Mining Class Exemplars using Affinity Propagation

Shengping Xia and Edwin R. Hancock

Dept. of Computer Science, THE UNIVERSITY of York, UK.

xiasp1227@vip.sohu.com, erh@cs.york.ac.uk

Rationale

- One of the most effective means of knowledge discovery from a large corpus of data is to search for class exemplars. Frey and Dueck has proposed an affinity propagation (AP) method for locating an optimal set of exemplars.
- However, AP is difficult to be applied to very large sparse similarity. Furthermore, it is difficult to efficiently obtain a sparse similarity matrix for large datasets, and this can cause difficulties in locating exemplars.
- Fortunately, we have proposed a similarity propagation (SP) method, using which class specific object clusters can be obtained.
- Combining SP and AP, rather than mining exemplars from the entire graph corpus, we prefer to cluster object specific exemplars. In that, AP clustering algorithm is individually applied to each object specific cluster. This largely improves the efficiency and precision to locate the exemplars.

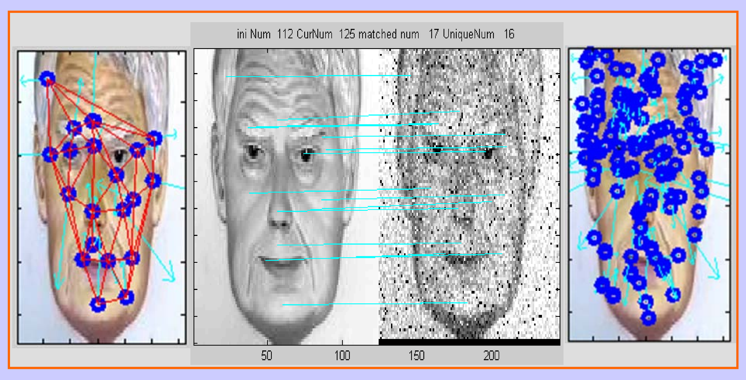
Motivation: Clustering images of specific objects from large image dataset

Two key problems include:

a) image representation; b) pairwise image similarity.

Canonical Image Representation : Attributed Graph

- For an image, a series of images are generated by randomly changing the image parameters or adding some noise. SIFT features are extracted for each image. Using SIFT features, each generated image is matched against the initial image. The matching frequencies are used to rank the SIFT features of the initial image.



- A group of top ranked SIFT features of an image are selected to construct an attributed graph G. Each feature is a node, and the descriptor corresponds the node attribution. The spatial configuration determines the edges of the graph, in that we use the edges of a Delaunay graph of the selected features.

Graph $G = (V, E)$ **Selected SIFT features** $V = \{\vec{X}_t, \vec{U}_t, t = 1,2,\ldots,N\}$

Pairwise Graph Similarity Measure

Using SIFT matching based pairwise graph matching and the goodness-of-fit of the geometric configuration of the graphs, we define a canonical pairwise similarity measure as follows : (MCS: maximal common subgraph)

$$\mathcal{R}^*(G_l, G_q) = \underbrace{\left\| MCS(G_l, G_q) \right\|}_{\text{Number of correctly matched SIFT feature pairs}} \times \underbrace{\exp(-e(X_l, X_q))^{\kappa}}_{\text{Goodness-of-fit of the geometric configuration between two graphs}}$$

K-Nearest Neighbour Graphs (KNNG)

$\forall G_l$, all graphs G_q, $q = 1,2,\ldots,N$ can be ranked in a descending order according to their similarity measure with graph G_l. Those graphs whose similarity is greater than a threshold among the top K graphs are selected to form a set of KNNG of G_l as follows:

$$ONNG^*_{K\tau}\{G_l\} = \{G_q \mid \mathcal{R}^*(G_l, G_q) \geq \mathcal{R}^*_\tau\}$$

$$\mathcal{S}\{G_l\} \triangleq \mathcal{S}_{\mathcal{R}^*_\tau}\{G_l\} = \left\{G_q \middle| G_q \in ONNG^*_{K\tau}\{G_l\},\ \mathcal{R}^*(G_l, G_q) \geq \mathcal{R}^*_{\tau 1}\right\}$$

Siblings of a graph

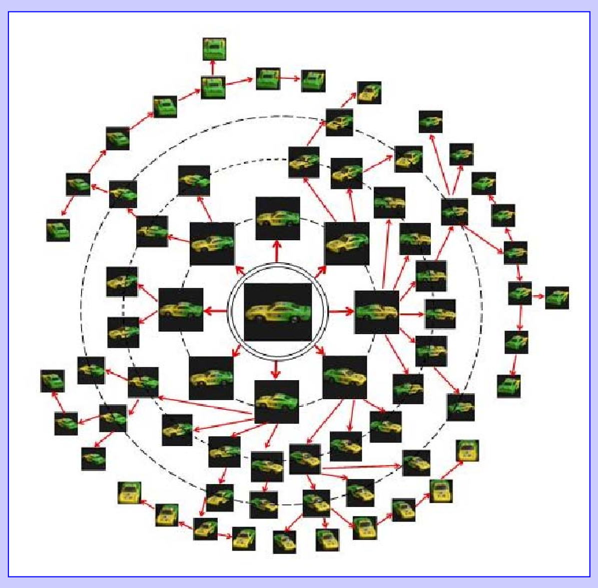
Similarity Propagation based Object Clustering

$$\mathcal{F}\{G_l, g\} = \mathcal{F}\{G_l, g-1\} \bigcup_{G_q \in \mathcal{F}\{G_l, g-1\}} \mathcal{S}_{\mathcal{R}^*_\tau}\{G_q\}$$

