Retrieval, Reconstruction, and other uses of Interest Points

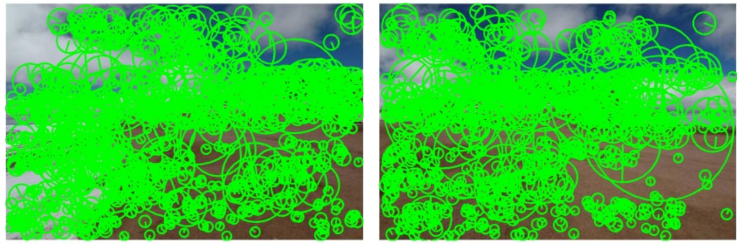
Magritte, *The Treachery of Images*

Computational Photography

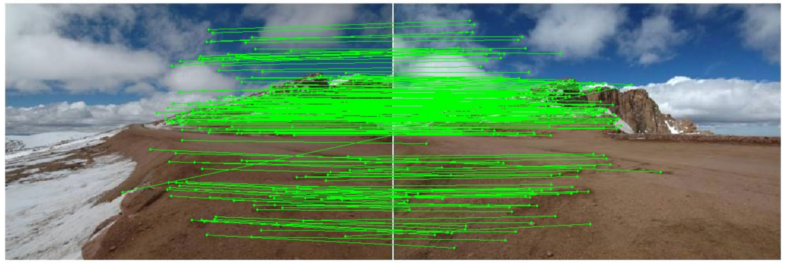
Derek Hoiem, University of Illinois

Last class: Image Stitching

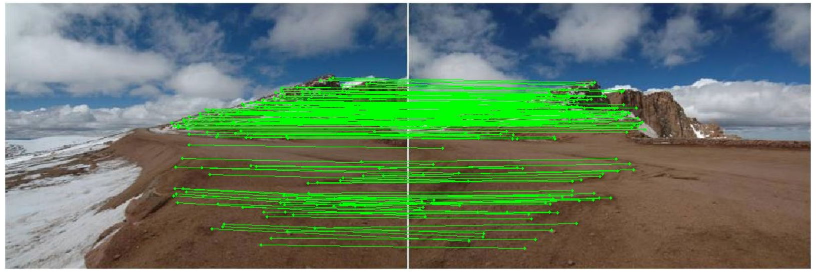
1. Detect keypoints



2. Match keypoints



3. Use RANSAC to estimate homography



4. Project onto a surface and blend

Project 5: coming up

1. Align frames to a central frame

2. Identify background pixels on panorama

3. Map background pixels back to videos

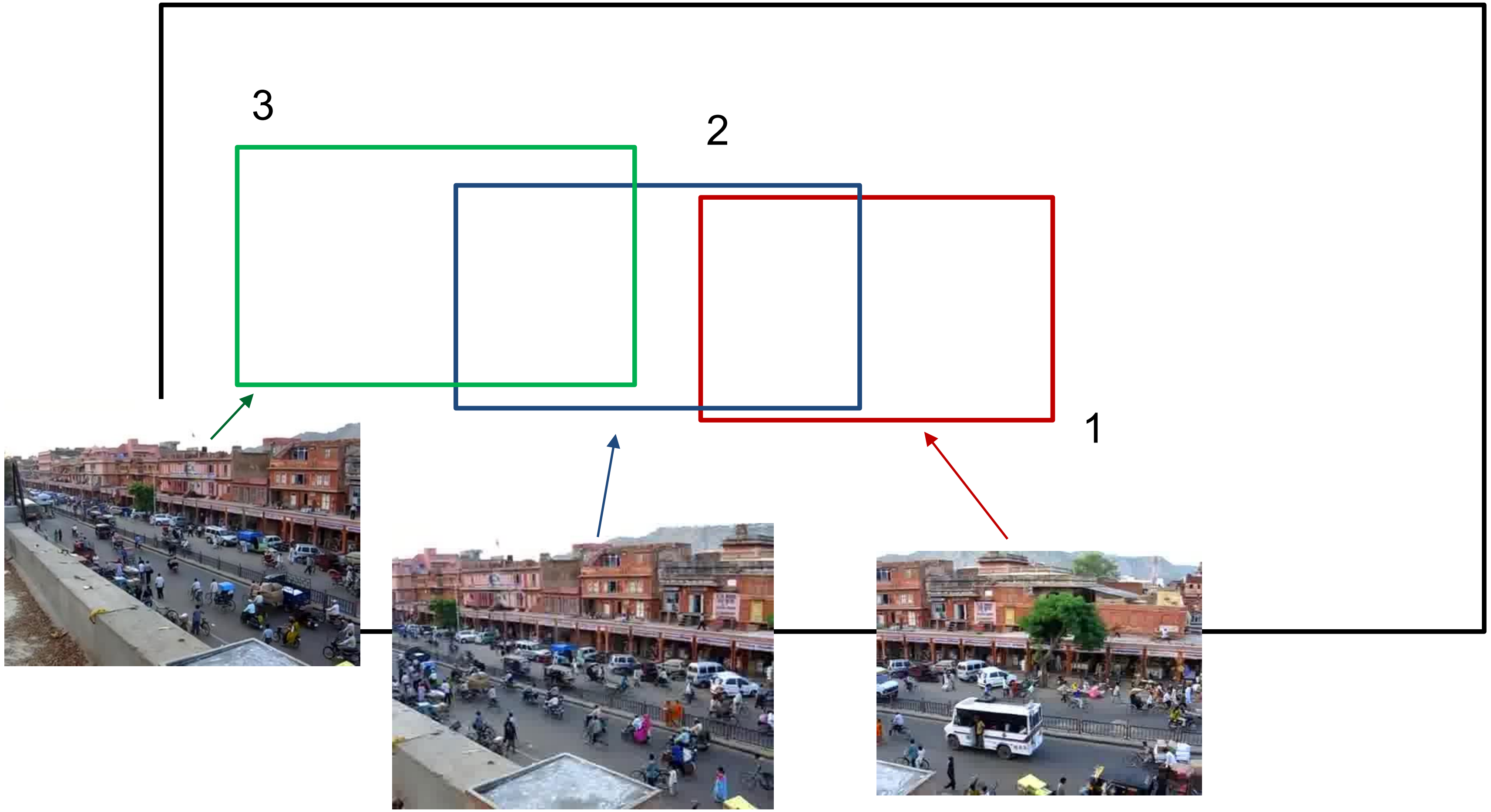
4. Identify and display foreground pixels

Lots of possible extensions for extra credit

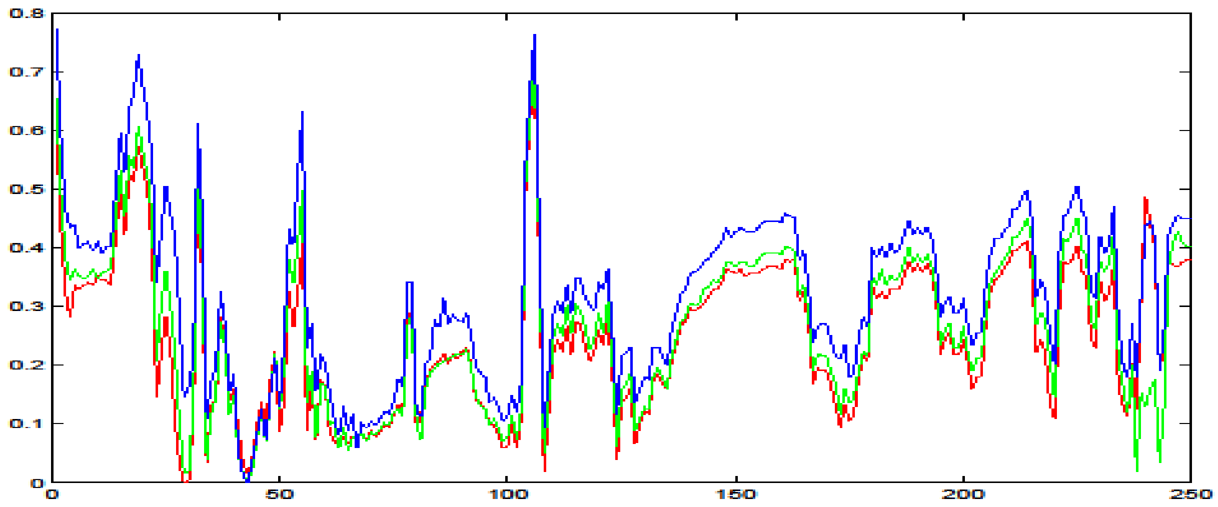
Aligning frames

$$x_1 = H_{21} x_2$$
$$x_2 = H_{32} x_3$$

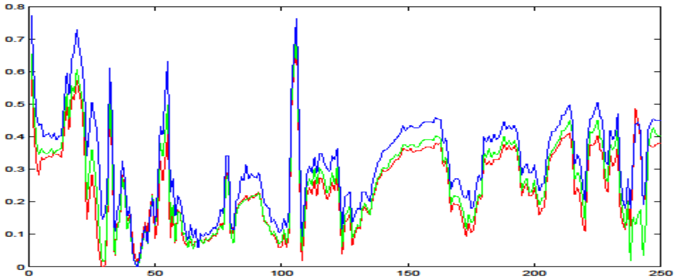
$$x_1 =?\, x_3$$



Background identification

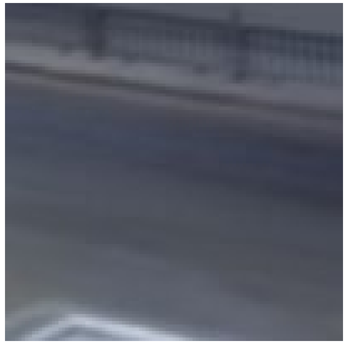


Background identification



Idea 1: take average (mean) pixel

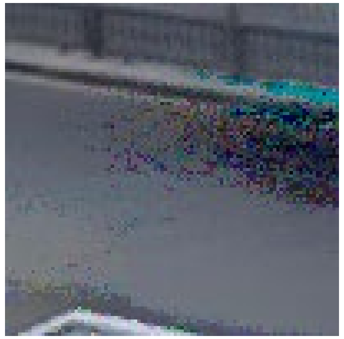
- Not bad but averages over outliers



mean

Idea 2: take mode (most common) pixel

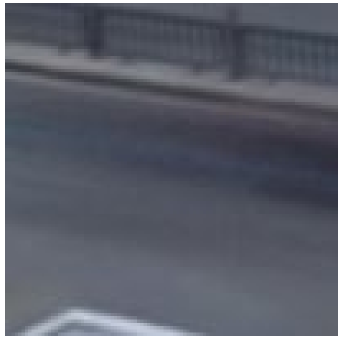
- Can ignore outliers if background shows more than any other single color



mode

Idea 3: take median pixel

- Can ignore outliers if background shows at least 50% of time, or outliers tend to be well-distributed



median

Identifying foreground

1. Simple method: foreground pixels are some distance away from background

2. Another method: count times that each color is observed and assign unlikely colors to foreground
   – Can work for repetitive motion, like a tree swaying in the breeze

Augmented reality

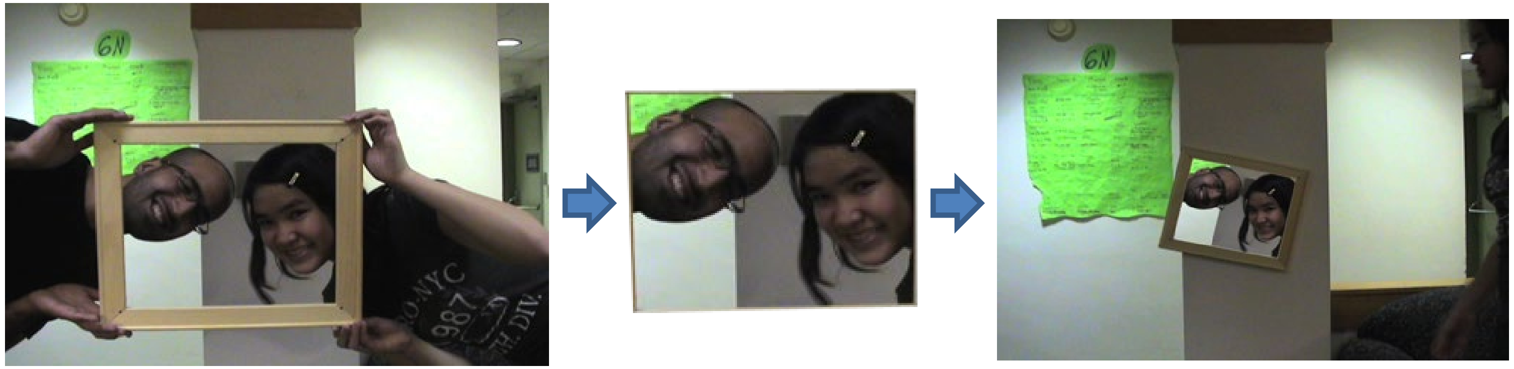
- Insert and/or interact with object in scene
  - Project by Karen Liu
  - Responsive characters in AR
  - Pokeman Go
- Overlay information on a display
  - Tagging reality
  - HoloLens
  - Google goggles

Adding fake objects to real video

Approach

1. Recognize and/or track points that give you a coordinate frame
2. Apply homography (flat texture) or perspective projection (3D model) to put object into scene

