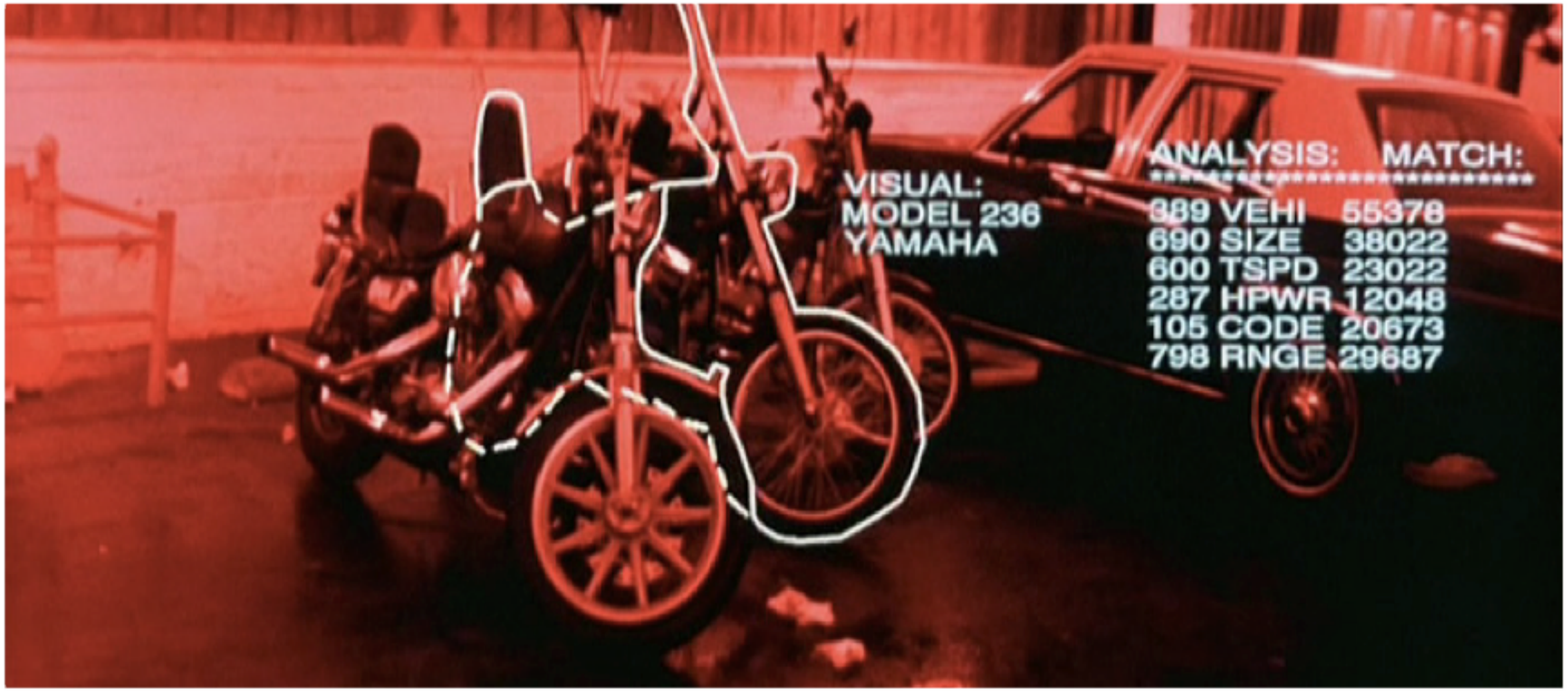

COMP3005: Computer Vision

Image search and classification

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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*

