

Utilization of Co-occurrence Relationships between Semantic Concepts in Re-ranking for Information Retrieval

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Abstract—Semantic information retrieval is a popular research topic in the multimedia area. The goal of the retrieval is to provide the end users with as relevant results as possible. Many research efforts have been done to build ranking models for different semantic concepts (or classes). While some of them have been proven to be effective, others are still far from satisfactory. Our observation that certain target semantic concepts have high co-occurrence relationships with those easy-to-retrieve semantic concepts (or called reference semantics) has motivated us to utilize such co-occurrence relationships between semantic concepts in information retrieval and re-ranking. In this paper, we propose a novel semantic retrieval and re-ranking framework that takes advantage of the co-occurrence relationships between a target semantic concept and a reference semantic concept to re-rank the retrieved results. The proposed framework discretizes the training data into a set of feature-value pairs and employs Multiple Correspondence Analysis (MCA) to capture the correlation in terms of the impact weight between feature-value pairs and the positive-positive class in which the data instances belong to both the target semantic concept and the reference semantic concept. A combination of all these impact weights is utilized to re-rank the retrieved results for the target semantic concept. Comparative experiments are designed and evaluated on TRECVID 2005 and TRECVID 2010 video collections with public-available ranking scores. Experimental results on different retrieval scales demonstrate that our proposed framework can enhance the retrieval results for the target semantic concepts in terms of average precision, and the improvements for some semantic concepts are promising.

Keywords—Multiple Correspondence Analysis (MCA); Co-occurrence Relationship; Semantic Information Retrieval; Re-ranking

I. INTRODUCTION

The recent decades have evidenced a rapid increase in the amount of information. With the expansion of the Internet and the advance of IT technologies, we have encountered an unprecedented era in which information is distributed fast and easily. Such an “information explosion” possesses a great challenge on retrieving relevant information from all different kinds of sources. In the multimedia domain, recent research has intensively studied on semantic concept retrieval that extracts semantic concepts from a collection of raw data [1][2][3][4][5][6][7]. The extracted semantic concepts could act as an intermediate features with the

potential to bridge the “semantic gap” between low-level features and high-level semantics [8][9].

Figure 1 shows a general semantic concept retrieval framework. There are three important components within the framework, namely preprocessing, ranking, and re-ranking. The preprocessing component generates low-level features from the unstructured raw data (RD). By default, the structured data SD ($SD \in R^{m \times n}$) consists of m data instances and n attributes/features. SD may further be applied with data cleaning and other filtering techniques to remove noisy and missing data so as to improve the data quality. The ranking component utilizes the ranking model of a target concept to render the ranking scores (RS) to the data instances of SD . The score value of each data instance reveals its relevance to the target concept. Although for some target concepts, a ranking model is sufficient to render satisfactory retrieved results, many concepts still call for improvements in the retrieved results. Therefore, the third component (re-ranking) is vital to refine the retrieved results.

The following abstract model is used to summarize the semantic concept retrieval task.

$$\text{Preprocessing: } SD = P(RD, f) \quad (1)$$

$$\text{Ranking: } RS = \Omega(SD, \varphi) \quad (2)$$

$$\text{Re-ranking: } RT = \delta(RS, X) \quad (3)$$

The whole preprocessing component can be described as a function P which outputs SD from RD with a set of predefined features f (adopted to describe RD) as shown in Equation (1). This component is significant to the performance of concept retrieval. One research direction of semantic concept retrieval is to explore discriminant features. Evolved from the traditional features like color histogram, shape, and texture to modern features like Local Binary Patterns (LBP) [10], Histograms of Oriented Gradients (HOG) [11], and Scale-Invariant Feature Transform (SIFT) [12], the discriminant ability of features keeps on increasing and thus pulls up the retrieval performance. However, it is still difficult to find a set of features that is effective to some particular concepts.

