Highlighted Project 2 Implementations

Vocabulary trees: complexity

Number of words given tree parameters: branching factor and number of levels

branching_factor^number_of_levels

Word assignment cost vs. flat vocabulary

O(k) for flat

$O(\log_{branching\_factor}(k) * branching\_factor)$

Is this like a kd-tree?

Yes, but with better partitioning and defeatist search.

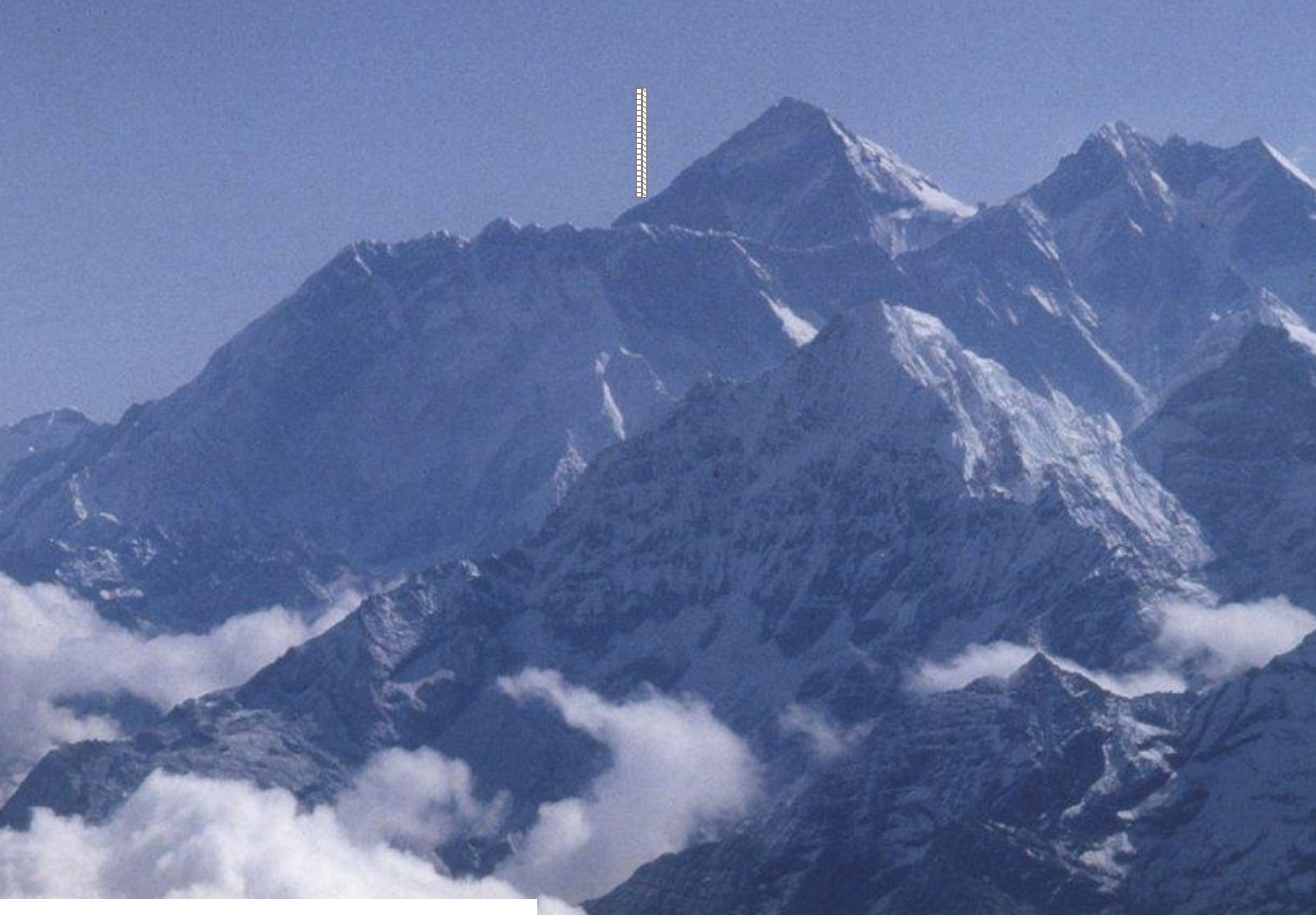
This hierarchical data structure is lossy – you might not find your true nearest cluster.