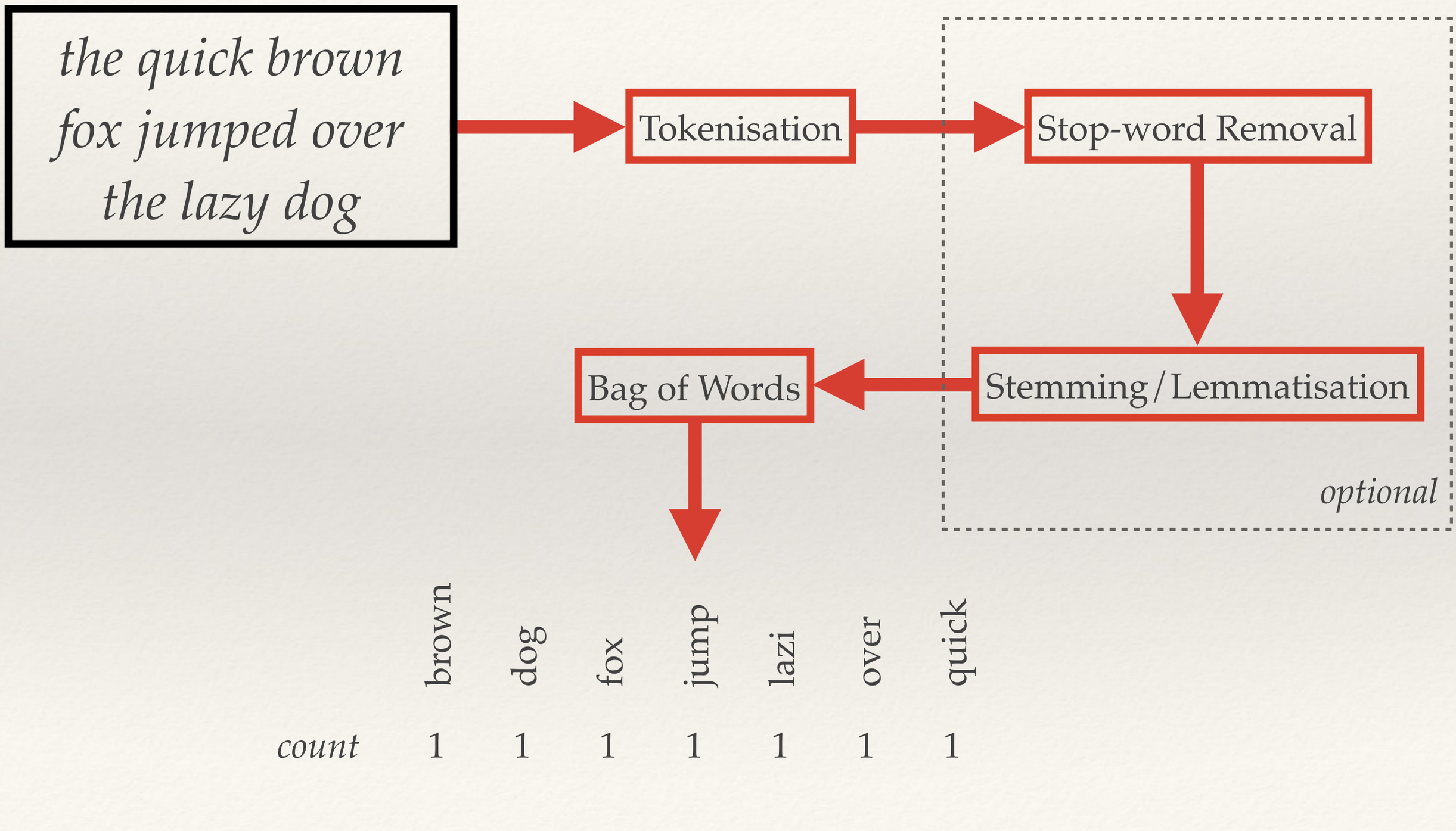
Bag of Words

A document

the quick brown fox jumped over the lazy dog

The bag of words describing the document

Text processing (feature extraction)



