# Web Retrieval

## Underlying models (II) and relevance feedback

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# Recapitulation

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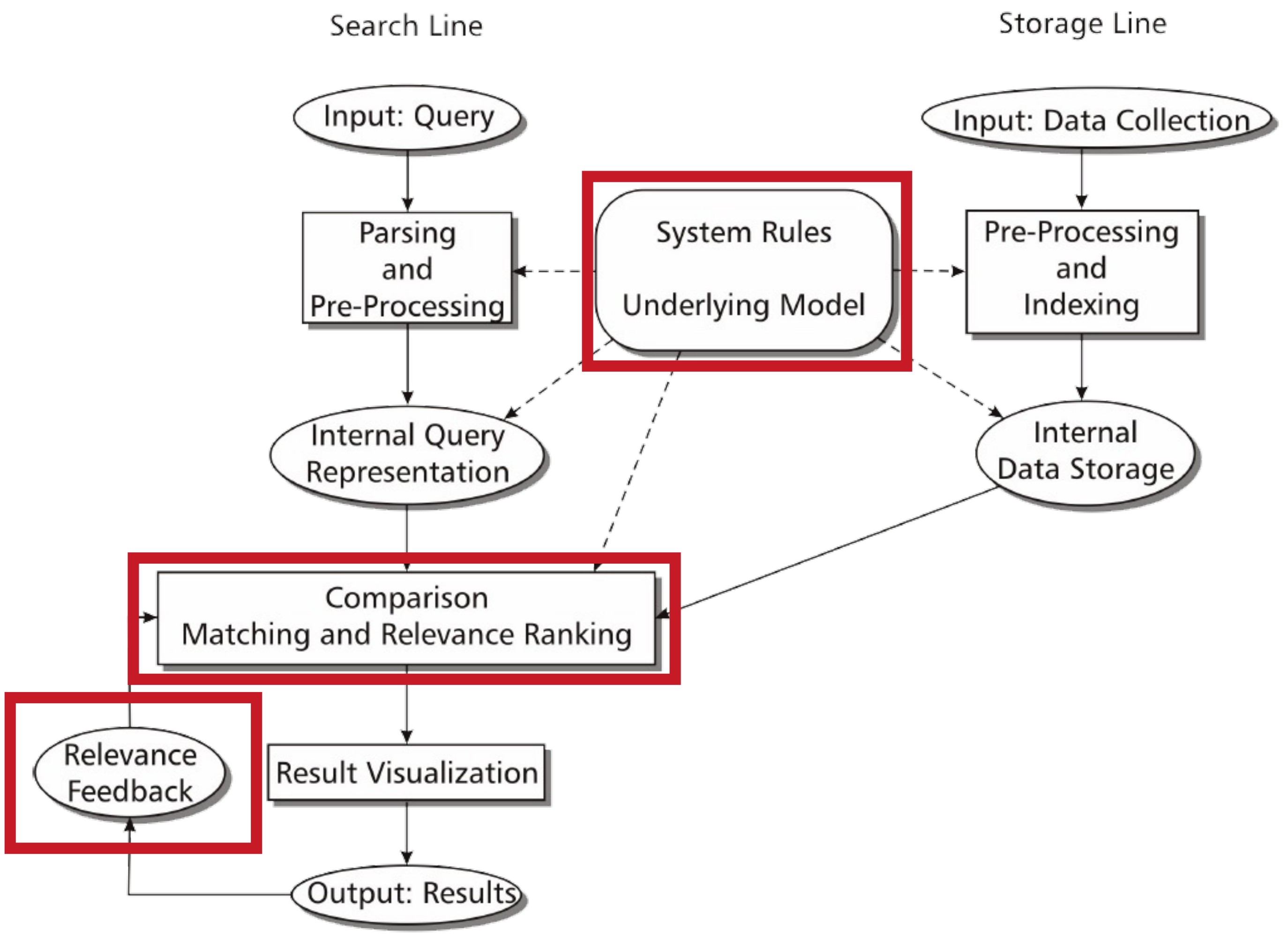
- Underlying models
  - What is a Boolean model?
- Internal data storage
  - What is an inverted index?
- Parsing and Pre-processing
  - What are phrase queries?
  - What are proximity queries?

# IR System Architecture



# Intended Learning Outcomes

At the end of this lecture, you will be able to:

- Explain the limitations of Boolean retrieval when compared to ranked retrieval models
- Outline underlying techniques of ranked retrieval models
- Describe the vector space model
- Summarise the importance of relevance feedback

# Outline

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- Boolean Model: Pros and Cons
- Ranked retrieval model
- Documents scoring
  - TF-IDF
- Query-document matching
  - Jaccard
  - Cosine
- Vector Space Model
- Relevance feedback

# 1. Boolean vs. Ranked Retrieval Models

# Boolean Model: pros and cons

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- Advantages
  - Good for expert users with precise understanding of their needs and the collection
  - Good for applications which can easily consume (process) 1000s of results
- Disadvantages
  - Not good for the majority of users: expressing information needs as Boolean expressions is unintuitive
  - Not practical for users: no ranking + too many results

