

Highlighted Project 2 Implementations

Vocabulary trees: complexity

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

$$\text{branching_factor}^{\text{number_of_levels}}$$

Word assignment cost vs. flat vocabulary

$O(k)$ for flat

$$O(\log_{\text{branching_factor}}(k) * \text{branching_factor})$$

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



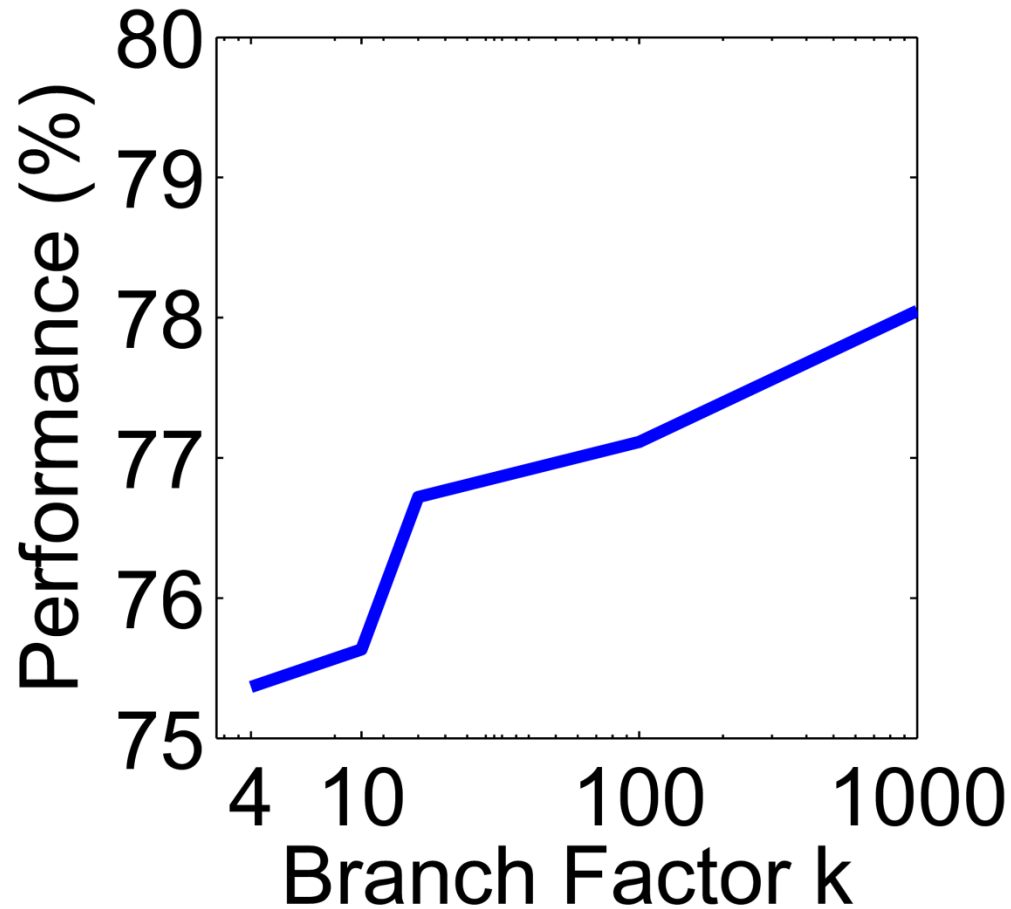
Slide Credit: Nister





Slide Credit: Nister

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

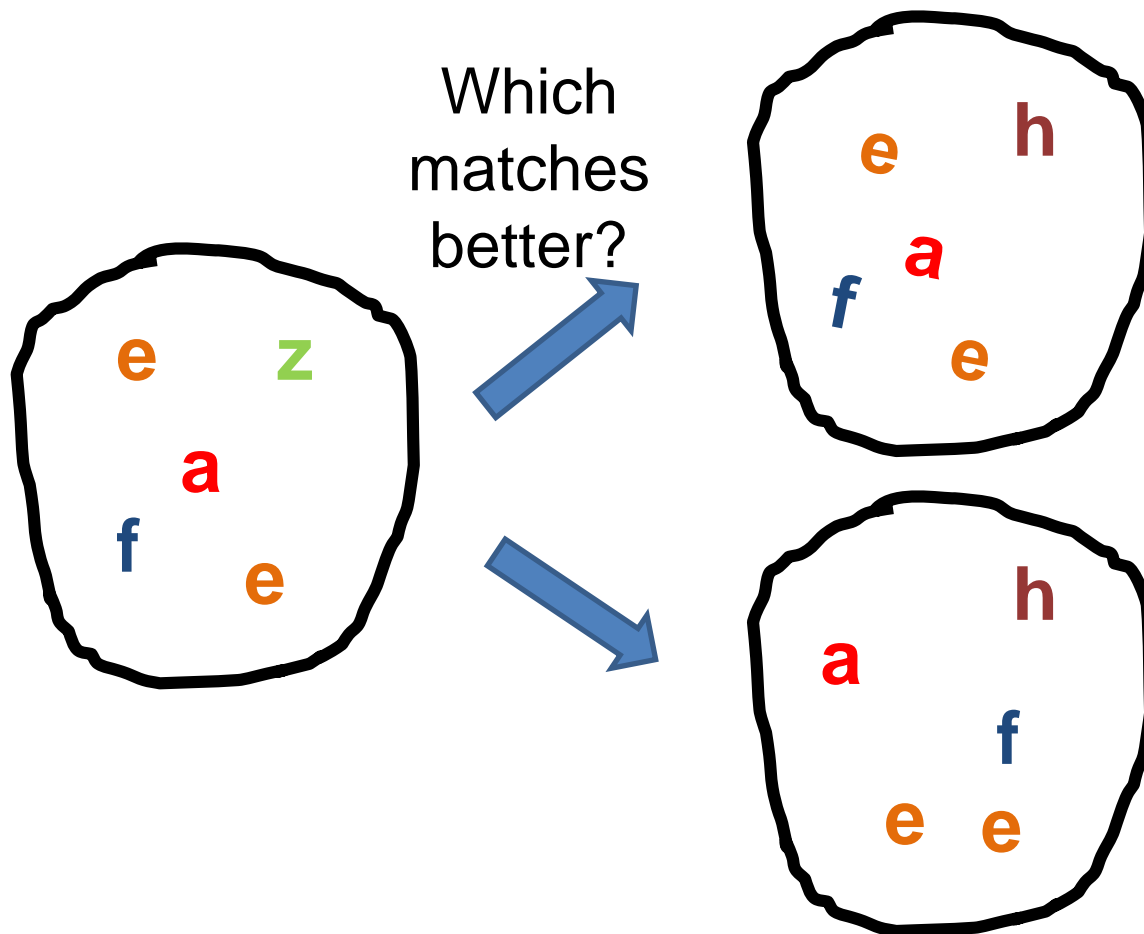
