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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

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Introducing ranked retrieval

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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*

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 ∩ B|/|A ∪ B| (Jaccard) for length normalization.

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Scoring with the Jaccard coefficient

Introduction to

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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

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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 $\text{tf}_{t,d}$ 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

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

- 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.

Log-frequency weighting

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- 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.

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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
  - $df_t \leq N$
- 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 = 1 million

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

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

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

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.
- 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.

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

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

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tf-idf weighting

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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

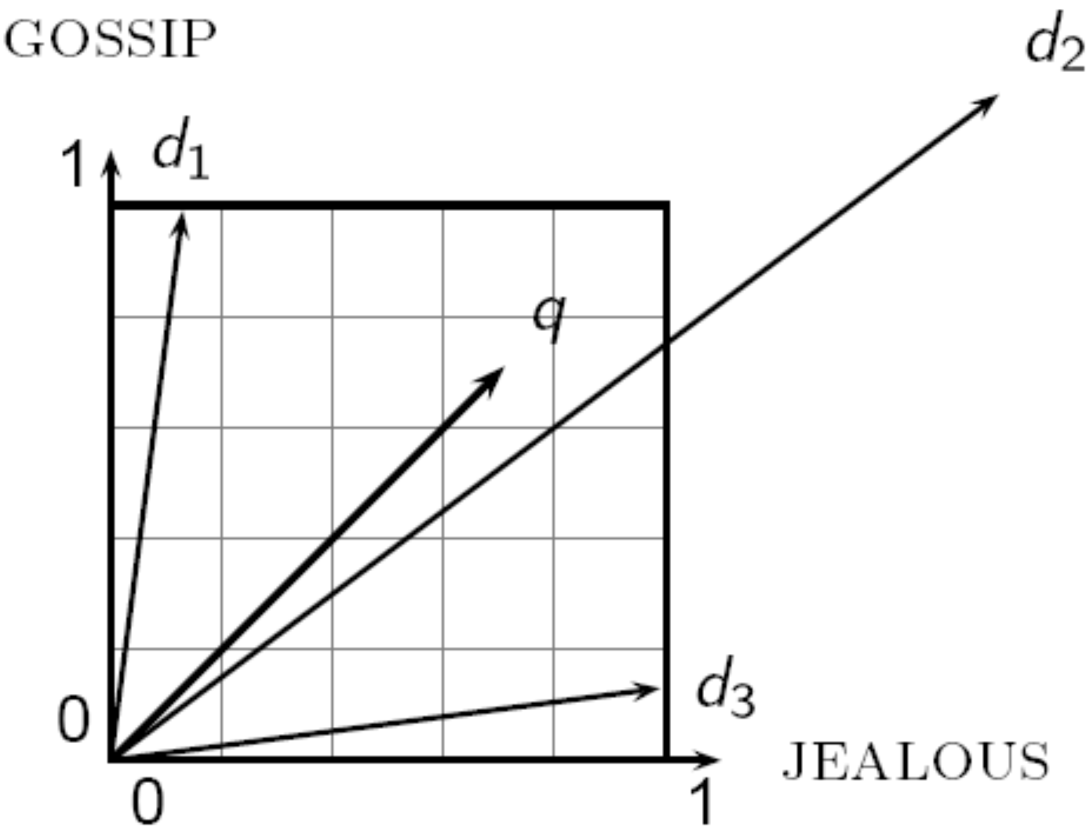
- Key idea 1: Do the same for queries: represent them as vectors in the space
- Key idea 2: Rank documents according to their proximity to the query in this space
- proximity = similarity of vectors
- proximity ≈ inverse of distance
- Recall: We do this because we want to get away from the you're-either-in-or-out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



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.

