Knowledge Propagation in Large Image Databases Using Neighborhood Information

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Motivation

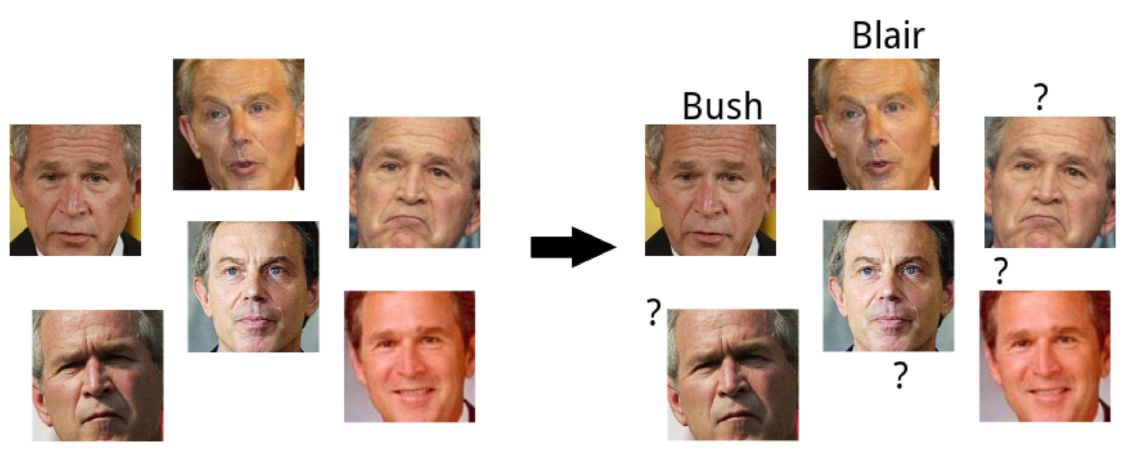
Practical methods for the indexing and querying of large-scale image databases often require that the images be annotated with semantic information beforehand. Unfortunately, due to the high costs associated with human annotation, or the unavailability of cameras with GPS functionality or other special devices, the number of labeled objects is often severely limited. Existing solutions to adding semantic information are labor intensive and not always accurate. The aim of this research is to reduce the level of human intervention in the semantic annotation process of images.

Approach

We propose a new method, *KProp*, that seeks to propagate labels from initially annotated data objects to new data objects that resemble them, according to a user-supplied measure of similarity. *KProp* builds an influence graph derived from neighborhoods of the objects with respect to the similarity measure, and then propagates knowledge scores through the graph from those nodes corresponding to objects with apriori semantic annotations.

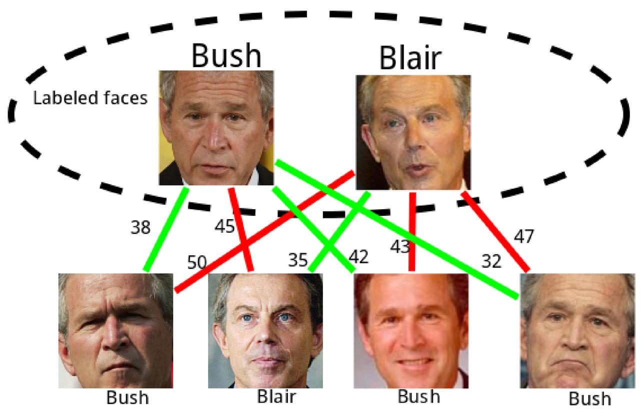
Objective

A few occurrences of each object of interest (e.g., a person) would be labeled manually. The problem is to determine the labels (e.g., names) of all other occurrences of objects in the database.

