Content retrieval

Structured vs. unstructured content

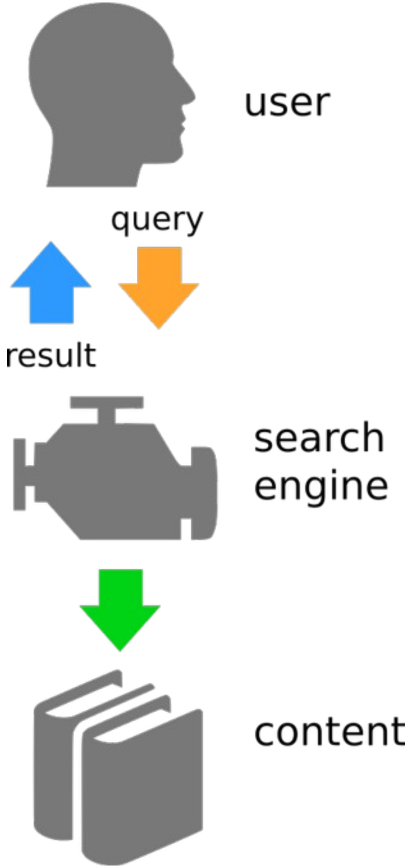
- Structured content
  - Relational databases (SQL)
  - NoSQL databases (JSON)
- Searching unstructured content in large databases
  - Text
  - Images
  - Video
  - Sound

Overview

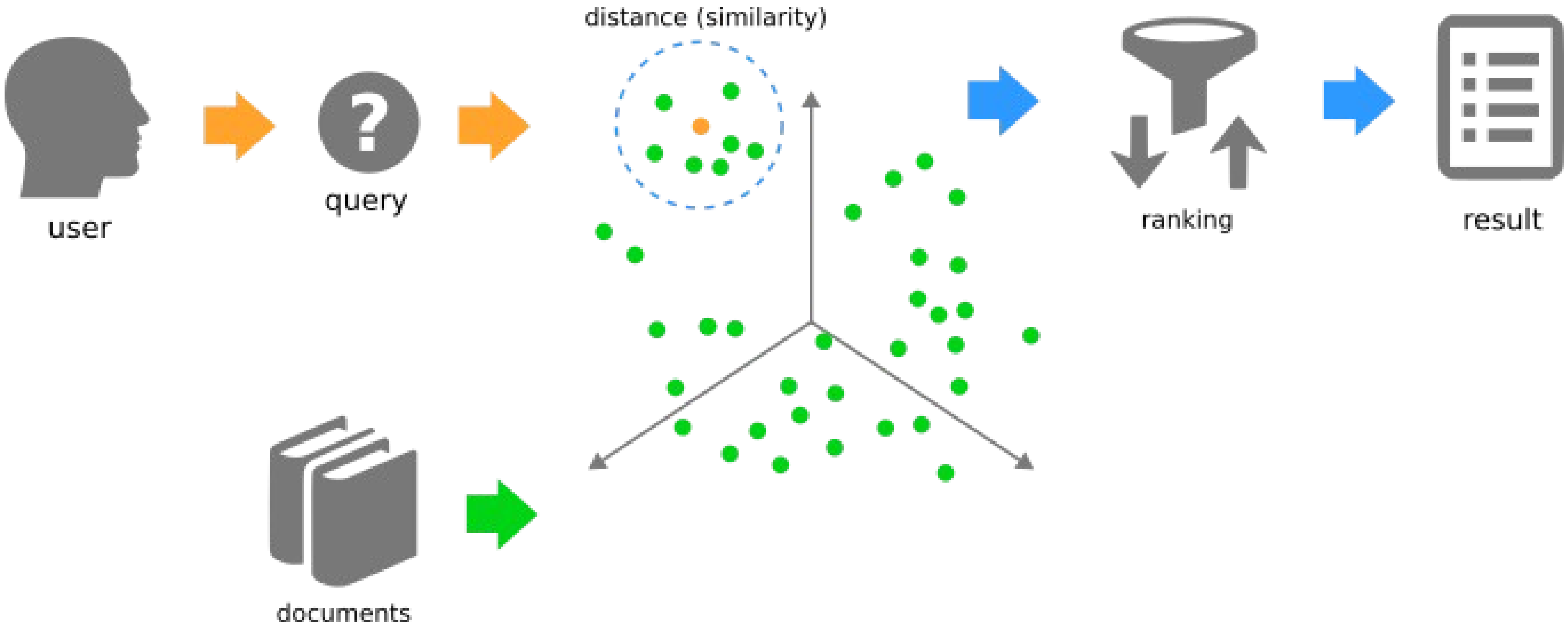
- Text retrieval
  - Search using Boolean expressions
  - Building search dictionary
  - Document similarity
  - Feedback loops
- Multimedia retrieval
  - Search for visual media
  - Search for audio
- Retrieval sysems evaluation

Conceptual model

- Content retrieval steps
  - User submits a query
    (how to use language to specify what we are looking for?)
  - Compose and rank results based on the data
    (how to match query with documents?)
  - User evaluates results
    (how to optimize the query for better experience?)
- Iteration of steps can improve results quality



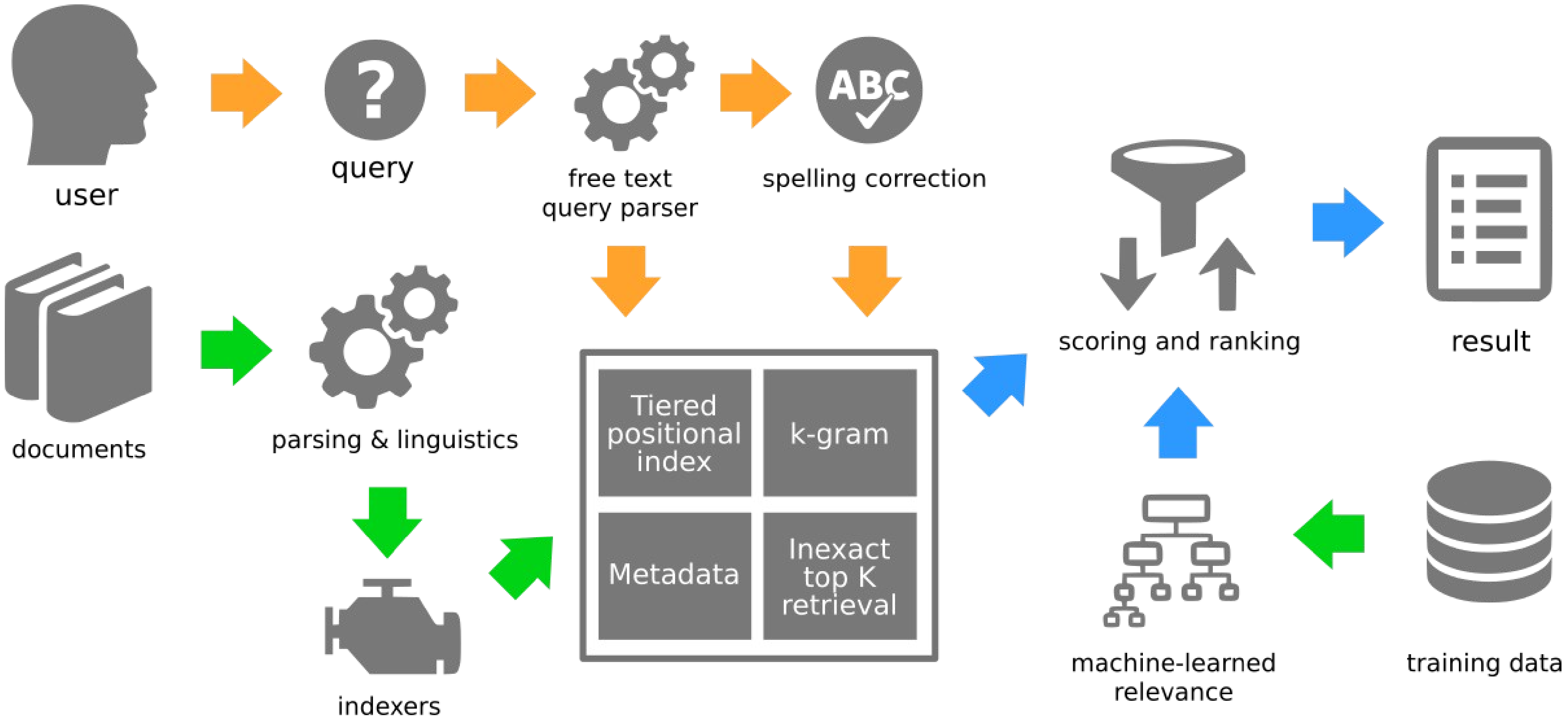
Representation matching



Search engine challenges

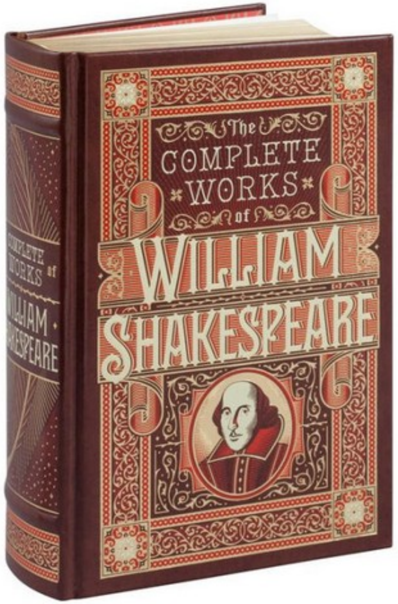
- Data is unstructured
  - Not suitable for direct retrieval
  - Describing important content
- Multiple ways to set up the same query
  - Recognize intent
  - Handle ambiguity
- Large quantities (data and queries)

Document search engine



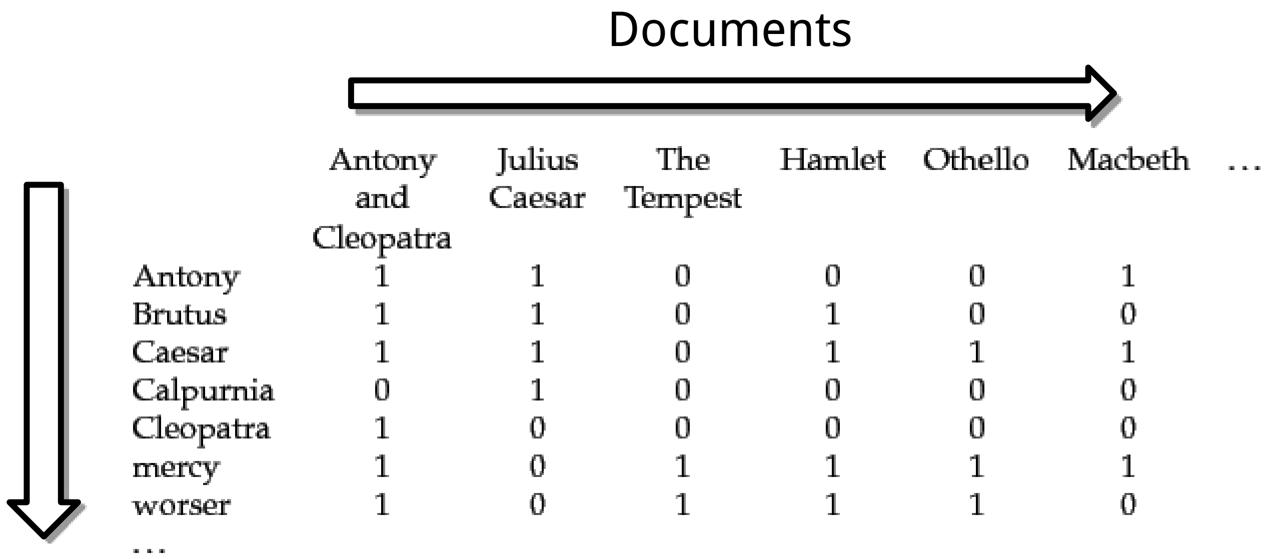
Searching using Boolean expressions

- Shakespeare – The Complete Works
- Which plays contain words Brutus and Caesar, but do not contain word Calpurnia?
- Naive approach:
  - Sequentially scan text of all plays
  - Takes a lot of time (especially on large databases)
- Better approach: pre-index all documents



Incidence matrix

For each term remember which documents contain it



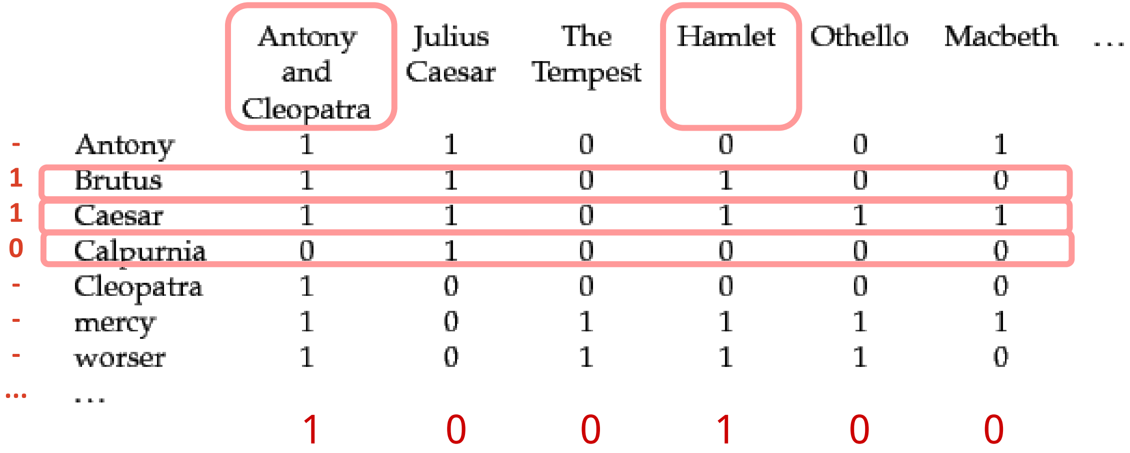
Documents

Terms

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth	…
Antony	1	1	0	0	0	1	
Brutus	1	1	0	1	0	0	
Caesar	1	1	0	1	1	1	
Calpurnia	0	1	0	0	0	0	
Cleopatra	1	0	0	0	0	0	
mercy	1	0	1	1	1	1	
worser	1	0	1	1	1	0	
…							

Retrieval example

- Query: »Brutus AND Caesar AND NOT Calpurnia«
- Obtain binary vectors for all three terms, negate the last one and join them with AND:

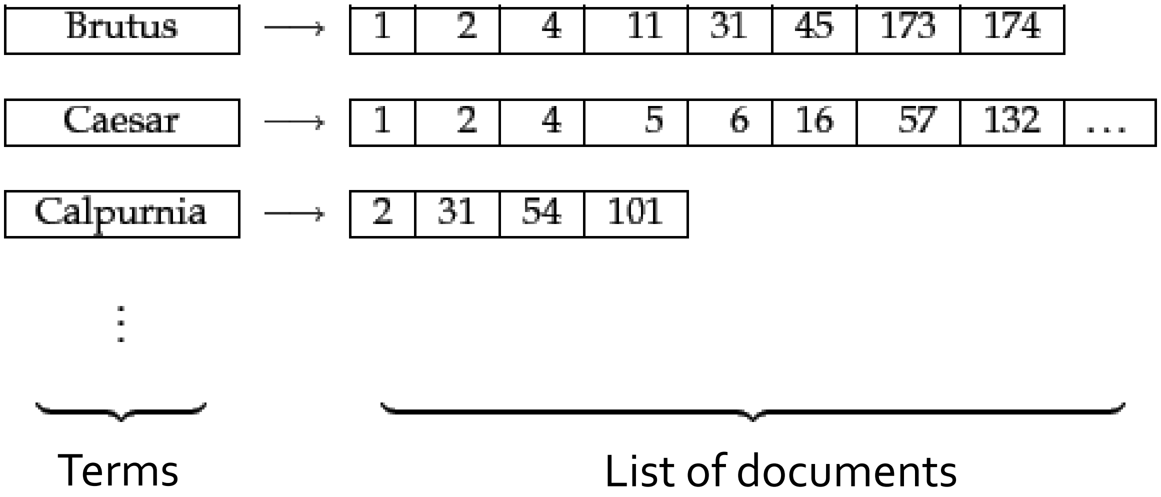


		Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth	…
-	Antony	1	1	0	0	0	1	
1	Brutus	1	1	0	1	0	0	
1	Caesar	1	1	0	1	1	1	
0	Calpurnia	0	1	0	0	0	0	
-	Cleopatra	1	0	0	0	0	0	
-	mercy	1	0	1	1	1	1	
-	worser	1	0	1	1	1	0	
…	…							
		1	0	0	1	0	0	

- Limitation: computer memory

Inverted index

- Incidence matrix is sparse
- Per-term list of documents that include the term



Brutus → 1 | 2 | 4 | 11 | 31 | 45 | 173 | 174

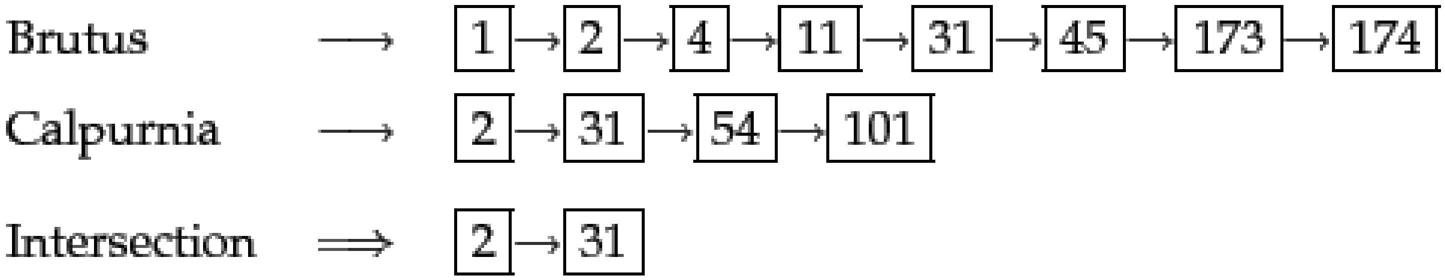
Caesar → 1 | 2 | 4 | 5 | 6 | 16 | 57 | 132 | ...

Calpurnia → 2 | 31 | 54 | 101

⋮

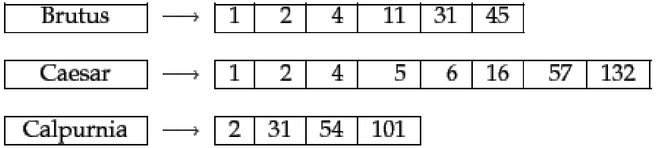
Processing queries

- Query: »Brutus AND Calpurnia«
- Find lists of documents that include »Brutus« and »Calpurnia«
- Compute intersection of lists (linear complexity for ordered lists)


Brutus ⟶ 1 → 2 → 4 → 11 → 31 → 45 → 173 → 174
Calpurnia ⟶ 2 → 31 → 54 → 101
Intersection ⟹ 2 → 31

Optimizing queries

- **AND query**: »Brutus AND Caesar AND Calpurnia«
  - Reduce number of comparisons – start with two least frequent terms



Brutus → 1 2 4 11 31 45

Caesar → 1 2 4 5 6 16 57 132

Calpurnia → 2 31 54 101

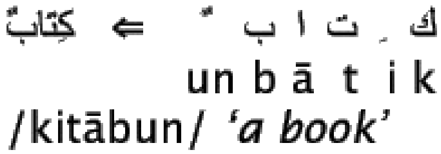
  - Optimized: »(Calpurnia AND Brutus) AND Ceasar«
- **OR query**: »(madding OR crowd) AND (killed OR slain)«
  - Sum terms in OR relation to obtain conservative estimates of combined lists
  - Sort AND queries based on the estimates

Choosing the »document« unit

- Granularity
  - Are documents files? (MS Word, LibreOffice, ...)
  - What about mailbox file full of emails? (Thunderbird, Outlook)
  - Attachments in email messages?
- Fine-grained – bad recall of relevant documents
- Coarse-grained – recall opacity
- Document selection depends on the use-case
- We can also search at multiple granularity levels

Decoding content

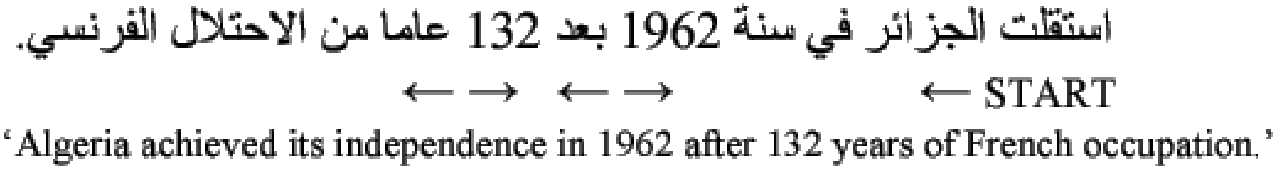
- Text is a sequence of bytes
- Different encoding schemes: ASCII, UTF-8, …
- Is text a linear, unambiguous sequence of characters?



ك ِ ت ا ب ٌ ⇐ كِتابٌ

un b ā t i k

/kitābun/ *'a book'*



استقلت الجزائر في سنة 1962 بعد 132 عاما من الاحتلال الفرنسي.

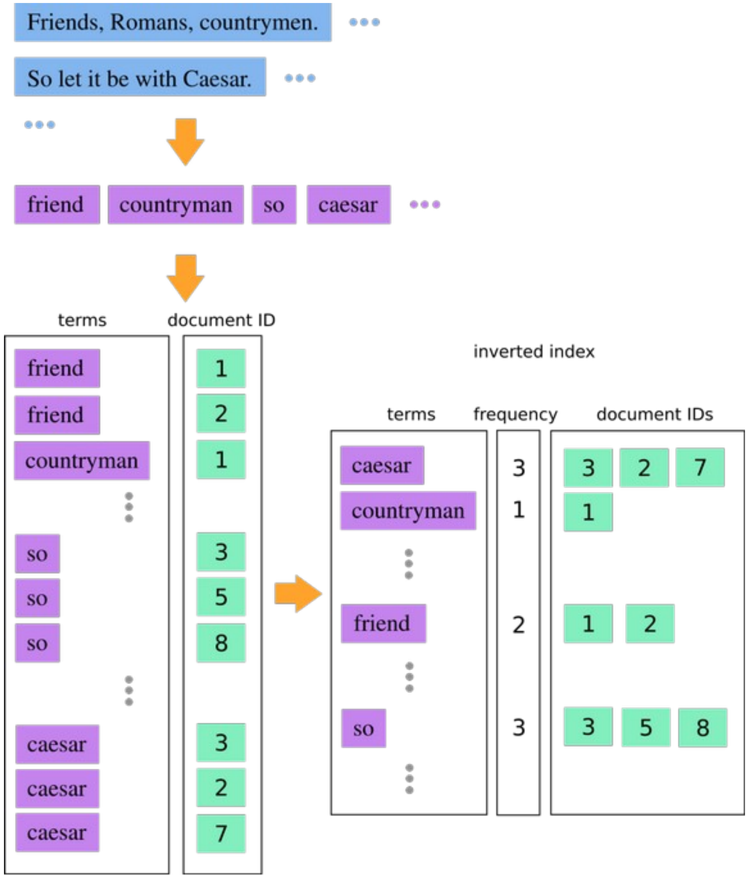
← → ← → ← START

'Algeria achieved its independence in 1962 after 132 years of French occupation.'

- Other modalities even more complicated (e.g. images)

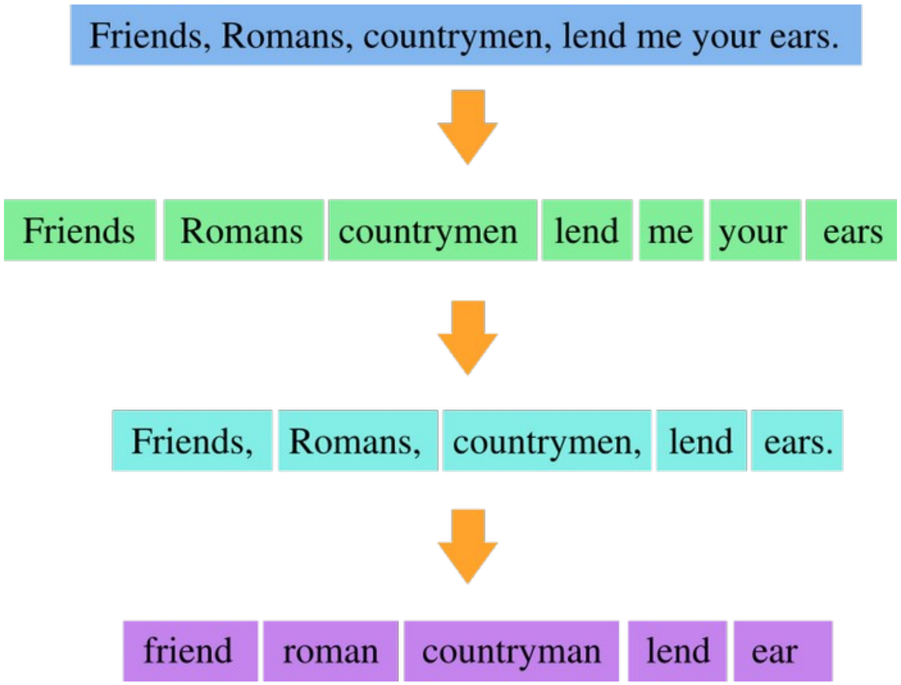
Building inverted index

- Split each document into a list of tokens
- Linguistic processing, tokens normalization
- Build a list of (token, document) pairs
- Sort the list alphabetically by token
- Group occurrences of same token into list
- Remember document frequency



Building term dictionary

- Tokenization (sequence to tokens)
- Exclude »stop« tokens/words
- Normalization (equivalence classes)
- Stemming and lemmatization



Friends, Romans, countrymen, lend me your ears.

Friends Romans countrymen lend me your ears

Friends, Romans, countrymen, lend ears.

friend roman countryman lend ear

Tokenization

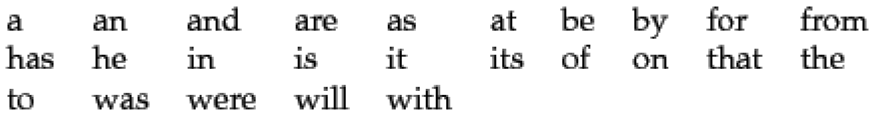
- Punctuation marks:
  - U.S.A = USA , O‘Niel = Oniel
  - Problems: C.A.T. = CAT ?? … Civil Air Transport (C.A.T)
- Connected words:
  - lower-case = lowercase,
  - San Francisco = SanFrancisco
  - San Francisco-Los Angeles = ?
  - Lebensversicherungsgesellschaftsangestellter = ?
- Numbers:
  - (800) 234-2333, (Mar 11 1983), (3/11/1983)
- More language-specific definitions (East Asia – no spaces)

Token normalization

- Removing accent marks (diacritics)
  - cliché = cliche
  - peña = pena
  - Universität = Universitaet
- Convert to lower-case
  - Father = father
  - General Motors = general motors (company name - phrase)
- Language specific conversions
  - colour = color
  - 30.10.1978 = 10.30.1978

Removing stop words

- Words that occur very often in all documents and therefore do not have any retrieval value



a	an	and	are	as	at	be	by	for	from
has	he	in	is	it	its	of	on	that	the
to	was	were	will	with					

- How to query “Let It Be“ or “The Who”?
- Some search engines do not use stop words to support phrase search

Stemming and lemmatization

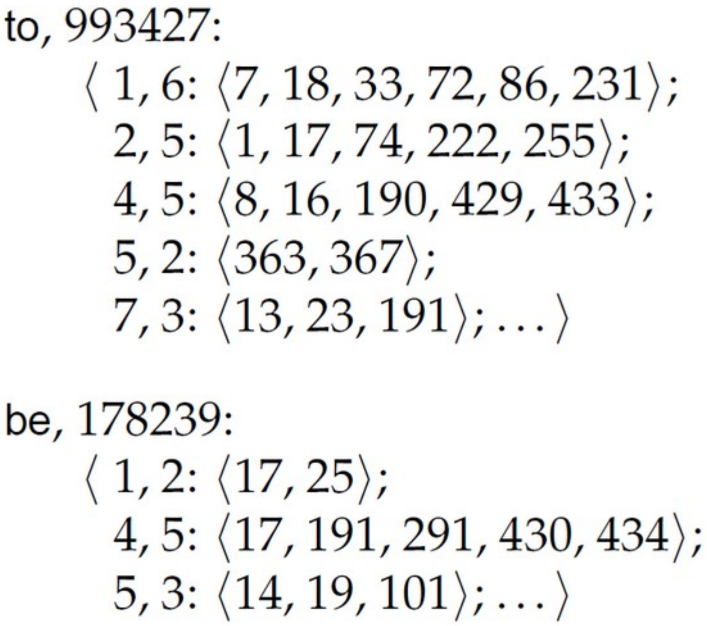
- Lemmatization – transformation based on language rules
  - am, are = be
  - car, cars, car's, cars' = car
  - »the boy's cars are different colors« = »the boy car be differ color«
- Stemming is heuristic approach where we only cut parts of words (faster)
  - Porter Stemming Algorithm
  - »boy ’ s car are differ color«

Querying phrases

- How to search for »multimedia systems«?
- Most engines support use of quotes to convey phrases
- Option 1: **Biword-index**
  - Use each sequential pair of terms as a combined term
  - Friends, Romans, Countrymen = [friends romans] [romans countrymen]
- Option 2: **Positional index**
  - For each term also store its positions in the document
  - Use positions to determine relations between words

Positional index example

Term »to« occurs **993427** times in the entire corpus. It occurs in documents {1,2,4,5,7}.
In document 1 it occurs six times at places <7,18,33,72,86,231>.

