Image Matching

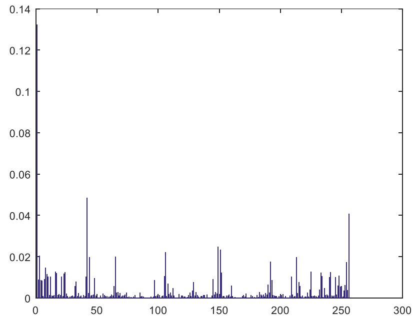
CPS592 – Visual Computing and Mixed Reality

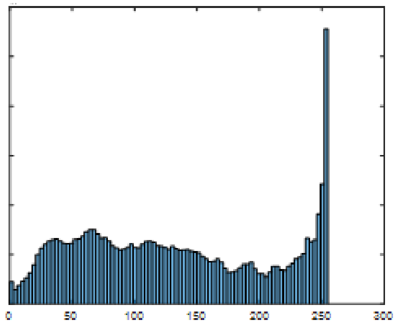
What did we study in the previous lecture?

- Features
  - Color Histogram
  - Tiny Image
  - Local Binary Pattern

What is the similar thing of these features?

- In histogram form
- Small dimensions
- Normalized feature

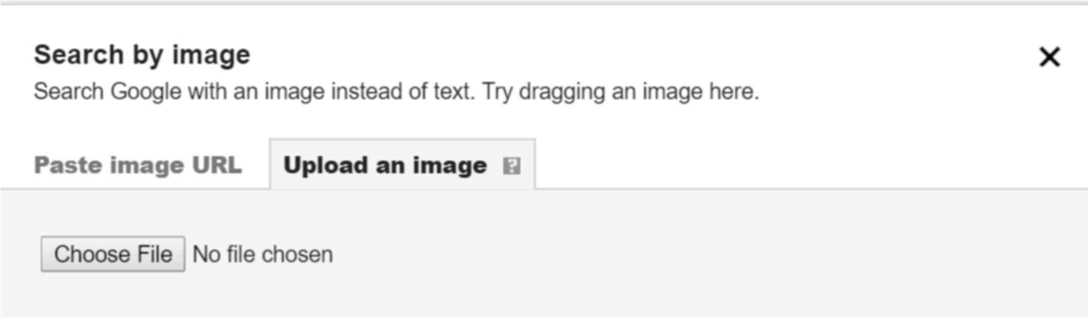




What is our goal?