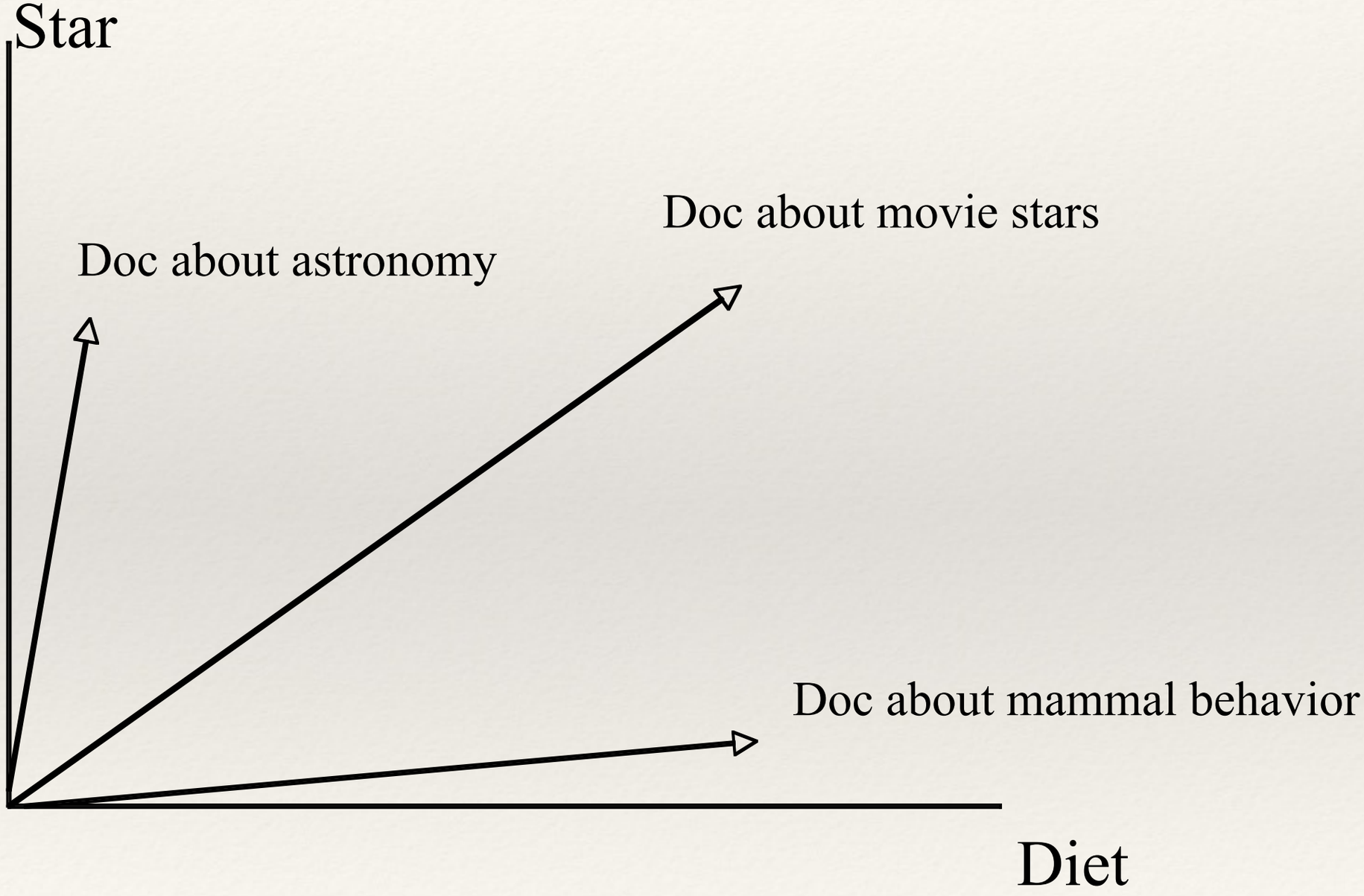
The Vector-Space Model

- 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



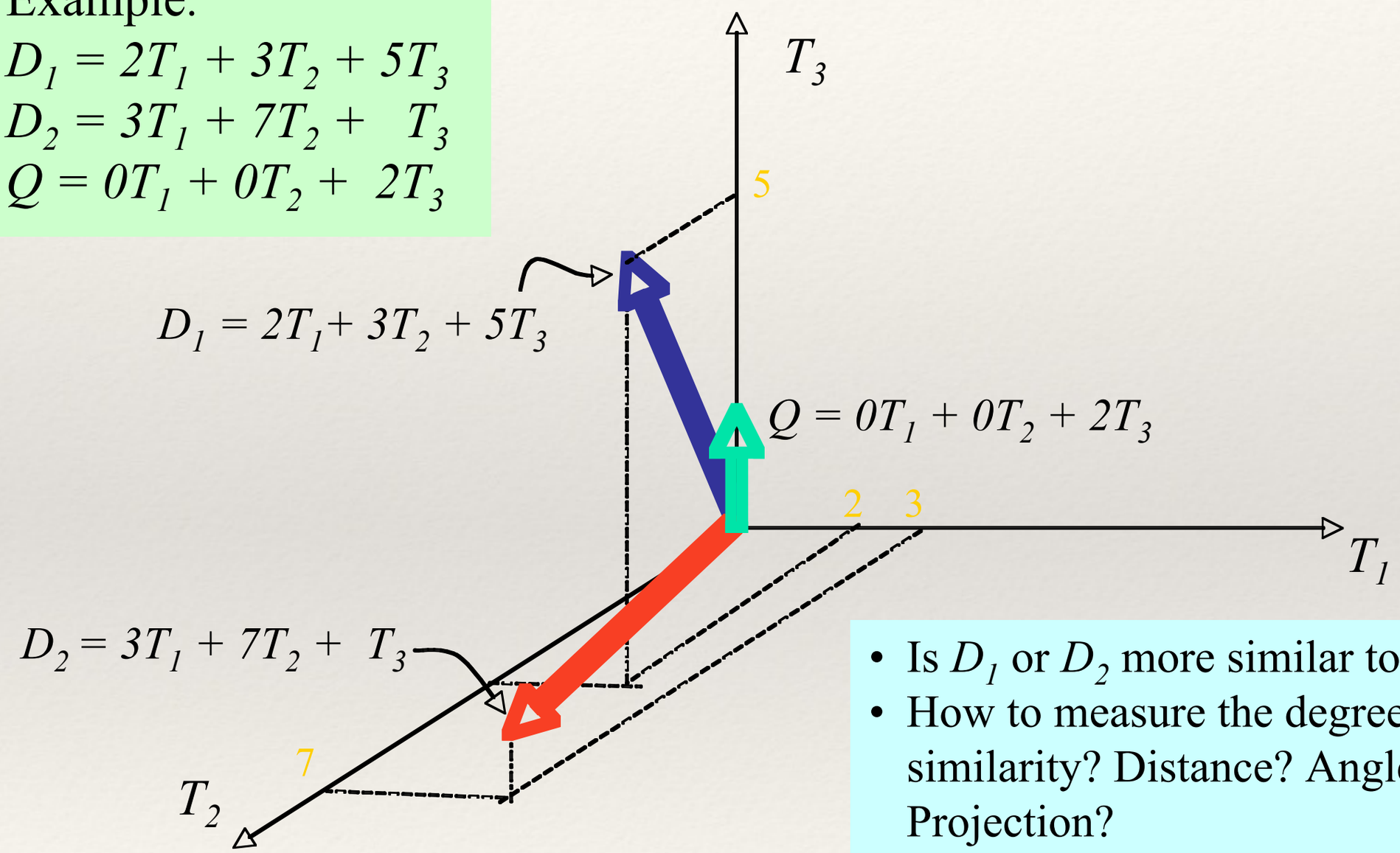
Searching the VSM

Example:

$D_1 = 2T_1 + 3T_2 + 5T_3$

$D_2 = 3T_1 + 7T_2 + T_3$

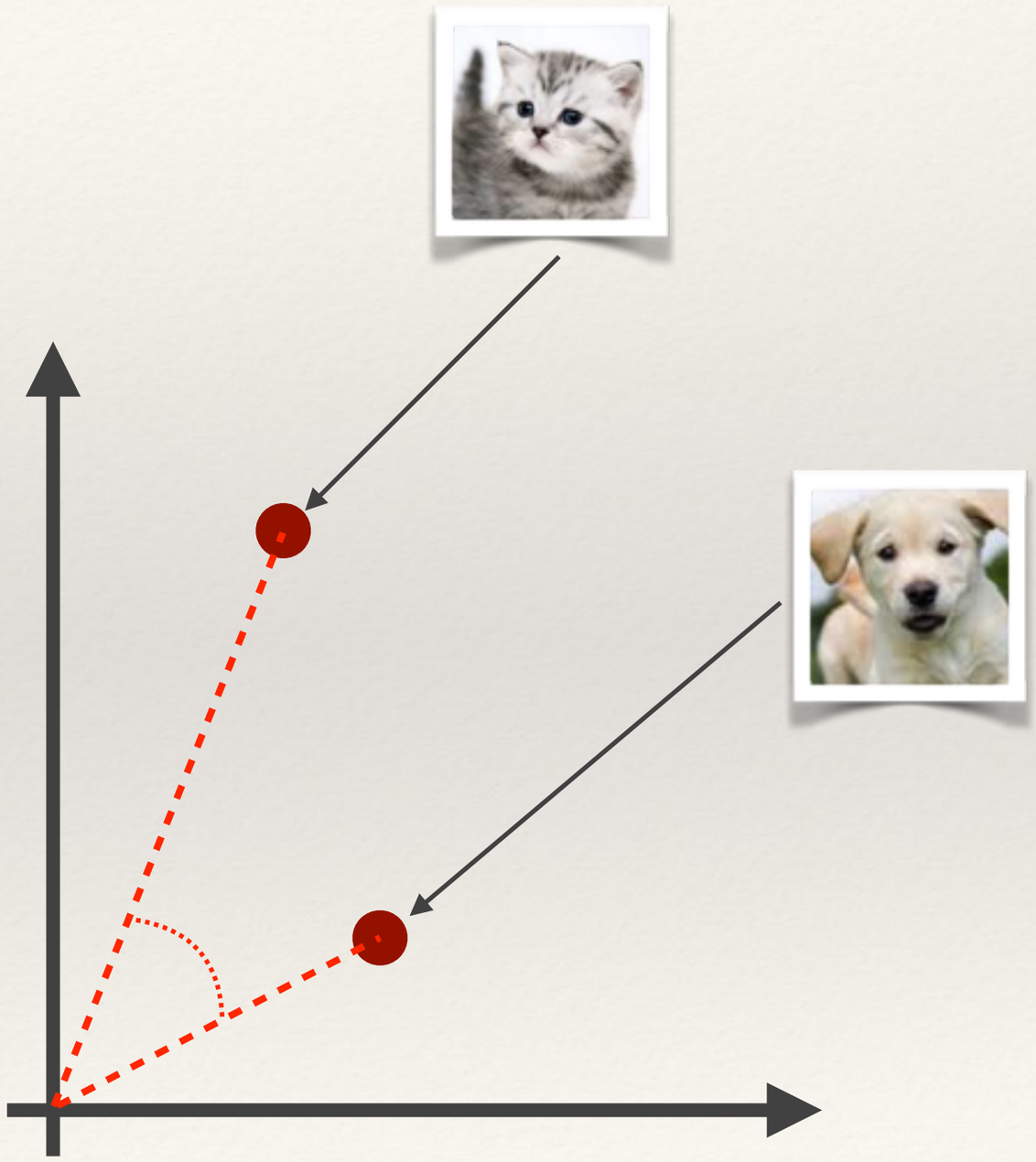
$Q = 0T_1 + 0T_2 + 2T_3$



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

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	10×1 + 4×1
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.

