

Metamorphosis III, 1967-8, M.C. Escher

Feature Correspondence and Deformable Object Matching via Agglomerative Correspondence Clustering

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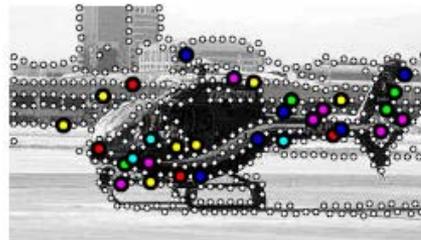
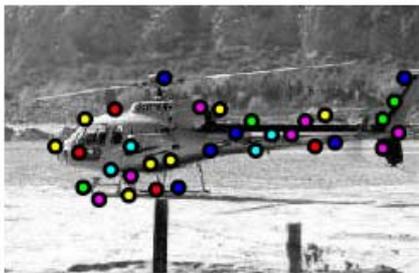
Seoul National University, Korea



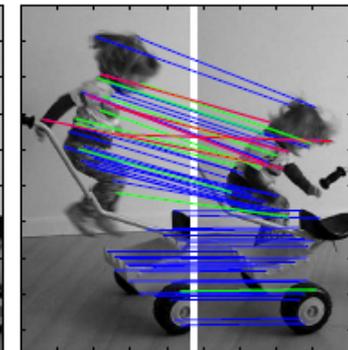
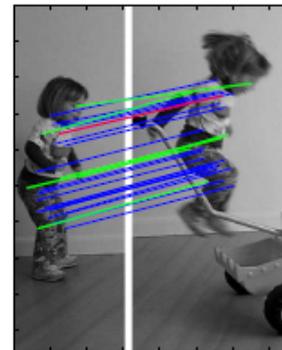
ComputerVisionLab
Seoul National University

Motivation

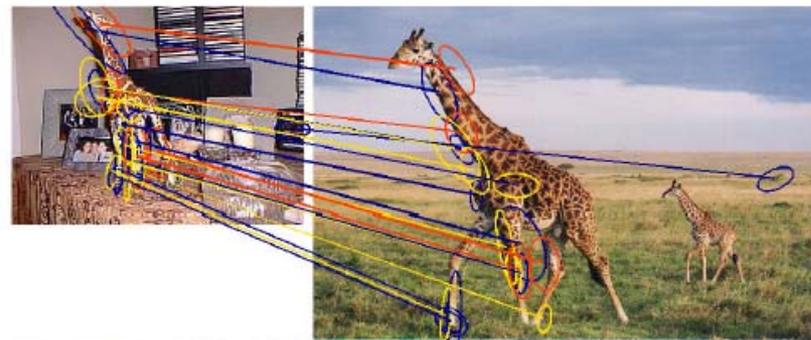
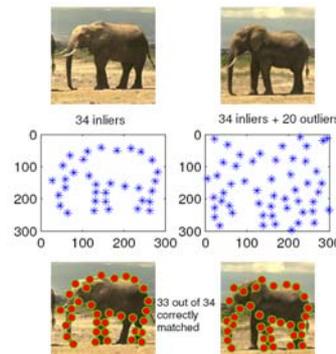
- Feature correspondence considering geometric distortion of objects between images



Berg *et al.* CVPR2005



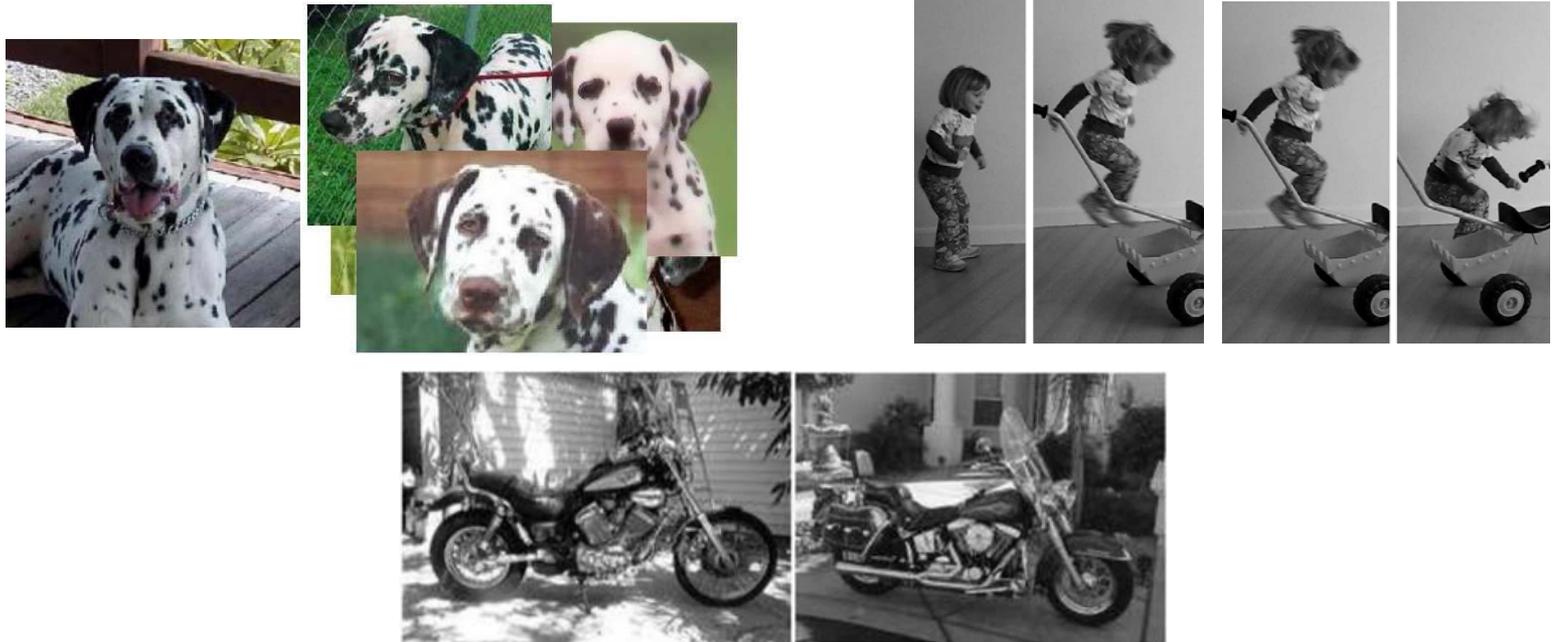
Torresani *et al.* ECCV2008



Leordeanu & Hebert ICCV2005

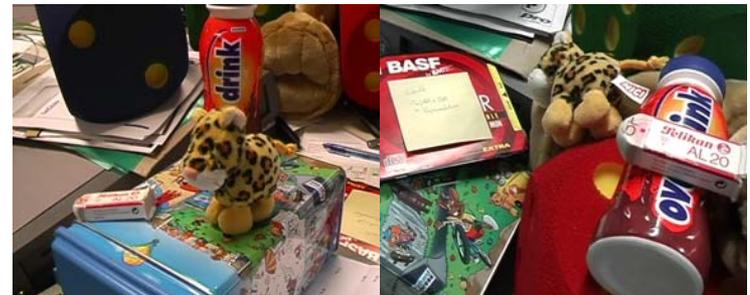
Motivation

- Previous works
 - Weakly supervised images with low clutter
 - one common object appears or a model image is used.
 - → low outlier ratio, a single group with geometric consistency



Motivation

- However, in real-world images
 - significant clutter, multiple common objects, even many-to-many object correspondences
 - → High outlier ratio, multiple groups with geometric consistency



Correspondences using Local Features

- Initial matching with a loose similarity threshold



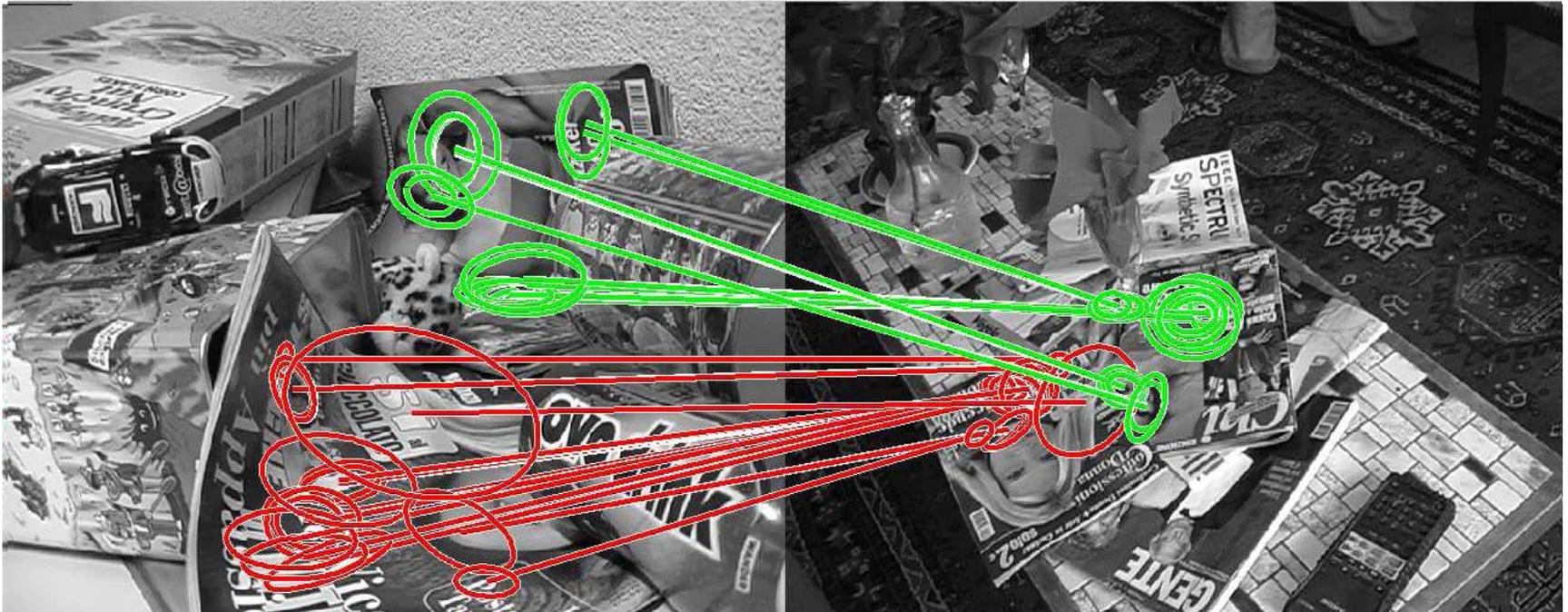
Motivation

- Feature correspondence problems in real-world
 - need to be interleaved with finding multiple object-level clusters of correspondences against significant outliers in an unsupervised way.
- Our goal
 - Feature correspondence considering geometric distortion
 - Establish their object-based clusters
 - Against significant clutter from arbitrary images.
 - Simple and efficient method

Main Idea

- How to extract multiple correspondence clusters with geometric consistency against outliers?
- Bottom-up aggregation strategy
 - If we start from confident correspondences and progressively merge them with reliable neighbors, inliers can be effectively collected in spite of enormous distracting outliers.
 - → Hierarchical Agglomerative Clustering (HAC) framework
- Connectedness between parts
 - For deformable objects, feature correspondences do not form global compactness in their pairwise geometric similarity, but deformed parts are locally connected by some mediating parts.
 - → A novel linkage model for HAC