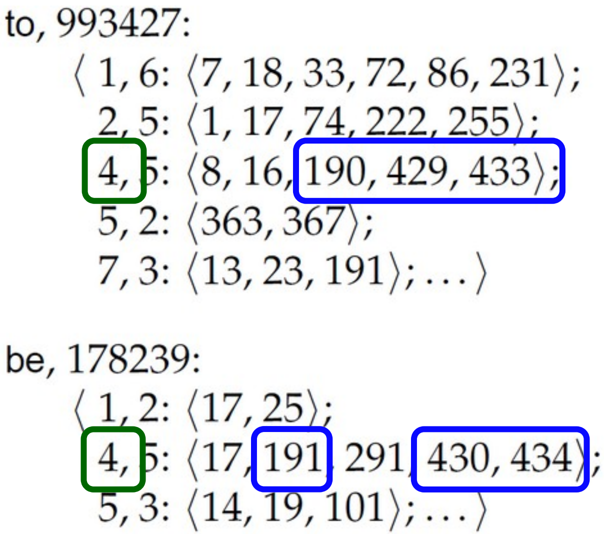


to, 993427:
  ⟨ 1, 6: ⟨7, 18, 33, 72, 86, 231⟩;
    2, 5: ⟨1, 17, 74, 222, 255⟩;
    4, 5: ⟨8, 16, 190, 429, 433⟩;
    5, 2: ⟨363, 367⟩;
    7, 3: ⟨13, 23, 191⟩; . . . ⟩

be, 178239:
  ⟨ 1, 2: ⟨17, 25⟩;
    4, 5: ⟨17, 191, 291, 430, 434⟩;
    5, 3: ⟨14, 19, 101⟩; . . . ⟩

Positional index

- Proximity constraint (documents where word A and B are in distance x).
- Example:
  - **Query**: »to be or not to be«
  - **Terms**: to, be, or, not
  - Intersection of lists for »to« and »be«



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4, 5: ⟨8, 16, 190, 429, 433⟩;
5, 2: ⟨363, 367⟩;
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5, 3: ⟨14, 19, 101⟩; . . . ⟩

Bi-word vs. positional index

- Bi-word index
  - More terms in index
  - Limited relations
- Positional index
  - Increased index size and complexity
  - Increased query time
- Combined approach:
  - Bi-word index for common phrases, e.g., »The Who«
  - Positional index for other terms

Typographical errors

- Example: »Britian Spears« instead of »Britney Spears«
- Correcting errors:
  - For each term separately: »padna« = »panda«
  - Based on neighbor terms (context) »Flew form Heathrow«
- Suggest corrections for terms that are not in dictionary
- Offer the most likely:
  - String distance (Levenshtein)
  - Phonetic distance (Soundex)
- Optional: with multiple equal possibilities offer the one that users use most often

Ranking documents

- Boolean queries only determine if a documents matches the query or not
  - Can generate large number of document
  - Time-consuming to check all of them
  - Show more relevant documents first

Ranking with term frequency

- Document that includes a queried term multiple times should be more relevant than the rest

$$\mathrm{tf}_{t,d} = \#\ \text{occurences of term } t \text{ in document } d$$

- Bag-of-words model
- Problem - no context:
  - »Mary is quicker than John« equals to »John is quicker than Marry«

Problems of term frequency

- Some terms do not discriminate between documents because they occur in all of them
    - Corpus of documents in automotive industry will include term »auto« a lot
- Reduce weights of frequent terms – document frequency

$$\mathrm{df}_t = \#\ \text{of document in which term } t \text{ appears at least once}$$

- Inverse document frequency:
    - N – number of all documents in corpus
    - idf is low for frequent terms and high for scarce ones

$$\mathrm{idf}_t = \log_{10} \frac{N}{\mathrm{df}_t}$$

Composite weights

- Term weight computed as : $\text{tf-idf}_{t,d} = \text{tf}_{t,d} \cdot \text{idf}_t = \text{tf}_{t,d} \log_{10} \frac{N}{\text{df}_t}$
- Weight is:
  - High: if t is frequent only in a small number of documents
  - Low: if t is rare or occurs in many documents
  - Very low: if term t occurs in almost all documents
- Compute document weight for query q

$$\text{Score}(q,d) = \sum_{t \in q} \text{tf-idf}_{t,d}$$

Ranking example

We have corpus of N=100 documents, in which we search for query q=»white pig«. We know in advance that »white« occurs in ten documents and that it occurs in document d1 five times. We also know that the word »pig« occurs in fifty documents and that it occurs in document d1 three times. Compute ranking weight of document d1 for query q.

$$\text{tf-idf}_{t,d} = \text{tf}_{t,d} \cdot \text{idf}_t = \text{tf}_{t,d} \log_{10} \frac{N}{\text{df}_t}$$

$$\text{Score}(q,d) = \sum_{t \in q} \text{tf-idf}_{t,d}$$

Document similarity

Vector of weights for all terms in the dictionary (histogram)

$$V(d) \; = \; [\text{tf-idf}_{t_1,d}, \text{tf-idf}_{t_2,d}, \ldots, \text{tf-idf}_{t_M,d}]$$

Customers Who Bought This Item Also Bought

SecondWorld
› Jeremy Robinson
★★★★☆ (40)

Threshold (Jack Sigler)
› Jeremy Robinson
★★★★½ (28)

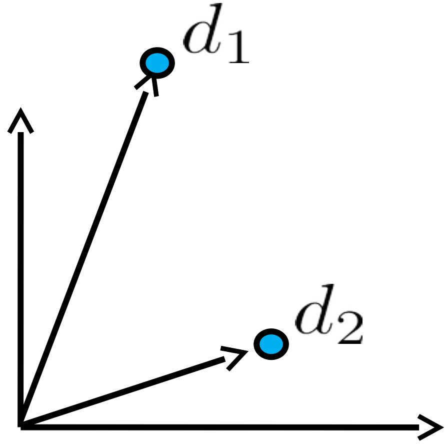
Instinct (Chess Team Adventure)
› Jeremy Robinson

Vector space

- Similarity as dot product

$$V(d) \;=\; [\text{tf-idf}_{t_1,d}, \text{tf-idf}_{t_2,d}, \ldots, \text{tf-idf}_{t_M,d}]$$

$$\mathrm{sim}(\mathrm{d}_1, d_2) = V(d_1) \cdot V(d_2)$$



- Vector normalization
  - Longer vectors will have larger norm
  - Longer documents are not more important
  - Euclidean normalization $\mathrm{v(d)} = \mathrm{V(d)} \;/\; \|V(d)\|$, where $\|V(d)\| = \sqrt{\sum_{i=1}^{M} x_i^2}$
  - Similarity interpreted as cosine of angle between vectors

Similarity example

- Left table shows tf values (not weighted with idf) for dictionary of three terms for three books: SaS, PaP, and WH.
- Which document is most similar to document SaS?

Term frequency

term	SaS	PaP	WH
affection	115	58	20
jealous	10	7	11
gossip	2	0	6

Normalized term frequency

term	SaS	PaP	WH
affection	0.996	0.993	0.847
jealous	0.087	0.120	0.466
gossip	0.017	0	0.254

Matching query with documents

- Vector space can be used to rank documents
- Similarity of query q and document d:
- Example: q = »jealous gossip« $score(q,d) \;=\; v(q)\cdot v(d)$

$$V(q) = [0,1,1] \rightarrow v(q) = [0, 0.707, 0.707]$$

$$score(q,\mathrm{SaS}) = ?, score(q,\mathrm{PaP}) = ?, score(q,\mathrm{WH}) = ?$$

Weighting schemes

- Other interpretations of tf and idf also exist
  - Can be different for query and documents
  - Proportional to the tf and idf qualities

$$0, 1 \ \text{(binary)}$$
$$f_{t,d}$$
$$\log(1 + f_{t,d})$$

$$1 \ \text{(unary)}$$
$$\log \frac{N}{df_t}$$
$$\log \left(\frac{N}{1 + df_t} \right) + 1$$

Weighting vectors example

Query q=»best car insurance« in corpus of documents (N=100000)

	Corpus		Query (unary-idf)		Document (tf-idf)		
term	df	idf	tf	w	tf	w	nw
auto	5000	1.3	0	0	1	1.3	0.21
best	50000	0.3	1	0.3	0	0	0
car	10000	1.0	1	1.0	1	1.0	0.16
insurance	100	3.0	1	3.0	2	6.0	0.96

# appearances in query

appearances in document

$$\mathrm{score}(\mathrm{q},\ \mathrm{d}) = 0 + 0 + 0.16 + 2.89 = 3.04$$

Document retrieval algorithm

- Cosine similarity between query sample and all documents
- Order documents by similarity
- Return top K documents
- Weighting with tf-idf requires:
  - For each term also store its document frequency
  - For every term in every document store term frequency

Feedback loops

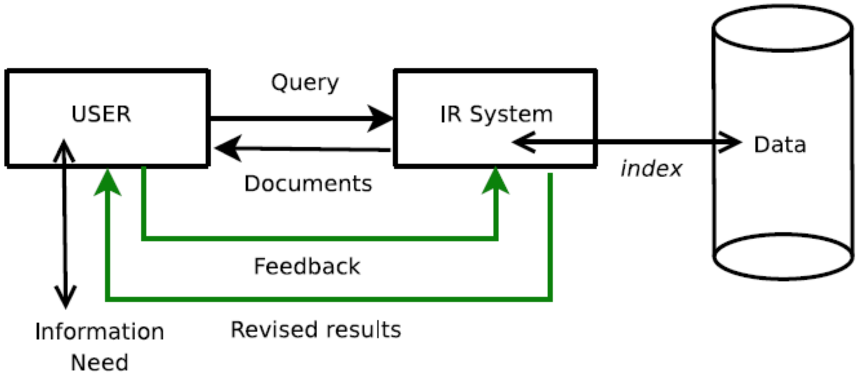
- Multiple »words«, same concept
  - User does not know how to form a sufficiently specific query
  - Examples: »aircraft« vs. »plane«; »ship« vs. »boat«
- Global methods:
  - Expand query to as many possibilities with as many possible terms with error correction, synonyms, etc.
- Local methods:
  - Based on interaction between the user and the system
  - Relevance feedback

Relevance feedback

User reports information about relevance of individual results back to the system to improve the query

- Forming good queries is hard if the entire corpus is not known to the user

- Assessing individual documents is simple

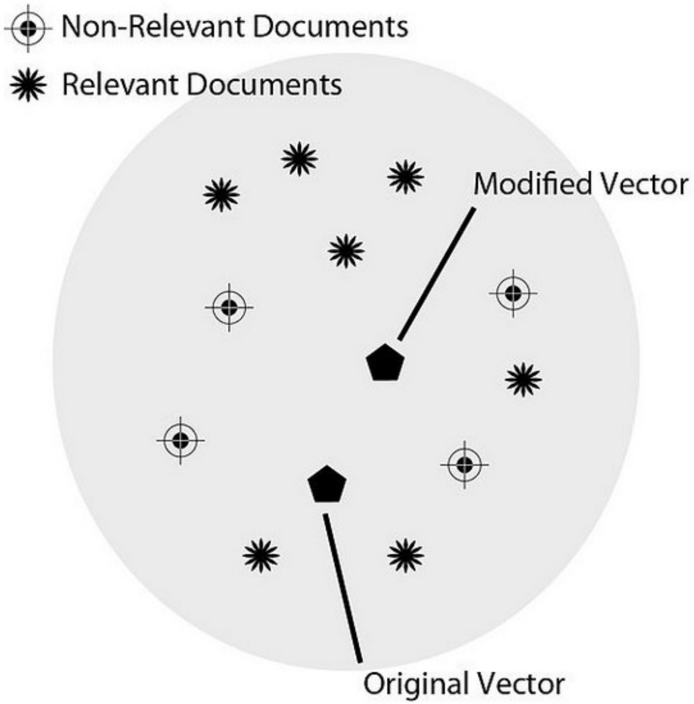


Rocchio algorithm

- Documents represented in vector space
- Known query and some relevant and irrelevant samples
- Formulate new query that is
  - Maximally similar to relevant results
  - Minimally similar to irrelevant results
- Use new query to retrieve better results

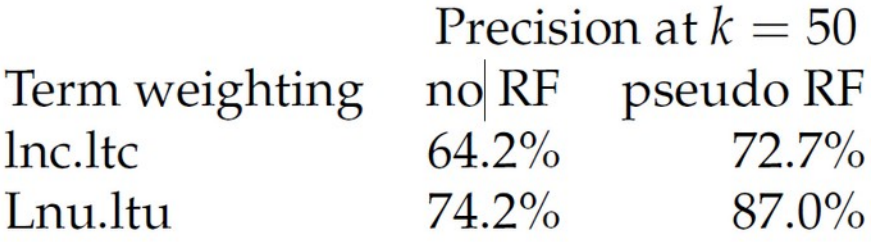
$$q_m = \alpha q_0 + \beta \frac{1}{|D_r|} \sum_{d_j \in D_r} d_j - \gamma \frac{1}{|D_n|} \sum_{d_j \in D_n} d_j$$

- q_0 - user query
- D_r - set of known relevant results
- D_n - set of known nonrelevant results
- α, β, γ - weights (e.g. $\alpha = 1, \beta = 0.75, \gamma = 0.15$)



Blind/pseudo relevance feedback

- Use default method to find most relevant documents
- Assume that K highest ranked documents are relevant
- Compute relevance feedback (Rocchio)
- Example TREC ad hoc task (Buckley et al. 1995)



	Precision at $k = 50$	
Term weighting	no RF	pseudo RF
lnc.ltc	64.2%	72.7%
Lnu.ltu	74.2%	87.0%

UŻYWAJ NARZĘDZI TYLKO W DOBRYM STANIE!
Porządek W MIEJSCU PRACY GWARANCJĄ BEZPIECZEŃSTWA!
UŻYWAJ NARZĘDZI TYLKO W DOBRYM STANIE
UWAGA! TRUCIZNA!
TOWAR MACANY NALEŻY DO MACANTA
ODCHODZĄC OD MASZYNY WYŁĄCZ SILNIK I ZGAŚ ŚWIATŁO
OBOWIĄZUJE KAŻDA KOBIETE
Chroń GŁOWĘ PRACUJ W HEŁMIE
PROSIMY NIE SIKIAĆ DO ZLEWU
Palenie NA TERENIE MAGAZYNU ZABRONIONE
Betreten der Werksanlagen verboten
nieupoważnionym WSTĘP WZBRONIONY
PRACUJ
TEREN BUDOWY WSTĘP ZABRONIONY
UWAGA! WYKOPY
BUTLE PEŁNE
ZWIĄZEK NAUCZYCIELSTWA POLSKIEGO oddział w Limanowej
DBAJ O STAN ZAPÓR
KOBIET

Multimedia Retrieval

Overview

- Visual information retrieval
- Audio information retrieval
- Making retrieval efficient
  - Hierarchical methods
  - Vector databases

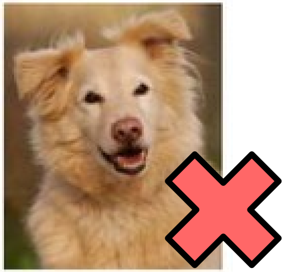
As text retrieval

- Documents can be queried using
  - Metadata (text)
  - User annotations (tags)
  - Manual annotations (tags, captions)
- Problems
  - Metadata is not complete/informative/available
  - User annotations not supported, unreliable
  - Captioning is selective / biased