# Boolean Model

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- Boolean queries often result in either too few (=0) or too many (1000s) results
- Query 1: "*standard user dlink 650*" → 200,000 hits
- Query 2: "*standard user dlink 650 no card found*": 0 hits
- It takes a lot of skill to come up with a query that produces a manageable number of hits
    - AND gives too few; OR gives too many

# Ranked retrieval models

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- Rather than a set of documents satisfying a query expression, in ranked retrieval, the system returns an ordering over the (top) documents in the collection for a query
- Free text queries: Rather than a query language of operators and expressions, the user's query is just one or more words in a human language
- In principle, there are two separate choices here, but in practice, ranked retrieval has normally been associated with free text queries and vice versa

# Ranked retrieval

- When a system produces a ranked result set, large result sets are not an issue
  - Indeed, the size of the result set is not an issue
  - We just show the top $k$ ( $\approx$ 10) results
  - We don't overwhelm the user

- Premise: the ranking algorithm works

# Scoring as the basis of ranked retrieval

- We wish to return in order the documents most likely to be useful to the searcher
  - How can we rank-order the documents in the collection with respect to a query?
    - Assign a score – say in [0, 1] – to each document
    - This score measures how well the document and query “match”

# Query-document matching scores

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- We need a way of assigning a score to a query-document pair
  - Let's start with a one-term query
    - If the query term does not occur in the document: score should be 0
    - The more frequent the query term in the document is, the higher the score (should be)
      - We will consider a number of alternatives to this

# Jaccard coefficient

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- A commonly used measure of overlap of two sets
- Let *A* and *B* be two sets
  - Jaccard coefficient

$$\text{JACCARD}(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

  - JACCARD ($A$, $A$) = 1
  - JACCARD ($A$, $B$) = 0 if $A \cap B = 0$
  - A and B don't have to be the same size
  - Always assigns a number between 0 and 1

# Jaccard coefficient: Example

- What is the query-document match score that the Jaccard coefficient computes for the
  - Query: “ides of March”, and
  - Document “Caesar died in March”
    - JACCARD(q, d) = 1/6

# Issues with Jaccard for scoring

$$\text{JACCARD}(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

- It doesn't consider *term frequency* (how many times a term occurs in a document)
- Are all words in a document equally important? *(stop words)*
  - Rare terms in a collection are more informative than frequent terms
    - Jaccard does not consider this aspect
- We need a more sophisticated way of normalizing for length

# Binary term-document incidence matrix

| | 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 |

- Each document is represented by a binary vector $\in \{0,1\}^{|V|}$

# Term-document count matrices

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- Consider the number of occurrences of a term in a document
  - Each document is a count vector in $\mathbb{N}^{v}$: a column below

| | Antony and Cleopatra | Julius Caesar | The Tempest | Hamlet | Othello | Macbeth |
|---|---|---|---|---|---|---|
| Antony | 157 | 73 | 0 | 0 | 0 | 0 |
| Brutus | 4 | 157 | 0 | 1 | 0 | 0 |
| Caesar | 232 | 227 | 0 | 2 | 1 | 1 |
| Calpurnia | 0 | 10 | 0 | 0 | 0 | 0 |
| Cleopatra | 57 | 0 | 0 | 0 | 0 | 0 |
| mercy | 2 | 0 | 3 | 5 | 5 | 1 |
| worser | 2 | 0 | 1 | 1 | 1 | 0 |

# *Bag of words* model

- Vector representation doesn't consider the ordering of words in a document
- *John is quicker than Mary* and *Mary is quicker than John* have the same vectors
- This is called the bag of words model
- In a sense, this is a step back: The positional index was able to distinguish these two documents
- We will look at “recovering” positional information later in this module
- For now: bag of words model

# Term frequency tf

- The term frequency $\mathbf{tf}_{t,d}$ of term *t* in document *d* is defined as the number of times that ***t*** occurs in ***d***
- We want to use **tf** when computing query-document match scores
  But how?
- Raw term frequency is not what we want
  - A document with 10 occurrences of the term is more relevant than a document with 1 occurrence of the term
  - But not 10 times more relevant
- Relevance does not increase proportionally with term frequency

# Log-frequency weighting



- The log frequency weight of term $t$ in $d$ is defined as follows

$$w_{t,d} = \begin{cases} 1 + \log_{10} tf_{t,d} & if\ tf_{t,d} > 0 \\ 0 & Otherwise \end{cases}$$

- $tf_{t,d} \rightarrow w_{t,d}$
  - $0 \rightarrow 0, 1 \rightarrow 1, 2 \rightarrow 1.3, 10 \rightarrow 2, 1000 \rightarrow 4$, etc.
- Score for a document-query pair: sum over terms t in both q and d:
  - tf-matching-score$(q, d) = \sum_{t \in q \cap d} (1 + \log tf_{t,d})$
- The score is 0 if none of the query terms is present in the document

# Document frequency

- Rare terms are more informative than frequent terms
  - Recall stop words
- Consider a term in the query that is rare in the collection (e.g., *archaeology*)
- A document containing this term is very likely to be relevant to the query *archaeology*
  - We want a high weight for rare terms like *archaeology*

