Introduction to

Information Retrieval

Introducing ranked retrieval

This unit and repetion

- **Today:** IR, VSM, mini intro to word embeddings
- **Repetition of last unit: NLP Basics**
  - Preprocessing: **tokenization –** what is it?
  - Preprocessing: **stopword removal –** what is it?
  - Preprocessing: **lemmatization / stemming –** what is it?
  - **NLTK** included corpora, functions to make: collocations, frequency distributions, …

Repetition – unit 1

- What is **IR**? What **evaluation measures** did we discuss?
- What is a **term-document matrix**? How to do Boolean queries on it?
- What is an **inverted index**?
  - Which **runtime** do basic (Boolean) **queries** have on an inverted index?
- What is a **Biword-index?** Why would we want to use it? Why not?

Repetition – unit 1

- What is a **positional index**?
- **Which queries** can we do with the positional index?

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

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Scoring with the Jaccard coefficient

Take 1: Jaccard coefficient

- Simple **starting point for ranking**
- 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*

- ***Do Jaccard(q, d1) and Jaccard(q, d2) – what are the results***

Exercise in Class (?)

- Implement Jaccard coefficient for some dataset which is short and simple (eg. first 100 words of documents in gutenberg NLTK corpus)
- Can also be used for **document similarity**

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
  - 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 (as used in cosine similarity (later))

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Scoring with the Jaccard coefficient

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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

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**

- 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 **$\mathrm{tf}_{t,d}$** 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** (linearly) 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*, *only for intersecting terms*:
- **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.

Exercise TDM with log10-tf

- For gutenberg corpus, create a TDM, with log-frequency weighting.
(To make it faster, again use only the first 100 words per document).

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Term frequency weighting

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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
- We define the idf (inverse document frequency) of t by

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

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

Will turn out the base of the log is immaterial.

idf example, suppose *N* = 1M

term	df_t	idf_t
calpurnia	1	→ 6
animal	100	?
sunday	1,000	?
fly	10,000	?
under	100,000	?
the	1,000,000	?

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

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

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 a collection, counting multiple occurrences. **Usually not used in IR, because:**
- 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)?

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(Inverse) Document frequency weighting

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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.

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

- 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

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

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 $\in \mathbb{R}^{|V|}$

Exercise

- Extend TDM from previous exercise to have tf-idf weights
- You can base your code on `code9_tdm.py`

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tf-idf weighting

Repetition of unit 2

- What is / how?
  - Document ranking
  - Term frequency
  - Inverted document frequency
  - Tf-idf

Term-Doc Matrix Creation

- Look at sample code:

  code10_tdm.py

This Unit: Overview

- Vector Space Model
- Term-term Matrix
- Word Embeddings

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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