Google image search

Image



Similar images

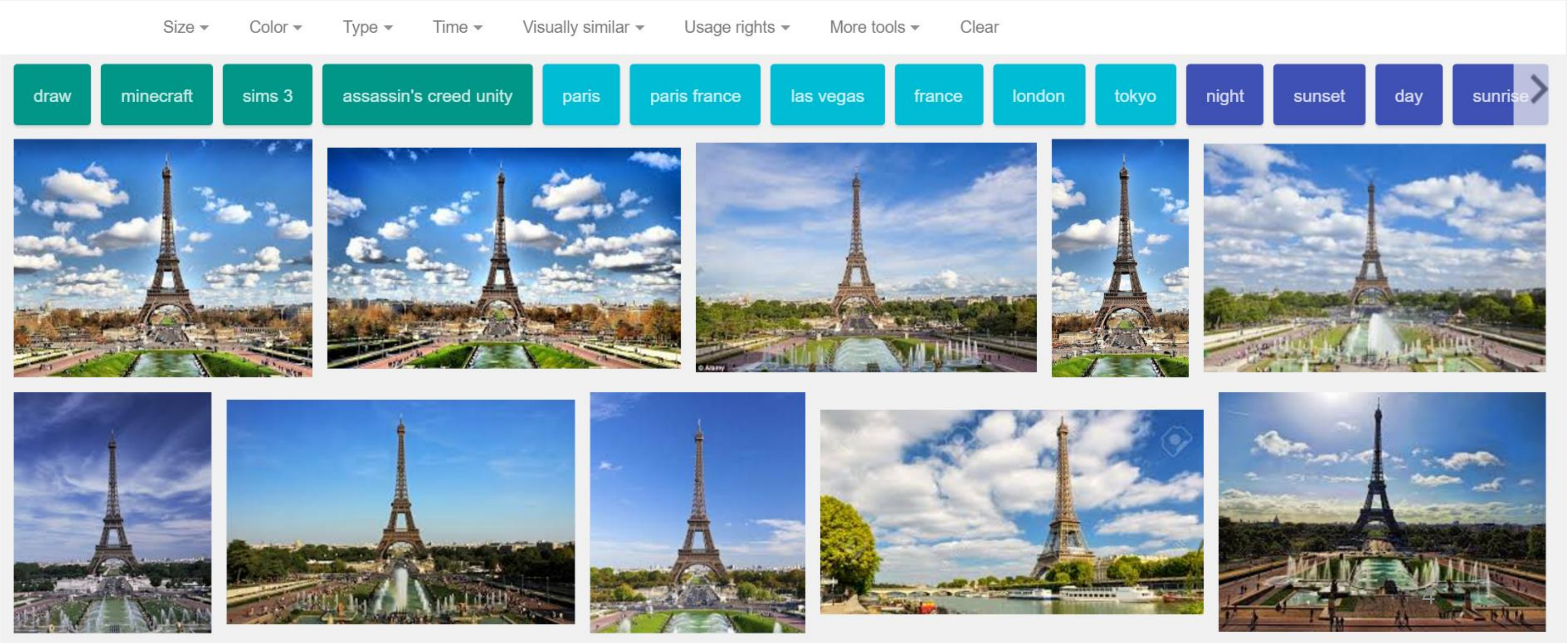
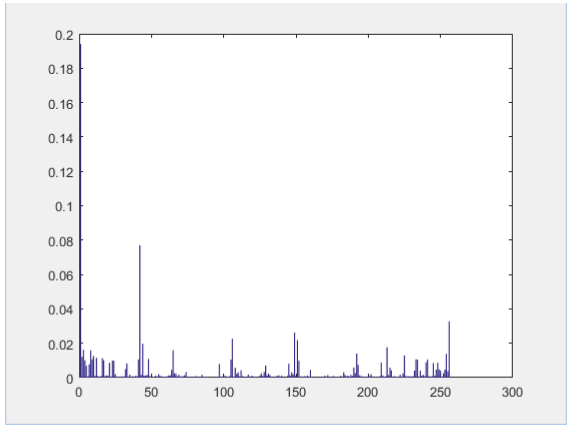


Image Matching



Which image is the most similar?

WHY?

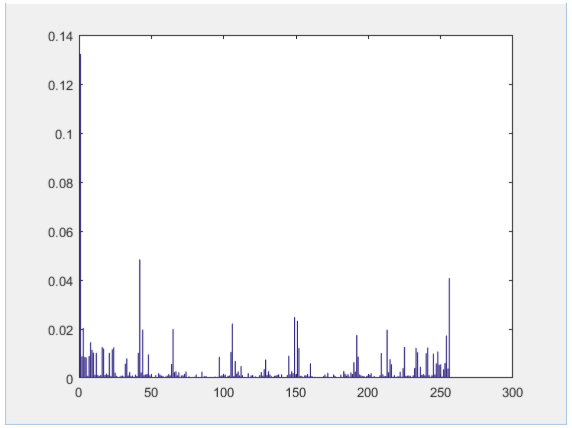
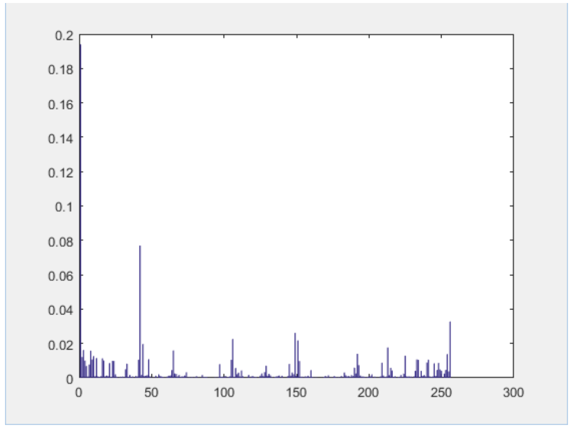
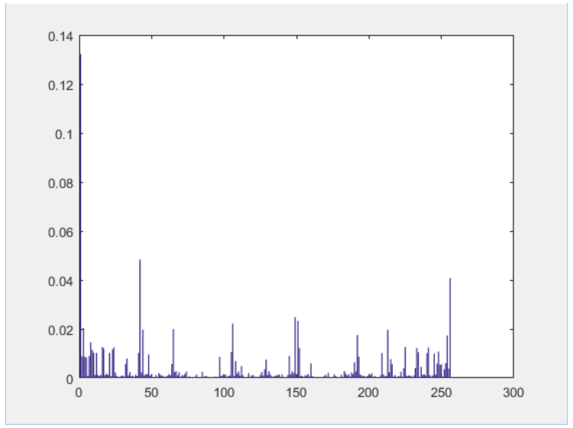


Image Matching



is similar to



HOW CAN WE DEFINE SIMILARITY?