Images and text queries

- Images in web documents
  - Use text around image (URL element name, neighborhood)
  - Same principles as in text retrieval systems
- Example of searching for images with word »Sunset«

Sunset at Rocky Point



Frank Smiles at Sunset

Sunset Beach

Problems with text queries

- Avoid using image content
  - Annotation bias
  - Metadata ambiguity
- Perceptual relevance
  - Impossible to describe composition
  - Abstract shapes

Development of retrieval systems that
encode image content directly

Querying image content

- Extract image content
  - Detecting object and categories
  - Describing relations, actions
  - Ambiguous problem
- Low-level features
  - Color
  - Texture
  - Shape
  - Structural elements

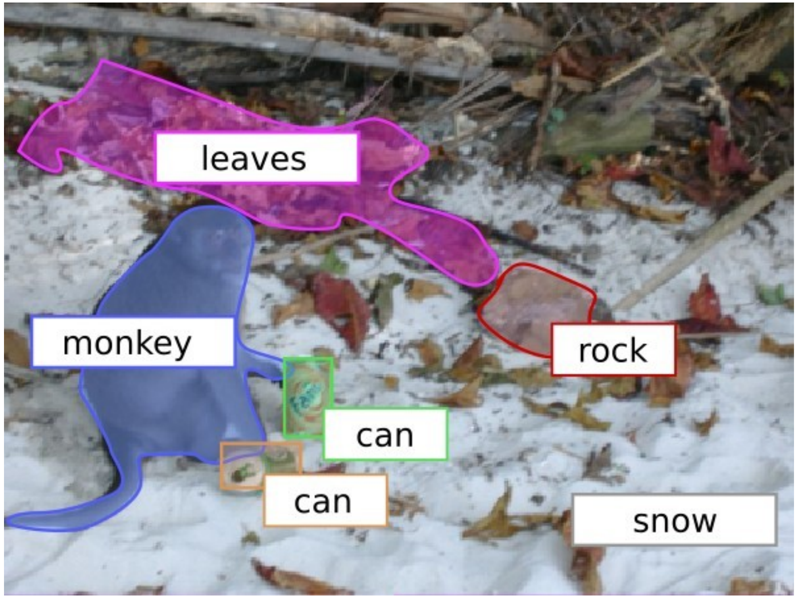
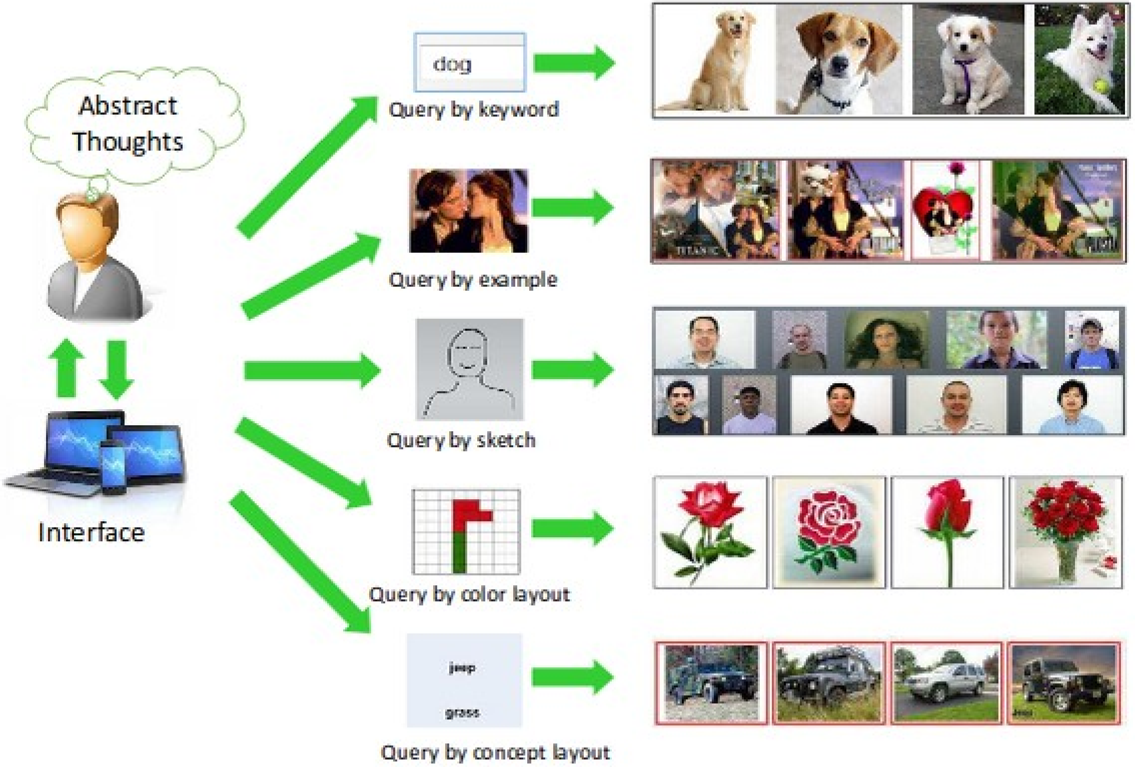


Image retrieval systems



Wengang Zhou, Houqiang Li, Qi Tian, Recent Advance in Content-based Image Retrieval: A Literature Survey, 2017

Image retrieval system

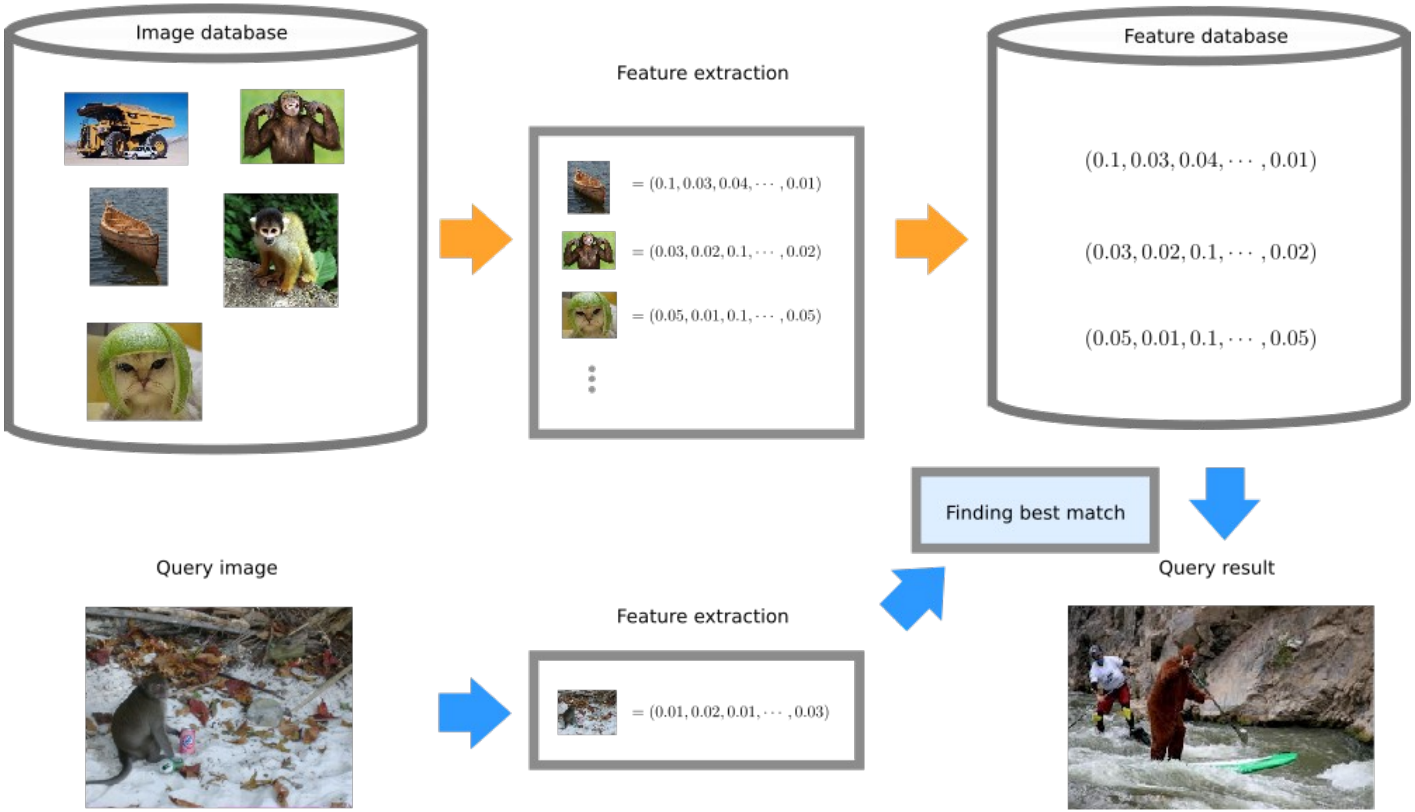


Image database

Feature extraction

$= (0.1, 0.03, 0.04, \cdots, 0.01)$

$= (0.03, 0.02, 0.1, \cdots, 0.02)$

$= (0.05, 0.01, 0.1, \cdots, 0.05)$

Feature database

$(0.1, 0.03, 0.04, \cdots, 0.01)$

$(0.03, 0.02, 0.1, \cdots, 0.02)$

$(0.05, 0.01, 0.1, \cdots, 0.05)$

Finding best match

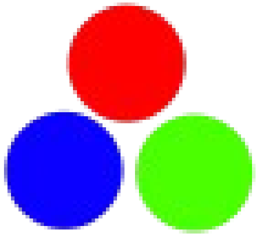
Query image

Feature extraction

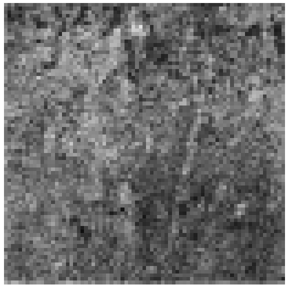
$= (0.01, 0.02, 0.01, \cdots, 0.03)$

Query result

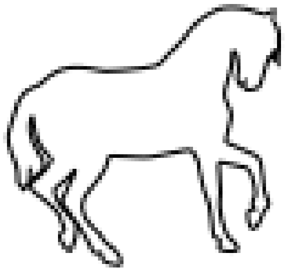
How to describe images?



Color



Texture



Shape

Color description

- Average color
- Parametric distribution (Gaussian)
  - Signle mode
- Color histogram
  - Multi-modal
  - Illumination change sensitivity

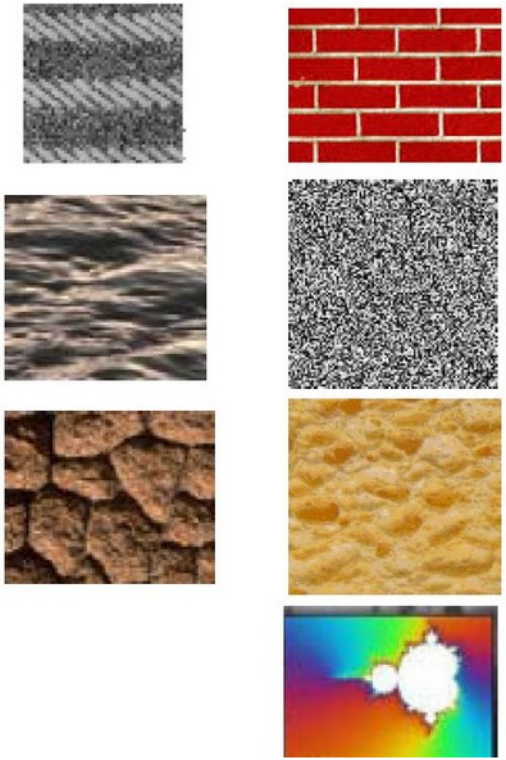
μ_a $\quad$ μ_b

(μ_a, σ_a) $\quad$ (μ_b, σ_b)

$[a_1, a_2, \ldots]$ $\quad$ $[b_1, b_2, \ldots]$

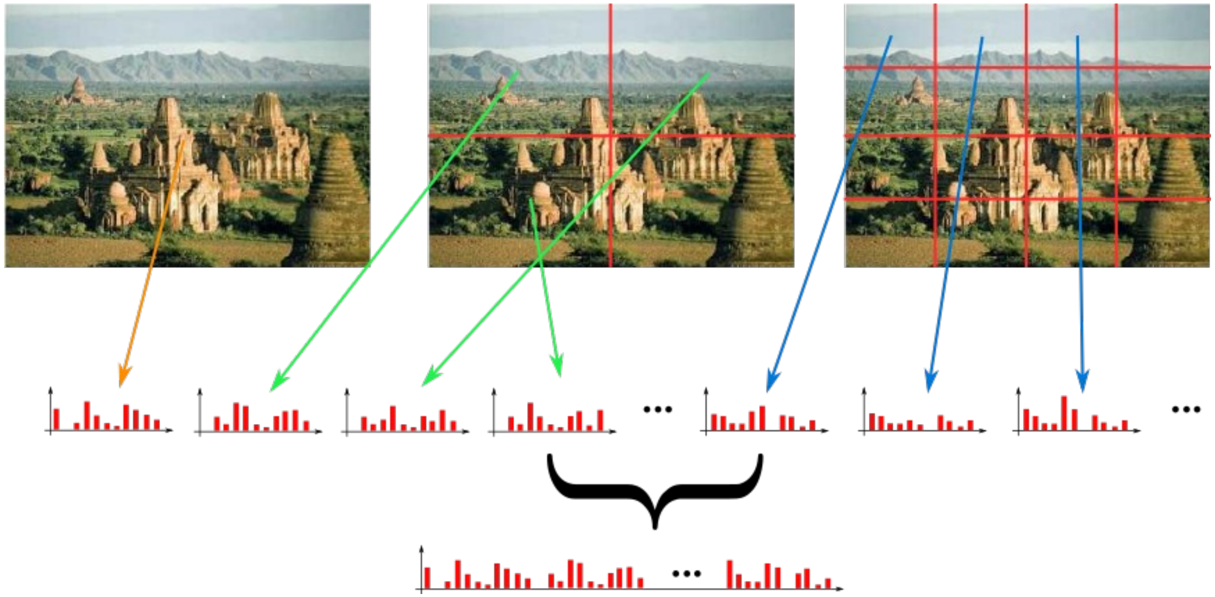
Describing texture

- Texture = spatial arrangement of color or intensities in an image or a selected region of an image
  - Fourier Transform
  - Local Binary Patterns
  - Co-occurence Matrix