- background and foreground mixed when bag covers whole image
- optimal vocabulary formation remains unclear
- basic model ignores geometry – must verify afterwards, or encode via features

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?

Can we be more accurate?

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



Can we be more accurate?

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



Real objects have consistent geometry

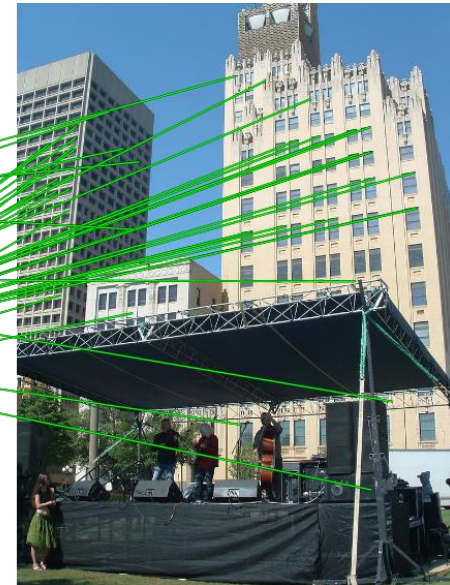
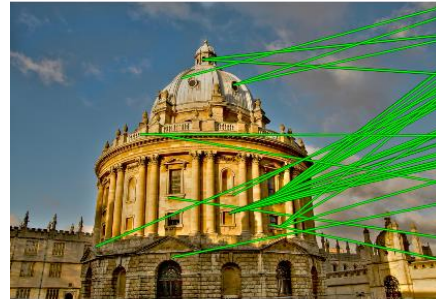
Spatial Verification