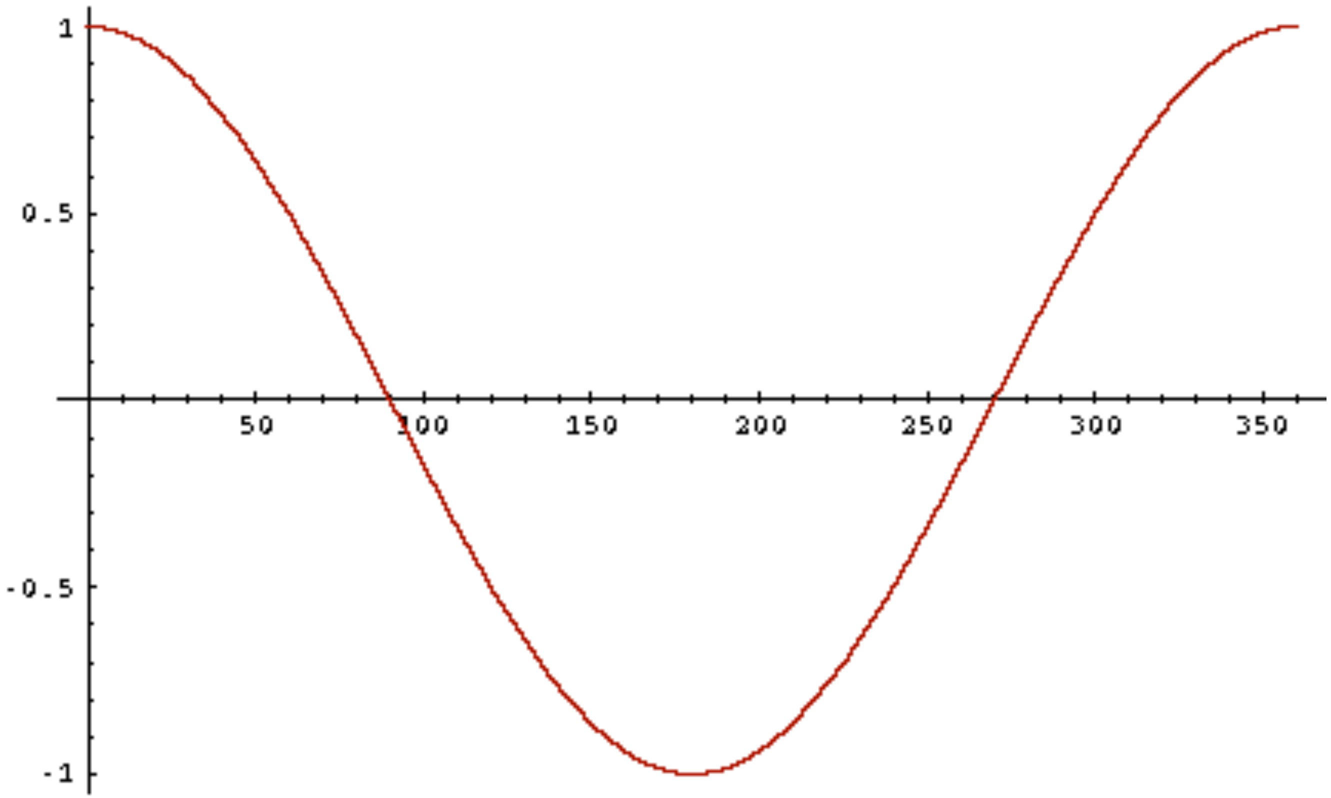
From angles to cosines

- 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 $\vec{d}$.

