COMP3204/COMP6223: Computer Vision

Image search and Bags of Visual Words

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Text Information Retrieval

The *bag* data structure

- A bag is an **unordered** data structure like a *set*, but which unlike a set allows elements to be **inserted multiple times**.
    - sometimes called a *multiset* or a *counted set*

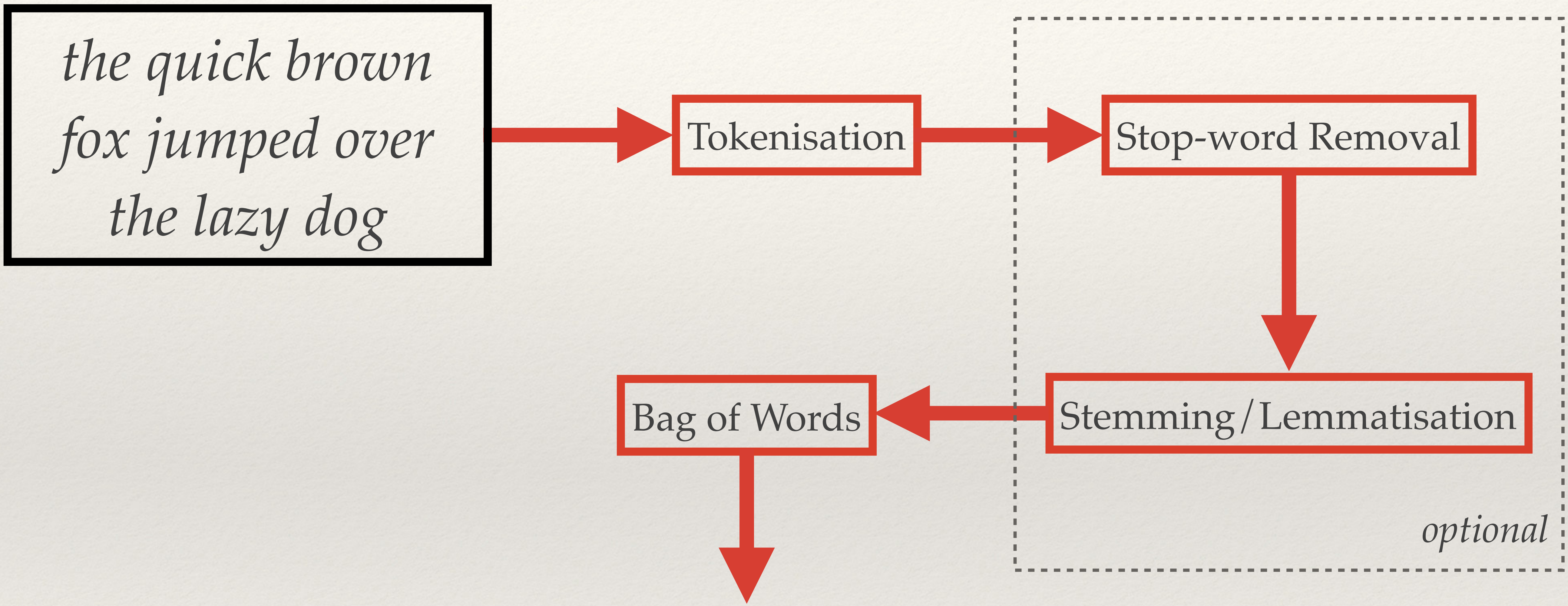
Bag of Words

A document

the quick brown fox jumped over the lazy dog

The bag of words describing the document

Text processing (feature extraction)



