CMP462: Natural Language Processing

Lecture 12: Ranked Information Retrieval

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Agenda

- Ranked Retrieval
- Jaccard Coefficient
- Term Frequency
- Inverse Document Frequency
- TF-IDF
- Vector Space Model
- Evaluation

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Introduction to

Information Retrieval

Introducing ranked retrieval

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 incapable of writing Boolean queries (or they are, but they think it's too much work).
  - Most users don't want to wade through 1000s of results.
    - This is particularly true of web search.

Problem with Boolean search: feast or famine

- 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

- 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

Feast or famine: 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
  - 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 document and 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

Introduction to

Information Retrieval

Scoring with the Jaccard coefficient

Take 1: Jaccard coefficient

- A commonly used measure of overlap of two sets *A* and *B* is the Jaccard coefficient
- jaccard$(A,B) = |A \cap B| / |A \cup B|$
- 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: Scoring example

- 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*

$$J(q, d_1) = \frac{|q \cap d_1|}{|q \cup d_1|} = \frac{1}{6}$$

$$J(q, d_2) = \frac{1}{5}$$

Score of d_2 is larger because it is shorter!

Issues with Jaccard for scoring

- 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 e.g. the vs. Stanford
  - Jaccard doesn't consider this information
- We need a more sophisticated way of normalizing for length
  - Later in this lecture, we'll use $|A \cap B| / \sqrt{|A \cup B|}$

  . . . instead of $|A \cap B| / |A \cup B|$ (Jaccard) for length normalization.

Introduction to

Information Retrieval

Term frequency weighting

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

binary vector of length |V|

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

Count vector of length |V|

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 on
  - For now: bag of words model

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.

NB: frequency = count in IR

Log-frequency weighting

- The log frequency weight of term *t* in *d* is

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

- 0 → 0 1 → 1 2 → 1.3 10 → 2 1000 → 4 ...
- Score for a document-query pair: sum over terms *t* in both *q* and *d*:

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

- The score is 0 if none of the query terms is present in the document.

Introduction to

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(Inverse) Document frequency weighting

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, 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 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*
  - $\text{df}_t \leq N$
- We define the idf (inverse document frequency) of *t* by

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

  - We use log (*N*/df*t*) instead of *N*/df*t* to "dampen" the effect of idf.

$$\text{score} = \sum_{t \in d \cap q} \log_{10}(N/\text{df}_t)$$

idf example, suppose N = 1 million

term	df_t	idf_t
calpurnia	1	$\log_{10} 1000000/1 = 6$
animal	100	$\log_{10} 1000000/100 = 4$
sunday	1,000	3
fly	10,000	2
under	100,000	1
the	1,000,000	0

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

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

$$\text{score} = \sum_{t \in d \cap q} \log_{10}\left(N / \text{df}_t\right)$$

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.

$$\text{score} = \sum_{t \in d \cap q} \log_{10}(N/\text{df}_t)$$

Collection vs. Document frequency

- The collection frequency of *t* is the number of occurrences of *t* in the collection, counting multiple occurrences (e.g. used in Unigram models).
- Example:

Word	Collection frequency	Document frequency
insurance	10440	3997
try	10422	8760

insurance tends to occur several times in documents that contain them, unline *try*

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

Introduction to

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tf-idf weighting

tf-idf weighting

- The tf-idf weight of a term is the product of its tf weight and its idf weight.

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

- 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

Final ranking of documents for a query

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

Binary → count → weight matrix

	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

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

Introduction to

Information Retrieval

The Vector Space Model (VSM)