Main challenge: dealing with lighting, shadows, occlusion



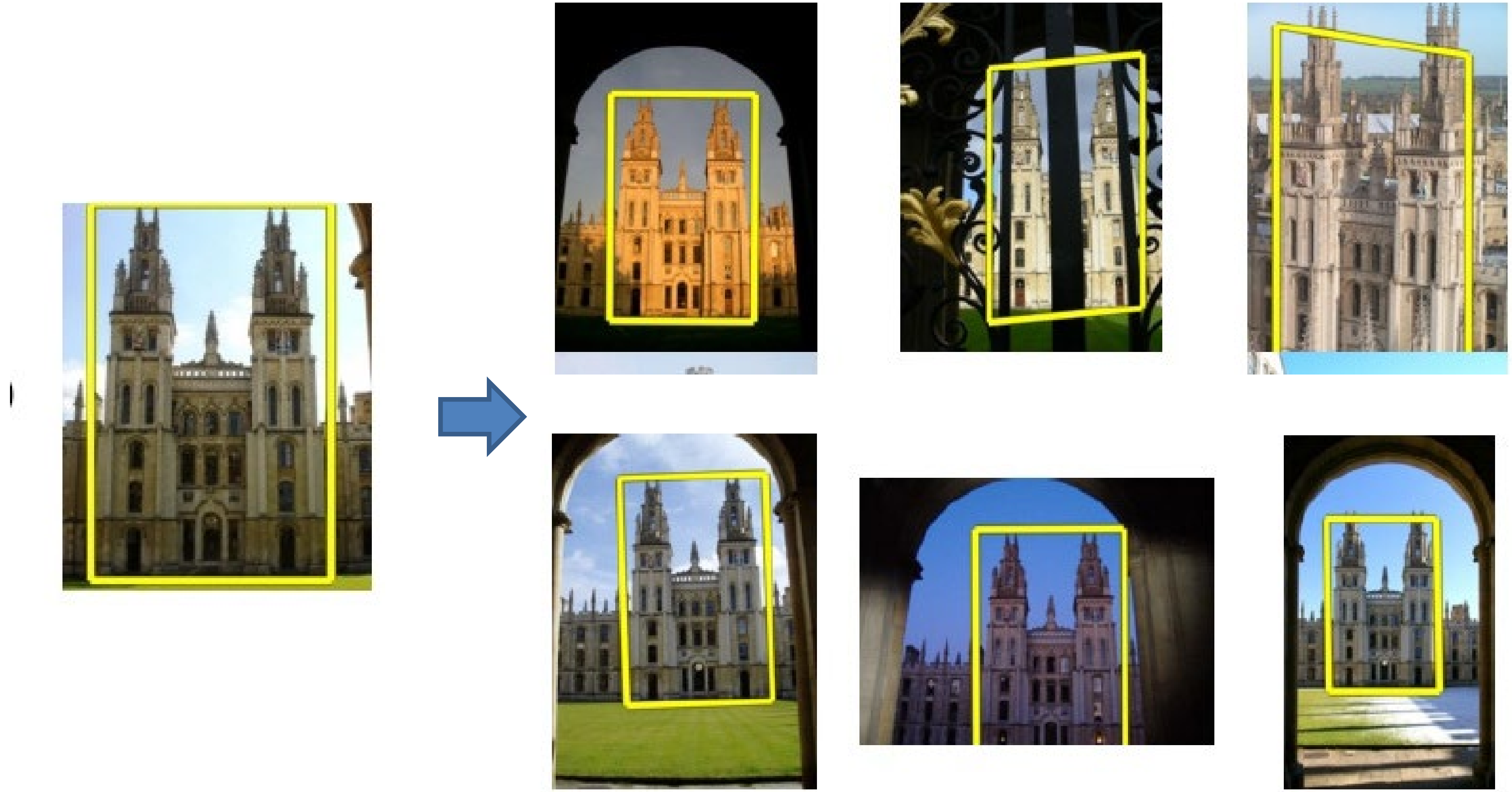
Information overlay

Approach

1. Recognize object that you've seen before
2. Possibly, compute its pose
3. Retrieve info and overlay

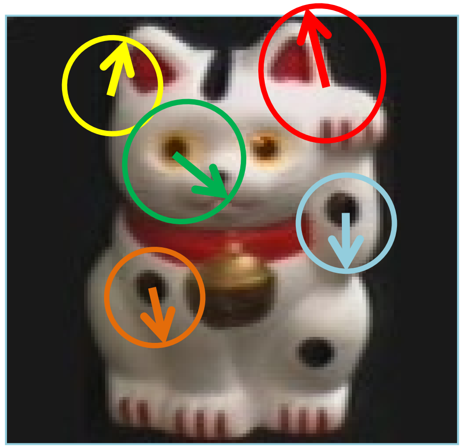
Main challenge: how to match reliably and efficiently?

How to quickly find images in a large database that match a given image region?



Let’s start with interest points

Query



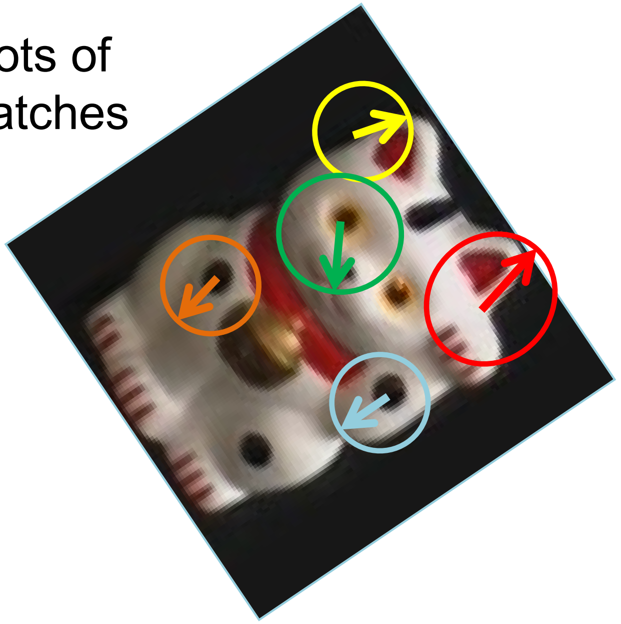
Database

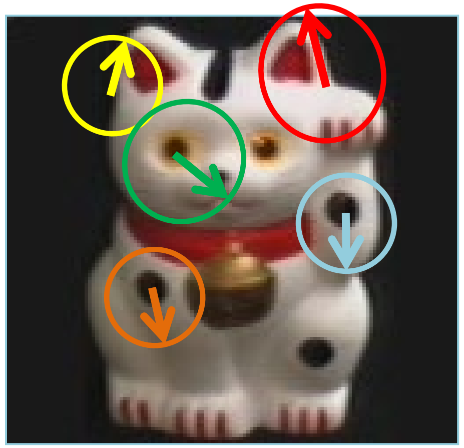
Compute interest points (or keypoints) for every image in the database and the query

Simple idea

See how many keypoints are close to keypoints in each other image

Lots of Matches





Few or No Matches

But this will be really, really slow!

Key idea 1: “Visual Words”

- Cluster the keypoint descriptors

Key idea 1: "Visual Words"

K-means algorithm

1. Randomly select K centers

2. Assign each point to nearest center

3. Compute new center (mean) for each cluster

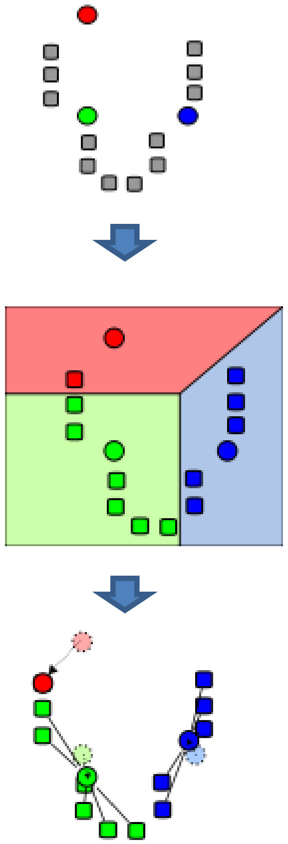


Illustration: http://en.wikipedia.org/wiki/K-means_clustering

Key idea 1: “Visual Words”

K-means algorithm

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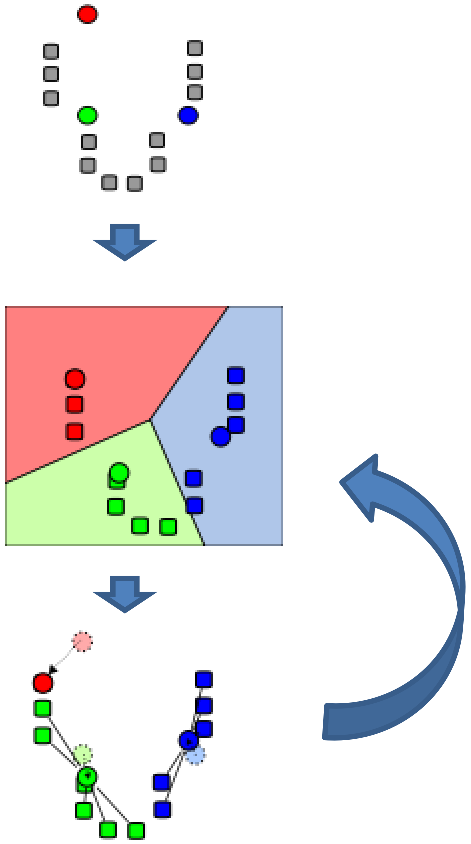


Back to 2

Illustration: http://en.wikipedia.org/wiki/K-means_clustering

Kmeans: Matlab code

```
function C = kmeans(X, K)

% Initialize cluster centers to be randomly sampled points
[N, d] = size(X);
rp = randperm(N);
C = X(rp(1:K), :);

lastAssignment = zeros(N, 1);
while true

  % Assign each point to nearest cluster center
  bestAssignment = zeros(N, 1);
  mindist = Inf*ones(N, 1);
  for k = 1:K
    for n = 1:N
      dist = sum((X(n, :)-C(k, :)).^2);
      if dist < mindist(n)
        mindist(n) = dist;
        bestAssignment(n) = k;
      end
    end
  end

  % break if assignment is unchanged
  if all(bestAssignment==lastAssignment), break; end;
  lastAssignment = bestAssignmnet;

  % Assign each cluster center to mean of points within it
  for k = 1:K
    C(k, :) = mean(X(bestAssignment==k, :));
  end
end
```

K-means Demo

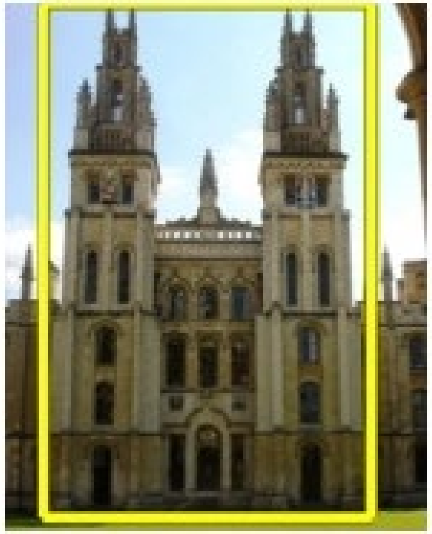
https://www.naftaliharris.com/blog/visualizing-k-means-clustering/

Key idea 1: “Visual Words”

- Cluster the keypoint descriptors
- Assign each descriptor to a cluster number
  - What does this buy us?
  - Each descriptor was 128 dimensional floating point, now is 1 integer (easy to match!)
  - Is there a catch?
    - Need **a lot** of clusters (e.g., 1 million) if we want points in the same cluster to be very similar
    - Points that really are similar might end up in different clusters

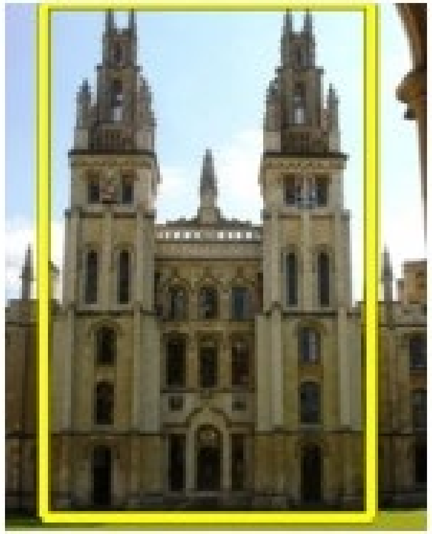
Key idea 1: “Visual Words”

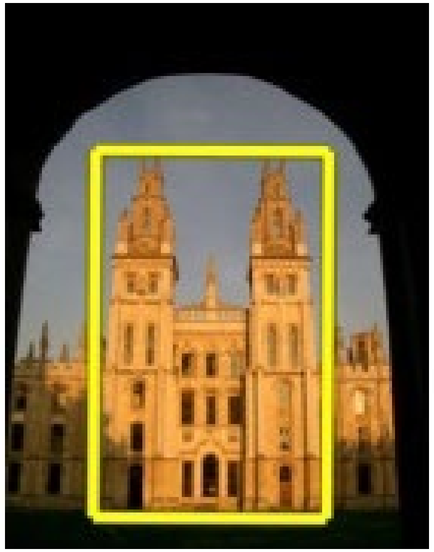
- Cluster the keypoint descriptors
- Assign each descriptor to a cluster number
- Represent an image region with a count of these “visual words”



Key idea 1: “Visual Words”

- Cluster the keypoint descriptors
- Assign each descriptor to a cluster number
- Represent an image region with a count of these “visual words”
- An image is a good match if it has a lot of the same visual words as the query region





Naïve matching is still too slow

Imagine matching 1,000,000 images, each with 1,000 keypoints

Key Idea 2: Inverse document file

- Like a book index: keep a list of all the words (keypoints) and all the pages (images) that contain them.

- Rank database images based on tf-idf measure.

