Semi-Supervised Biased Maximum Margin Analysis for SVM Relevance Feedback Image Retrieval

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Outline

• Background
• Problem and motivation
• Proposed solutions
• Experimental Results
• Conclusions
Background

- Digital cameras and mobile phone cameras are prevalent rapidly:
  - More and more digital images
  - Retrieving an image from a large image collection becomes a more and more important research topic
Background

• Early Image Retrieval System (Text-based image retrieval)
Background

- Drawbacks of the early text-based image retrieval system
  - Hard labor
    
    \[
    80,000,000 / 3600 / 24 = 926 \text{ days}
    \]
  - Beyond the technology
Background

• Dynamic interpretation of one image

• An image says thousands of words!
Background

- Some Representative Content-Based Image Retrieval systems
  - Query By Image Content system: IBM corporation
  - Virage system: Viarage corporation
  - Photobook system: MIT media lab
  - Multimedia Analysis and Retrieval System: UIUC
The framework of the CBIR system

Feedback

Query Image

Visual Features

Relevance Feedback Model

Retrieval

Refine

Final Results

Image Database
Background

  - Query Movement and Reweighting algorithms
  - Density Estimation RF algorithm
  - Subspace learning algorithms
  - Statistical sampling algorithms
  - Classification-based algorithms
  - Etc…
Problem and motivation

- The most famous classification method

Cite: Burr Settles
Review of the SVM RF for CBIR

• Support Vector Machine Relevance Feedback for Image Retrieval
  – SVM RF was first proposed in (Huang et al ICIP 2000)
    P. Hong, Q. Tian, and T. S. Huang. Incorporate support vector machines to
    content-based image retrieval with relevant feedback. *ICIP’00*, Vancouver, BC,
  – Improvement for SVM RF image retrieval
    ACM TOIS 2009, Tao et al TCSVT 2008, etc…. 
Review of the SVM RF for CBIR

- Support Vector Machine Relevance Feedback for Image Retrieval
A typical set of feedback samples in a RF iteration

“All positive examples are alike; and each negative example is negative in its own way.”  ---------X. Zhou, T. Huang 2001
Two drawbacks when using the SVM RF

- The SVM treats positive and negative feedbacks equally; **However, it is not proper.**

- The SVM ignores the unlabelled samples; **However they are very helpful in constructing a good classifier.**
How to explore solutions to the first drawback?

- **Assumption:** “Different semantic concepts live in different subspaces and each image lives in many different subspaces----X. Zhou T. Huang 2001”

- **Solution:** Therefore, we can solve the first problem by finding a semantic subspace associated with the human perception.
How to explore solutions to the second drawback?

• **Assumption:** Unlabelled samples lie on or around a low dimensional manifold in a high dimensional Euclidean space

• **Solution:** Therefore, we can use the manifold structure of the unlabelled samples to refine the semantic subspace.

One Example

From 3-D data to 2-D data
How to explore solutions to the two drawbacks?

- **Subspace Learning Techniques:**
  - Principle Component Analysis (PCA)
  - Linear Discriminant Analysis (LDA)
  - Biased Discriminant Analysis (BDA)
  - Etc…

- **Graph Embedding (GE) framework** (Yan et al TPAMI 2007)
  - GE can unify all the representative subspace learning method within one framework
  - The manifold learning algorithms can be listed as follows:
    - ISOMAP, Locally Linear Embedding, Locality Preserving Projection, Margin Fisher Analysis, Etc…
Graph Embedding Framework

• Two graphs in graph embedding framework
  – The intrinsic graph
    • Characterize the similarity relationship between vertex pairs
  – The penalty graph
    • Characterize the dissimilarity relationship between vertex pairs

• The formula of Graph Embedding techniques

\[ y^* = \arg \min \sum_{i \neq j} \| y_i - y_j \|^2 W_{ij} = \arg \min tr(YLY^T) \]

or

\[ Y^* = \min_y \frac{tr(YLY^T)}{tr(YBY^T)} \]

Similar objective

Dissimilar objective
Proposed solutions to solve the two drawbacks

- **Biased Maximum Margin Analysis (BMMA) for SVM RF**
  - Assumption: “All positive examples are alike and each negative example is negative in its own way----X. Zhou T. Huang et al”

  - Construct two graphs to describe the similarity and dissimilarity
    - Intrinsic graph: we use the intrinsic graph to describe the similarity between positive feedbacks.
    - Penalty graph: we use the penalty graph to describe the dissimilarity between positive feedbacks and negative feedbacks
The intrinsic graph in BMMA

• All positive feedbacks are alike (Decrease the pairwise distance)
The intrinsic graph in BMMA