110,000,000 Images in 5.8 Seconds

Slide Credit: Nister

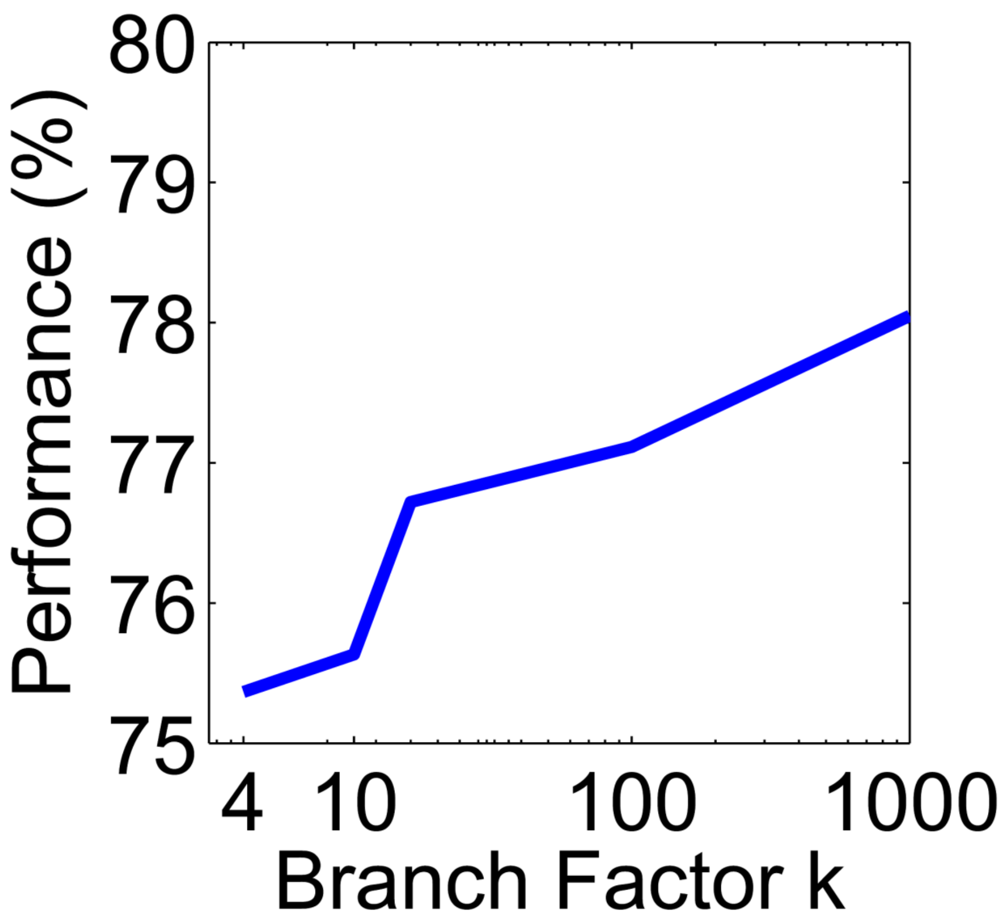
Slide Credit: Nister

Slide Credit: Nister



Slide Credit: Nister

Higher branch factor works better (but slower)



Visual words/bags of words

+ flexible to geometry / deformations / viewpoint
+ compact summary of image content
+ provides fixed dimensional vector representation for sets
+ very good results in practice

- background and foreground mixed when bag covers whole image
- optimal vocabulary formation remains unclear
- basic model ignores geometry – must verify afterwards, or encode via features

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Instance recognition: remaining issues

- How to summarize the content of an entire image? And gauge overall similarity?
- How large should the vocabulary be? How to perform quantization efficiently?
- Is having the same set of visual words enough to identify the object/scene? How to verify spatial agreement?
- How to score the retrieval results?

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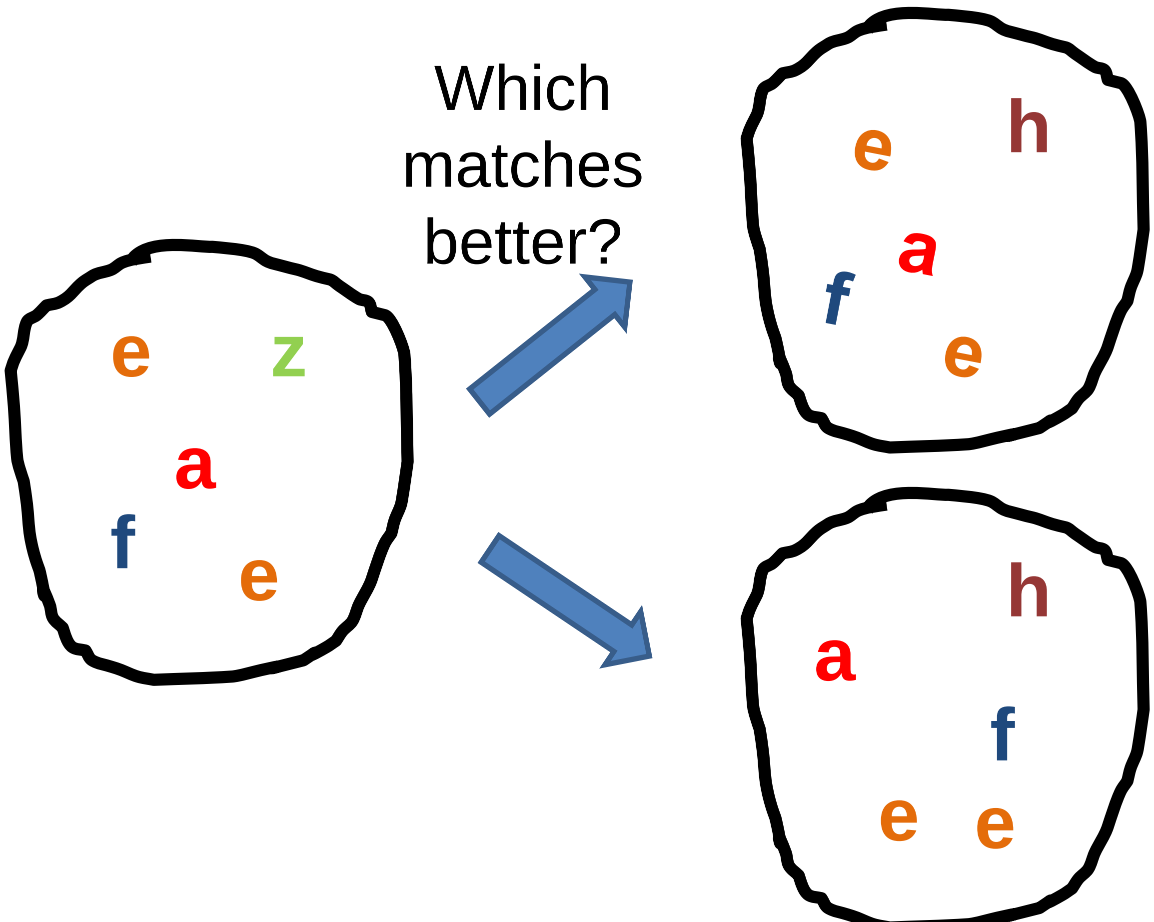
Can we be more accurate?