	brown	dog	fox	jump	lazi	over	quick
count	1	1	1	1	1	1	1

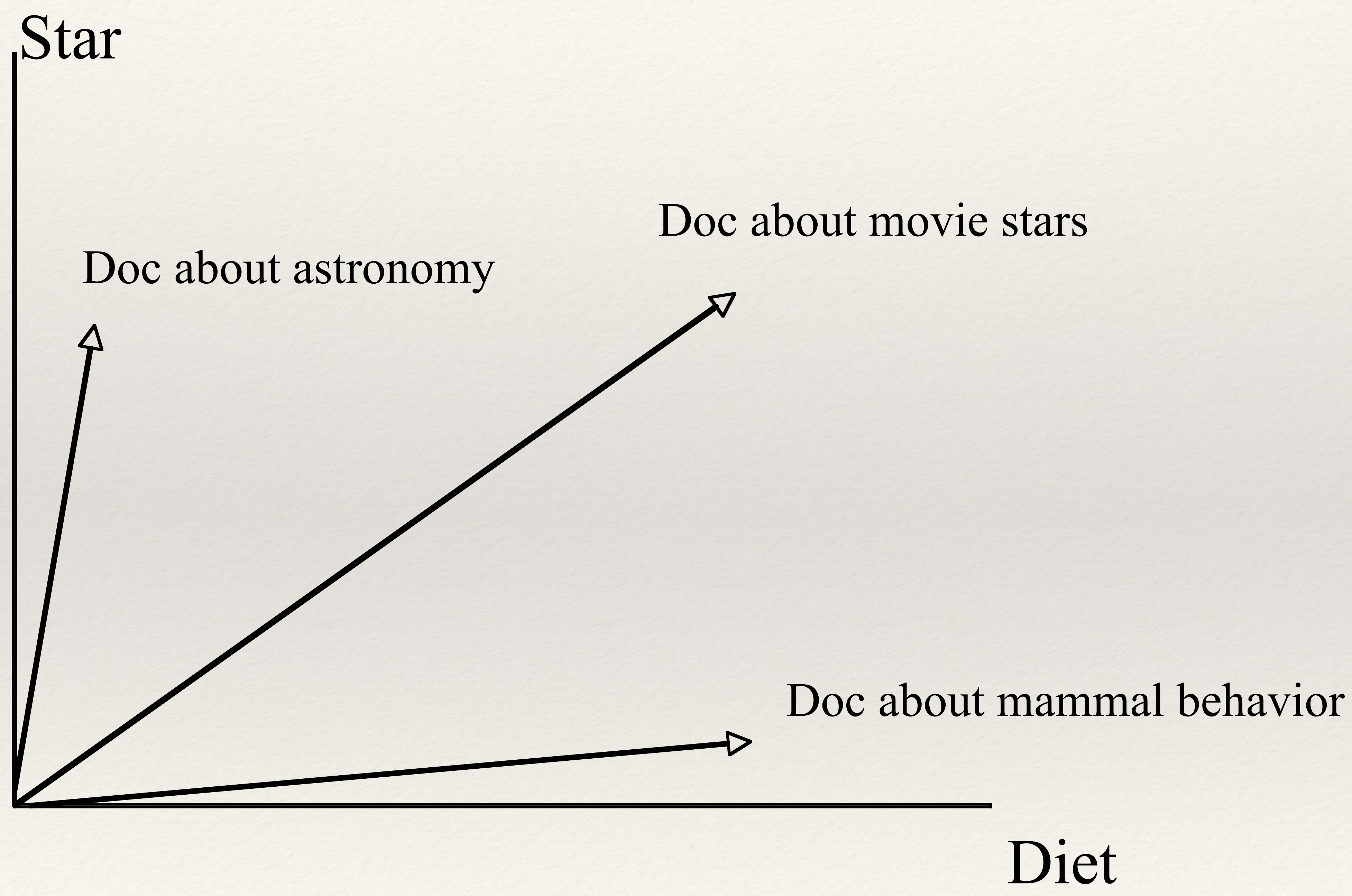
The Vector-Space Model

- Conceptually simple:
  - Model each document by a vector
  - Model each query by a vector
  - Assumption: documents that are "close together" in space are similar in meaning.
  - Use standard similarity measures to rank each document to a query in terms of decreasing similarity

