Exploiting Socially-Generated Side Information in Dimensionality Reduction
in 2nd International Workshop on Socially-Aware Multimedia (IWSAM 2013)

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Motivation

Side information available

- text (labels, descriptions)
- geo (lat/long, locations)
- popularity (ratings, diffusions)
- users (owners, networks)
- etc.

already used to solve some problems.

How can we use side information for all applications?
Pinterest is now an emerging social network
Pinterest 2.0

Source: www.pinterest.com
Problem setting

- Original features: $x$
- Side information: $v$
- Class label: $y$

$$D = \{(x_i, v_i, y_i)\}_{i=1}^n$$

**Linear dimensionality reduction**

Find a transformation matrix $T$ from $D$ such that

$$z = T^\top x \quad \text{with} \quad \dim(z) \ll \dim(x)$$

Note: no need of side information for new images
Local Fisher Discriminant Analysis (LFDA)

- supervised method
- idea: minimize the within-class scatter $S_w$ while maximizing the between-class scatter $S_b$
- $T$ is obtained by eigendecomposition
Local Fisher Discriminant Analysis

\[
S_b = \frac{1}{2} \sum_{i,j=1}^{n} D_{i,j}^b (x_i - x_j) (x_i - x_j)^\top
\]

\[
S_w = \frac{1}{2} \sum_{i,j=1}^{n} D_{i,j}^w (x_i - x_j) (x_i - x_j)^\top
\]

where

\[
D_{i,j}^b = \begin{cases} 
A_{i,j} \left(1/n - 1/n_c\right) & \text{if } y_i = y_j = c, \\
1/n & \text{if } y_i \neq y_j,
\end{cases}
\]

\[
D_{i,j}^w = \begin{cases} 
A_{i,j}/n_c & \text{if } y_i = y_j = c, \\
0 & \text{if } y_i \neq y_j.
\end{cases}
\]
Affinity matrix $A$

Original approach

\[
A_{i,j} = \exp \left( -\frac{\|x_i - x_j\|^2}{\sigma_i \sigma_j} \right)
\]

where $\sigma_i = \|x_i - x_K\|$ where $x_K$ is the $K$-th nearest neighbor of $x_i$.

Original approach

- uses only $x$ and $y$
- if features $x$ are very noisy, then $A$ is noisy and $A$ leads poor dimensionality reduction
Affinity matrix $A$

Proposed approach

$$A_{i,j} = \exp \left( -\frac{\|v_i - v_j\|^2}{2\sigma^2} \right)$$

Proposed approach
- very simple modification
- uses $x$, $y$ and $v$
- adds new information
- can be seen a kind of regularization of LFDA
Side information

We propose three types of side information for Pinterest:

- users
- boards
- clusters of boards
### Users’ information

\[ U = \text{set of users} \]

\[ v^\text{user}_i \in \{0, 1\}^{|U|} \]

where

\[ v^\text{user}_i = \begin{bmatrix} 1 & 0 & \cdots & 1 & 0 & \cdots & 1 \end{bmatrix} \]

\[ \rightarrow \text{user } j \text{ pinned image } i \]

### Boards’ information

\[ B = \text{set of boards} \]

\[ v^\text{board}_i \in \{0, 1\}^{|B|} \]

where

\[ v^\text{board}_i = \begin{bmatrix} 1 & 1 & \cdots & 1 & 0 & \cdots & 0 \end{bmatrix} \]

\[ \rightarrow \text{image } i \text{ is pinned to board } j \]
Clusters of boards information

Preliminary step: board clustering

(Kimura et al. ‘Image Context Discovery from Socially Curated Contents’ in ACM MM 2013)

\[ K = \text{set of clusters} \]

\[ \mathbf{v}_{i}^{\text{cluster}} \in [0, 1]^{|K|} \]

such that

\[ \mathbf{v}_{i}^{\text{cluster}}(k) = \frac{n_{i,k}}{n_{i}} \]

where

- \( n_{i,k} \) = the number of times image \( i \) is pinned to a board that is part of cluster \( k \)
- \( n_{i} \) = the number of times image \( i \) has been pinned
Supervised side-information-based dimensionality reduction

Results

Methods comparison

- 12,500 images downloaded from Pinterest
- compute GIST features and side info vectors for each image
- 1/2 for learning and 1/2 for testing

<table>
<thead>
<tr>
<th>$m$</th>
<th>GIST</th>
<th>PCA</th>
<th>LFDA</th>
<th>Proposed</th>
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<td>960</td>
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<td>10</td>
<td>10</td>
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<td>Linear reg.</td>
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<td>$k=15$</td>
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<td>38.2</td>
<td>36.4</td>
<td>42.8</td>
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Classification accuracy (%)
Conclusions:
- generic, simple and easy-to-implement approach
  - does not depend on the application
  - does not degrade applications’ performances
  - applicable to other dimensionality reduction methods
- no need to have side information for new images

Open questions:
- platform-dependent side information vectors
- evolution of the side information space
Acknowledgments

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Local Fisher Discriminant Analysis

\[ T^* = \arg \max_{T \in \mathbb{R}^{d \times m}} \text{tr} \left[ \left( T^\top (S_w + \eta I_d) T \right)^{-1} T^\top S_b T \right] \]  

(1)

where \( I_d \in \mathbb{R}^{d \times d} \) is the identity matrix and \( \eta > 0 \) is a regularization parameter.

\[ T^* = (\varphi_1 | \varphi_2 | \cdots | \varphi_m) \]

where \( \{ \varphi_i \}_{i=1}^d \) represent the generalized eigenvectors associated with the generalized eigenvalues \( \lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_d \) of the following generalized eigenvalue problem:

\[ S_b \varphi = \lambda (S_w + \eta I_d) \varphi \]  

(2)
Appendix

Methods comparison

(a) Linear regression

(b) 25-Nearest neighbors
Side information comparison

(c) Linear regression

(d) 25-Nearest neighbors
2-D visualization

(a) PCA visualization

(b) LFDA visualization

(c) Proposed method visualization
Image retrieval

Original

PCA

LFDA

Proposed

Images’ source: www.pinterest.com
Unsupervised case: classification accuracy

<table>
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![Graphs showing accuracy for different methods under varying numbers of dimensions.](image-url)