Hyperspectral images retrieval with Support Vector Machines (SVM)

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Outline

1. Introduction
2. One-Class SVM for Learning in Image Retrieval [1]
3. Non-Relevance Feedback Document Retrieval Based on One-Class SVM and SVDD [2]
4. Active Learning Methods for Interactive Image Retrieval [3]
    - Introduction
    - Classification framework for CBIR
    - Active learning
    - Retin active learning scheme

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Two-class problem

- For CBIR, retrieving image concepts is modeled as a two-class problem:
  - Relevant class: the set of images in the searched concept.
  - Irrelevant class: composed by the remaining database images.
- Let $\{x_i\}_{i=1,n}$ be the n image indexes of the database containing the feature characterization.
- A training set is expressed as $A_y = \left\{(x_i, y_i)_{i=1,n} | y_i \neq 0\right\}$, where:
  - $y_i = 1$ if the image x_i is labeled as relevant.
  - $y_i = -1$ if the image x_i is labeled as irrelevant.
  - $y_i = 0$ otherwise.
- The classifier is trained using these labels, and a relevance function $f_{A_y}(x_i)$ is determined to rank the whole database.

Feature distribution

- In order to compute the relevance function $f_{A_y}(x_i)$ for any image x_i, a classification method has to estimate the density of each class and/or the boundary.
- In the CBIR context, relevant images may be distributed in a single mode for one concept, and in large number of modes for another concept, thereby inducing nonlinear classification problems.

Gaussian mixtures

- Highly used in CBIR since their ability to represent complex distributions.
- However, to get an optimal estimation of the density of a concept, data have to be gaussian distributed.
- The large number of parameters required leads to high computational complexity.

Kernel framework

- Map image indexes x_i to vectors $\Phi(x_i)$ in Hilbert space, turning nonlinear problem into a linear one.
- Kernel vectors never compute explicitly the vectors $\Phi(x_i)$, working only on their dot product $\langle \Phi(x_i), \Phi(x_j) \rangle$, hence allowing to work on very large or even infinite Hilbert spaces.
- The value of the kernel function between images x_i and x_j is denoted as $k(x_i, x_j)$, and is considered as the default similarity function in the following.

Comparison of classifiers

- Experiments with ANN and Corel databases using several classification methods: Bayes with Parzen density estimation, KNN, SVM, kernel Fisher discrimant.
- SVM performs slightly better and it has an efficient algorithm implementation.
- Anyway, global performances remain very low.

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Introduction

- Close to supervised learning, except that training data are not independent and identically distributed variables.
- Some of them are added to the training set thanks to a dedicated process.
- In this context, the main challenge is to find data that, once added to the training set, will allow to archive the best classification function.

Pool based active learning [4]

- When the learner can only choose new data in a pool of unlabeled data.
- In CBIR the whole set of images is available anytime.
- This data will be considered as the pool of unlabeled data during the selective sampling process.

Notation

- Let $\{x_i\}_{i=1,n}$ be the image signatures, $A_y = \left\{ (x_i, y_i)_{i=1,n} | y_i \neq 0 \right\}$ the training set and $f_{A_y}(x_i)$ the relevance function, already defined.
- Introduce now the following notation for the teacher:

$$s : X \rightarrow \{-1, 1\}$$

  that labels images as -1 or 1.
- The indexes of the labeled images will be denotes as I, and the unlabelled ones as $\bar{I}$.

Optimization scheme

- The active learning aims at selecting the unlabeled data x_{i^*} that will enhance the most the relevance function f trained with the label $s(x_{i^*})$ added to A_y.
- To formalize the selection process as a minimization problem, a cost function g_{A_y} is introduced.
- According to any active learning method, the selected image is x_{i^*} minimizing $g_{A_y}(x)$ over the pool of unlabeled images

$$i^* = \arg\min_{i \in \bar{I}} \left(g_{A_y}(x_i) \right) \tag{1}$$

Active learning methods

- Two different strategies are usually considered for active learning:
  - The uncertainty based sampling: selects the images for which the relevance function is the most uncertain.
  - The error reduction strategy: aims at minimizing the generalization error of the classifier.

Uncertainty based sampling

- Selects the images for which the relevance function is the most uncertain.
- To archive it a relevance function f_{A_y} is trained, adapting it from a distribution, a membership to a class or an utility function.
- Using this relevance function, uncertain data x will be close to 0: $f_{A_y}(x) \sim 0$.
- The solution to the minimization problem in (1) is:

$$i^* = \arg\min_{i \in \bar{I}} \left(\left| f_{A_y}(x_i) \right| \right) \tag{2}$$

- Its efficiency depends on the accuracy of the relevance function estimation close to the boundary between relevant and irrelevant classes.

Error reduction based strategy I

- Aims at minimizing the generalization error of the classifier.
- Let denote $P(y|x)$ the unknown probability of sample x to be in class y (relevant or irrelevant), and $P(x)$ the also unknown distribution of the images.
- With A_y the training provides the estimation $\hat{P}_{A_y}(y|x)$ of $P(y|x)$, and the expected error of generalization is

$$E\left(\hat{P}_{A_y}\right) = \int_x L\left(P(y|x), \hat{P}_{A_y}(y|x)\right) dP(x)$$

being L a loss function which evaluates the loss between the estimation $\hat{P}_{A_y}(y|x)$ and the true distribution $P(y|x)$.