Bag of Words Vectors

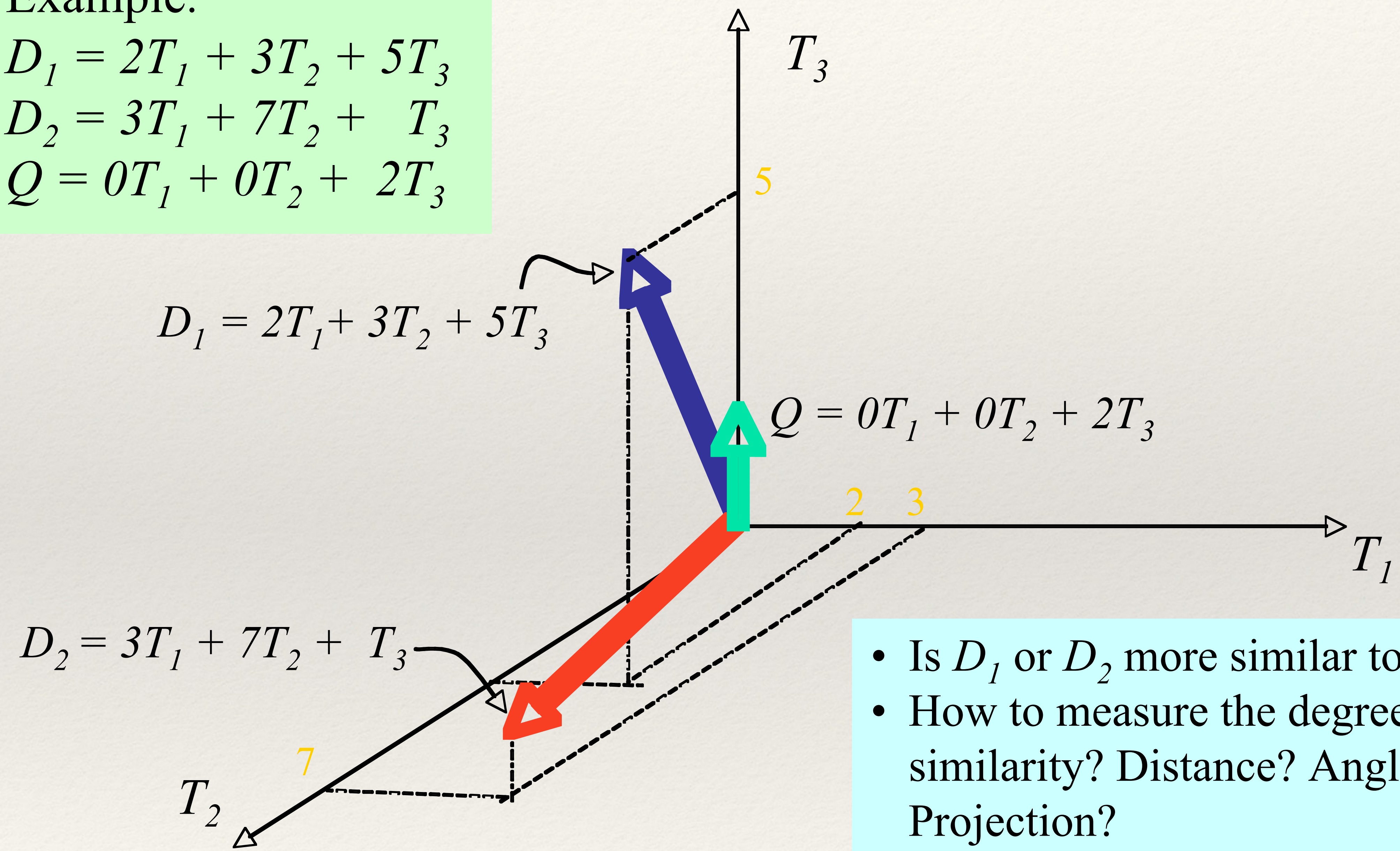
- The lexicon or vocabulary is the **set** of all (processed) words across all documents known to the system.
- We can create vectors for each document with as many dimensions as there are words in the lexicon.
  - Each word in the document's bag of words contributes a count to the corresponding element of the vector for that word.
    - In essence, each vector is a histogram of the word occurrences in the respective document.
    - **Vectors will have very high number of dimensions, but will be very sparse.**

The Vector-space Model



Searching the VSM

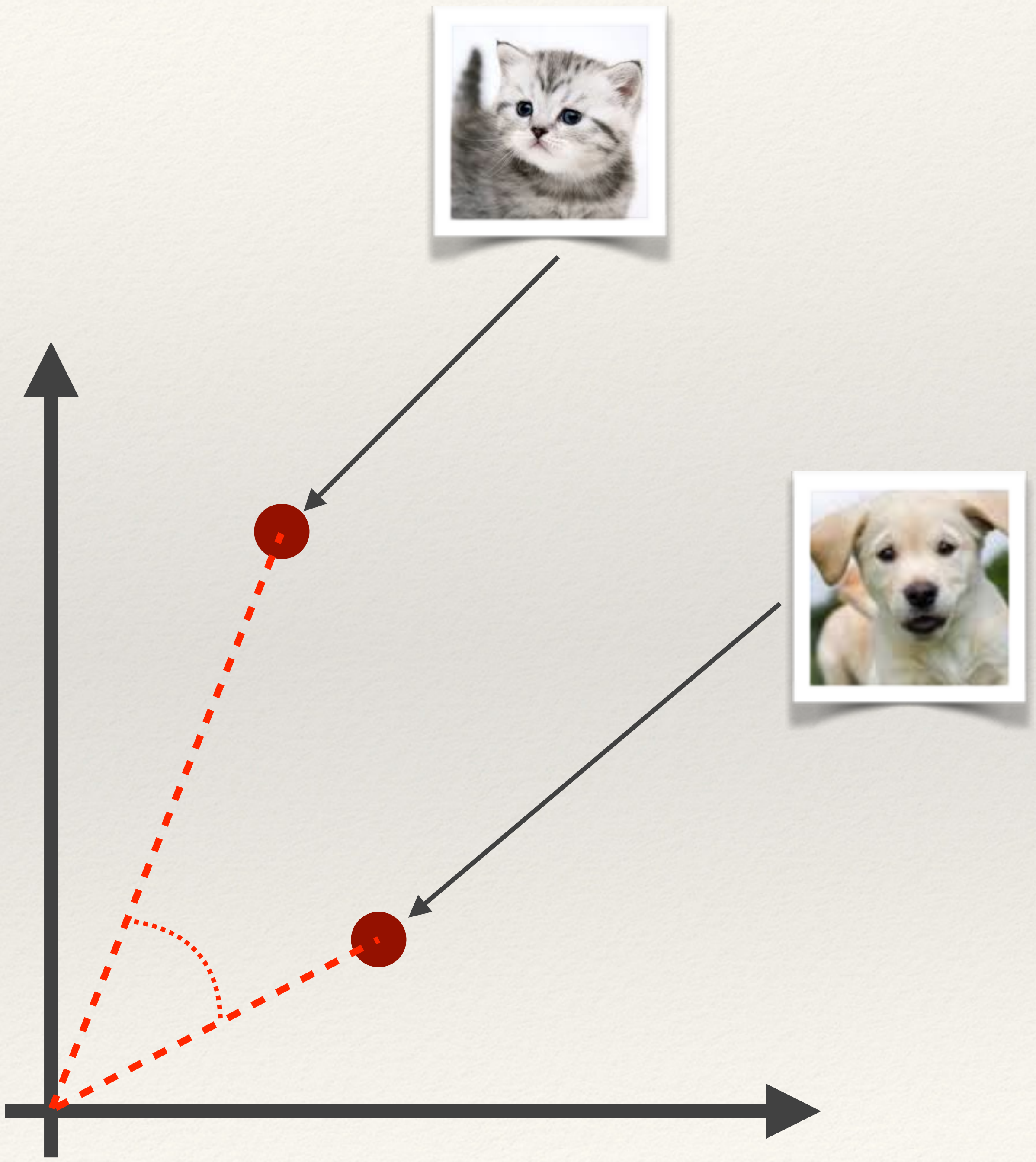
Example:
$D_1 = 2T_1 + 3T_2 + 5T_3$
$D_2 = 3T_1 + 7T_2 + T_3$
$Q = 0T_1 + 0T_2 + 2T_3$