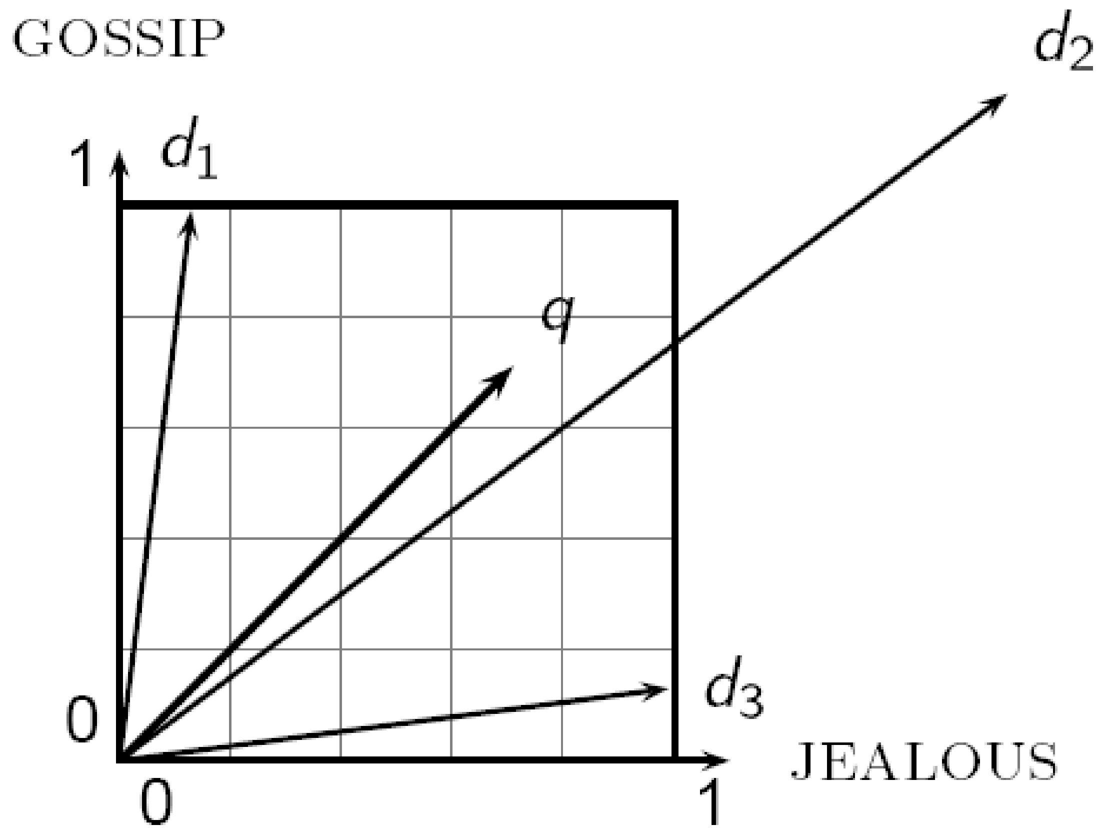
- Key idea 1: Do the same for queries: represent them as vectors in the space
- Key idea 2: Rank documents according to their **proximity to the query** in this space
- proximity = similarity of vectors
- proximity ≈ inverse of distance
- Reason: We do this because we want to get away from the you're-either-in-or-out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

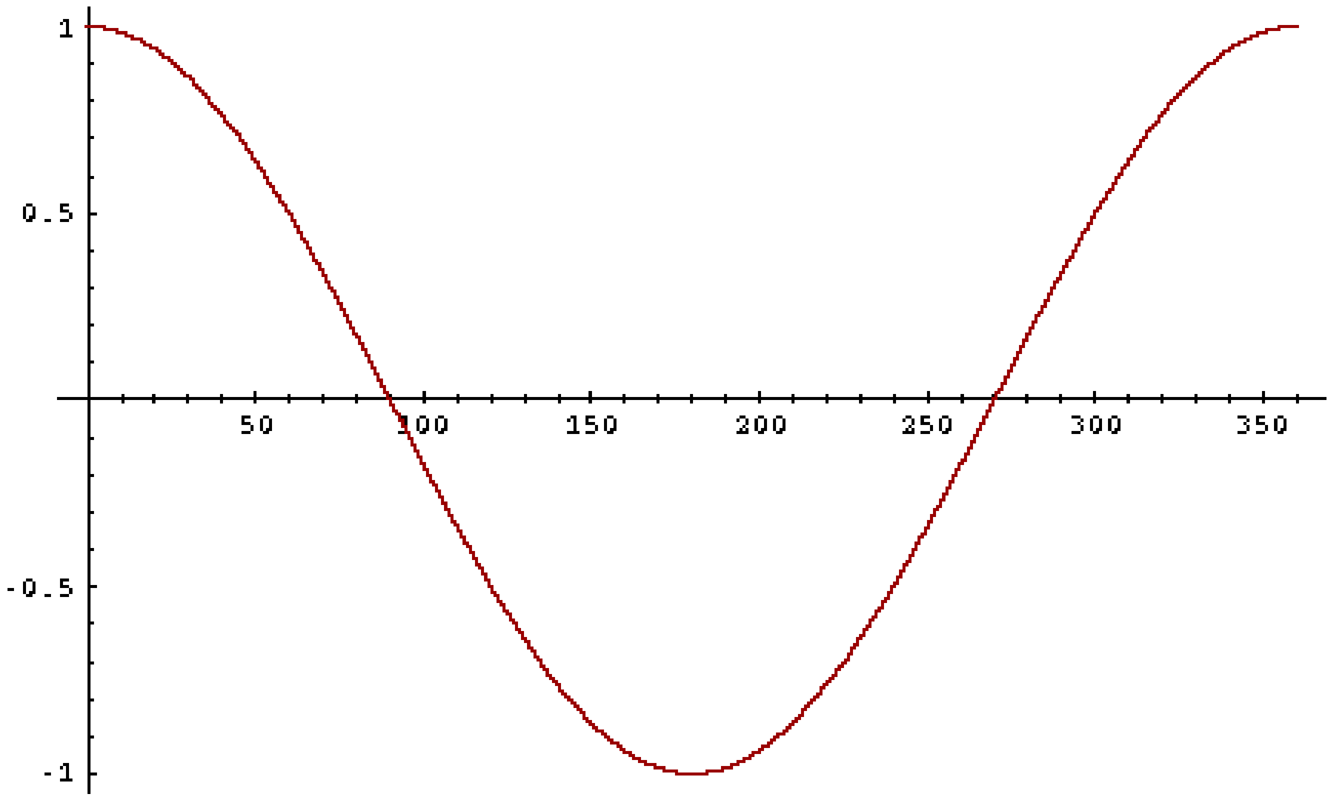
- Key idea: Rank documents according to angle with query.

