# Image Retrieval Using Kernel Methods Mini Proposal Defense

### Foong Joan Tack

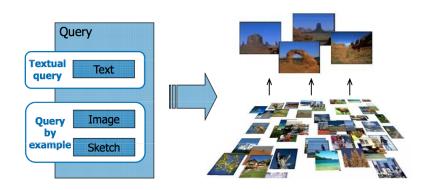
Department of Computer Science and Networked System
Faculty of Science and Technology
Sunway University
cloverevolc@yahoo.com
12058590@imail.sunway.edu.my

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### Overview

- What is Content-based Image Retrieval?
- What is Kernel Methods?
- Why is it a good idea to use Kernel Methods?

### What is Image Retrieval

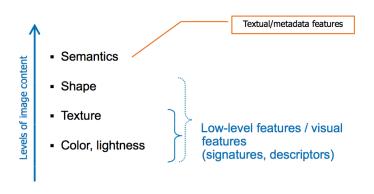


Courtesy of Natalia Vassilieva, Russian Summer School in Information Retrieval 2009

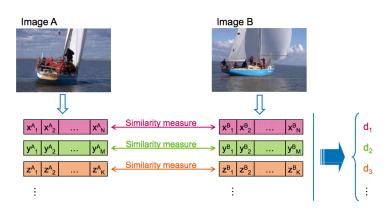
### Content-based vs. Description-based

	DBIR	CBIR
+	<ul> <li>Fulltext search algorithms are applicable</li> </ul>	Automatic index construction
	Search results corresponds to image semantics	Index is objective
_	<ul> <li>Manual annotating is hardly feasible</li> </ul>	Semantic gap
	Manual annotations are subjective	Querying by example is not convenient for a user

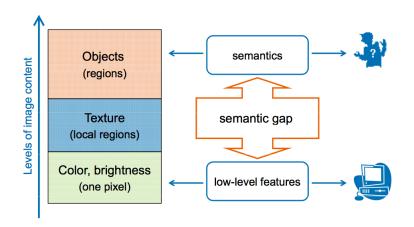
### **Features**



### Similarity



## Semantic Gap



## Application: Image Archives











- personal photo collection
- art gallery
- search for uncle John's photos
- search for Monet's painting

### Application: Medical Images









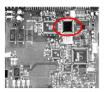
- x-ray
- MRI
- pathological vs healthy

## Application: Security



- suspicious items
- face recognition

# Application: Industry







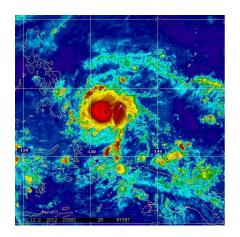


(a) CD-ROM controller (b) Pack of pills

(c) Level of liquid

(d) Air-bladders in plastic

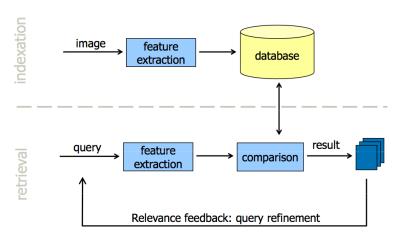
# Application: Satellite Images



- weather monitoring
- military

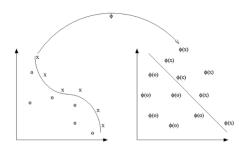


### Main Components



Courtesy of Natalia Vassilieva, Russian Summer School in Information Retrieval 2009

# Kernel Methods (1)



$$\phi:X\mapsto H$$

## Kernel Methods (2)

- no explicit representation, only kernel function
- implicitly calculate in higher dimensional space
- higher dimension ⇒ higher capacity
- separation of data representation and algorithm

# Kernel Methods (3)

### Definition

A positive definite kernel k(x, x') is a function from  $X^2$  to real number such that:

$$\sum_{i,j} a_i a_j k(x_i, x_j) > 0$$

### Theorem (Aronszajn theorem)

k is a positive definite kernel if and only if there exist a Hilbert Space H and a mapping  $\phi: X \mapsto H$  such that  $k(x,x') = \phi(x)^T \phi(x')$  for all  $(x,x') \in X^2$ 



### Kernel Methods (4)

### Definition (Kernel Trick)

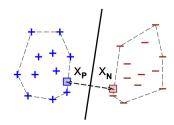
any algorithm for finite-dimensional vectors that only uses pairwise dot-products can be applied in the feature space.