- Is D_1 or D_2 more similar to Q?
- How to measure the degree of similarity? Distance? Angle? Projection?
- …cosine similarity

Recap: Cosine Similarity

$$cos(\theta) = \frac{p.q}{||p|| \, ||q||} = \frac{\sum_{i=1}^{n} p_i q_i}{\sqrt{\sum_{i=1}^{n} p_i^2} \sqrt{\sum_{i=1}^{n} q_i^2}}$$



Recap: Cosine Similarity

If *p* and *q* are both high dimensional and sparse, then you're going spend a lot of time multiplying 0 by 0 and adding 0 to the accumulator

$$cos(\theta) = \frac{p.q}{||p||\,||q||} = \frac{\sum_{i=1}^{n} p_i q_i}{\sqrt{\sum_{i=1}^{n} p_i^2}\sqrt{\sum_{i=1}^{n} q_i^2}}$$

These can be pre-computed and stored!

Inverted Indexes

Aardvark	[doc3:4]
Astronomy	[doc1:2]
Diet	[doc2:9; doc3:8]
…	
Movie	[doc2:10]
Star	[doc1:13; doc2:4]
Telescope	[doc1:15]

…A map of words to lists of postings…

Inverted Indexes

Aardvark	[doc3:4]
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…	
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A **posting** is a pair formed by a **document ID** and the **number of times** the specific word appeared in that document

Computing the Cosine Similarity

- For each word in the query, lookup the relevant postings list and accumulate similarities for only the documents seen in those postings lists
  - much more efficient than fully comparing vectors…

Query: “**Movie Star**”

Aardvark	[doc3:4]
Astronomy	[doc1:2]
Diet	[doc2:9; doc3:8]
…	
Movie	[doc2:10]
Star	[doc1:13; doc2:4]
Telescope	[doc1:15]

Query: “**Movie Star**”

Accumulation table:

doc2	10x1

Aardvark	[doc3:4]
Astronomy	[doc1:2]
Diet	[doc2:9; doc3:8]
…	
Movie	[doc2:10]
Star	[doc1:13; doc2:4]
Telescope	[doc1:15]

Query: “**Movie Star**”

Accumulation table:

doc2	$10\times1 + 4\times1$
doc1	13×1

Aardvark	[doc3:4]
Astronomy	[doc1:2]
Diet	[doc2:9; doc3:8]
…	
Movie	[doc2:10]
Star	[doc1:13; doc2:4]
Telescope	[doc1:15]

Query: "**Movie Star**"

Accumulation table:

doc2	(10×1 + 4×1) / 14.04 = **0.997**
doc1	13×1 / 19.95 = **0.652**
doc3	***0***

Aardvark	[doc3:4]
Astronomy	[doc1:2]
Diet	[doc2:9; doc3:8]
…	
Movie	[doc2:10]
Star	[doc1:13; doc2:4]
Telescope	[doc1:15]

Weighting the vectors

- The number of times a word occurs in a document reflects the importance of that word in the document.
- Intuitions:
  - A term that appears in many documents is not important: e.g., the, going, come, …
  - If a term is frequent in a document and rare across other documents, it is probably important in that document.

