |
| 008 | 0.3293 | 0.3306 | 0.3354 | 0.2809 |
| 009 | 0.2986 | 0.2978 | 0.2999 | 0.2579 |
| 010 | 0.3362 | 0.3346 | 0.3440 | 0.2844 |
| Average | 0.3180 | 0.3157 | 0.3200 | 0.2712 |




(a) B500 data set (b) AdaptB data set

Figure 5 Annotation accuracy of unweighted vs. weighted data sets

Table 6 Average recall, precision, and the number of used words

| | EM | Corr | Cos | SvdCorr | SvdCos |
|---|---|---|---|---|---|
| # of used words | 36 | 57 | 72 | 56 | 132 |
| Avg. Recall | 0.0425 | 0.1718 | 0.1820 | 0.1567 | 0.2128 |
| Avg. Precision | 0.0411 | 0.1131 | 0.1445 | 0.1197 | 0.2079 |

Figure 5 shows the effect of the proposed "uniqueness" weighting on the captioning accuracy comparing B500 data sets and AdaptB data sets. We also observed that weighting does not affect the result of **EM** method.

Another measurement of the performance is the recall and precision values for each word. Given a word w, let the set $R_w$ contains $r$ test images captioned with the word $w$ by the method we are evaluating. Let $r^*$ be the actual number of test images that have the word w (set $R^*_w$), and $r'$ be size of the intersection of $R_w$ and $R^*_w$. Then, the precision of word w is $r'/r$, and the recall is $r'/r^*$. Note that some words could never be used in the automatic captioning, if they are never used or are always used for the wrong images(un-annotatable words). We prefer a method which has fewer unused words, since it could generalize better to unseen images. Table 6 shows that the proposed methods use two to three times more predictable words on average than the baseline **EM** approach dose. In Figure 6 which illustrates recall and precision for each word, **SvdCorr** and **SvdCos** show more words are located in non-zero points than **Corr** and **Cos**. **EM** approach captions the frequent words with high precision and recall, but misses many words compare to **SvdCorr/SvdCos**. That is, **EM** approach is biased to the training set.

Figure 7 illustrates recall and precision scores of the top 20 frequent words in the test set. **SvdCorr**

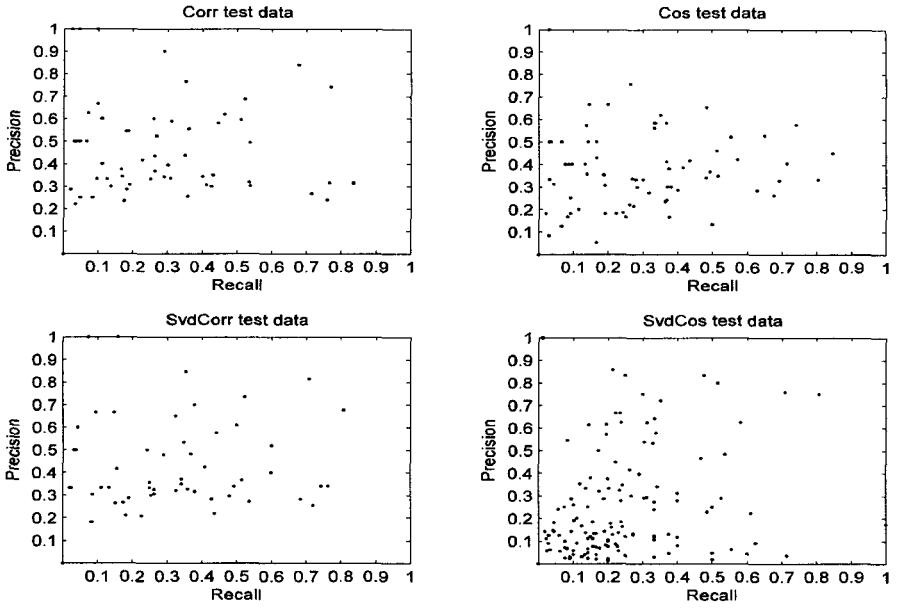
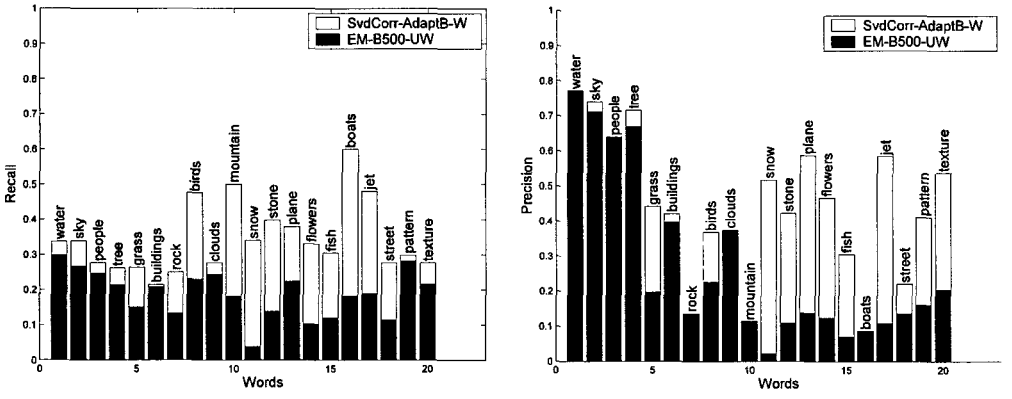