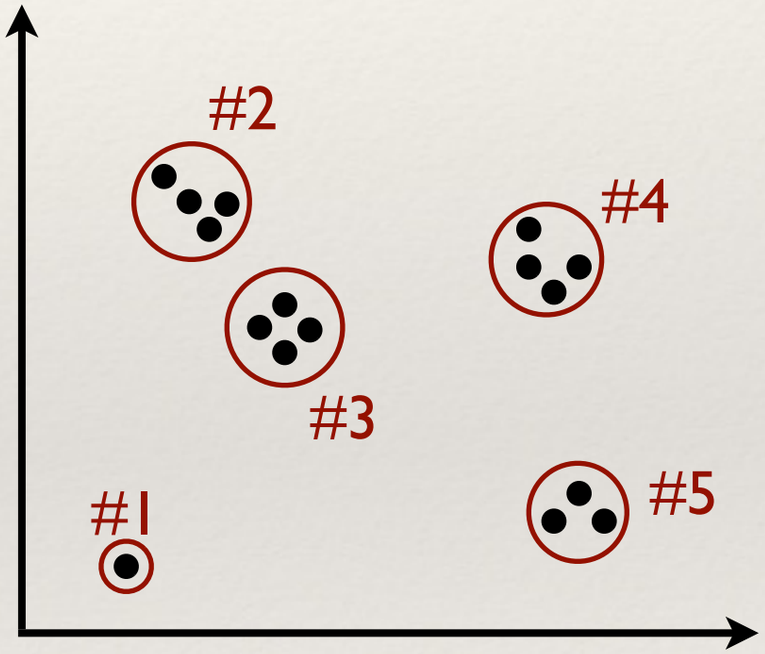
Possible weighting schemes

- 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

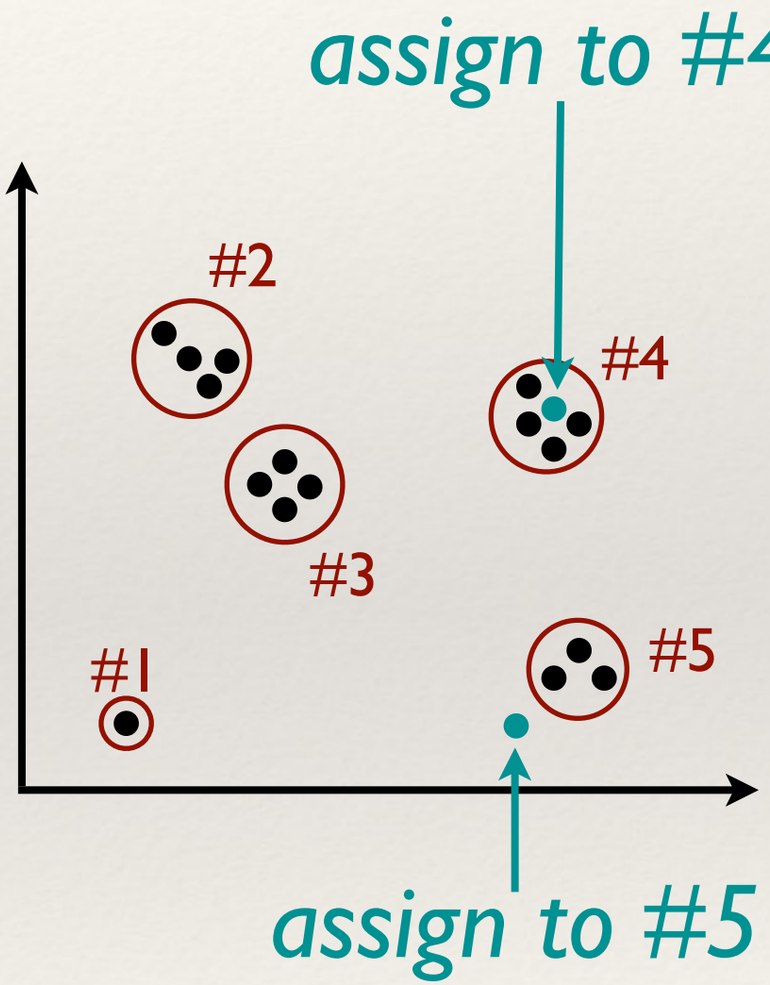
Learning a Vector Quantiser

- 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

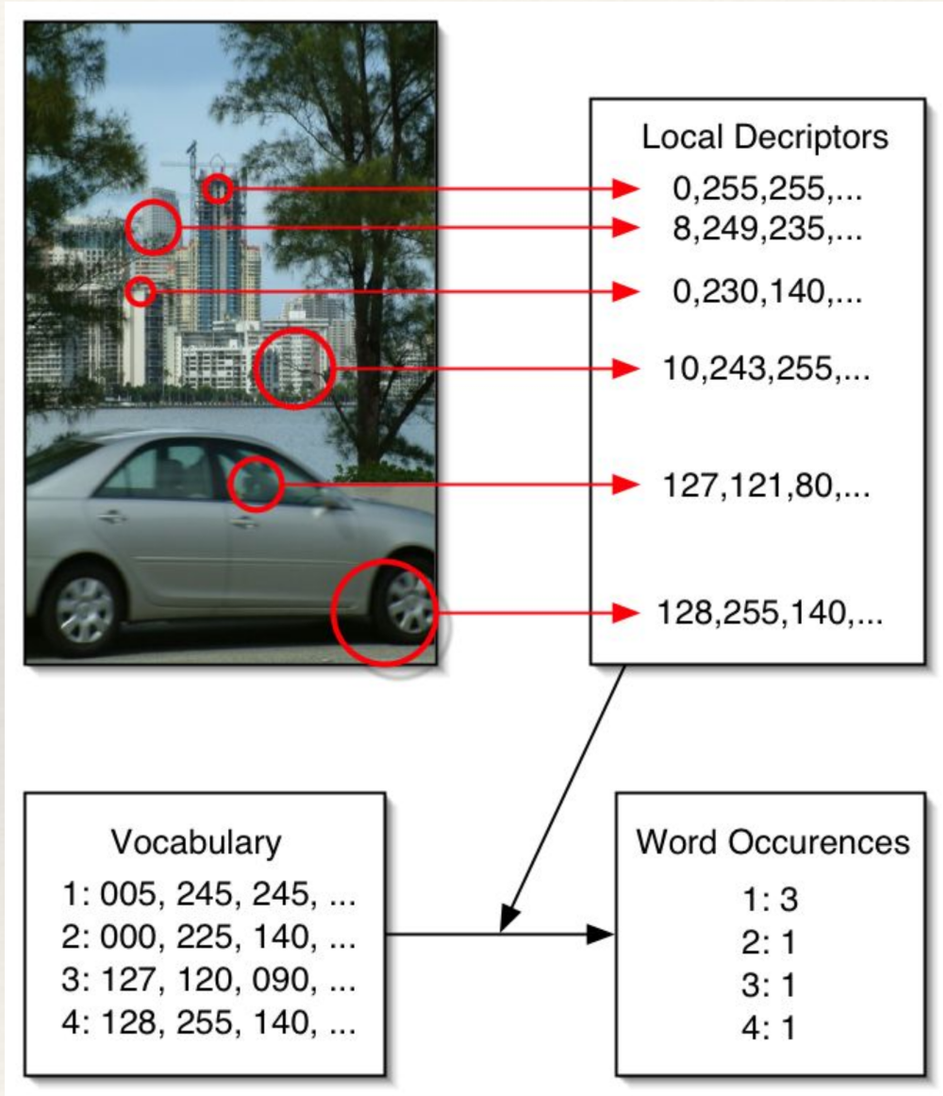
- We can vector quantise SIFT descriptors (or any other local feature)
  - Each descriptor is replaced by a representative vector known as a **visual word**
    - In essence the *visual word* describes a small image patch with a certain pattern of pixels
    - In many ways the process of applying vector 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)