# Document frequency, continued

- Frequent terms are less informative than rare terms
- Consider a query term that is frequent in the collection (e.g., *high, increase, line*)
- A document containing such a term is more likely to be relevant than a document that doesn't
- But it’s not a sure indicator of relevance
- For frequent terms, we want high positive weights for words like *high, increase, and line*
- But lower weights than for rare terms
- We will use document frequency (df) to capture this

# Inverse document frequency (idf) weight

- **$\mathbf{df}_t$** is the document frequency of term *t*: the number of documents in the collection that contain a term *t*
  - $\mathrm{df}_t$ is an inverse measure of the informativeness of *t*
  - $\mathrm{df}_t \leq N$
- We define the **idf** (inverse document frequency) of *t* by

$$\mathrm{idf}_t = \log \; (N/\mathrm{df}_t)$$

  - We use $\log(N/\mathrm{df}_t)$ instead of $N/\mathrm{df}_t$ to "dampen" the effect of idf

# idf example, suppose $N$ = 1 million

| term | $\mathrm{df}_t$ | $\mathrm{idf}_t$ |
|---|---:|---:|
| calpurnia | 1 | 6 |
| animal | 100 | 4 |
| sunday | 1,000 | 3 |
| fly | 10,000 | 2 |
| under | 100,000 | 1 |
| the | 1,000,000 | 0 |

$$\mathrm{idf}_t = \log_{10}\left(N/\mathrm{df}_t\right)$$

- There is one idf value for each term *t* in a collection

# Effect of idf on ranking

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- Does idf have an effect on ranking for one-term queries, like
  - iPhone
- idf has no effect on ranking one term queries
  - idf affects the ranking of documents for queries with at least two terms
  - For the query *capricious person*, $idf$ weighing makes occurrences of *capricious* count for much more in the final document ranking than occurrences of *person*

# Collection vs. Document frequency

- The collection frequency of *t* is the number of occurrences of *t* in the collection, counting multiple occurrences
- Example

| Word | Collection frequency | Document frequency |
|---|---|---|
| Insurance | 10440 | 3997 |
| Try | 10422 | 8760 |

- Which word is a better search term (and should get a higher weight)?

# tf-idf weighting

- The $\mathbf{tf\text{-}idf_{t,d}}$ weight of a term *t* in a document *d* is the product of its tf weight and its idf weight

$$\text{tf-idf}_{\text{t,d}} = \text{tf}_{t,d} \times \text{idf}_{\text{t,d}}$$
$$= \text{tf}_{t,d} \times \log\left({}^{N}/_{\text{df}_t}\right)$$

- Best known weighting scheme in information retrieval
  - Note: the “-” in tf-idf is a hyphen, not a minus sign!
  - Alternative names: tf.idf, tf x idf
- Increases with the number of occurrences within a document
- Increases with the rarity of the term in the collection

# Score for a document given a query

$$Score(q,d) = \sum_{t \in q \cap d} \mathrm{tf.idf}_{t,d}$$

- There are many variants based on
  - how "tf" is computed (with/without logs)
  - whether the terms in the query are weighted too
  - and more

# 2. Vector Space Model

# Binary term-document incidence matrix

| | Antony and Cleopatra | Julius Caesar | The Tempest | Hamlet | Othello | Macbeth |
|---|---|---|---|---|---|---|
| Antony | 1 | 1 | 0 | 0 | 0 | 0 |
| 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 |

Each document is represented by a binary vector $\in \{0,1\}^{|V|}$

# Count matrices

| | Antony and Cleopatra | Julius Caesar | The Tempest | Hamlet | Othello | Macbeth |
|---|---|---|---|---|---|---|
| Antony | 157 | 73 | 0 | 0 | 0 | 0 |
| Brutus | 4 | 157 | 0 | 1 | 0 | 0 |
| Caesar | 232 | 227 | 0 | 2 | 1 | 1 |
| Calpurnia | 0 | 10 | 0 | 0 | 0 | 0 |
| Cleopatra | 57 | 0 | 0 | 0 | 0 | 0 |
| mercy | 2 | 0 | 3 | 5 | 5 | 1 |
| worser | 2 | 0 | 1 | 1 | 1 | 0 |

# Binary → count → weight matrix



| | Antony and Cleopatra | Julius Caesar | The Tempest | Hamlet | Othello | Macbeth |
|---|---|---|---|---|---|---|
| Antony | 5,25 | 3,18 | 0 | 0 | 0 | 0 |
| Brutus | 1,21 | 6,1 | 0 | 1 | 0 | 0 |
| Caesar | 8,59 | 2,54 | 0 | 1,51 | 0,25 | 1.95 |
| Calpurnia | 0 | 1,54 | 0 | 0 | 0 | 0 |
| Cleopatra | 2,85 | 0 | 0 | 0 | 0 | 0 |
| mercy | 1,51 | 0 | 1,9 | 0,12 | 5,25 | 0,88 |
| worser | 1,37 | 0 | 0,11 | 4,15 | 0,25 | 0 |