Distance Metrics

- The Minkowski metric is a generalization of a Euclidean distance:

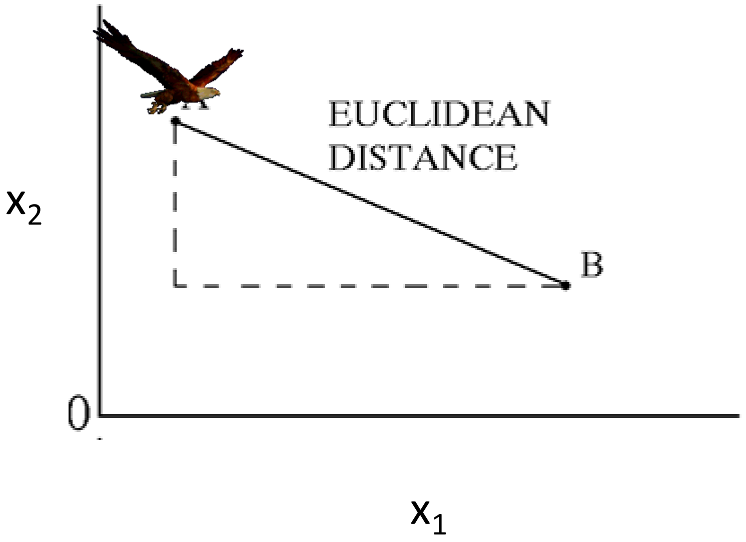
$$L_p(\mathbf{a},\mathbf{b}) = \left(\sum_{k=1}^{d} \left| a_k - b_k \right|^p \right)^{1/p}$$

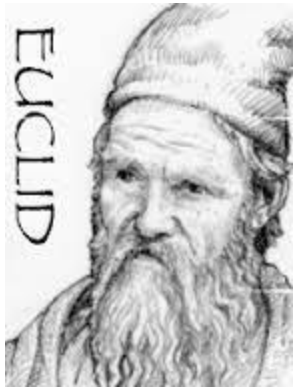
, where d is the number of dimensions, and is often referred to as the L_p norm.

- Special cases:
  - L_1: absolute, cityblock, or Manhattan distance
  - L_2: Euclidian distance

Distance Metrics

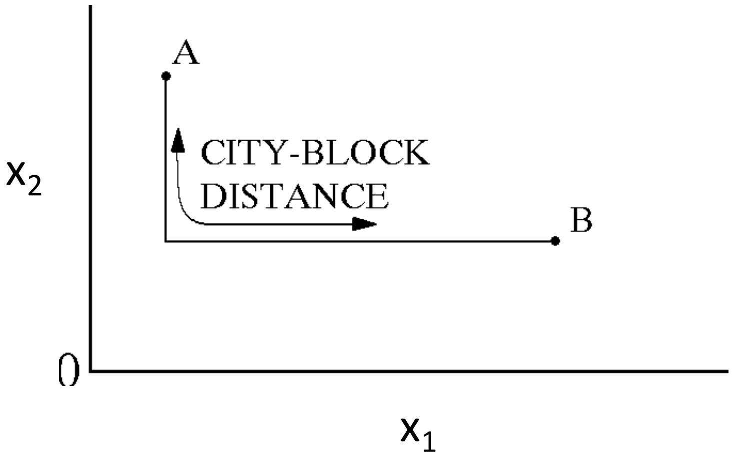
- Euclidean Distance: $$dist(\mathbf{a},\mathbf{b}) = \left(\sum_{k=1}^{d} (a_k - b_k)^2 \right)^{1/2}$$