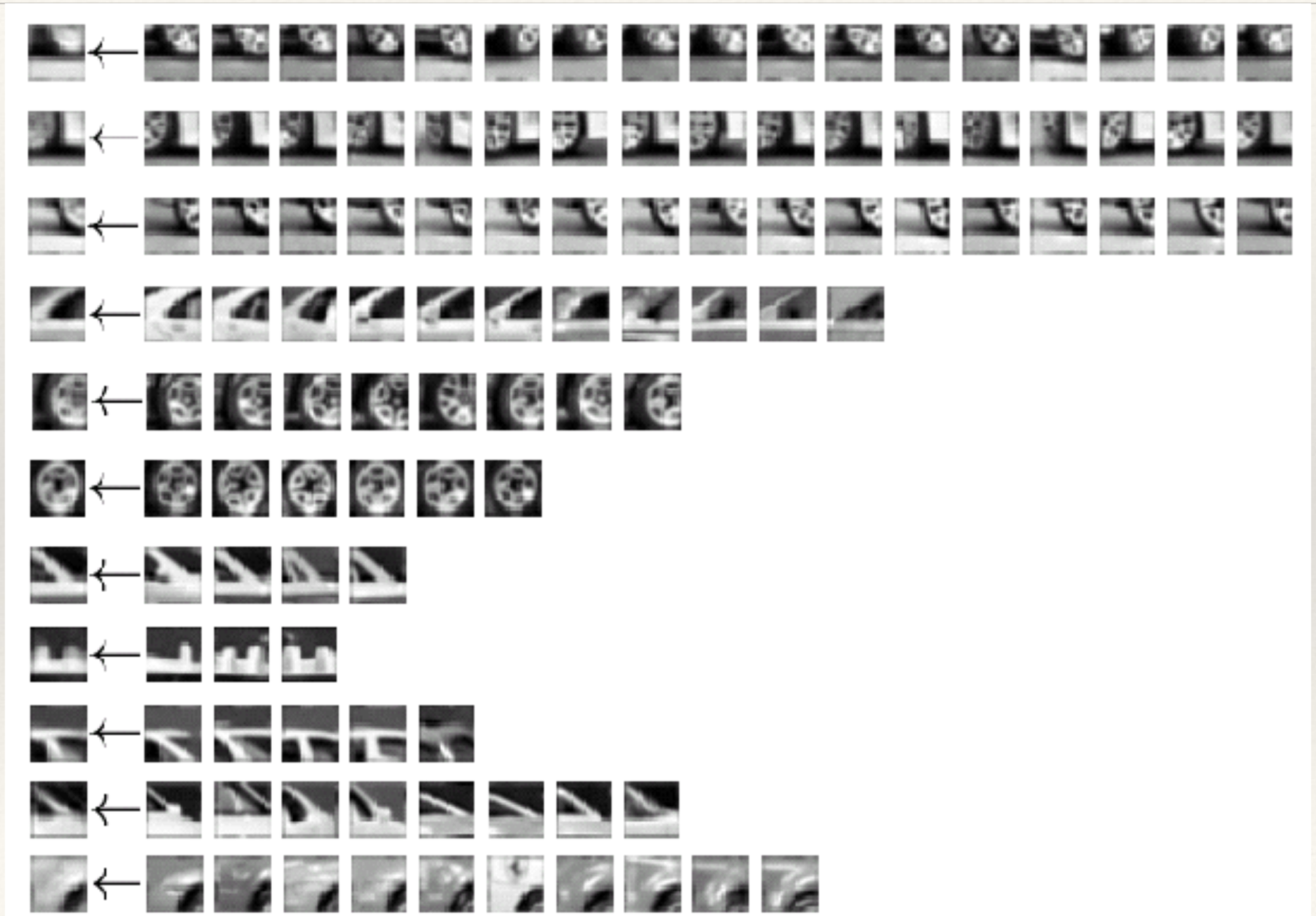
Histograms of Bags of Visual Words

- 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

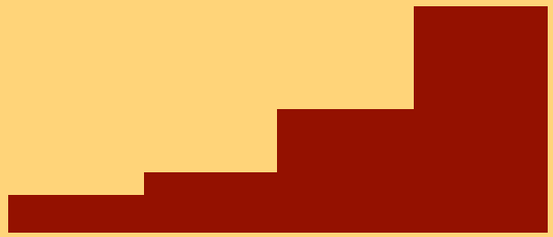
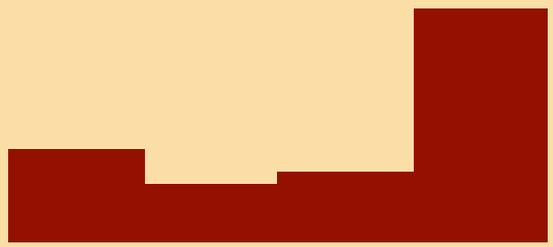
- There is one **key parameter** in building visual words representations - **the size of the vocabulary**.
  - Too small, and all vectors look the same
    - Not distinctive
  - Too big, and the same visual words might never appear across images
    - Too distinctive

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

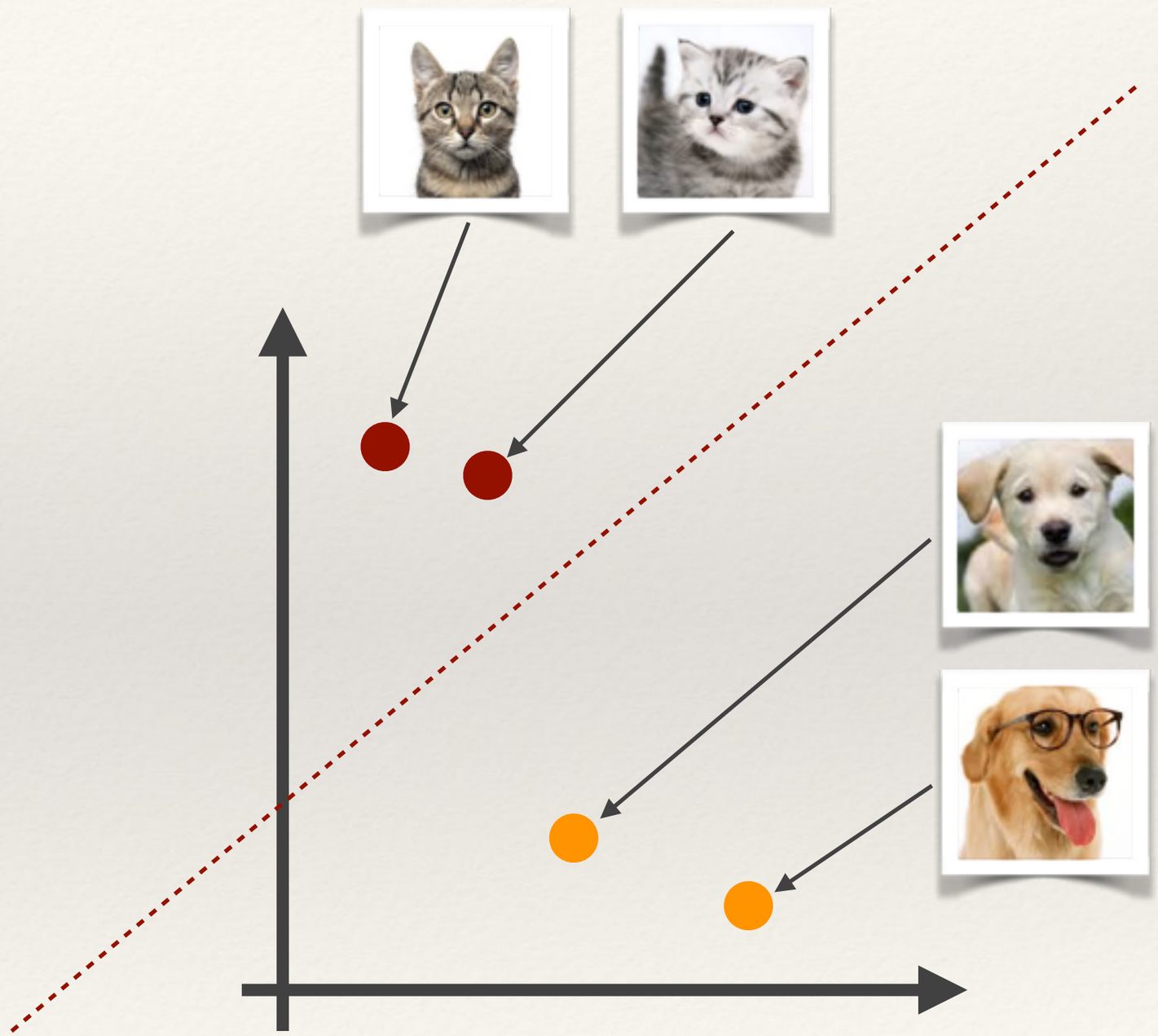
- Collect the corpus of images that are to be indexed and made searchable
- Extract local features from each image
- Learn a *large* codebook from (a sample of) the features
- Vector quantise the features, and build BoVW representations for each image
- Construct an inverted index with the BoVW representations

Demo: A BoVW retrieval system for geo-location estimation

BoVW Image Classification

Classifying with BoVW

- BoVW histogram representations are incredibly useful for image classification and object detection
  - Commonly used with linear classifiers and SVMs



Optimal codebook size

- The codebook vocabulary needs to be much smaller than for doing image search
  - In general, machine-learning techniques need much smaller vectors (for both performance and effectiveness)
  - The visual words can be allowed to be a less distinctive, allowing a little more variation between matching features.
  - Typically, the number of visual words might be as small as a few hundred, and up to a few thousand.