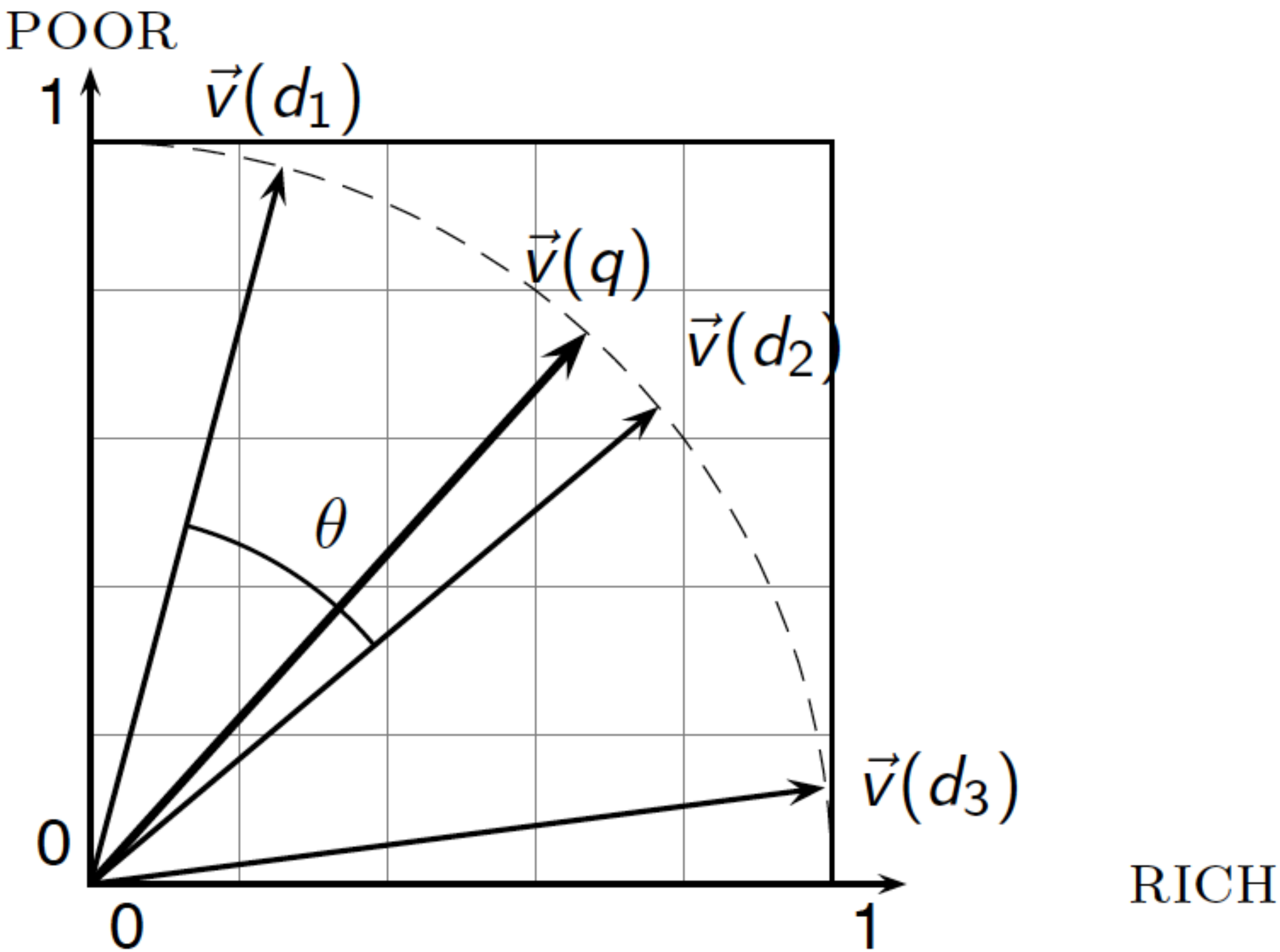
Cosine for length-normalized vectors

- 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.

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.

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

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

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The Vector Space Model (VSM)

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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.

Why is the base of the log in idf immaterial?

tf-idf weighting has many variants

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

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 …

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

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

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

Score = 0+0+0.27+0.53 = 0.8

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

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Calculating tf-idf cosine scores in an IR system

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Using many features to determine relevance

Integrating multiple features to determine relevance

- Modern systems – especially on the Web – use a great number of features:
    - Arbitrary useful features – not a single unified model
  - Log frequency of query word in anchor text?
  - Query word in color on page?
  - # of images on page?
  - # of (out) links on page?
  - PageRank of page?
  - URL length?
  - URL contains "~"?
  - Page edit recency?
  - Page length?
- The *New York Times* (2008-06-03) quoted Amit Singhal as saying Google was using over 200 such features.

How to combine features to assign a relevance score to a document?

