An Unsupervised Learning Approach to Content-Based Image Retrieval

Yixin Chen & *James Z. Wang*

The Pennsylvania State University

Outline

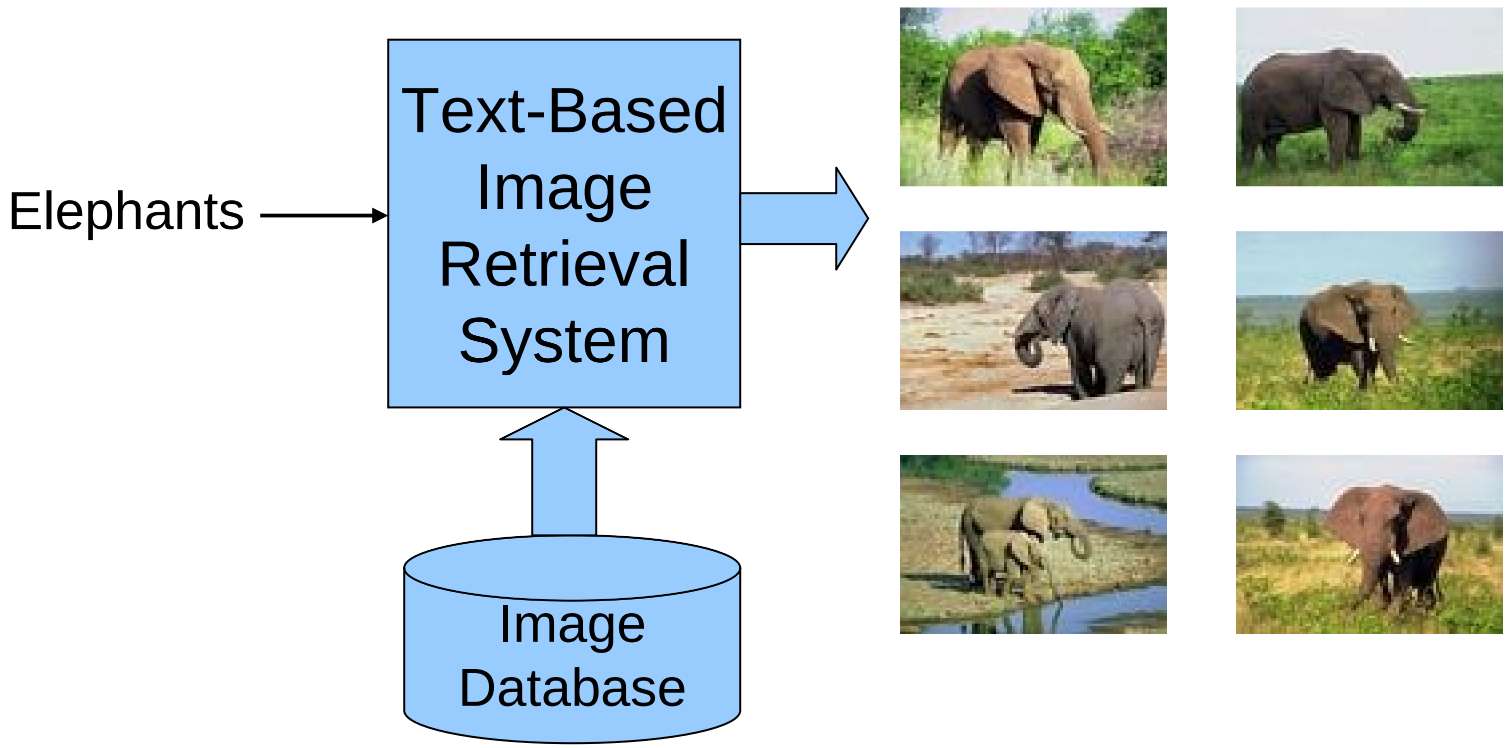
- Introduction
- Cluster-based retrieval of images
- Experiments
- Conclusions and future work

Image Retrieval

- The driving forces
  - Internet
  - Storage devices
  - Computing power
- Two approaches
  - Text-based approach
  - Content-based approach