Documents as vectors

- Now 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

Queries as vectors

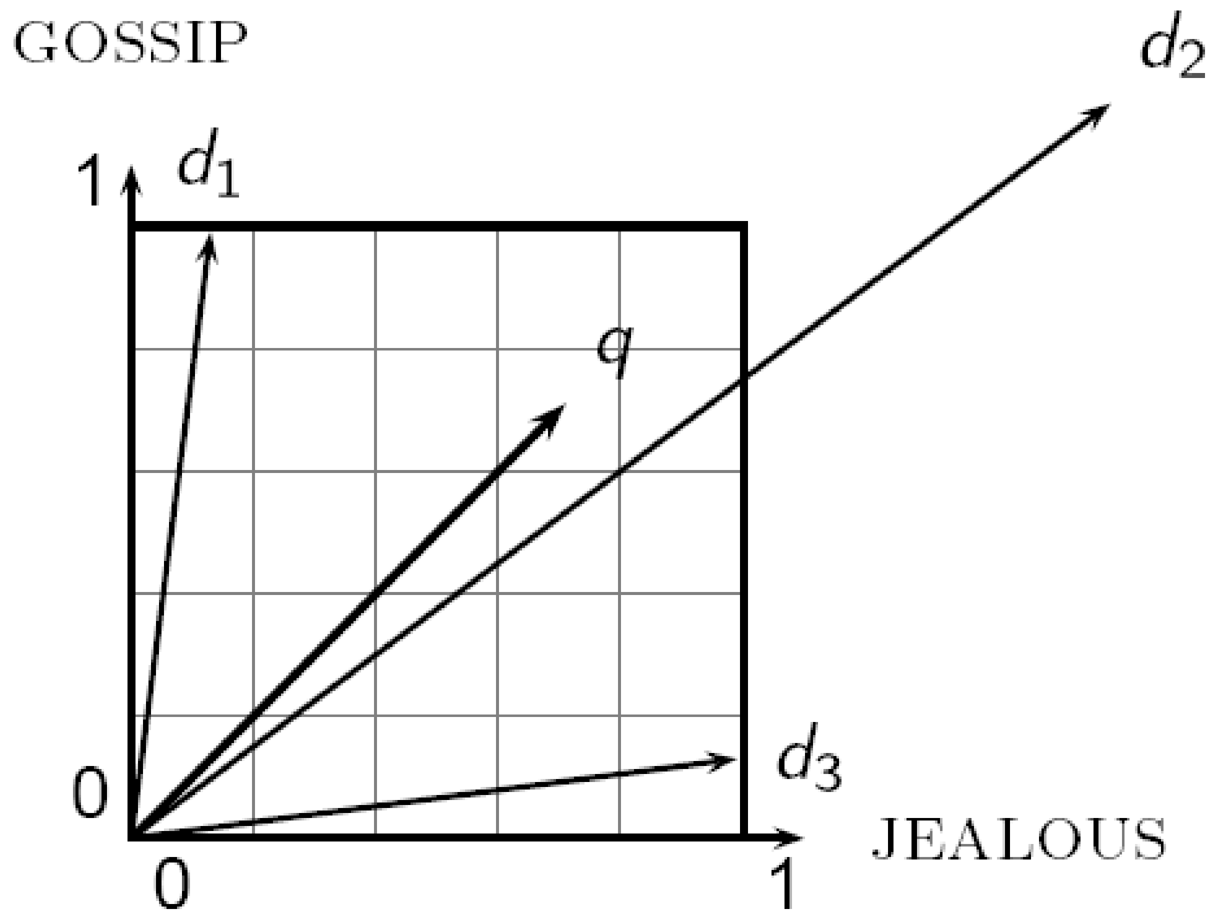
- Key idea 1: Do the same for queries: represent them as vectors in the space
- Key idea 2: Rank documents according to their proximity to the query in this space
- proximity = similarity of vectors
- proximity ≈ inverse of distance
- Recall: We do this because we want to get away from the you're-either-in-or-out 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.

Why distance is a bad idea

The Euclidean distance between *q* and d_2 is large even though the distribution of terms in the query *q* and the distribution of terms in the document d_2 are very similar.



q and d_2 have different absolute frequencies of the words, but their ratio is 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.