Query



DB image with high BoW
similarity

Query



DB image with high BoW
similarity

Both image pairs have many visual words in common.

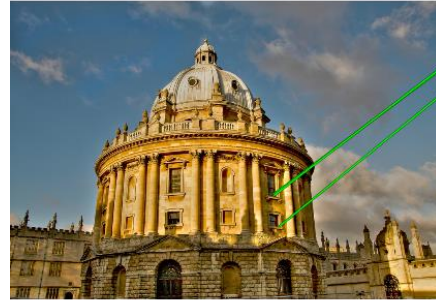
Spatial Verification

Query



DB image with high BoW similarity

Query



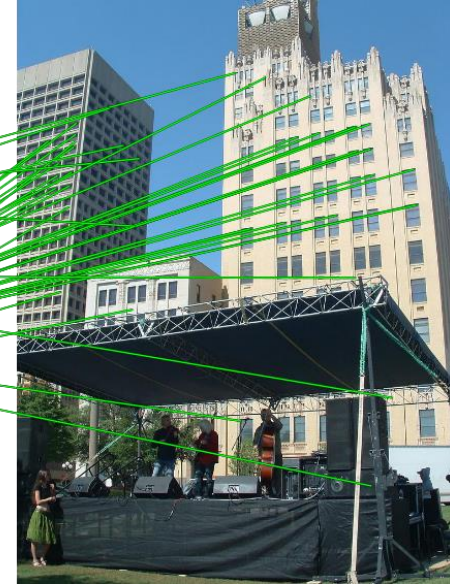
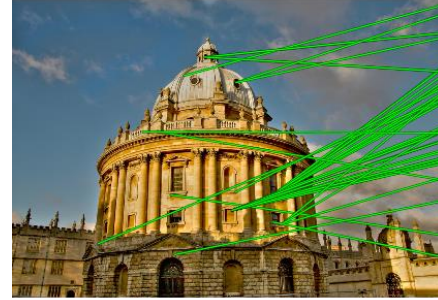
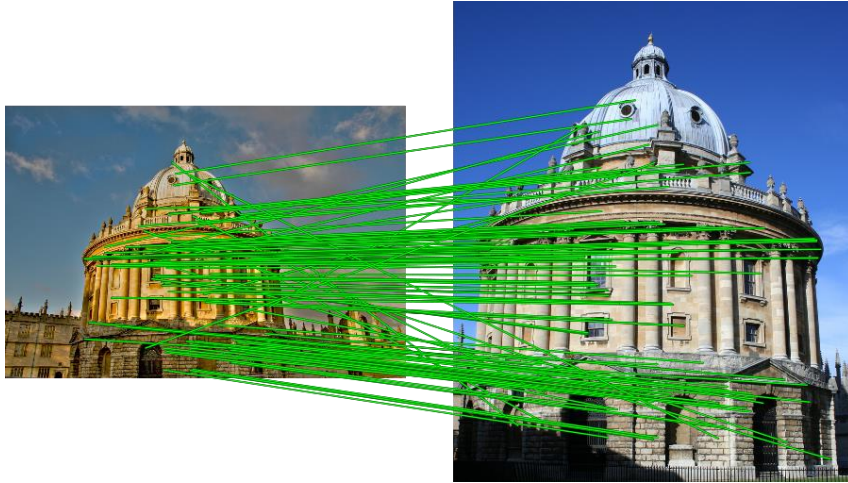
DB image with high BoW similarity