Text-Based Approach

- Input keywords descriptions

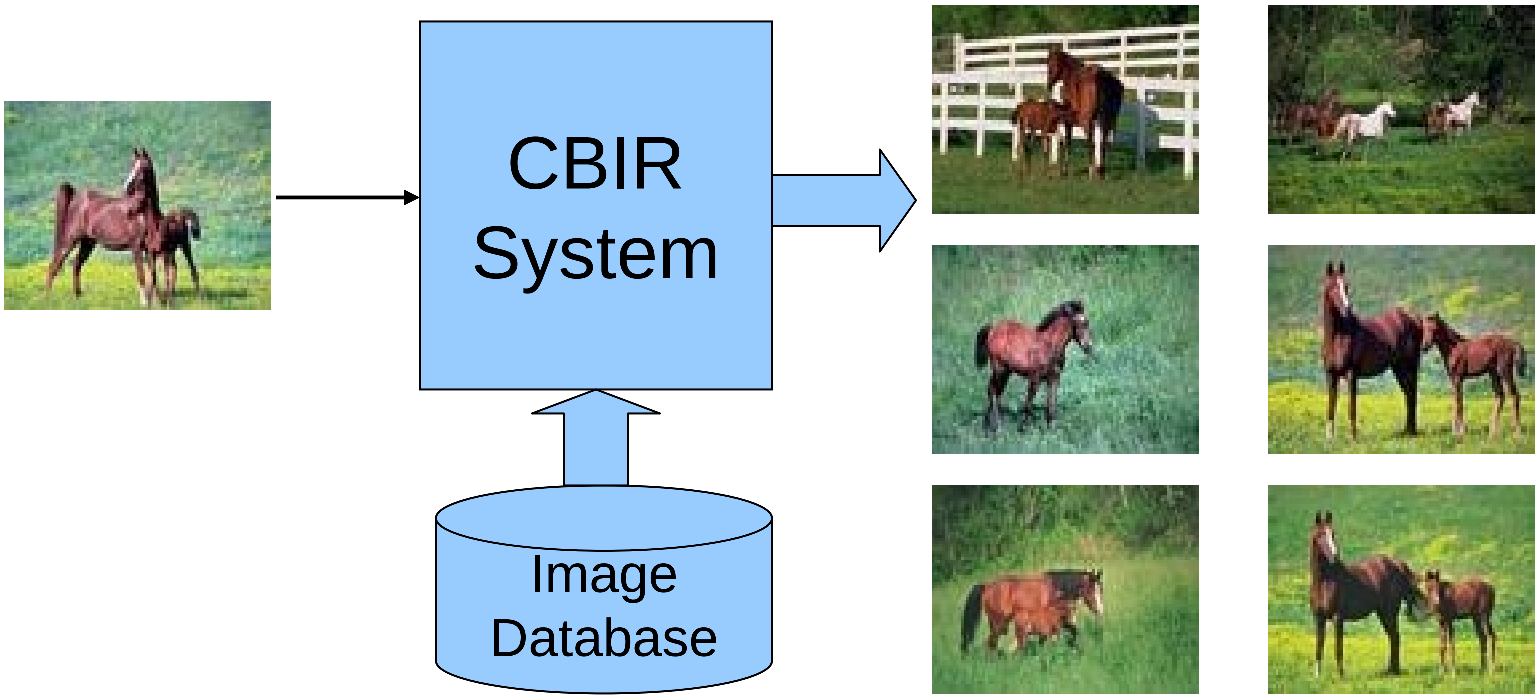


Text-Based Approach

- Index images using keywords (Google, Lycos, etc.)
  - Easy to implement
  - Fast retrieval
  - Web image search (surrounding text)
  - Manual annotation is not always available
  - A picture is worth a thousand words
  - Surrounding text may not describe the image