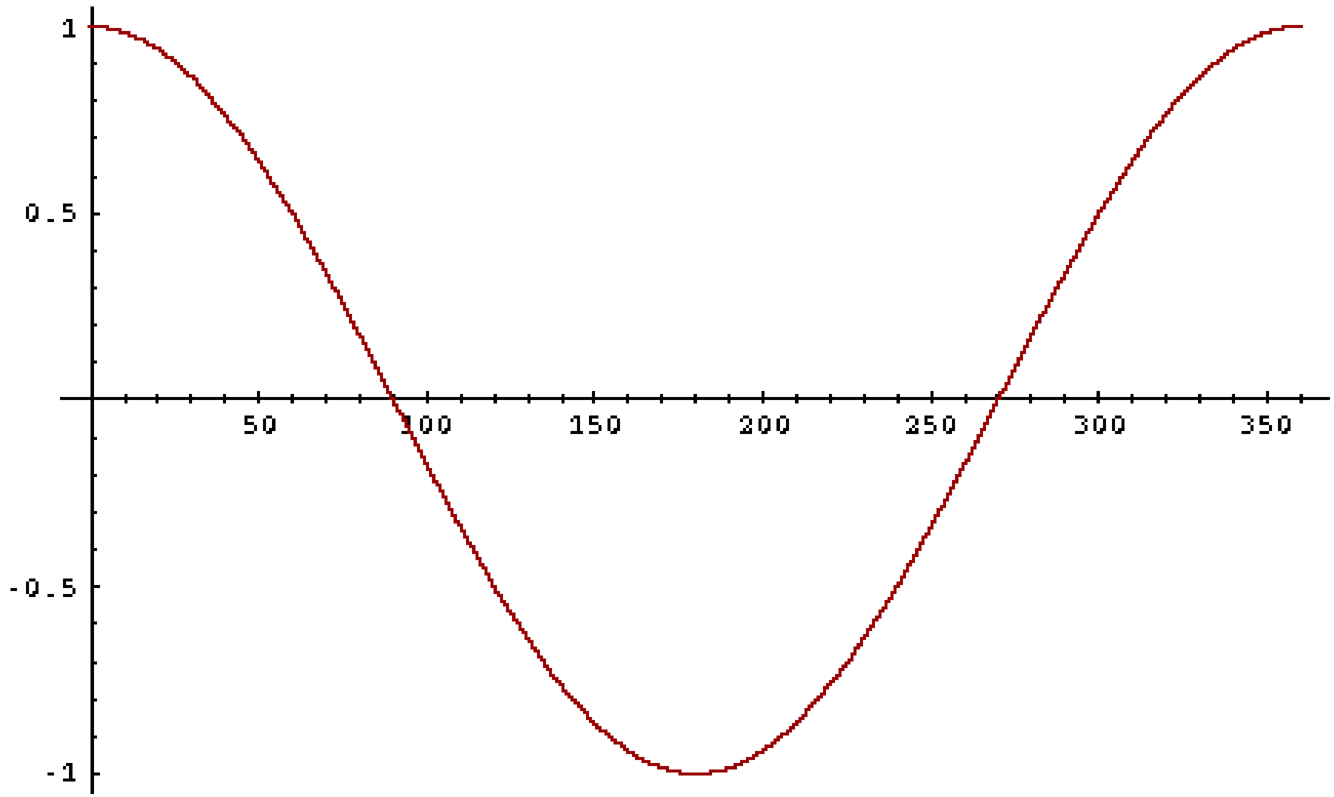
- Key idea: Rank documents according to *angle* with query.

From angles to cosines

- 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)

- Cosine is a monotonically decreasing function for the interval [0°, 180°] and ranges from 1 → -1

From angles to cosines



- But how – *and why* – should we be computing cosines?

Length normalization

- A vector can be (length-) normalized by dividing each of its components by its length – for this we use the L_2 norm:

$$\left\|\vec{x}\right\|_2 = \sqrt{\sum_i x_i^2}$$

- Dividing a vector by its L_2 norm makes it a unit (length) vector (on surface of unit hypersphere)
- Effect on the two documents d and d′ (d appended to itself) from earlier slide: they have identical vectors after length-normalization.
  - Long and short documents now have comparable weights

cosine(query,document)

Dot product | Unit vectors

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

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(*q*,*d*) is the cosine similarity of *q* and *d* … or, equivalently, the cosine of the angle between *q* and *d*.