tf-idf: Term Frequency – Inverse Document Frequency

times word appears in document

words in document

$$t_i = \frac{n_{id}}{n_d} \log \frac{N}{n_i}$$

documents

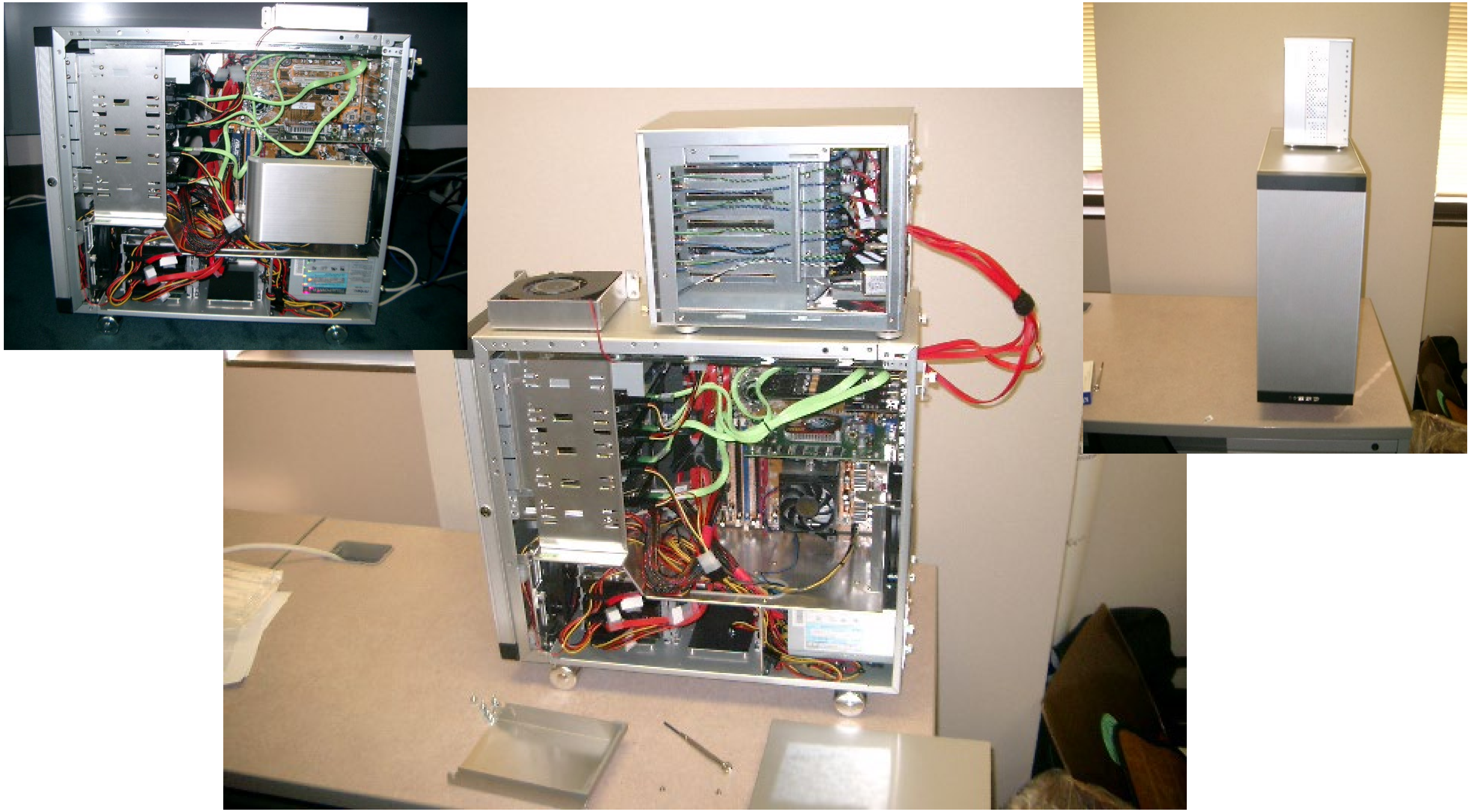
documents that contain the word

Fast visual search

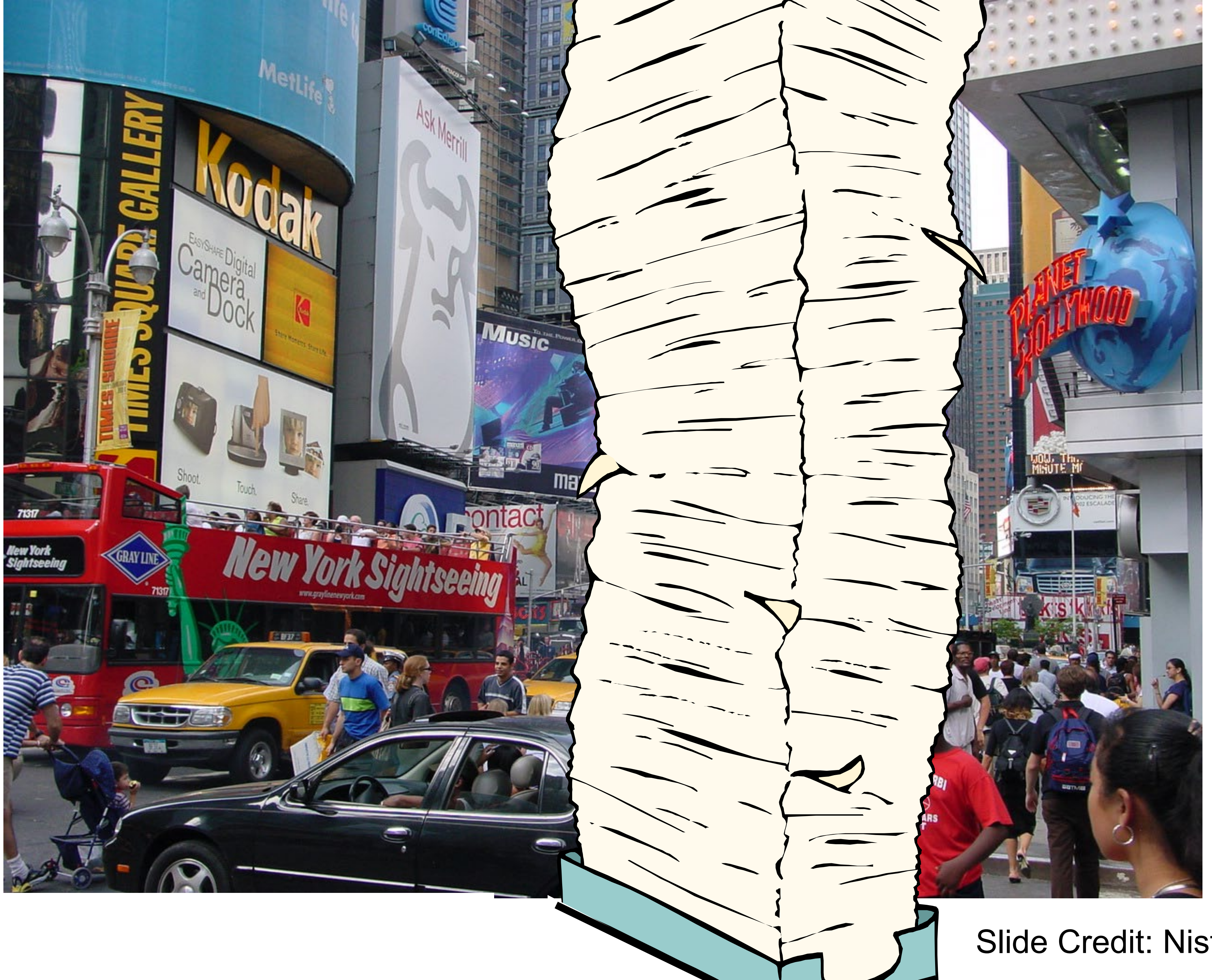
"Video Google", Sivic and Zisserman, ICCV 2003

"Scalable Recognition with a Vocabulary Tree", Nister and Stewenius, CVPR 2006.

110,000,000 Images in 5.8 Seconds



Slide Credit: Nister



Slide Credit: Nister

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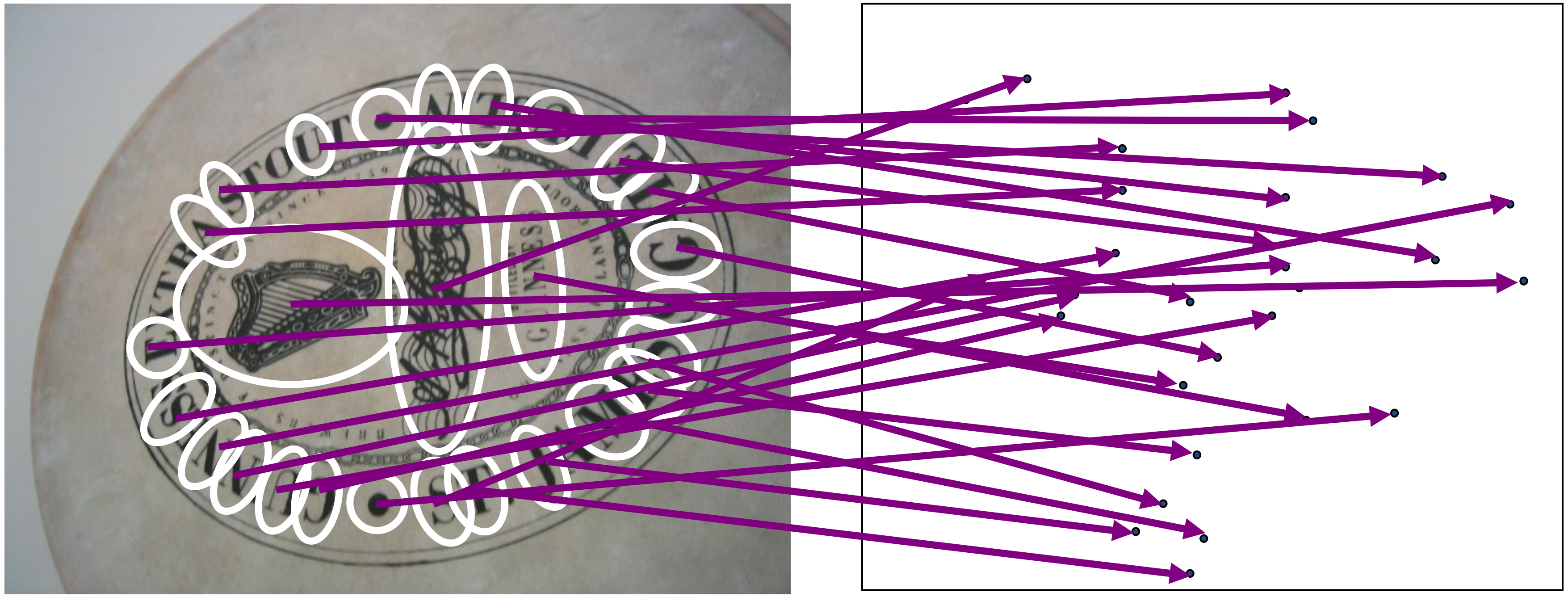
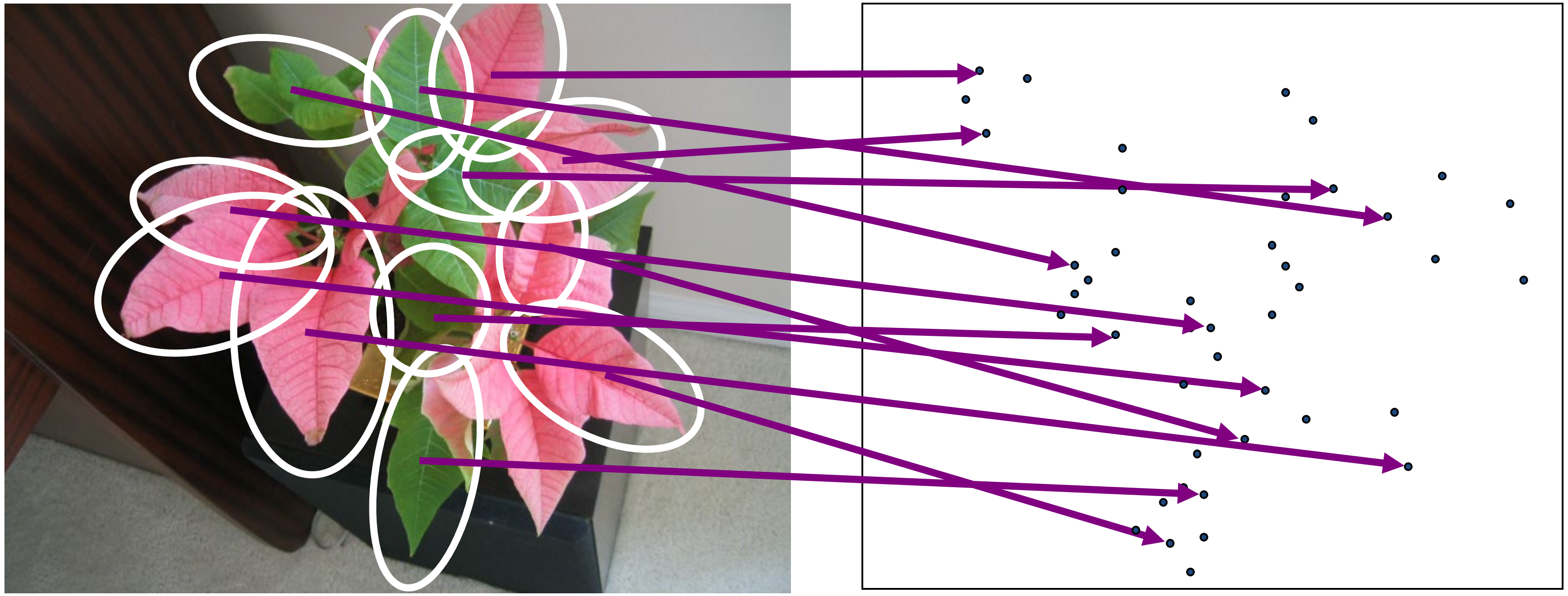
Center for Visualization & Virtual Environments