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



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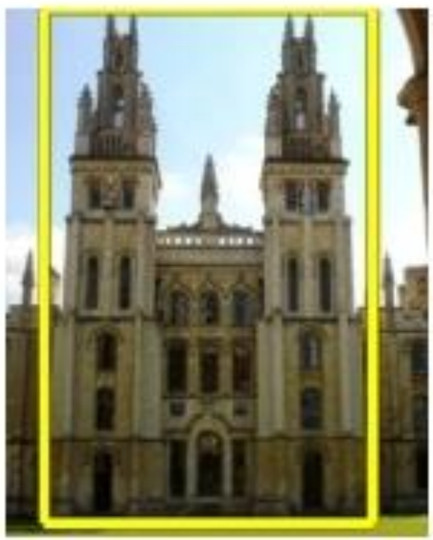


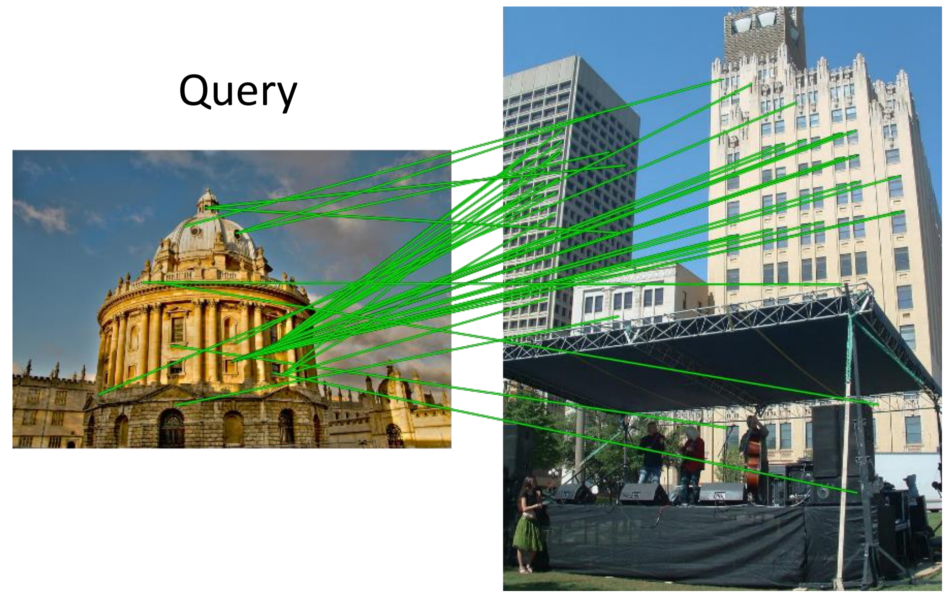
Real objects have consistent geometry

Spatial Verification

Query

DB image with high BoW similarity

Query



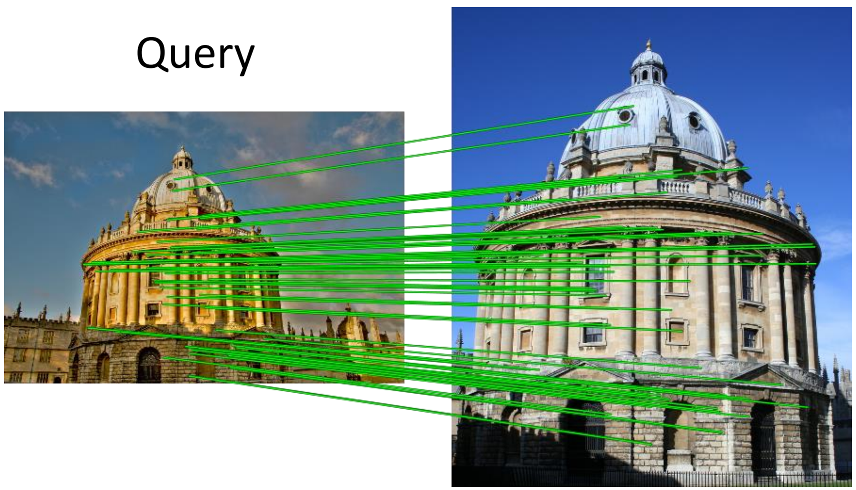
DB image with high BoW similarity

Both image pairs have many visual words in common.