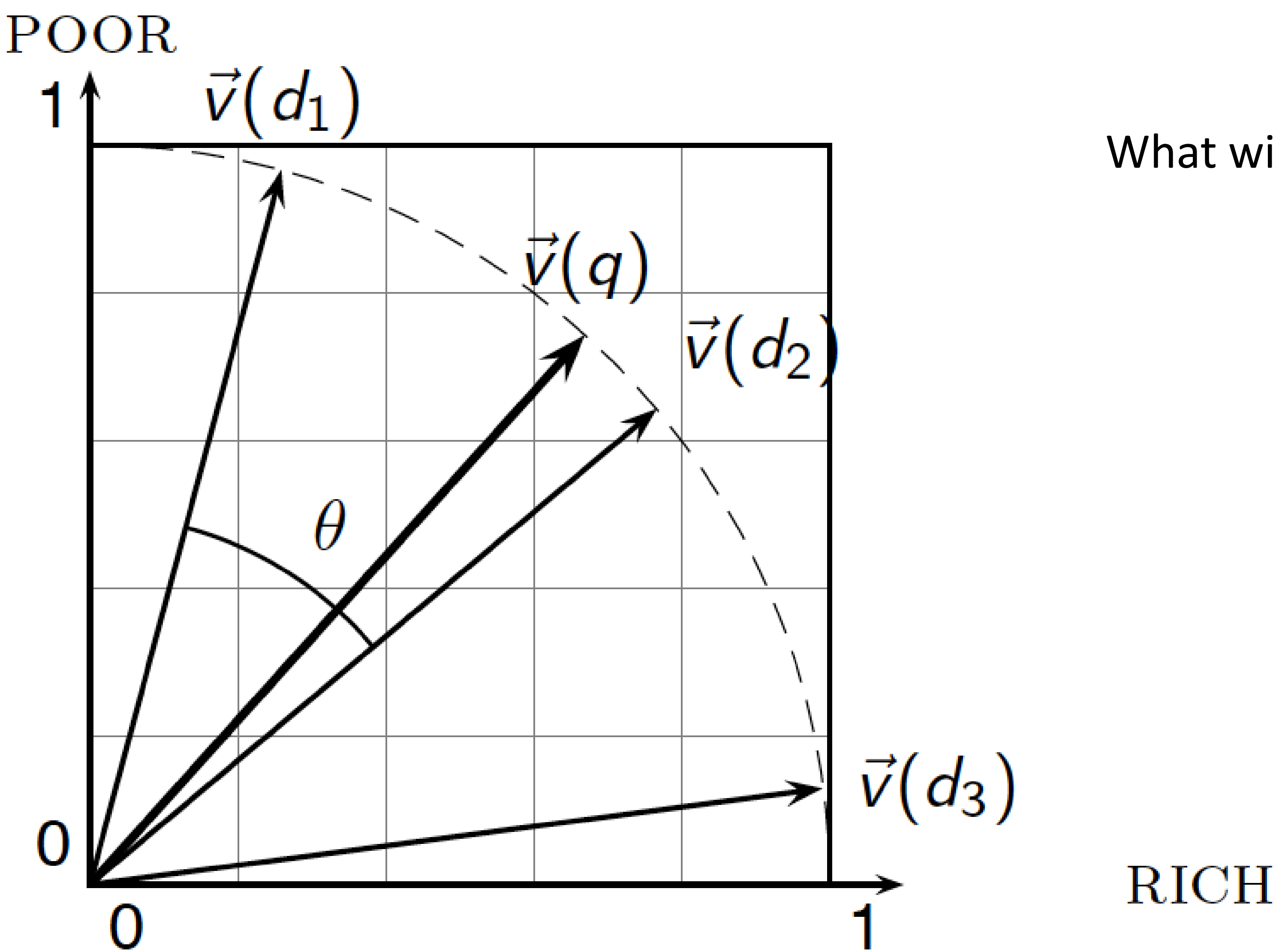
Cosine for length-normalized vectors

- For length-normalized vectors, cosine similarity is simply the dot product (or scalar product):

$$\cos(q, d) = q \cdot d = \sum_{i=1}^{|V|} q_i d_i$$

for *q*, *d* length-normalized.