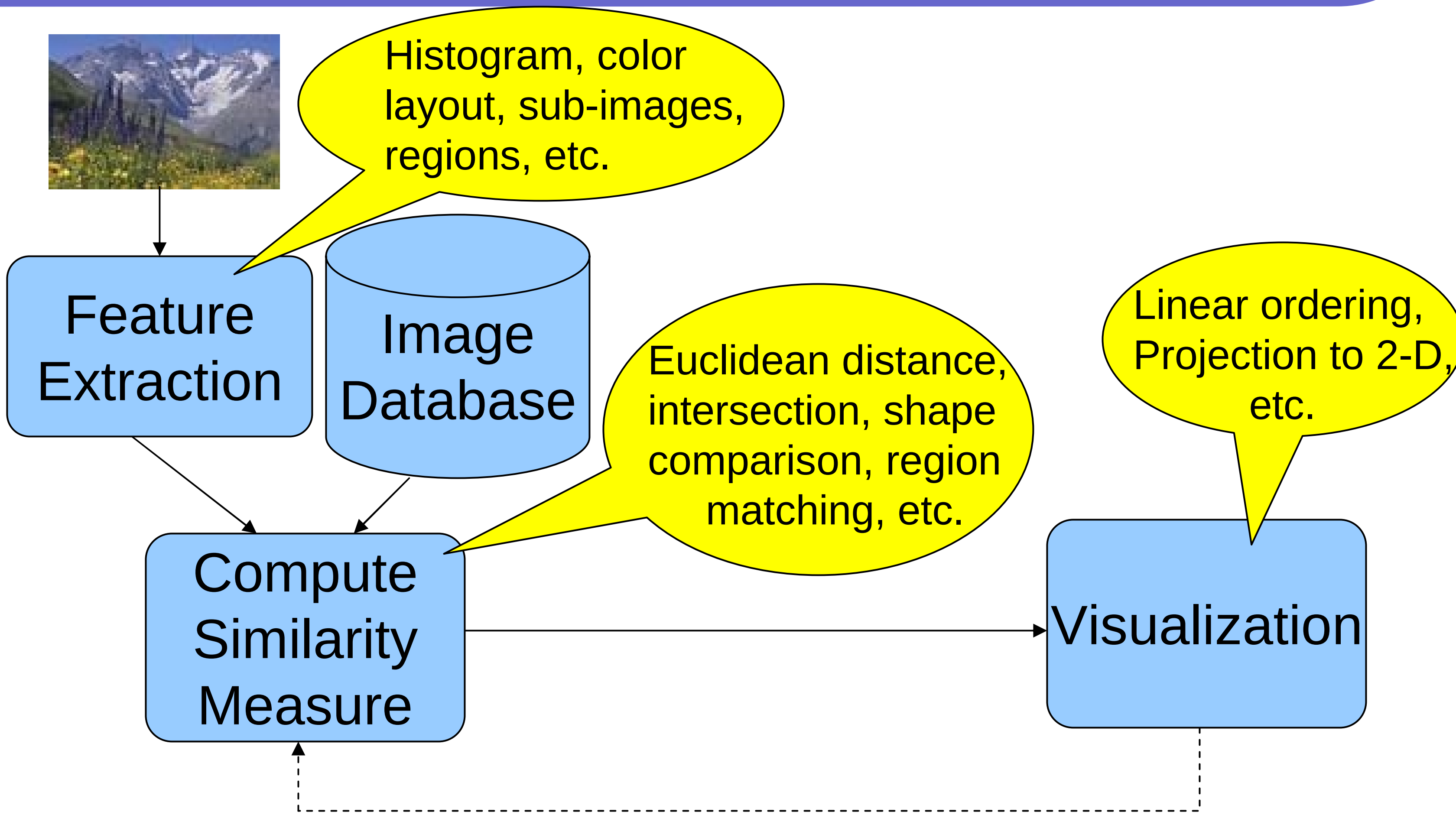
Content-Based Approach

- Index images using low-level features



Content-based image retrieval (CBIR): search pictures as pictures

A Data-Flow Diagram



Open Problem

- Nature of digital images: arrays of numbers
- Descriptions of images: high-level concepts
  - Sunset, mountain, dogs, ……
- Semantic gap
  - Discrepancy between low-level features and high-level concepts
  - High feature similarity may not always correspond to semantic similarity

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Motivation

- A query image and its top 29 matches returned by a CBIR system

Horses (11 out of 29), flowers (7 out of 29), golf player (4 out of 29)