Slide credit: Ondrej Chum

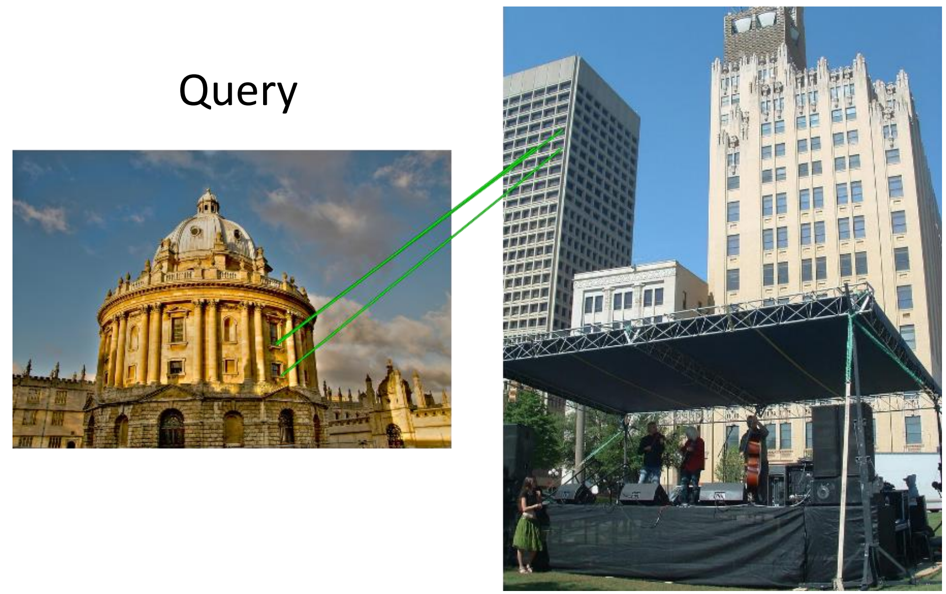
Spatial Verification

Query



DB image with high BoW similarity

Query



DB image with high BoW similarity

Only some of the matches are mutually consistent

Slide credit: Ondrej Chum

Spatial Verification: two basic strategies

- RANSAC
  - Typically sort by BoW similarity as initial filter
  - Verify by checking support (inliers) for possible transformations
    - e.g., “success” if find a transformation with > N inlier correspondences

- Generalized Hough Transform
  - Let each matched feature cast a vote on location, scale, orientation of the model object
  - Verify parameters with enough votes

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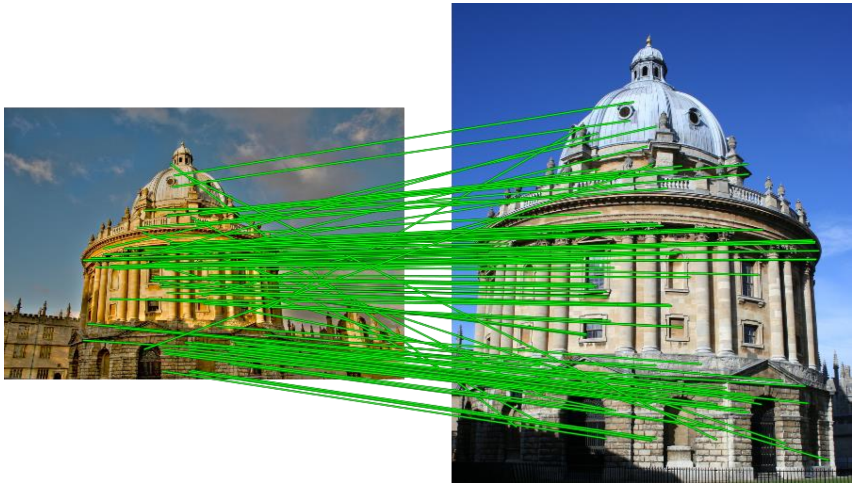
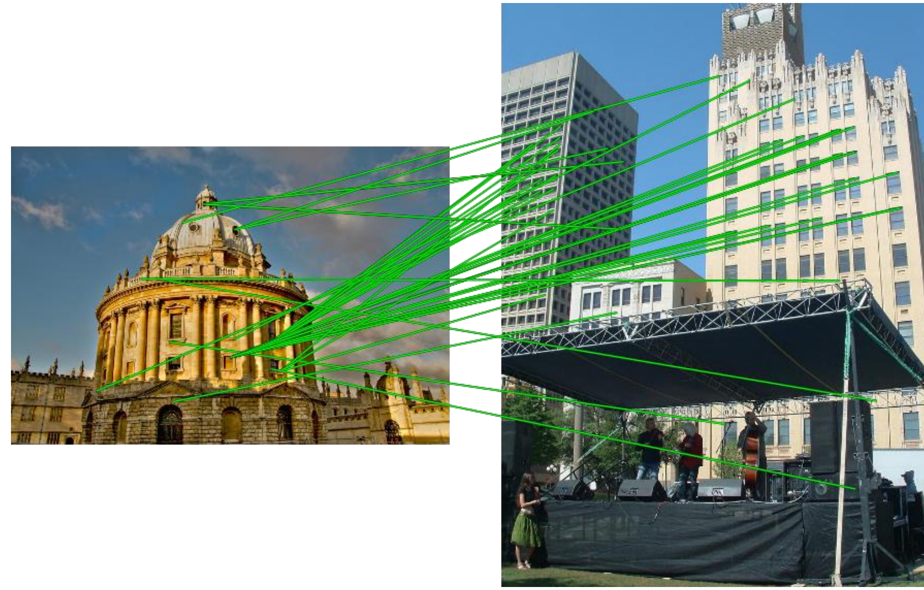
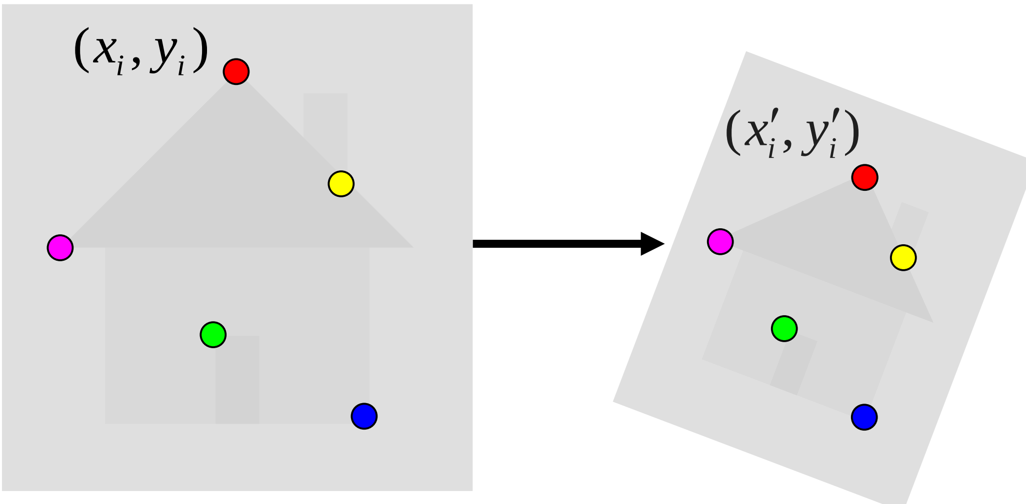
RANSAC verification





