Unsupervised Manifold Learning By Correlation Graph and Strongly Connected Components for Image Retrieval

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Outline

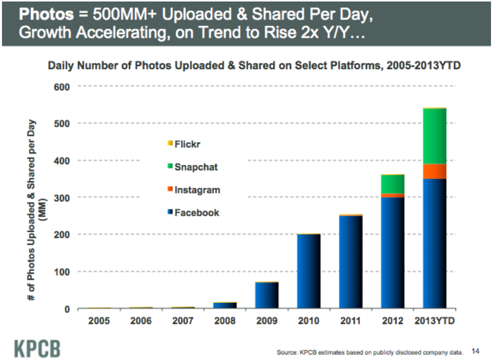
Content-Based Image Retrieval

Content-Based Image Retrieval:

- **Input:**
  - Image collection
  - Query image
- **Objective:**
  - To retrieve similar images according to visual properties

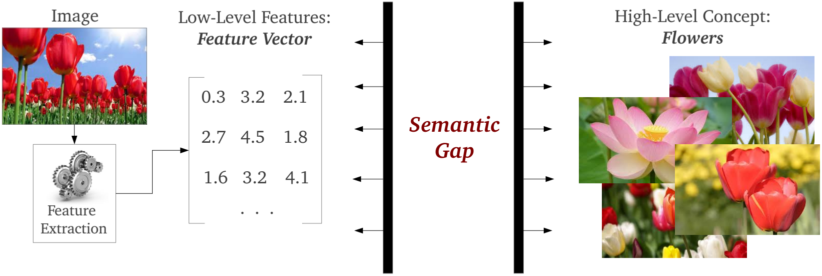
Content-Based Image Retrieval

- **Motivation:**
  - Huge growth of image collections:
    - People moved from consumers to producers!
  - Image retrieval based on keywords ignores the visual content



Content-Based Image Retrieval

- Limitations of CBIR Systems:
  - **“Semantic Gap”**:
  - Gap between low-level features and high-level concepts



Unsupervised Methods for Image Retrieval

- Recently, *Unsupervised Post-Processing* [25, 8, 26] approaches have been proposed:
  - Aiming at improving effectiveness of image retrieval tasks.
  - By reducing the Semantic Gap.
- Unsupervised approaches use more *global affinity measures* instead of pairwise distance computations.
- Exploiting the *global dataset structure* becomes a central problem in computer vision applications.

Unsupervised Manifold Learning by Correlation Graph and Strongly Connected Components

Contribution:

A novel Unsupervised Manifold Learning Algorithm based on the Correlation Graph and Strongly Connected Components (SCCs).

- The proposed algorithm computes a new distance which takes into account the **intrinsic geometry of the dataset manifold**.

Correlation Graph Motivation

Main ideas:

1. Constructing a graph representation of the dataset by exploiting the distance correlation between kNN constrained by a correlation threshold
2. Strongly Connected Components (SCCs) of the graph are analyzed with the aim of discovering the *intrinsic geometry of the dataset manifold*;
3. A similarity score combines information from the Correlation Graph Adjacency and Strongly Connected Components;
4. A new **Correlation Graph Distance** is computed based on the similarity score.

Correlation Graph Motivation

Discussion:

- The edges defined by the Correlation Graph provide a very strong indication of similarity among images (specially for high correlation thresholds).
- However, although very precise, the edges include a very small neighborhood.
- We aim at expanding the similarity neighborhood, but still considering the geometry of the dataset manifold, by using SCCs .

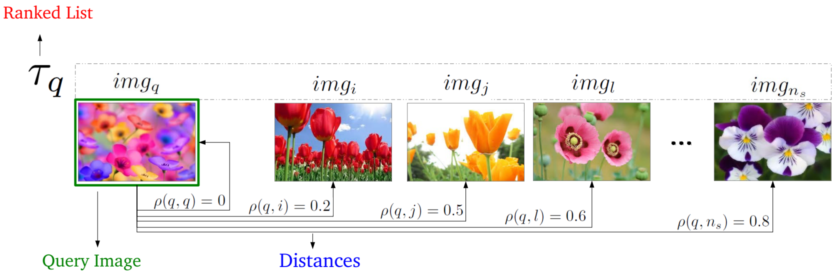
Correlation Graph

Image Retrieval Model:

- Let $\mathcal{C}=\{img_1, img_2, \ldots, img_n\}$ be an image collection, where n is the size of the collection.
- Let $\rho(i,j)$ denotes the distance between two images img_i and img_j, according to a given image descriptor.
- Let $\tau_q=(img_1, img_2, \ldots, img_{n_s})$ be a ranked list, which can be defined as a permutation of the subset $\mathcal{C}_s \subset \mathcal{C}$.
  - The subset $\mathcal{C}_s$ contains the n_s most similar images to query image img_q, such that and $|\mathcal{C}_s| = n_s$.