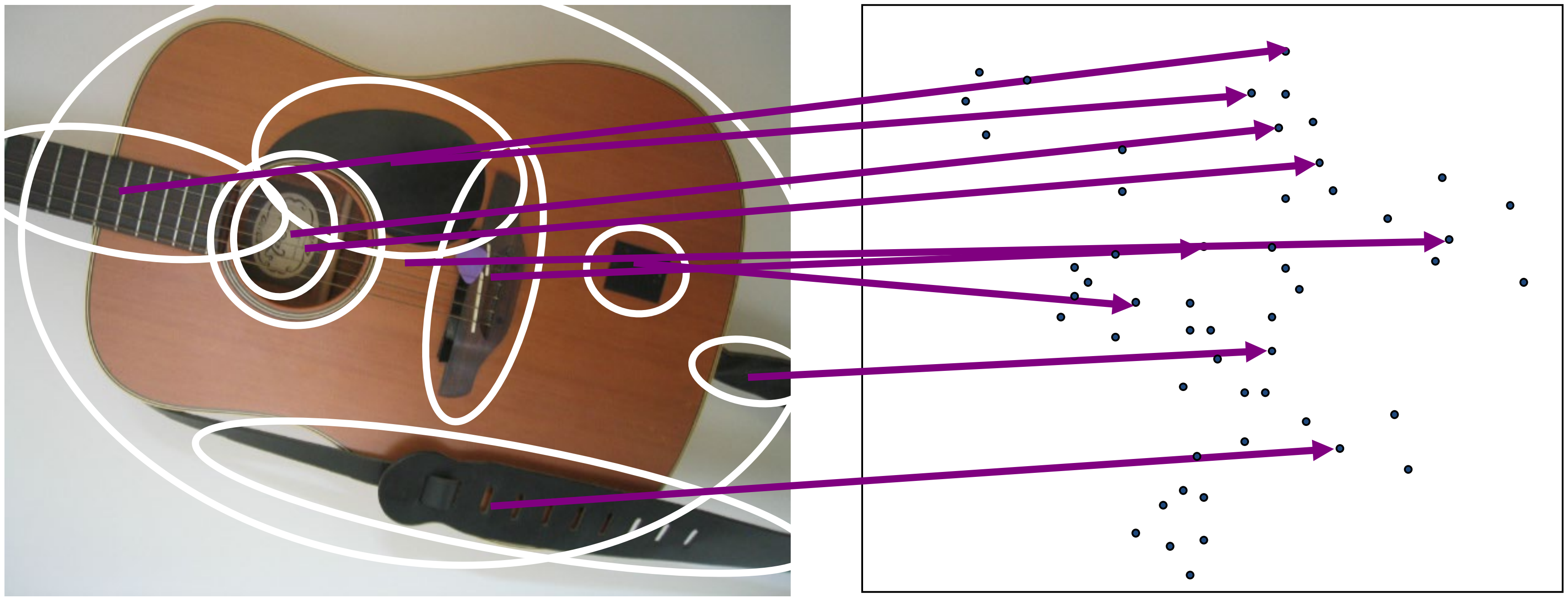
Slide Credit: Nister

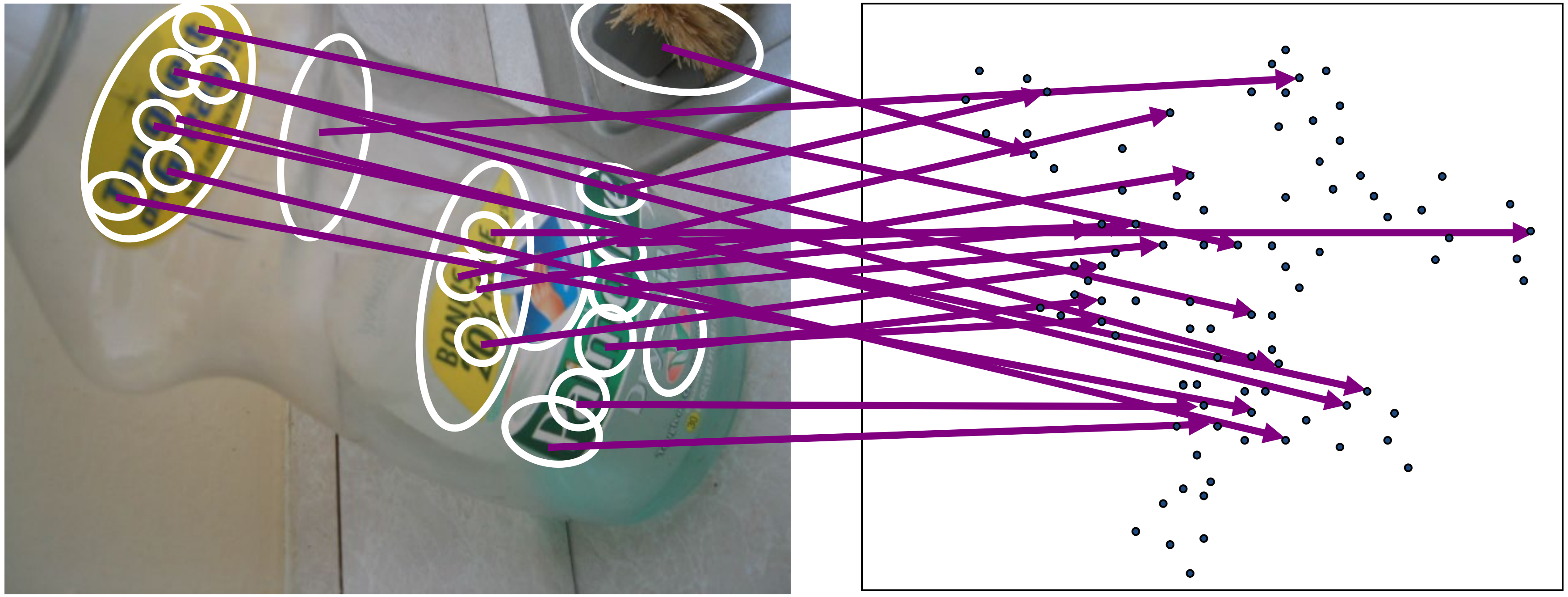
Recognition with K-tree

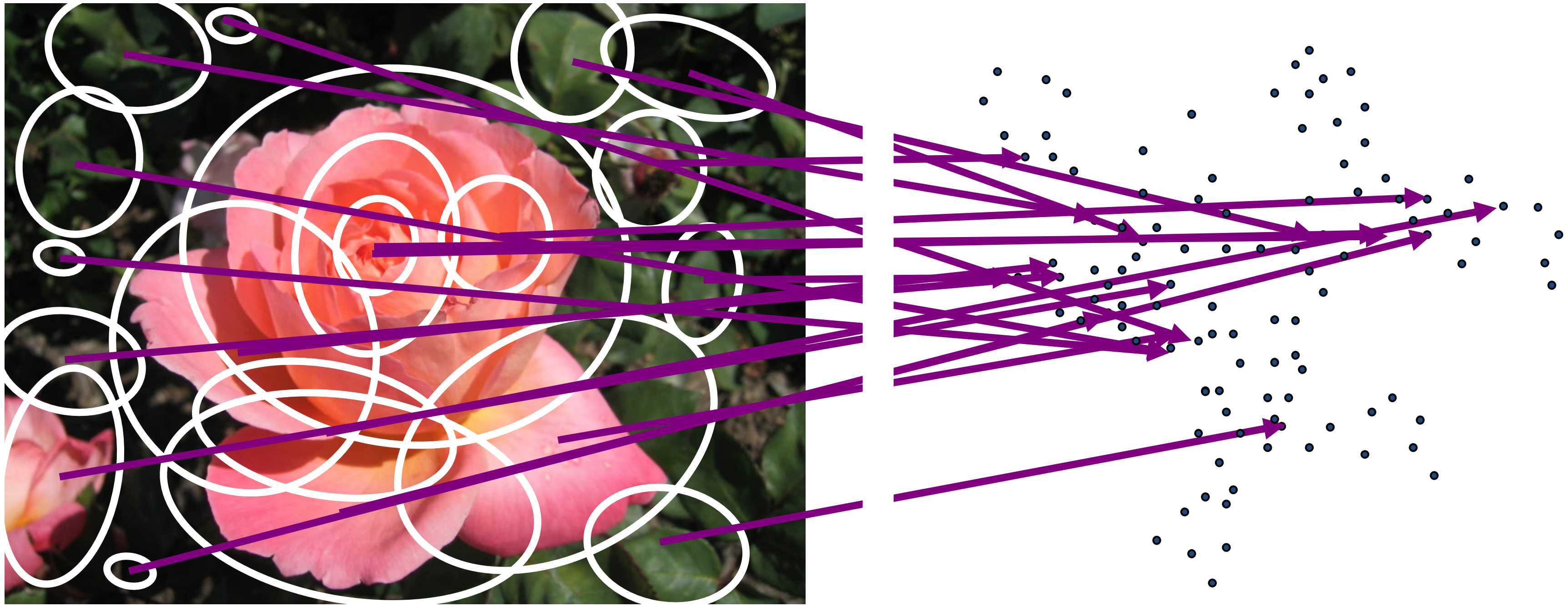
Following slides by David Nister (CVPR 2006)