Error reduction based strategy II

- The optimal pair (x_i^*, y_i^*) minimizes the expectation over the pool of unlabeled images

$$(x_i^*, y_i^*) = \arg \min_{(x_i,y_i), i \in \bar{I}} \left(E\left(\hat{P}_{A_y + (x_i,y_i)} \right) \right) \tag{3}$$

  with $A_y^* = A_y + (x_i^*, y_i^*)$.

- As the expected error is usually not accesible, the integral over $P(x)$ is usually approximated using the unlabeled set.
- With $0/1$ loss function L, the estimation of the expectation is expressed for any A

$$\hat{E}\left(\hat{P}_A\right) = \frac{1}{|\bar{I}|} \sum_{x_i, i \in \bar{I}} \left(1 - \max_{y \in \{-1,1\}} \hat{P}_A(y|x_i) \right)$$

Error reduction based strategy III

- As the labels $s(x_i)$ on $\bar{I}$ are unknown, they are estimated by computing the expectation for each possible label. Hence, the cost function is given by

$$g_{A_y}(x) = \sum_{y \in \{-1,1\}} \hat{E}\left(\hat{P}_{A_y+(x,y)}\right) \hat{P}_A(y|x) \tag{4}$$

- The following relation between $\hat{P}_{A_y}(y|x)$ and $f_{A_y}(x)$ is used:

$$\hat{P}_{A_y}(y|x) = \frac{y}{2}\left(f_{A_y}(x) + y\right)$$

Active learning in CBIR context

- Unbalance of classes: the class of relevance images is generally 20 to 100 times smaller than the class of irrelevant images.
  - As a result, the boundary is very innacurate.
  - This is specially true in the first iteration of relevant feedback where the size of the training set is dramatically small.
- Selection criterion: whenever minimizing the error of classification is interesting for CBIR, this criterion does not completely reflect the user satisfaction.
  - Other more adecuated utility criteria as precision can be used.
- Batch selection: more than one image has to be proposed to label between two feedback steps, contrary to many active learning techniques which are only able to select a single image.
- Computation time.

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Introduction

- Active learning scheme based on binary classification in order to interact with a user looking for image concepts in databases.

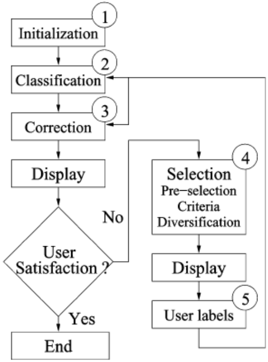

Figure: Retin active learning scheme

Scheme

1. *Initialization*: a retrieval session is initialized with an image brought by the user. Image's features are computed and added to the database.
2. *Classification*: a binary classifier is trained with the labels the user gives. The result is a function $f_{A_y}(x_i)$ which returns the relevance of each image x_i according to the examples A_y.
3. *Boundary correction*: an active correction is added to the boundary in order to deal with the few training data and the inbalance of the classes.
4. *Selection*: when the user is not satisfied with the current classification, the user selects a set of images the user shold label. The selection must be such so that the labeling os those images provides the best performance.
5. *Feedback*: the user labels the selected images, an a new classification and correction are computed if necessary.

Boundary correction I

- During the first steps of relevance feedback, classifiers are trained with very few data.
- A method to correct the boundary is proposed in order to reduce this problem.
- The correction is a shift of the boundary:

$$\hat{f}_{A_{y_t}}(x_i) = f_{A_{y_t}}(x_i) - b_t \tag{5}$$

with $f_{A_{y_t}}$ the relevance function and b_t the correction at feedback step t.

Boundary correction II

- The correction is computed to move the boundary towards the most uncertain area of the database.
- It is wanted a positive value of $\hat{f}_{A_{y_t}}$ for any image in the concept, and a negative value for others.
- In order to get this behaviour a ranking of the database is computed

$$()_{A_{y_t}} = argsort\left(f_{A_{y_t}}(X)\right)$$

with $argsort(v)$ being a function returning the indexes of the sorted values of v.

Boundary correction III

- Let $()_{r_t}$ be the rank of the image whose relevance is the most uncertain

$$x_{()_1}, x_{()_2}, \ldots, x_{()_{r_t-1}}, x_{()_{r_t}}, x_{()_{r_t+1}}, \ldots, x_{()_{n-1}}, x_{()_n}$$

  with the images on its left approach the concept, and images on its right are the less relevants.
- The correction is expressed by: $b_t = f\left(x_{()_{r_t}}\right)$.
- In order to compute the correction, an algorithm based on adaptative tuning of $()_{r_t}$ during the feedback steps is proposed.
- The value at the $(t+1)$th iteration is computed considering the set of labels provided by the user at the current iteration t.

For Further Reading I

- One-Class SVM for Learning in Image Retrieval. Yunqiang Chen, Xiang Zhou, Thomas S. Huang. Proc. IEEE Int. Conf. on Image Processing, Thessaloniki, Greece. 2001.
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Questions?

Thank you very much for your attention.

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