- Given lots of relevant features…
- You can continue to hand-engineer retrieval scores
- Or, you can build a classifier to learn weights for the features
  - Requires: labeled training data
  - This is the “learning to rank” approach, which has become a hot area in recent years
    - I only provide an elementary introduction here

Simple example: Using classification for ad hoc IR

- Collect a training corpus of (*q, d, r*) triples
  - Relevance *r* is here binary (but may be multiclass, with 3–7 values)
  - Document is represented by a feature vector
    - **x** = (α, ω) α is cosine similarity, ω is minimum query window size
      - ω is the the shortest text span that includes all query words
      - Query term proximity is a **very important** new weighting factor
  - Train a machine learning model to predict the class *r* of a document-query pair

example	docID	query	cosine score	ω	judgment
Φ_1	37	linux operating system	0.032	3	*relevant*
Φ_2	37	penguin logo	0.02	4	*nonrelevant*
Φ_3	238	operating system	0.043	2	*relevant*
Φ_4	238	runtime environment	0.004	2	*nonrelevant*
Φ_5	1741	kernel layer	0.022	3	*relevant*
Φ_6	2094	device driver	0.03	2	*relevant*
Φ_7	3191	device driver	0.027	5	*nonrelevant*

Simple example: Using classification for ad hoc IR

- A linear score function is then:

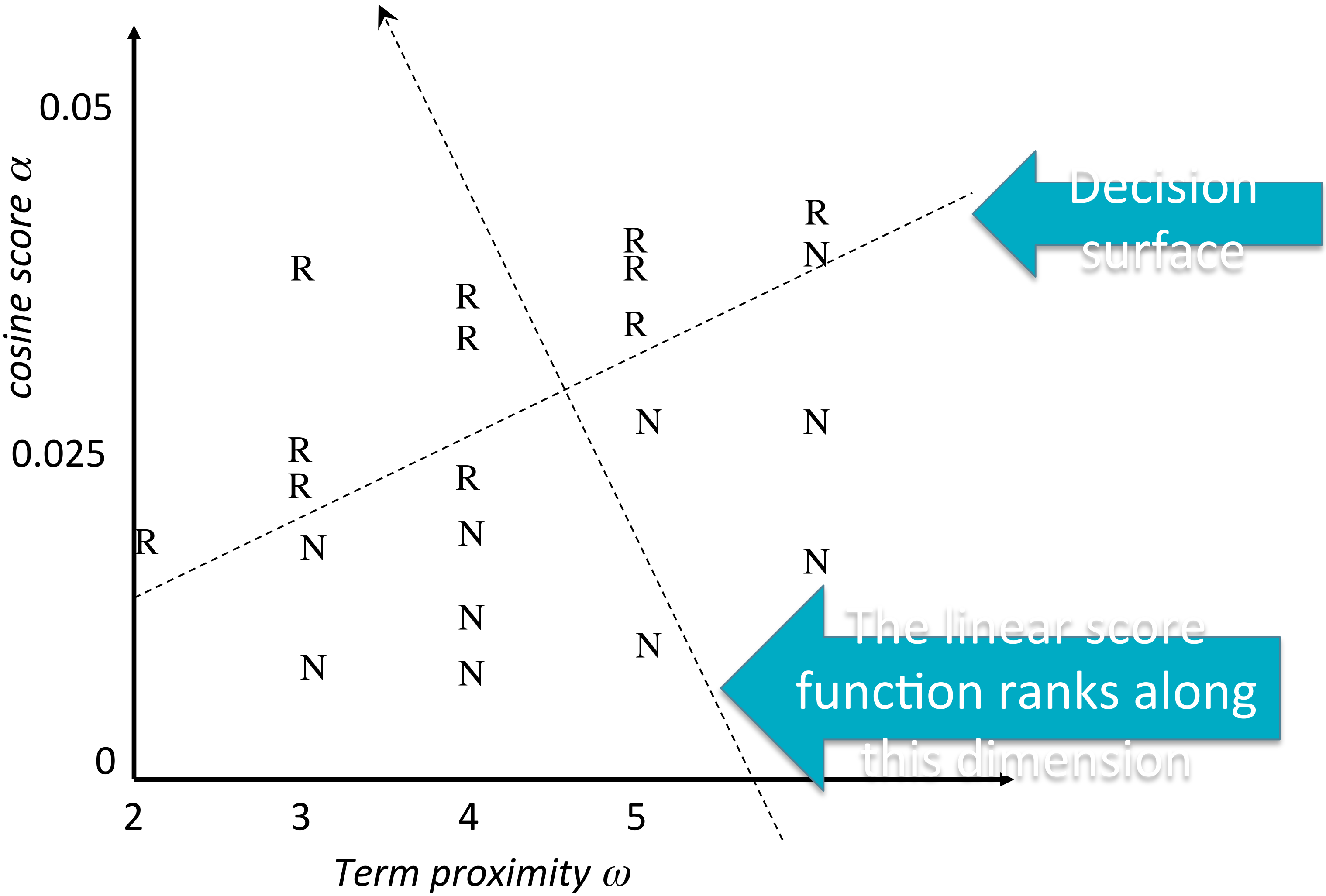
$$Score(d, q) = Score(\alpha, \omega) = a\alpha + b\omega + c$$