Figure 6 Recall and precision for each word




(a) Recall (b) Precision

Figure 7 Recall and precision of the top 20 frequent words

Table 7 Annotation examples of the proposed methods

| | Figure 1(a) | Figure 1(b) |
|---|---|---|
| **EM-B500-UW** | sun, clouds, sky, water | grass, rocks, sky, snow |
| **Corr-AdaptB-W** | sun, sky, sunset, clouds | grass, cat, tiger, tree |
| **Cos-AdaptB-W** | sun, sunset, sky, sea | grass, tiger, cat, leaves |
| **SvdCorr-AdaptB-W** | sun, clouds, sky, water | grass, cat, tiger, water |
| **SvdCos-AdaptB-W** | sunset, sun, sea, light | tiger, grass, cat, bengal |
| True caption | sea, sun, sky, waves | cat, forest, grass, tiger |

(white bars) gives more general performance than baseline **EM** approach (black bar).

As an example of how well the captioning is performed, we show annotation words for the image in Figure 1(a) and Figure 1(b) in Table 7. **EM-B500-UW** and **SvdCorr-AdaptB-W** both give "sky", "cloud", "sun" and "water" for the image in Figure 1(a). EM-B500-UW gives "grass", "rocks",

"sky" and "snow" for the image in Figure 1(b), while **SvdCorr-AdaptB-W** gives "grass", "cat", "tiger", and "water". Although the captions do not match the truth perfectly, they describe the content quite well. This indicates that the "truth" caption may be just one of the many ways to describe the image.

We summarize the results of our experiments as follows:

- Method **SvdCorr** has the best captioning accuracy over the 10 testing sets.
- The uniqueness weighting has no effect on method Cos (neither improve nor deteriorate).
- Methods **Cos** and **SvdCorr** have the same level of performance as **Cos** after applying the uniqueness weighting.
- Setting the size of the blob-token set is crucial for achieving good captioning accuracy. All proposed methods and the baseline method improve their performance, when working on the **AdaptB** data sets.

## 6. Discussions

The task of captioning images automatically is difficult, due to factors ranging from the property of the data set and the proposed framework for solving this problem (in our case, we caption an image via captioning the image's blobs).

In our experiments, we found that the Corel data set has several properties which introduce noise to our process. The ideal situation is each term has unique visual counterpart (blob-token), such as "cat" is always a yellow blob, and "sky" is always a blue blob. However, in the data set, a general term like "cat" appears with specific terms "tiger" or "lion" which have different blobs (one with strips, one without); and, "sky" is not always blue, there are sky during sunset which is yellow or orange.

Since our proposed methods caption an image through captioning its constituent blob-tokens, the quality of the blob-tokens in an image are critical. In practice, we have more blob-tokens than the captioning terms for each image. The extra blob-tokens may correspond to small objects in the background, or common objects such as "sky", "sea" which are captioned by human experts for some images but are not captioned for some other images which also contain the sky or sea. These uncaptioned blob-tokens introduce noise to our proposed methods and effect the performance.

For our experiments, we found that our proposed methods achieve a 45% relative improvement over the state-of-the-art EM approach. Why do the proposed methods perform better? What else can we do to do even better? The proposed methods weigh different terms and blob-tokens according to their power of discrimination (Definition 7). If a term (blob-token) is common among many images, it is likely to be mixed up with many different blob-tokens (terms). As a result, it should get lower weight, to constrain the possibility of our estimate being messed up by it. In other words, weighting suppresses the noise in the data matrix. The ongoing work is to incorporate this idea of weighting into the EM approach, which we suspect may as well boost its performance.

