Index Compression (II)

Previously…

- Heap's law
- Zipf law
- Dictionary-as-a-string
- Blocking

FRONT CODING

- Front-coding:
  - Sorted words usually have long common prefix – store differences only
  - (for last *k-1* in a block of *k*)

8***automata***8***automate***9***automatic***10***automation***

→8***automat*********a***1◊***e***2◊***ic***3◊***ion***

Encodes ***automat***

Extra length beyond ***automat.***

Begins to resemble general string compression.

Quiz (Front Coding)

- What does the following code decode into?

7liber*ty2◊al3◊ate5◊alize

RCV1 DICTIONARY COMPRESSION SUMMARY

Technique	Size in MB
Fixed width	11.2
Dictionary-as-String with pointers to every term	7.6
Also, blocking *k* = 4	7.1
Also, Blocking + front coding	5.9

Postings compression

- The postings file is much larger than the dictionary, factor of at least 10.
- Key consideration: store each posting compactly.
- A posting for our purposes is a docID.
- For Reuters (800,000 documents), we would use 32 bits per docID when using 4-byte integers.
- Alternatively, we can use $\log_2 800{,}000 \approx 20$ bits per docID.
- Our goal: use far fewer than 20 bits per docID.

POSTINGS: TWO CONFLICTING FORCES

- A term like ***arachnocentric*** occurs in maybe one doc out of a million – we would like to store this posting using $\log_2$ 1M ~ 20 bits.
- A term like ***the*** occurs in virtually every doc, so 20 bits/posting is too expensive.
  - Prefer 0/1 bitmap vector in this case

POSTINGS FILE ENTRY

- We store the list of docs containing a term in *increasing* order of docID.
  - ***computer***: 33,47,154,159,202 …
- <u>Consequence</u>: it suffices to store *gaps*.
  - 33,14,107,5,43 …
- <u>Hope</u>: most gaps can be encoded/stored with far fewer than 20 bits.

Three postings entries

	encoding	postings list									
THE	docIDs	...		283042		283043		283044		283045	...
	gaps				1		1		1		...
COMPUTER	docIDs	...		283047		283154		283159		283202	...
	gaps				107		5		43		...
ARACHNOCENTRIC	docIDs	252000		500100							
	gaps	252000	248100								

Variable length encoding

- Aim:
  - For ***arachnocentric***, we will use ~20 bits/gap entry.
  - For ***the***, we will use ~1 bit/gap entry.
- If the average gap for a term is G, we want to use ~$\log_2 G$ bits/gap entry.
- Key challenge: encode every integer (gap) with about as few bits as needed for that integer.
- This requires a *variable length encoding*
- Variable length codes achieve this by using short codes for small numbers

Variable Byte (VB) codes

- For a gap value G, we want to use close to the fewest bytes needed to hold $\log_2 G$ bits
- Begin with one byte to store G and dedicate 1 bit in it to be a continuation bit c
- If $G \leq 127$, binary-encode it in the 7 available bits and set $c = 1$ (indicating the last byte)
- Else encode G's lower-order 7 bits and then use additional bytes to encode the higher order bits using the same algorithm
- At the end set the continuation bit of the last (lowest) byte to 1 ($c = 1$) – and for the other bytes $c = 0$.

EXAMPLE

824 → 0b1100111000

docIDs	824	829	215406
gaps		5	214577
VB code	00000110 10111000	10000101	00001101 00001100 10110001

Postings stored as the byte concatenation
000001101011100010000101000011010000110010110001

Key property: VB-encoded postings are uniquely prefix-decodable.

For a small gap (5), VB uses a whole byte.

OTHER VARIABLE UNIT CODES

- Instead of bytes, we can also use a different "unit of alignment": 32 bits (words), 16 bits, 4 bits (nibbles).
- Variable byte alignment wastes space if you have many small gaps – nibbles do better in such cases.
- Variable byte codes:
  - Used by many commercial/research systems
  - Good low-tech blend of variable-length coding and sensitivity to computer memory alignment matches (vs. bit-level codes, which we look at next).
- There is also recent work on word-aligned codes that pack a variable number of gaps into one word

Quiz: Nibbles

- What is the disadvantage of using smaller alignment units such as nibbles (4 bits) in VB encoding?

UNARY CODE

- Represent n as n 1s with a final 0.
- Unary code for 3 is 1110.
- Unary code for 40 is

11111111111111111111111111111111111111110 .