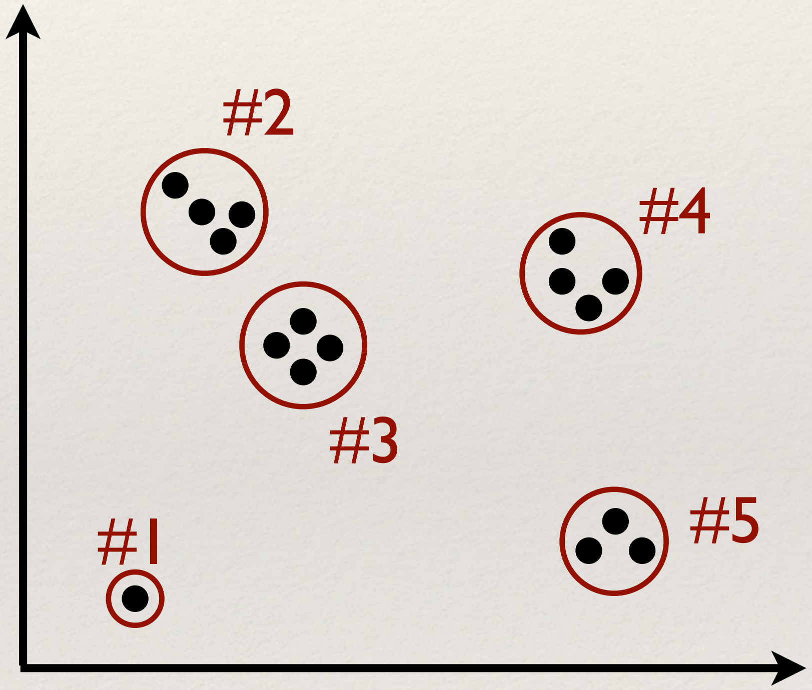
Possible weighting schemes

- Binary weights
  - Only presence (1) or absence (0) of a term recorded in vector.
- Raw frequency
  - Frequency of occurrence of term in document included in vector.
- TF-IDF
  - Term frequency is the frequency count of a term in a document.
  - Inverse document frequency (idf) provides high values for rare words and low values for common words.

Vector Quantisation

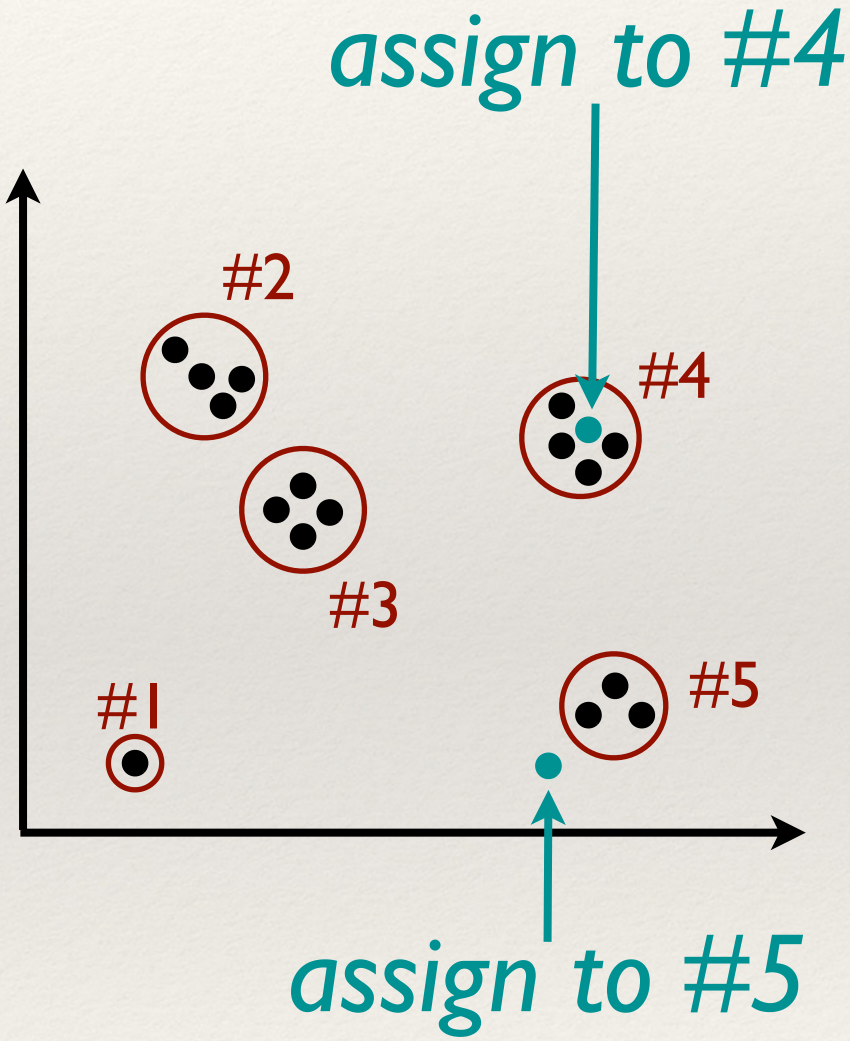
Learning a Vector Quantiser

- Vector quantisation is a lossy data compression technique.
- Given a set of vectors, a technique like K-Means clustering can be used to learn a fixed size set of representative vectors.
    - The representatives are the mean vector of each cluster in k-means
    - The set of representation vectors is called a **codebook**



Vector Quantisation

- Vector quantisation is achieved by representing a vector by another approximate vector, which
  is drawn from a pool of representative vectors.
  - Each input vector is assigned to the "closest" vector from the pool.