- And the linear classifier would be:

Decide relevant if $Score(d, q) > \theta$

- … just like when we were doing text classification

Simple example:
Using classification for ad hoc IR



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Using many features to determine relevance

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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

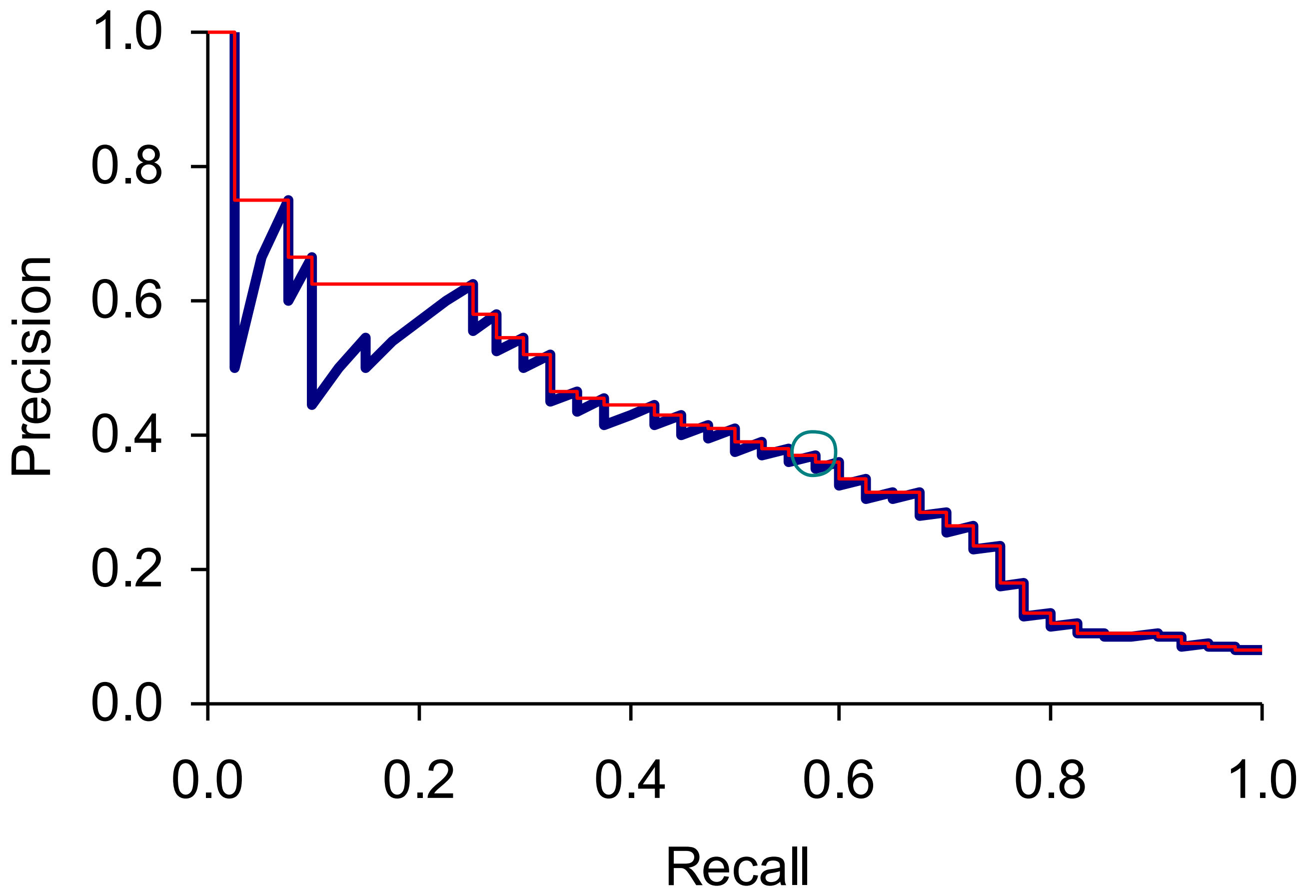
  Then we can use Precision/Recall/F measure as before
- Evaluation of ranked results:
  - The system can return any number of results
  - By taking various numbers of the top returned documents (levels of recall), the evaluator can produce a *precision-recall curve*