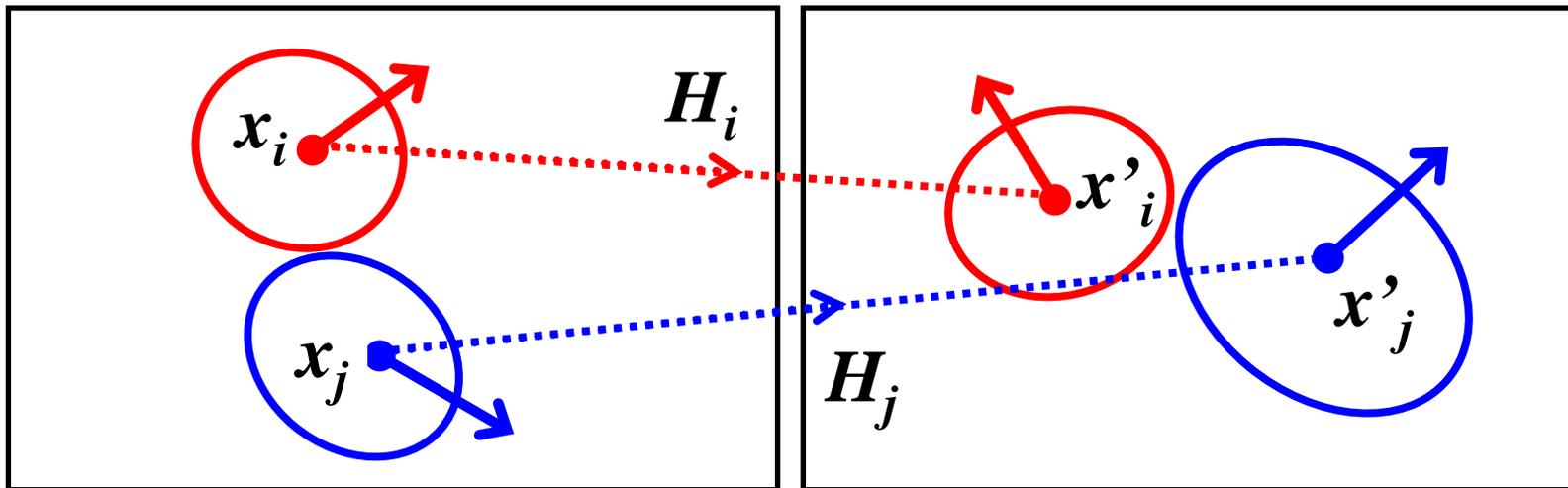
Main Idea



Pairwise Dissimilarity of Correspondences

- Given two feature correspondences

$$m_i = (x_i, x'_i, H_i) \quad m_j = (x_j, x'_j, H_j)$$



$$d_{\text{geo}}(m_j|m_i) = \frac{1}{2}(|x'_j - H_i x_j| + |x_j - H_i^{-1} x'_j|)$$

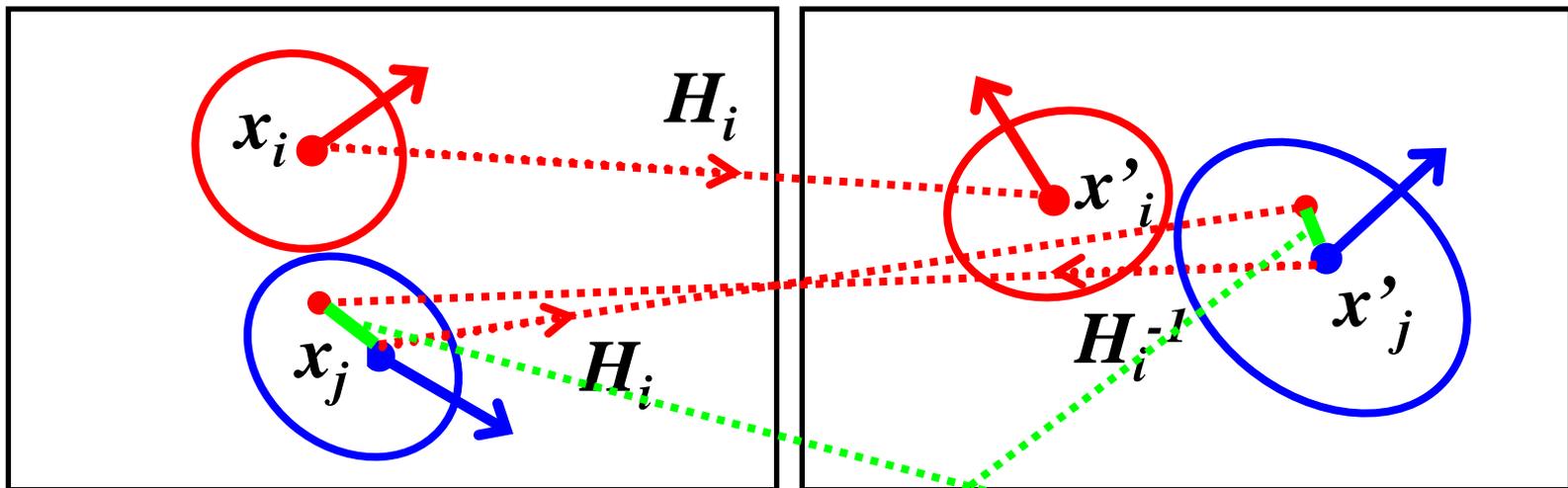
$$d_{\text{geo}}(m_i|m_j) = \frac{1}{2}(|x'_i - H_j x_i| + |x_i - H_j^{-1} x'_i|)$$

$$d_{\text{geo}}(m_i, m_j) = \frac{1}{2}(d_{\text{geo}}(m_j|m_i) + d_{\text{geo}}(m_i|m_j))$$

Pairwise Dissimilarity of Correspondences

- Given two feature correspondences

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Pairwise Dissimilarity of Correspondences

- Given two feature correspondences

$$m_i = (x_i, x'_i, H_i) \quad m_j = (x_j, x'_j, H_j)$$

- The pairwise Geometric dissimilarity is defined by

$$d_{\text{geo}}(m_i, m_j) = \frac{1}{2} (d_{\text{geo}}(m_j | m_i) + d_{\text{geo}}(m_i | m_j))$$

- a mutual projection error, which will be small if H_i and H_j are similar to each other
- The overall pairwise dissimilarity

$$d(m_i, m_j) = d_{\text{geo}}(m_i, m_j) + \alpha \max(d_{\text{app}}(m_i), d_{\text{app}}(m_j))$$