Visual Words

SIFT Visual Words

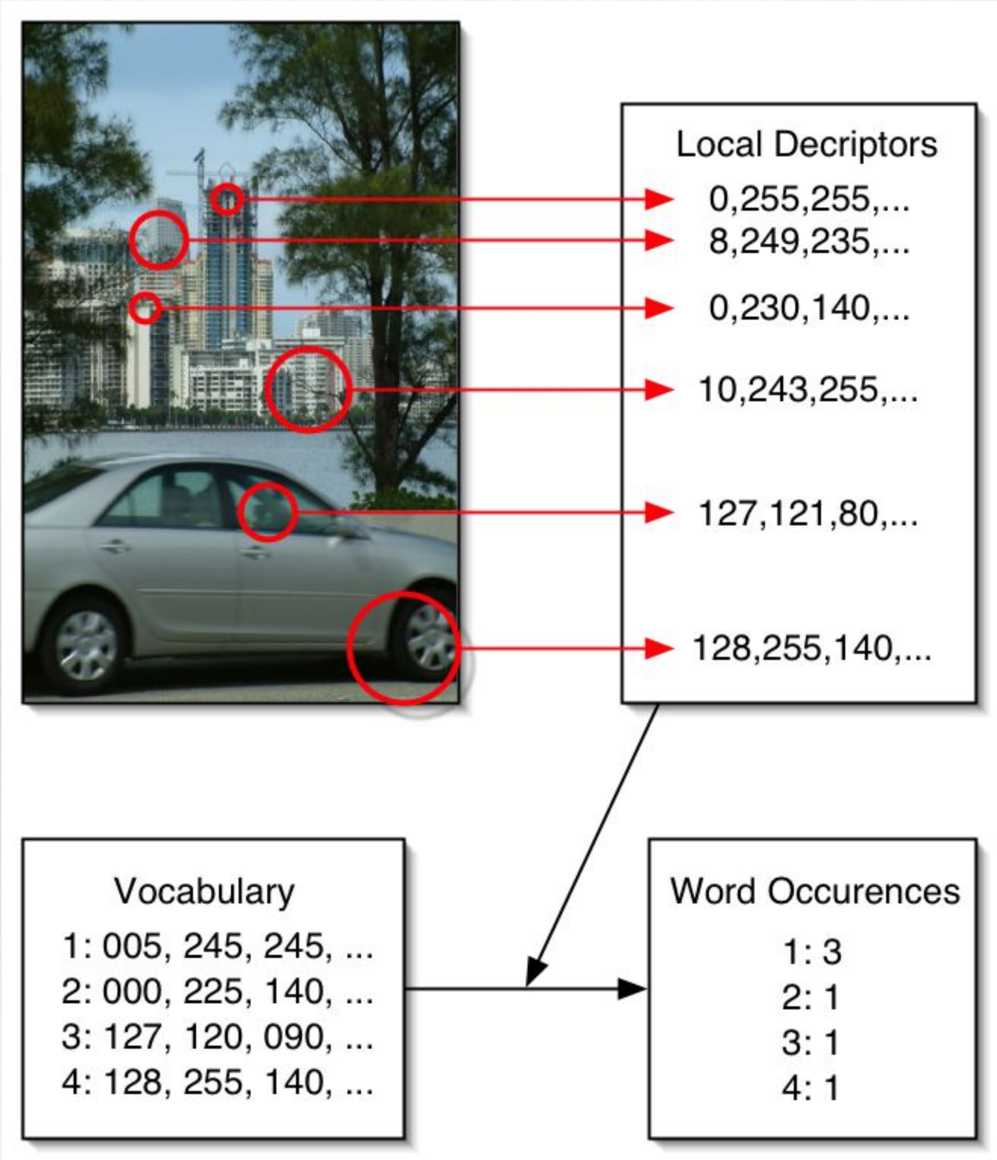
- We can vector quantise SIFT descriptors (or any other local feature)
  - Each descriptor is replaced by a representative vector known as a **visual word**
    - In essence the *visual word* describes a small image patch with a certain pattern of pixels
    - In many ways the process of applying vector quantisation to local features is analogous to the process of stemming words.
  - The codebook is the visual equivalent of a lexicon or vocabulary.