Image Retrieval Model

- Query Image
- Distances
- Ranked Lists



Correlation Graph

Graph Definition:

- Given a directed graph $G = (V, E)$, the set of vertices V is defined by the image collection $\mathcal{C}$, such that each image is represented by a node and $V = \mathcal{C}$.
- The edge set E is defined considering the distances correlation among images at the top n_s positions of each ranked list:
    - $E = \{(img_q, img_j) \mid \tau_q(j) \leqslant n_s \wedge cor(q, j) \geqslant t_c\}$,
    - $cor(q, j)$ is the correlation score between img_q and img_j
    - t_c is the correlation threshold considered.

Correlation Graph

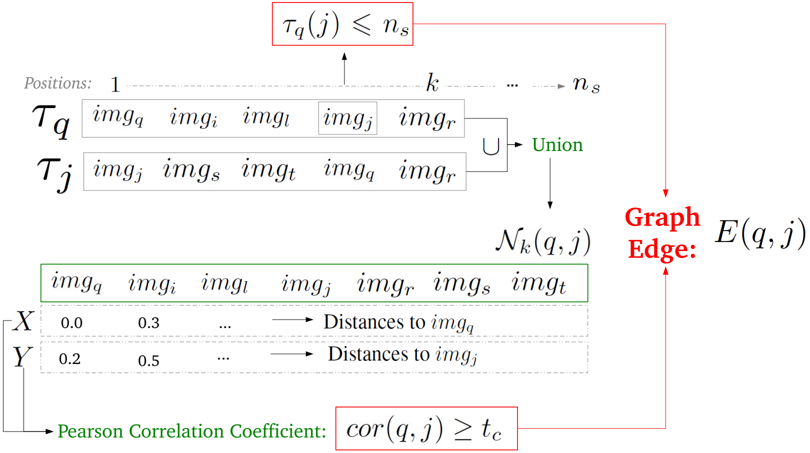
Correlation Score:

The correlation score $cor(q,j)$ is computed by the Pearson's Correlation Coefficient, considering the distances to the kNN.

- Let $\mathcal{N}_k(q)$ be the set containing the k-nearest neighbors to given image img_q and $\mathcal{N}_k(q,j) = \mathcal{N}_k(q) \cup \mathcal{N}_k(j)$.
- Vectors X and Y contain the distances from images img_q, img_j to $img_i \in \mathcal{N}_k(q,j)$:
  - $X_i = \rho(q,i)$ and $Y_i = \rho(j,i)$

$$cor(q,j) = \frac{\sum_{i=1}^{k_u}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{k_u}(X_i - \overline{X})^2}\sqrt{\sum_{i=1}^{k_u}(Y_i - \overline{Y})^2}}. \quad (1)$$

Correlation Graph



Correlation Graph

Strongly Connected Components (SCCs)

The Strongly Connected Components of a directed graph are defined by subgraphs that are themselves strongly connected.

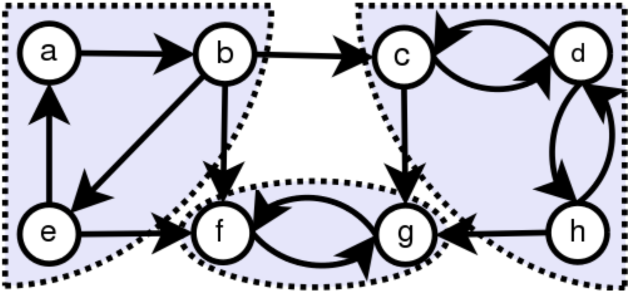
- Every vertex is reachable from every other vertex.

SCCs Computation

- Each SCC is defined as a set of images $\mathcal{S}_i$, computed using Tarjan's [22] Algorithm.
- The overall output of the algorithm is a set of SCCs $\mathcal{S} = \{\mathcal{S}_1, \mathcal{S}_2, \dots, \mathcal{S}_m\}$

Correlation Graph

- Strongly Connected Components (SCCs):
  - Sets of similar images



Correlation Graph Distance - Algorithm

Require: Correlation Graph $G = (V, E)$, Set of SCCs $\mathcal{S}$
Ensure: Correlation Graph Similarity Score $W_{i,j}$

$t_c \leftarrow t_{start}$
while $t_c \leqslant 1$ **do**
  { Correlation Graph Adjacency }
  for all $img_q \in V$ **do**
    for all $img_i, img_j \in E(q)$ **do**
      $W_{i,j} \leftarrow W_{i,j} + t_c$
    end for
  end for
  { Strongly Connected Components }
  for all $\mathcal{S}_c \in \mathcal{S}$ **do**
    for all $img_i, img_j \in \mathcal{S}_c$ **do**
      $W_{i,j} \leftarrow W_{i,j} + t_c$
    end for
  end for
  $t_c \leftarrow t_c + t_{inc}$
end while