- provide a discriminative measure for our algorithm

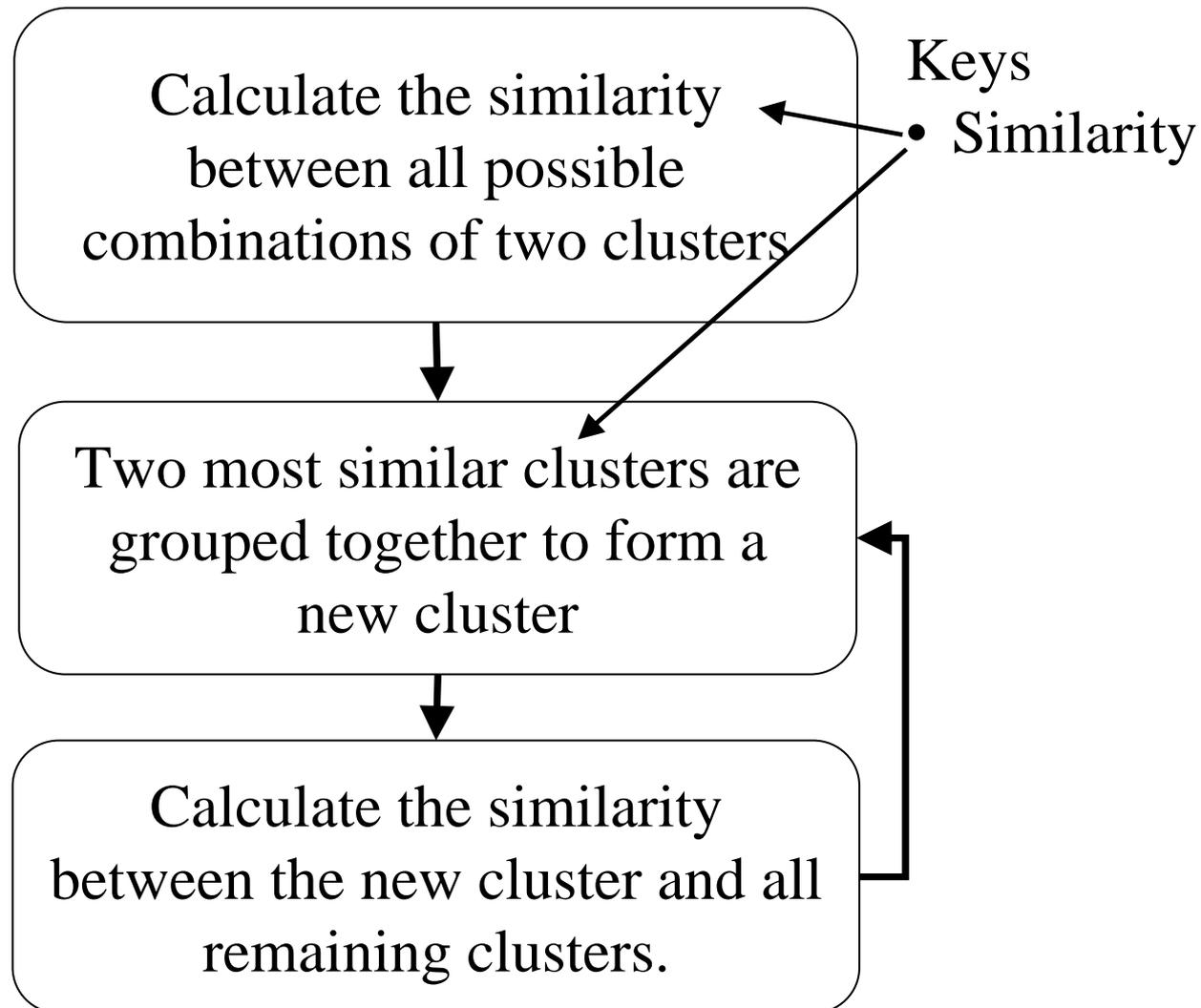
Features and Their Geometric Distance

- How to extract multiple correspondence clusters with geometric consistency?
- Bottom-up aggregation strategy
 - If we start from confident correspondences and progressively merge them with reliable neighbors, inliers can be effectively collected in spite of enormous distracting outliers.
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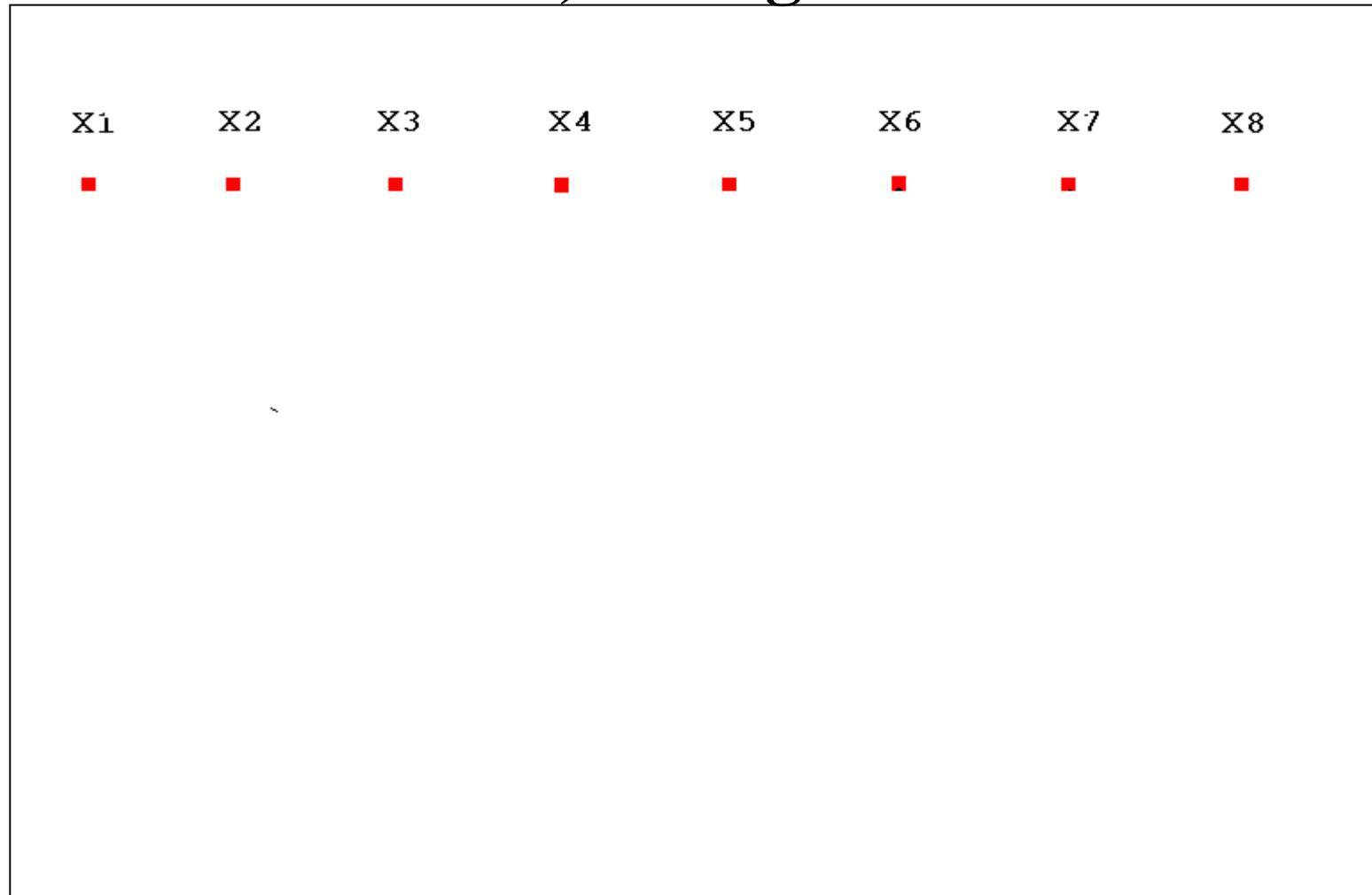
Hierarchical Agglomerative Clustering

- Hierarchical agglomerative clustering
 - A set of classic algorithms widely used in various fields
 - Does not require explicit global model
 - a particular algorithm can be obtained by the definition of the dissimilarity measure (linkage model) between two clusters, which determines the priority of a cluster pair to merge.

Hierarchical Agglomerative Clustering

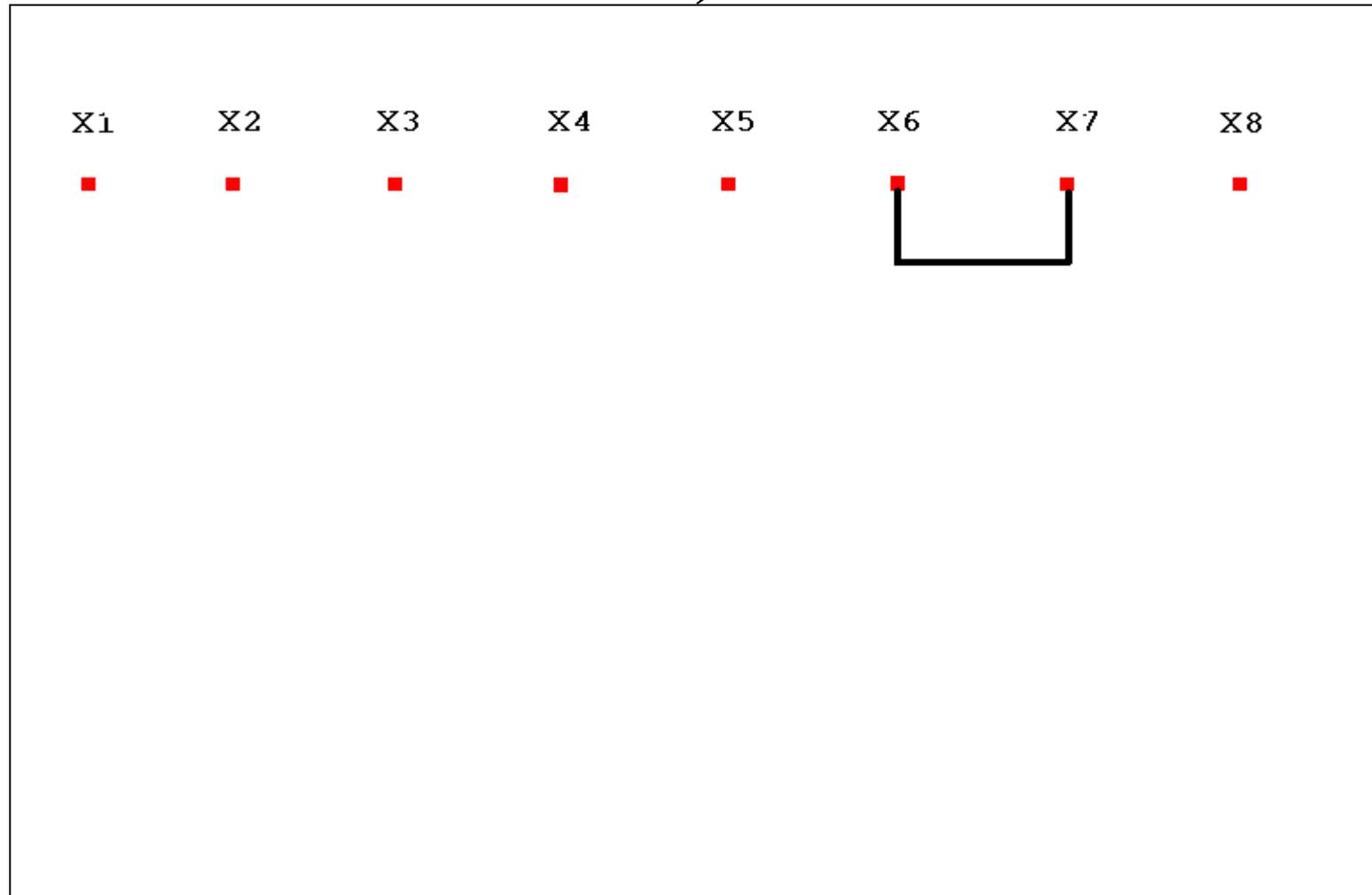


Initialization, 8 singleton clusters.



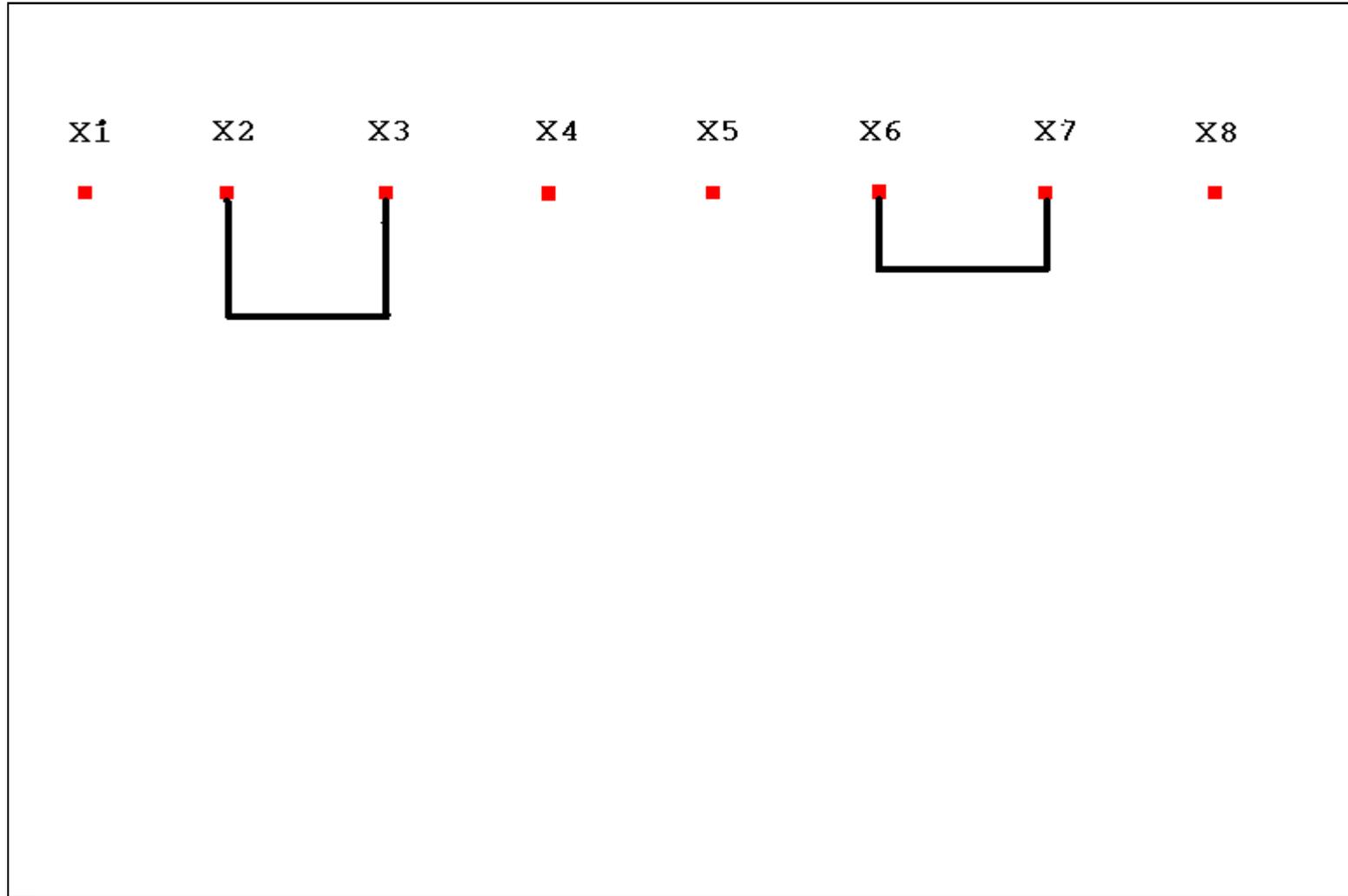
From <http://www.stat.unc.edu/postscript/papers/marron/Stat321FDA/Rimalzempresentation.ppt>

1st Iteration, 7 clusters.