Equation (2) describes a ranking process, where Ω stands

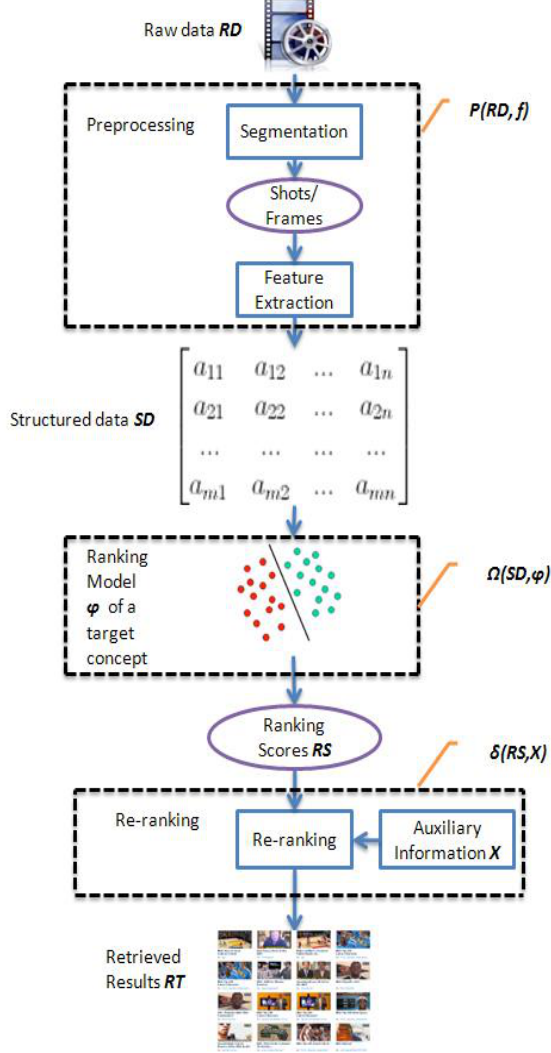


Figure 1. A general semantic concept retrieval framework

for a function which utilizes a learning model φ to give the ranking scores to SD . The ranking process is directly linked to the retrieval performance and therefore becomes a core problem in semantic concept retrieval. In the information retrieval area, there are plenty of learning algorithms to choose, including RankSVM [13], RankBoost [14], RankNet [15], etc. In semantic concept retrieval, the most popular ranking algorithms are RankSVM and its derivatives. Some papers also report good results by employing Logistic Regression, MFoM [16], and other learning schemes. However, the ranking model cannot guarantee to be effective to all concepts. Some concepts like “people” and “outdoor” may be easy-to-retrieve but others still require further efforts to improve the relevance of retrieved results.

A re-ranking strategy can provide a better ranking of the retrieval results based on the ranking scores from the ranking models with additional auxiliary information. In Equation

(3) of the abstract model, δ is used to describe the process of re-ranking in which X denotes the auxiliary information and RS are the ranking scores from the ranking models. As mentioned earlier, some semantic concepts may be difficult to be retrieved, resulting in poor retrieval performance. However, an appropriate re-ranking strategy would make it possible to significantly increase the retrieval performance for these concepts. Therefore, this paper focuses on the re-ranking part of semantic retrieval task. Observations show that many target semantic concepts have a high co-occurrence relationship with those easy-to-retrieval concepts (called reference concepts in this study). This means that the occurrence of some target semantic concepts usually accompanies with the occurrence of several other reference concepts. For example, the concept “road” appears together with the concept “outdoor”, and the concept “entertainment” is often accompanied with the concept “people”. This motivates us to utilize the co-occurrence relationships between the target concept and reference concept as auxiliary information X to re-rank the retrieval results given by the ranking model.

The paper is organized as follows. Section II discusses several existing models that discover the relationship between concepts. The proposed framework is presented in Section III. Section IV describes the experimental setup and presents our experimental results and analyses. Finally, the conclusion is presented in Section V.

II. RELATED WORK

Re-ranking methods are mostly used by utilizing auxiliary information to re-rank the text-based search list information. For example, a Bayesian re-ranking framework was introduced in [17]. By maximizing the product of the conditional prior probability and the likelihood, the consistency of the ranking scores among visually similar video segments could be maximized; while by minimizing the hinge distance and the preference strength distance, the ranking distance between the objective ranking list and the initial text-based list was minimized. Their experiments on TRECVID 2007 concepts demonstrated 61% improvement over the text-based search. Another example was discussed in [18]. Their re-ranking method was based on co-occurrence patterns obtained from a ranking function “ListNet,” a list-wise approach transforming the initial text-based rank scores and the re-ranked scores into probability distributions. It used cross-entropy to measure the distance between these two distributions. Evaluations on TRECVID 2005 data showed 35.6% improvement relative to the text search baseline.