Only some of the matches are mutually consistent

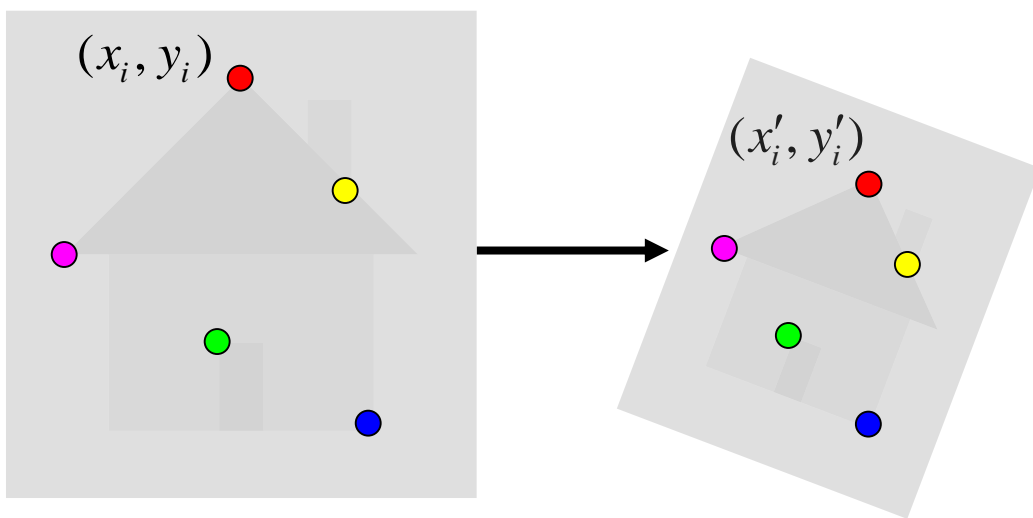
Spatial Verification: two basic strategies