CLUE: CLUsters-based rEtrieval of images by unsupervised learning

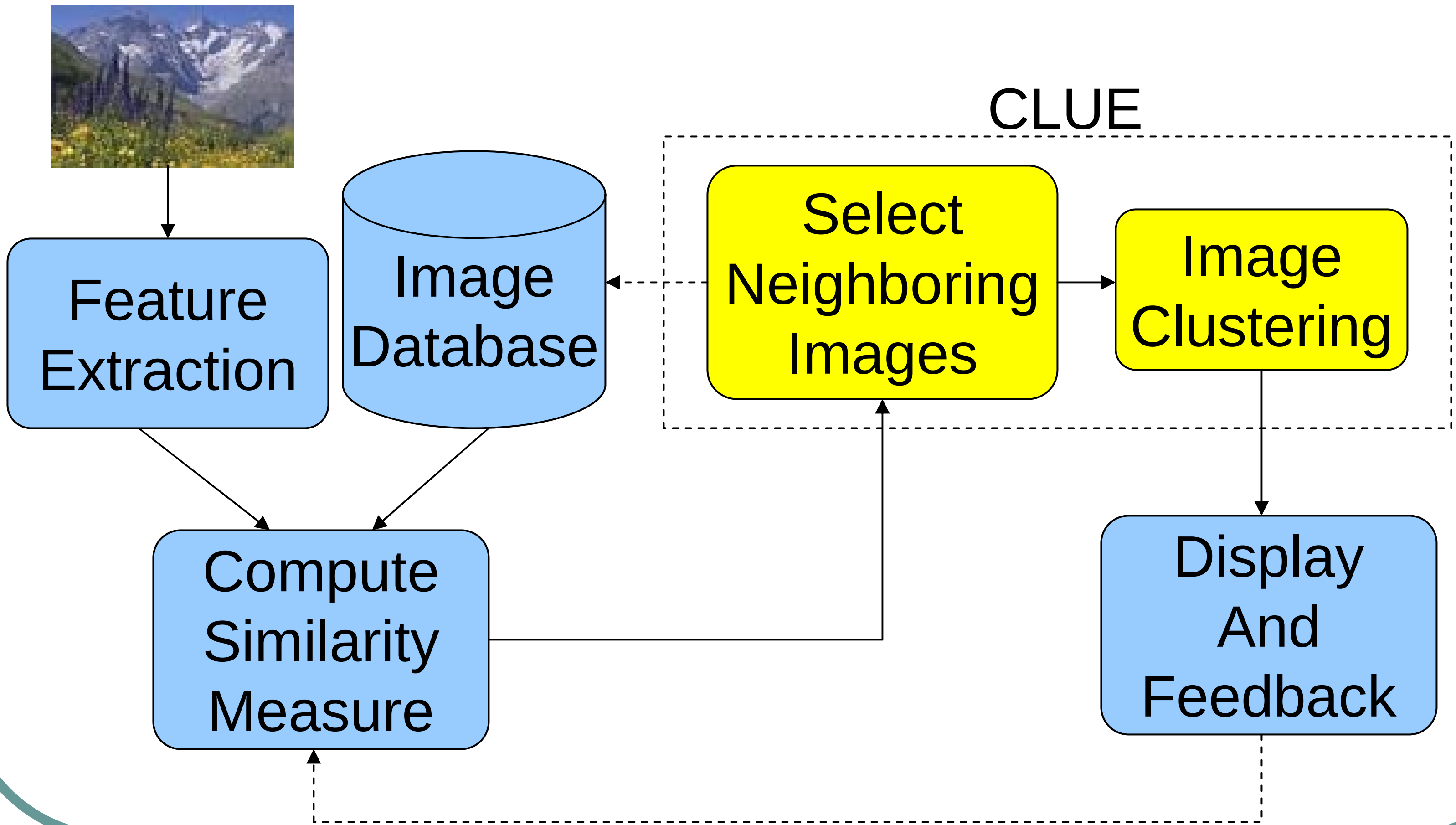
- Hypothesis

  In the "vicinity" of a query image, images tend to be semantically clustered

- CLUE attempts to capture high-level semantic concepts by learning the way that images of the same semantics are similar

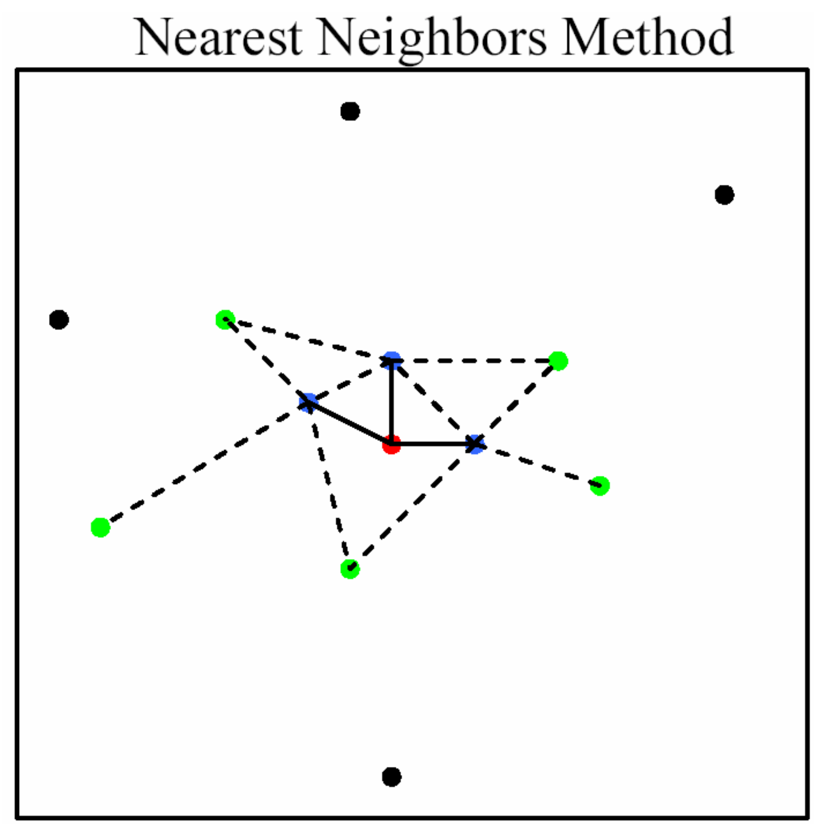
System Overview

A general diagram of a CBIR system using CLUE



Neighboring Images Selection

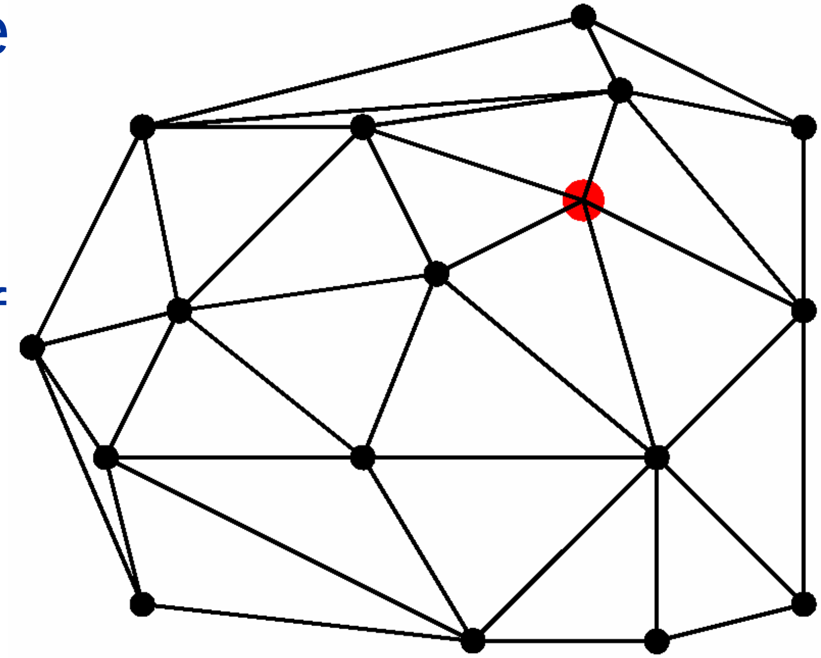
- Nearest neighbors method
  - Pick *k* nearest neighbors of the query as seeds
  - Find *r* nearest neighbors for each seed
  - Take all distinct images as neighboring images



k=3, r=4

Weighted Graph Representation

- Graph representation
  - Vertices denote image
  - Edges are formed between vertices
  - Nonnegative weight of an edge indicates the similarity between two vertices



