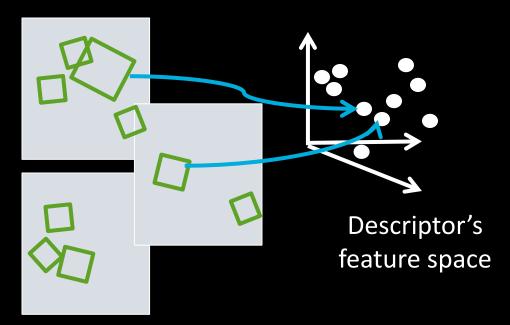
CS4495/6495 Introduction to Computer Vision

8C-L4 Bag of visual words



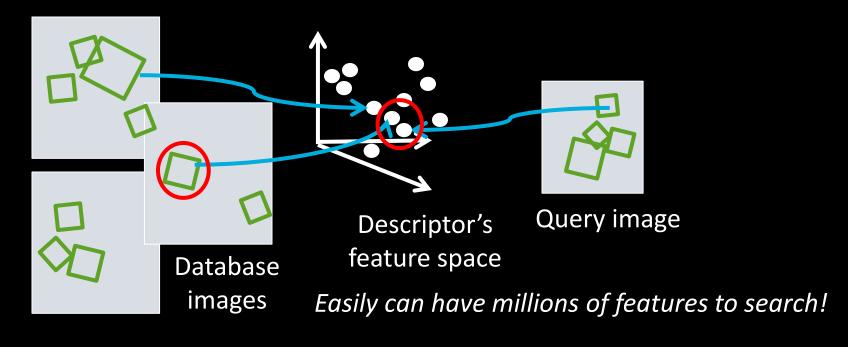
Indexing local features

 Each patch / region has a descriptor, which is a point in some high-dimensional feature space (e.g., SIFT)



Indexing local features

 When we see close points in feature space, we have similar descriptors, which indicates similar local content.



Indexing local features

 With potentially thousands of features per image, and hundreds to millions of images to search, how to efficiently find those that are relevant to a new image?

Indexing local features: inverted file index

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: 511 Traffic Information: 83 A1A (Barrier Isi) - I-95 Access; 86 AAA (and CAA); 83 AAA National Office: 88 Abbreviations. Colored 25 mile Maps; cover Exit Services; 196 Traveloque: 85 Africa: 177 Agricultural Inspection Stns: 126 Ah-Tah-Thi-Ki Museum: 160 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

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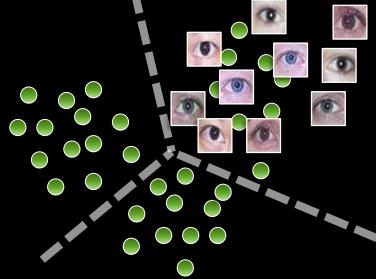
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 For text documents, an efficient way to find all pages on which a word occurs is to use an index...

- We want to find all *images* in which a *feature* occurs.
- To use this idea, we'll need to map our features to "visual words"

Visual words (discretization)

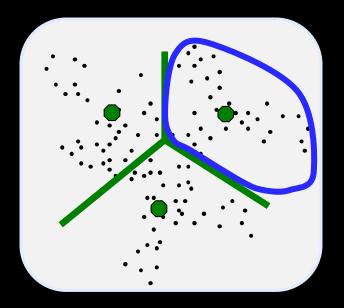
Words are discrete, visual features are typically continuous...



Discretization via clustering/vector quantization

Visual words

Example: each group of patches belongs to the same visual word



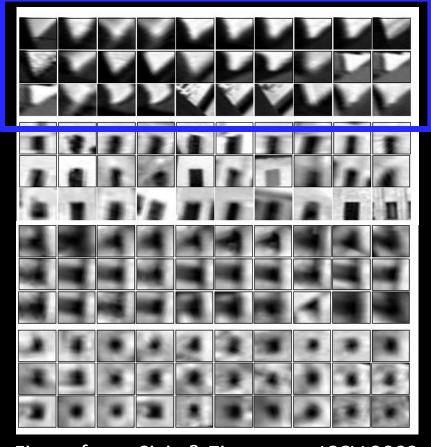


Figure from Sivic & Zisserman, ICCV 2003

Analogy to documents

Of all the sensory impressions proceeding to the brain, the visual experiences are the dominant ones. Our perception of the world around us is based essentially or that reach the brain from our thought that sensory, brain, point by: visual, perception, cerebra1 retinal, cerebral cortex, upon w Throug eye, cell, optical we now nerve, image visual pel Hubel, Wiesel considerab. events. By for their path to the cortex, Hubel and Wieser demonstrate that the *message about tr*. falling on the retina undergoes a step-vi analysis in a system of nerve cells stored columns. In this system each cell has its spa function and is responsible for a specific deta in the pattern of the retinal image.