Cosine similarity illustrated



What will the rank be?

d_2

d_1

d_3

Cosine similarity amongst 3 documents

How similar are the novels

SaS: *Sense and Sensibility*

PaP: *Pride and Prejudice*

WH: *Wuthering Heights*?

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.

3 documents example contd.

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) ≈
$0.789 \times 0.832 + 0.515 \times 0.555 + 0.335 \times 0.0 + 0.0 \times 0.0 \approx 0.94$
cos(SaS,WH) ≈ 0.79
cos(PaP,WH) ≈ 0.69

Introduction to

Information Retrieval

Calculating tf-idf cosine scores

in an IR system

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)	$1/CharLength^{\alpha}$, $\alpha < 1$
L (log ave)	$\frac{1+\log(\mathrm{tf}_{t,d})}{1+\log(\mathrm{ave}_{t\in d}(\mathrm{tf}_{t,d}))}$				

Columns headed 'n' are acronyms for weight schemes.
e.g. ltc

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

For some efficiency reasons, since it's already included in the query

tf-idf example: lnc.ltc

Document: *car insurance auto insurance*
Query: *best car insurance*

Term	Query						Document				Prod
	tf-raw	tf-wt	df	idf	wt	n'lize	tf-raw	tf-wt	wt	n'lize	
auto	0	0	5000	2.3	0	0	1	1	1	0.52	0
best	1	1	50000	1.3	1.3	0.34	0	0	0	0	0
car	1	1	10000	2.0	2.0	0.52	1	1	1	0.52	0.27
insurance	1	1	1000	3.0	3.0	0.78	2	1.3	1.3	0.68	0.53

Score = 0+0+0.27+0.53 = 0.8

Exercise: what is *N*, the number of docs? 1,000,000

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, tf_{t,d}) in postings list
    do Scores[d] += w_{t,d} × 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

Introduction to

Information Retrieval

Evaluating search engines

Measures for a search engine

- How fast does it index
  - Number of documents/hour
  - (Average document size)
- How fast does it search
  - Latency as a function of index size
- Expressiveness of query language
  - Ability to express complex information needs
  - Speed on complex queries
- Uncluttered UI
- Is it free?

Measures for a search engine

- All of the preceding criteria are *measurable*: we can quantify speed/size
  - we can make expressiveness precise
- The key measure: user happiness
  - What is this?
  - Speed of response/size of index are factors
  - But blindingly fast, useless answers won't make a user happy
- Need a way of quantifying user happiness with the results returned
  - Relevance of results to user's information need

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 as before

- 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*

Recall/Precision

		R	P
1	R	0.1	1.0
2	N	0.1	0.5
3	N	0.1	0.33
4	R	0.2	0.5
5	R	0.3	0.6
6	N	0.3	0.5
7	R	0.4	0.57
8	N	0.4	0.5
9	N	0.5	0.44
10	N	0.5	0.4

Assume 10 rel docs in collection

Average Precision (AP)

		R	P		AP =
1	R	0.1	1.0	→	1.0 +
2	N	0.1	0.5		
3	N	0.1	0.33		
4	R	0.2	0.5	→	0.5 +
5	R	0.3	0.6	→	0.6 +
6	N	0.3	0.5		
7	R	0.4	0.57	→	0.57
8	N	0.4	0.5		
9	N	0.5	0.44		
10	N	0.5	0.4		

/ 4 = 0.67

Assume 10 rel docs in collection

Average of *precisions* at each relevant document e.g. each time *recall* changes

Two current evaluation measures…

- Mean average precision (MAP)
  - AP: Average of the precision value obtained for the top *k* documents, each time a relevant doc is retrieved
  - Avoids interpolation, use of fixed recall levels
  - Does weight most accuracy of top returned results
  - MAP for set of queries is arithmetic average of APs
    - Macro-averaging: each query counts equally

Recap

- Ranked Retrieval
- Jaccard Coefficient
- Term Frequency
- Inverse Document Frequency
- TF-IDF
- Vector Space Model
- Evaluation