- Unary code for 80 is:

111111111111111111111111111111111111111111
11111111111111111111111111111111111111110

- This doesn't look promising, but….

Gamma codes

- We can compress better with bit-level codes
  - The Gamma code is the best known of these.
- Represent a gap G as a pair *length* and *offset*
- *offset* is G in binary, with the leading bit cut off
  - For example $13 \rightarrow 1101 \rightarrow 101$
- *length* is the length of offset
  - For 13 (offset 101), this is 3.
- We encode *length* with *unary code*: 1110.
- Gamma code of 13 is the concatenation of *length* and *offset*: 1110101

Gamma code examples

number	length	offset	γ-code
0			none
1	0		0
2	10	0	10,0
3	10	1	10,1
4	110	00	110,00
9	1110	001	1110,001
13	1110	101	1110,101
24	11110	1000	11110,1000
511	111111110	11111111	111111110,11111111
1025	11111111110	0000000001	11111111110,0000000001

Gamma code properties

- G is encoded using $2\lfloor \log G \rfloor + 1$ bits
  - Length of offset is $\lfloor \log G \rfloor$ bits
  - Length of length is $\lfloor \log G \rfloor + 1$ bits
- All gamma codes have an odd number of bits
- Almost within a factor of 2 of best possible, $\log_2 G$

- Gamma code is uniquely prefix-decodable, like VB
- Gamma code can be used for any distribution
- Gamma code is parameter-free

Gamma seldom used in practice

- Machines have word boundaries – 8, 16, 32, 64 bits
  - Operations that cross word boundaries are slower
- Compressing and manipulating at the granularity of bits can be slow
- Variable byte encoding is aligned and thus potentially more efficient
- Regardless of efficiency, variable byte is conceptually simpler at little additional space cost

RCV1 COMPRESSION

Data structure	Size in MB
dictionary, fixed-width	11.2
dictionary, term pointers into string	7.6
with blocking, k = 4	7.1
with blocking & front coding	5.9
collection (text, xml markup etc)	3,600.0
collection (text)	960.0
Term-doc incidence matrix	40,000.0
postings, uncompressed (32-bit words)	400.0
postings, uncompressed (20 bits)	250.0
postings, variable byte encoded	116.0
postings, γ–encoded	101.0

Index compression summary

- We can now create an index for highly efficient Boolean retrieval that is very space efficient
- Only 4% of the total size of the collection
- Only 10-15% of the total size of the text in the collection
- However, we've ignored positional information
- Hence, space savings are less for indexes used in practice
  - But techniques substantially the same.

Resources for today's lecture

- *IIR* 5
- *MG* 3.3, 3.4.
- F. Scholer, H.E. Williams and J. Zobel. 2002. Compression of Inverted Indexes For Fast Query Evaluation. *Proc. ACM-SIGIR 2002.*
  - Variable byte codes
- V. N. Anh and A. Moffat. 2005. Inverted Index Compression Using Word-Aligned Binary Codes. *Information Retrieval* 8: 151–166.
  - Word aligned codes

More resources

- K. Kukich. Techniques for automatically correcting words in text. ACM Computing Surveys 24(4), Dec 1992.
- Dean, Jeffrey, and Sanjay Ghemawat. *MapReduce: simplified data processing on large clusters, OSDI* (4) (2004).

Scoring, Term Weighting & Vector Space Model

Recap of Last Lecture

- Collection and vocabulary statistics: Heaps' and Zipf's laws
- Dictionary compression for Boolean indexes
  - Dictionary string, blocks, front coding
- Postings compression: Gap encoding, prefix-unique codes
  - Variable-Byte and Gamma codes

collection (text, xml markup etc)	3,600.0	MB
collection (text)	960.0	
Term-doc incidence matrix	40,000.0	
postings, uncompressed (32-bit words)	400.0	
postings, uncompressed (20 bits)	250.0	
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Outline

- Ranked retrieval
- Scoring documents
- Term frequency
- Collection statistics
- Weighting schemes
- Vector space scoring

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, 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, these are two separate choices here, but in practice, ranked retrieval has 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 ($\approx$ 10) results
  - We don't overwhelm the user

  - Premise: the ranking algorithm works

Google Result	Impressions	Percentage
1	2,834,806	34.35%
2	1,399,502	16.96%
3	942,706	11.42%
4	638,106	7.73%
5	[illegible]	6.19%
6	416,887	5.05%
7	331,500	4.02%
8	286,118	3.47%
9	235,197	2.85%
10	223,320	2.71%
11	91,978	1.11%
12	69,778	0.85%
13	[illegible]	0.70%
14	46,822	0.57%
15	39,635	0.48%
16	32,168	0.39%
17	26,933	0.33%
18	23,131	0.28%
19	22,027	0.27%
20	23,953	0.29%

1st Page 94%

2nd Page 6%

Scoring as the basis of ranked retrieval

- We wish to return the documents in an order 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.