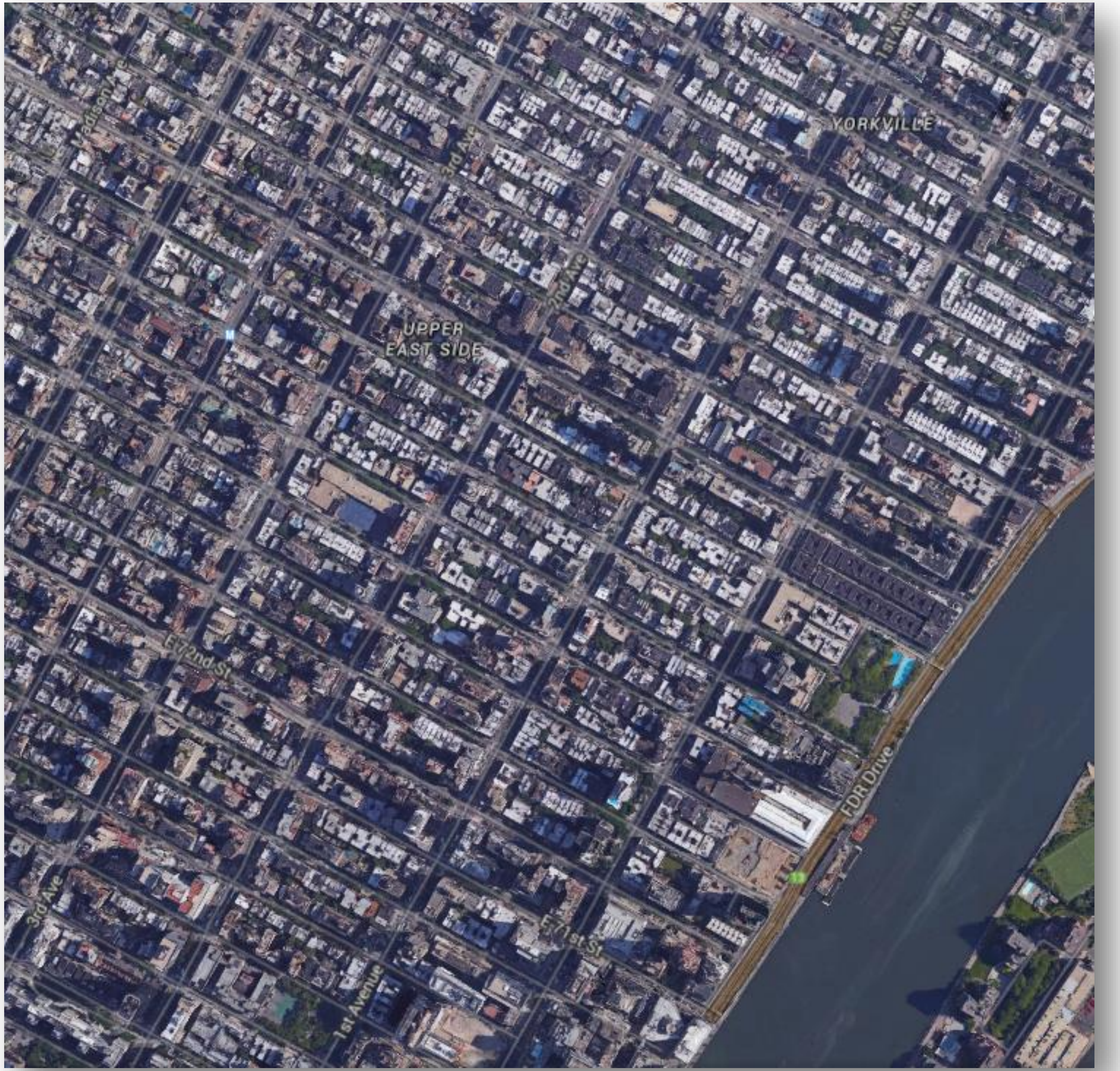
Distance Metrics

- Manhattan distance: $dist(\mathbf{a},\mathbf{b}) = \sum_{k=1}^{d} \left| a_k - b_k \right|$



Distance Metrics

- It is named Manhattan distance because it is the shortest distance a car would drive in a city laid out in square blocks, like Manhattan.



