UNIVERSITÀ DEGLI STUDI DI NAPOLI PARTHENOPE

Natural Language Processing

Information retrieval: Ranked retrieval

LESSON 12

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Ranked retrieval

- Thus far, our queries have all been Boolean
  - Documents either match or don't
- Good for expert users with precise understanding of their needs and the collection
  - Also good for applications: Applications can easily consume 1000s of results
- Not good for the majority of users
  - Most users are incapable of writing Boolean queries
  - Most users don't want to wade through 1000s of results
    - This is particularly true of web search

Problem with Boolean search

- 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
- With a ranked list of documents, it does not matter how large the retrieved set is

Ranked retrieval models

- Rather than a set of documents satisfying a query expression, in ranked retrieval models, the system returns an ordering over the (top) documents in the collection with respect to 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 models have normally been associated with free text queries and vice versa

Large set results not a problem in 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 (≈ 10) results
  - We don't overwhelm the user

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 the query “match”

Query-document matching scores

- 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, the higher the score (should be)
- We will look at a number of alternatives for this

Alternative 1: Jaccard coefficient

- A commonly used measure of overlap of two sets A and B is the Jaccard coefficient
- jaccard(A,B) = |A ∩ B| / |A ∪ B|
  - jaccard(A,A) = 1
  - jaccard(A,B) = 0 if A ∩ B = 0
- A and B don't have to be the same size
- Always assigns a number between 0 and 1

Jaccard coefficient: Scoring example and issues

- What is the query-document match score that the Jaccard coefficient computes for each of the two documents below?
  - Query: *ides of march*
  - Document 1: *caesar died in march*
  - Document 2: *the long march*
- It doesn't consider term frequency (how many times a term occurs in a document)
  - Rare terms in a collection are more informative than frequent terms
  - Jaccard doesn't consider this information

Recall: 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

- 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
- A bag of words model
- In a sense, this is a step back: The positional index was able to distinguish these two documents

Term frequency tf

- The term frequency $tf_{t,d}$ 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
  - N.B.: frequency = count in IR

Log-frequency weighting

- The log frequency weight of term t in d is

$$w_{t,d} = \begin{cases} 1 + \log_{10} \mathrm{tf}_{t,d}, & \text{if } \mathrm{tf}_{t,d} > 0 \\ 0, & \text{otherwise} \end{cases}$$

- Score for a document-query pair: sum over terms t in both q and d

$$\text{score} = \sum_{t \in q \cap d} (1 + \log \mathrm{tf}_{t,d})$$

- 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., *arachnocentric*)
- A document containing this term is very likely to be relevant to the query *arachnocentric*
  - We want a high weight for rare terms like arachnocentric

Document frequency (cont'd)

- 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 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

idf weight

- df_t is the document frequency of t
    - the number of documents that contain t
        - df_t is an inverse measure of the informativeness of t
        - $df_t \leq N$
- We define the idf (inverse document frequency) of t
    - We use log (N/df_t) instead of N/df_t to "dampen" the effect of idf

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

Example: N = 1 million

term	df_t	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*

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

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

Effect of idf on ranking

- Question: 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 weighting 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
- Document frequency is the number of documents in the collection containing the term
- 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 tf-idf weight of a term is the product of its tf weight and its idf weight

$$\mathrm{w}_{t,d} = (1 + \log \mathrm{tf}_{t,d}) \times \log_{10}(N / \mathrm{df}_t)$$

- Best known weighting scheme in information retrieval
- Increases with the number of occurrences within a document
- Increases with the rarity of the term in the collection
- Final ranking of documents for a query

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

Binary → count → weight matrix

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

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
Antony	5,25	3,18	0	0	0	0,35
Brutus	1,21	6,1	0	1	0	0
Caesar	8,59	2,54	0	1,51	0,25	0
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	1,95

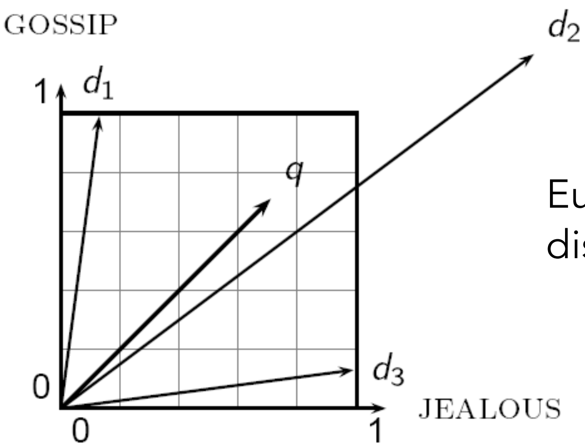
- Now we have a $|V|$-dimensional vector space