Recall: Fitting an affine transformation

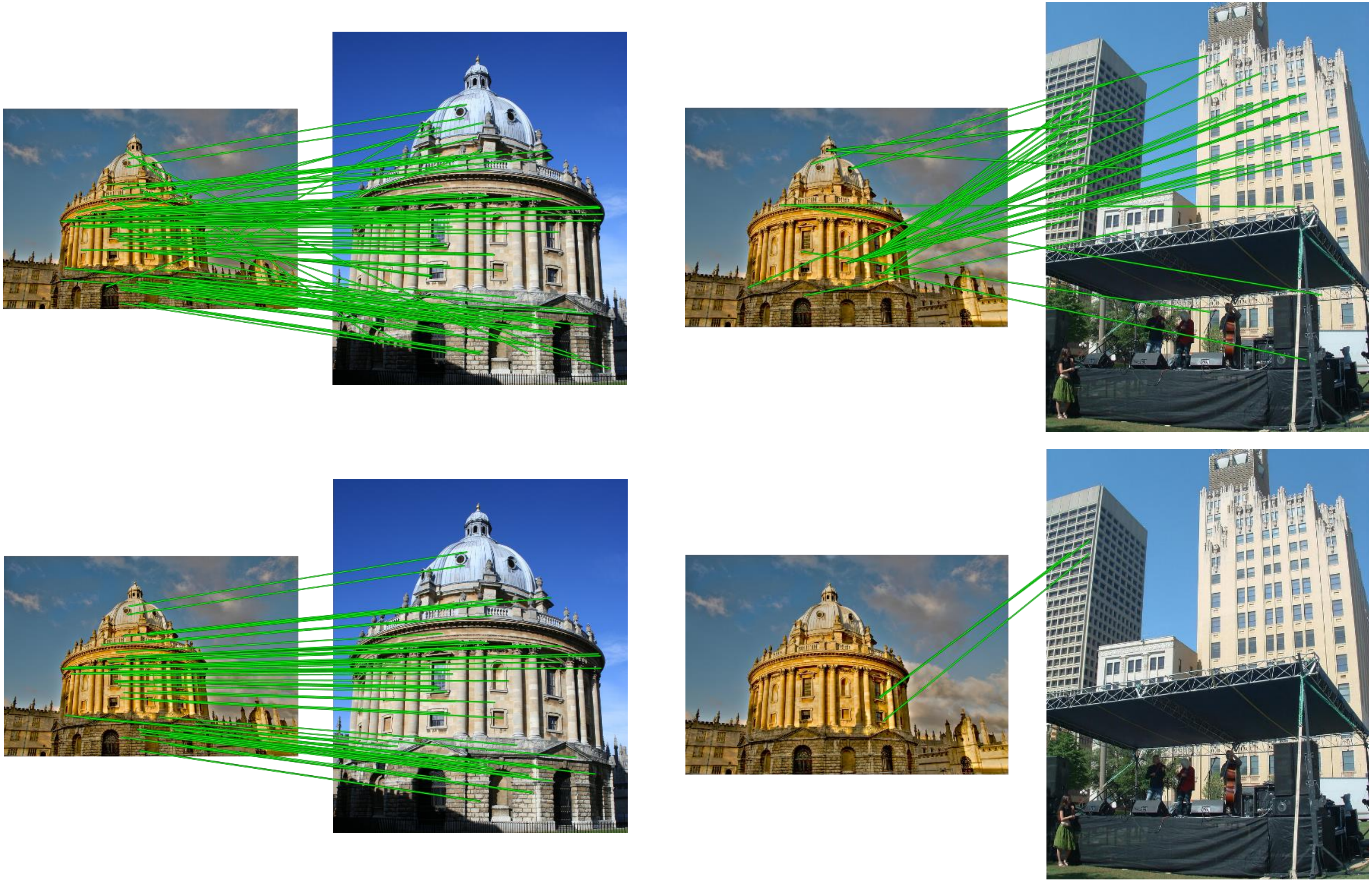


Approximates viewpoint changes for roughly planar objects and roughly orthographic cameras.