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

A precision-recall curve

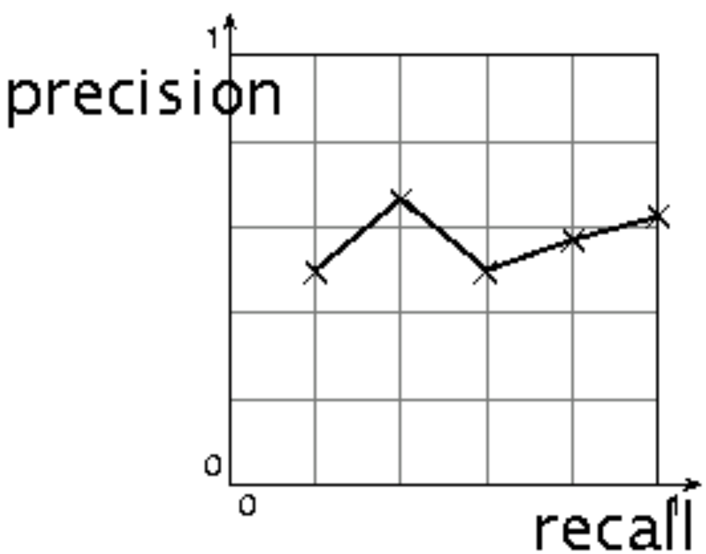


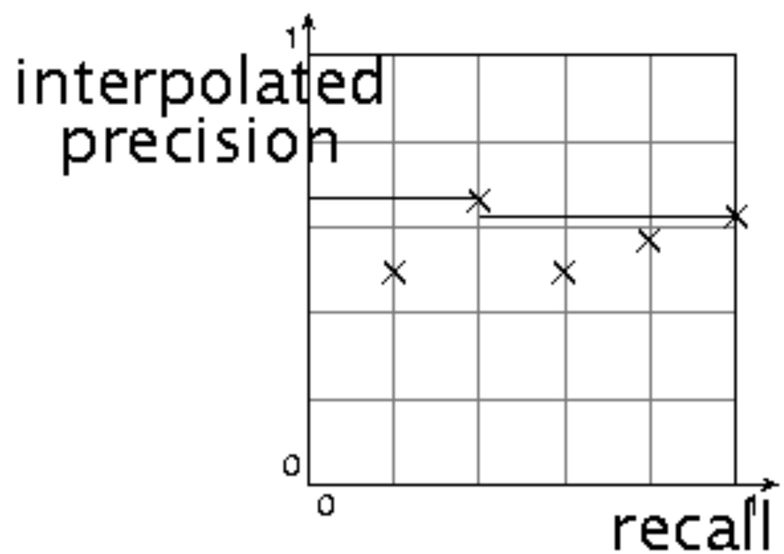
Averaging over queries

- A precision-recall graph for one query isn't a very sensible thing to look at
- You need to average performance over a whole bunch of queries.
- But there's a technical issue:
  - Precision-recall calculations place some points on the graph
  - How do you determine a value (interpolate) between the points?