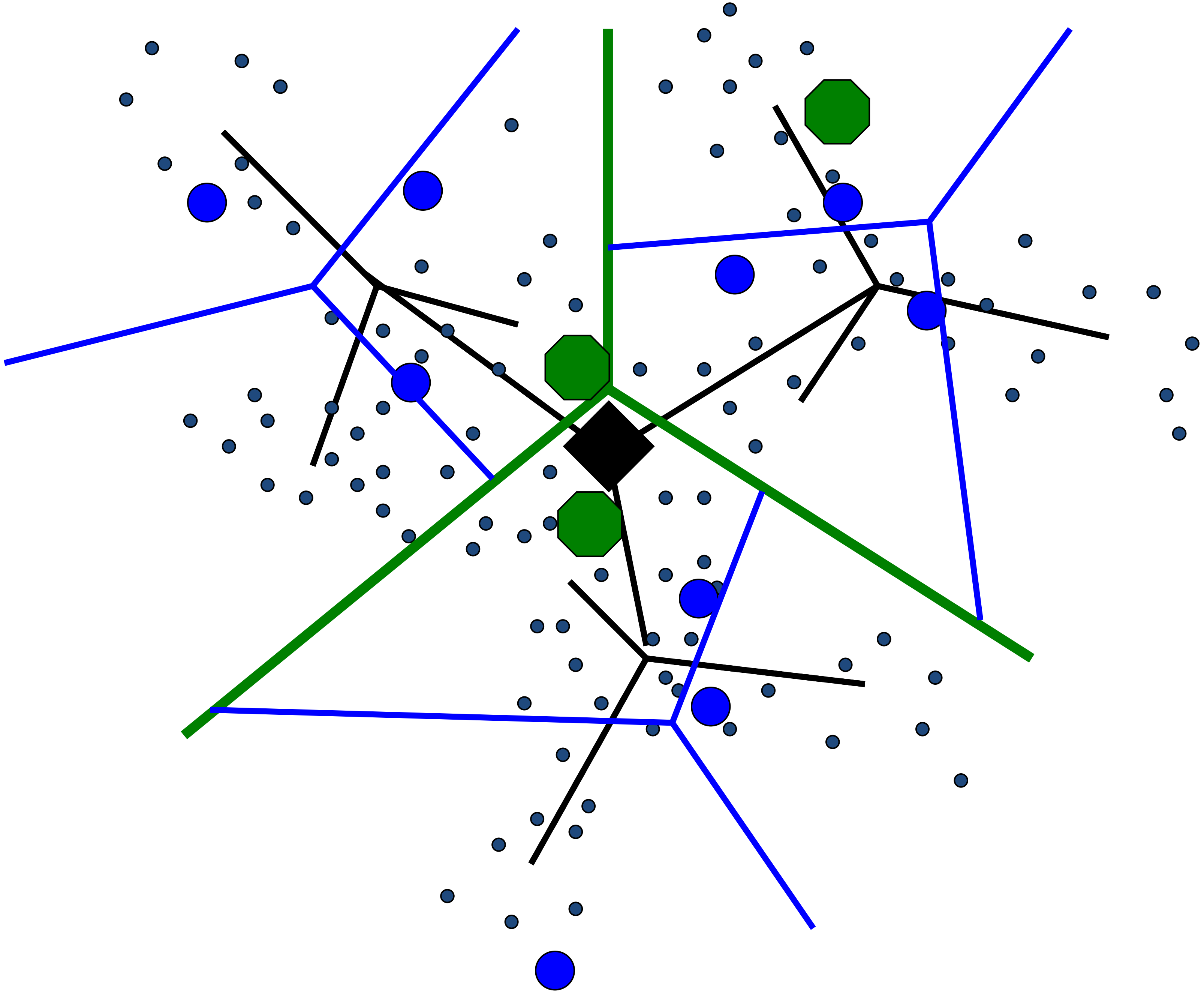


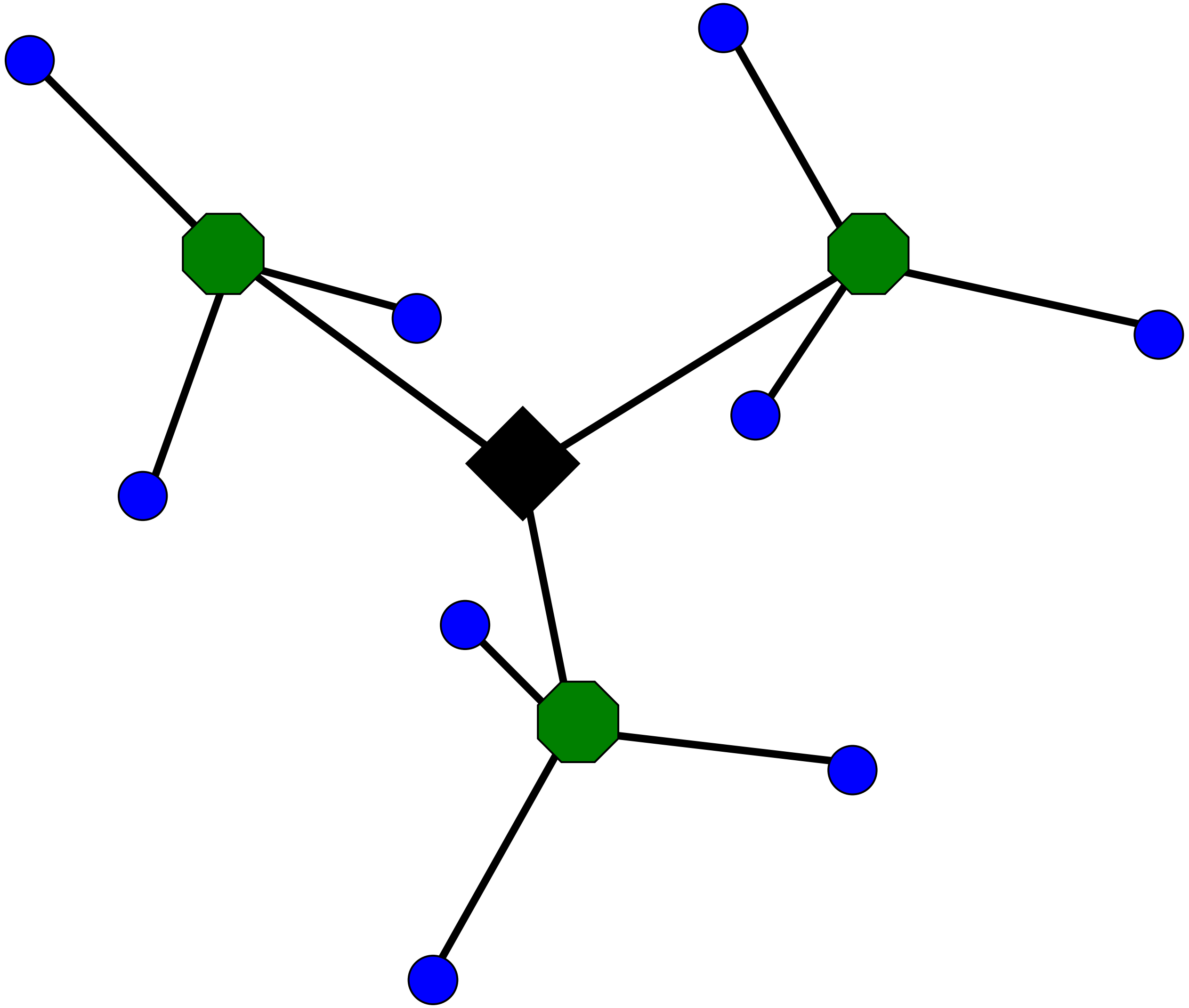


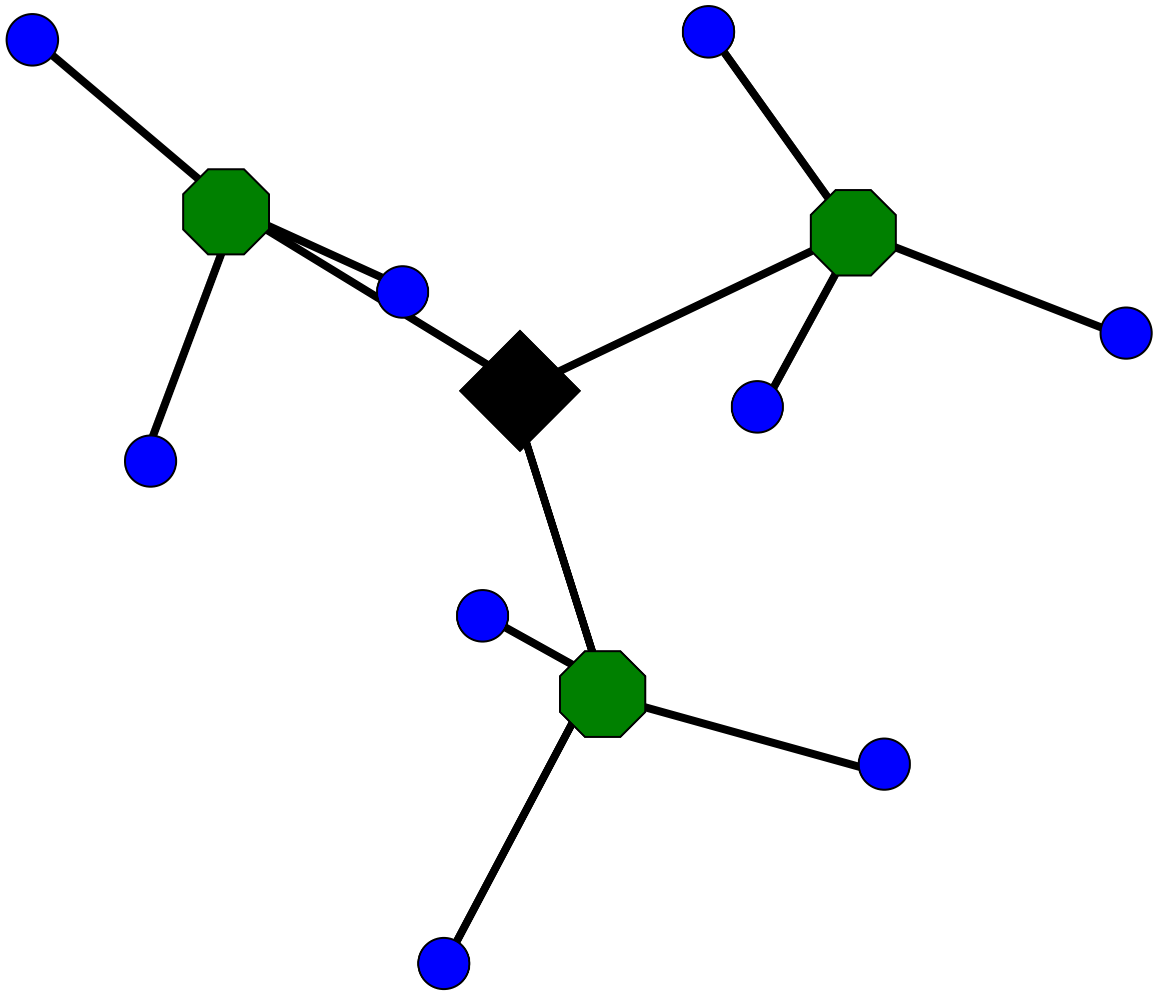


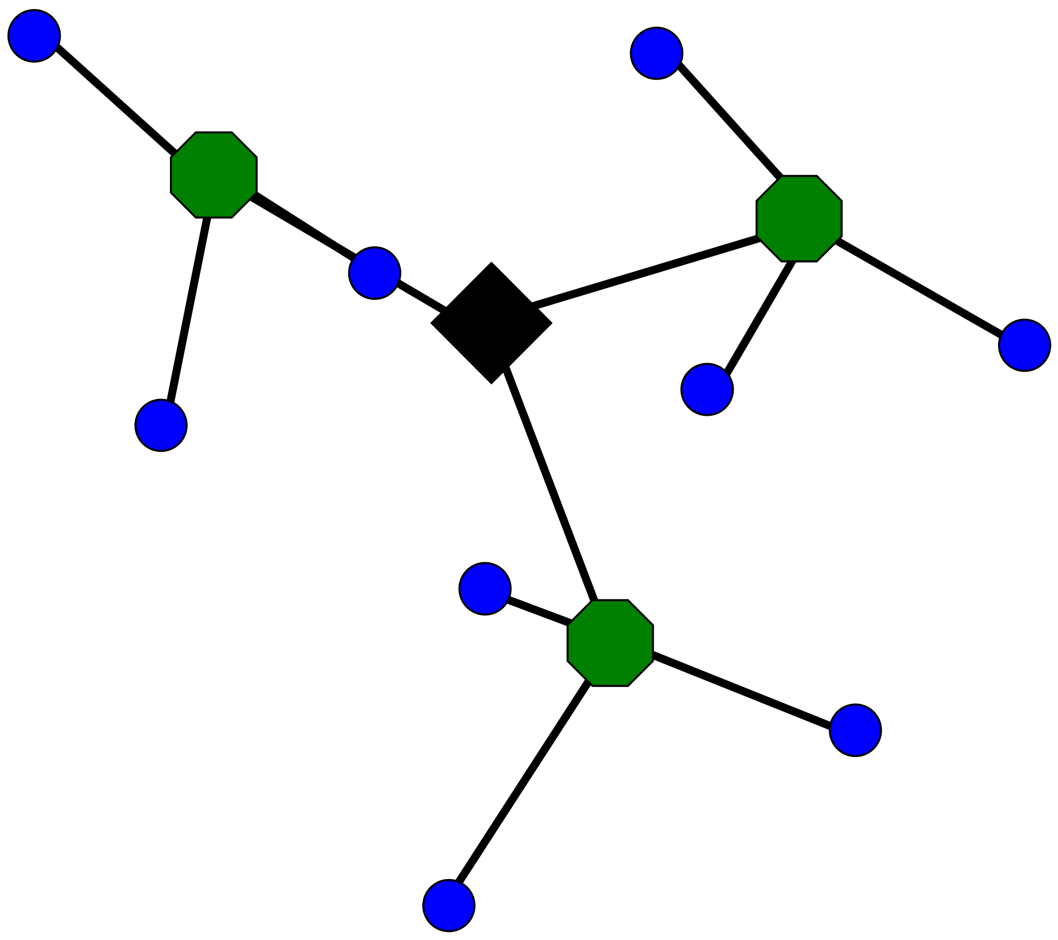


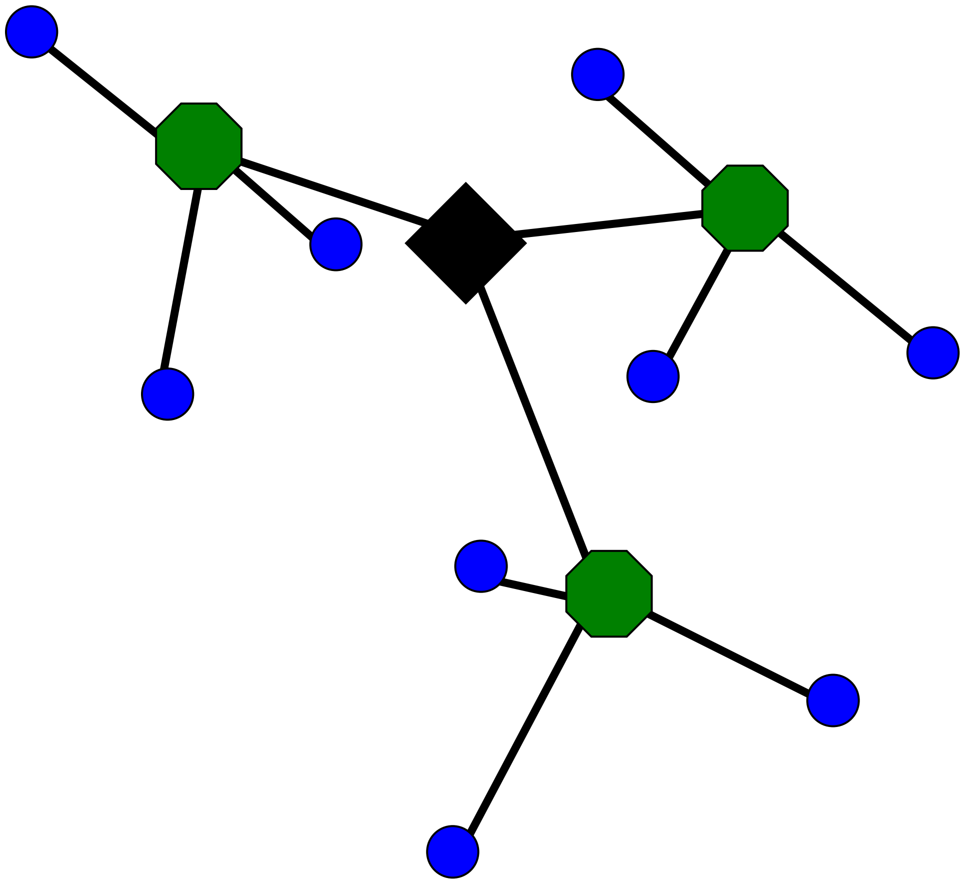


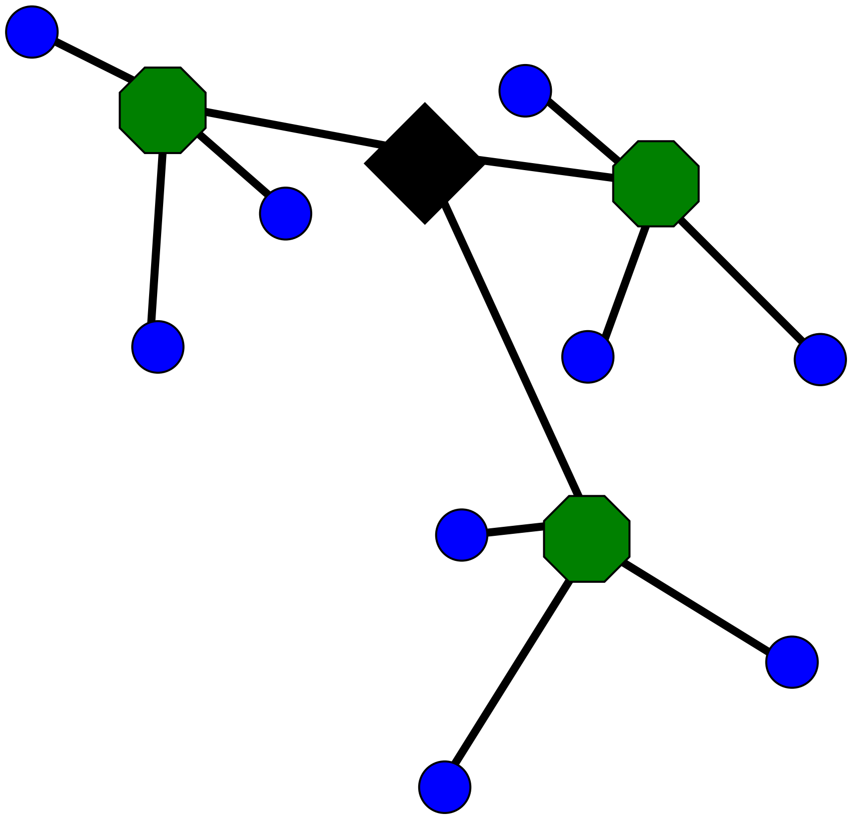


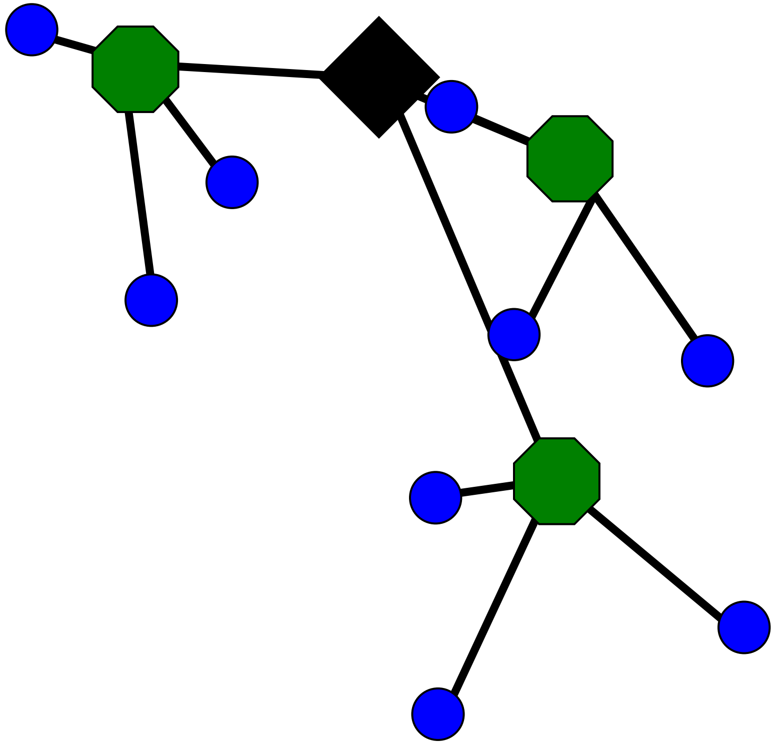


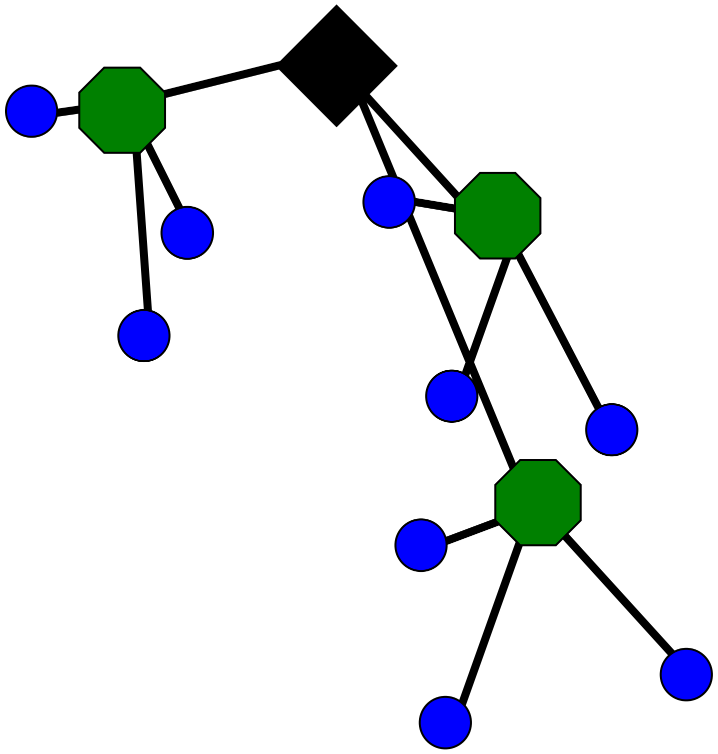


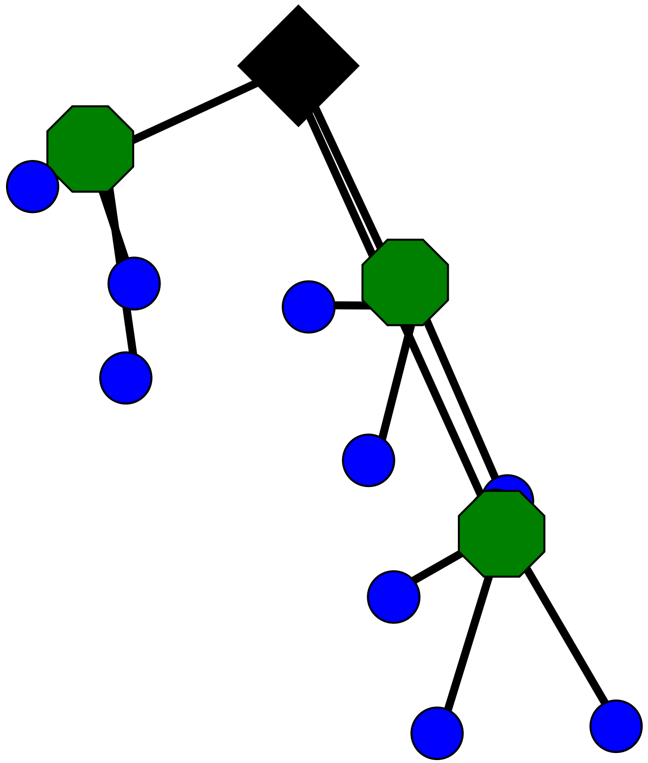


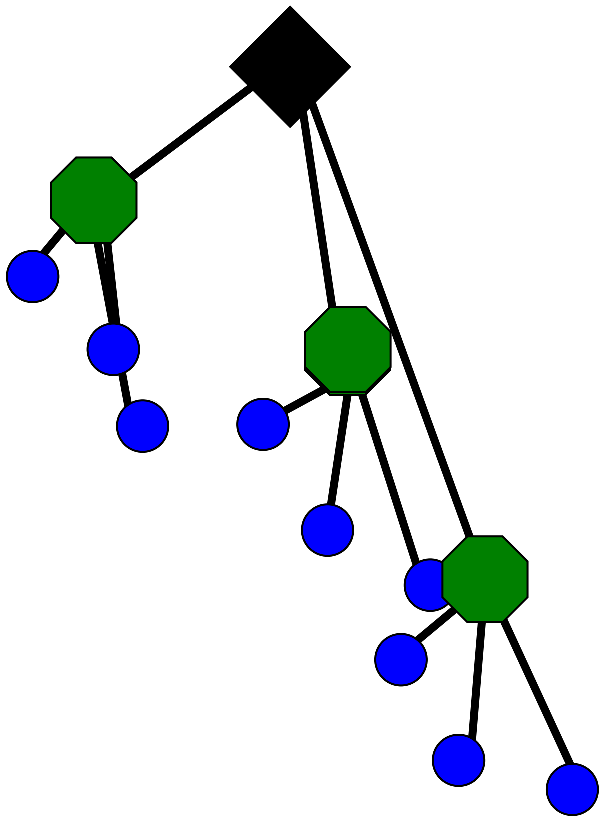