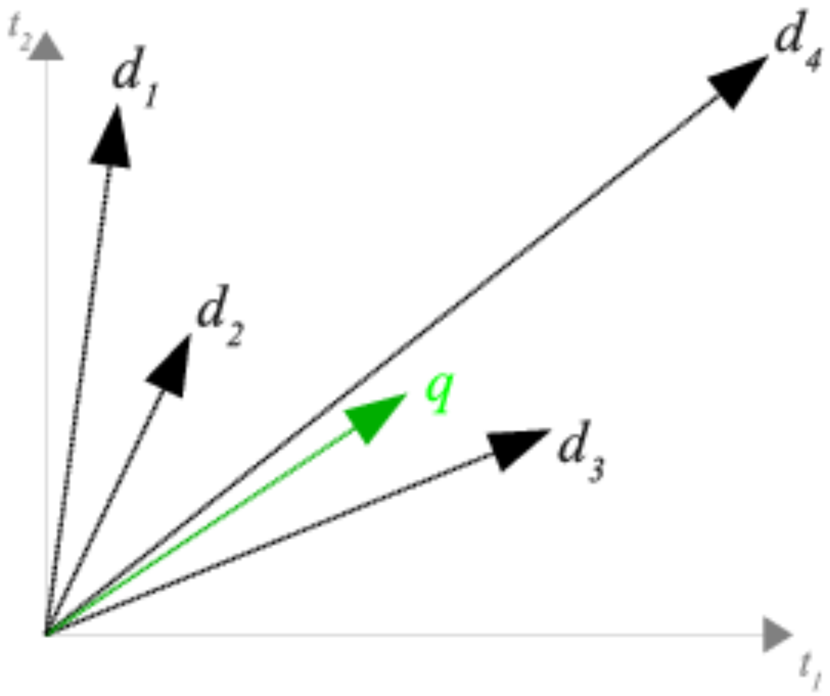
- Each document is now represented by a real-valued vector of tf-idf weights $\in \mathbb{R}^{|V|}$

# Documents as vectors

- So we have a $|V|$-dimensional vector space
- Terms are axes of the space
- Documents are points or vectors in this space
- Very high-dimensional: tens of millions of dimensions when you apply this to a web search engine
- These are very sparse vectors - most entries are zero

# Idea

- Documents as vectors in a high dimensional space
  - Queries are documents
- Terms define dimensions (base vectors)
- Assumptions
  - Base vectors orthogonal
  - Similar documents have similar vectors
  - Vector similarity indicates document similarity
    - Distance
    - Angle



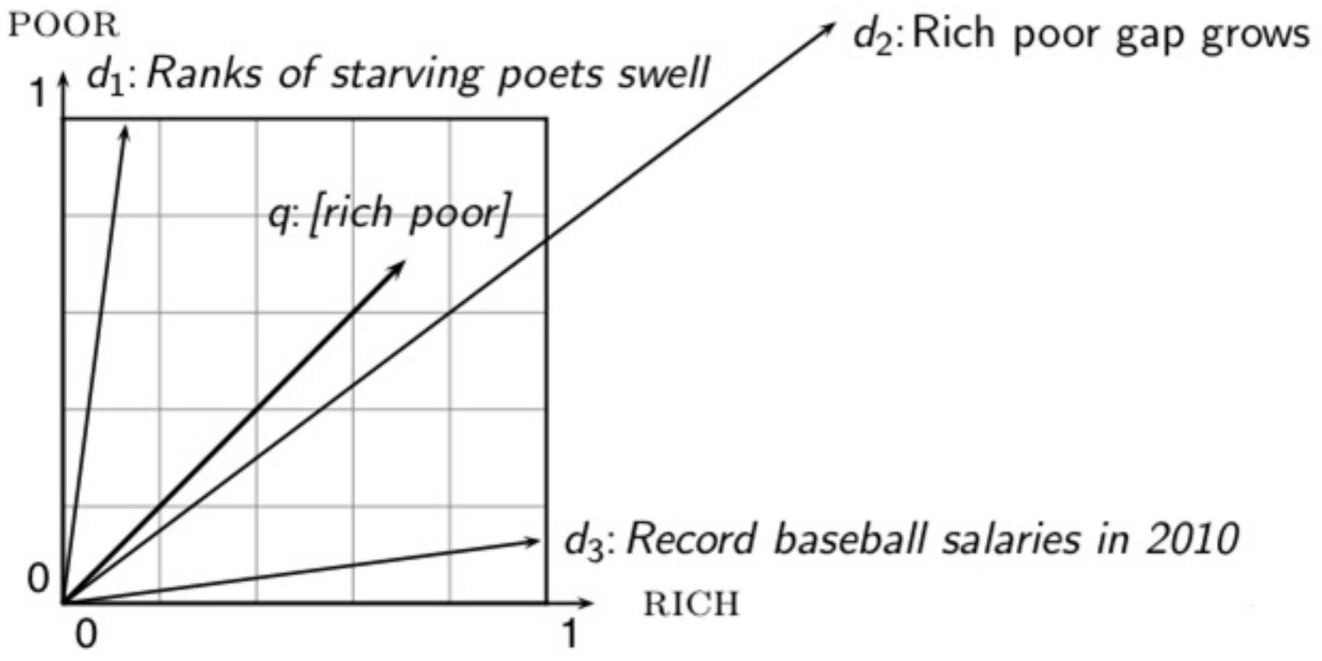

Similarity ranking for *q*?
- With distance
- With angle

# Formalizing vector space proximity

- First cut: distance between two points
  - ( = distance between the end points of the two vectors)
- Euclidean distance?
  - Euclidean distance is a bad idea . . .
    - … because Euclidean distance is <u>large</u> for vectors of <u>different lengths</u>