Other Distance Measures

- Chi-Squared (χ^2) Distance

$$\chi^2(h_1, h_2) = \frac{1}{2}\sum_{m=1}^{K}\frac{[h_1(m) - h_2(m)]^2}{h_1(m) + h_2(m)}$$

- Histogram intersection (for normalized histograms)

$$D_{\mathrm{int}}(h_1, h_2) = 1 - \sum_{m=1}^{K}\min\left(h_1(m), h_2(m)\right)$$

Examples

- Euclidean Distance:

$$dist(tiny_{\mathbf{a}}, tiny_{\mathbf{b}}) = \left(\sum_{k=1}^{3072} \left(tiny_{ak} - tiny_{bk} \right)^2 \right)^{1/2}$$

Examples

- Chi-Squared (χ^2) Distance

$$\chi^2(lbp_1, lbp_2) = \frac{1}{2}\sum_{m=1}^{256}\frac{[lbp_1(m) - lbp_2(m)]^2}{lbp_1(m) + lbp_2(m)}$$

- Histogram intersection (for normalized histograms)

$$D_{\mathrm{int}}(lbp_1, lbp_2) = 1 - \sum_{m=1}^{256}\min\left(lbp_1(m), lbp_2(m)\right)$$

Properties of Metrics

- Nonnegativity: $dist(\mathbf{a},\mathbf{b}) \geq 0$
- Reflexivity: $dist(\mathbf{a},\mathbf{b}) = 0 \quad iff \quad \mathbf{a} = \mathbf{b}$
- Symmetry: $dist(\mathbf{a},\mathbf{b}) = dist(\mathbf{b},\mathbf{a})$
- Triangle Inequality: $dist(\mathbf{a},\mathbf{b}) + dist(\mathbf{b},\mathbf{c}) \geq dist(\mathbf{a},\mathbf{c})$

Which distance metrics should we use?

- We have many types of features: color histogram, tiny image, and local binary patterns.
- Which distance metrics should we use?

Histogram normalization

To compute normalized histogram:

$$p_{in}(r_k) = \frac{n_k}{n} \qquad 0 \le r_k \le 1 \qquad 0 \le k \le L-1$$

L: Total number of histogram bins

n_k: Value of bin r_k

n: Total values of all histogram bins

How about "Tiny Image" features?

“Tiny Image” feature normalization

- Normally, for non-histogram based features, L_2 normalization will be applied.
- This usually means dividing each component by the Euclidean length of the vector.

$$x = \frac{x}{\| x \|} \quad \text{, where } \| x \| = \sqrt{\sum_{i=1}^{3072} x_i^2}$$

Which distance metrics should we use?

- For histogram-based features, we use Chi-Squared ($\chi 2$) Distance.

- For non-histogram based features, we use Euclidean Distance.

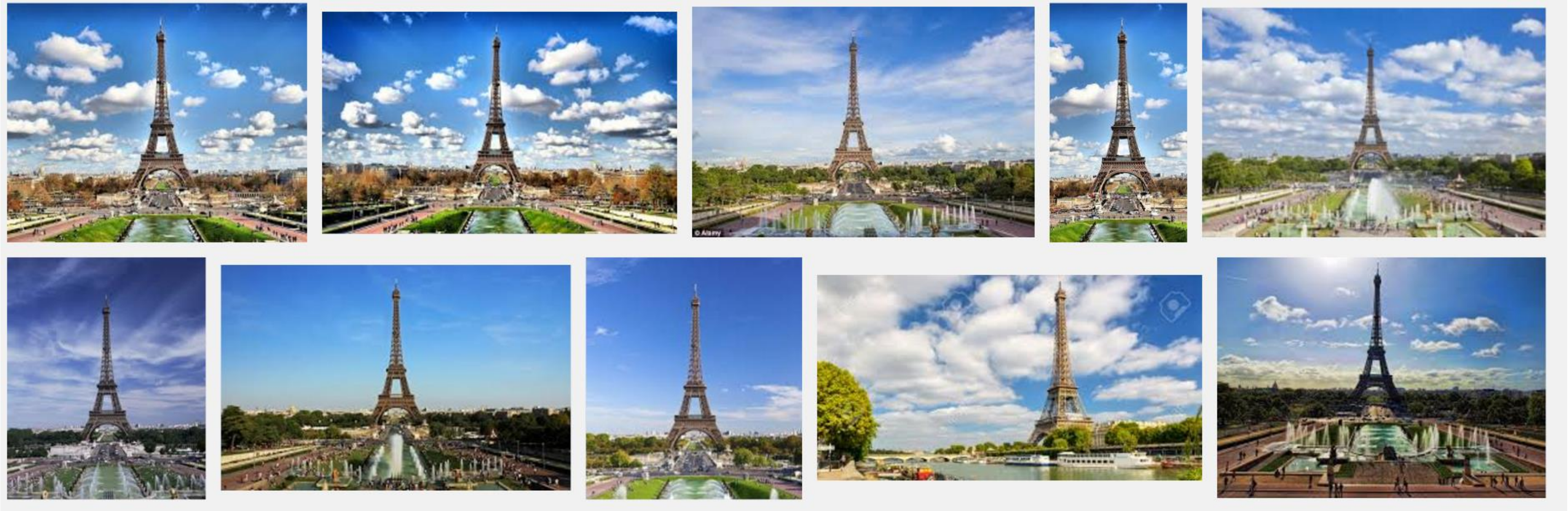
- If use all 3 types of features, we can combine all distances together.