Clustering

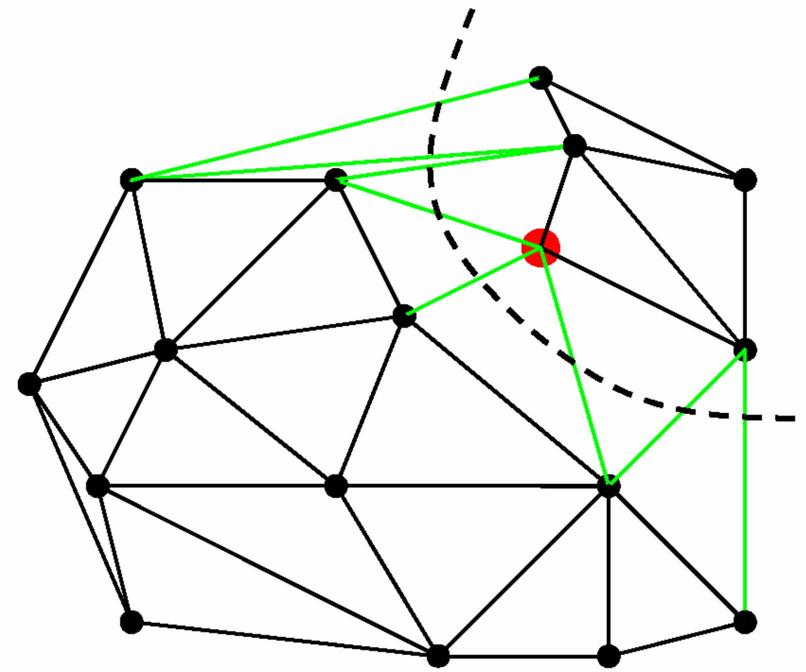
- Graph partitioning and cut

$$cut(\mathbf{A},\mathbf{B}) = \sum_{i\in\mathbf{A},j\in\mathbf{B}} w_{ij}$$

- Normalized cut (Ncut) [Shi et al., IEEE Trans. PAMI 22(8)]

$$Ncut(\mathbf{A},\mathbf{B}) = \frac{cut(\mathbf{A},\mathbf{B})}{assoc(\mathbf{A},\mathbf{V})} + \frac{cut(\mathbf{A},\mathbf{B})}{assoc(\mathbf{B},\mathbf{V})}$$

- Recursive Ncut



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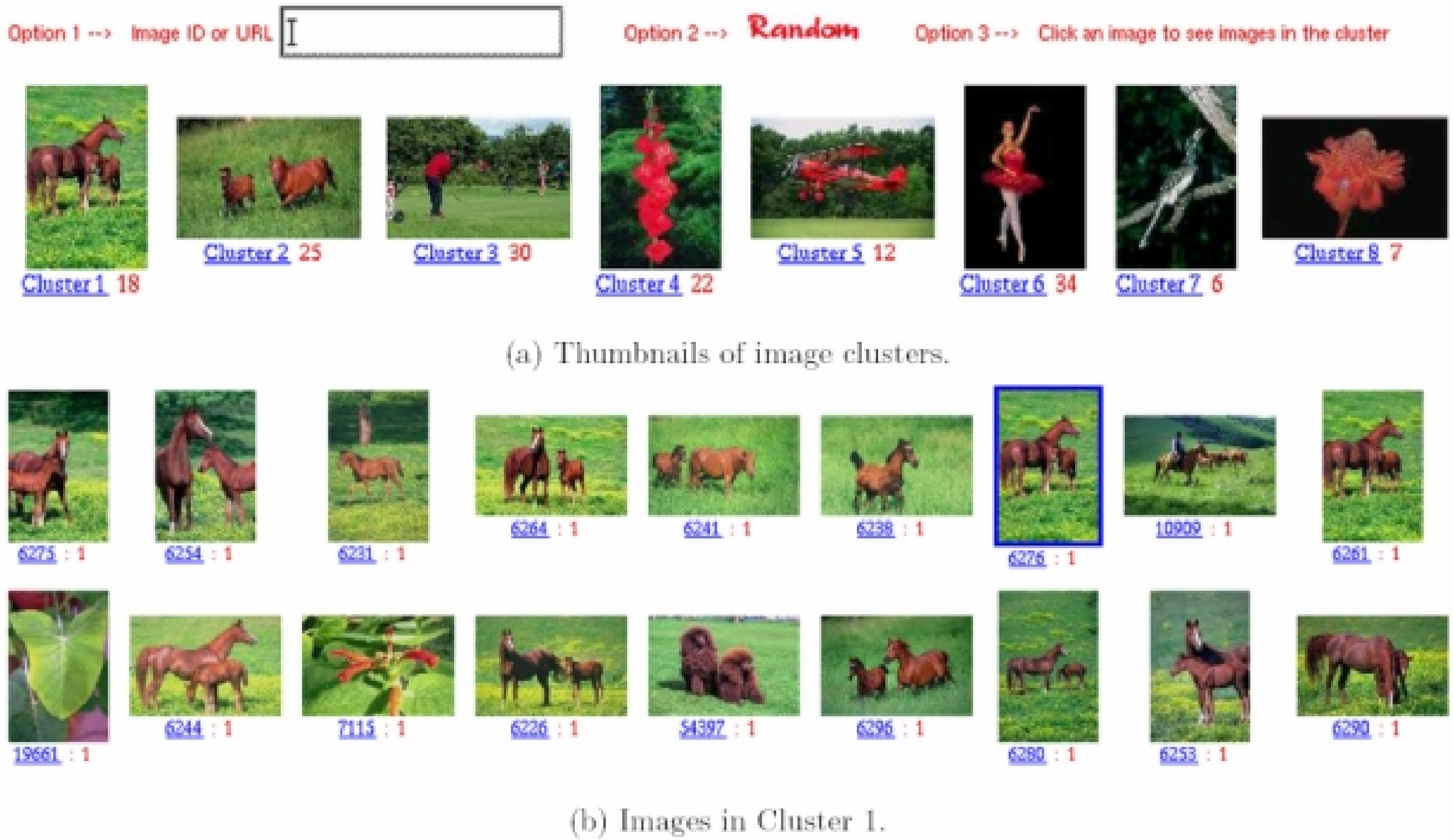
An Experimental System