# Why distance is a bad idea

- The Euclidean distance between $\vec{q}$ and $\vec{d_2}$ is large even though the distribution of terms in the query $\vec{q}$ and the distribution of terms in the document $\vec{d_2}$ are very similar



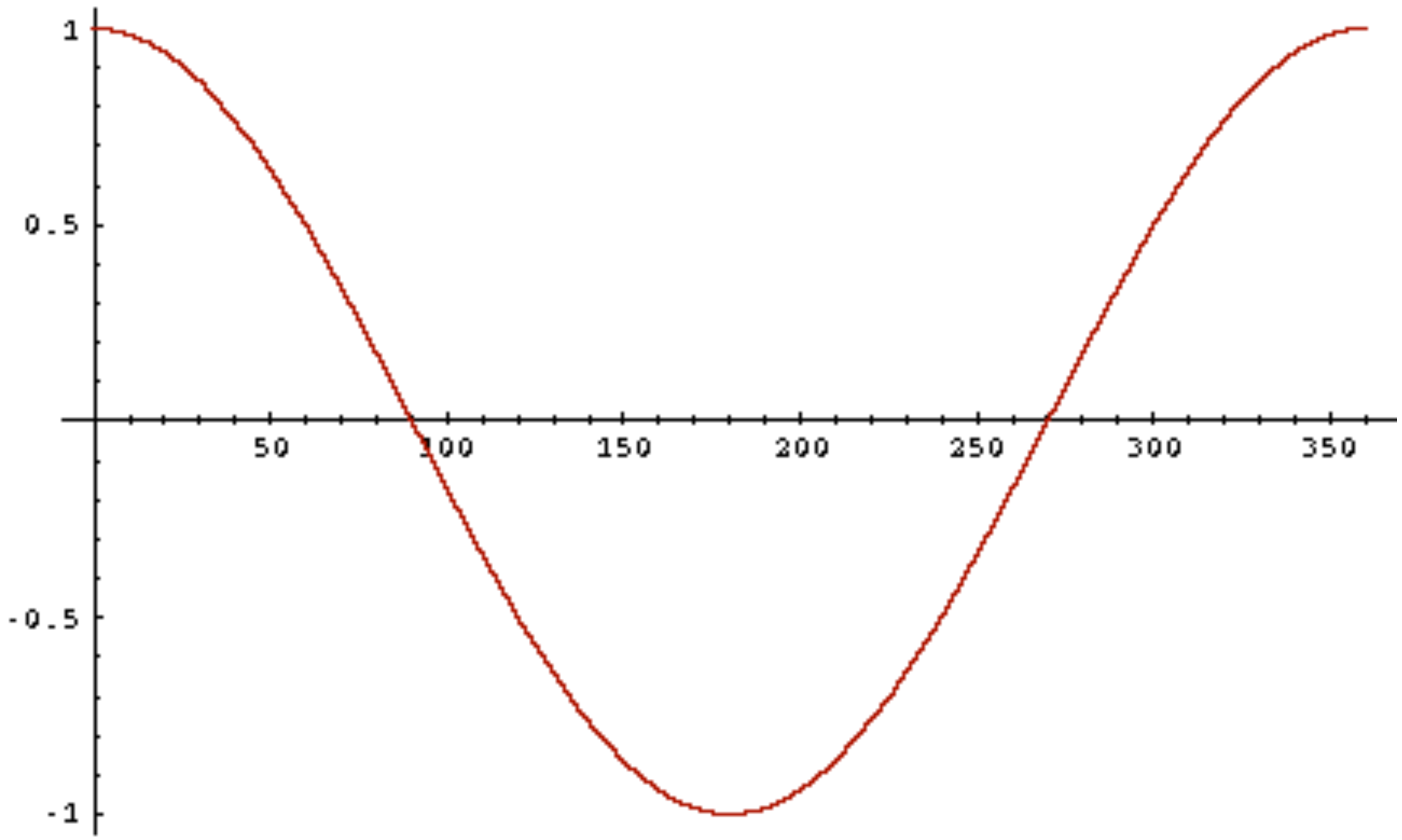
# Use angle instead of distance

- Thought experiment: take a document *d* and append it to itself. Call this document *d*'
- "Semantically" $d$ and $d'$ have the same content
- The Euclidean distance between the two documents can be quite large
- The angle between the two documents is 0, corresponding to maximal similarity

- Key idea: Rank documents according to angle with query

# From angles to cosines

- Cosine is a monotonically decreasing function for the interval [0º, 180º]




The following two notions are equivalent

- Rank documents in decreasing order of the angle between query and document
- Rank documents in increasing order of cosine(query,document)

- But how – *and why* – should we compute cosines?