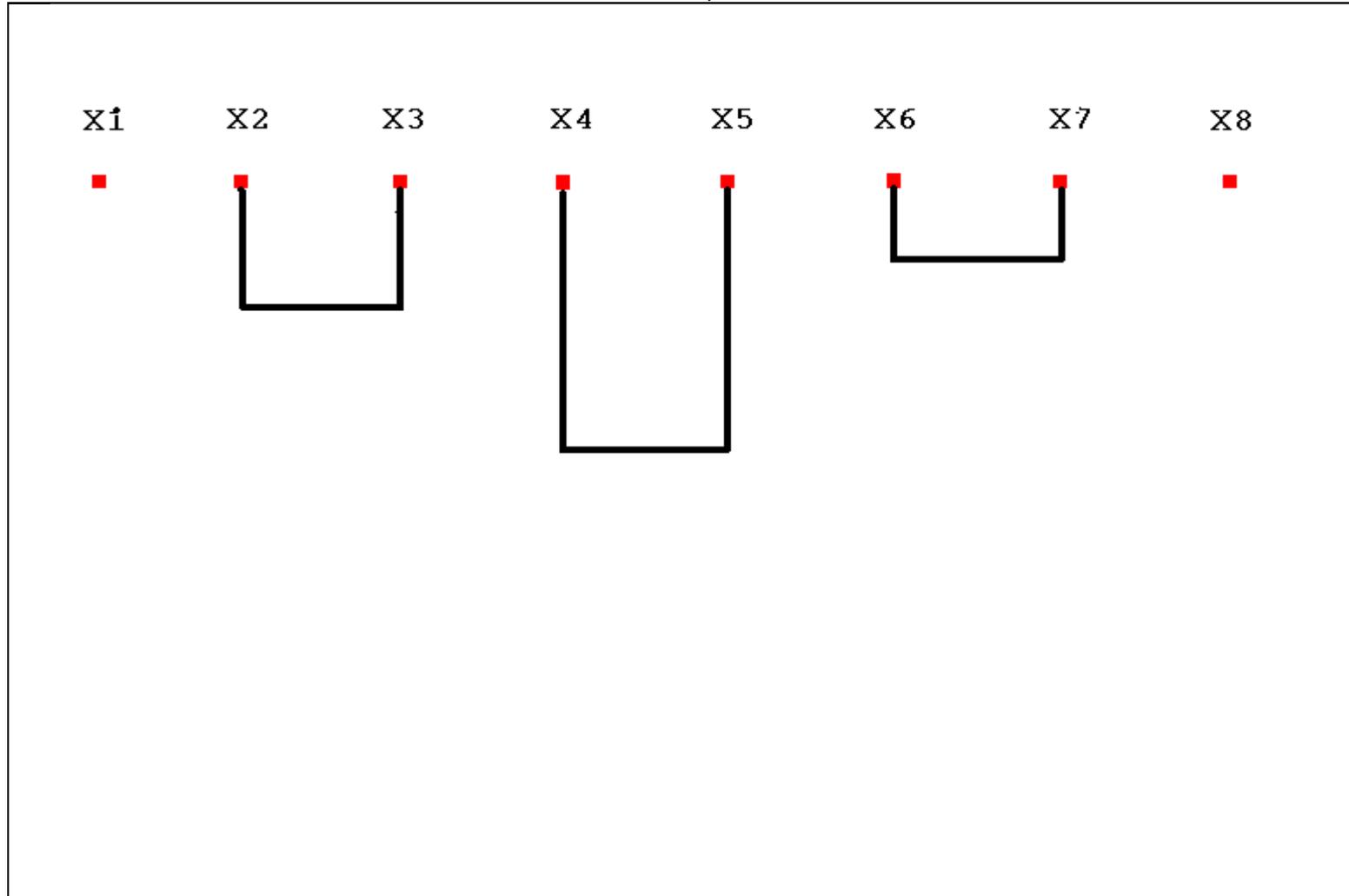


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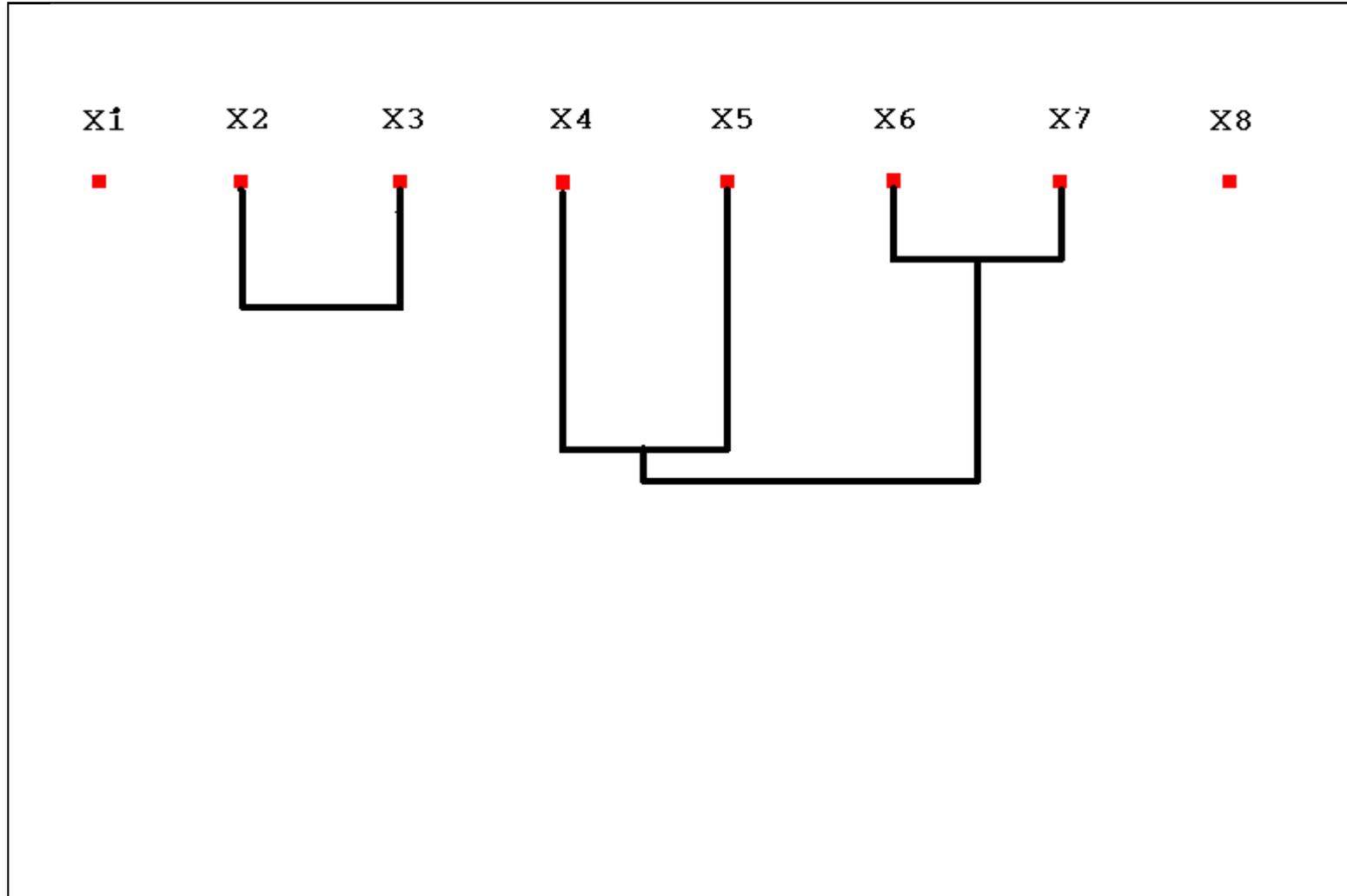
2nd Iteration , 6 clusters.



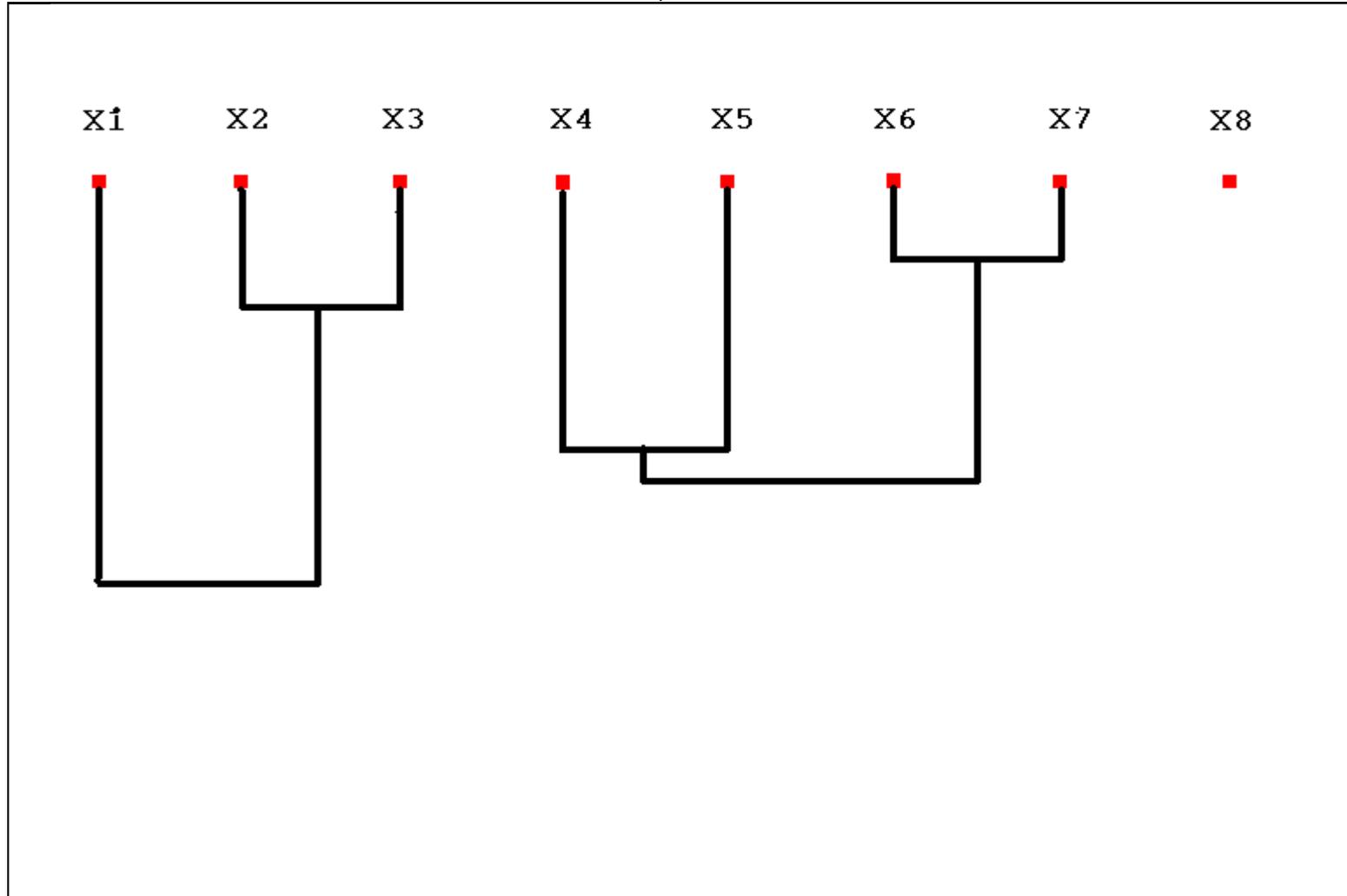
3rd Iteration, 5 clusters.



4th Iteration, 4 clusters.