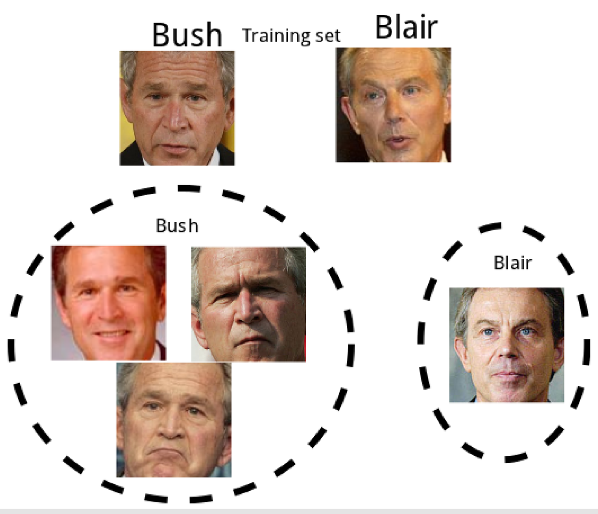


Existing Solutions

- Query-based baseline: The label of an unlabeled object is decided by its nearest labeled neighbor.



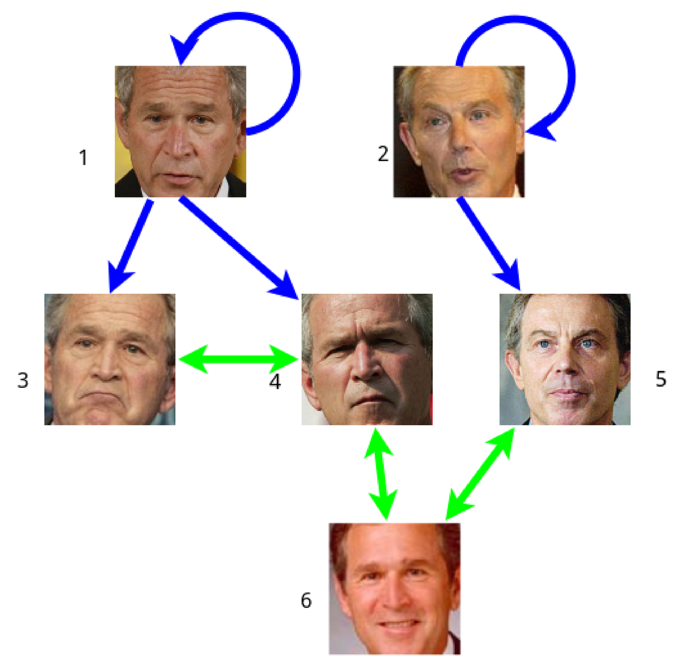
- Supervised or semi-supervised learning methods: Labeled objects are treated as training set and each of the unlabeled objects is classified.



KProp – Influence Graph

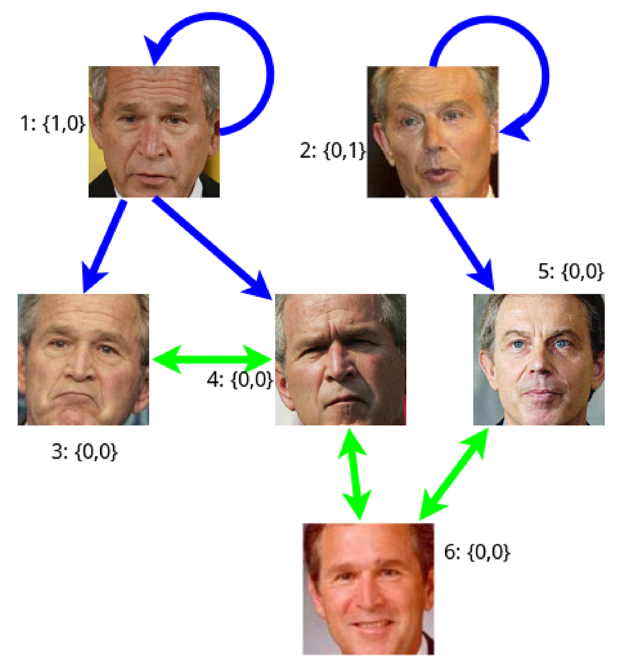
KProp propagates labels from labeled data objects to new data objects that resemble them through an influence graph derived from neighborhoods of the objects.

- Draw self-edges for labeled objects.
- If an unlabeled object is one of the *k-NN* of a labeled object, draw an edge from the labeled object to the unlabeled.
- Draw bi-directional edges between two unlabeled objects if either is one of the other's *K-NN*.