Interpolated precision

- Idea: If locally precision increases with increasing recall, then you should get to count that…
- So you use the max of precisions to right of value



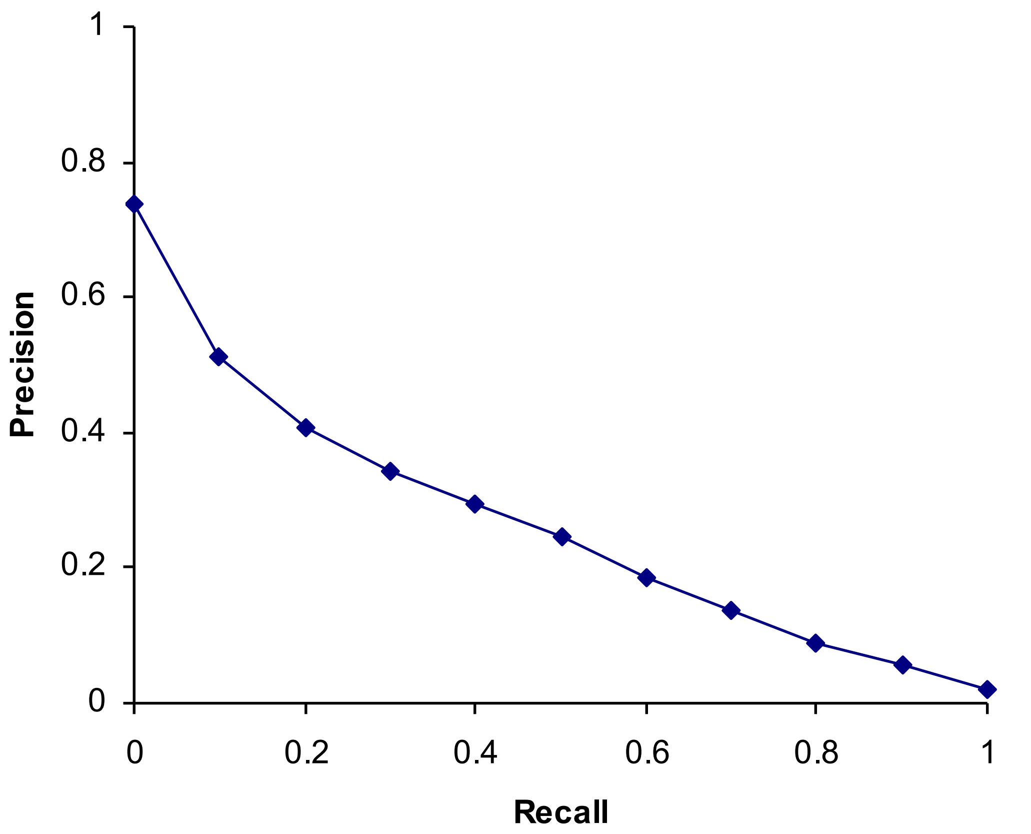


Evaluation

- Graphs are good, but people want summary measures!
  - Precision at fixed retrieval level
    - Precision-at-*k*: Precision of top *k* results
    - Perhaps appropriate for most of web search: all people want are good matches on the first one or two results pages
    - But: averages badly and has an arbitrary parameter of *k*
  - 11-point interpolated average precision
    - The standard measure in the early TREC competitions: you take the precision at 11 levels of recall varying from 0 to 1 by tenths of the documents, using interpolation (the value for 0 is always interpolated!), and average them
    - Evaluates performance at all recall levels

Typical (good) 11 point precisions

- SabIR/Cornell 8A1 11pt precision from TREC 8 (1999)



Two current evaluation measures…

- R-precision
  - If have known (though perhaps incomplete) set of relevant documents of size *Rel,* then calculate precision of top *Rel* docs returned
  - Perfect system could score 1.0.