Improving classification performance

- Local features extracted around interest points work ok for classification, but there are alternative strategies that can work better…

Dense SIFT

Rather than extracting your SIFT features at DoG interest points, you could extract them across a dense grid - this gives much more coverage of the entire image.

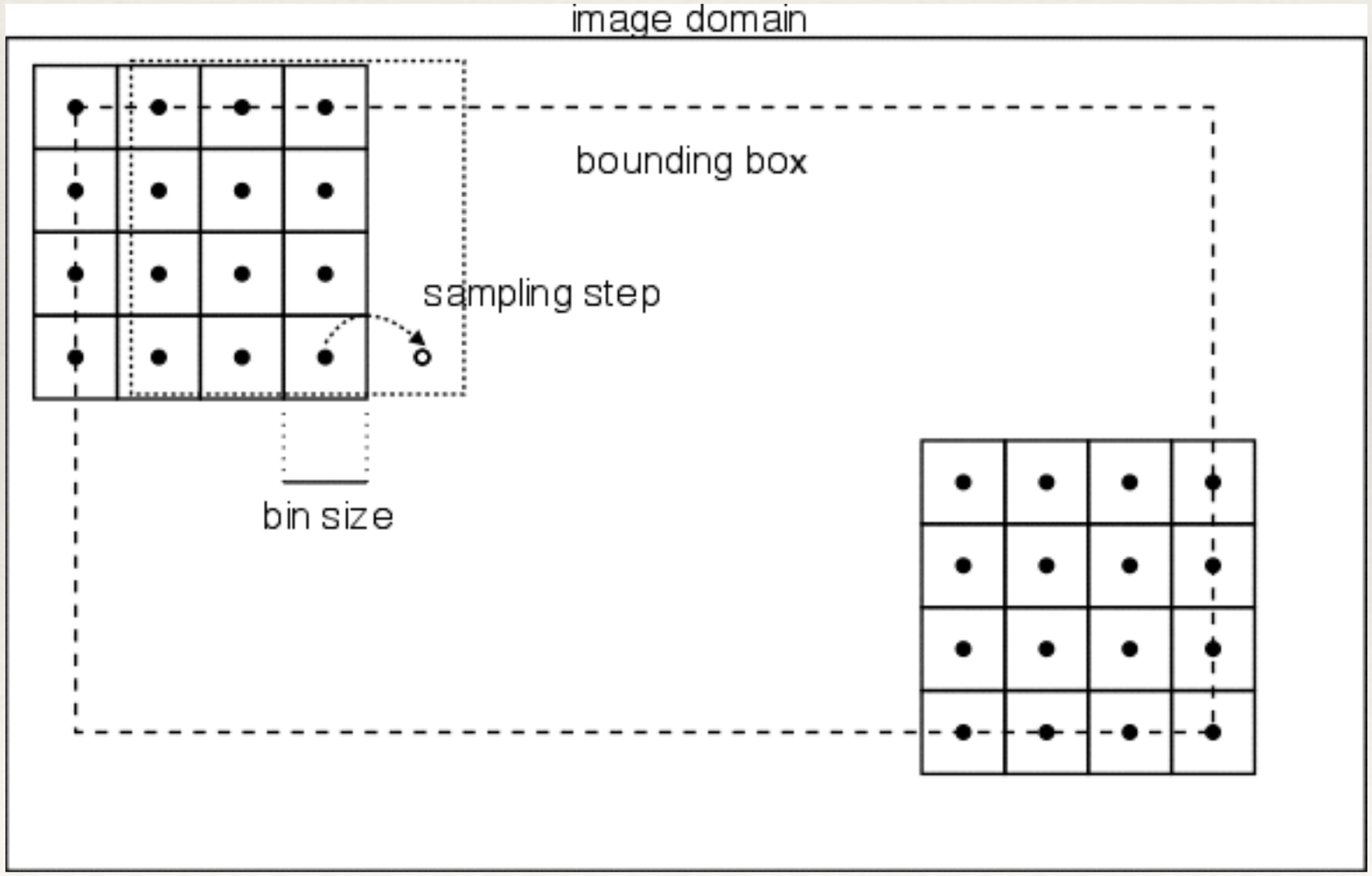
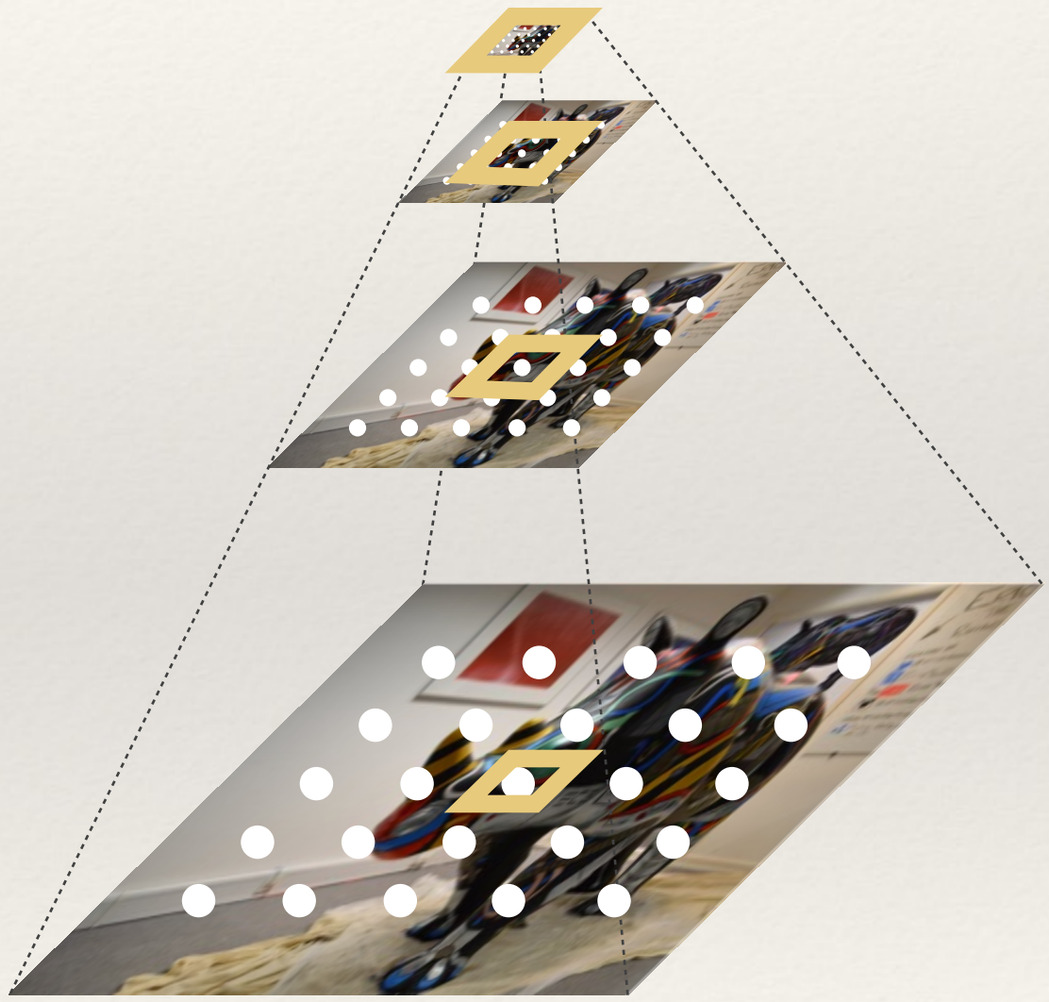