The algorithm and data are separated, hence *Modularity* 

### Kernel Methods (5) - Examples

- linear kernel,  $k_L(x, x') = x^T x'$  and
- polynomial kernel,  $k_P(x, x') = (x^T x')^d$
- Gaussian RBF kernel,  $k_G(x, x') = exp(-\frac{|x-x'|^2}{2\sigma^2})$

# Support Vector Machine



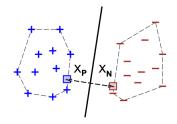
The points  $X_p$  and  $X_n$  can be parametrized as:

$$X_P = \sum_{i \in P} a_i x_i, \sum a_i = 1$$

$$X_N = \sum_{j \in N} a_j x_j, \sum a_j = 1$$



# Support Vector Machine



The solution can be found by optimizing:

$$max||X_{P} - X_{N}||^{2}$$

### Online SVM

#### $\mathbf{UPDATE}(k)$ :

- Compute X<sub>P</sub>x<sub>k</sub>, X<sub>N</sub>x<sub>k</sub>, and x<sub>k</sub>x<sub>k</sub>.
- Compute λ<sub>u</sub> using equations (4) or (5).
- Compute λ using equation (6)
- $\alpha_i \leftarrow (1 \lambda)\alpha_i$  for all i such that  $y_i = y_k$ .
- $\alpha_k \leftarrow \alpha_k + \lambda$ .
- Update  $X_P X_P$ ,  $X_N X_P$  and  $X_N X_N$  using equation (7) or (8).

#### HULLER:

- Initialize  $X_P$  and  $X_N$  by averaging a few points.
- Compute initial  $X_P X_P$ ,  $X_N X_P$ , and  $X_N X_N$ .
- Iterate:
  - Pick a random p such that  $\alpha_p = 0$ 
    - UPDATE(p)
    - Pick a random r such that  $\alpha_r \neq 0$
    - UPDATE(r)

The Huller: a simple and efficient online SVM, Antoine Bordes and Leon Bottou

### Future Work - Rigorous Formulation of Problem

- only empirical justification
- hard to compare result
- hidden assumption
  - fixed distribution
  - independent sampling

### Future Work - Clustering with SVD

Suppose that our database contains images  $I_1, I_2, ..., I_k$ , and the image  $I_j$  is represented by  $[O_1^j, O_2^j, ..., O_n^j]$  then we can construct the matrix below:

$$O = \begin{pmatrix} O_1^1 & O_1^2 & \cdots & O_1^k \\ O_2^1 & O_2^2 & \cdots & O_2^k \\ \vdots & \vdots & \cdots & \vdots \\ O_n^1 & O_n^2 & \cdots & O_n^k \end{pmatrix}$$

### Future Work - Clustering with SVD

$$O = U\Sigma V^*$$

where U is an  $n \times n$  unitary matrix,  $\Sigma$  is a  $n \times k$  diagonal matrix, and V is a  $k \times k$  unitary matrix. The core of this method is that we truncate the matrix  $\Sigma$  down to a rank r matrix  $\Sigma_r$ , and U, V to  $U_r$ ,  $V_r$  by keeping only their first r columns.

- SVM is a kind of supervised learning need label
- similar to PCA

### Future Work - Improvement on Algorithm

- multi-classes
- soft margin

### Future Work - Kernel Design

- Fisher Kernel is a general framework to design kernel for for probabilistic distribution.
- Pyramid Match Kernel is a kernel used for unordered features sets with variable length

 ${\sf Questions}\ ?$