Correlation Graph Distance

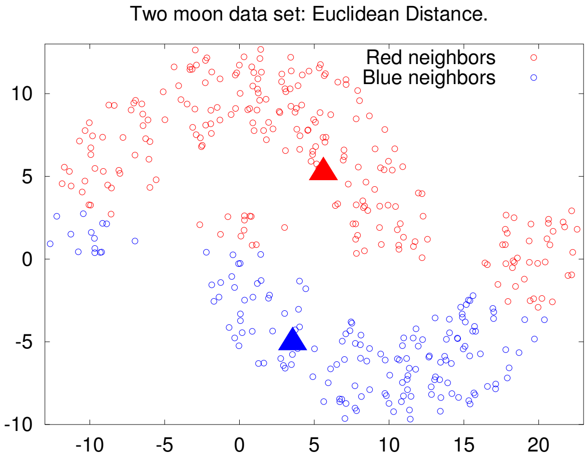
The similarity score $W_{i,j}$ uses information from both Correlation Graph Adjacency and Strongly Connected Components (SCCs).

Correlation Graph Distance

Based on the similarity score $W_{i,j}$, the *Correlation Graph Distance* $\rho_c(i,j)$ is computed:

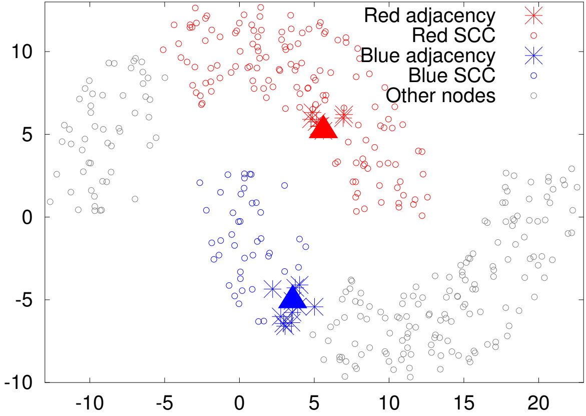
$$\rho_c(i,j) = \frac{1}{1 + W_{i,j}}. \quad (2)$$

Example: Euclidean Distance

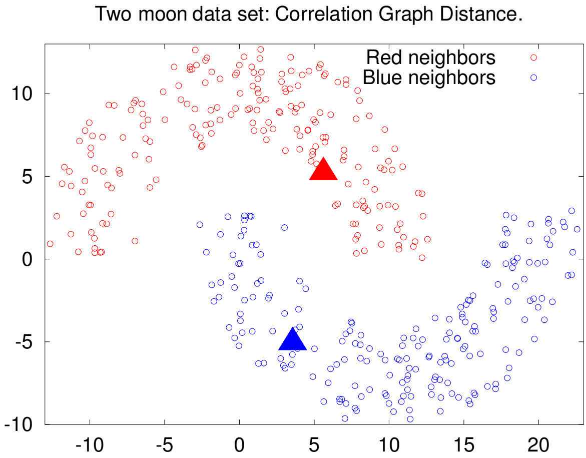


Example: Intermediary Correlation Graph Structures

Two moons data set: Correlation Graph at an intermediary threshold.



Example: Correlation Graph Distance



Experimental Evaluation

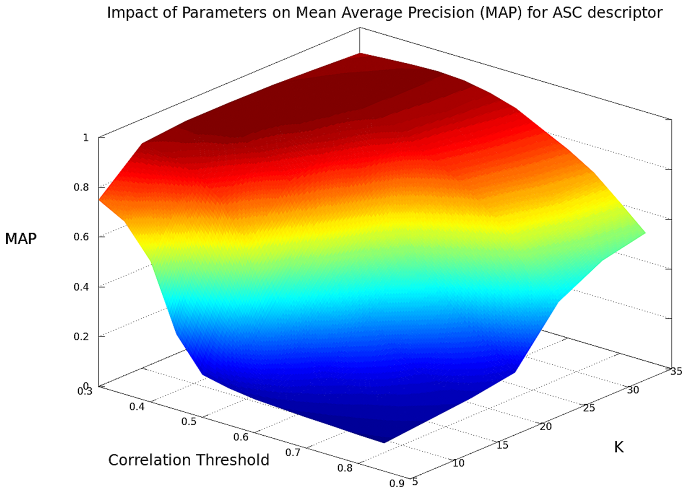
Experimental Evaluation

- Evaluation of impact of parameters
- 4 different datasets
- 13 CBIR descriptors
  - shape, color, and texture
- Statistical tests (t-tests)
- Comparison with state-of-the-art approaches

Results

- Effectiveness gains up to +34.54%.