Moreover, re-ranking methods have been applied by discovering the relationship between concepts. Qi et al. [19] utilized a Correlative Multi-Label (CML) framework to model correlations between concepts with strong interactivity. For some concepts, their work reported more than 10% improvement in terms of average precision (AP). Aytar et al. [20] presented a video retrieval framework using semantic word

similarity and visual co-occurrence. The context between concepts was exploited by point-wise mutual information. The visual co-occurrence relations between concepts were also obtained. Evaluating the concepts from TRECVID 2006 and 2007 data sets, the semantic retrieval results performed 81% better than those of the text-based retrieval method.

Yan et al. [21] proposed a probabilistic graphic model to mine the relationship between video concepts. In their work, a set of concepts were grouped together to learn a multi-concept relation model via a probabilistic graphic model. Their paper reported that some concepts had benefited from the multi-concept relation model; while others could render worse performance than that of the baseline method. Their pioneer work actually implied that although such a multi-concept relation model showed encouraging results, there still existed “gold” undermined the relationship between concepts that required a deeper discovery. Jiang et al. [22] proposed an impressive approach called domain adaptive semantic diffusion method (DASD) that utilized the consistency between semantic concepts to improve the annotation results. DASD treated concepts as nodes and the concept affinities as the weights of the edges and thus built a semantic graph model to capture the relationships between concepts. Their experiments on TRECVID 2007 data sets [23] reported a 6.3% performance gain than the baseline method by using DASD. It revealed that such an inter-concept relationship is potentially significant for an effective concept retrieval framework.

The difference between our proposed framework and the previous work lies in the following aspects. First, previous work regards correlation information as mutually useful. In other words, it considers concept “A” and concept “B” as both target and reference concepts to each other under the assumption that concept “A” and concept “B” would both benefit from their correlation. However, this may not be true in reality since the difficulty to retrieve concepts “A” and “B” is not consistent. For example, although concepts “road” and “outdoor” have strong correlation, “road” is much more difficult to retrieve than “outdoor” as can be seen from [24]. Therefore, “road” may benefit from such a correlation from “outdoor” because the correlation information from “outdoor” is quite reliable. Unfortunately on the other side, “outdoor” may render worse performance if it utilizes the correlation information with “road”. Therefore, in our work, the correlation information is utilized uni-directional. Only those easy-to-retrieve concepts are regarded as the reference concepts and of which the relationship will be used to refine the ranking of the retrieved results of the target concepts. Second, the information of co-occurrence between concepts is viewed in a mutual manner in previous work. That is, only when concept “A” and concept “B” both appear frequently, the relationship between “A” and “B” becomes valuable. However, we view this co-occurrence between concepts in an individual manner. As long as there is a large chance

(e.g., 90%) that “B” will occur when “A” appears, this co-occurrence relationship from “B” is valuable and should be taken into consideration, no matter how low the chance of “A” would appear when “B” occurs. It is worth mentioning that previous work may miss the co-occurrence relationship that is not mutual, such as the co-occurrence relationship between “snow” and “outdoor”. Finally, previous work studied the correlation between concepts on the concept level. The inter-concept relationship is derived from the class labels. However, our proposed framework further explores such an inter-concept relationship in the attribute level (details to be explained in Section III-A).

III. FRAMEWORK

Before elaborating our framework, several basic concepts and terms to be used in the framework are first introduced.

Definition 1 (Target Concept): A **target concept** refers to a concept whose retrieval performance is concerned by the current task.

Definition 2 (Reference Concept): A **reference concept** refers to a concept whose occurrence is accompanied with the target concept with a high chance. A concept is considered as a reference concept when (i) the concept has a high percentage of chance to occur if the target concept appears, and (ii) the concept is easy to retrieve.