Take 1: Jaccard coefficient

- Recall from last lecture: A commonly used measure of overlap of two sets A and B

  jaccard$(A,B) = |A \cap B| \ / \ |A \cup B|$

  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.

QUIZ: JACCARD COEFFICIENT

- 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*

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.

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 in this course.
- 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 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, etc.
- 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.

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.
- In general, we want **high positive weights** for a term that appears many times in a doc
- But **lower weights** for a frequent term than for rare terms.
- We will use document frequency (df) to capture this.

IDF WEIGHT

- df_t is the <u>document</u> frequency of t: the number of documents that contain t
  - df_t is an inverse measure of the informativeness of t
  - $\mathrm{df}_t \leq N$ (total number of docs)
- We define the idf (inverse document frequency) of t by

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

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

It turns out the base of the log is insignificant.

IDF EXAMPLE, SUPPOSE $N = 1$ 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

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

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

Quiz: IDF

- Why is the idf of a term *in a document* always finite?

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

Effect of idf on ranking

- 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.
- Example:

Word	Collection frequency	Document frequency
insurance	10440	3997
try	10422	8760

Quiz: Collection Frequency

Word	Collection frequency	Document frequency
insurance	10440	3997
try	10422	8760

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

TF-IDF WEIGHTING

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

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

- 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

Score for a document given a query

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

- q is a multi-term query.
- There are many variants
  - How "tf" is computed (with/without logs)
  - Whether the terms in the query are also weighted
  - …

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

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.

Queries as vectors

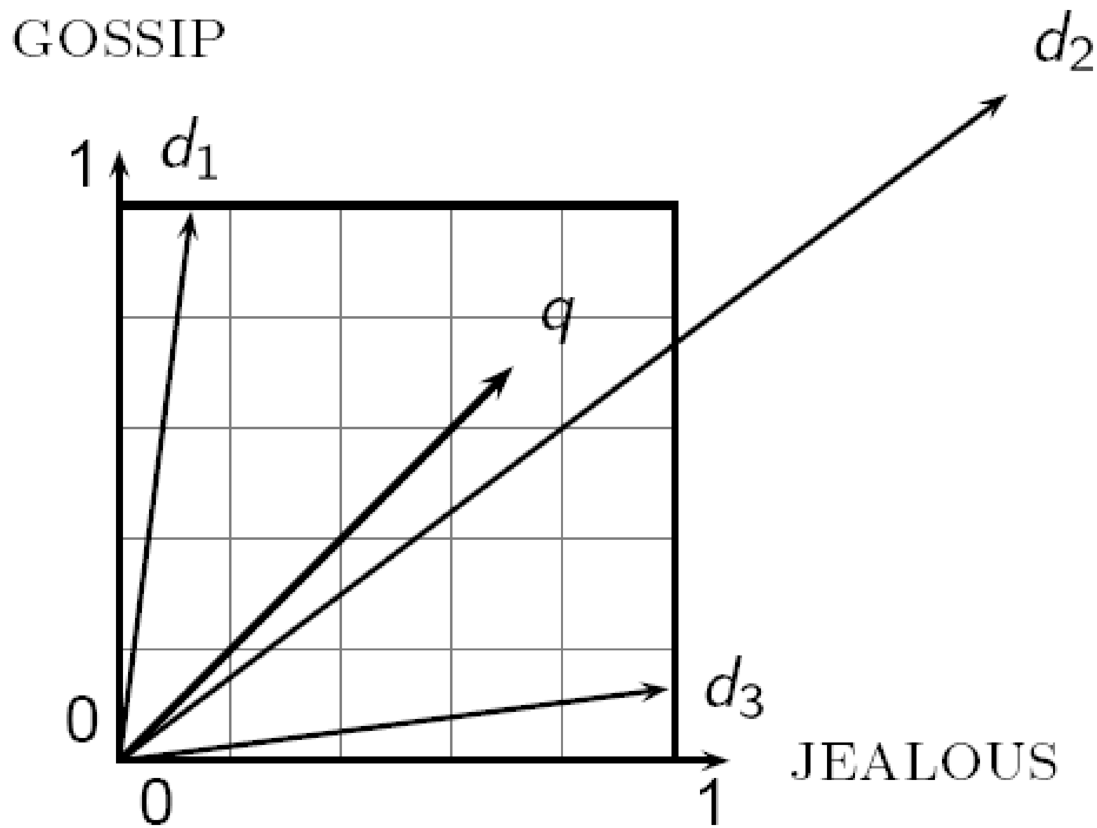
- Key idea 1: Do the same for queries: represent them as vectors in the space
- Key idea 2: Rank documents according to their proximity to the query in this space
- proximity = similarity of vectors
- proximity ≈ inverse of distance
- Recall: We do this because we want to get away from the you're-either-in-or-out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