- Similarity measure
  - UFM [Chen et al. IEEE PAMI 24(9)]
- Database
  - COREL
  - 60,000

User Interface



(a) Thumbnails of image clusters.

(b) Images in Cluster 1.

Query Examples

- Query Examples from 60,000-image COREL Database

Bird, car, food, historical buildings, and soccer game

CLUE

Bird, 6 out of 11

UFM

Bird, 3 out of 11

Query Examples

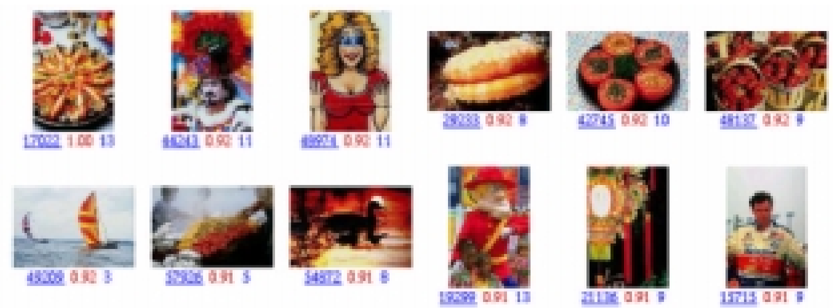
CLUE

Car, 8 out of 11

Food, 8 out of 11

UFM

Car, 4 out of 11



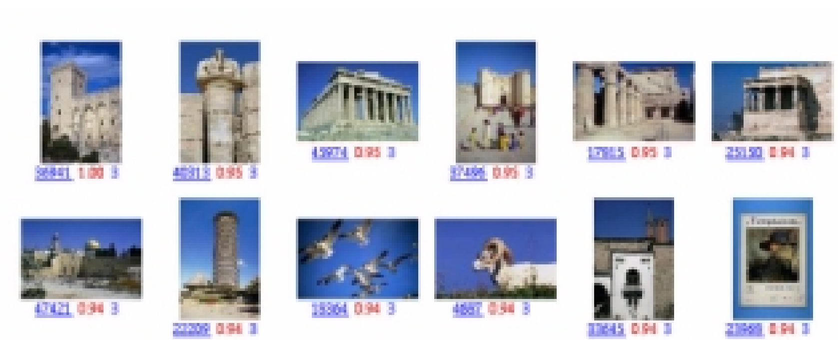
Food, 4 out of 11

Query Examples

CLUE

UFM

Historical buildings, 10 out of 11