Definition 3 (Feature-value Pair): Suppose that one discretization method is applied to an attribute A_i and creates a few partitions $A_i^1, A_i^2, \dots, A_i^P$, where i is an identifier of the attribute and P is the number of partitions created for attribute A_i . Each partition is called a **feature-value pair**. Particularly, A_i^j stands for the j -th partition of attribute A_i .

Definition 4 (DIAG Function): Let $A = \{a_1, a_2, \dots, a_N\}^T$ be an $N \times 1$ vector. A DIAG function is defined in Equation (4) which transforms A into an $N \times N$ matrix D .

$$D = \text{DIAG}(A), \quad (4)$$

where each element d_{ij} in D satisfies

$$d_{ij} = \begin{cases} a_i & \text{if } i = j; \\ 0 & \text{otherwise.} \end{cases}$$

A. Deriving attribute-based co-occurrence relationships

There are a number of ways to capture the inter-concept relationship. In this paper, our focus is put on the correlations between the attributes of the target and reference concepts as well as the co-occurrence between the target concept and the reference concept. From our point of view, it will be more accurate to utilize the inter-concept relationship on attribute or sub-attribute level than on the concept labels. Compared with those methods that capture the correlation between concepts based on the class labels [19][22], the proposed correlation in this paper is more closely related with the observation details of the data instances.

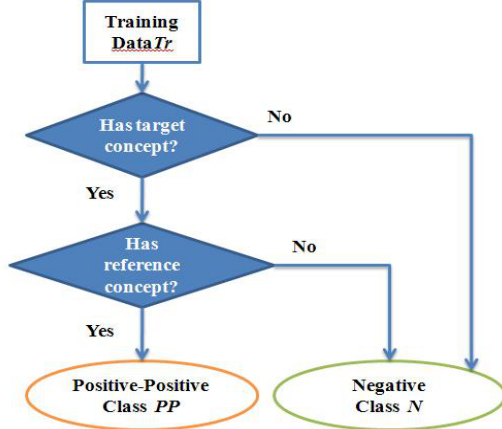


Figure 2. Construction of a co-occurrence class

Table I
A DISCRETIZED INPUT MATRIX

Attribute 1	...	Attribute T	PP	N
A_1^1	...	A_T^1	1	0
A_1^2	...	A_T^1	0	1
...
A_1^T	...	A_T^2	0	0

In order to capture the correlation and co-occurrence relationships, a co-occurrence class is built from the training set as shown in Figure 2. The training data instances which belong to both the target concept and the reference concept are in the positive-positive class (PP). The rest of the training data instances are in the negative class (N). Since the attributes used in semantic concept retrieval are mostly numeric, but some techniques that describe the relationship between two attributes like correspondence analysis only take nominal data as the input, a discretization method can be applied before deriving the correlation and co-occurrence relationships. In this paper, the Minimum Description Length (MDL)-based supervised discretization method is employed to discretize the training and testing data into several feature-value pairs corresponding to co-occurrence classes. After discretization, Multiple Correspondence Analysis (MCA), which is able to capture the correlation between more than two variables [25][26], is employed to build a correlation table for each feature-value pair and its impact weight.

The construction of the correlation table using MCA is discussed as follows. Suppose there is a discretized input matrix $\Pi \in R^{\eta \times \eta}$ as shown in Table I. Each row stands for a data instance. A_1^1 and A_T^1 are the feature-value pairs. For concept classes such as PP and N, 1 means a data instance belongs to that class; while 0 means not. For example, in Table I, the first data instance has 1 on PP, meaning it belongs to both target class and reference class.

The input matrix is accompanied with an indicator matrix and a burt matrix. The indicator matrix is an equivalent form

Table II
INDICATOR MATRIX OF THE INPUT MATRIX

A_1^1	A_1^2	...	A_T^1	A_T^2	...	PP	N
1	0	...	1	0	...	1	0
0	1	...	1	0	...	0	1
...
1	0	...	0	1	...	0	0

to represent the discretized input matrix, where each element is either 1 or 0. For example, the indicator matrix I of Table I is shown in Table II. The burt matrix B is generated using Equation (5). Let g be the grand total of B as shown in Equation (6). The probability matrix Γ is defined as $\Gamma = B/g$. It is easy to observe that Γ is as symmetric as B and the element of Γ is between 0 and 1. CODE 1 shows the procedure to derive the impact weight of each feature-value pair towards class PP from the probability matrix Γ .