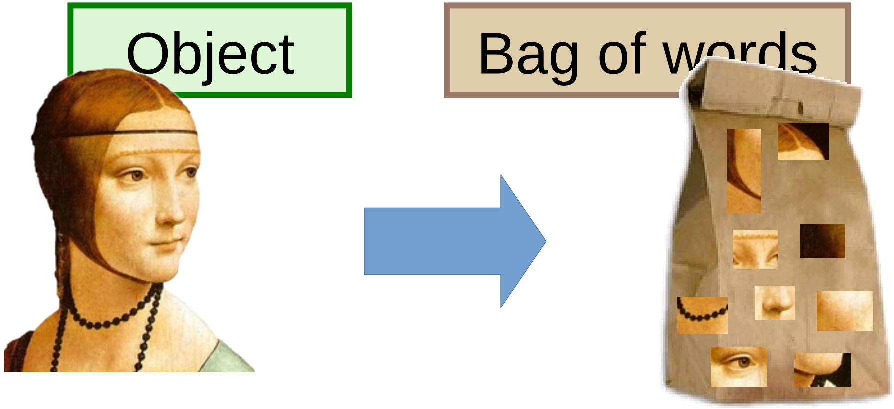
Including spatial information

- Divide image into sub-regions
- Stack histograms

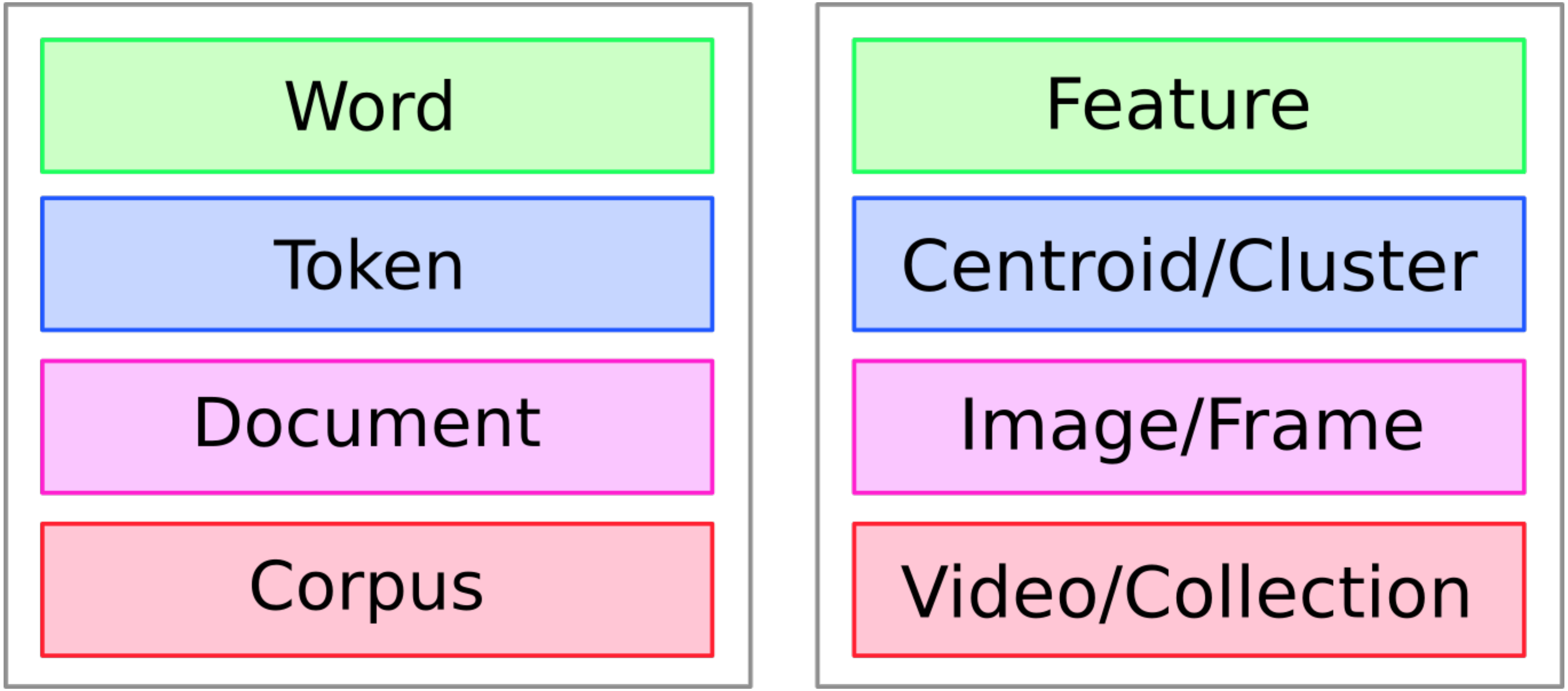


Bag of words

- Inspired by text retrieval systems
- General object categories
  - No clear spatial consistency
  - Objects composed of important parts - words
- Ignoring relationships between parts
  - Dictionary – list of known parts
  - Descriptor – histogram of part occurrences



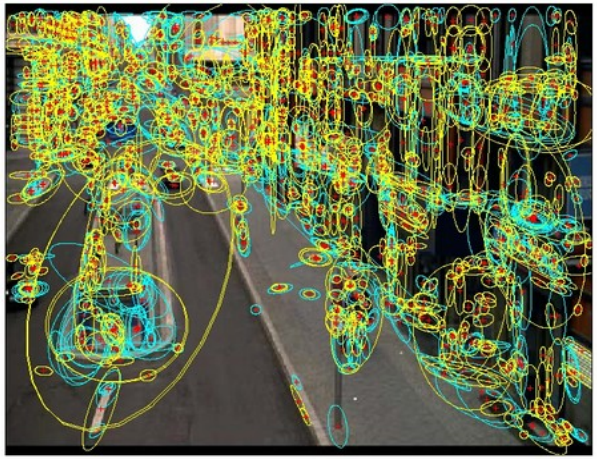
Visual words

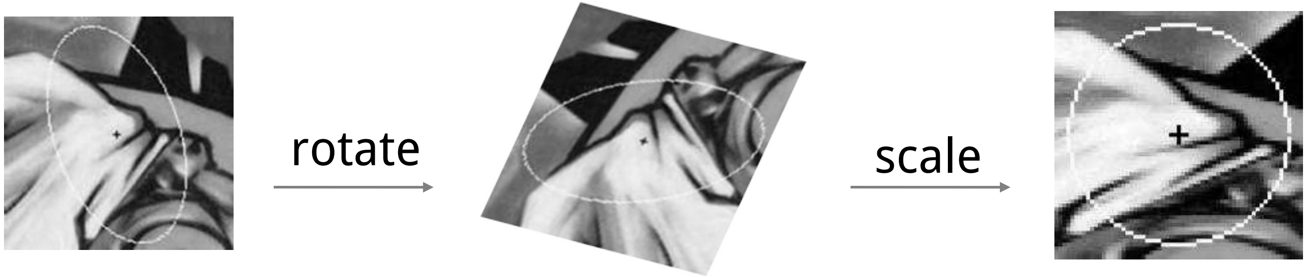


Word	Feature
Token	Centroid/Cluster
Document	Image/Frame
Corpus	Video/Collection

Local regions

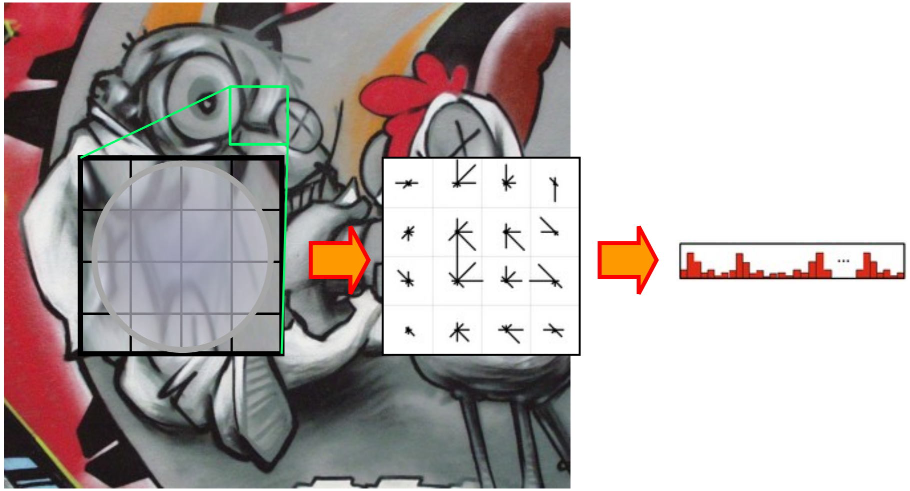
- Detecting stable regions
  - Robustness
  - Corners, blobs
- Describing neighborhood
  - Invariance (illumination, rotation, scale)





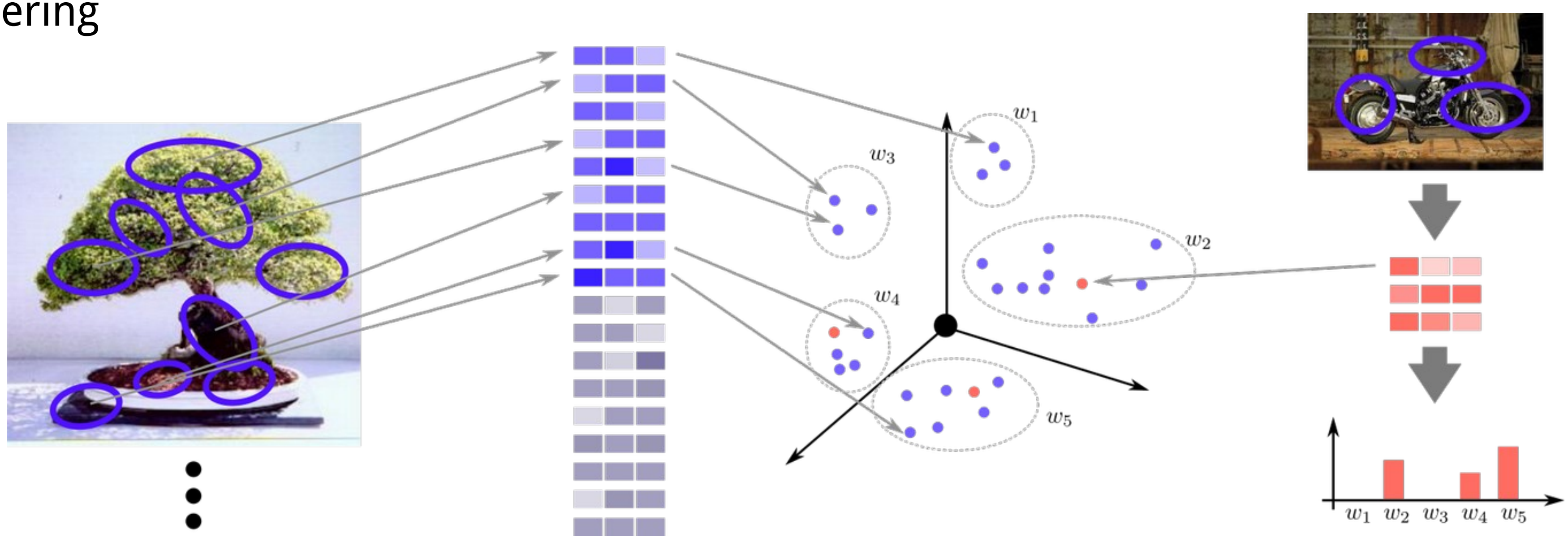
SIFT features

- Scale invariant feature transform
  - Divide region into 4x4 sub-regions: 16 cells
  - Compute gradients in each sub-region
  - Discretize orientation (8 directions)
  - Compute orientation histogram based on magnitude
  - Stack histograms and normalize: 4x4x8 = 128



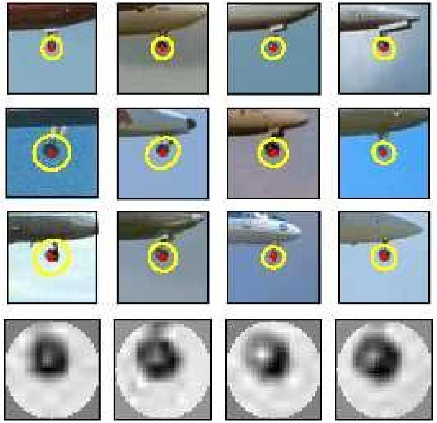
Building a dictionary

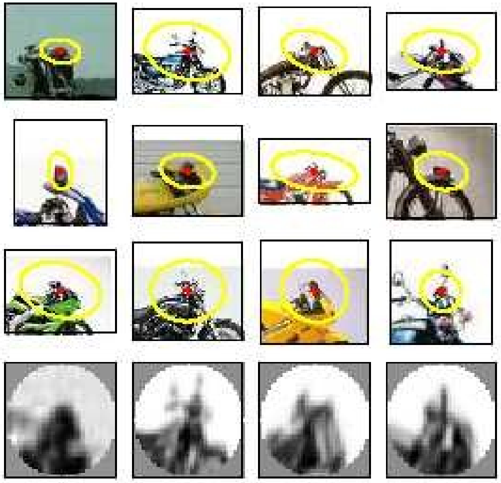
- Unsupervised learning
  - Large number of different local descriptors
  - Finite amount of words
  - Clustering

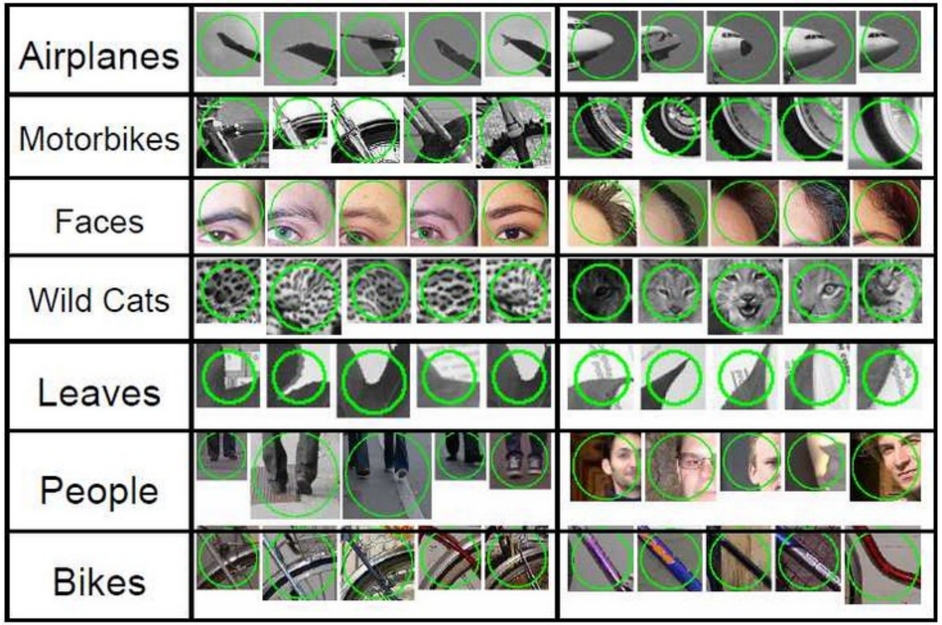


Fei-Fei Li; Perona, P. "A Bayesian Hierarchical Model for Learning Natural Scene Categories". CVPR 2005