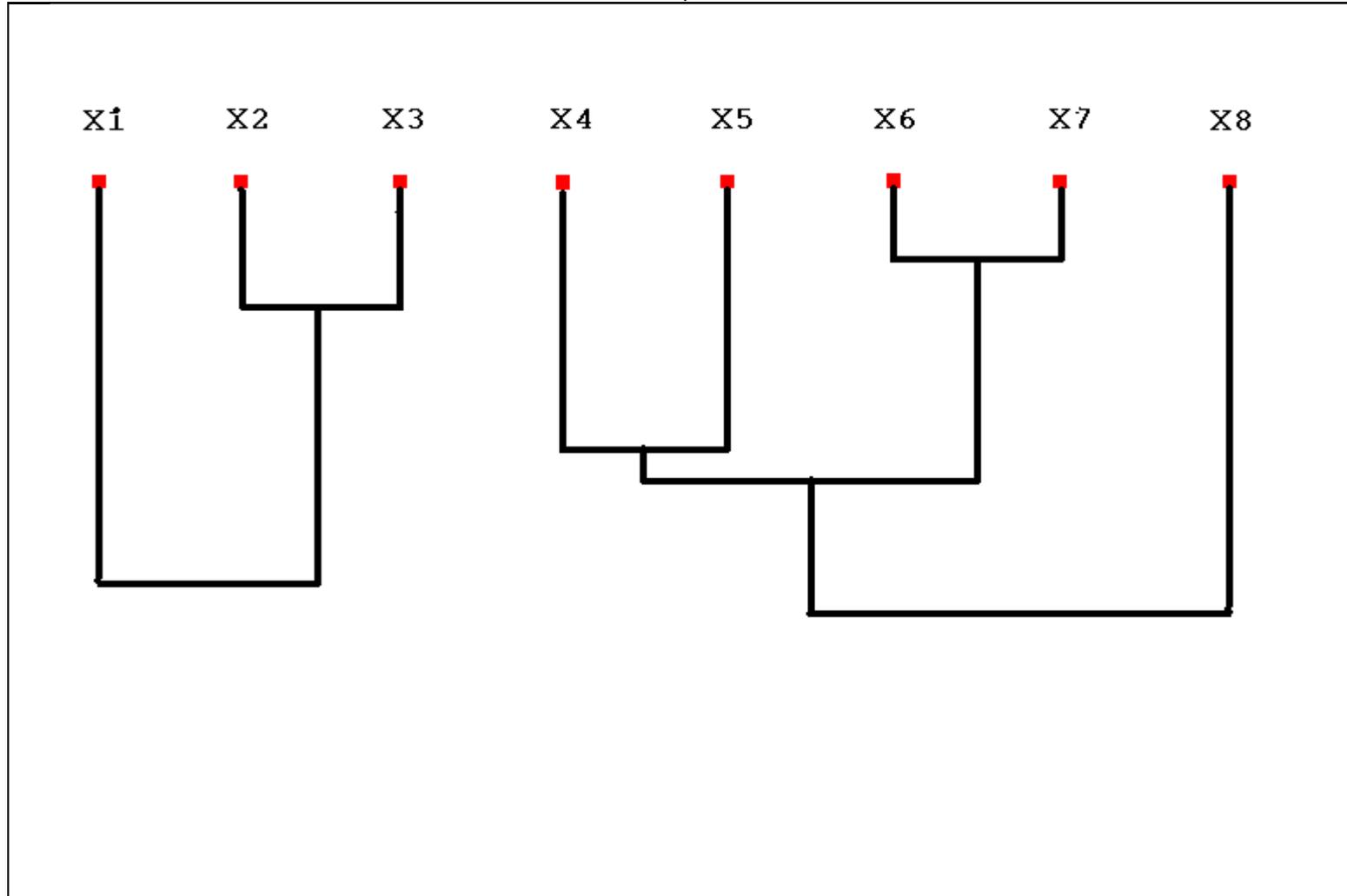


5th Iteration, 3 clusters.



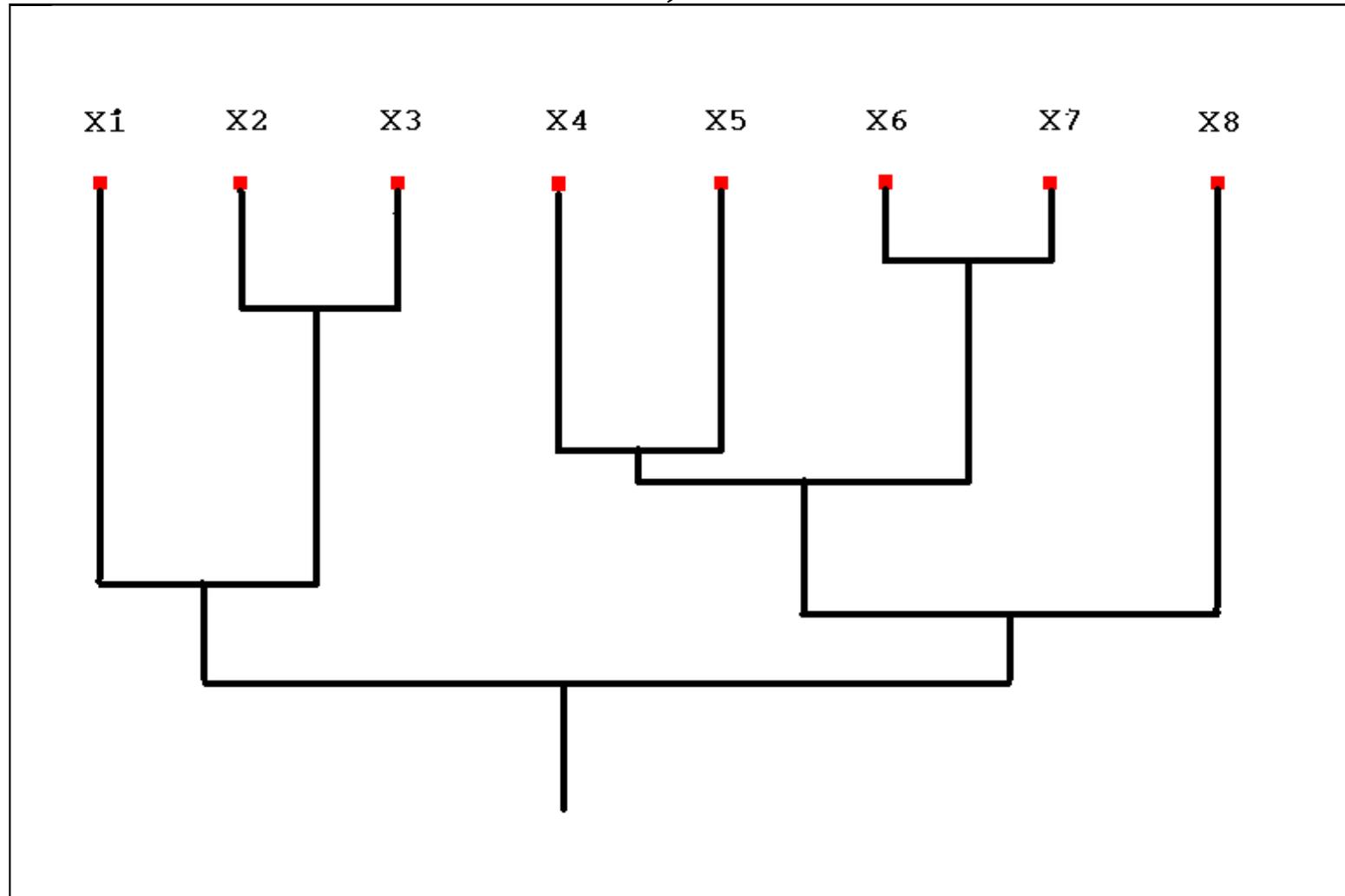


6th Iteration, 2 clusters.

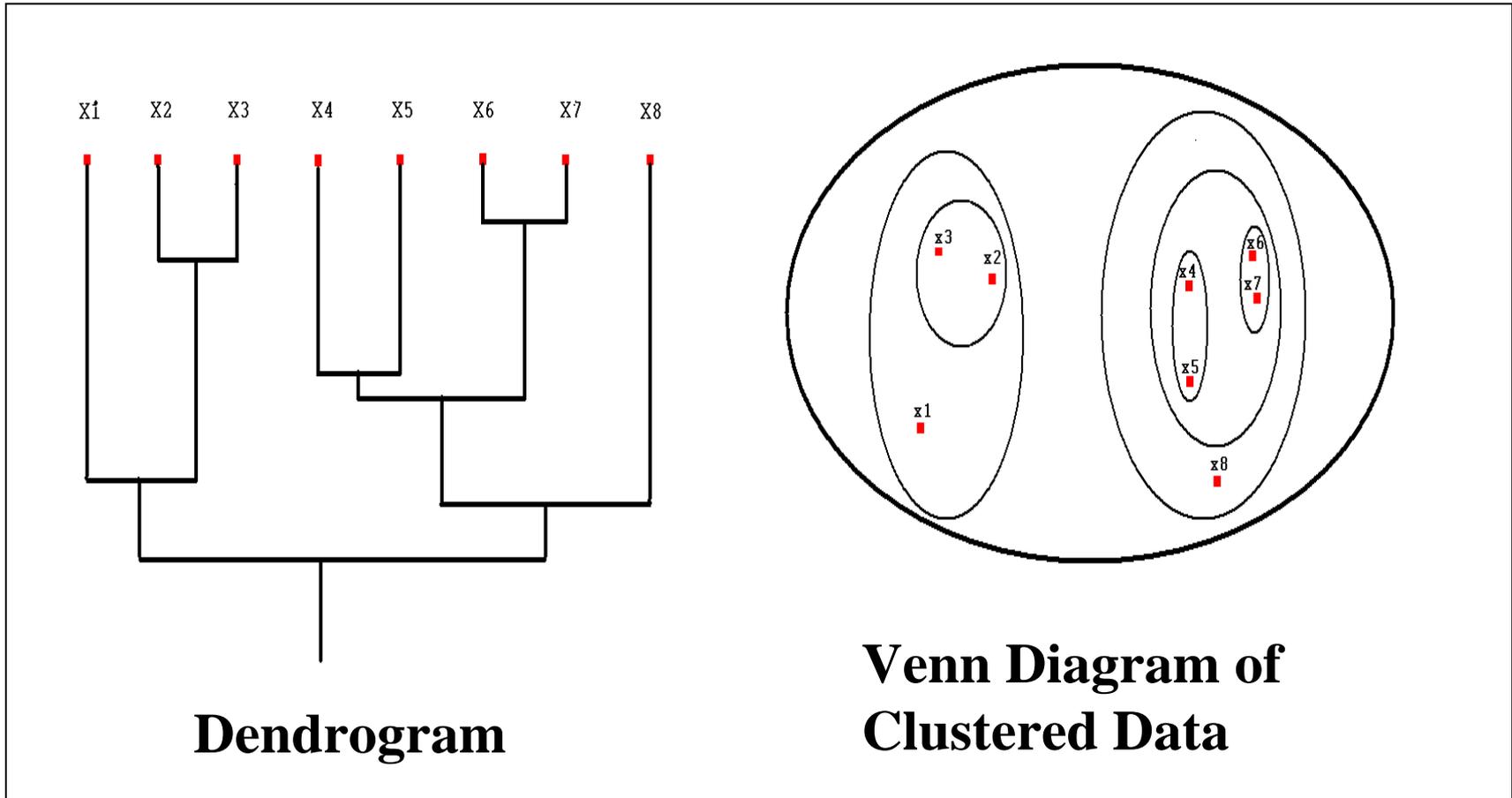




7th Iteration, 1 clusters.

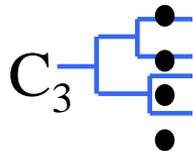
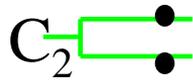
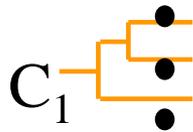


Hierarchical Clustering



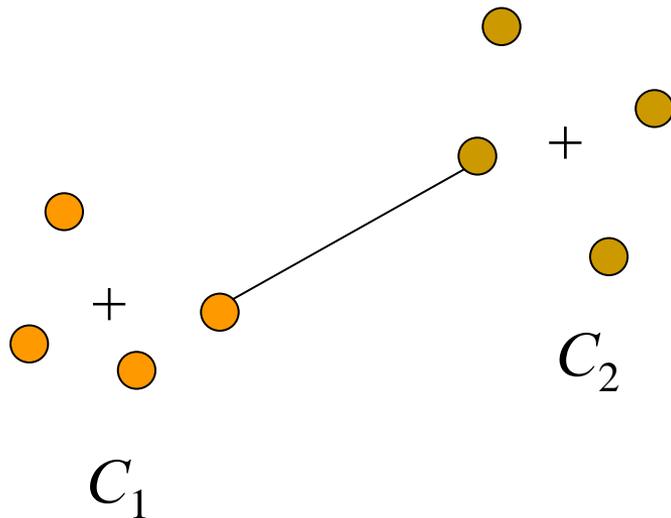
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Dissimilarity between Clusters



Merge which pair of clusters?