CODE 1: DERIVING IMPACT WEIGHTS FROM Γ

- 1 **Input:**
a probability matrix $\Gamma \in R^{\eta \times \eta}$
 - 2 **Output:**
impact weights $W(A_i^j, PP)$
-
- 3 Calculate $V \in R^{\eta \times 1}$, which are the column totals of Γ .
 - 4 Derive diagonal matrix D by applying Equation (4) (see Definition 4) to V.
 - 5 Generate a centralized matrix Z using Equation (7).
 - 6 Apply eigendecomposition (see Equation (8)) on Z to derive its eigenvectors $Q = \{q_1, q_2, \dots, q_\eta\}$ in a descending order of the corresponding eigenvalues.
 - 7 Project Z as (X, Y) on the the subspace spanned by q_1 and q_2 , as shown in Equation (9).
 - 8 Derive impact weights $W(A_i^j, PP)$ for each feature-value pair A_i^j on class PP using Equation (10).
 - 9 Output impact weights $W(A_i^j, PP)$ for A_i^j on PP.
-

$$B = I^T I; \quad (5)$$

$$g = \sum_{i=1}^K \sum_{j=1}^K b_{ij}; \quad (6)$$

$$Z = D^{-\frac{1}{2}} (\Gamma - VV^T) (D^T)^{-\frac{1}{2}}; \quad (7)$$

$$Z = Q\Lambda Q^{-1}; \quad (8)$$

$$(X, Y) = Z * (q_1, q_2); \quad (9)$$

$$W(A_i^j, PP) = \frac{(X_{PP}, Y_{PP})^T \cdot (X_{A_i^j}, Y_{A_i^j})}{|(X_{PP}, Y_{PP})| \cdot |X_{A_i^j}, Y_{A_i^j}|}. \quad (10)$$

B. The proposed re-ranking framework

The proposed re-ranking framework consists of two phases: Learning phase and Re-ranking phase. It is assumed

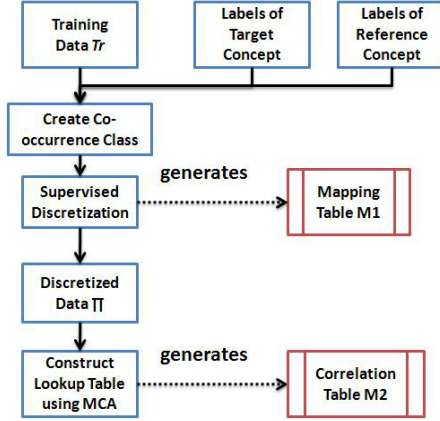


Figure 3. Detailed procedure of learning phase

Table III
AN EXAMPLES OF MAPPING TABLE M1

Feature-value pair	Partition range
A_1^1	$(-\infty, -0.1]$
A_1^2	$(-0.1, 2.2]$
...	...
A_7^j	$(-5.1, -3]$
...	...

that the target concept is known and the reference concept is appropriately selected based on the defined criteria or by empirical study. In the learning step, the correlation between feature-value pairs and PP is learned and a relationship is established via constructing a correlation table for each feature-value pair and class PP from the training data instances (Tr). The detailed procedure of the learning phase is shown in Figure 3 and CODE 2. The generated mapping table M1 (Table III) records the feature-value pair with their ranges of values for an attribute. The generated correlation table M2 (Table IV) is made of feature-value pairs and their corresponding impact weights to class PP .

Table IV
A CORRELATION TABLE M2

Feature-value pair	impact weight
A_1^1	$W(A_1^1, PP)$
A_1^2	$W(A_1^2, PP)$
...	...
A_7^j	$W(A_7^j, PP)$
...	...