Example of visual words

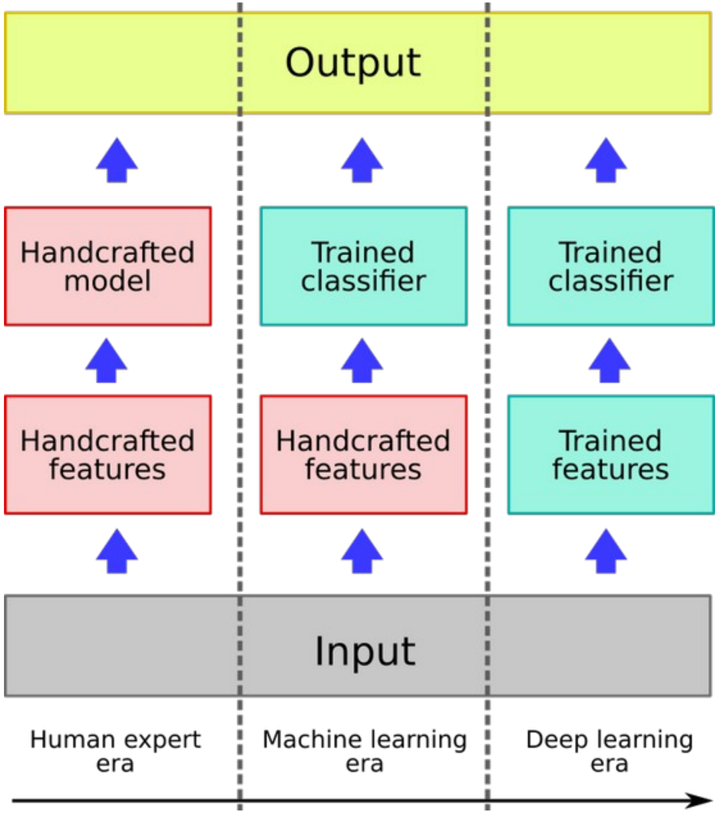




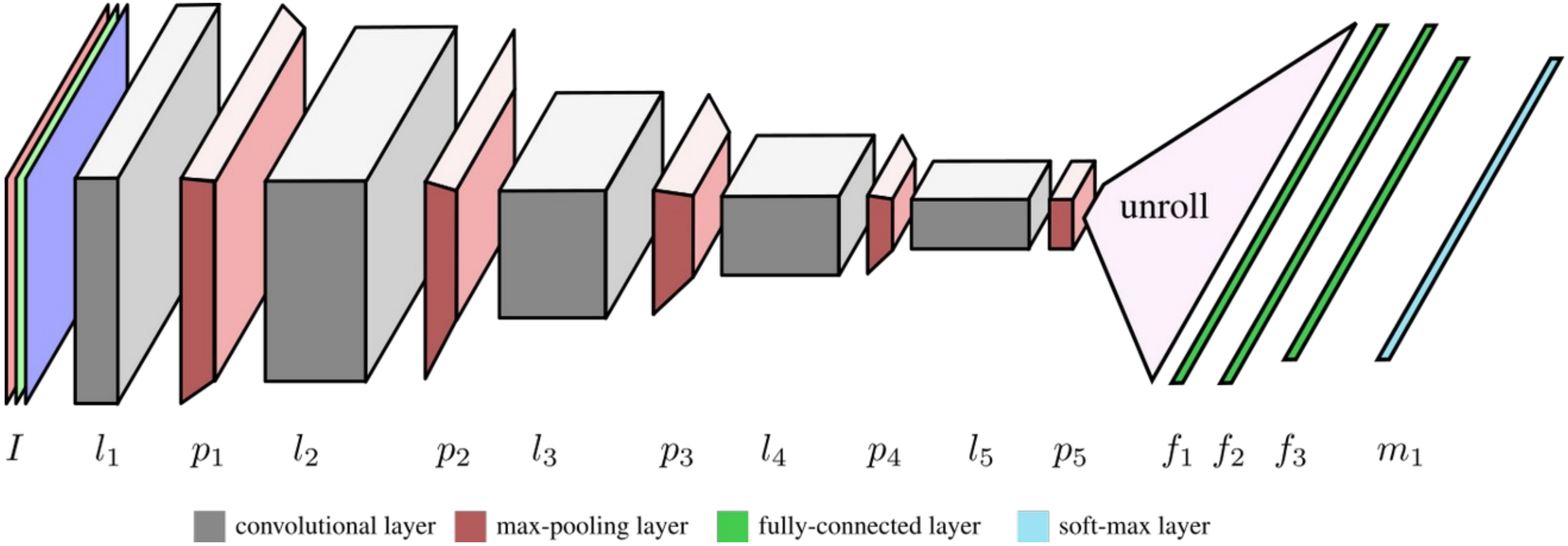


Sivic, Josef, and Andrew Zisserman. "Video Google: A text retrieval approach to object matching in videos." IEEE CVPR, 2003

Deep learning



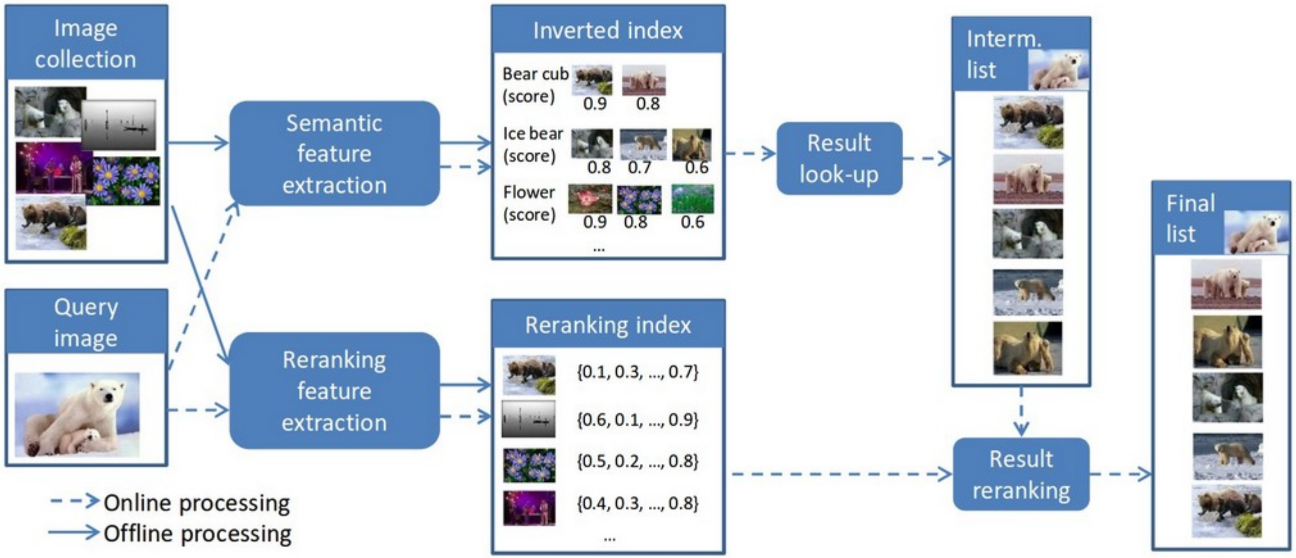
CNN example – VGG16



Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition. arXiv 2014

Image retrieval with inverted index

- Multi-object detector (semantic tokens)
- Use Boolean queries to per-process database



A. Popescu, A, Ginsca, H. Le Borgne, “Scale-free content based image retrieval (or nearly so)”, ICCV 2017 Workshops

Towards image understanding

- Semantic segmentation
- Spatial relationships
- Describing scene

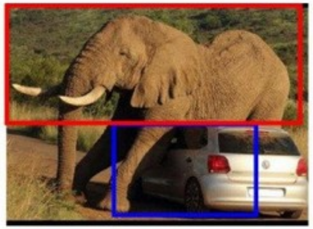
"man in black shirt is playing guitar."

"construction worker in orange safety vest is working on road."

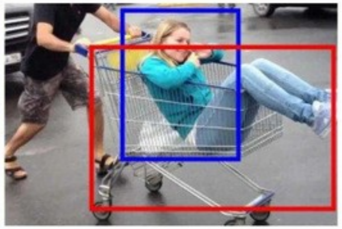
"two young girls are playing with lego toy."

"boy is doing backflip on wakeboard."

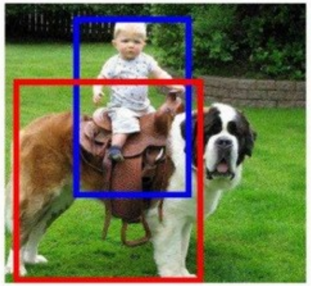
cs.stanford.edu/people/karpathy/deepimagesent/



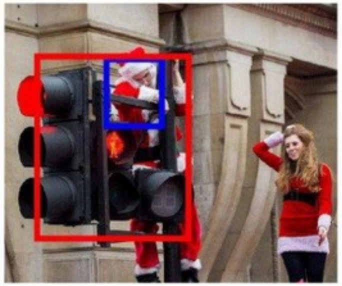
car under elephant



person in cart



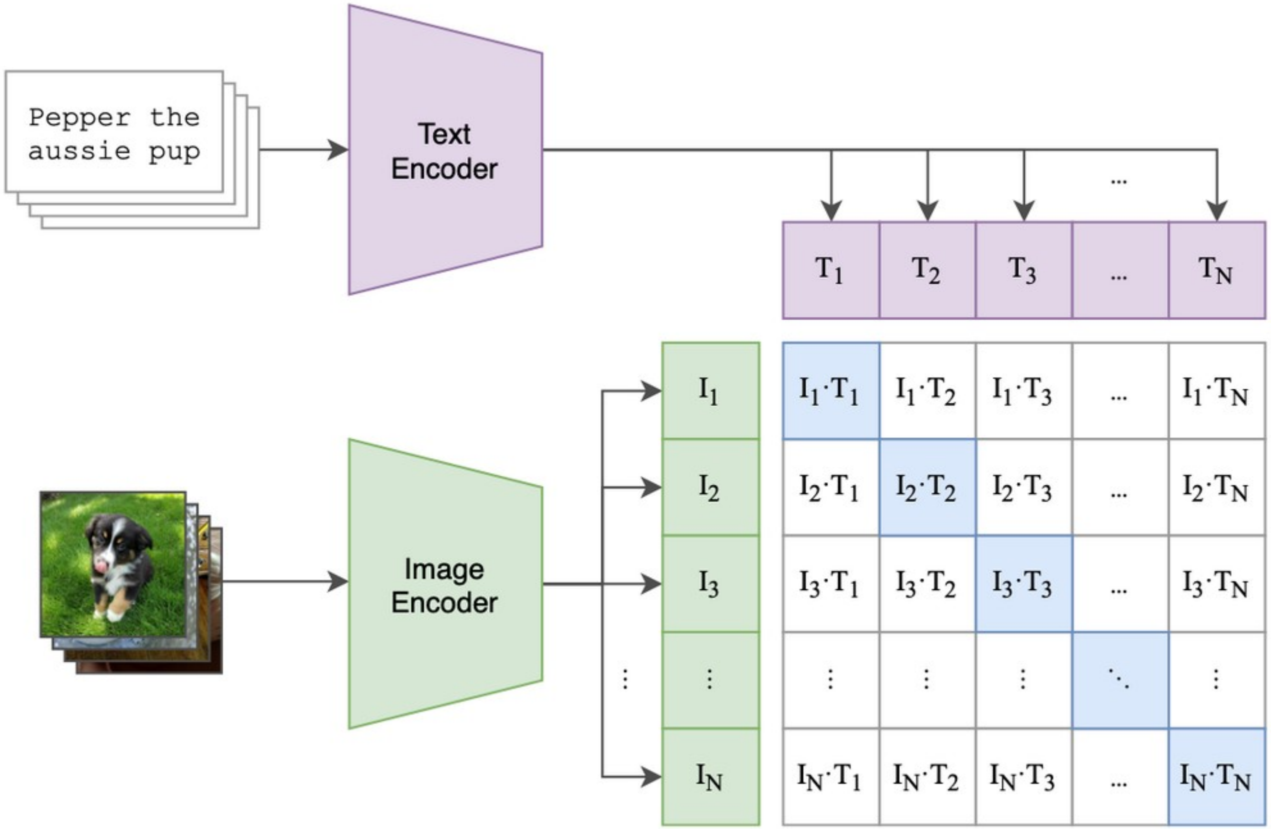
person ride dog



person on top of traffic light

www.di.ens.fr/willow/research/unrel/

Connecting text and images



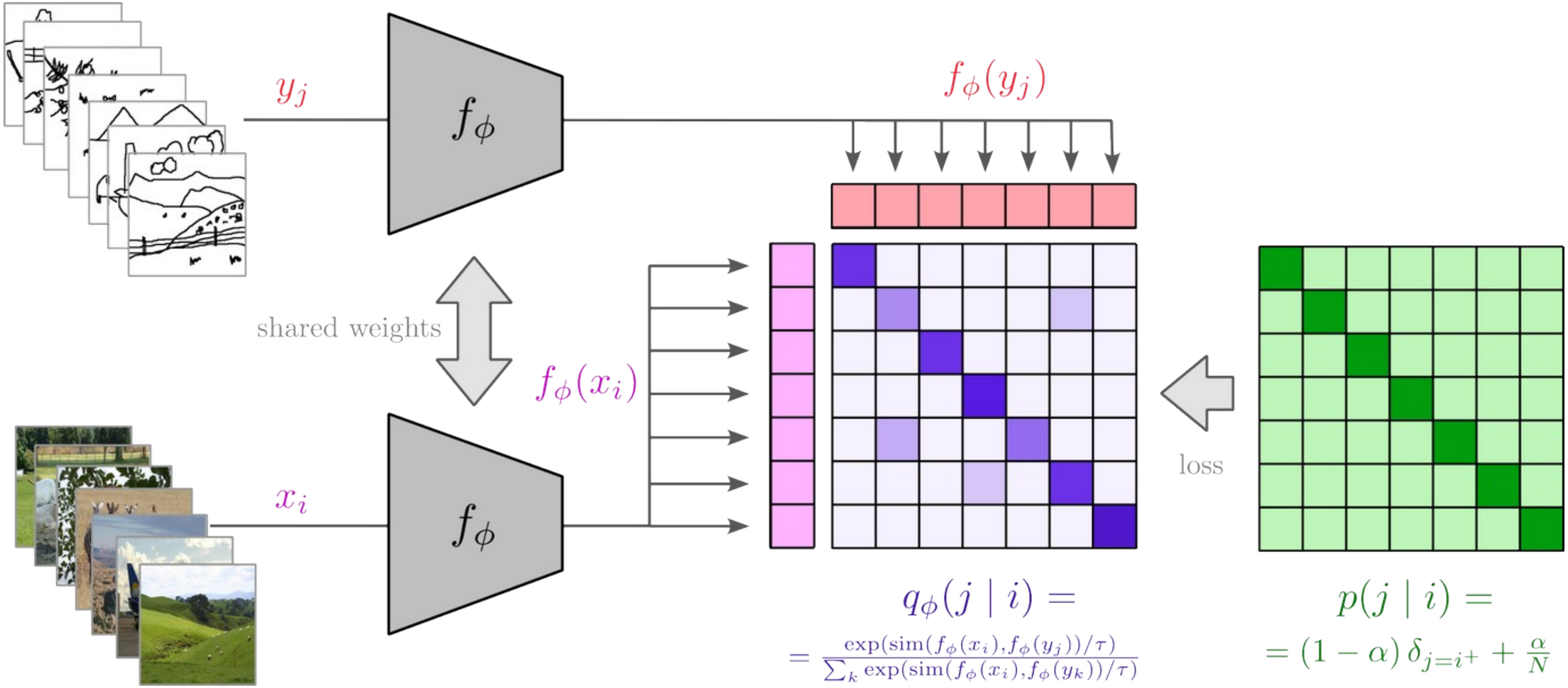
$I_1 \cdot T_1$	$I_1 \cdot T_2$	$I_1 \cdot T_3$	...	$I_1 \cdot T_N$
$I_2 \cdot T_1$	$I_2 \cdot T_2$	$I_2 \cdot T_3$	...	$I_2 \cdot T_N$
$I_3 \cdot T_1$	$I_3 \cdot T_2$	$I_3 \cdot T_3$	...	$I_3 \cdot T_N$
⋮	⋮	⋮	⋱	⋮
$I_N \cdot T_1$	$I_N \cdot T_2$	$I_N \cdot T_3$	...	$I_N \cdot T_N$

Radford, Alec, et al. "Learning transferable visual models from natural language supervision." ICML, 2021.