- The objective function of the intrinsic graph

\[
S_1 = \sum_i \sum_{j: j \in \mathbb{N}_i \text{ or } j \in \mathbb{N}_j} \| \alpha^T x_i - \alpha^T x_j \|^2 * W_{ij} \\
= 2 \text{tr}[\alpha^T X (D - W) X^T \alpha]
\]

Weighting matrix

\[
W_{ij} = \begin{cases} 
1 / |\mathbb{N}_i|, & \text{if } l(i) = 1 \text{ and } l(j) = 1, \ i \in \mathbb{N}_j \text{ or } j \in \mathbb{N}_i \\
0, & \text{else}
\end{cases}
\]
The penalty graph in BMMA

• Each negative sample is negative in its own way (Increase the pairwise distance)
The penalty graph in BMMA

- The objective function of the penalty graph

Dissimilarity objective

\[ S_p = \sum_{i} \sum_{j: j \in \mathbb{N}_i^p \text{ or } i \in \mathbb{N}_j^p} \| \alpha^T x_i - \alpha^T x_j \|_2^2 * W_{ij}^p \]

\[ = 2 \text{tr}[\alpha^T X (D_p^p - W_p^p) X^T \alpha] \]

Weighting matrix

\[ W_{ij}^p = \begin{cases} 1/|\mathbb{N}_p^p|, & \text{if } l(i) = 1 \text{ and } l(j) = -1, \ i \in \mathbb{N}_j^p \text{ or } j \in \mathbb{N}_i^p \\ 0, & \text{else} \end{cases} \]
The proposed BMMA for SVM Relevance Feedback

- Biased Maximum Margin Analysis for SVM RF
  - **Maximize** the objective function of the penalty graph
  - **Minimize** the objective function of the intrinsic graph

\[
\alpha^* = \arg \max_{\alpha} 2 \text{tr}[\alpha^T (D^p - W^p) X^T \alpha] - 2 \text{tr}[\alpha^T (D - W) X^T \alpha]
\]

\[
= \arg \max_{\alpha} \text{tr}(\alpha^T XBX^T \alpha) - \text{tr}(\alpha^T X LX^T \alpha)
\]

\[
= \arg \max_{\alpha} \text{tr}[\alpha^T (B - L) X^T \alpha]
\]
The proposed BMMA for SVM Relevance Feedback

• Solutions:
  – The solution to the above problem is trivial. Therefore, we should remove an arbitrary scaling factor in the projection.

\[ \max_{\alpha} \text{tr} (\alpha^T X (B - L) X^T \alpha) \]

\[ = \sum_{k=1}^{l} \alpha_k^T X (B - L) X^T \alpha_k \]

\[ \text{s.t. } \alpha_k^T \alpha_k - 1 = 0, \ k = 1, 2, \ldots, l \]

  – Note that we can use other constraints, for example, \( \text{tr}(\alpha^T X B X^T \alpha) = 1 \). However, it will encounter the “Small Sample Size” problem
The proposed BMMA for SVM Relevance Feedback

• The dimensionality of the embedding subspace
  – In general, we have

\[
\max_{\alpha} \text{tr}(\alpha^T X (B - L) X^T \alpha) = \sum_{i=1}^{l} \lambda_i
\]

where \(\lambda_i\)'s are the associated eigenvalues and we have

\[
\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_{d-1} \geq 0 \geq \lambda_d \geq \cdots \geq \lambda_l
\]

Therefore, we should preserve all directions associated with the nonnegative eigenvalues
Semi-Supervised Biased Maximum Margin Analysis

- Another intrinsic graph for unlabeled samples in SemiBMMA
Semi-Supervised Biased Maximum Margin Analysis

- The objective function of the intrinsic graph for unlabeled samples

\[
S_u = \frac{1}{2} \sum_i \sum_{j: j \in N^u_i, i \in N^u_j} \| \alpha^T x_i - \alpha^T x_j \|^2 * W_{ij}^u
\]

\[
= \text{tr}[\alpha^T X (D^u - W^u) X^T \alpha]
\]

\[
= \text{tr}[\alpha^T XUX^T \alpha]
\]

\[
W_{ij}^u = \begin{cases} 
\frac{1}{|\mathbb{N}_i|} \exp(-\frac{\| x_i - x_j \|^2}{\delta^2}), & \text{if } l(i) = l(j) = 0, i \in \mathbb{N}_j \text{ or } j \in \mathbb{N}_i \\
0, & \text{else}
\end{cases}
\]
Semi-Supervised Biased Maximum Margin Analysis

- Introduce the intrinsic graph of unlabelled samples into BMMA, we can have Semi-Supervised BMMA (SemiBMMA):

\[ \alpha^* = \arg \max_{\alpha} \text{tr}[\alpha^T X (B - L - \beta \ast U) X^T \alpha] \]