This process stops when $\mathcal{F}\{G_l, g\} = \mathcal{F}\{G_l, g+1\}$

where, if $g = 1$, $\mathcal{F}\{G_l, 1\} = \mathcal{F}\{G_l, 0\} \cup \mathcal{S}\{G_l\}$

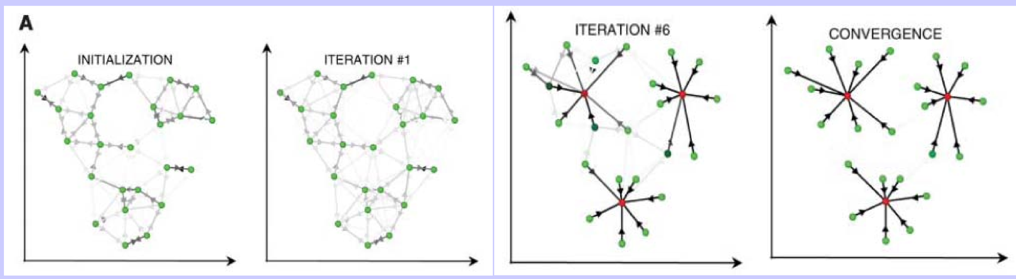
and $\mathcal{F}\{G_l, 0\} = \{G_l\}$

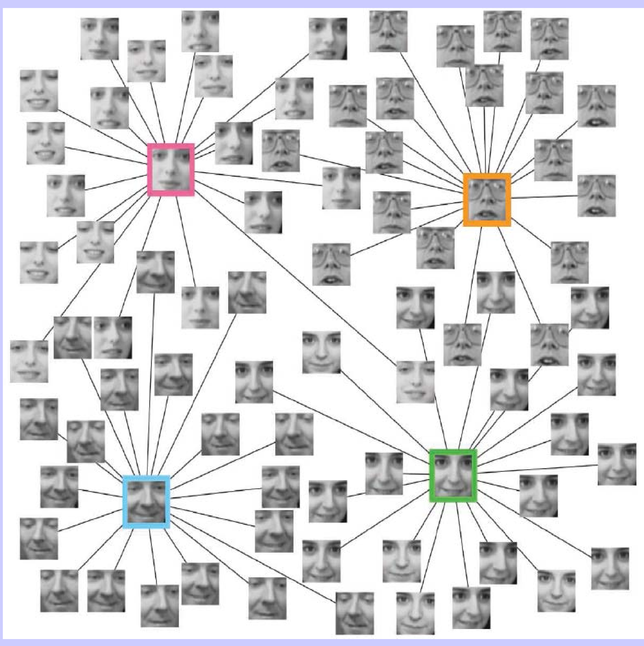


FTOG: Family Tree of Graphs

Affinity Propagation

- Clustering algorithm that works by finding a set of exemplars (prototypes) in the data and assigning other data points to the exemplars [Frey07]I
- Input: pair-wise similarities (negative squared error), data point preferences (larger = more likely to be an exemplar)
- Approximate maximization of the sum of similarities to exemplars
- Mechanism – message passing in a factor graph