Despite the success of our proposed methods, we applied context-aware captioning to further improve the performance, where the relation among the blobs of an image are taking into consideration. For example, if an image is a seascape scene which contains three blob-tokens, with a blob-token suggesting the term "sea" and another suggesting "sky". Then, the term "table" is less likely to be correct than the term "boat" for the third blob-token (e.g., a wood-like blob-token which is shared by both "table" and "boat"), even the term "table" has greater likelihood than "boat" as indicated in the term-likelihood vector. We model this inter-blob-token relation by a term-term association table, which is estimated based on the co- occurrence of the terms in the annotated image set. It successfully boosts the performance of the inferior ones of our proposed methods to the same level of the best proposed method. However, surprisingly, the proposed context-aware captioning does not boost the best proposed method further. This may due to the inherent limitation of the correlation-based approach which uses only co-occurrence information. We believe adding extra information or assumptions into the process might help.

## 7. Conclusions

In this paper, we studied the problem of automatic image captioning. The problems we are interested in are: *"Given an image, give terms which describe its content." "Find images which can be described by the word "tiger"*. The technique developed will be useful for image retrieval applications. Our main contribution is the proposed correlation-based methods (**Corr, Cos** and **SvdCorr**) that consistently outperform the state of the art (**EM**) by up to a 45% relative improvement in captioning accuracy. **SvdCos** shows the best performance with recall and precision measurement that is **SvdCos** is general to unseen images. Specifically, in this paper,

- we do thorough experiments on large datasets of different image content styles, and examine all possible combinations of the proposed techniques for improving captioning accuracy;
- the proposed *uniqueness weighting* scheme on terms and blob-tokens boosts the captioning accuracy;
- our improved, "adaptive" clustering (to form blob-tokens) consistently leads to performance gains;
- dimension reduction by SVD reveals latent structures between visual vocabulary and content vocabulary so that **SvdCorr** and **SvdCos** are generalized for captioning of the unseen images.

The proposed techniques can be applied to other domains. For example, given a set of microscopic images with descriptions (e.g. the location of the cells, the symptoms of some diseases shown in the images) [29], the proposed methods can automatically give medical suggestions given a microscopic image of a new patient.

## References

[1] Benitez, A. B. and Chang, S.-F., "Image Classification Using Multimedia Knowledge Networks," Proceeding of the International Conference on Image Processing (ICIP-2003), 2003.

[2] Jaimes, A., Tseng, B., and Smith, J., "Modal Keywords, Ontologies, and Reasoning for Video Understanding," CIVR 2003, pp.248-259, 2003.

[3] Na, Y., "Image Content Modeling for Meaning-based Retrieval," Journal of Korean Information Science Society, Vol. 30, No. 2, pp. 145-156, 2003.

[4] Cho, M., Choi, J., Shin, J., and Kim, P., "Concept-based image retrieval using similarity measurement between concepts," Proc. of Korean Information Science Society Conference, No. 2483, pp. 253-255, 2003.

[5] Blei, D.M. and Jordan, M. I., "Modeling Annotated Data", 26th Annual International ACM SIGIR Conference", 2003.

[6] Barnard, K. and Forsyth, D. A., "Learning the semantics of words and pictures", Int. Conf. on Computer Vision",pp. 408-15, 2001.

[7] Jeon, J., Lavrenko, V. and Manmatha, R., "Automatic Image Annotation and Retrieval using Cross-Media Relevance Models," 26th Annual International ACM SIGIR Conference, 2003.

[8] Lee, J., and Oh, H., "Design of Indexing Agent for Semantic-based Video Retrieval," Journal of Korean Information Processing Society, Vol. 10, No.6, pp.687-694, 2003.

[9] Barnard, K., Duygulu, P., Guru, R., Gabbur, P. and Forsyth, D. A., "The effects of segmentation and feature choice in a translation model of object recognition," IEEE Conf. on Computer Vision and Pattern Recognition, 2003.

[10] Duygulu, P., Barnard, K., Freitas, J. F. G. de and Forsyth, D. A., "Object Recognition as Machine Translation: Learning a Lexicon for a Fixed Image Vocabulary," The Proceedings of the Seventh European Conference on Computer Vision, pp. IV:97-112, 2002.

[11] Li, J. and Wang, J. Z., "Automatic linguistic indexing of pictures by a statistical modeling approach," IEEE Trans. on Pattern Analysis and Machine Intelligence, Vol. 25, No. 10, 2003.

[12] Mori, Y. and Takahashi, H. and Oka, R. "Image-to-word transformation based on dividing and vector quantizing images with words," First International Workshop on Multimedia Intelligent Storage and Retrieval Management, 1999.

[13] Maron, O. and Ratan, A. L., "Multiple-Instance Learning for Natural Scene Classification," The Fifteenth International Conference on Machine Learning, 1998.