# cosine(query, document)

Dot product

Unit vectors

$$\cos(\vec{q},\vec{d}) = \frac{\vec{q}\bullet\vec{d}}{|\vec{q}||\vec{d}|} = \frac{\vec{q}}{|\vec{q}|}\bullet\frac{\vec{d}}{|\vec{d}|} = \frac{\sum_{i=1}^{|V|} q_i d_i}{\sqrt{\sum_{i=1}^{|V|} q_i^2}\sqrt{\sum_{i=1}^{|V|} d_i^2}}$$

- $q_i$ is the tf-idf weight of term *i* in the query
- $d_i$ is the tf-idf weight of term *i* in the document

$\cos(\vec{q}, \vec{d})$ is the cosine similarity of *q* and *d* … or,
equivalently, the cosine of the angle between *q* and *d*

# Vector Space Model (VSM) Framework

- Corpus: $D = \{d_1, \dots, d_N\}$
- Vocabulary: $V = \{t_1, \dots, t_M\}$
- Documents as vectors in $R^M$

$$\vec{d}_i = \left(w_i^{[1]}, w_i^{[2]}, \cdots, w_i^{[M]}\right)$$

  – Where $w_i^{[j]}$ weight of term $t_j$ in document $d_i$
- Queries:

$$\vec{q} = \left(w_q^{[1]}, w_q^{[2]}, \cdots, w_q^{[M]}\right)$$

# VSM Framework

- Retrieval function

$$\rho\left(\vec{d}_i, \vec{q}\right) = \mathrm{sim}\left(\vec{d}_i, \vec{q}\right)$$

- Similarity measure

$$\mathrm{sim} : \mathrm{R}^M \times \mathrm{R}^M \rightarrow [0,1]$$

  - With
    - Value 1: same vector
    - Value 0: „completely different“ vector
- Result list
  - All documents with $\rho>0$, sorted by descending score

# Combined Weights

- Combined weight: TF-IDF

$$w_{\mathrm{TF.IDF}}(t_j, d_i) = w_{\mathrm{local}}(t_j, d_i) \times w_{\mathrm{global}}(t_j)$$
$$= \mathrm{tf}(t_j, d_i) \times \log\left({}^{N}\!/_{\mathrm{df}(t_j)}\right)$$

  – In particular: weight zero for $\mathrm{tf}(t_j, d_i)=0$ or $\mathrm{df}(t_j)=N$

- Similarity: Cosine measure

$$\mathrm{sim}(d_i, q) = \cos(\vec{d}_i, \vec{q}) = \frac{\vec{d}_i \cdot \vec{q}}{|\vec{d}_i| \cdot |\vec{q}|}$$

  – Includes length normalization

# Example

- Global weights
  - E.g. for „cup“

$$w_{\text{global}}(\text{cup}) = \log\left({}^{N}/_{\text{df(cup)}}\right)$$

$$\log\left({}^{5}/_{3}\right) \approx 0.22$$

| $t_j$ | $df(t_j)$ | $w_{global}(t_j)$ |
|---|---|---|
| coffee | 3 | 0.22 |
| cup | 3 | 0.22 |
| jar | 4 | 0.10 |
| tea | 2 | 0.40 |
| water | 1 | 0.70 |

1. coffee, coffee
2. cup, jar, jar, tea, tea
3. coffee, cup, cup, jar
4. coffee, coffee, coffee, cup, cup, cup, jar, jar, jar, tea
5. jar, jar, water, water

# Example

- Combined with local weights

| $t_j$ | $d_1$ | $d_2$ | $d_3$ | $d_4$ | $d_5$ |
|---|---|---|---|---|---|
| coffee | 2 | | 1 | 3 | |
| cup | | 1 | 2 | 3 | |
| jar | | 2 | 1 | 3 | 2 |
| tea | | 2 | | 1 | |
| water | | | | | 2 |

$$\vec{d}_2 = (0\cdot 0.22, 1\cdot 0.22, 2\cdot 0.10, 2\cdot 0.4, 0\cdot 0.7)$$

| $t_j$ | $d_1$ | $d_2$ | $d_3$ | $d_4$ | $d_5$ |
|---|---|---|---|---|---|
| coffee | 0.44 | 0 | 0.22 | 0.66 | 0 |
| cup | 0 | 0.22 | 0.44 | 0.66 | 0 |
| jar | 0 | 0.20 | 0.10 | 0.30 | 0.20 |
| tea | 0 | 0.80 | 0 | 0.40 | 0 |
| water | 0 | 0 | 0 | 0 | 1.40 |

1. coffee, coffee
2. cup, jar, jar, tea, tea
3. coffee, cup, cup, jar
4. coffee, coffee, coffee, cup, cup, cup, jar, jar, jar, tea
5. jar, jar, water, water

| $t_j$ | $df(t_j)$ | $w_{global}(t_j)$ |
|---|---|---|
| coffee | 3 | 0.22 |
| cup | 3 | 0.22 |
| jar | 4 | 0.10 |
| tea | 2 | 0.40 |
| water | 1 | 0.70 |

# Query vector

- Construction of query vector
  - Just like a document
  - Using global weights from corpus

$$
\begin{aligned}
w_{\mathrm{TF.IDF}}(t_j, q) &= w_{\mathrm{local}}(t_j, q) \times w_{\mathrm{global}}(t_j) \\
&= \mathrm{tf}(t_j, q) \times \log\left( {}^{N}\!/_{\mathrm{df}(t_j)} \right)
\end{aligned}
$$

