1. Multi-Attribute Image Retrieval

1.1 Problem Definition

Query attributes can be used to retrieve images that are relevant to a user's query. However, retrieving images based on attributes can be a challenging task due to the large variability of images in the wild and the difficulty in accurately labeling attributes.

1.2 Related Works

Individual Classifiers: Train attribute classifiers independently and then sum up the scores for multi-attribute queries. MARR [2] Image Ranking and Retrieval, based on Multi-Attribute Queries: Model dependency of query attributes. MARR improves over individual classifiers [2].

1.3 Problem to Solve

- MARR relies only on the pre-labeled attributes to design the dependency model.
- User labeling is a burdensome process. The small amount of attributes is far from sufficient in forming an expressive feature space.

2. Our Solution

- Weak Attributes are a collection of mid-level representations, which could be comprised of automatic classifier scores, distances to certain template instances, or even quantization to certain patterns derived through unsupervised learning, all of which can be easily acquired with very little or no human labor.
- Examples: Automatic Classifiers (Columbia3074, Classences 2,459); Discriminative Attribute (A is similar to B); Relative Attribute (A is more natural than B); Topic Models (pLSA LDA);
- Build dependency model of query attributes on the large-scale (thousands) weak attributes.

3. The Contributions

- We propose weak attributes that unify various kinds of mid-level image representations which can be easily acquired with no or little human labor.
- We apply weak attributes to image retrieval, by modeling dependency of query attributes on weak attributes under the framework of structural learning.
- To achieve efficiency and avoid overfitting, we propose a novel semi-supervised graphical model to select a subset of weak attributes adaptively for each query. This makes the proposed method applicable to large and general datasets.
- We compile the largest multi-attribute image retrieval dataset to date, named a TRECVID, including 126 fully labeled query attributes and 6,000 weak attributes of 0.26 million images.

4. How to select a subset of weak attributes for answering a specific query?

4.1 Maximizing mutual information

\[
\max_{X_0 \in \mathcal{X}} I(Q; X_0) \quad s.t. \quad (X_0) = \emptyset
\]

Where \( Q \) is a multi-attribute query, and \( X_0 \) is a subset of weak attributes.

- After some simplification, the above problem can be transformed to model \( P(Q | X_0) \) for every \( X_0 \) (weak attribute).
- \( P(Q | X_0) \) plays a key role in bridging weak attributes to multi-attribute query.
- Modeling \( P(Q | X_0) \) based on training data only may bias the model, since in large-scale image retrieval, the number of training images is always limited.

- Solution: the semi-supervised graphical model with the alternating inference algorithm.

4.3 Alternating Inference

To get \( P(Q | X_0) \) from semi-supervised graphical model, Inference in each layer is by belief propagation.

Algorithm 1 Alternating Inference

Given a query \( Q \), compute \( P(Q | X_0 = \emptyset) \) (without loss of generality, \( X_0 \subset X \))

while not convergent (the change of \( P_{old}(X_0) \) is large) do

\[ \text{Inference on the ununsupervised graph to get its marginal distribution} \quad P_{old}(X_0) \subseteq P_{old}(X_0) \]

\[ \text{Inference on the supervised graph, to get updated} \quad P_{new}(X_0) \subseteq P_{new}(X_0) \]

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end while

Compute joint distribution \( P_{new}(X_0 | Q) \) in the supervised graph as output \( P(Q | X_0 = \emptyset) \).

4.2 The Semi-supervised Graphical Model

A two-layer tree graphical model, which can capture the high-order dependency structure of query and weak attributes with consideration of both training/test data.

5. How to learn the weights? (Retrieval Model)

- We use structural SVM as the retrieval model.
- The advantages of structural SVM:
  - Joint optimization of all kinds of queries
  - Direct optimization of different loss functions

5.1 Retrieval

\[ Y^* = \arg \max_{Y \in \mathcal{Y}} \sum_{i \in \mathcal{X}} w_i \psi_i(Q, X_i) \]

5.2 Training

\[ \text{argmin} \quad \frac{1}{2} \sum_{i \in \mathcal{X}} \| Y^* - \hat{Y}_i \|_2^2 \]

where

\[ \psi_i(X_i, Y_i) = \sum_{j \in \mathcal{Y}_i} \alpha_j \| X_i - Y_j \|_2^2 \]

5.3 Experiments


5.4 Contributions (weights) of different types of weak attributes

5.5 Experiments


References