Impact of Parameter on Effectiveness



Experimental Evaluation - Shape

Shape Descriptors

Positive gains ranging from +7.25% to +34.54%, considering MAP scores.

Descriptor	Dataset	Score (MAP)	Correlation Graph Distance	Gain	Statistical Significance 99%
SS [4]	MPEG-7 [10]	37.67%	50.68%	+34.54%	•
BAS [1]	MPEG-7 [10]	71.52%	81.97%	+14.61%	•
IDSC [12]	MPEG-7 [10]	81.70%	89.39%	+9.41%	•
CFD [16]	MPEG-7 [10]	80.71%	91.93%	+13.90%	•
ASC [13]	MPEG-7 [10]	85.28%	92.53%	+7.25%	•
AIR [5]	MPEG-7 [10]	89.39%	97.98%	+9.61%	•

Experimental Evaluation - Shape

Shape Descriptors

Positive gains ranging from +6.90% to +29.28%, considering Bull's Eye Score (Recall@40).

Shape Descriptor	Bull's Eye Score	Correlation Graph Distance	Gain
SS [4]	43.99%	56.88%	+29.28%
BAS [1]	75.20%	86.52%	+15.05%
IDSC [12]	85.40%	92.20%	+7.80%
CFD [16]	84.43%	94.27%	+11.65%
ASC [13]	88.39%	95.22%	+7.73%
AIR [5]	93.67%	100%	+6.90%

Experimental Evaluation - Color

Color Descriptors

Positive gains ranging from +7.29% to +21.51%, considering MAP scores.

Descriptor	Dataset	Score (MAP)	Correlation Graph Distance	Gain	Statistical Significance 99%
GCH [20]	Soccer [23]	32.24%	34.59%	+7.29%	•
ACC [6]	Soccer [23]	37.23%	45.24%	+21.51%	•
BIC [19]	Soccer [23]	39.26%	47.37%	+20.65%	•

Experimental Evaluation - Texture

Texture Descriptors

Positive gains ranging from +6.28% to +12.44%, considering MAP scores.

Descriptor	Dataset	Score (MAP)	Correlation Graph Distance	Gain	Statistical Significance 99%
LBP [15]	Brodatz [3]	48.40%	50.12%	+3.55%	•
CCOM [9]	Brodatz [3]	57.57%	64.73%	+12.44%	•
LAS [21]	Brodatz [3]	75.15%	79.87%	+6.28%	•

Experimental Evaluation - Object Retrieval

Object Retrieval - Color Descriptors

Positive gains ranging from +4.39% to +18.10%, considering MAP scores.

Descriptor	**Dataset**	**Score (MAP)**	**Correlation Graph Distance**	**Gain**
BIC [19]	ETH-80 [11]	49.72%	54.20%	+9.01%
ACC [6]	ETH-80 [11]	48.50%	50.63%	+4.39%
CSD [14]	ETH-80 [11]	48.46%	57.23%	+18.10%
GCH [20]	ETH-80 [11]	41.62%	45.07%	+8.29%

Comparison to State-of-the-Art

Algorithm	Descriptor(s)	Bull's Eye Score
LCDP [25]	IDSC [12]	93.32%
Shortest Path Propagation [24]	IDSC [12]	93.35%
Mutual kNN Graph [8]	IDSC [12]	93.40%
Pairwise Recommendation [17]	ASC [13]	94.66%
RL-Sim [18]	ASC [13]	94.69%
Correlation Graph Distance	**ASC [13]**	**95.22%**
LCDP [25]	ASC [13]	95.96%
Tensor Product Graph [26]	ASC [13]	96.47%
Self-Smoothing Operator [7]	SC [2] +IDSC [12]	97.64%
Pairwise Recommendation [17]	CFD [16]+IDSC [12]	99.52%
RL-Sim [18]	AIR [5]	99.94%
Tensor Product Graph [26]	AIR [5]	99.99%
Correlation Graph Distance	**AIR [5]**	**100%**

Conclusions

Contributions:

- A novel manifold learning approach is presented using the distance correlation for representing the dataset.
- The use of Strongly Connected Components (SCCs) for discovering the intrinsic geometry of the dataset manifold.
- Experimental results demonstrated the high effectiveness of the proposed method in several image retrieval tasks.

Future Work

- Investigation of distance fusion approaches for descriptors combination.
- Investigation of rank correlation measures for construction the Correlation Graph.

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Questions?

Thank you for your attention!
Questions?

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