From angles to cosines

- 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^o, 180^o]

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

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

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 $\vec{q}$ and $\vec{d}$ … or, equivalently, the cosine of the angle between $\vec{q}$ and $\vec{d}$.

Cosine for length-normalized vectors

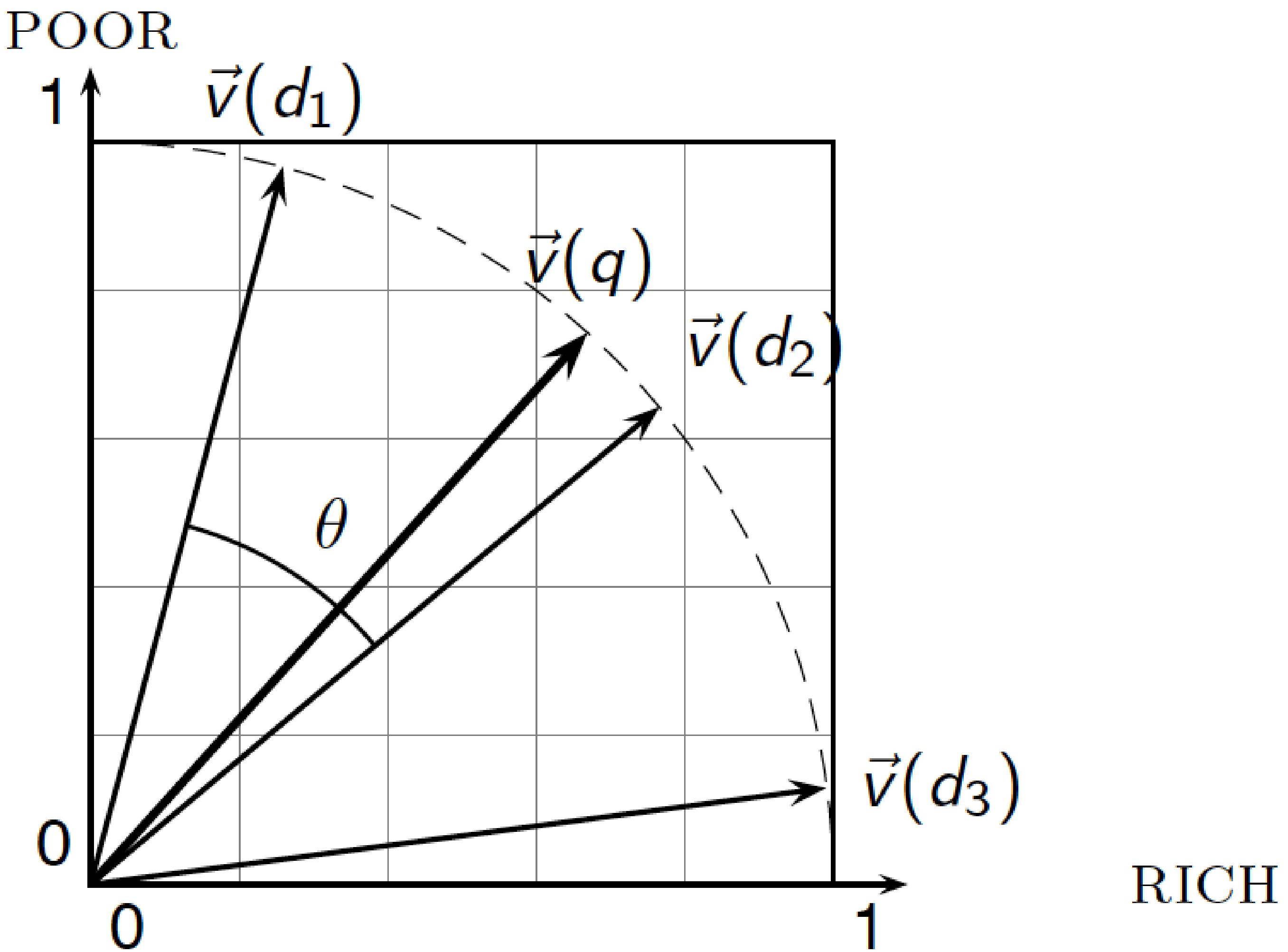
- For **length-normalized vectors**, cosine similarity is simply the **dot product** (or scalar product):