[14] Wenyin, L., Dumais, S., Sun, Y., Zhang, H., Czerwinski, M. and Field, B., "Semi-Automatic Image Annotation," INTERACT2001, 8th IFIP TC.13 Conference on Human-Computer Interaction, 2001.

[15] Brown, P. F., Pietra, S. A., Della, P. and Mercer, R. L., "The mathematics of statistical machine translation: Parameter estimation," Computational Linguistics, Vol. 19, No. 2, pp. 263-311, 1993.

[16] Barnard, K., Duygulu, P. and Forsyth, D. A., "Clustering art," IEEE Conf. on Computer Vision and Pattern Recognition, pp. 434-441, 2001.

[17] Hofmann, T., "Unsupervised Learning by Probabilistic Latent Semantic Analysis," Machine Learning Journal, Vol. = 42, No. 1, pp. 177-196, 2001.

[18] Lavrenko, V., Manmatha, R. and Jeon, J., "A

Model for Learning the Semantics of Pictures," NIPS, 2003.
[19] Carbonetto, P., Freitas, N. de and Barnard, K., "A Statistical Model for General Contextual Object Recognition," ECCV 2004.
[20] Han, J. and Kamber, M., Data Mining: Concepts and Techniques, Morgan Kaufmann, 2000.
[21] Zhang, B., "Generalized K-Harmonic Means - Dynamic Weighting of Data in Unsupervised Learning," Proceeding of the First SIAM Intl. Conf. On Data Mining, 2001.
[22] Ankerst, M., Breung, M. M., Kriegel, H. and Sander, J., "OPTICS: Ordering Points to Identify the Clustering Structure," Proc. ACM SIGMOD '99, 1999.
[23] Foss, A. and Zaane, O. "A Parameterless Method for Efficiently Discovering Clusters of Arbitrary Shape in Large Datasets", Proc. of the IEEE International Conference on Data Mining (ICDM '2002), pp. 179-186, 2002.
[24] Pelleg, Dan and Moore, A., "X-means: Extending K-means with Efficient Estimation of the Number of Clusters," Proceedings of the Seventeenth International Conference on Machine Learning, 2000.
[25] Hamerly, G. and Elkan, C. "Learning the k in k-means," Proceedings of the NIPS, 2003.
[26] Shi, J. and Malik, J., "Normalized cuts and image segmenatation," IEEE Trans. on Pattern Analysis and Machine Itelligence, Vol 22, No. 8, pp = "888-905", 2000.
[27] Furmas, G. W., Deerwester, S., Dumais, S. T., Landauer, T., Harshman, R. A., Streeter, L. A., and Lochbaum, K. E., "Information retrieval using a singular value decomposition model of latent semantic structure," Proceedings of the 11th annual international ACM SIGIR conference on Research and development in information retrieval, pp. 465-480, 1998.
[28] Monay, F. and Gatica-Perez, D. "On Image Auto-Annotation with Latent Space Models," Proc. ACM Int. Conf. on Multimedia (ACM MM), 2003.
[29] Velliste, M. and Murphy, R.F., "Automated Determination of Protein Subcellular Locations from 3D Fluorescence Microscope Images," Proc. 2002 IEEE Intl Symp Biomed Imaging (ISBI 2002), pp. 867-870, 2002.

양 형 정
정보과학회논문지 : 소프트웨어 및 응용
제 31 권 제 8 호 참조

Jia-yu Pan

Jia-Yu Pan received an M.S. degree from National Taiwan University, and a B.S. degree from National Chiao Tung University, Taiwan, both in Computer Science. He is currently a Ph.D. student at Carnegie Mellon University, working on video data mining and multimedia correlation discovery.

Pinar Duygulu

Pinar Duygulu has received her BSc, MSc and PhD degrees from Department of Computer Engineering at Middle East Technical University, Ankara, Turkey. During her PhD, she was a visiting scholar at University of California at Berkeley. After being a post-doctoral researcher at Informadia Project at Carnegie Mellon University, recently she joined to Department of Computer Engineering at Bilkent University, Ankara, Turkey. She is the co-director of RETINA Vision and Learning Group at Bilkent. She received the best paper in Cognitive Vision award at European Conference on Computer Vision in 2002. Her current research interests include computer vision and multimedia data mining, specifically object recognition and semantic analysis of large image and video collections.

Christos Falout

Christos Faloutsos is a Professor at Carnegie Mellon University. He has received the Presidential Young Investigator Award by the National Science Foundation (1989), four "best paper" awards, and several teaching awards. He is a member of the executive committee of SIGKDD; he has published over 120 refereed articles, one monograph, and holds four patents. His research interests include data mining for streams and networks, fractals, indexing methods for spatial and multimedia bases, and data base performance.