Historical buildings, 8 out of 11

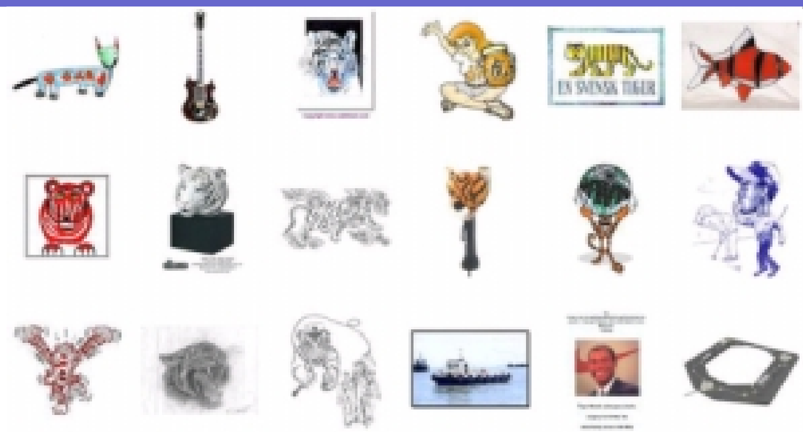
Soccer game, 10 out of 11

Soccer game, 4 out of 11

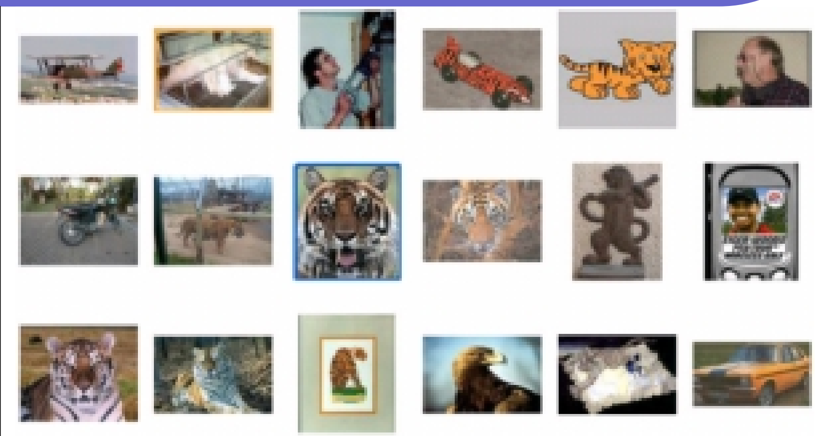
Clustering WWW Images

- Google Image Search
  - Keywords: tiger, Beijing
  - Top 200 returns
  - 4 largest clusters
  - Top 18 images within each cluster

Clustering WWW Images

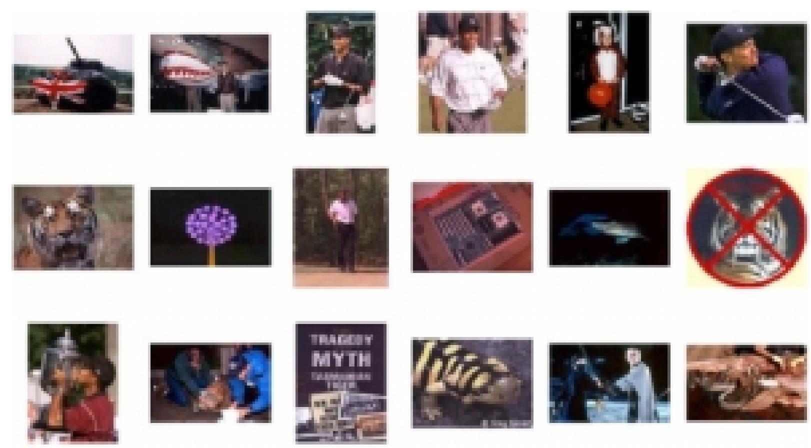


Tiger Cluster 1 (75 images)



Tiger Cluster 2 (64 images)

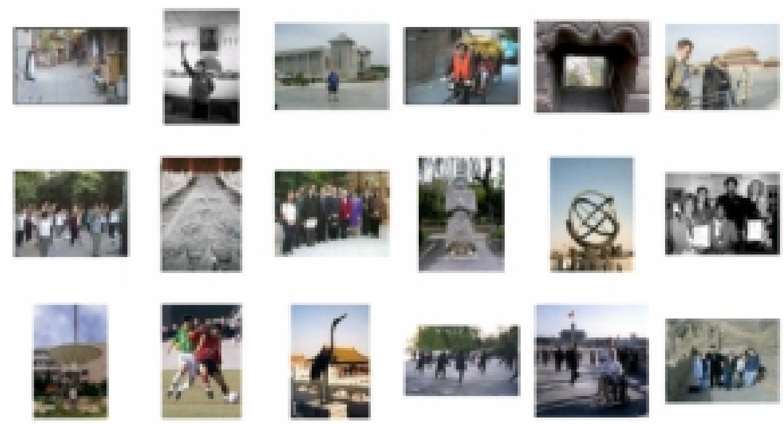
Tiger Cluster 3 (32 images)



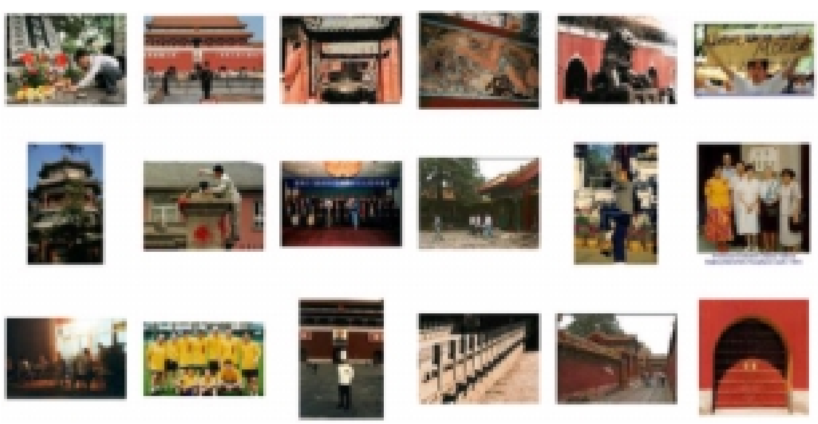
Tiger Cluster 4 (24 images)