From Euclidean to Angle Distance

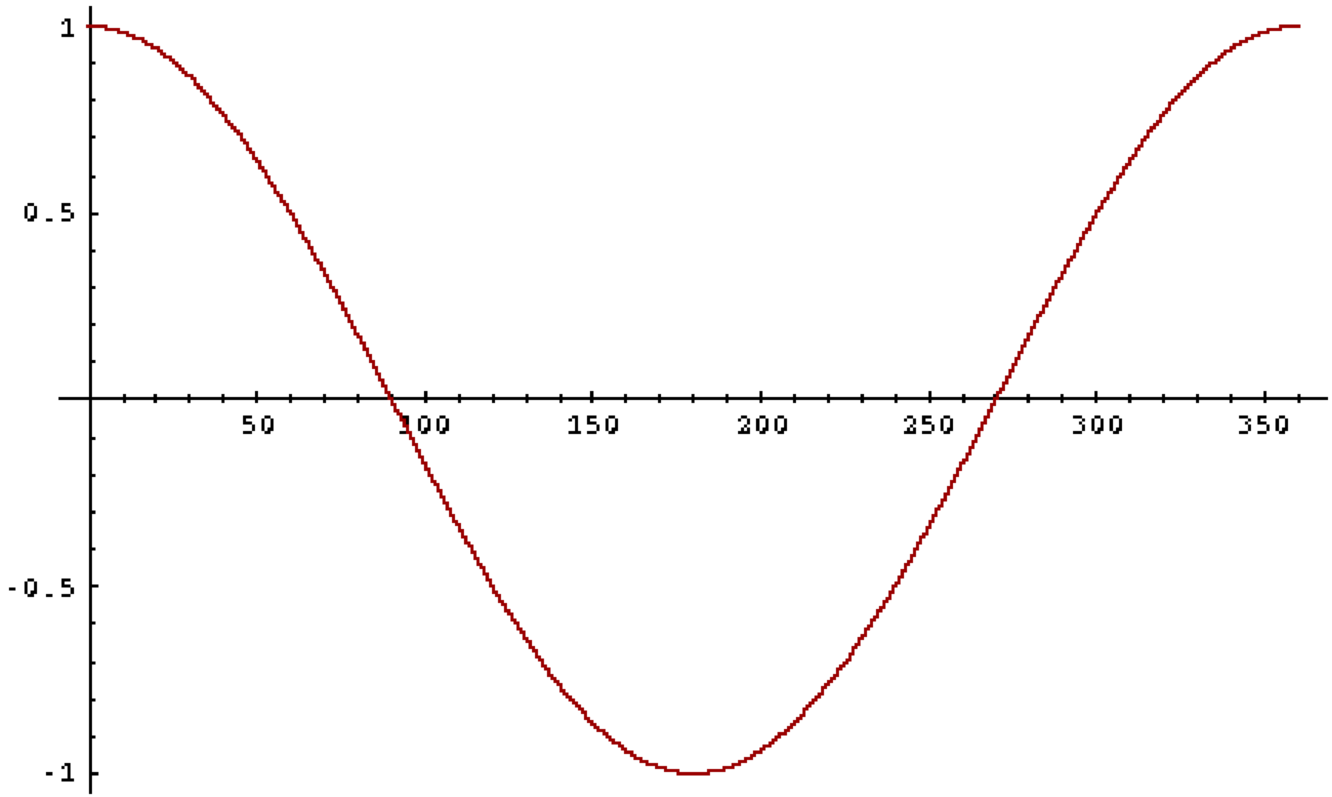
- Thought experiment: take a document *d* and append it to itself. Call this document *d*′.
- "Semantically" d and d′ have the same content
- The Euclidean distance between the two documents can be quite large
- The angle between the two documents is 0, corresponding to maximal similarity.