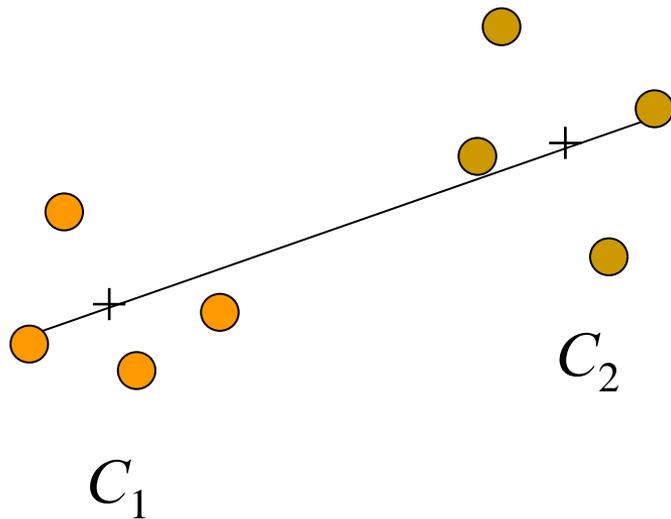
Single Linkage



Dissimilarity between two clusters = Minimum dissimilarity between the members of two clusters

Tend to generate “long chains”

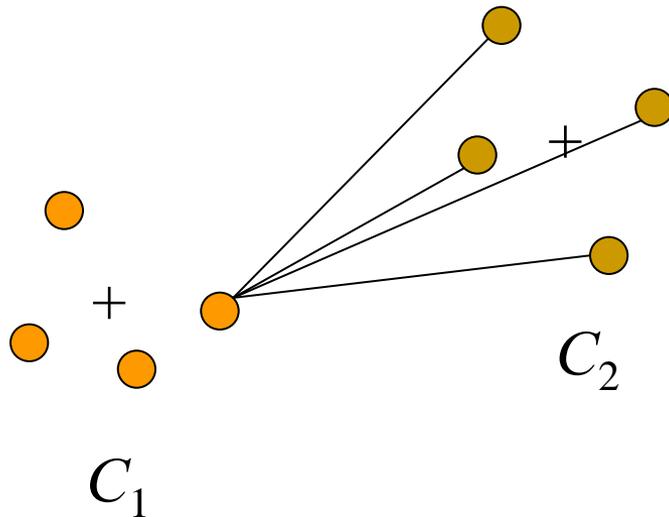
Complete Linkage



Dissimilarity between two clusters = Maximum dissimilarity between the members of two clusters

Tend to generate “clumps”

Average Linkage



Dissimilarity between two clusters = Averaged distances of all pairs of objects (one from each cluster).

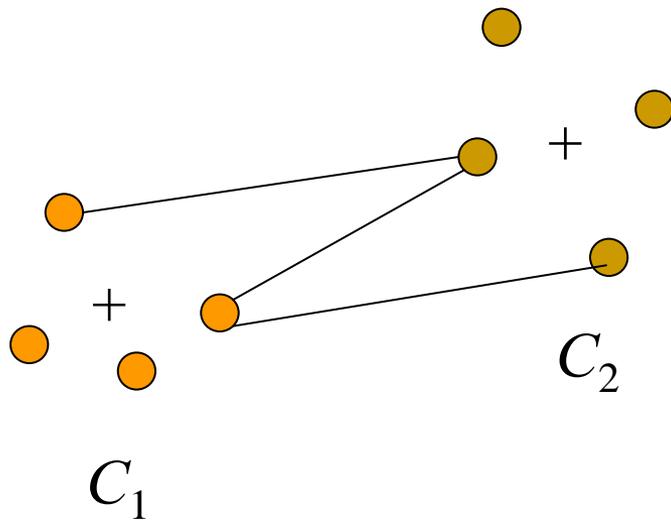


Properties of linkage models

- Single linkage
 - Consider connectedness of clusters
 - Strong chaining effect
 - Sensitive to chaining outliers
- Complete linkage and average linkage
 - Robust to outliers
 - Tends to make spherical and compact clusters

Proposed Linkage Model

- kNN Linkage model (e.g k=3)

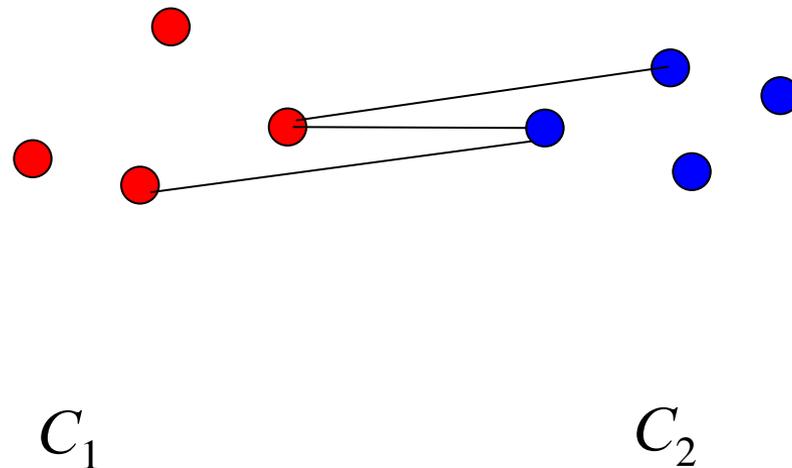


Dissimilarity between two clusters = mean of minimum k dissimilarity between the members of two clusters

kNN linkage can avoid “chain effects” of accidental linkages

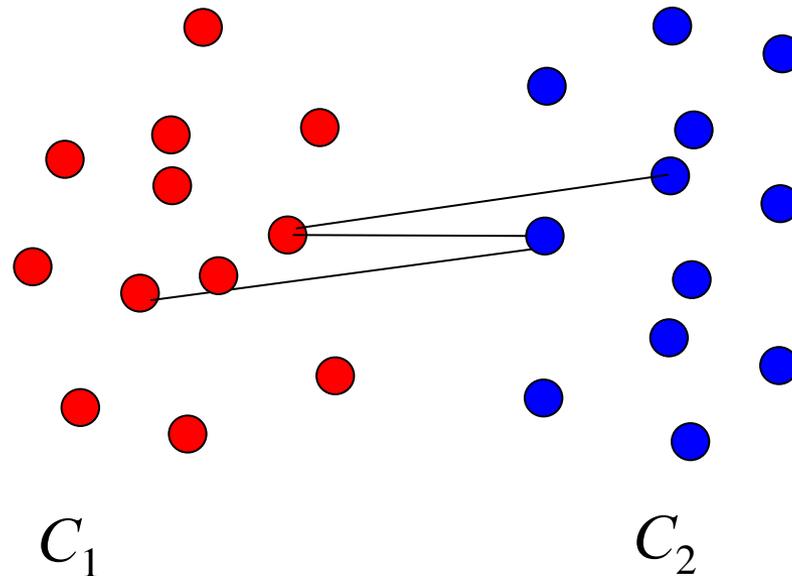
Proposed Linkage Model

- Asymtotic chaining effect
 - Chaining arises again as cluster grows



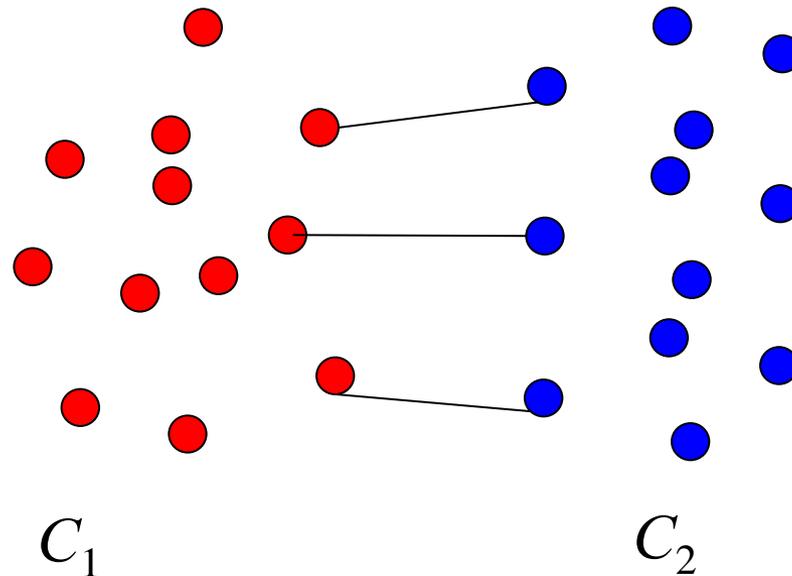
Proposed Linkage Model

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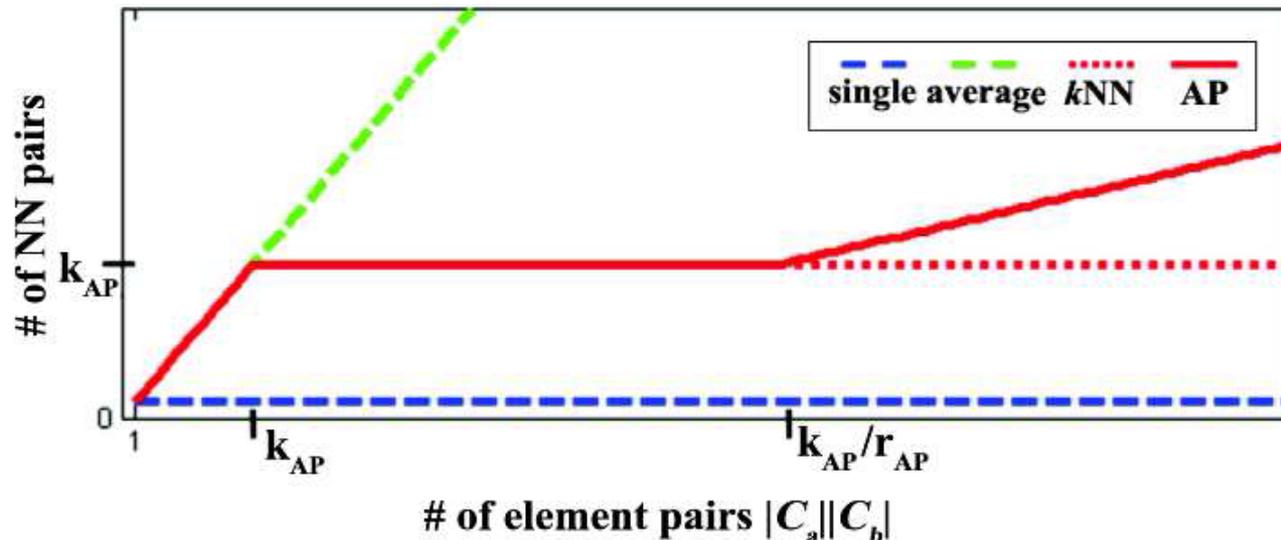
Proposed Linkage Model