$$dist(a, b) = dist_{color}(a, b) + dist_{tinyimage}(a, b) + dist_{lbp}(a, b)$$

Application: Classification

Image

Google image search



Eiffel Tower

Other Applications

Image Colorization:

Other Applications

Detecting Image Orientation:

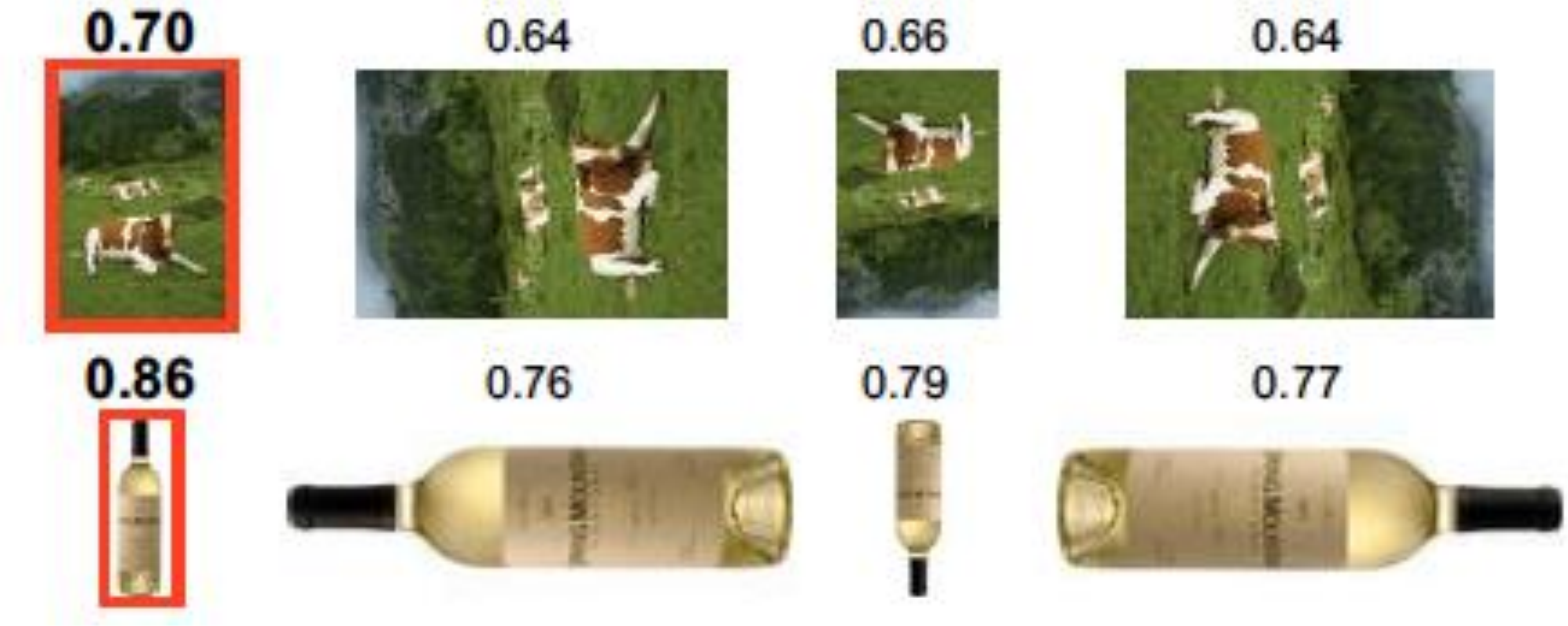
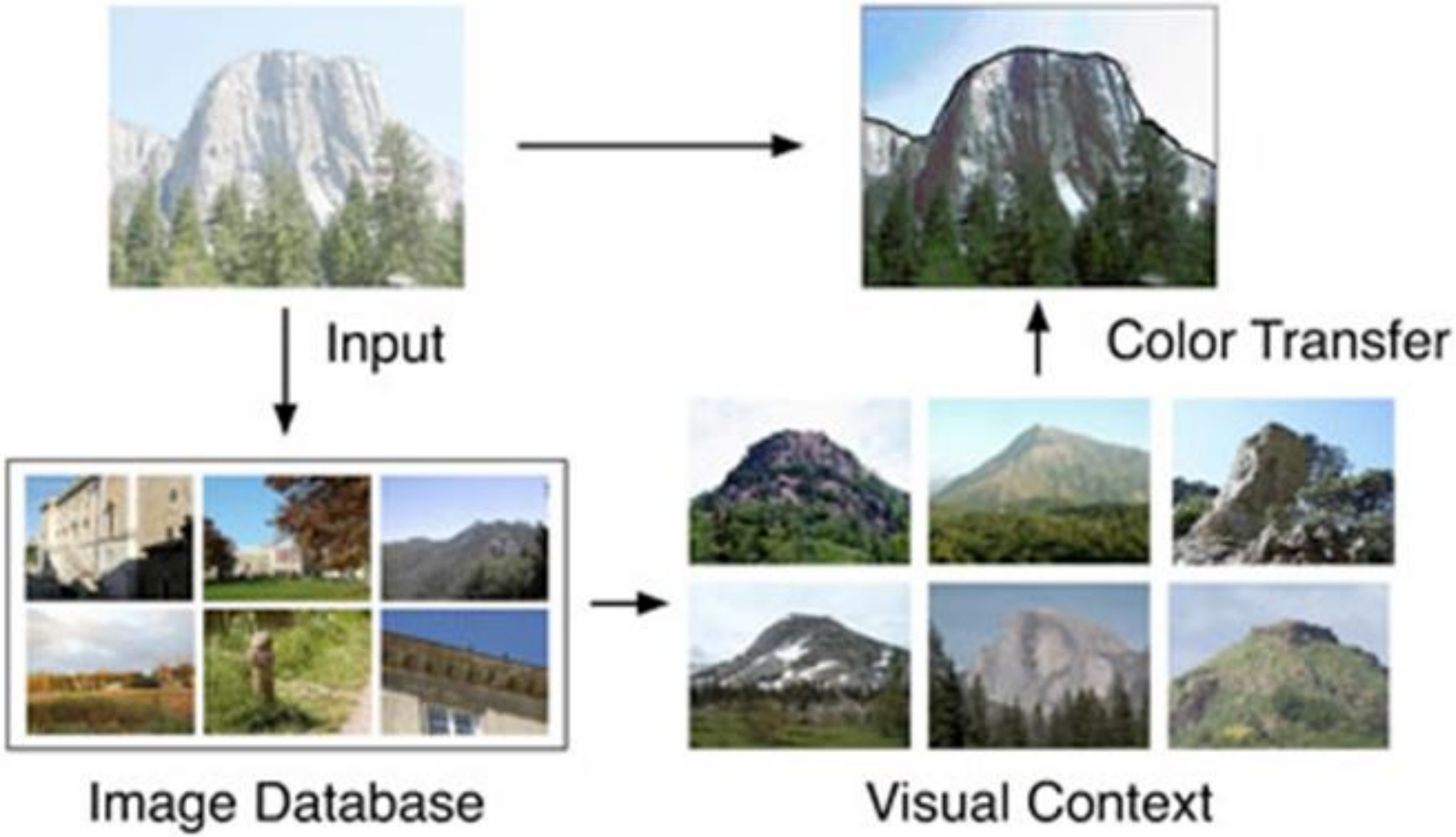


Image restoration using online photo collections



Q&A