CODE 2: LEARNING PHASE

- 1 **Input:**
Training data instance Tr , Training labels of the target concept and reference concept.
- 2 **Output:**
Mapping Table M1 and Correlation Table M2

- 3 Create co-occurrence class following the procedure of Figure 2.
- 4 Apply supervised discretization method to discretize the numeric training data. Create a Mapping Table M1 to store the generated feature-value pairs and their corresponding ranges of partitions.
- 5 Apply MCA on the discretized data \mathbb{I} to generate a Correlation Table M2 between feature-value pairs and impact weights by following the procedure of Code 1.
- 6 Output Tables M1 and M2

The re-ranking phase utilizes these two tables generated from the learning phase to re-rank the ranking scores by considering the correlation between the target concept and reference concept. Each test data instance (Ts) is described by a vector of attributes. Therefore, after looking up Mapping Table M1 and Correlation Table M2, a vector of feature-value pairs and impact weights are generated. The generated impact weights are then summed together to form the re-ranking weight for each data instance. The details of re-ranking phase can be found in Figure 4 and CODE 3.

CODE 3: RE-RANKING PHASE

- 1 **Input:**
Testing data instance Ts , Mapping Table M1 and Correlation Table M2 from the learning phase.
- 2 **Output:**
Re-ranking Score ReS

- 3 Get $RS(Ts, \phi_t)$, the ranking score of Ts from ranking model ϕ_t for Target Concept.
- 4 Look up Mapping Table M1 and find the Feature-Value Pair Vector.
- 5 Look up Correlation Table M2 and find the corresponding Impact Weight Vector.
- 6 Calculate the summation total W of the impact weight vector and use W as re-ranking weight.
- 7 Calculate ReS, the re-ranking score of Ts with regards to Target Concept by using $ReS = RS(Ts, \phi_t) \cdot (1 + W)$.
- 8 Output re-ranking Score ReS

IV. EXPERIMENTAL RESULTS AND ANALYSES

A. Experiment Setup

To show the effectiveness of our framework, experiments are conducted on MediaMill Challenge Data Set [27]

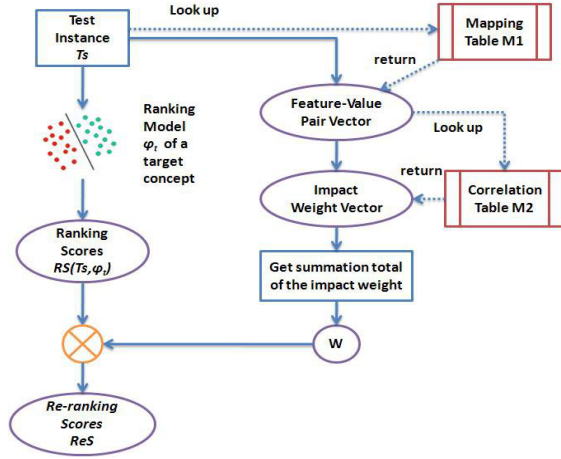


Figure 4. Detailed procedure of re-ranking phase

(Trecvid2005 news and broadcast videos) and Trecvid2010 Video Collections [23]. For MediaMill Challenge Data Set, there are 101 semantic concepts and 5 different experiments within the data set. In our experiment, the features in the first experiment are used. There are 30993 data instances in the training data set and 12914 data instances in the testing data set. For different semantic concepts, the testing data set provides the ranking scores and labels of all testing data instances for evaluation. For Trecvid2010 training video collections, 362-dimensional low-level features are extracted for each keyframe of the videos, including color dominant, color histogram, edge histogram, wavelet texture, etc. The training data set includes 71149 data instances and the testing data set has 47432 data instances. Subspace models [28] are built on the training data set to generate the testing scores for the testing data set concept by concept. The generated testing scores are used as a baseline in the experiments.

The experiment is carried out by first building a co-occurrence probability matrix CP from the training data set, in which each element CP_{ij} is given by Equation (11).

$$CP_{ij} = \frac{\# \text{ of instances belonging to both concepts } i \text{ and } j}{\# \text{ of instances belonging to concept } i} \quad (11)$$

For a target concept i , a reference concept k is selected if

- $CP_{ik} = \max\{CP_{ij}\}$;
- $CP_{ik} > 0.9$; and
- $k \neq i$.