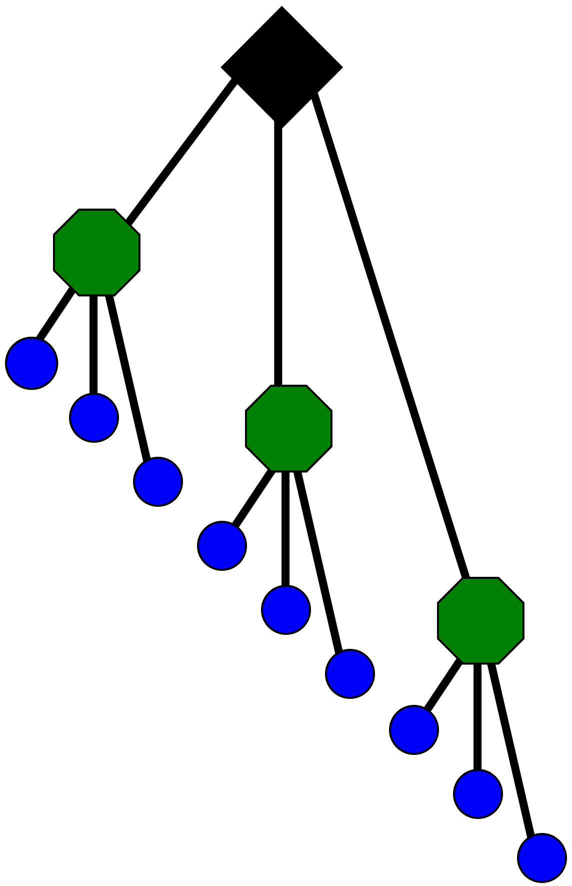


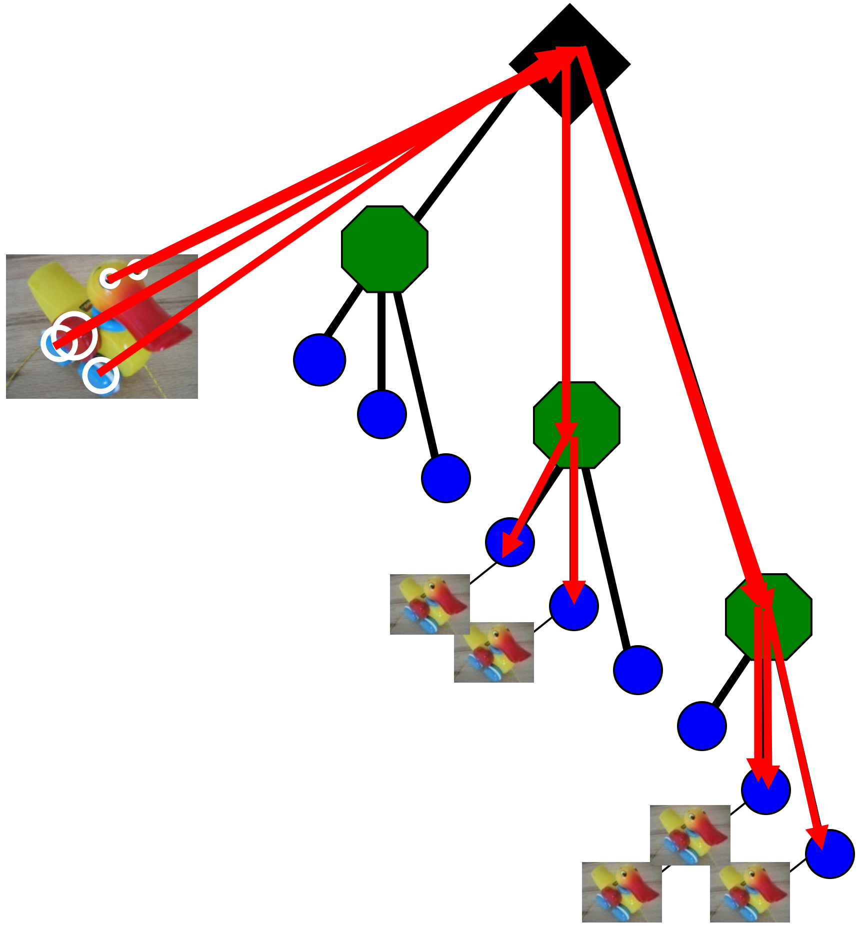


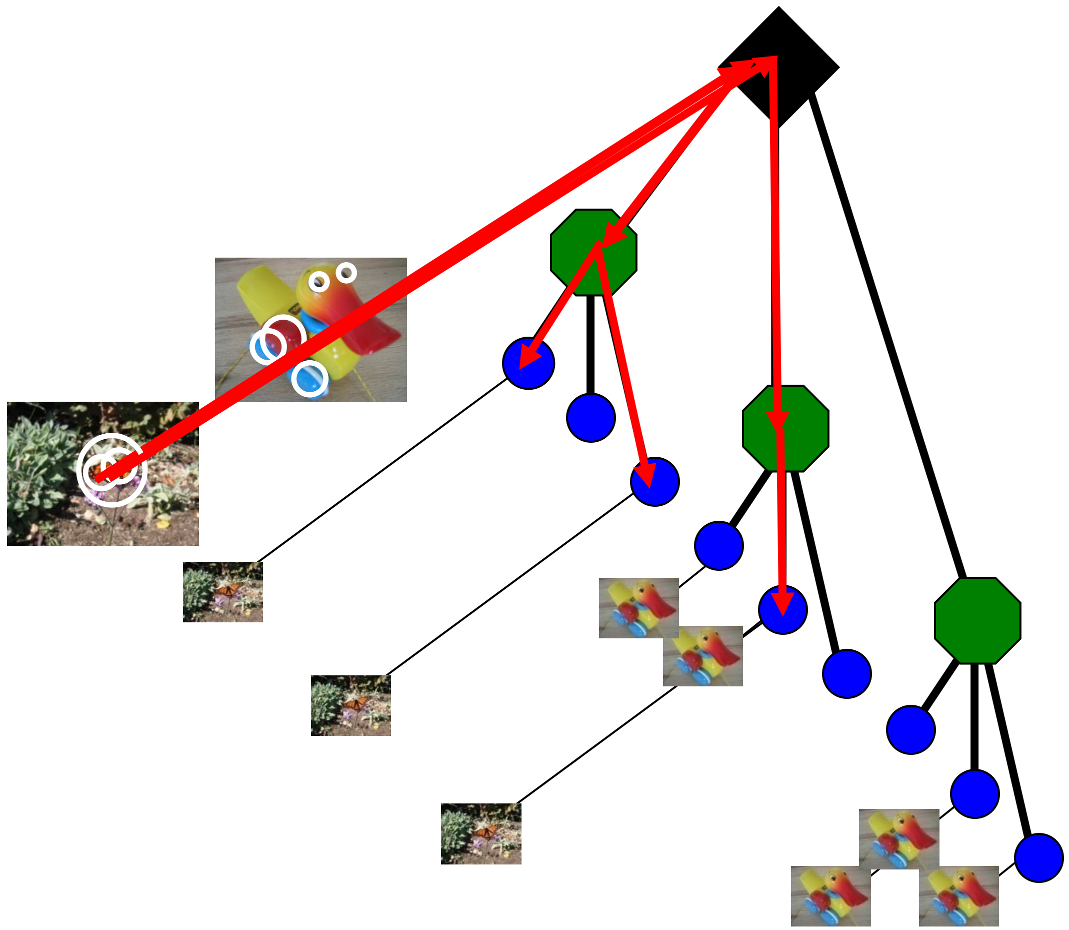


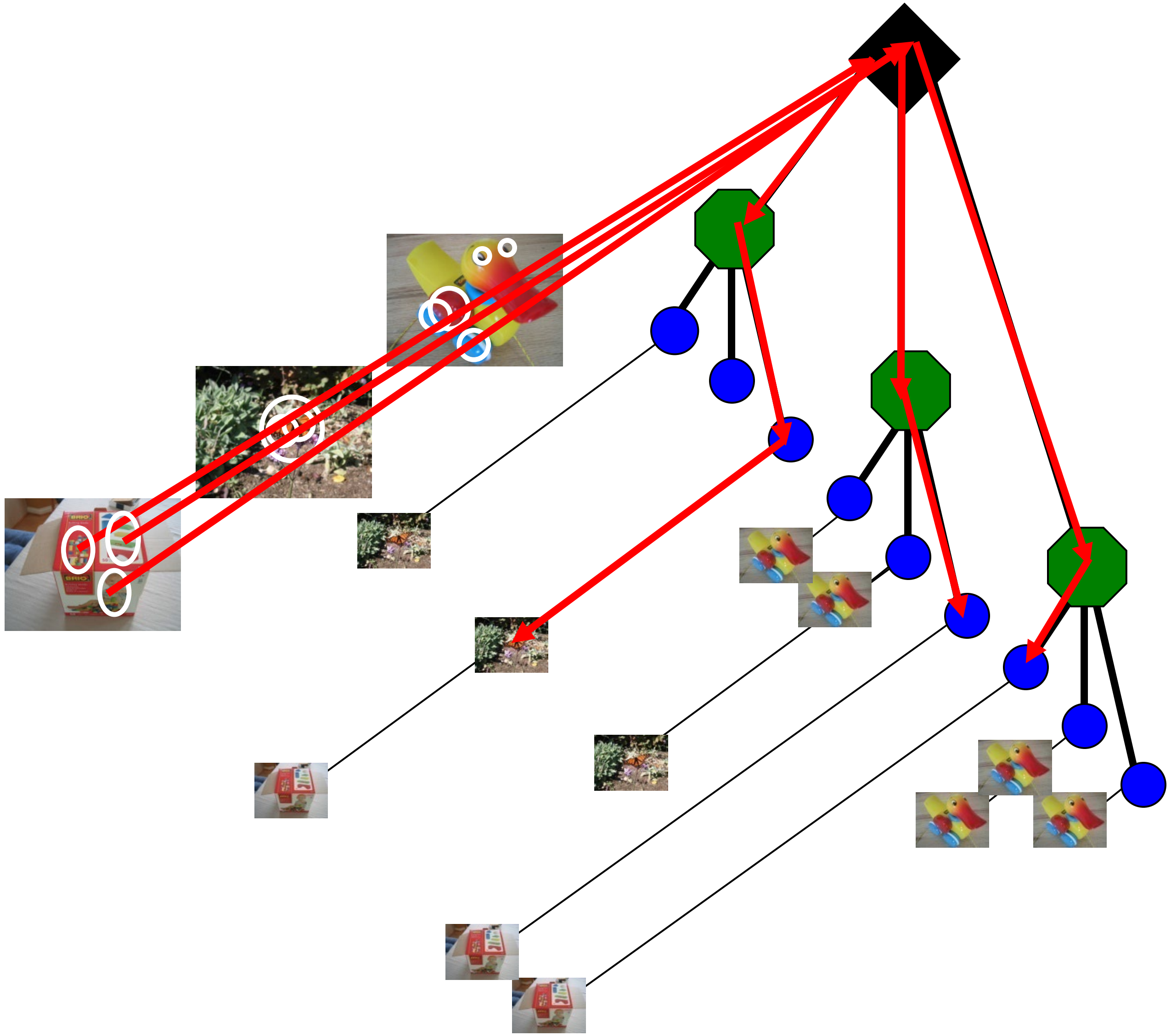


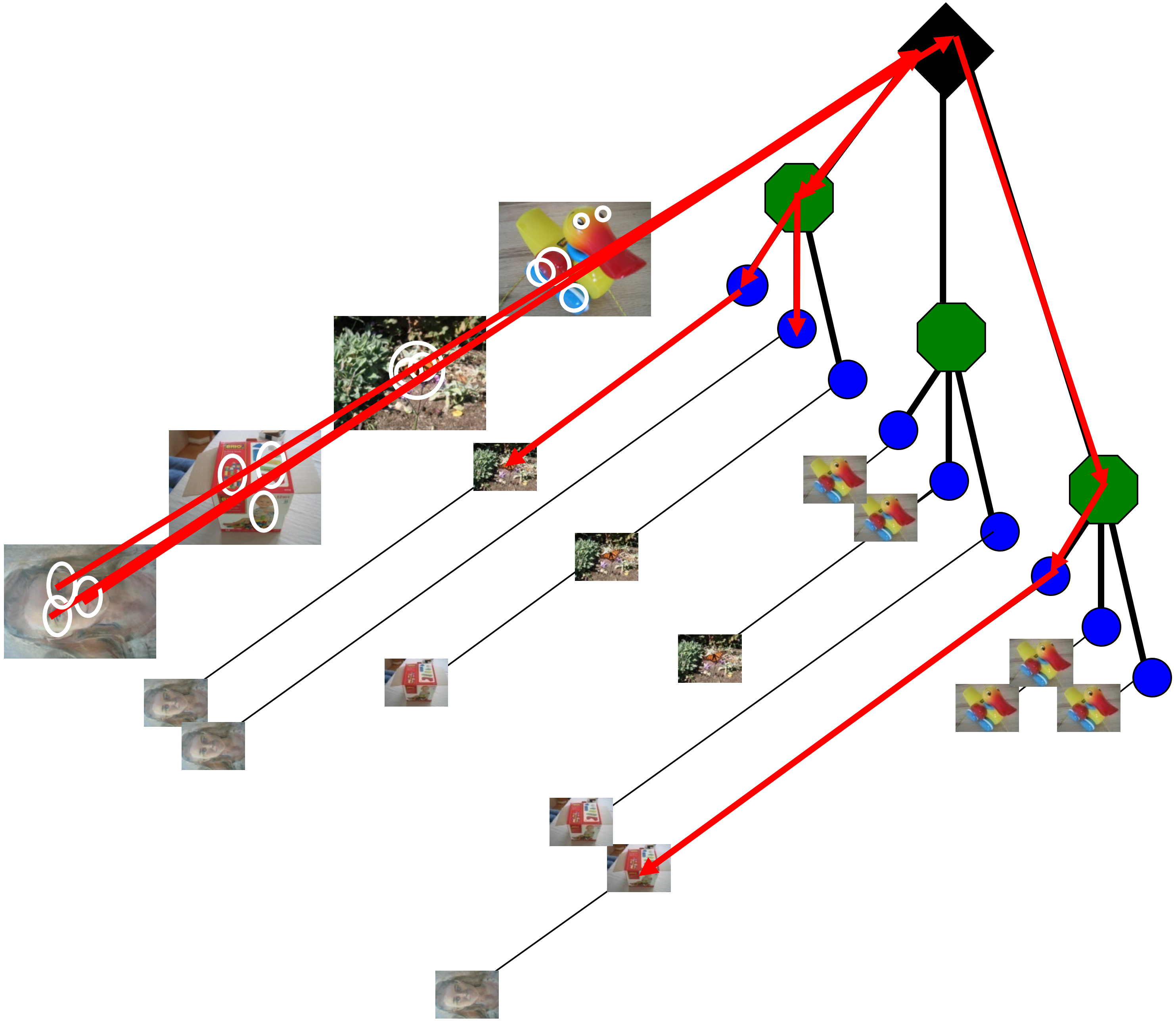


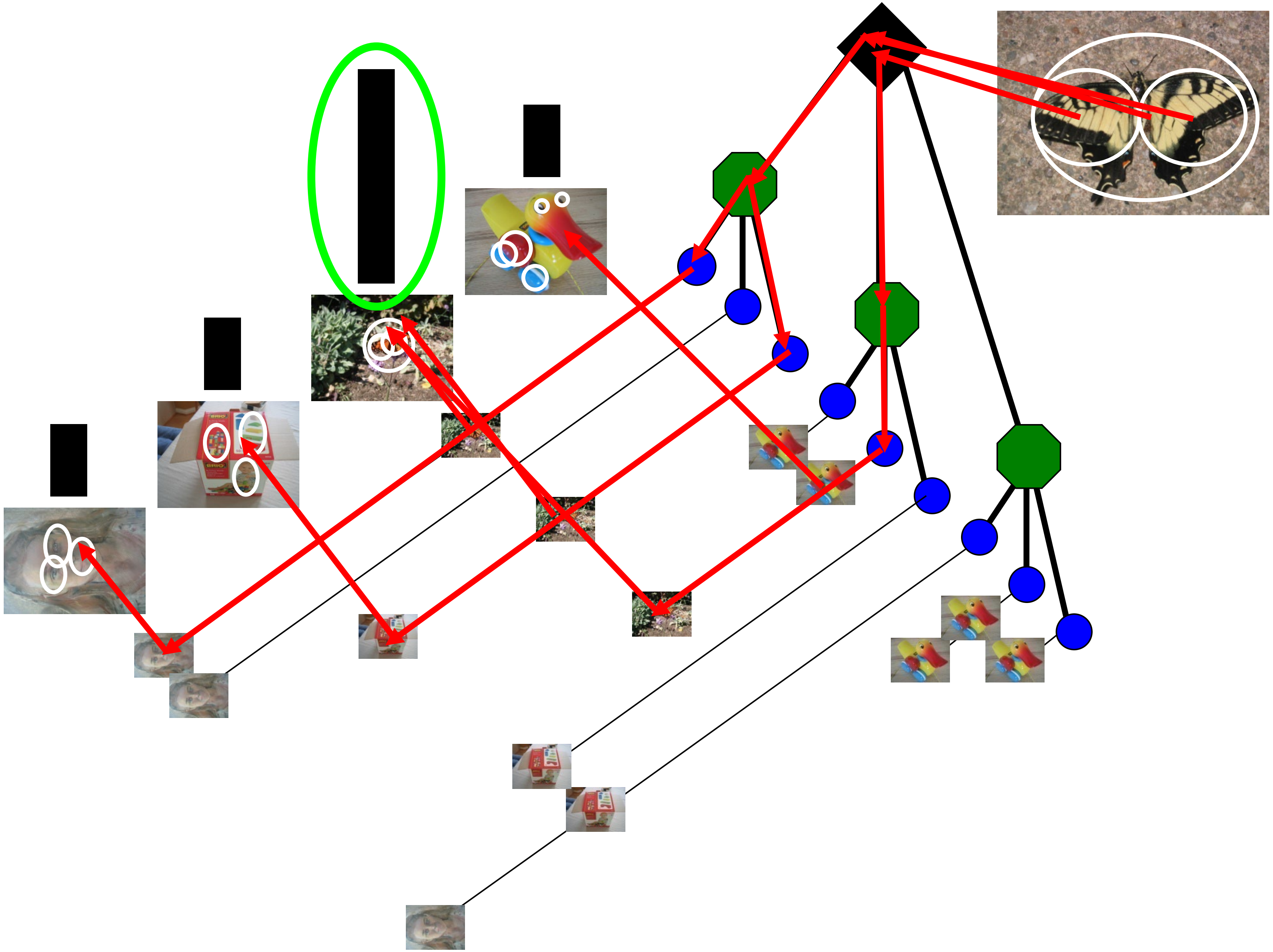




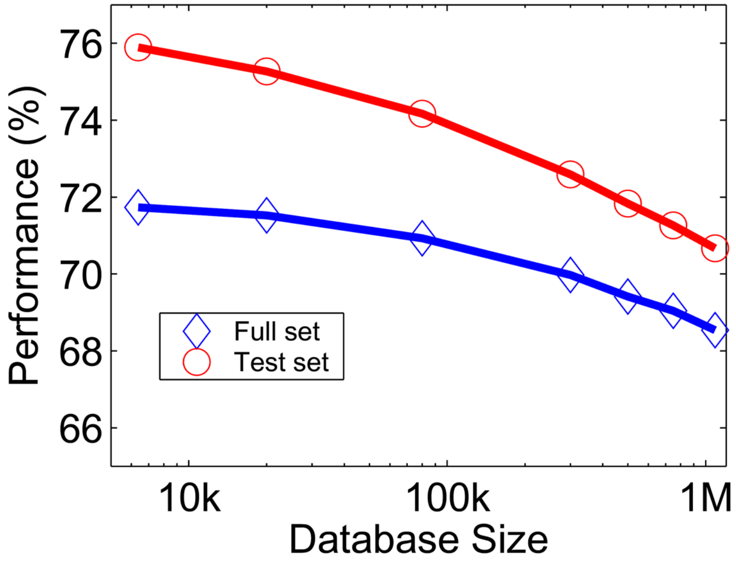








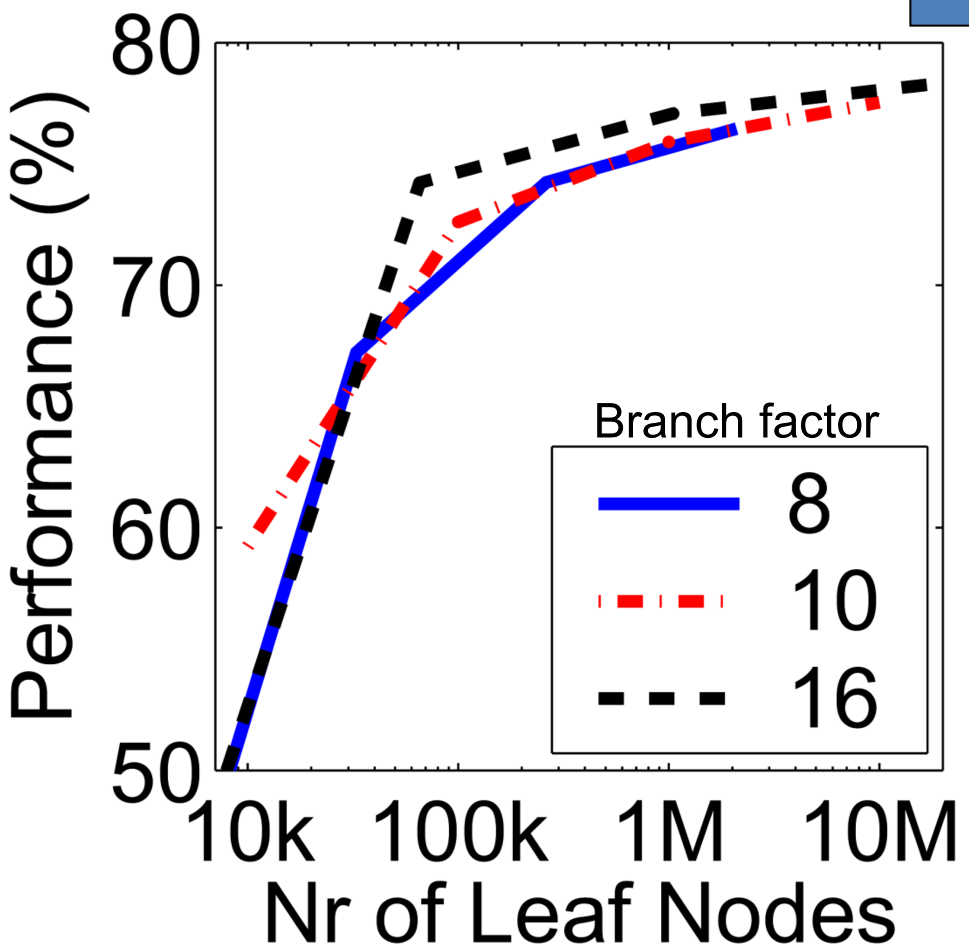
Performance



More words is better

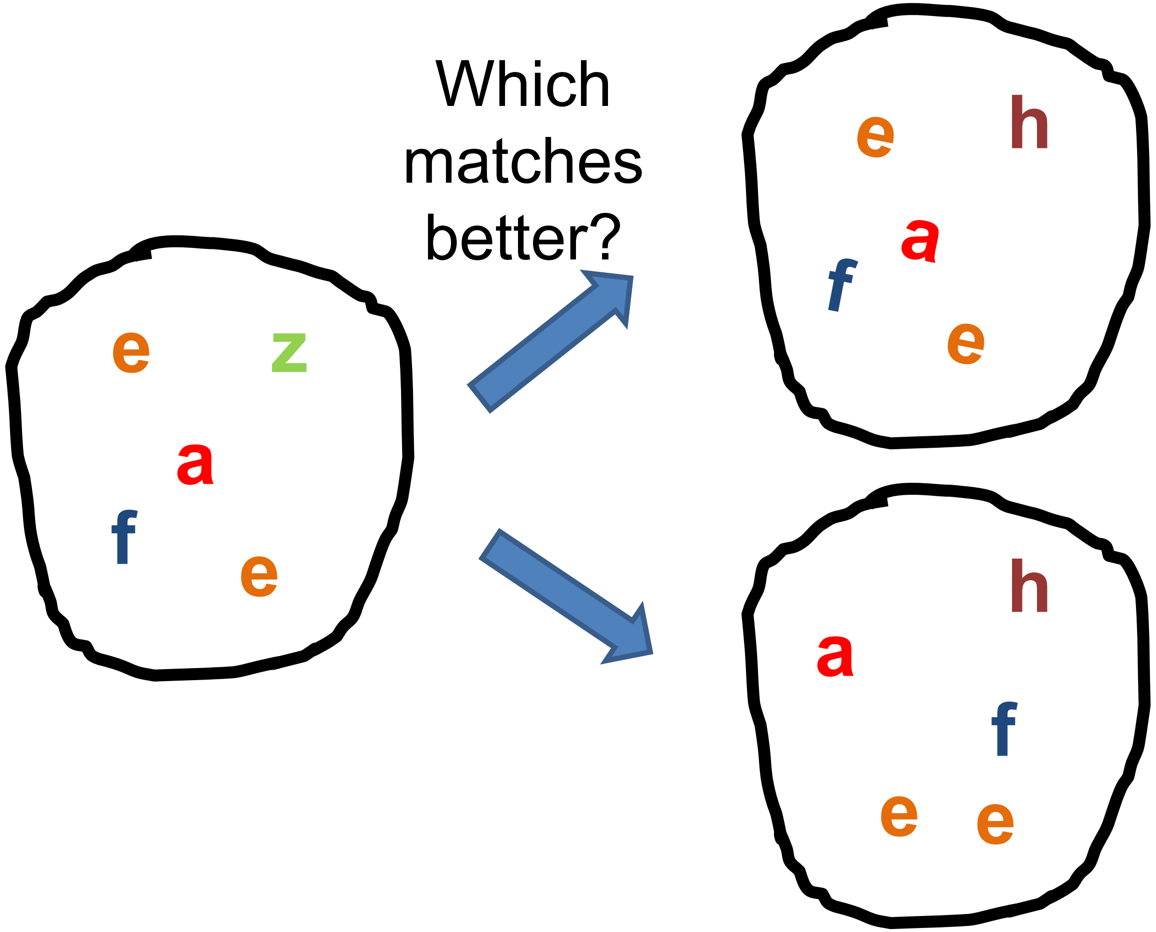
Improves Retrieval

Improves Speed