KProp – Label Propagation

- Scores measuring the degree of association between labels and objects are computed iteratively. Only labeled objects with the label being propagated are given initial scores of 1 (all others are given initial scores of 0). Compute the initial score matrix S^0 from the graph.



$$S^0 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{pmatrix}$$

- Each object's score is computed by averaging all its incoming neighbors' scores. Compute the propagation matrix P from the graph.
  - Adjacency matrix:

$$\begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 1 & 0 \end{pmatrix}$$

  - Row normalized:

$$\begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0.5 & 0 & 0 & 0.5 & 0 & 0 \\ 0.33 & 0 & 0.33 & 0 & 0 & 0.33 \\ 0 & 0.5 & 0 & 0 & 0 & 0.5 \\ 0 & 0 & 0 & 0.5 & 0.5 & 0 \end{pmatrix}$$

  - The propagation matrix P (damping factor $df = 0.9$ is applied to non-self edges):

$$\begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0.45 & 0 & 0 & 0.45 & 0 & 0 \\ 0.297 & 0 & 0.297 & 0 & 0 & 0.297 \\ 0 & 0.45 & 0 & 0 & 0 & 0.45 \\ 0 & 0 & 0 & 0.45 & 0.45 & 0 \end{pmatrix}$$

- The score propagation can be performed by iterative matrix multiplication of the propagation matrix P and the score matrix S: $S^q = PS^{q-1}$.

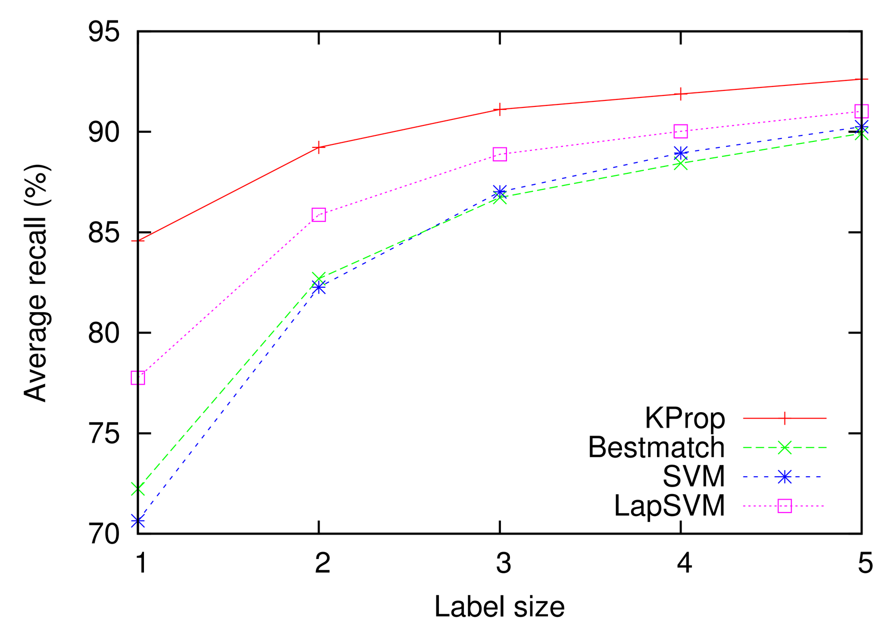
KProp – Stabilized Status

- It can be proved that in equation $S^q = PS^{q-1}$, S will converge in finite steps, as long as the damping factor $0 < df < 1$.
- If we interpret the final score matrix by sorting each row in non-increasing order, we can obtain ranked lists of labels, with the first entries corresponding to the maximum likelihood assignment of labels to objects.