Clustering WWW Images

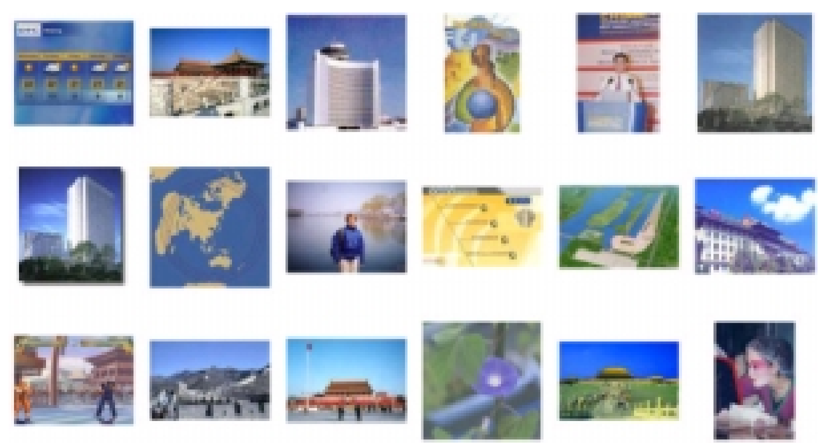
Beijing Cluster 1 (61 images)



Beijing Cluster 2 (59 images)

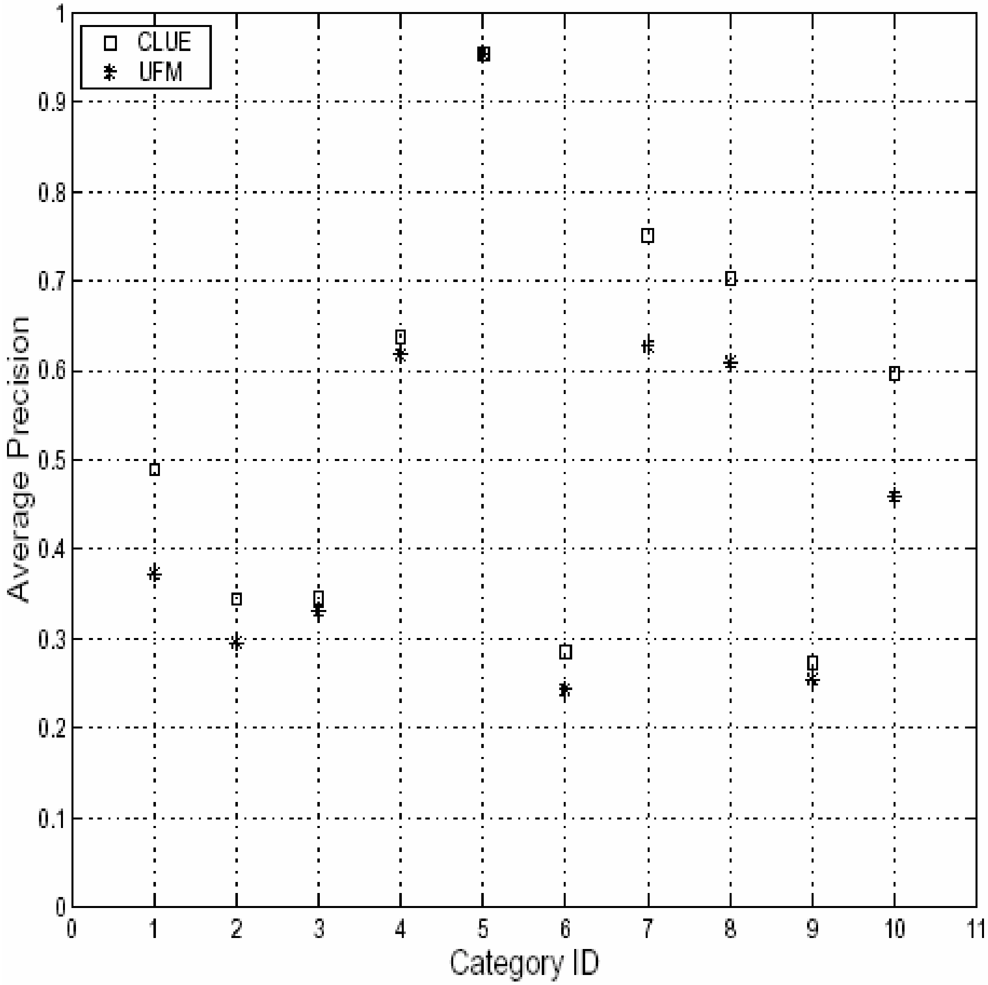


Beijing Cluster 3 (43 images)



Beijing Cluster 4 (31 images)

Retrieval Accuracy



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Conclusions

- Retrieving image clusters by unsupervised learning
- Tested using 60,000 images from COREL and images from WWW

Future Work

- Recursive Ncut
- Representative image
- Other graph theoretic clustering techniques
- Nonlinear dimensionality reduction

Thank You!