Bags of Visual Words

- Once we've quantised the local features into visual words, they can be put into a bag.
  - This is a **Bag of Visual Words (BoVW)**
  - We're basically ignoring where in the image the local features came from (including ignoring scale)

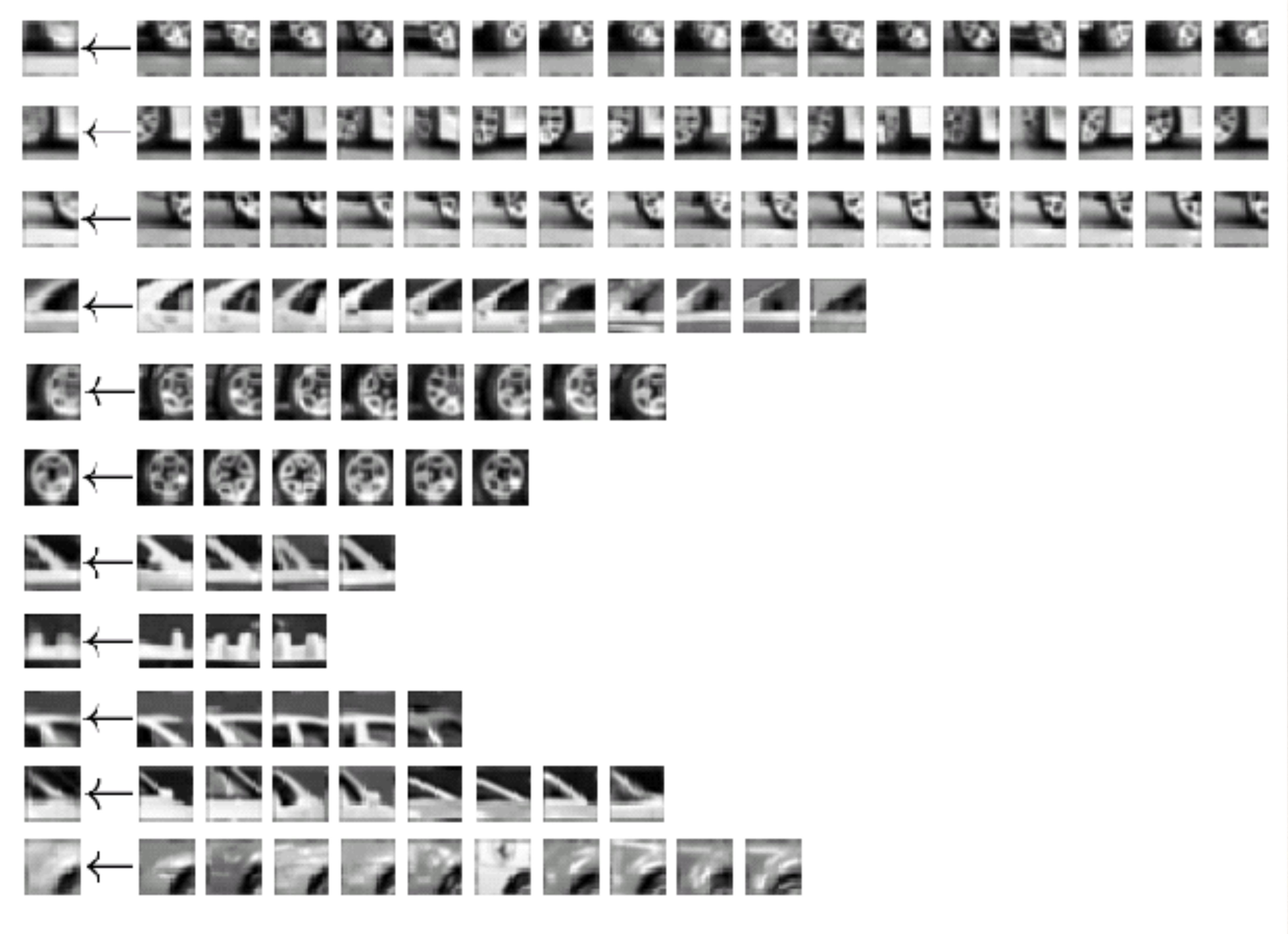
Histograms of Bags of Visual Words

- Like in the case of text, once we have a BoVW and knowledge of the complete vocabulary (the codebook) we can build histograms of visual word occurrences!
  - This is rather nice… it gives us a way of aggregating a variable number of local descriptors into a fixed length vector.
    - Useful for machine learning
    - But also allows us to apply techniques for text retrieval to images