Sketch-Based Image Retrieval

- Query = sketch
  - Specify composition
  - Large variance
  - Ambiguity
- Documents = images
  - Cross-modal scenario

Handling ambiguity



y_j

f_ϕ

$f_\phi(y_j)$

shared weights

$f_\phi(x_i)$

x_i

f_ϕ

loss

$$q_\phi(j \mid i) = \\ = \frac{\exp(\mathrm{sim}(f_\phi(x_i), f_\phi(y_j))/\tau)}{\sum_k \exp(\mathrm{sim}(f_\phi(x_i), f_\phi(y_k))/\tau)}$$

$$p(j \mid i) = \\ = (1-\alpha)\,\delta_{j=i^+} + \frac{\alpha}{N}$$

Demić and Čehovin Zajc, “Back To The Drawing Board: Rethinking Scene-Level Sketch-Based Image Retrieval” BMVC 2025

Describing video content

- Structure: frame, shot, scene
- Content
  - Dynamics: still, moving objects, camera movement
  - Activity in a frame interval, e.g. jumping, robbery, horse race
  - Categories, e.g. cats, horses, cars
  - Object instances: e.g. Harry Potter, Jack Sparrow, Han Solo

MPEG-7

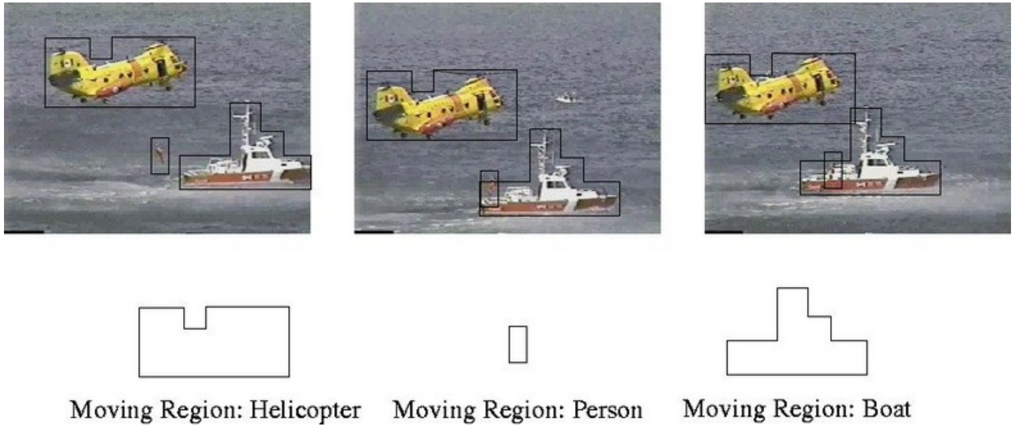
- Efficient access and manipulation of multimedia content
- Complementary to MPEG-4
- Standardized text-less object retrieval
    - D – Object descriptors (audio and video)
    - DS – Description schemes
    - DDL – Description definition language (XML)

Examples of descriptors

- Color
  - Color space
  - Color layout
  - Dominant color
  - Color structure
  - GoP color
- Texture
  - Homogenous
  - Non-homogenous
- Shape
  - Shape descriptor
  - Contour
  - 2D-3D shape
- Motion
  - Activity
  - Camera motion
  - Warping parameters
  - Trajectory
  - Parametric motion
- Localization
  - Spatio-temporal
  - Region

Structure description

Describing content at the level of video segment



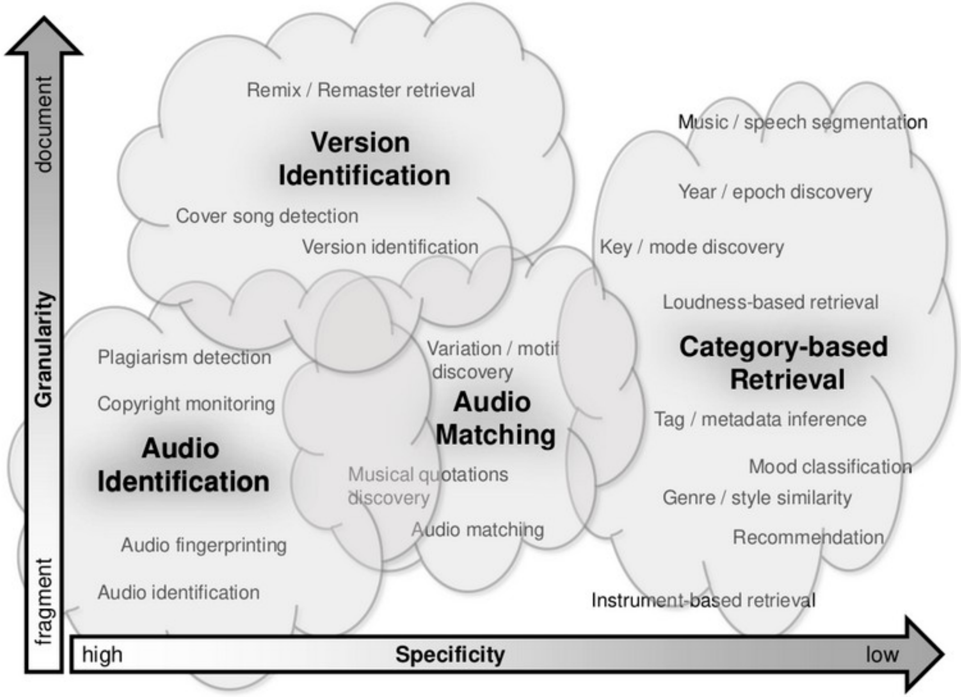
Example: three moving objects, describe relations ...

Three forms of sound

- Speech
  - Words and grammar
  - Can be converted to text
- Music
  - Vocal and/or instrumental sounds
  - Can be represented by a score
- Waveform
  - No dedicated semantic representation
  - Superset

Retrieval in Audio

- Identification
  - Exact match
  - Versions, variations
- Segment matching
  - Finding motives, quotations
- Category-based retrieval
  - Genre, mood, tempo
- Recommendation
  - Finding audio with similar qualities

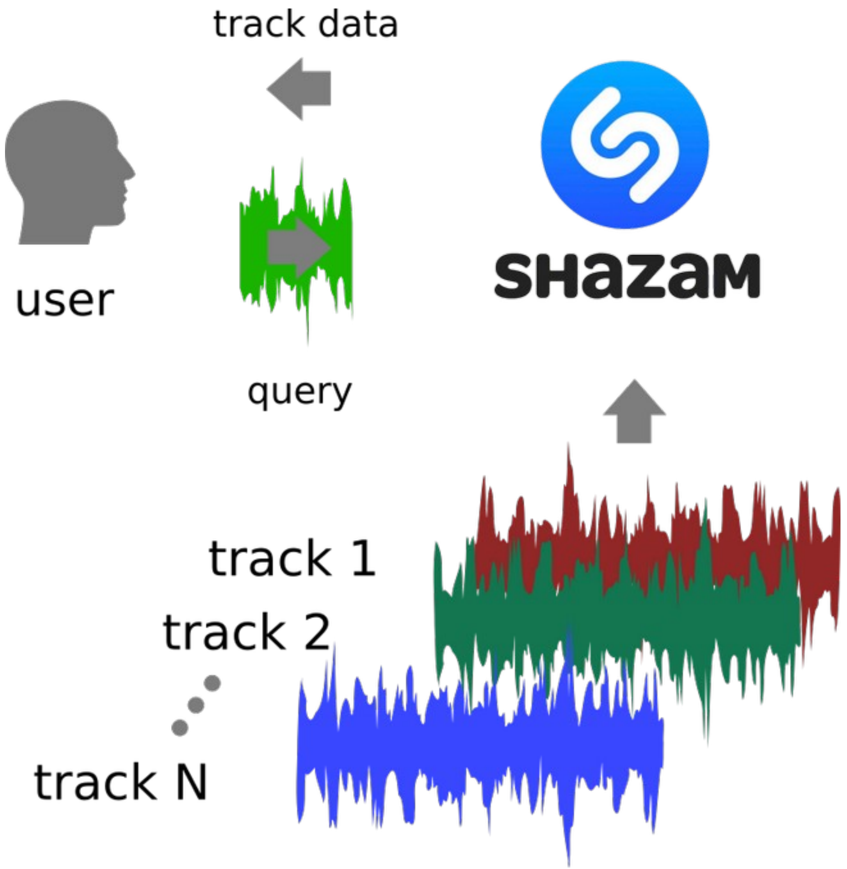


Example-based music search

- Dataset of audio samples (music recordings)
- Look for most similar sample
- Identification
  - High specificity
- Variations
  - Low specificity
  - Semantic meaning

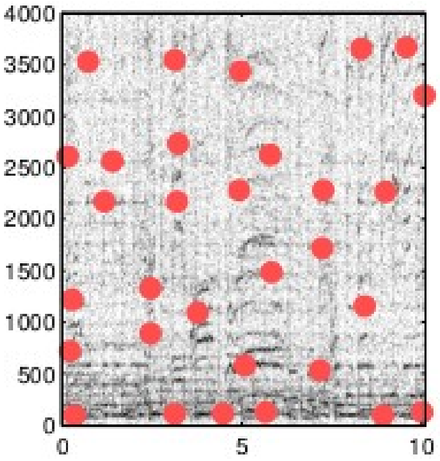
Shazam

- Query by example
  - Short fragments
- Identification
  - High specificity
  - Large database
- Fast, noise resistant
  - Fingerprinting
  - Hashing

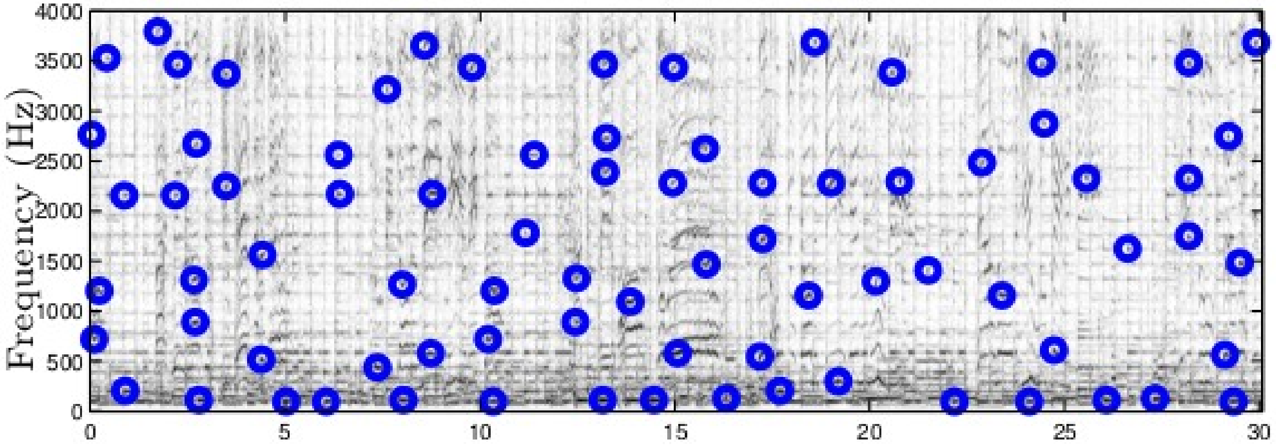


Peak fingerprinting

- Spectrogram
- Local peaks – features (time, frequency)



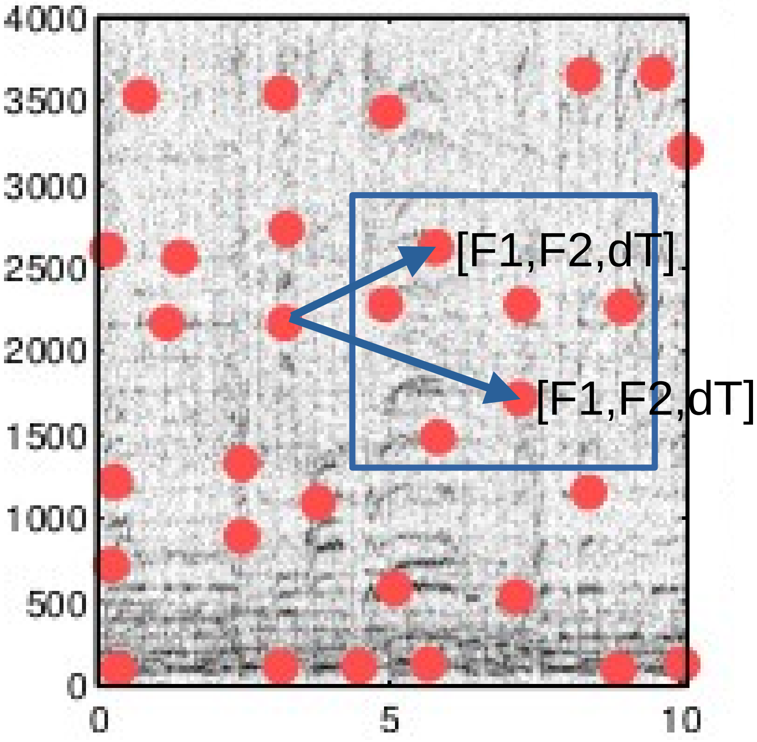
Clip / query



Track / document

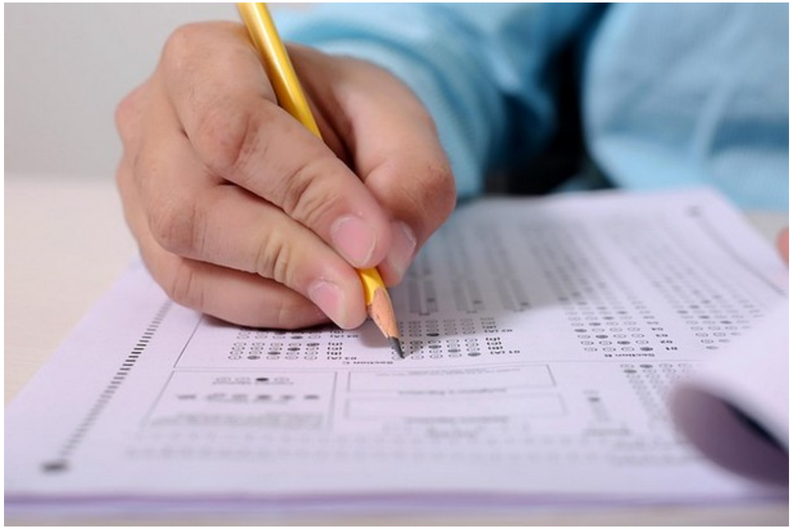
Combinatorial Hashing

- Combinations of peaks
  - Target zone
  - Triplet: F1, F2, dT
  - 30bit hash (+ onset time, song ID)
- Performance
  - Lower survival (specific)
  - Much higher speed