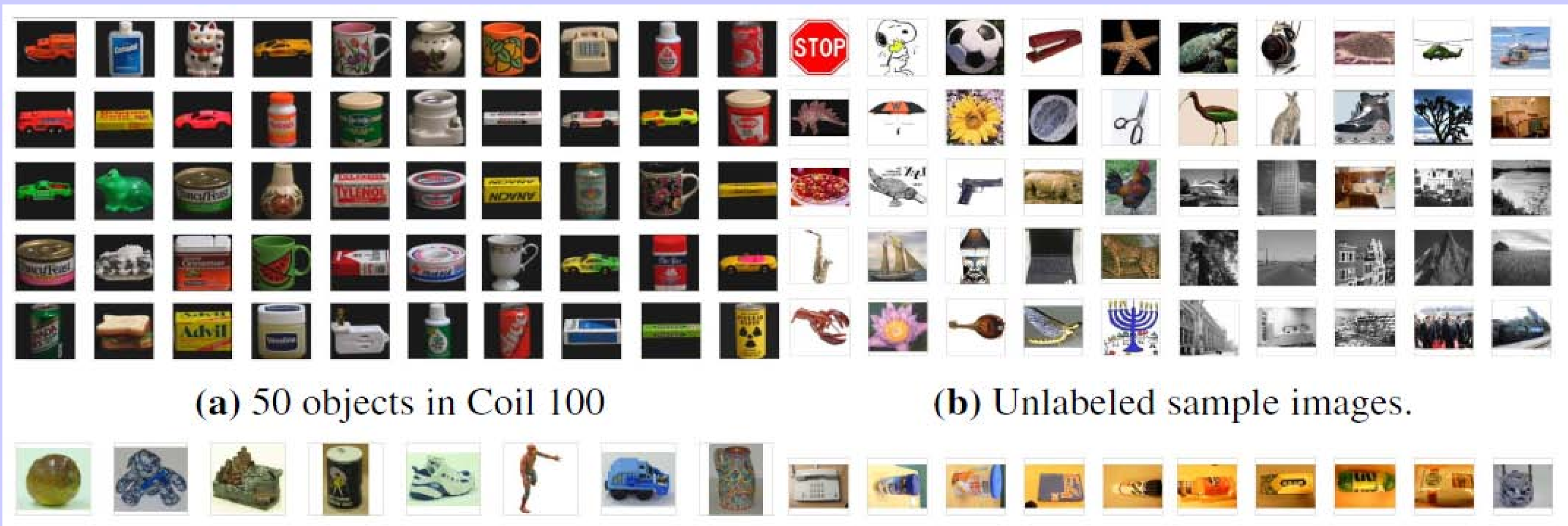
However AP cannot be applied to very large datasets. It is also unnecessary to apply AP to global datasets.

Two Stage Exemplar Mining Strategy

– S1. Obtain the FTOG in a weakly supervised manner using SP;

– S2. Detect exemplars for each FTOG individually using AP.

Experimental Settings



(a) 50 objects in Coil 100 (b) Unlabeled sample images.

(c) 8 objects in[19] (d) 10 objects collected by the authors.

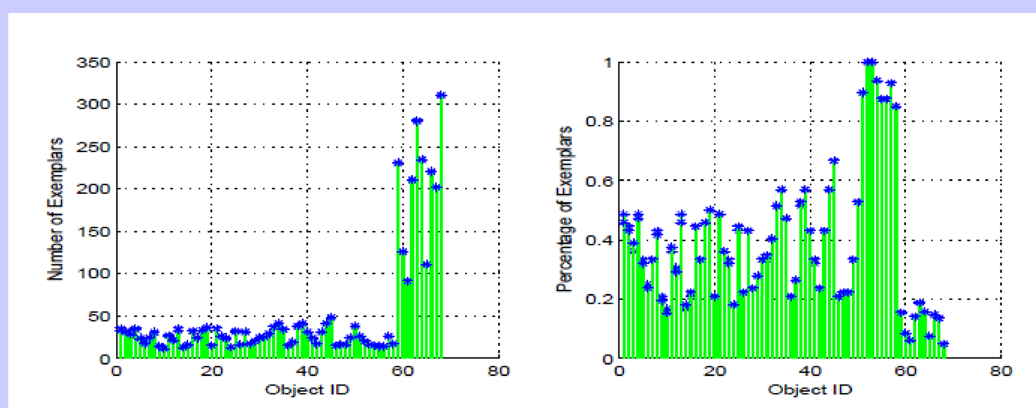
- We have collected 53536 training images. The data spans more than 500 objects including human faces and natural scenes. For each of these images, we extract ranked SIFT features. We thus have collected over 2,140,000 SIFT features and 53536 graphs for the training set. We use the 68 objects to test our method.

Experimental Results

- 68 objects are clustered with high precision and recall using SP as the first stage.

Par \ ID	1~50 Except 3, 39	3	39	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68
N_i	72	72	72	29	20	16	16	16	16	28	20	1500	1500	1500	1500	1500	1500	1500	1500	1500	6500
N_d	72	64	66	22	16	15	15	16	16	27	20	1491	1483	1500	1500	1500	1475	1487	1500	1467	6488
p	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
r	1.0	.875	.917	.759	.80	.938	.938	1.0	1.0	.964	1.0	.994	.989	1.0	1.0	1.0	.983	.991	1.0	.978	.998
N_c	1	2	2	3	1	3	3	3	3	4	2	6	8	4	5	3	9	3	3	4	1

- AP is then individually applied to each cluster. The numbers and percentages of the exemplar graphs obtained by using SP and AP for object of interests are shown in left figures.



Conclusion

- This paper focuses on the problem of locating object class exemplars from a large corpus of images using affinity propagation.
- We use attributed relational graphs to represent groups of local invariant features together with their spatial arrangement.
- Rather than mining exemplars from the entire graph corpus, we prefer to cluster object specific exemplars. Firstly, we obtain an object specific cluster of graphs using a similarity propagation based graph clustering method. The popular AP clustering algorithm is then individually applied to each object specific cluster.
- Using this clustering method, we obtain object specific exemplars together with a high precision for the data associated with each exemplar. The strategy adopted is one of divide and conquer, and this greatly increases the efficiency of mining exemplars.
- Using the exemplars, we perform recognition using a majority voting strategy that is weighted by nearest neighbour similarity.