- 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

RANSAC verification



Recall: Fitting an affine transformation

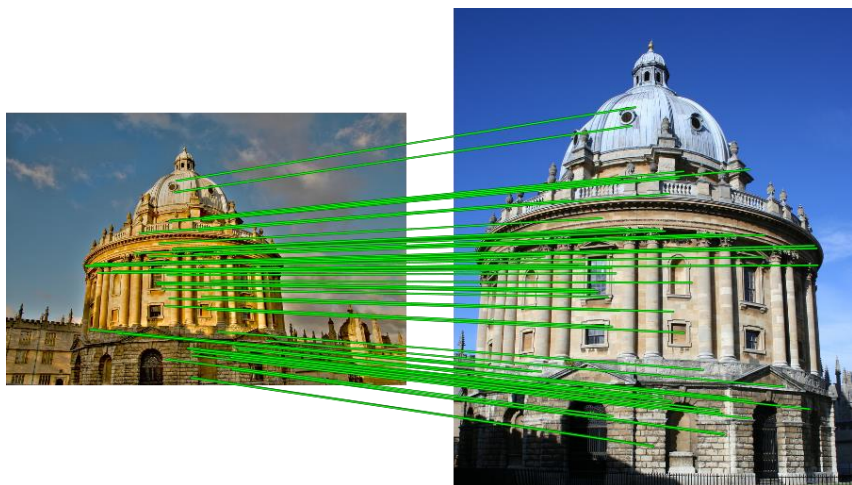
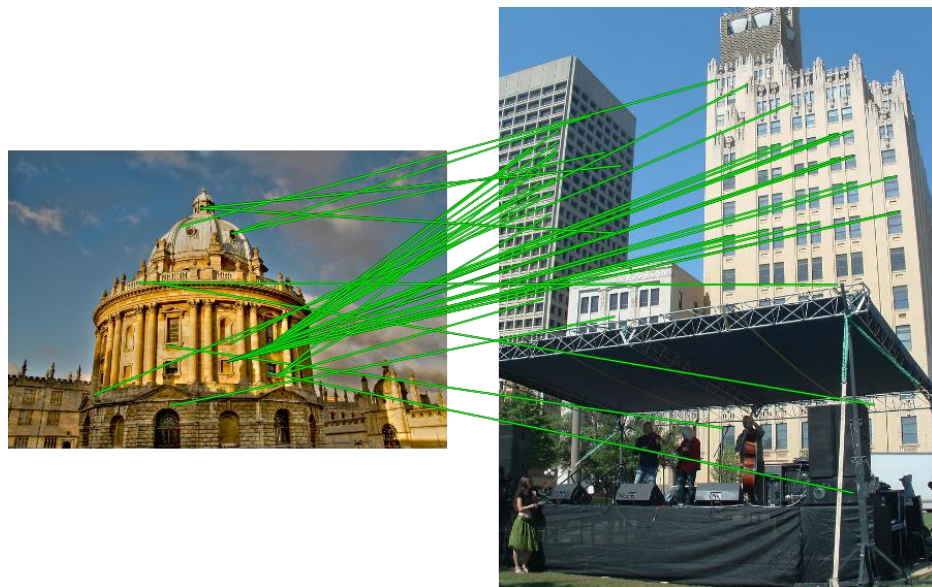
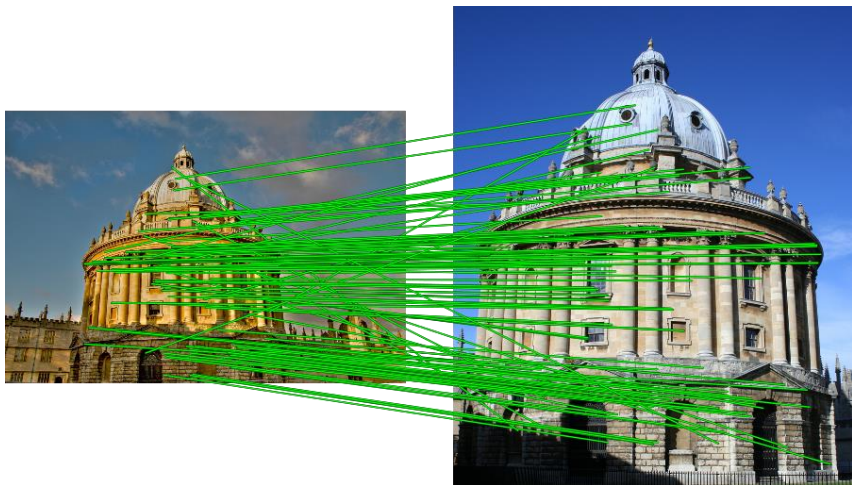


Approximates viewpoint changes for roughly planar objects and roughly orthographic cameras.

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

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

RANSAC verification



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?