- Comparison between the BMMA SVM and the SemiBMMA SVM
Experiments

- Corel Image Database (10763 images with 80 concepts)

- Content-Based Image Retrieval System framework
Experiment Platform

- **Image Representations**
  - **Color**: hue, saturation value color histograms and color moments to form $256+9$ dimensional features
  
  - **Local Image Descriptor**: Weber Local Descriptor (WLD) - (Jie Chen et.al *TPAMI* 2009), 240 dimensional features
  
  - **Shape**: Edge Direction Histogram (EDH) 5 dimensional features
Experiments

• Subsection I : Visualization of problems in the SVM RF
  – A feature subset selection problem for the SVM RF
  – An unstable problem for the SVM RF
• Subsection II : Subspace learning based on different methods
  – Six group of comparison results for toy problems
• Subsection III : Statistical experimental results
  – Experiments on a small size image database
  – Experiments on a large scale image database
• Subsection IV : Visualization of the image retrieval results
Experiments: Subsection I

- A feature subset selection problem for the SVM RF

Positive

Negative

Random select 2-d features, the resultant SVM classifiers
Experiments: Subsection I

• An unstable problem for the SVM RF in the first few iterations
  – (a) 4 positive feedbacks and 6 negative feedbacks
  – (b) 5 positive feedbacks and 6 negative feedbacks
  – (c) 6 positive feedbacks and 6 negative feedbacks
Experiments: Subsection II

- Subspace learning based on different methods
Experiments: Subsection III

• Part I: On a small scale Corel image database
  – **Objective:** To validate the effectiveness of BMMA combined with the SVM RF
  – **Experimental settings:**
    • Database: 3899 corel images with 30 different categories
    • Feedback sample number: first 5 relevant images and first 5 irrelevant images in top 20 results are labeled as positive and negative feedbacks
    • Feedback iteration number: as queries to do 2 rounds of feedback iterations.
Experiments: Subsection III

- The average precision values for all 30 categories after 2\textsuperscript{nd} feedback

Observation: BMMA combined with the SVM RF can significantly improve the performance of the SVM RF for most of the 30 categories
Experiments: Subsection III

- Average Precision after 1\textsuperscript{st} feedback and 2\textsuperscript{nd} feedback iteration

Observation: BMMA combined with the SVM RF can significantly improve the performance of the SVM RF after 1\textsuperscript{st} feedback. However, over fitting problem will occur after more feedback iterations.
Experiments: Subsection III

• Part II: On a large scale Corel image database
  – Objective: To evaluate the effective of the BMMA and SemiBMMA combined with the SVM RF
  – Experimental settings:
    • Database: 10763 corel images with 80 different categories; five cross validation dataset
    • Feedback schemes: first 3 relevant and all irrelevant images in top 20 results are labeled as positive and negative feedbacks respectively; 400 independent queries; 9 feedback iterations
Experiments: Subsection III

• Experimental results on large scale image database (Average Precision)

Observations: SemiBMMA combined with the SVM RF shows much better performance, BMMA combined with the SVM RF also show good performance comparing with the SVM RF
Experiments: Subsection III

• Experimental results on large scale image database (Standard Deviation)
Experiments: Subsection III

- The average precision results after 9\textsuperscript{th} feedback

**Observation:** SemiBMMA SVM RF and BMMA SVM RF can improve the performance of SVM RF after 9-th feedback significantly in all top 10-top 90 results. OCCA ignores the negative feedbacks and thus will cause the over-fitting problems as shown in top 50-top 90 results.
Experiments: Subsection III

- Conclusions on the experimental results on a large scale image database
  - a) BMMA combined with the SVM RF can improve the performance of the SVM RF; therefore BMMA SVM can integrate the distinct properties of feedbacks into the SVM RF.
  - b) SemiBMMA combined with the SVM RF show much better performance comparing with the SVM RF and BMMA SVM RF; therefore SemiBMMA can integrate the information of the unlabeled samples into the SVM RF.
  - c) It should be noted that the different performance between the small and large image database are because of the different feedback schemes in two experiments.
Experiments: Subsection IV

• Visualization of the retrieval results
  – Query images: Randomly select 4 images as the queries (e.g., bobsled, cloud, cat and car)
  – Feedback Scheme: around 4 positive and 4 negative feedbacks in top 20 images.
Experiments: Visualization of the results
Conclusions

- Support Vector Machine based RFs have been widely used to enhance the image retrieval system.
- BMMA can combine the properties of the feedbacks with SVM RF and enhance the performance of the CBIR system.
- Semi-Supervised BMMA can integrate the information of unlabelled samples into SVM RF and thus further enhance the performance of the CBIR system.
Thank you