- Note
  - Frequency of query terms matters
  - Sequence does not matter (bag of words)

# Example

- Query: „cup jar“
- Query vector

$$\vec{q} = (0, 0.22, 0.1, 0, 0)$$

- Vector lengths:

$$|\vec{q}| = \sqrt{0.22^2 + 0.1^2} = 0.24$$

$$|\vec{d}_1| = 0.44$$

$$|\vec{d}_2| = 0.85$$

$$|\vec{d}_3| = 0.50$$

$$|\vec{d}_4| = 1.06$$

$$|\vec{d}_5| = 1.41$$

1. coffee, coffee
2. cup, jar, jar, tea, tea
3. coffee, cup, cup, jar
4. coffee, coffee, coffee, cup, cup, cup, jar, jar, jar, tea
5. jar, jar, water, water

| $t_j$ | $d_1$ | $d_2$ | $d_3$ | $d_4$ | $d_5$ |
|---|---|---|---|---|---|
| coffee | 0.44 | 0 | 0.22 | 0.66 | 0 |
| cup | 0 | 0.22 | 0.44 | 0.66 | 0 |
| jar | 0 | 0.20 | 0.10 | 0.30 | 0.20 |
| tea | 0 | 0.80 | 0 | 0.40 | 0 |
| water | 0 | 0 | 0 | 0 | 1.40 |

# Example

- Query vector:

$$\vec{q} = (0, 0.22, 0.1, 0, 0)$$

- Relevance (e.g. $d_5$):

$$\rho(\vec{d}_5, \vec{q}) = \frac{0 \cdot 0 + 0.22 \cdot 0 + 0.1 \cdot 0.2 + 0 \cdot 0 + 0 \cdot 1.4}{0.24 \cdot 1.41}$$

- Ranking

| Rank | Document | $\rho$ |
|---|---|---|
| 1 | $d_3$ | 0.89 |
| 2 | $d_4$ | 0.69 |
| 3 | $d_2$ | 0.33 |
| 4 | $d_5$ | 0.05 |

$d_1$ not in result list as $\rho(d_1,q)=0$

1. coffee, coffee
2. cup, jar, jar, tea, tea
3. coffee, cup, cup, jar
4. coffee, coffee, coffee, cup, cup, cup, jar, jar, jar, tea
5. jar, jar, water, water

| $t_j$ | $d_1$ | $d_2$ | $d_3$ | $d_4$ | $d_5$ |
|---|---|---|---|---|---|
| coffee | 0.44 | 0 | 0.22 | 0.66 | 0 |
| cup | 0 | 0.22 | 0.44 | 0.66 | 0 |
| jar | 0 | 0.20 | 0.10 | 0.30 | 0.20 |
| tea | 0 | 0.80 | 0 | 0.40 | 0 |
| water | 0 | 0 | 0 | 0 | 1.40 |
| ***Length*** | ***0.44*** | ***0.85*** | ***0.50*** | ***1.06*** | ***1.41*** |

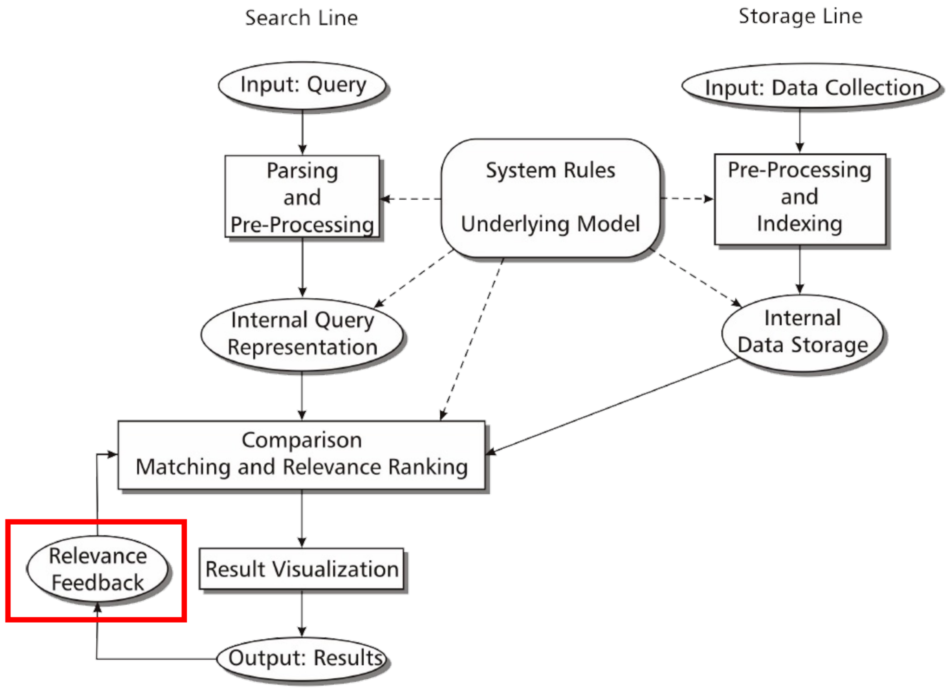
# Summary – vector space ranking

- Represent the query as a weighted tf-idf vector
- Represent each document as a weighted tf-idf vector
- Compute the cosine similarity score for the query vector and each document vector
- Rank documents with respect to the query by score
- Return the top $K$ (e.g., $K = 10$) to the user