Table V shows the target concept, reference concept and the Co-occurrence Probability (CP) with regards to the target concepts that are used in our experiment. It is worth noting that the selection of the reference concepts does not require domain knowledge. The selection is rather objective and depends only on the co-occurrence probability between the concepts. The performance is evaluated using Average Precision (AP), which is commonly adopted to evaluate the

Table V
CONCEPTS AND THEIR CO-OCCURRENCE PROBABILITY

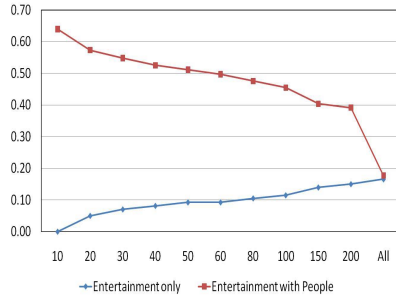
Target Concept	Reference Concept	CP	Source
Entertainment	People	0.93	Trecvid2005
Urban	Outdoor	1	Trecvid2005
Sky	Outdoor	1	Trecvid2005
Road	Outdoor	1	Trecvid2005
Map	Graphics	1	Trecvid2005
Snow	Outdoor	1	Trecvid2005
Adult	Person	1	Trecvid2010
Cheering	Person	1	Trecvid2010
Plant	Vegetation	1	Trecvid2010

effectiveness of the retrieval. We compare the AP values before and after applying our re-ranking framework in different scales to show the gain of the performance.

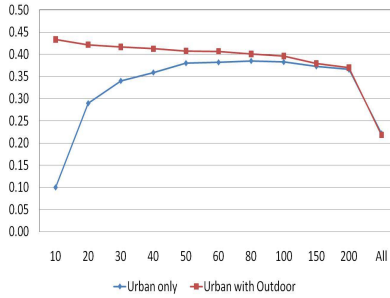
B. Results and Analyses

The AP values of the baseline and re-ranking results by applying the proposed re-ranking method are demonstrated in Figure 5(a) to Figure 5(i). The AP values are evaluated at the first 10, 20, 30, 40, 50, 60, 80, 100, 150, 200, and all data instances. From these figures, the improvement on average precision made by our proposed re-ranking framework is quite obvious, especially for the first 10, 20 and 30 retrieved results. In Figure 5(a), the AP values of the baseline are almost 0; while it can reach above 60% after re-ranking. The AP value on the first 200 is still almost 20% better after the proposed re-ranking is applied. In Figure 5(d), the target Concept ‘‘Road’’ provides an AP value of 60% for the first 10 retrieved results. It is even more exciting to see that the AP value on the first 10 is improved to be perfect after re-ranking using the correlation between ‘‘Road’’ and ‘‘Outdoor’’. The same result is achieved on the target Concept ‘‘Map’’. After re-ranking using its correlation with ‘‘Graphics’’, the AP value of the first 10 retrieved data instances reaches 100%. Even for the easy-to-retrieve concepts like ‘‘Sky’’ and ‘‘Plant’’, the correlation with the reference concepts ‘‘Outdoor’’ and ‘‘Vegetation’’ can further improve their retrieval performance.

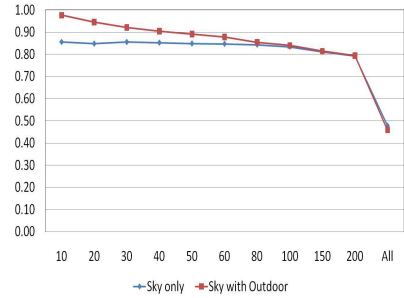
In addition to the aforementioned promising results, it can also be observed that the AP values after re-ranking tend to get close to the baseline with an increased number of retrieved data instances. There are several aspects to interpret the phenomena. First, the number of misclassified data instances increases when more data instances are retrieved. The increase on misclassification will definitely compromise the retrieval performance in terms of AP. Second, for some positive data instances with lower ranking scores that are very easy to be misclassified, the correlation in terms of the impact weights does not help boost their rankings. It is reasonable since the attribute values of these positive data instances may be either on the margin or deeply in the distribution area of negative data instances.