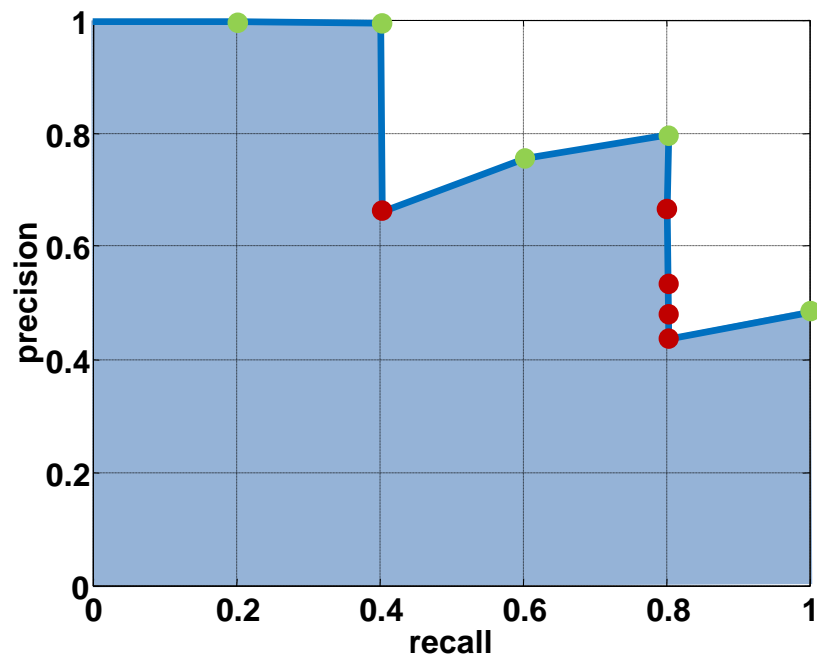
Scoring retrieval quality



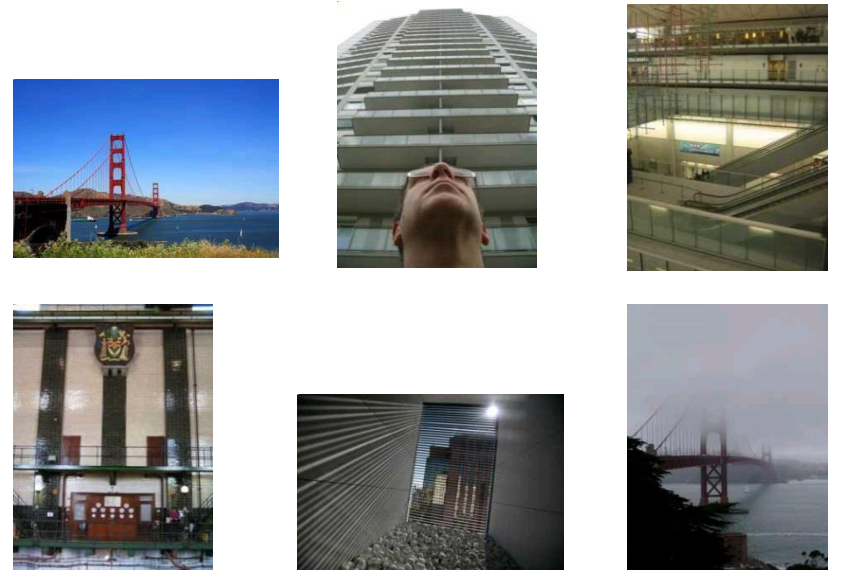
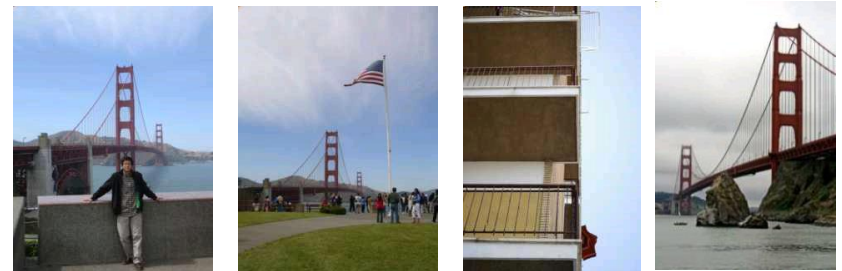
Query

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

precision = $\frac{\text{\#relevant}}{\text{\#returned}}$
recall = $\frac{\text{\#relevant}}{\text{\#total relevant}}$



Results (ordered):



What else can we borrow from text retrieval?