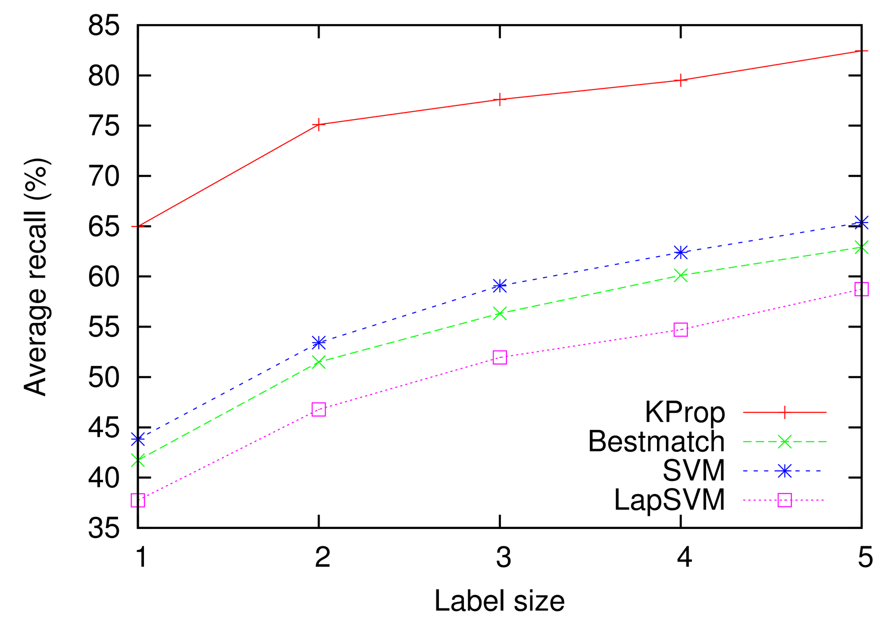
$$S^f = \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 0.73 & 0.05 \\ 0.63 & 0.11 \\ 0.16 & 0.59 \\ 0.35 & 0.32 \end{pmatrix} \begin{matrix} \text{Bush} \\ \text{Blair} \\ \text{Bush} \\ \text{Bush} \\ \text{Blair} \\ \text{Bush} \end{matrix}$$

Experiments

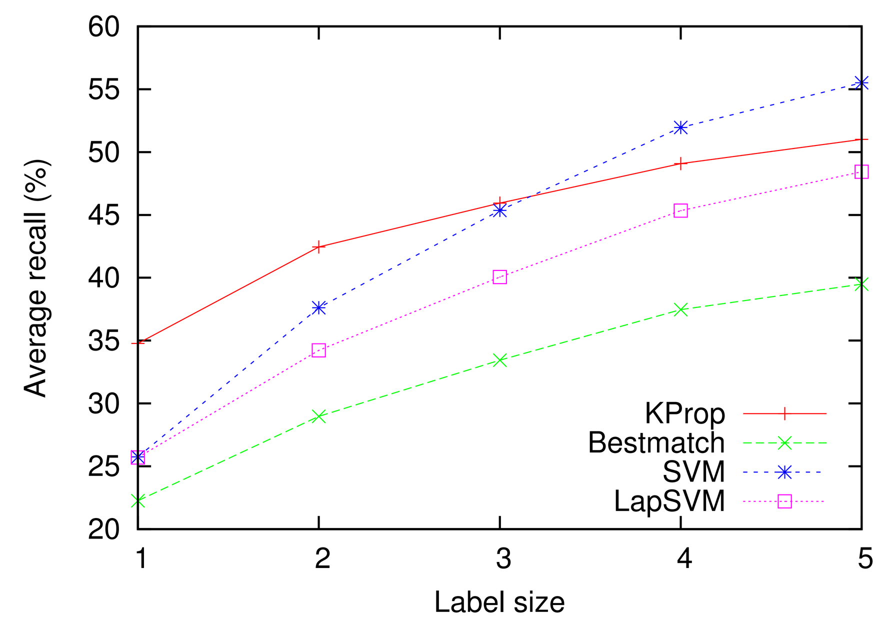
- *KProp* is compared with Query-based baseline (Bestmatch), *SVM* and *LapSVM* using three datasets: ALOI-100 (simple objects), MNIST (handwritten digits) and Google-23 (faces).
- *KProp* performs consistently better than the others in ALOI-100 and MNIST. In Google-23, it is outperformed by *SVM* when the label size is sufficiently large.
- The relative performance of *KProp* can be explained in terms of the transitivity of object relationships.



(a) ALOI-100



(b) MNIST



(c) Google-23

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