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Proposed Linkage Model

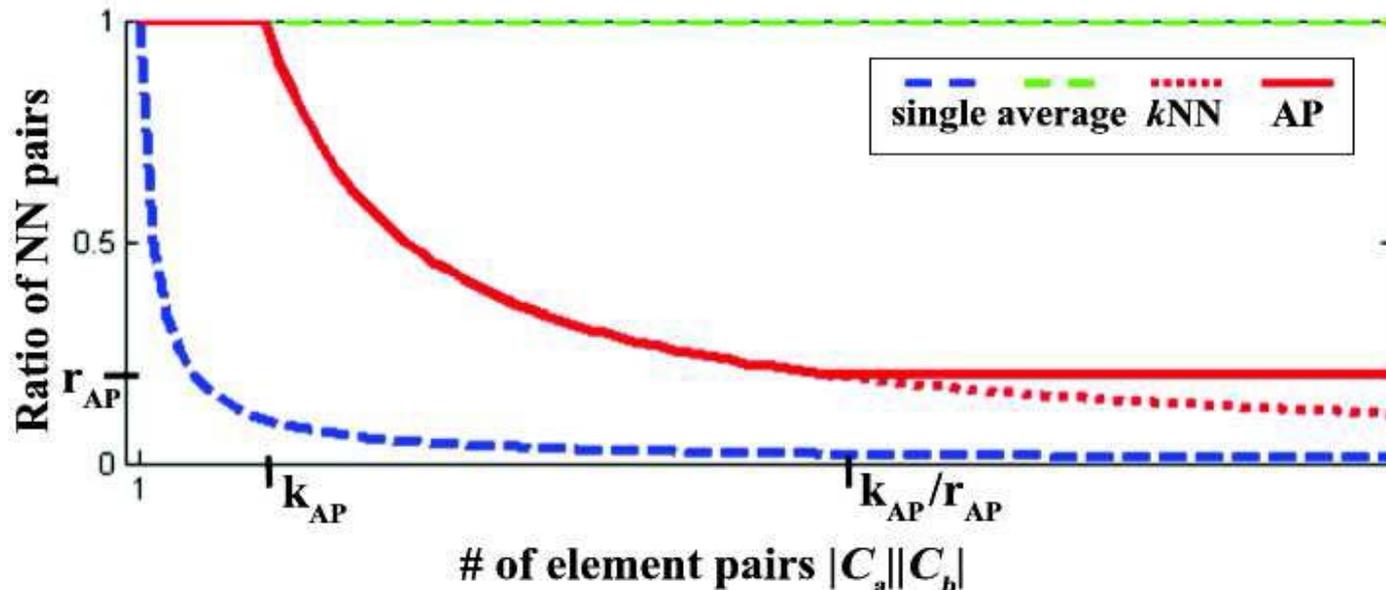
- Adaptive Partial Linkage model
 - adaptively grows the number of NN according to the ratio r_{AP}



- Property of AP linkage as the clusters grow
 - Average link \rightarrow kNN link of k_{AP} \rightarrow partial link of the ratio r_{AP}

Proposed Linkage Model

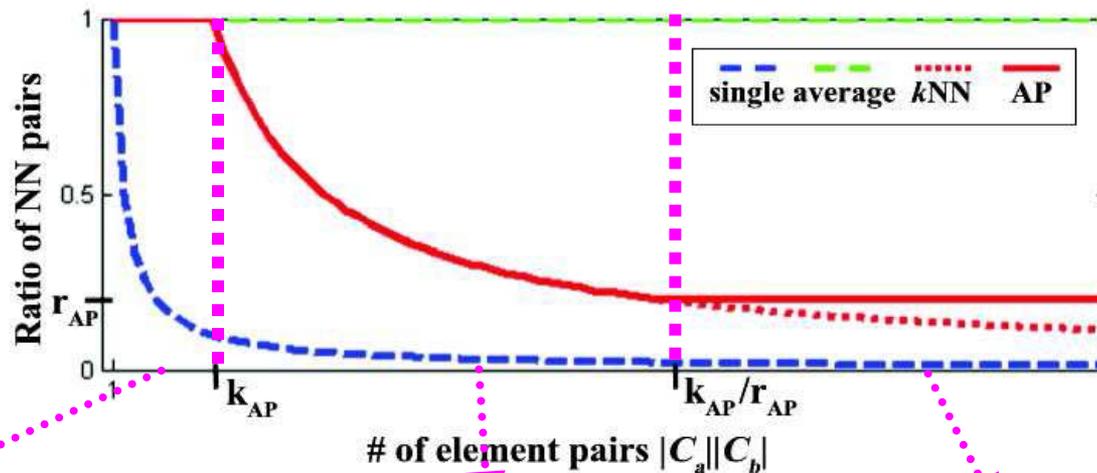
- Adaptive Partial Linkage model
 - adaptively grows the number of NN according to the ratio r_{AP}



- Unlike kNN link, AP link avoid 'asymtotic chaing effect'

Proposed Linkage Model

- Effects of AP linkage as the clusters grow



- | | | |
|--|---|---|
| <ul style="list-style-type: none"> Early stage <ul style="list-style-type: none"> Average link All as supporters Compact clusters avoids chaining outliers | <ul style="list-style-type: none"> Intermediate stage <ul style="list-style-type: none"> kNN link k_{AP} supporter Connected clusters | <ul style="list-style-type: none"> Late stage <ul style="list-style-type: none"> Partial link $r_{AP} C_a C_b$ supporter Connected clusters avoids asymptotic chaining effect |
|--|---|---|

Agglomerative Correspondence Clustering

Calculate the pairwise dissimilarity of all initial matches

Construct singleton clusters

Find two cluster C_a, C_b with the lowest AP-link dissimilarity $D_{AP}(C_a, C_b)$

$D_{AP}(C_a, C_b) \leq \delta_D$

Eliminate small clusters

End

Merge C_a and C_b

Eliminate conflicting matches with C_a and C_b

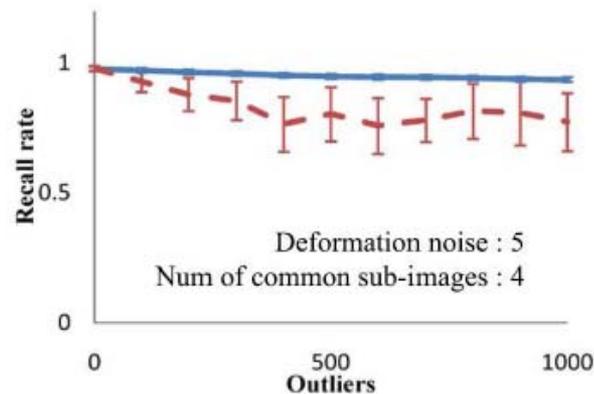
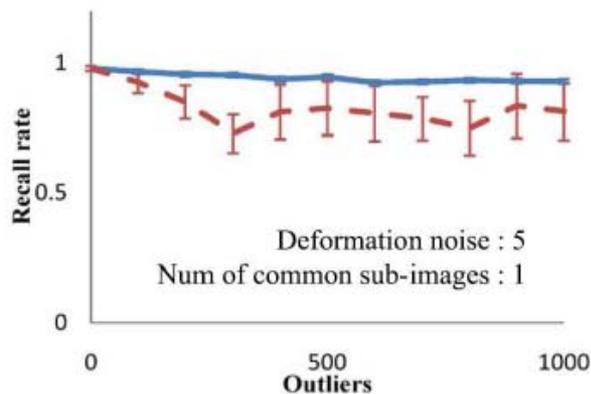
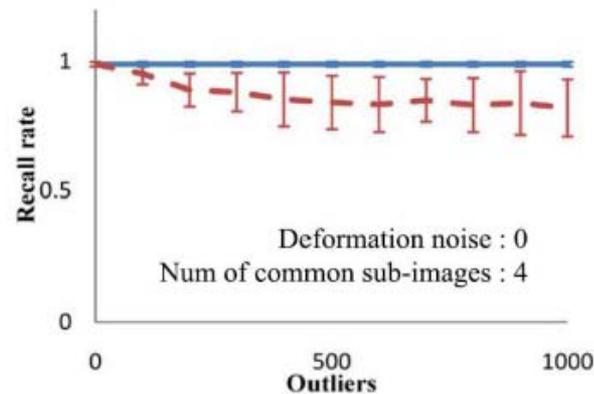
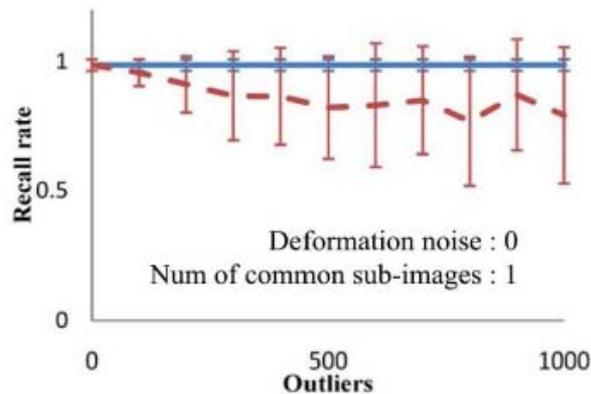
Experiments

- Feature correspondence experiments
 - Synthetic image pairs having common parts
 - Deform using TPS warping



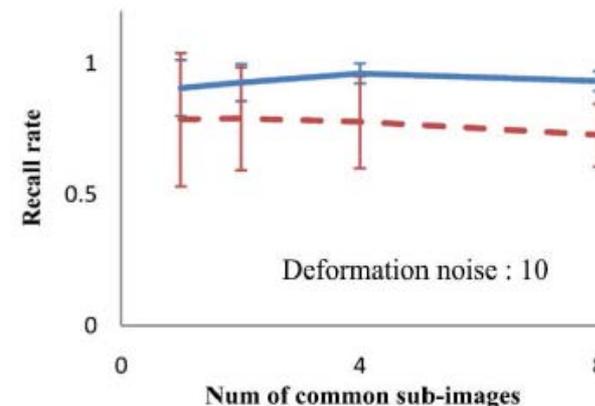
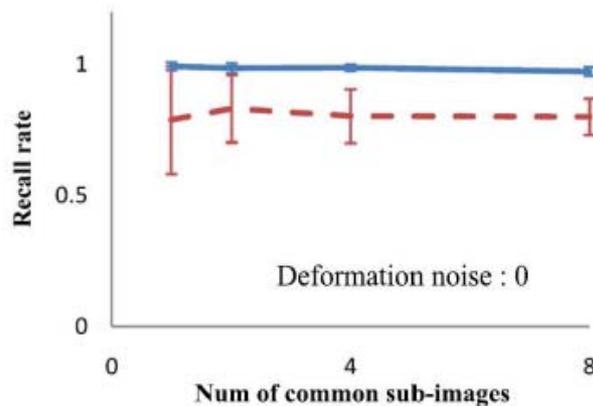
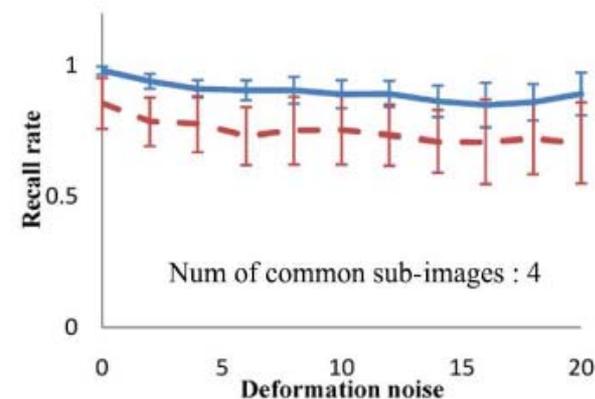
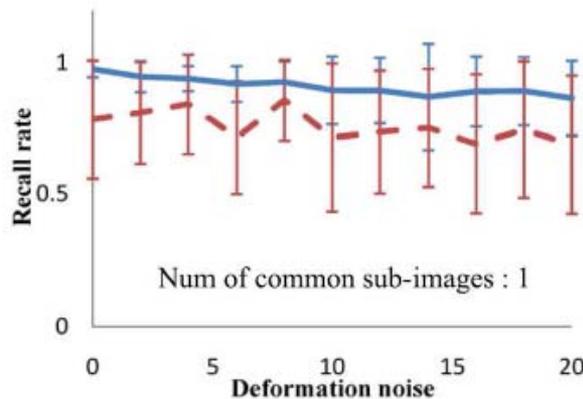
Experiments