$$\begin{bmatrix} x_i' \\ y_i' \end{bmatrix} = \begin{bmatrix} m_1 & m_2 \\ m_3 & m_4 \end{bmatrix} \begin{bmatrix} x_i \\ y_i \end{bmatrix} + \begin{bmatrix} t_1 \\ t_2 \end{bmatrix}$$

$$\begin{bmatrix} & & \cdots & & & \\ x_i & y_i & 0 & 0 & 1 & 0 \\ 0 & 0 & x_i & y_i & 0 & 1 \\ & & \cdots & & & \end{bmatrix} \begin{bmatrix} m_1 \\ m_2 \\ m_3 \\ m_4 \\ t_1 \\ t_2 \end{bmatrix} = \begin{bmatrix} \cdots \\ x_i' \\ y_i' \\ \cdots \end{bmatrix}$$

RANSAC verification



Instance recognition: remaining issues

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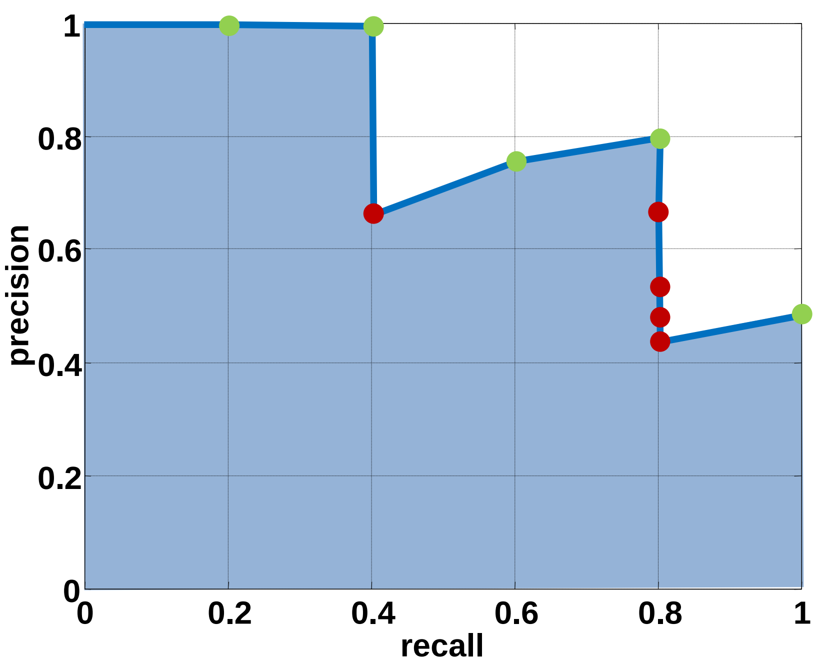
Scoring retrieval quality