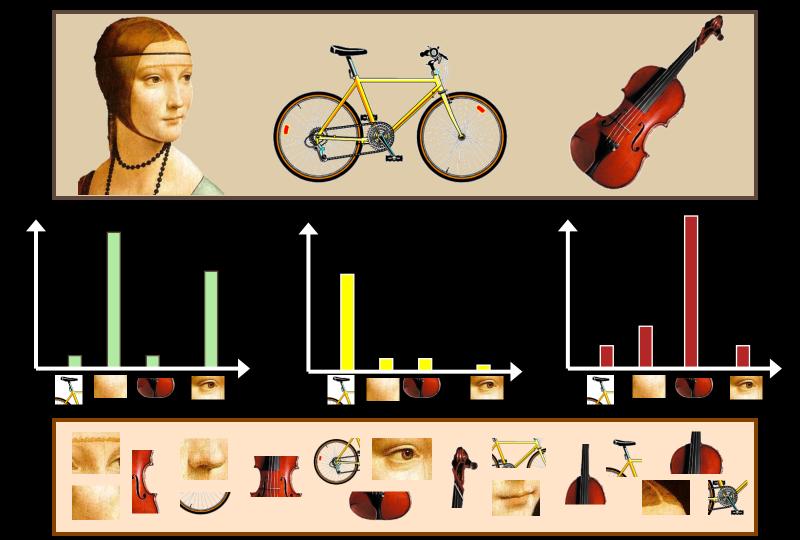
China is forecasting a trade surplus of \$90bn (£51bn) to \$100bn this year, a threefold increase on 2004's \$32bn. The Commerce Ministry said the surplus would be created by a predicted 30% jump in ey ared with a 18% rise i es are likely to argued by a de oorts, imports, US. agrees is only Zhou X do more t trade, value goods stave increased the v dollar by 2.1% in Jan trade within a narrow band, but the US wa yuan to be allowed to trade freely. Ho Beijing has made it clear that it will take and tread carefully before allowing the yu rise further in value.

Object

Bag of 'words'



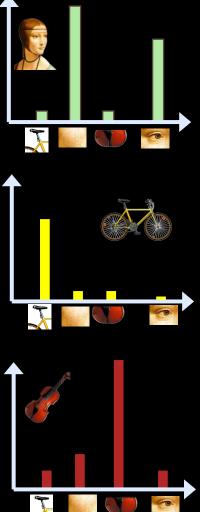




Bags of visual words

- Summarize entire image based on its distribution (histogram) of word occurrences.
- Analogous to bag of words representation commonly used for documents.

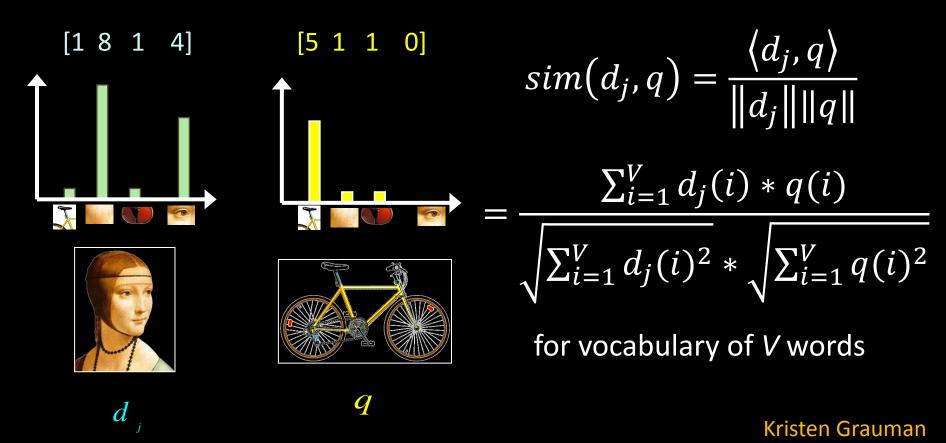




Comparing bags of words

 Rank by normalized scalar product between their (possibly weighted) occurrence counts-- nearest neighbor search for similar images.

Comparing bags of words



Object classification with bag of words

 Performance on Caltech 101 dataset with linear SVM on bagof-word vectors:







			0.000		0.00
True classes →	faces (frontal)	airplanes (side)	cars (rear)	cars (side)	motorbikes (side)
faces(frontal)	94	0.4	0.7	0	1.4
airplanes (side)	1.5	96.3	0.2	0.1	2.7
cars (rear)	1.9	0.5	97.7	0	0.9
cars(side)	1.7	1.9	0.5	99.6	2.3
motorbikes (side)	0.9	0.9	0.9	0.3	92.7
Mean ranks	1.07	1.04	1.03	1.01	1.09

[Csurka et al., '04]