Can we be more accurate?

So far, we treat each image as containing a “bag of words”, with no spatial information



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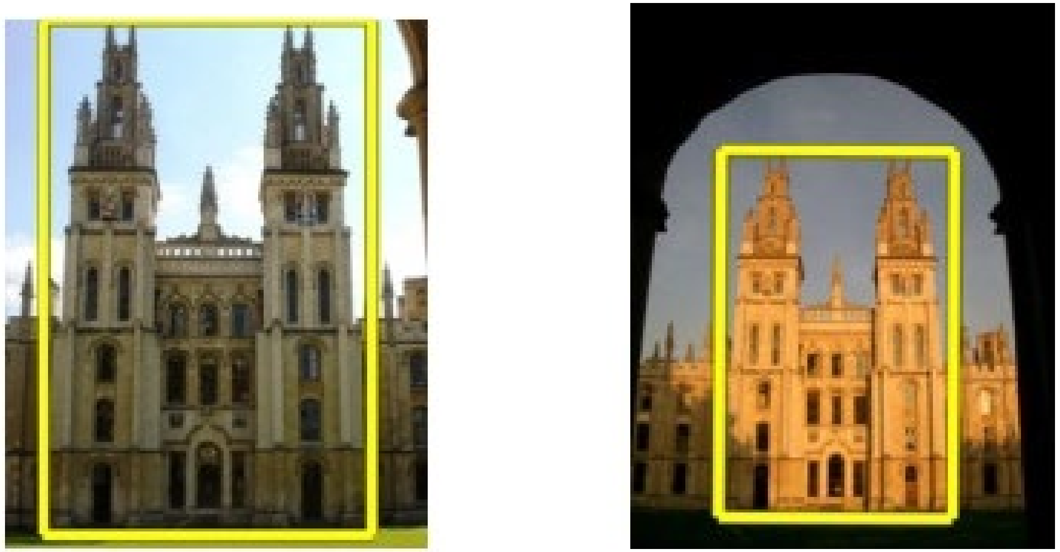


Real objects have consistent geometry

Final key idea: geometric verification

- Goal: Given a set of possible keypoint matches, figure out which ones are geometrically consistent

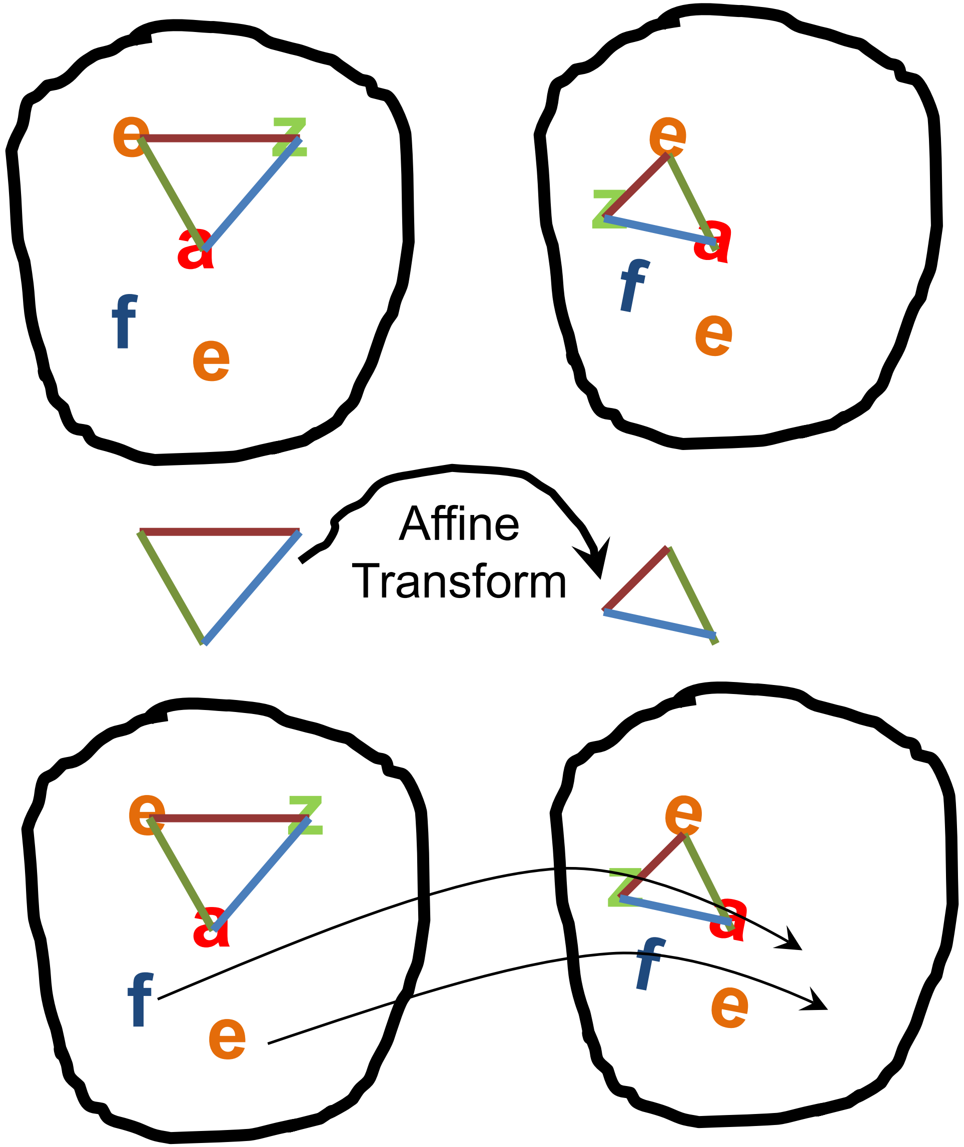
How can we do this?