Queries as vectors

- Key idea 1: Do the same for queries: represent them as vectors in the space
- Key idea 2: Rank documents according to their proximity to the query in this space
- proximity = similarity of vectors
- proximity ≈ inverse of distance
- Recall: We do this because we want to get away from the *either-in-or-out* Boolean model
- Instead: rank more relevant documents higher than less relevant documents

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 large for vectors of different lengths



Euclidean(q, d_2) is large even though the distribution of terms in q and d_2 are very similar

Cosine similarity

- Key idea: Rank documents according to angle with query

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

- 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

Example

- Novels' similarity
  - SaS: *Sense and Sensibility*
  - PaP: *Pride and Prejudice*
    - *Jane Austen*
  - WH: *Wuthering Heights*
    - *Emily Bronte*

term	SaS	PaP	WH
affection	115	58	20
jealous	10	7	11
gossip	2	0	6
wuthering	0	0	38

Term frequencies (counts)

- Note: To simplify this example, we don't do idf weighting

Example (cont'd)

Log frequency weighting

term	SaS	PaP	WH
affection	3.06	2.76	2.30
jealous	2.00	1.85	2.04
gossip	1.30	0	1.78
wuthering	0	0	2.58

After length normalization

term	SaS	PaP	WH
affection	0.789	0.832	0.524
jealous	0.515	0.555	0.465
gossip	0.335	0	0.405
wuthering	0	0	0.588

- cos(SaS,PaP) ≈ 0.789 × 0.832 + 0.515 × 0.555 + 0.335 × 0.0 + 0.0 × 0.0 ≈ 0.94
- cos(SaS,WH) ≈ 0.79
- cos(PaP,WH) ≈ 0.69

tf-idf weighting has many variants

Term frequency		Document frequency		Normalization	
n (natural)	$\mathrm{tf}_{t,d}$	n (no)	1	n (none)	1
l (logarithm)	$1 + \log(\mathrm{tf}_{t,d})$	t (idf)	$\log \frac{N}{\mathrm{df}_t}$	c (cosine)	$\frac{1}{\sqrt{w_1^2 + w_2^2 + \ldots + w_M^2}}$
a (augmented)	$0.5 + \frac{0.5 \times \mathrm{tf}_{t,d}}{\max_t(\mathrm{tf}_{t,d})}$	p (prob idf)	$\max\{0, \log \frac{N - \mathrm{df}_t}{\mathrm{df}_t}\}$	u (pivoted unique)	$1/u$
b (boolean)	$\begin{cases} 1 & \text{if } \mathrm{tf}_{t,d} > 0 \\ 0 & \text{otherwise} \end{cases}$			b (byte size)	$1/\mathit{CharLength}^{\alpha}$, $\alpha < 1$
L (log ave)	$\frac{1 + \log(\mathrm{tf}_{t,d})}{1 + \log(\mathrm{ave}_{t \in d}(\mathrm{tf}_{t,d}))}$				

Weighting may differ in queries vs documents

- Many search engines allow for different weightings for queries vs. documents
- SMART Notation: denotes the combination in use in an engine, with the notation *ddd.qqq*, using the acronyms from the previous table
- A very standard weighting scheme is: lnc.ltc
- Document: logarithmic tf (l as first character), no idf and cosine normalization

A bad idea?

- Query: logarithmic tf (l in leftmost column), idf (t in second column), cosine normalization …

Computing cosine scores

CosineScore(q)

float $Scores[N] = 0$
float $Length[N]$
for each query term t
do calculate $w_{t,q}$ and fetch postings list for t
    for each pair$(d, \mathrm{tf}_{t,d})$ in postings list
    do $Scores[d] += w_{t,d} \times w_{t,q}$
Read the array *Length*
for each d
do $Scores[d] = Scores[d]/Length[d]$
return Top K components of $Scores[]$

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

Evaluating an IR system

- An **information need** is translated into a **query**
- Relevance is assessed relative to the **information need** *not* the **query**
- E.g., Information need: *I'm looking for information on whether drinking red wine is more effective at reducing your risk of heart attacks than white wine.*
- Query: ***wine red white heart attack effective***
- You evaluate whether the doc addresses the information need, not whether it has these words

Evaluating ranked results

- Evaluation of a result set:
  - If we have
    - a benchmark document collection
    - a benchmark set of queries
    - assessor judgments of whether documents are relevant to queries

  Then we can use Precision/Recall/F measure
- Evaluation of ranked results:
  - The system can return any number of results
  - By taking various numbers of the top returned documents (levels of recall), the evaluator can produce a *precision-recall curve*

IR System Evaluation

- More details on Further readings
  - Chapter 8 from Chris Manning's Book (up to paragraph 8.4 included)
  - On the elearning platform