- Comparison with Leordeanu & Hebert ICCV2005
- Varying outliers



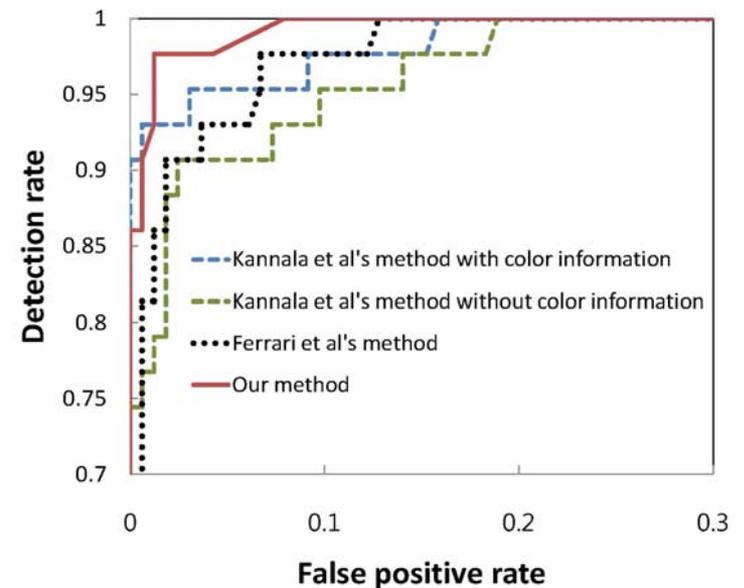
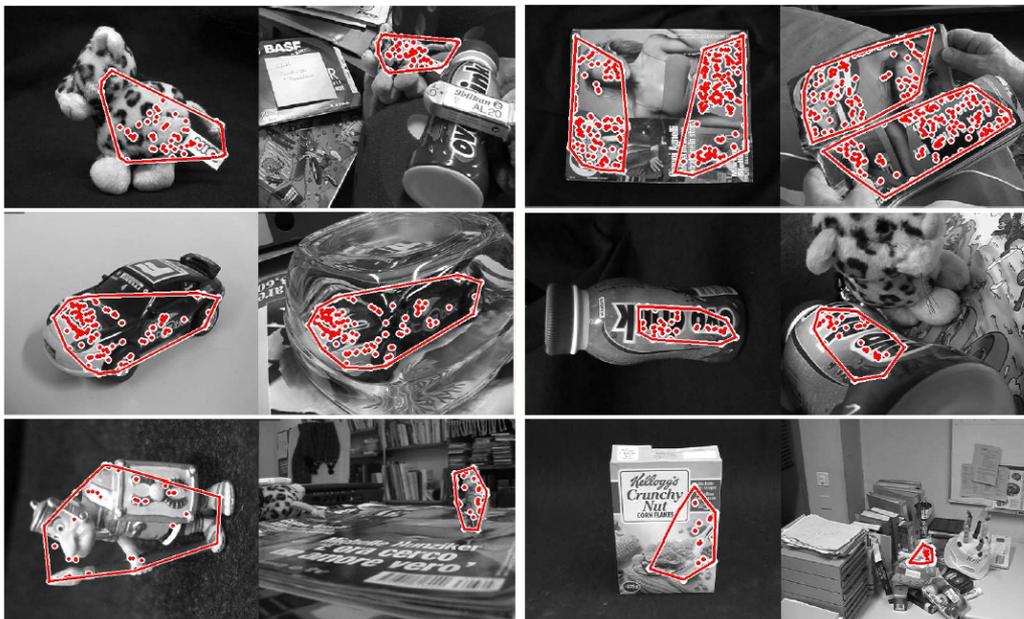
Experiments

- Comparison with Leordeanu & Hebert ICCV2005
- Varying deformation & the num of common sub-images



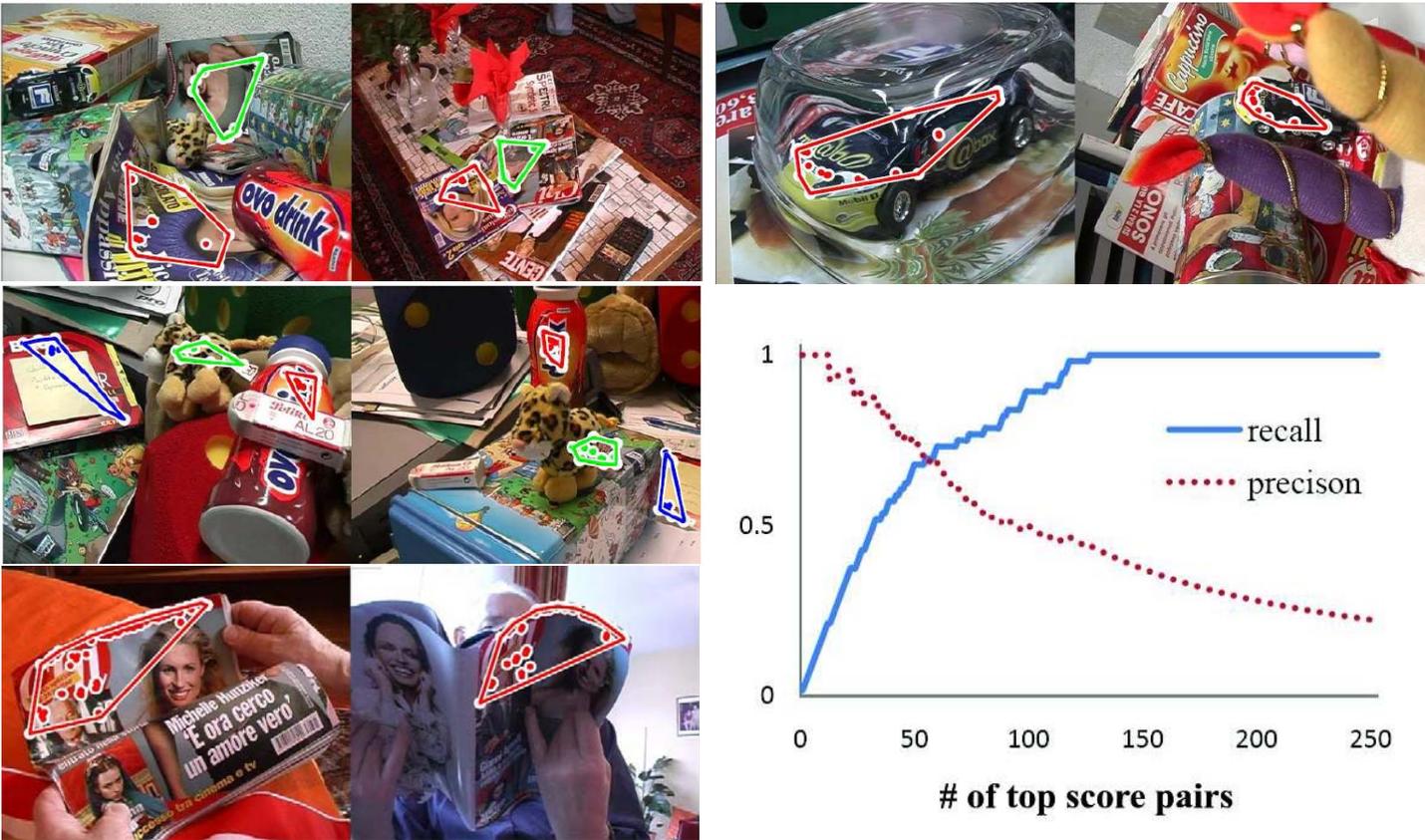
Experiments

- Object recognition on the ETHZ toys dataset



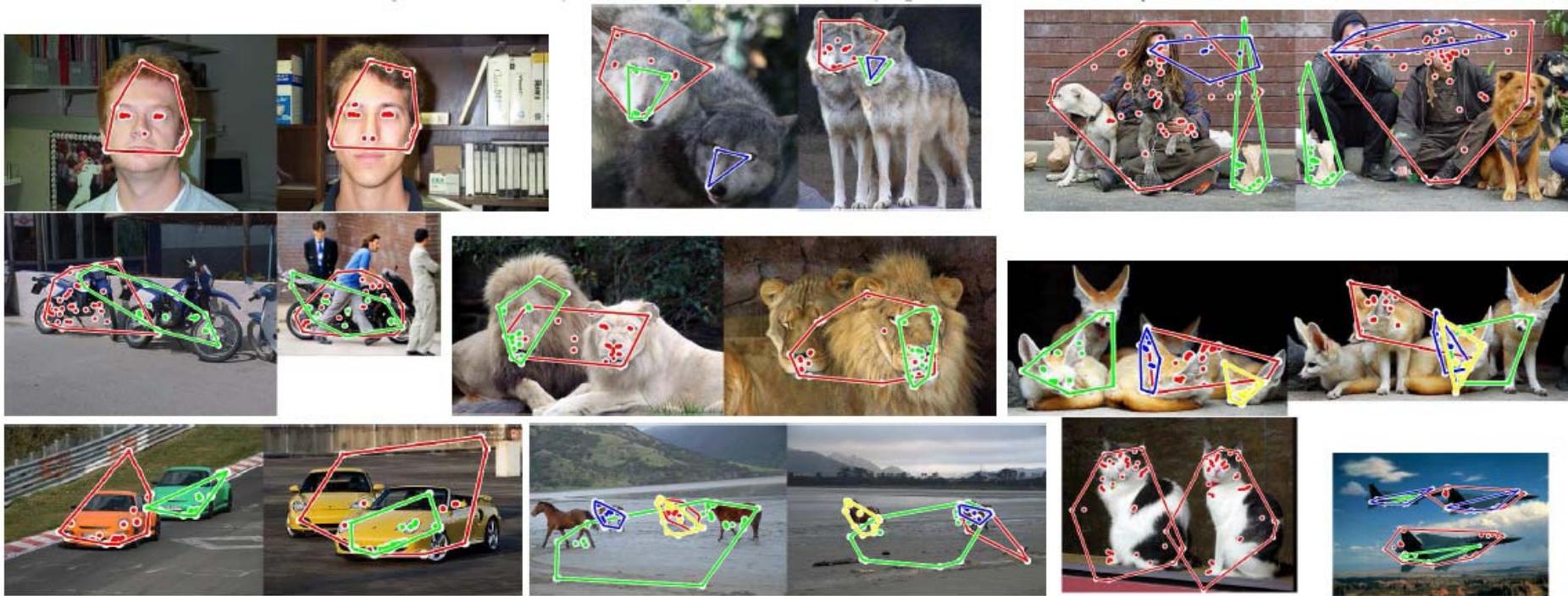
Experiments

- Object-based image matching on the test images



Experiments

- Object-based image matching examples





Conclusion and Discussion

- Simple and efficient bottom-up feature matching in HAC framework
- Feature correspondence interleaved with object-level clustering and outlier elimination
- robust to both background clutter and geometric distortion of objects in images
- Complexity
 - $O(N^2 \cdot \log N)$ w.r.t initial matches
 - Not bad
- Applicable to unsupervised object learning and categorization



Thanks for your attention!

<http://cv.snu.ac.kr>