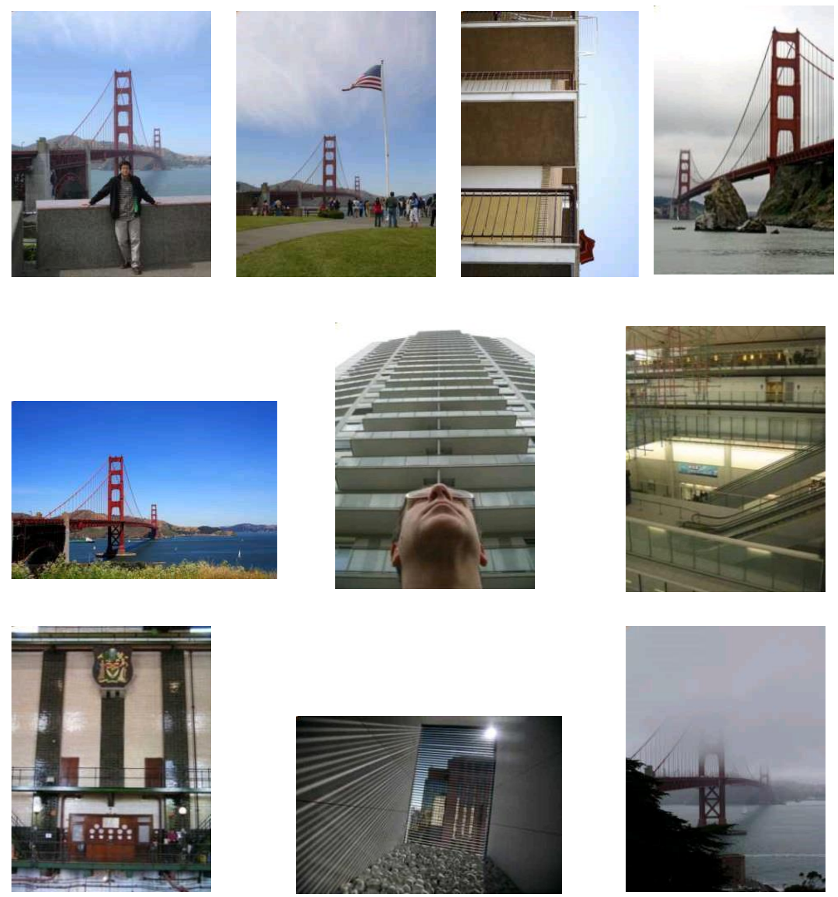
Query

Database size: 10 images
Relevant (total): 5 images

precision = #relevant / #returned
recall = #relevant / #total relevant

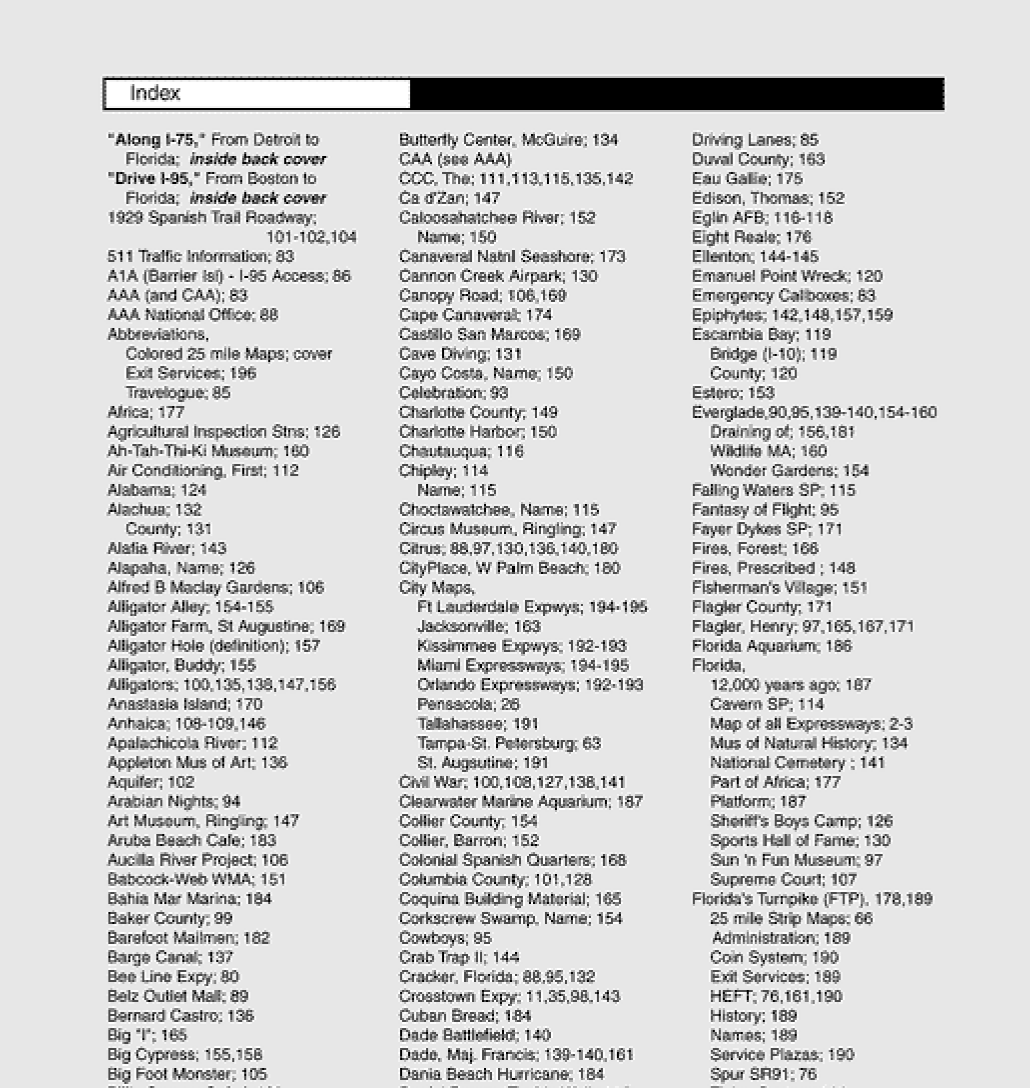


Results (ordered):



Slide credit: Ondrej Chum

What else can we borrow from text retrieval?



Index

tf-idf weighting

- **T**erm **f**requency – **i**nverse **d**ocument **f**requency
- Describe frame by frequency of each word within it, downweight words that appear often in the database
- (Standard weighting for text retrieval)

Number of occurrences of word i in document d

Number of words in document d

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

Total number of documents in database

Number of documents word i occurs in, in whole database

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Query expansion

Query: ***golf green***

Results:

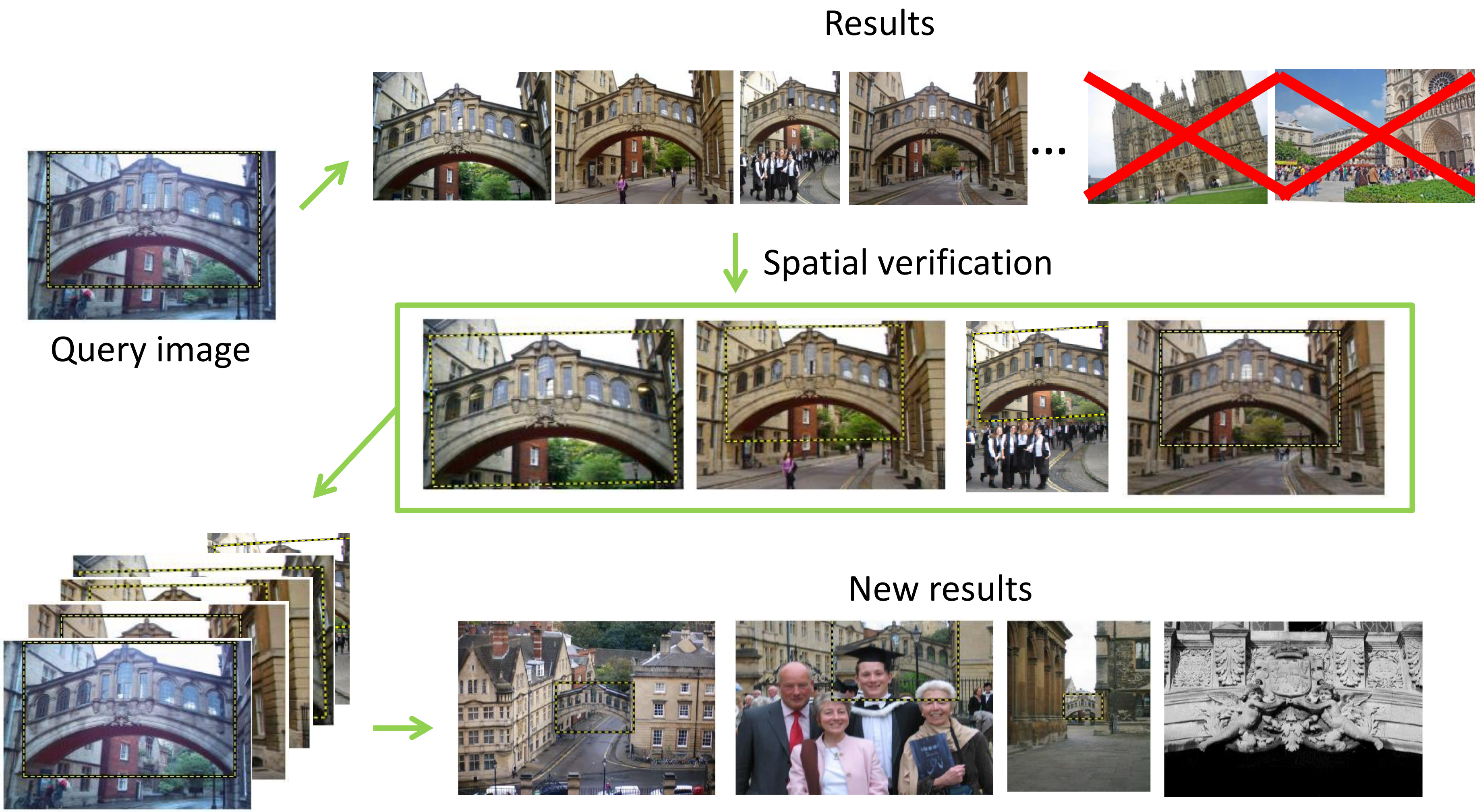
- How can the grass on the ***greens*** at a ***golf*** course be so perfect?
- For example, a skilled ***golf***er expects to reach the ***green*** on a par-four hole in **...**
- Manufactures and sells synthetic ***golf*** putting ***green****s* and mats.

Irrelevant result can cause a `topic drift':

- Volkswagen ***Golf***, 1999, ***Green***, 2000cc, petrol, manual, , hatchback, 94000miles, 2.0 GTi, 2 Registered Keepers, HPI Checked, Air-Conditioning, Front and Rear Parking Sensors, ABS, Alarm, Alloy

Slide credit: Ondrej Chum

Query Expansion



Chum, Philbin, Sivic, Isard, Zisserman: Total Recall..., ICCV 2007

Slide credit: Ondrej Chum

Recognition via alignment

Pros:

- Effective when we are able to find reliable features within clutter
- Great results for matching specific instances

Cons:

- Spatial verification as post-processing – not seamless, expensive for large-scale problems
- Not suited for category recognition.

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Summary

- **Matching local invariant features**
  - Useful not only to provide matches for multi-view geometry, but also to find objects and scenes.
- **Bag of words** representation: quantize feature space to make discrete set of visual words
  - Summarize image by distribution of words
  - Index individual words
- **Inverted index**: pre-compute index to enable faster search at query time
- **Recognition of instances via alignment:** matching local features followed by spatial verification
  - Robust fitting : RANSAC, GHT

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Lessons from a Decade Later

- For *Category* recognition (project 4)
  - Bag of Feature models remained the state of the art until Deep Learning.
  - Spatial layout either isn't that important or its too difficult to encode.
  - Quantization error is, in fact, the bigger problem. Advanced feature encoding methods address this.
  - Bag of feature models are nearly obsolete. At best they seem to be inspiring tweaks to deep models e.g. NetVLAD.

James Hays

Lessons from a Decade Later

- For *instance* retrieval (this lecture)
  - deep learning is taking over.
  - learn better local features (replace SIFT) e.g. MatchNet
  - or learn better image embeddings (replace the histograms of visual features) e.g. Vo and Hays 2016.
  - or learn to do spatial verification e.g. DeTone, Malisiewicz, and Rabinovich 2016.
  - or learn a monolithic deep network to recognition all locations e.g. Google's PlaNet 2016.

James Hays