- 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 the same unit 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 $\vec{d}$.

The law of cosines generalizes the Pythagorean theorem, which holds only for right triangles: if the angle γ is a right angle (of measure 90° or $\frac{\pi}{2}$ radians), then $\cos\gamma = 0$, and thus the law of cosines reduces to the Pythagorean theorem:

$$c^2 = a^2 + b^2.$$

The law of cosines is useful for computing the third side of a triangle when two sides and their enclosed angle are known, and in computing the angles of a triangle if all three sides are known.

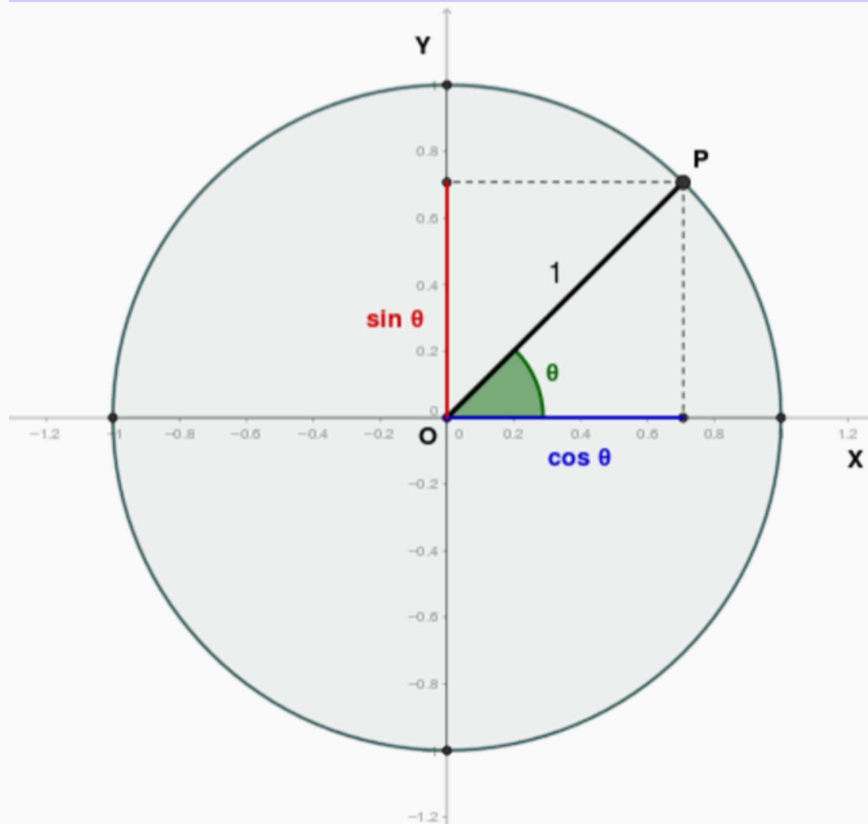
By changing which sides of the triangle play the roles of a, b, and c in the original formula, the following two formulas also state the law of cosines:

$$a^2 = b^2 + c^2 - 2bc\cos\alpha$$
$$b^2 = a^2 + c^2 - 2ac\cos\beta.$$

Though the notion of the cosine was not yet

sides a, b, and c.