Query matching

- {(H_i, T_i)} = query fingerprints
- For each (H_i, T_i)
  - For each {(T_j, S_j) where H_j == H_i} in database:
    - T_ij = T_j – T_i
    - votes[(S_j, T_ij)] += 1
- Sort by number of votes
- Select top K matches (can be in same song)

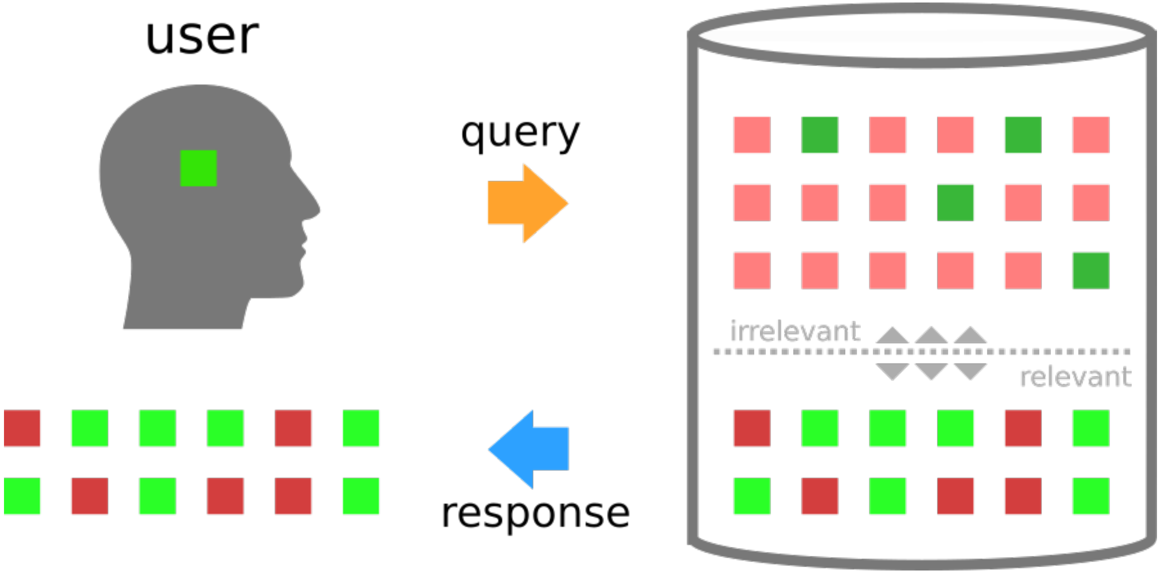


Retrieval Evaluation

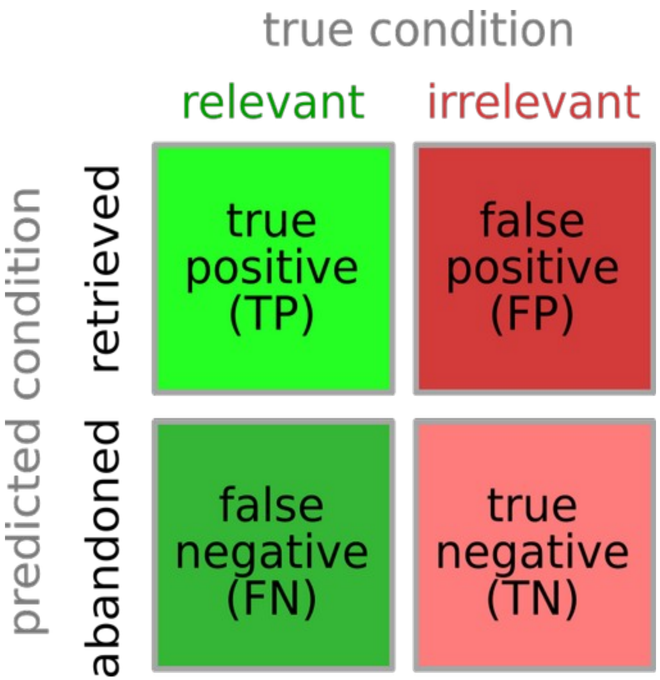
Objective retrieval performance

How many of the retrieved documents are relevant?

- Precision – percentage of relevant documents among retrieved documents
- Recall – percentage of returned relevant documents with respect to all relevant documents



Retrieval as classification



		true condition	
		relevant	irrelevant
predicted condition	retrieved	true positive (TP)	false positive (FP)
	abandoned	false negative (FN)	true negative (TN)

$$Precision = \frac{TP}{TP+FP}$$

$$Recall = \frac{TP}{TP+FN}$$

$$TP_{rate} = \frac{TP}{TP+FN}$$

$$FP_{rate} = \frac{FP}{FP+TN}$$

Precision vs. recall

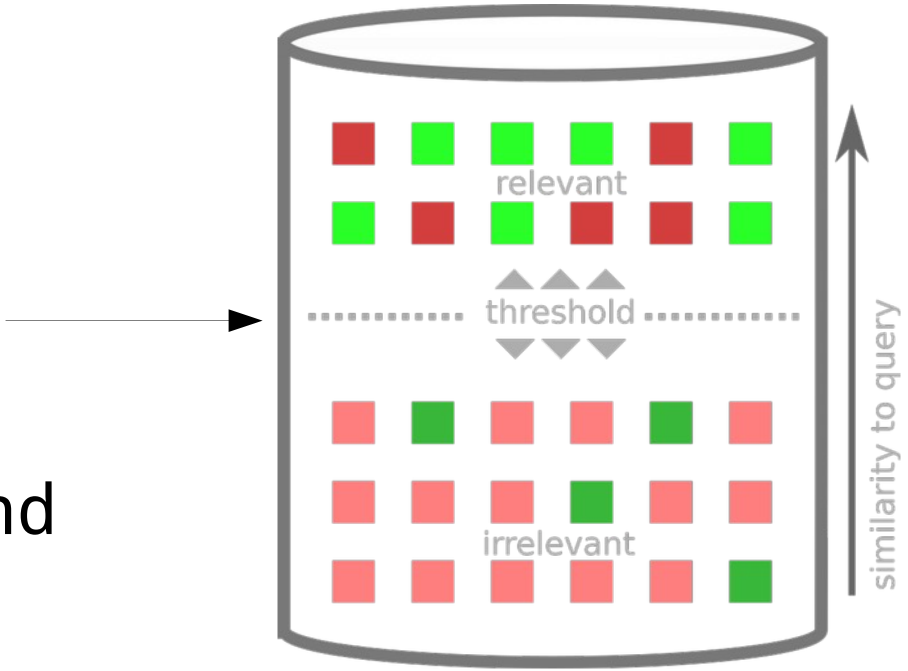
- Precision and Recall are related measures
  - Precision typically falls if the number of retrieved documents is increased
  - Recall increases if the number of retrieved documents is increased
- F-measure as a compromise
  - Typical weight
- Higher value is better (maximum is 1)

$$F = \frac{1}{\frac{\alpha}{Pr} + \frac{1-\alpha}{Re}}$$

$$\alpha = 0.5 \rightarrow F = 2\frac{Pr Re}{Pr + Re}$$

Similarity threshold

- Decide which documents to return
  - Document similarity
  - Threshold $sim(q, d_i) > \epsilon$
- Depending on the threshold we get different precision and recall



Retrieval performance analysis

- Dataset with ground-truth
  - Compute similarity for all documents
  - Compute TPR and FPR for threshold

$$Precision = \frac{TP}{TP+FP}$$

$$Recall = \frac{TP}{TP+FN}$$

$$TP_{rate} = \frac{TP}{TP+FN}$$

$$FP_{rate} = \frac{FP}{FP+TN}$$

	🟩	🟩	🟥	🟩	🟥	🟩
True condition:	1	1	0	1	0	1
Similarity:	**1.0**	**0.2**	**0.1**	**0.8**	**0.9**	**0.8**
For threshold **0.3**:	1 (TP)	0 (FN)	0 (TN)	1 (TP)	1 (FP)	1 (TP)

➡

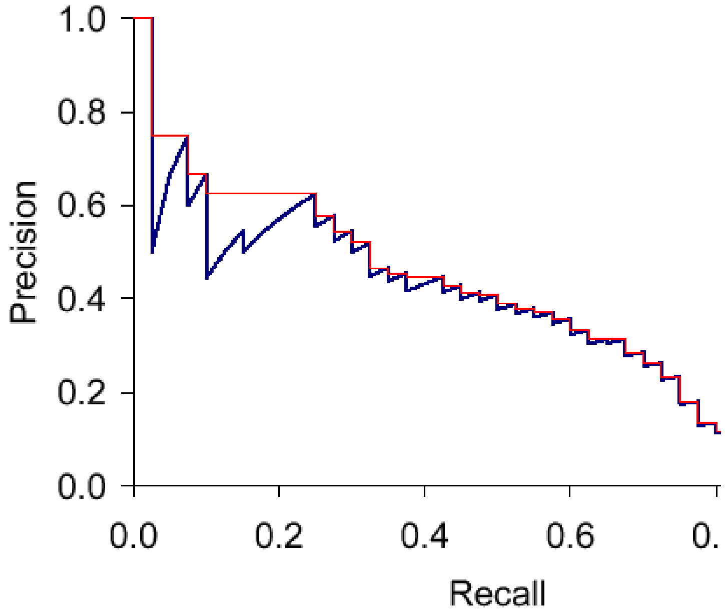
Precision=3/4=0.75
Recall=3/4=.75
TP_{rate}=3/4=0.75
FP_{rate}=1/2=0.5

Plotting performance

- For each threshold we get a point in 2D space
- Visualize performance as plot for all thresholds
- Average Precision (AP) - Averaging over multiple thresholds (k)

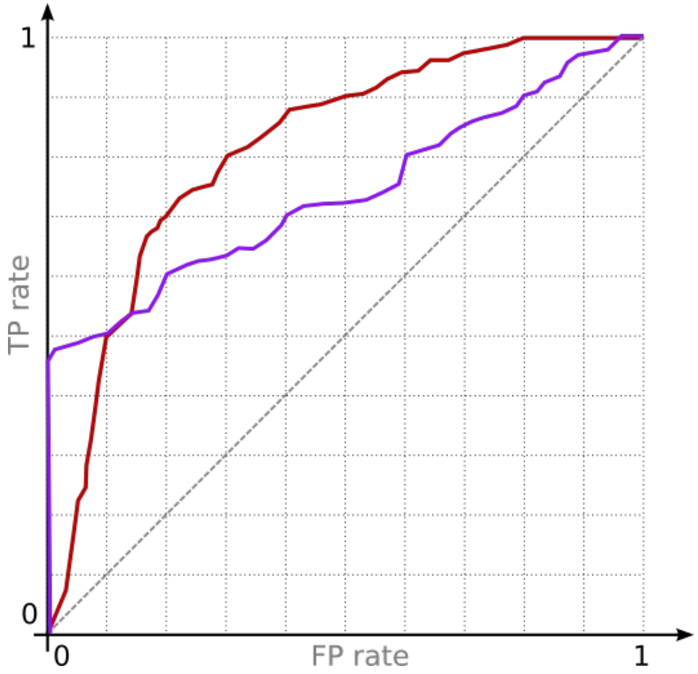
$$AP = 1/|M| \sum_{k \in M} Precision(R_k)$$

- MAP (average of AP for multiple queries)



The ROC curve

- Receiver operating characteristic with respect to criterion (threshold)
  - True positive rate
  - False positive rate
- Interpretable measures
  - Distance to (0, 1)
  - Area under the curve (AUC)



ROC analysis example

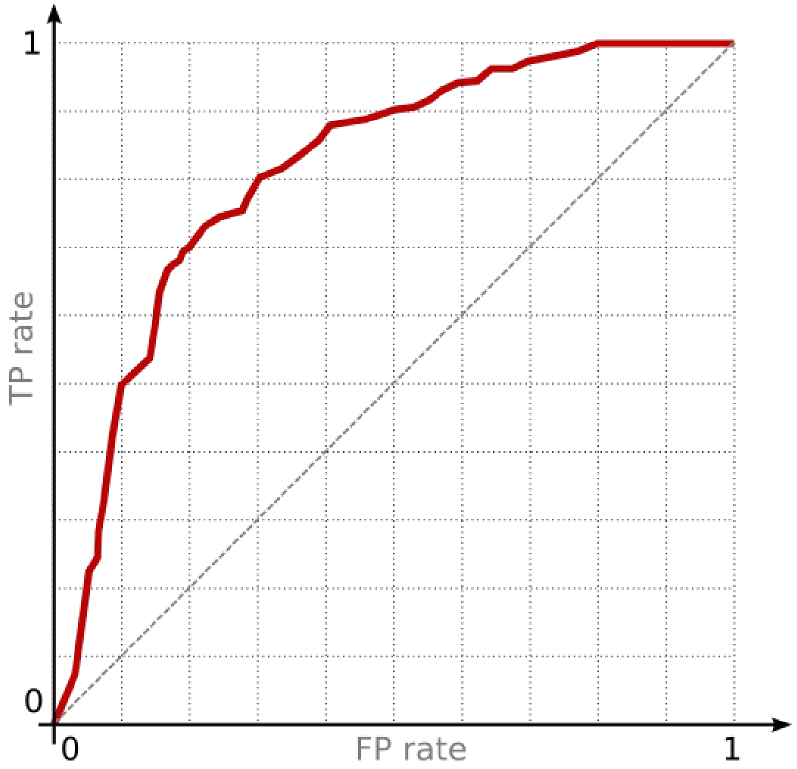
- Documents are scored for relevance by their similarity to the query

	Q	T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8
scores:		0.6	0.2	0.5	0.2	0.5	0.35	0.3	0.4
groundtruth:		1	1	0	0	1	0	0	1

- Calculate the ROC curve and determine optimal threshold
  - Sort documents by similarity
  - Set of unique similarity scores is threshold pool
  - For each threshold in pool calculate TPrate and FPrate
  - Each pair (FPrate, TPrate) is a point on a ROC curve
  - Select threshold that maximizes chosen criteria (e.g. point closest to (0,1))

Reading a ROC curve

- What is the percentage of retrieved relevant documents if we allow 20% of irrelevant documents in the result?
- What percentage of irrelevant results do we get if we want at least 90% of relevant documents in the results?



Efficient retrieval

- Most descriptors are dense
  - Inverted index not efficient
  - Comparison is slow
- Approximate nearest neighbor
  - Accuracy vs. speed

Approximate nearest neighbor

- Random projection
  - Low-dimensional space
- Structure the space
  - Hierarchical Clustering
  - Product Quantization
  - Hierarchical Navigable Small Worlds
- Locality-sensitive hashing
  - Similar descriptors have the same hash value

Vector databases

- Efficient storage of representations
  - Organization
  - Metadata
- Management
  - Sharding
  - Monitoring
  - Access

Pinecone

Milvus

chroma