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

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

(→ Length-normalize document vectors in advance!)

Cosine similarity illustrated



Cosine similarity amongst 3 documents

How similar are the novels

SaS: *Sense and Sensibility*

PaP: *Pride and Prejudice*, and

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.

Exercise VSM

- Given the frequency counts of the SaS, PaP, WH books:
  - Put them into vectors (lists)
  - Compute log-frequency
  - Create functions for L2-norm and dot-product
  - Apply L2-norm to vectors
  - Compute similarity between documents, print it.
  - Which 2 documents are most similar?

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

Why do we have cos(SaS,PaP) > cos(SAS,WH)?

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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		
2	N		
3	N		
4	R		
5	R		
6	N		
7	R		
8	N		
9	N		
10	N		

Assume 10 rel docs in collection

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

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Evaluating search engines

Term-Term Matrices

- In IR systems we typically use Term-Document matrices
- But in many NLP applications we are interested in **term-term co-occurrence** matrices
- Co-occurrence can be measured in different ways, for example
  - Within a unit like a **sentence** or **paragraph**
  - Within a **word window** (left and/or right) of the target word – eg. a word window of 5
  - Q: when could a co-occurrence matrix be useful?

Co-occurrence matrix - Example

1. I enjoy flying.
2. I like NLP.
3. I like deep learning.

The resulting counts matrix will then be:

$$X = \begin{array}{c} \\ I \\ like \\ enjoy \\ deep \\ learning \\ NLP \\ flying \\ . \end{array} \begin{array}{c} \begin{array}{cccccccc} I & like & enjoy & deep & learning & NLP & flying & . \end{array} \\ \begin{bmatrix} 0 & 2 & 1 & 0 & 0 & 0 & 0 & 0 \\ 2 & 0 & 0 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \end{bmatrix} \end{array}$$

Co-occurrence Matrices

- Distributional hypothesis – "a word is characterized by the company it keeps"
- Words are defined by their context (words)

A bottle of **tesgüino** is on the table
Everybody likes **tesgüino**
Tesgüino makes you drunk
We make **tesgüino** out of corn.

Co-occurrence Matrices

- These matrices are often input to further processing, eg. for word embeddings, SVD, etc.
- Weighting of the matrix:
  - Raw counts: but not best option
    - “the” and “of” are very frequent, but maybe not the most discriminative
  - PPMI (see next slide)
    - Goal: context is informative about the target word
  - …

Co-occurrence Matrices – PPMI

- Starts from co-occurrence counts

PMI between two words: (Church & Hanks 1989)

Do words x and y co-occur more than if they were independent?

$$\text{PMI}(word_1, word_2) = \log_2 \frac{P(word_1, word_2)}{P(word_1)P(word_2)}$$

- PMI goes from neg. inf. to pos. inf.
- **PPMI:** we just set all negative values to 0.
  - Low counts are unreliable, and neg. relation hard to understand for humans

Co-occurrence Matrices

- Co-occ. matrices are sparse representations
- Next time we look at dense representations, like word embeddings

Mini Intro to Language Models and Word Embeddings

- What are **language models**?
- What are **word embeddings**?
  - Dense, floating point
  - Popular esp since word2vec (Mikolov et al, 2013)
  - Based on distributional hypothesis (Harris, 1957)
  - What does a vector look like, what are characteristics?
  - Trained on large corpora
  - Different training algorithms (GloVe, word2vec, ..)
  - Applications: many, eg. clustering, input to ML/DL, almost NLP task as representations of words