Trigonometry



Outline · History · Usage

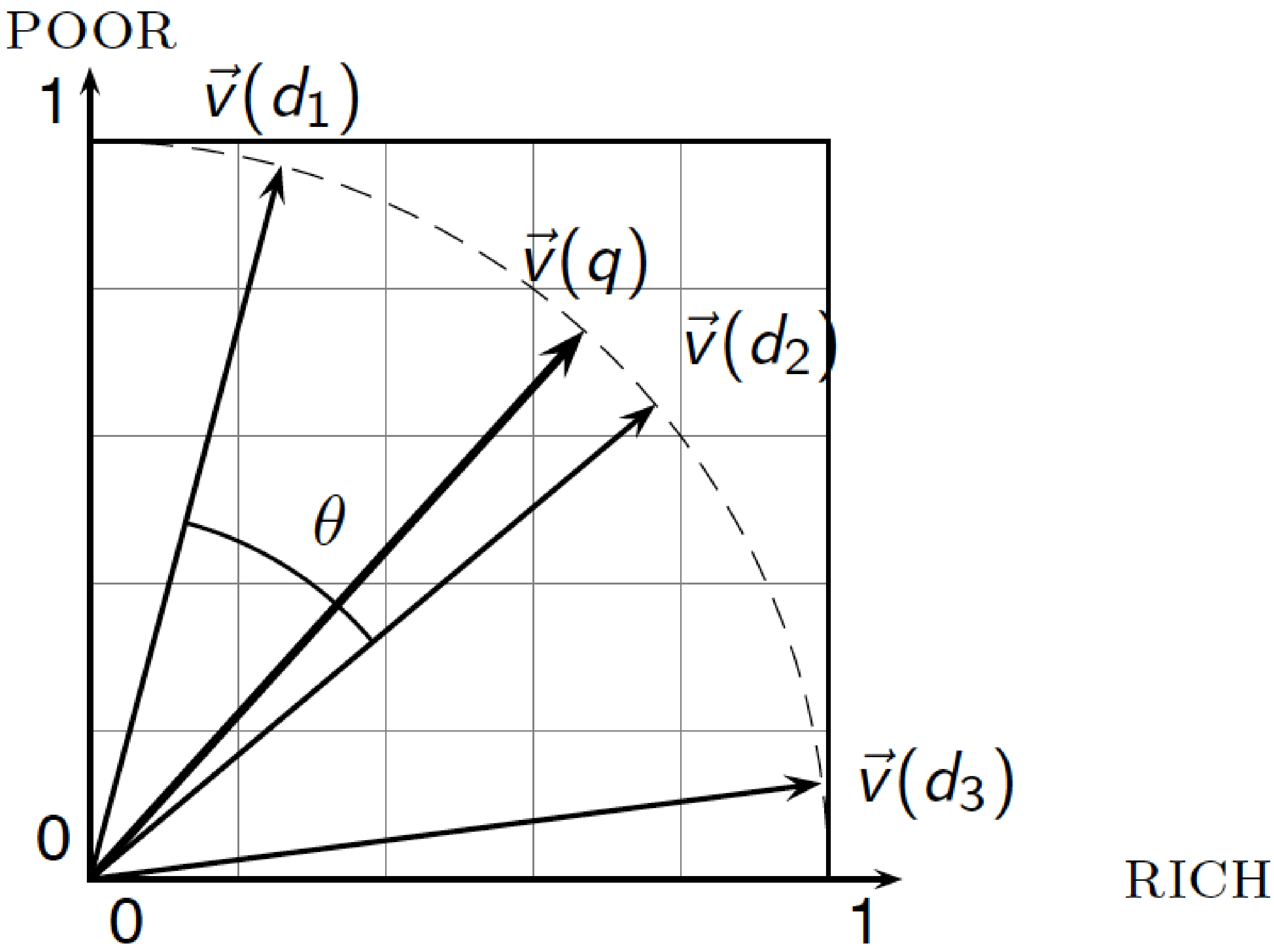
Cosine for length-normalized vectors

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

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

for q, d length-normalized.

COSINE SIMILARITY ILLUSTRATED



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 × 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

Quiz: Novels

- We can see that

  cos(SaS,PaP) > cos(SaS,WH)
- Why?

Computing cosine scores

CosineScore(q)

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

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)	$\frac{1 + \log(\mathrm{tf}_{t,d})}{1 + \log(\mathrm{ave}_{t \in d}(\mathrm{tf}_{t,d}))}$				

‘n’, ‘l’, ‘a’, ‘t’, ‘p’, etc. are acronyms for weight schemes.

Quiz: Why is the base of the log in idf insignificant?

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), no normalization …

TF-IDF EXAMPLE: LNC.LTC

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

Term	Query						Document				Prod
	tf-raw	tf-wt	df	idf	tfidf wt	n'lize	tf-raw	tf-wt	tfidf 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

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

Doc vector length $= \sqrt{1^2 + 0^2 + 1^2 + 1.3^2} \approx 1.92$

Score = 0+0+0.27+0.53 = 0.8

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

Resources for today's lecture

- IIR 6.2 – 6.4.3

- http://www.miislita.com/information-retrieval-tutorial/cosine-similarity-tutorial.html
  - Term weighting and cosine similarity tutorial for SEO folk!