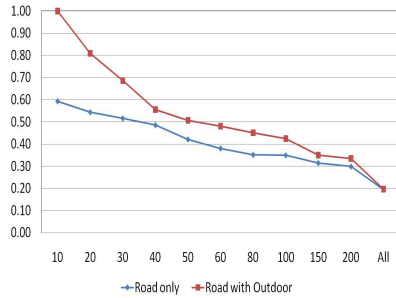
(a) Average Precision of concept ‘Entertainment’ with or without reference concept ‘People’



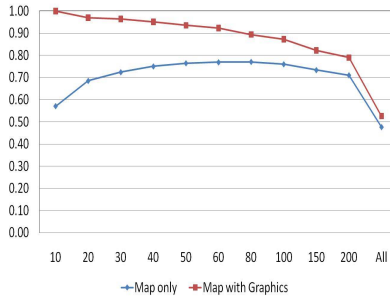
(b) Average Precision of concept ‘Urban’ with or without reference concept ‘Outdoor’



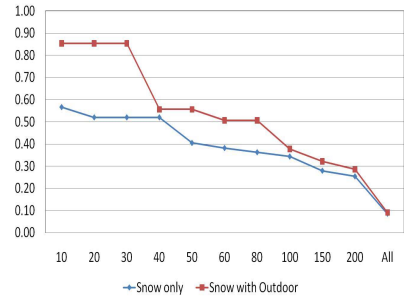
(c) Average Precision of concept ‘Sky’ with or without reference concept ‘Outdoor’



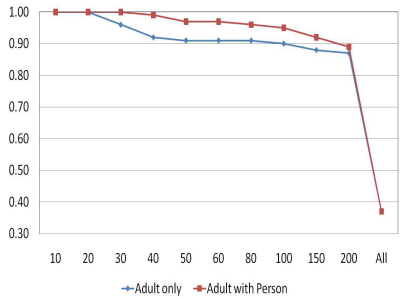
(d) Average Precision of concept ‘Road’ with or without reference concept ‘Outdoor’



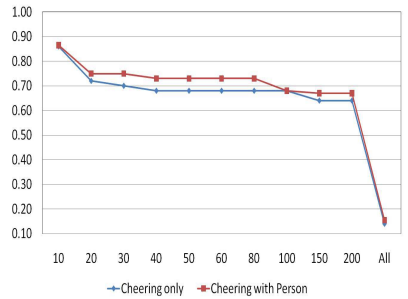
(e) Average Precision of concept ‘Map’ with or without reference concept ‘Graphics’



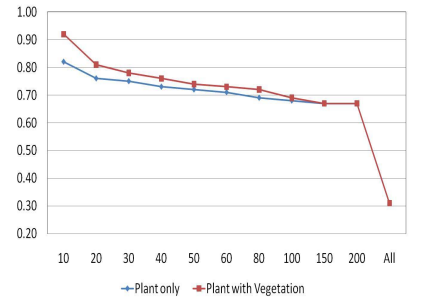
(f) Average Precision of concept ‘Snow’ with or without reference concept ‘Outdoor’



(g) Average Precision of concept ‘Adult’ with or without reference concept ‘Person’



(h) Average Precision of concept ‘Cheering’ with or without reference concept ‘Person’



(i) Average Precision of concept ‘Plant’ with or without reference concept ‘Vegetation’

Figure 5. Average Precision of 9 target concepts with/without reference concepts (the horizontal axis denotes the number of retrieved instances and the vertical axis denotes the average precision values)

V. CONCLUSION

In this paper, a new re-ranking framework that utilizes co-occurrence relationships between semantic concepts is proposed. The proposed framework creates a co-occurrence class based on a target concept and its reference concept. The co-occurrence class is further divided into subclasses PP and N depending on whether or not the data instances belong to both target and reference classes. Next, MCA is utilized to generate the Correlation Tables of the feature-value pairs and PP from the discretized training data instances. The Correlation Table as well as the Mapping Table that are generated during discretization are looked up for testing data instances to get the impact weights and final re-ranking weights. Finally, the scores from the ranking model are re-

ranked by multiplying the ranking scores with the summation of the re-ranking weight. Experimental results show that our proposed re-ranking framework achieves promising improvements on the AP (average precision) values in semantic concept retrieval, especially for the first 10, 20 and 30 retrieved results.

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