Demo: SIFT visual word histogram

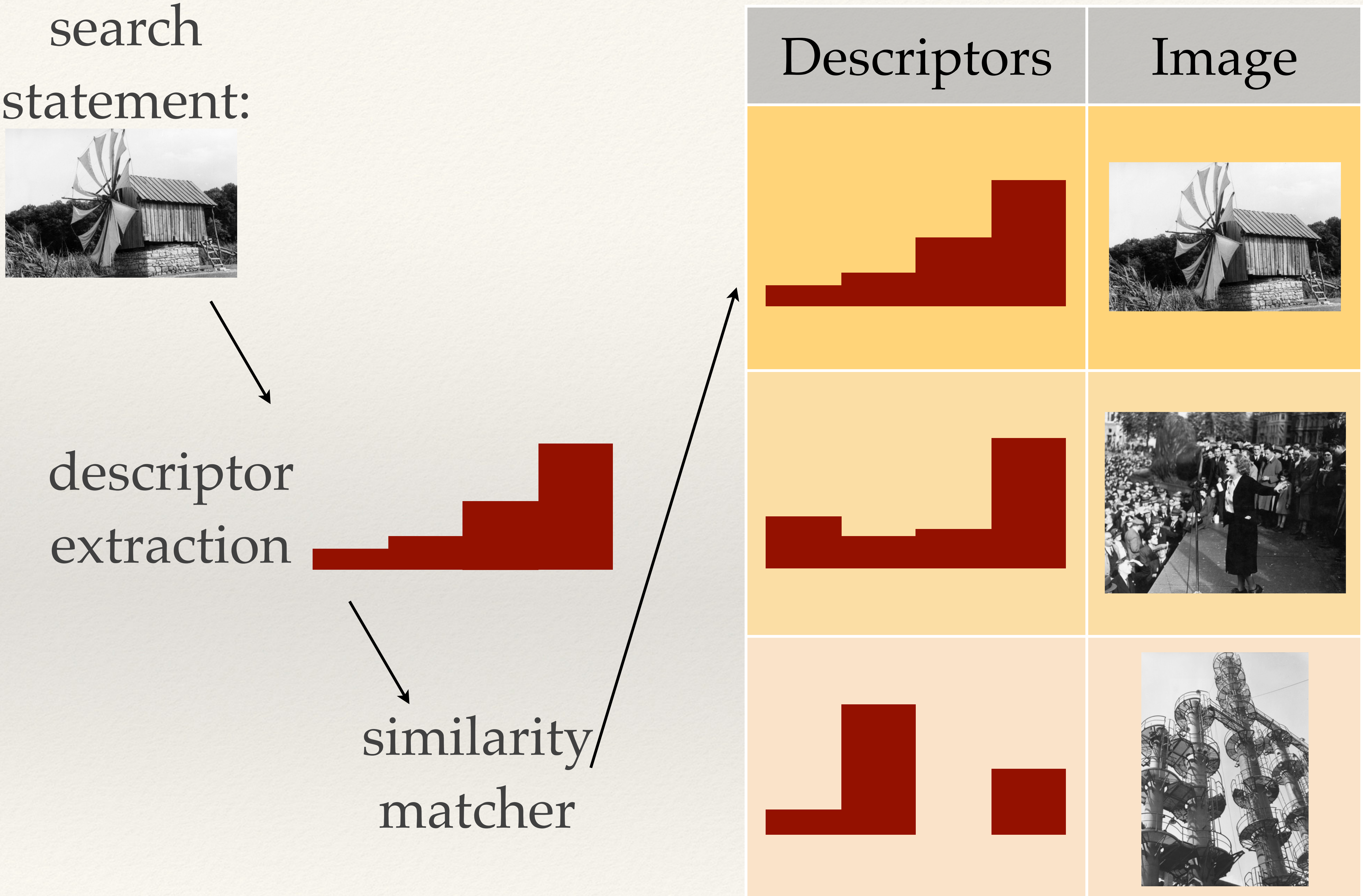
Visualising Visual Words



The effect of codebook size

- There is one **key parameter** in building visual words representations - **the size of the vocabulary**.
  - Too small, and all vectors look the same
    - Not distinctive
  - Too big, and the same visual words might never appear across images
    - Too distinctive

Content-based Image Retrieval


search statement:
descriptor extraction
similarity matcher
Descriptors
Image

BoVW Retrieval

- With the visual word representation, everything used for text retrieval can be applied directly to images
  - vector space model
  - cosine similarity
  - weighting schemes
  - inverted index

Optimal codebook size

- Inverted index only gives a performance gain if the vectors are sparse (you don't want to end up explicitly scoring all documents)
- Visual words also need to sufficiently distinctive to minimise mismatching
  - Implies a very big codebook
    - Modern research systems often use 1 Million or more visual words for SIFT vectors

Problems with big codebooks

- There's a slight problem…
  - Need to use k-means to learn 1 million clusters in 128 dimensions from 10's of millions of features
    - Non-trivial!
    - Vector quantisation has the same problems
      - Have to use approximate methods, like approximate k-d trees

Overall process for building a BoVW retrieval system

- Collect the corpus of images that are to be indexed and made searchable
- Extract local features from each image
- Learn a *large* codebook from (a sample of) the features
- Vector quantise the features, and build BoVW representations for each image
- Construct an inverted index with the BoVW representations

Demo: A BoVW retrieval system for geo-location estimation

Current research

- Lot of interest in content-based search for *massive* datasets
  - Two directions:
    - Hashing of local features
    - Tiny features (~16 bytes per image!)
      - Local features still used as the basis, but encoded in a different way to make dense features
        - Still uses k-means, but much smaller k
        - known as *VLAD: Vector of Locally Aggregated Descriptors*
        - VLAD descriptors then vector quantised using a "product quantiser"

Summary

- Effective and efficient text search can be achieved with bags of words, the vector-space model and inverted indexes.
- Vector-quantisation can be applied to local features, making them into visual words.
    - Then you can apply all the same techniques used for text to make efficient retrieval systems!
        - This is a good way of making highly scalable, effective and efficient content-based image retrieval systems