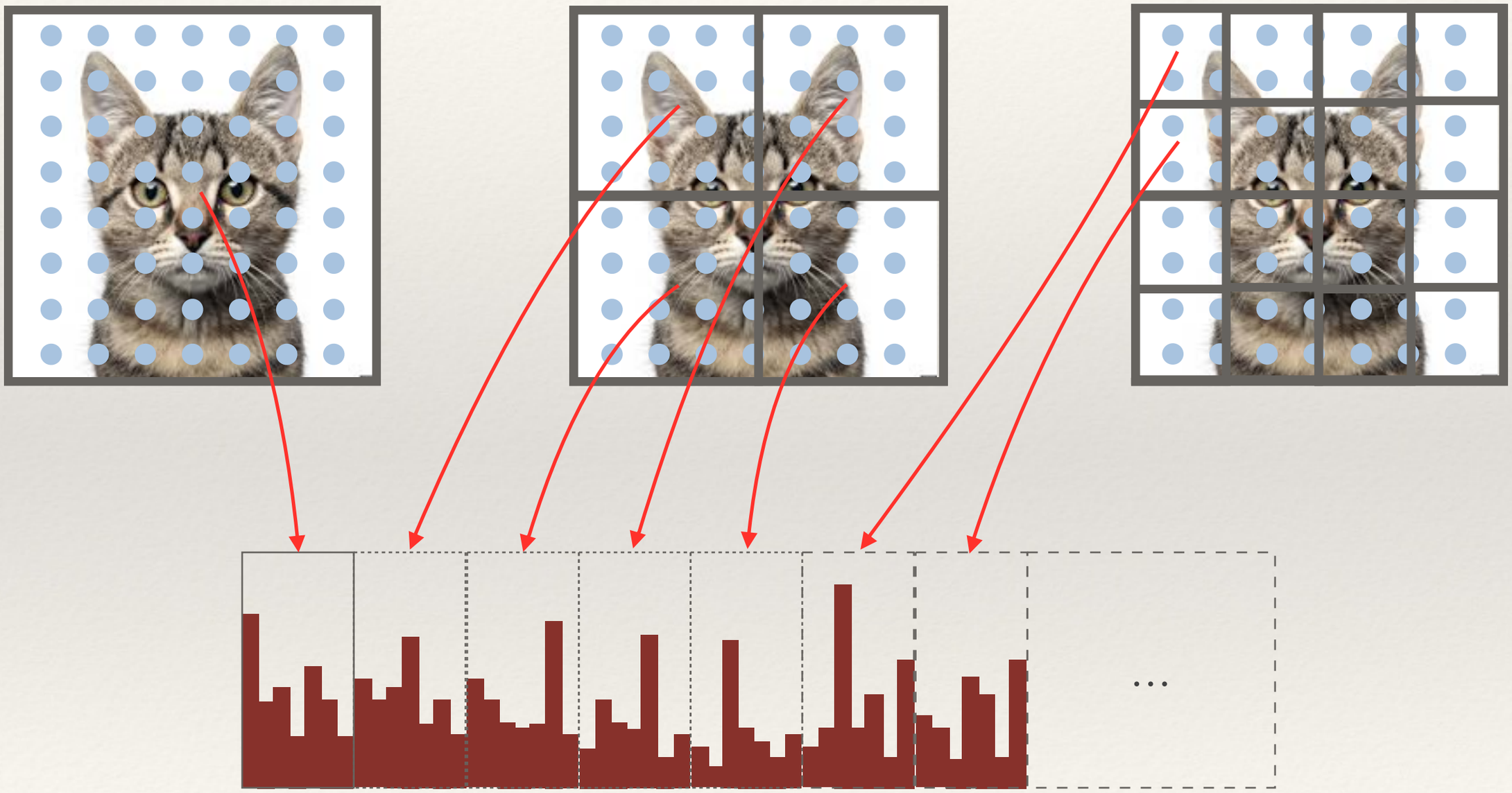
Image from http://www.vlfeat.org/api/dsift.html

Pyramid Dense SIFT

- For even better performance and coverage, you can sample in a Gaussian pyramid
- Note that the sampling region is a fixed size, so at higher scales you sample more content



Spatial Pyramids



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!