Index

"Along I-75," From Detroit to Florida; *inside back cover*
"Drive I-95," From Boston to Florida; *inside back cover*
1929 Spanish Trail Roadway; 101-102,104
511 Traffic Information; 83
A1A (Barrier Is) - I-95 Access; 86
AAA (and CAA); 83
AAA National Office; 88
Abbreviations,
 Colored 25 mile Maps; cover
 Exit Services; 196
 Travelogue; 85
Africa; 177
Agricultural Inspection Stns; 126
Ah-Tah-Thi-Ki Museum; 180
Air Conditioning, First; 112
Alabama; 124
Alachua; 132
 County; 131
Alafia River; 143
Alapaha, Name; 126
Alfred B MacLay Gardens; 106
Alligator Alley; 154-155
Alligator Farm, St Augustine; 169
Alligator Hole (definition); 157
Alligator, Buddy; 155
Alligators; 100,135,138,147,156
Anastasia Island; 170
Anhaica; 108-109,146
Apalachicola River; 112
Appleton Mus of Art; 136
Aquifer; 102
Arabian Nights; 94
Art Museum, Ringling; 147
Aruba Beach Cafe; 183
Aucilla River Project; 106
Babcock-Web WMA; 151
Bahia Mar Marina; 184
Baker County; 99
Barefoot Mailmen; 182
Barge Canal; 137
Bee Line Expy; 80
Belz Outlet Mall; 89
Bernard Castro; 136
Big "I"; 165
Big Cypress; 155,158
Big Foot Monster; 105
Butterfly Center, McGuire; 134
CAA (see AAA)
CCC, The; 111,113,115,135,142
Ca d'Zan; 147
Caloosahatchee River; 152
 Name; 150
Canaveral Natnl Seashore; 173
Cannon Creek Airpark; 130
Canopy Road; 106,169
Cape Canaveral; 174
Castillo San Marcos; 169
Cave Diving; 131
Cayo Costa, Name; 150
Celebration; 93
Charlotte County; 149
Charlotte Harbor; 150
Chautauqua; 116
Chipley; 114
 Name; 115
Choctawatchee, Name; 115
Circus Museum, Ringling; 147
Citrus; 88,97,130,136,140,180
CityPlace, W Palm Beach; 180
City Maps,
 Fl Lauderdale Expwys; 194-195
 Jacksonville; 163
 Kissimmee Expwys; 192-193
 Miami Expressways; 194-195
 Orlando Expressways; 192-193
 Pensacola; 26
 Tallahassee; 191
 Tampa-St. Petersburg; 63
 St. Augustine; 191
Civil War; 100,108,127,138,141
Clearwater Marine Aquarium; 187
Collier County; 154
Collier, Barron; 152
Colonial Spanish Quarters; 168
Columbia County; 101,128
Coquina Building Material; 165
Corkscrew Swamp, Name; 154
Cowboys; 95
Crab Trap II; 144
Cracker, Florida; 88,95,132
Crosstown Expy; 11,35,98,143
Cuban Bread; 184
Dade Battlefield; 140
Dade, Maj. Francis; 139-140,161
Dania Beach Hurricane; 184
Driving Lanes; 85
Duval County; 163
Eau Gallie; 175
Edison, Thomas; 152
Eglin AFB; 116-118
Eight Reale; 176
Ellenton; 144-145
Emanuel Point Wreck; 120
Emergency Callboxes; 83
Epiphytes; 142,148,157,159
Escambia Bay; 119
 Bridge (I-10); 119
 County; 120
Estero; 153
Everglade; 90,95,139-140,154-160
 Draining of; 156,181
 Wildlife MA; 160
 Wonder Gardens; 154
Falling Waters SP; 115
Fantasy of Flight; 95
Fayer Dykes SP; 171
Fires, Forest; 166
Fires, Prescribed ; 148
Fisherman's Village; 151
Flagler County; 171
Flagler, Henry; 97,165,167,171
Florida Aquarium; 186
Florida,
 12,000 years ago; 187
 Cavern SP; 114
 Map of all Expressways; 2-3
 Mus of Natural History; 134
 National Cemetery ; 141
 Part of Africa; 177
 Platform; 187
 Sheriff's Boys Camp; 126
 Sports Hall of Fame; 130
 Sun 'n Fun Museum; 97
 Supreme Court; 107
Florida's Turnpike (FTP); 178,189
25 mile Strip Maps; 66
 Administration; 189
 Coin System; 190
 Exit Services; 189
 HEFT; 76,161,190
 History; 189
 Names; 189
 Service Plazas; 190
 Spur SR91; 76

China is forecasting a trade surplus of \$90bn (£51bn) to \$100bn this year, a threefold increase on 2004's \$32bn. The Commerce Ministry said the surplus would be created by a predicted 30% increase in exports to \$750bn,

compared with \$566bn. The surplus will annoy the US because China's deliberate policy is to agree to a yuan is also needed to demand so much country. China's yuan against the dollar and permitted it to trade within a narrow band but the US wants the yuan to be allowed to trade freely. However, Beijing has made it clear that it will take its time and tread carefully before allowing the yuan to rise further in value.