Final key idea: geometric verification

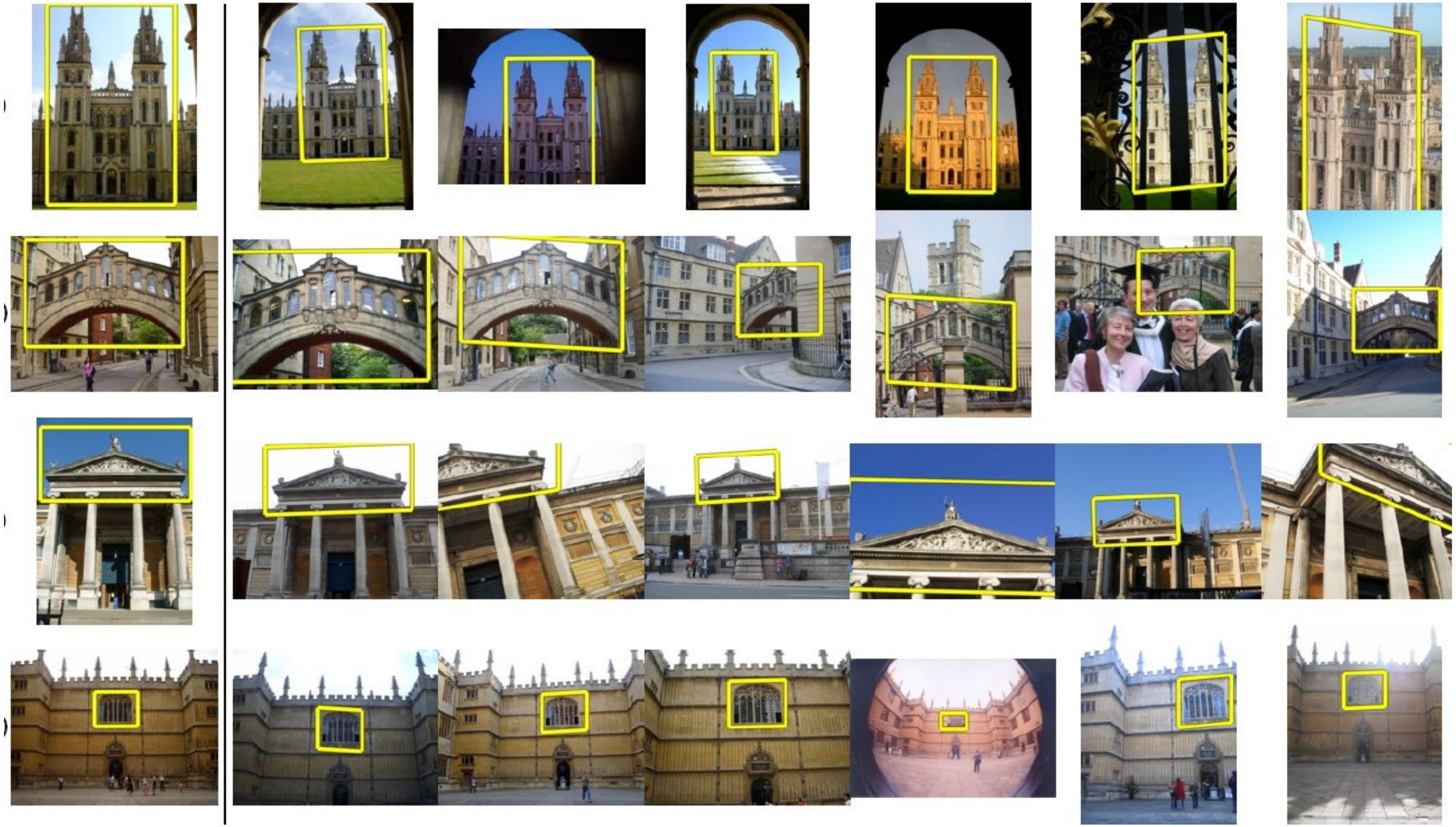
RANSAC for affine transform

Repeat N times:

- Randomly choose 3 matching pairs
- Estimate transformation
- Predict remaining points and count “inliers”



Application: Large-Scale Retrieval

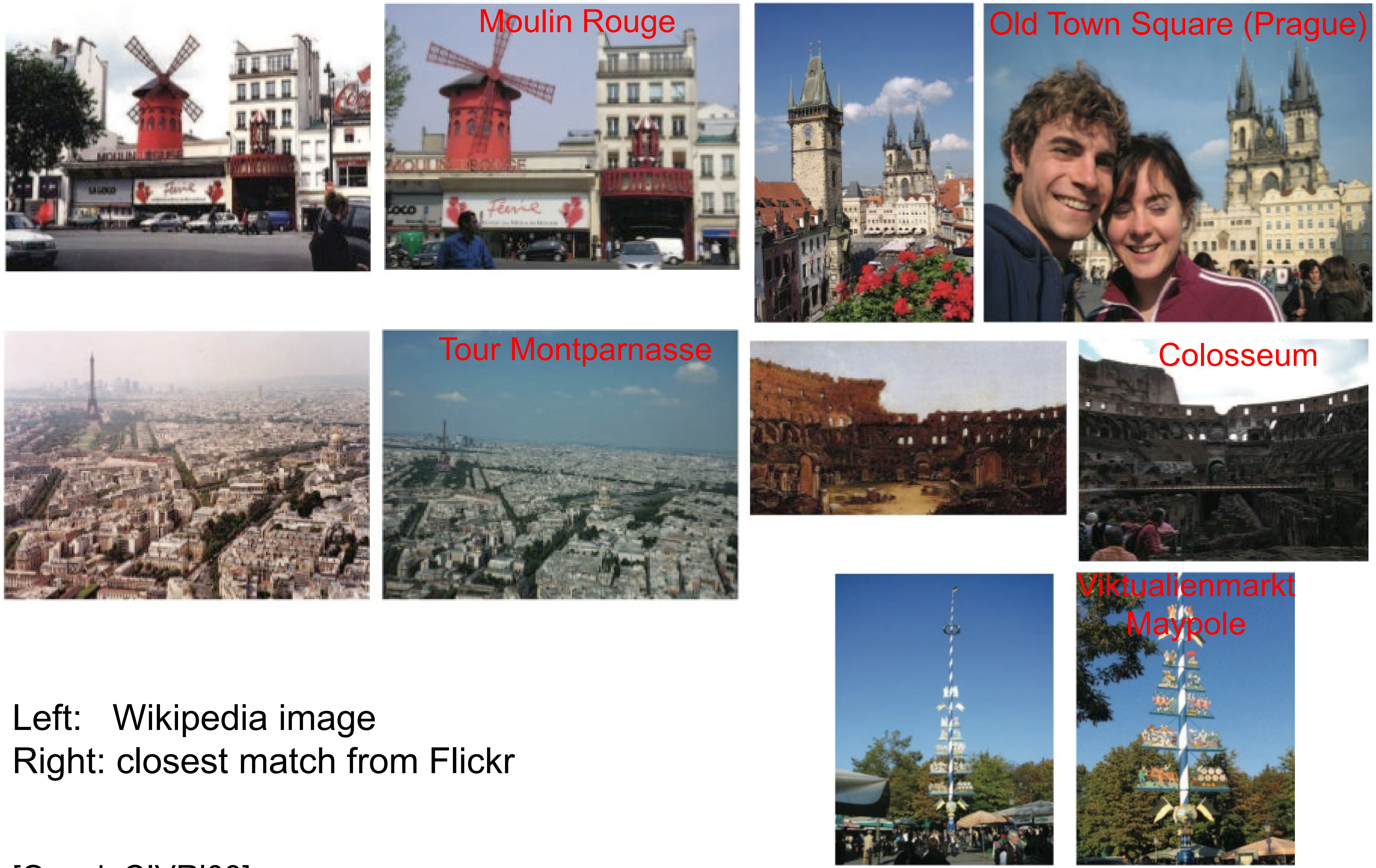


Query

Results on 5K (demo available for 100K)

[Philbin CVPR'07]

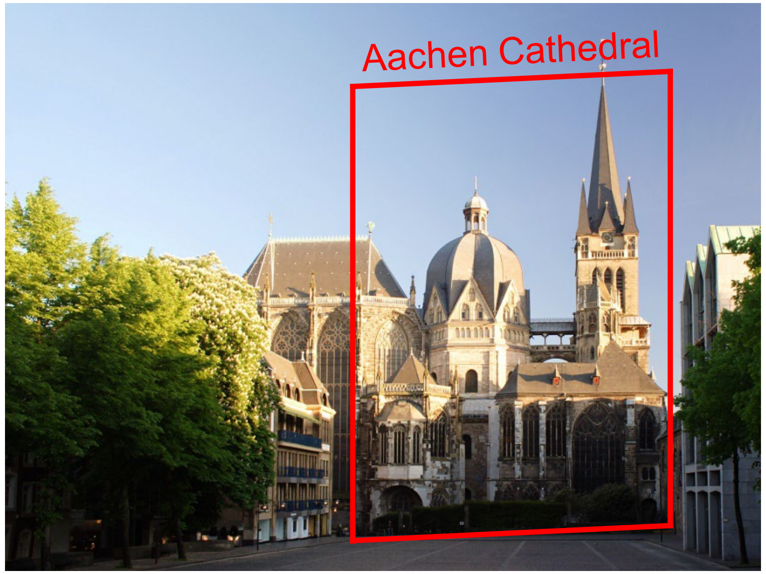
Application: Image Auto-Annotation



Left: Wikipedia image
Right: closest match from Flickr

[Quack CIVR'08]

Example Applications



Mobile tourist guide

Self-localization
Object/building recognition
Photo/video augmentation

[Quack, Leibe, Van Gool, CIVR'08]

Video Google System

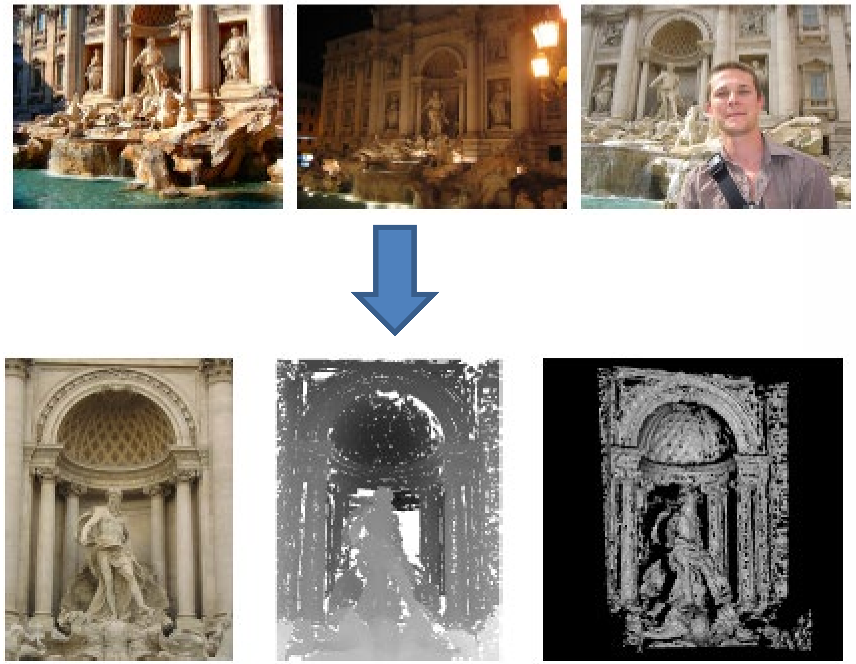
1. Collect all words within query region
2. Inverted file index to find relevant frames
3. Compare word counts
4. Spatial verification

Sivic & Zisserman, ICCV 2003

- Demo online at : http://www.robots.ox.ac.uk/~vgg/research/vgoogle/index.html

3D Reconstruction from Flickr

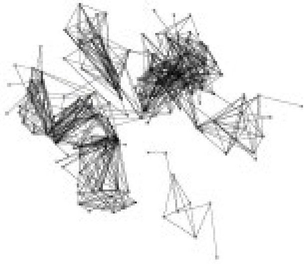
- Create detailed 3D scenes from thousands of consumer photographs
- Challenges include variations in season, lighting, occluding objects, etc.



“Building Rome in a Day”, Agarwal et al. 2009

3D Reconstruction from Flickr: How it works

1. Download ~10,000 images, convert to grayscale, compute SIFT keypoints
2. Match images
   1. Get similar images with vocabulary tree
   2. Match keypoints across similar images and perform geometric verification with RANSAC (similar to photo stitching)
3. Form a graph of matched images and features



4. 3D Reconstruction by triangulating points, bundle adjustment

Large-scale 3D Reconstruction

Useful references

- Snavely thesis: [“Scene Reconstruction and Visualization from Internet Photo Collections”]

- COLMAP: package for sparse and dense reconstruction (with two related papers) https://colmap.github.io/

- List of good papers and tutorials
https://github.com/openMVG/awesome_3DReconstruction_list

Summary: Uses of Interest Points

- Interest points can be detected reliably in different images at the same 3D location
  - DOG interest points are localized in x, y, scale

- SIFT is robust to rotation and small deformation

- Interest points provide correspondence
  - For image stitching
  - For defining coordinate frames for object insertion
  - For object recognition and retrieval
  - For 3D reconstruction

Next class

- Opportunities of scale: stuff you can do with millions of images
  - Texture synthesis of large regions
  - Colorization
  - Recognition
  - Etc.