# 3. Relevance Feedback (Rocchio)

# Relevance feedback

- Filter
  - Reduces the result set
  - Filter criteria are metadata
  - Date
  - Domain
  - File type
  - …



# Incorporate Feedback

- User provides for some documents if they are relevant or irrelvant:
  - $D^p$ : set of documents with positive feedback (relevant)
  - $D^n$ : set of documents with negative feedback (irrelevant)
- Adjust query vector

$$\vec{q}_{FB} = \alpha \cdot \vec{q} + \beta \frac{1}{|D^p|} \sum_{d_i \in D^p} \vec{d}_i - \gamma \frac{1}{|D^n|} \sum_{d_i \in D^n} \vec{d}_i$$

  - Parameters: typically $\alpha > \beta > \gamma$
  - Adjust negative term weights to 0

# Example

- Query:
  - paris hilton
- Documents

| | paris | hilton | hotel | france | eiffel | blonde | heiress | actress |
|---|---|---|---|---|---|---|---|---|
| $d_1$ | 3 | 1 | 1 | 2 | 1 | | | |
| $d_2$ | 1 | 3 | 4 | 1 | 3 | | | |
| $d_3$ | 2 | 1 | | 1 | | | | |
| $d_4$ | 3 | | | 2 | | | 1 | |
| $d_5$ | | 1 | 3 | | | | | |
| $d_6$ | 3 | 3 | | | | 2 | | |
| $d_7$ | 2 | 2 | | | | | 2 | |
| $d_8$ | 2 | 1 | 1 | | | 1 | 1 | |
| $d_9$ | 3 | 2 | | | | 1 | | 4 |
| $d_{10}$ | 3 | 2 | | 1 | | | 2 | 3 |

# Example



- Initial result list based on VSM
- User provides relevance feedback
  - Positive
  - Negative
- Parameter:
  - $\alpha = 1$
  - $\beta = 0.75$
  - $\gamma = 0.15$

| Rank | Doc | ρ |
|---|---|---|
| 1 | $d_3$ | 0.395 |
| 2 | $d_6$ | 0.183 |
| 3 | $d_7$ | 0.161 |
| 4 | $d_4$ | 0.132 |
| 5 | $d_1$ | 0.128 |
| 6 | $d_8$ | 0.125 |
| 7 | $d_{10}$ | 0.071 |
| 8 | $d_9$ | 0.057 |
| 9 | $d_2$ | 0.049 |
| 10 | $d_5$ | 0.027 |

# Example

$$\vec{q}_{FB} = \alpha \cdot \vec{q} + \beta \frac{1}{|D^p|} \sum_{d_i \in D^p} \vec{d}_i - \gamma \frac{1}{|D^n|} \sum_{d_i \in D^n} \vec{d}_i$$

- Adjust query

$\alpha = 1$
$\beta = 0.75$
$\gamma = 0.15$

$$\vec{q}_{FB} = 1 \cdot \begin{pmatrix} 0.046 \\ 0.046 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} + 0.75 \cdot \frac{1}{2} \cdot \left[ \begin{pmatrix} 0.137 \\ 0.046 \\ 0.398 \\ 0.602 \\ 0.699 \\ 0 \\ 0 \\ 0 \end{pmatrix} + \begin{pmatrix} 0.092 \\ 0.092 \\ 0 \\ 0.301 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} \right]$$

$$-0.15 \cdot \frac{1}{2} \cdot \left[ \begin{pmatrix} 0.092 \\ 0.092 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0.796 \\ 0 \end{pmatrix} + \begin{pmatrix} 0.092 \\ 0.046 \\ 0 \\ 0 \\ 0 \\ 0.523 \\ 0.398 \\ 0 \end{pmatrix} \right] \mapsto \begin{pmatrix} 0.118 \\ 0.087 \\ 0.119 \\ 0.339 \\ 0.262 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

| Rank | Doc | ρ |
|---|---|---|
| 1 | $d_1$ | 0.957 |
| 2 | $d_3$ | 0.787 |
| 3 | $d_2$ | 0.691 |
| 4 | $d_4$ | 0.640 |
| 5 | $d_5$ | 0.262 |
| 6 | $d_8$ | 0.172 |
| 7 | $d_{10}$ | 0.119 |
| 8 | $d_6$ | 0.056 |
| 9 | $d_7$ | 0.050 |
| 10 | $d_9$ | 0.018 |

- Retrieve new results

# Relevance Feedback in Practice

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- Users unwilling to give feedback
  - Query reformulation is easier
- Pseudo relevance feedback
  - Retrieve result list (do not show to user)
  - Use top-k results as positive feedback
    - Rarely low-ranking documents as negative feedback
  - Adjust query vector
  - Retrieve final result list
- Works good, when initial results are good

# 4. Summary

# Summary

- At the end of this lecture you should understand the following concepts
  - Boolean Model
  - Ranked retrieval model
  - Scoring
  - Term frequency
  - Document frequency
  - TF-IDF
  - Vector Space Model
  - Relevance feedback