China, trade, surplus, commerce, exports, imports, US, yuan, bank, domestic, foreign, increase, trade, value

tf-idf weighting

- Term frequency – inverse document frequency
- Describe frame by frequency of each word within it, downweight words that appear often in the database
- (Standard weighting for text retrieval)

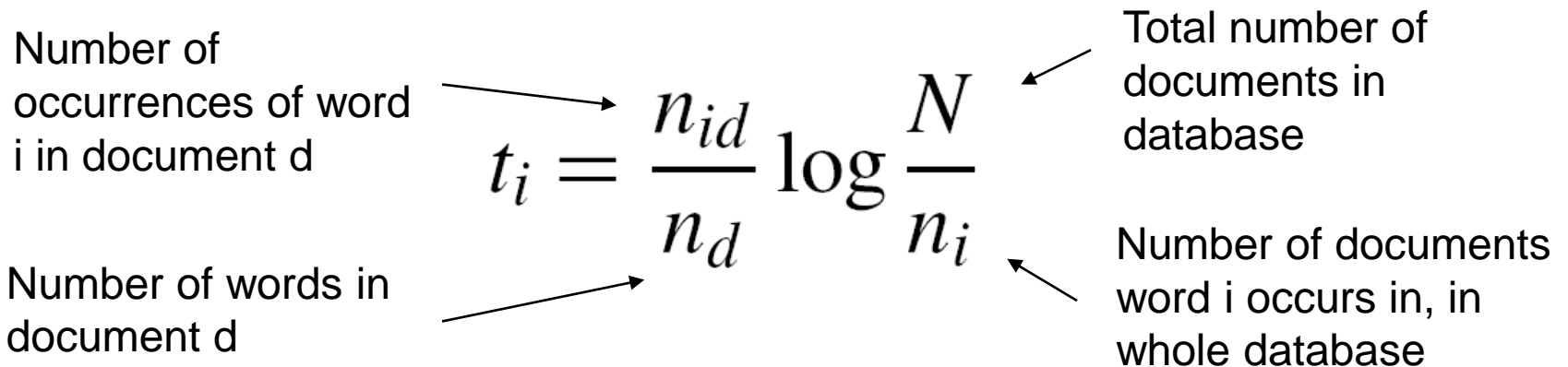
Number of occurrences of word i in document d

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

The diagram illustrates the components of the tf-idf formula. On the left, two text labels are connected to the formula by arrows: 'Number of occurrences of word i in document d' points to the numerator n_{id} , and 'Number of words in document d' points to the denominator n_d . On the right, two more text labels are connected to the formula by arrows: 'Total number of documents in database' points to the numerator N of the logarithm, and 'Number of documents word i occurs in, in whole database' points to the denominator n_i of the logarithm.

Query expansion

Query: ***golf green***

Results:

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

Query Expansion

Results



Query image

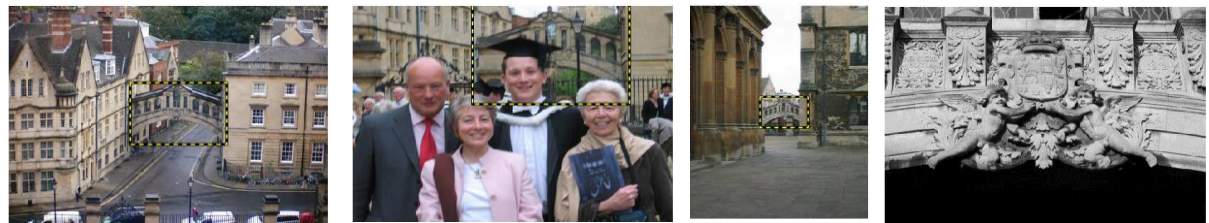
Spatial verification



New results



New query



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.

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

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.

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.