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

Introduction to

Information Retrieval

Evaluating search engines

Introduction to

Information Retrieval

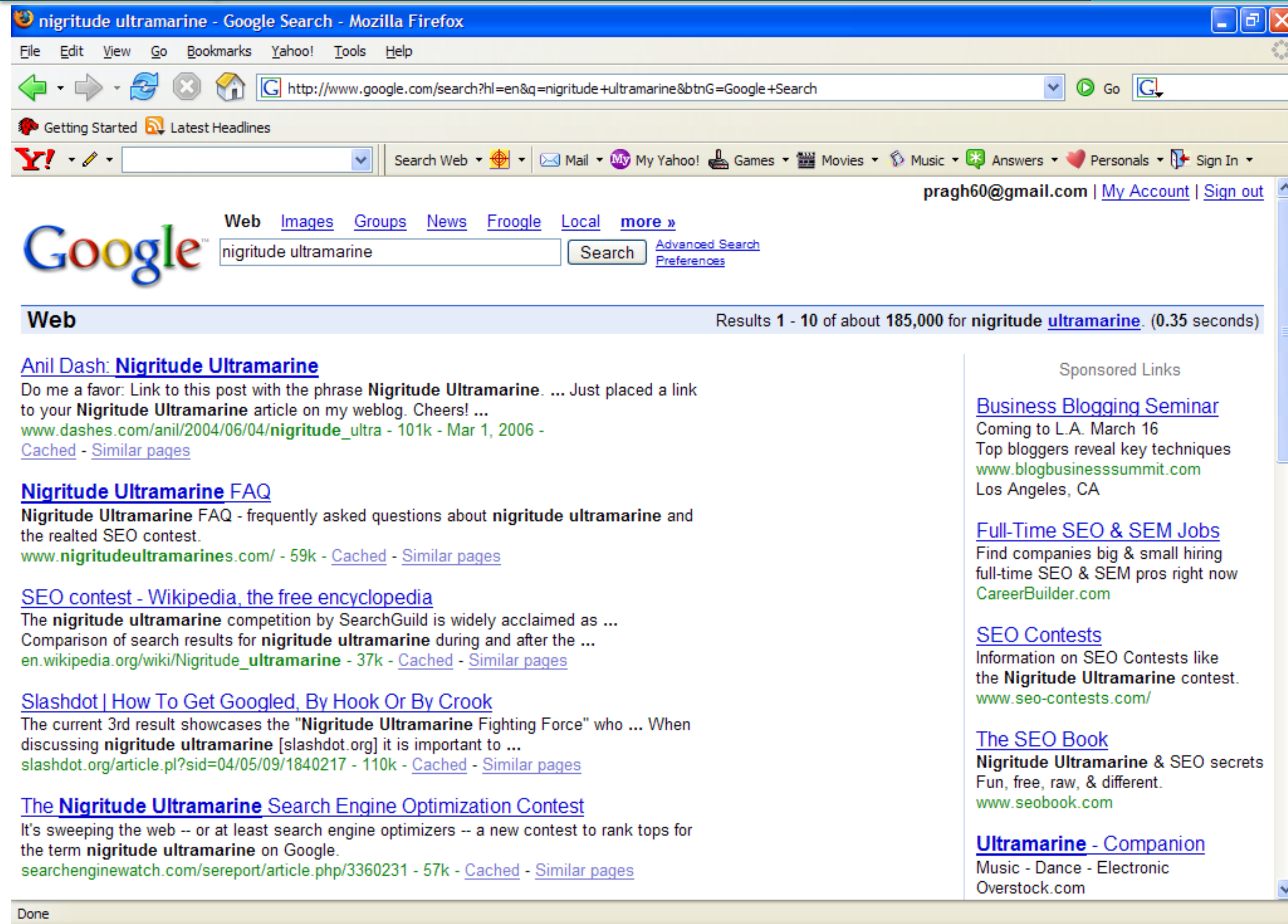
Web search

Brief (non-technical) history

- Early keyword-based engines ca. 1995–1997
  - Altavista, Excite, Infoseek, Inktomi, Lycos
  - Often not very good IR
- Paid search ranking: Goto (morphed into Overture.com → Yahoo!)
  - Your search ranking depended on how much you paid
  - Auction for keywords: ***casino*** was expensive!

Brief (non-technical) history

- 1998+: Link-based ranking pioneered by Google
  - Blew away all early engines save Inktomi
  - Great user experience in search of a business model
  - Meanwhile Goto/Overture's annual revenues were nearing $1 billion
- Result: Google added paid search "ads" to the side, independent of search results
  - Yahoo followed suit, acquiring Overture (for paid placement) and Inktomi (for search)
- 2005+: Google gains search share, dominating in Europe and very strong in North America
  - Some strong regional players: Yandex (Russia), Baidu (China)
  - 2009: Yahoo! and Microsoft propose combined paid search offering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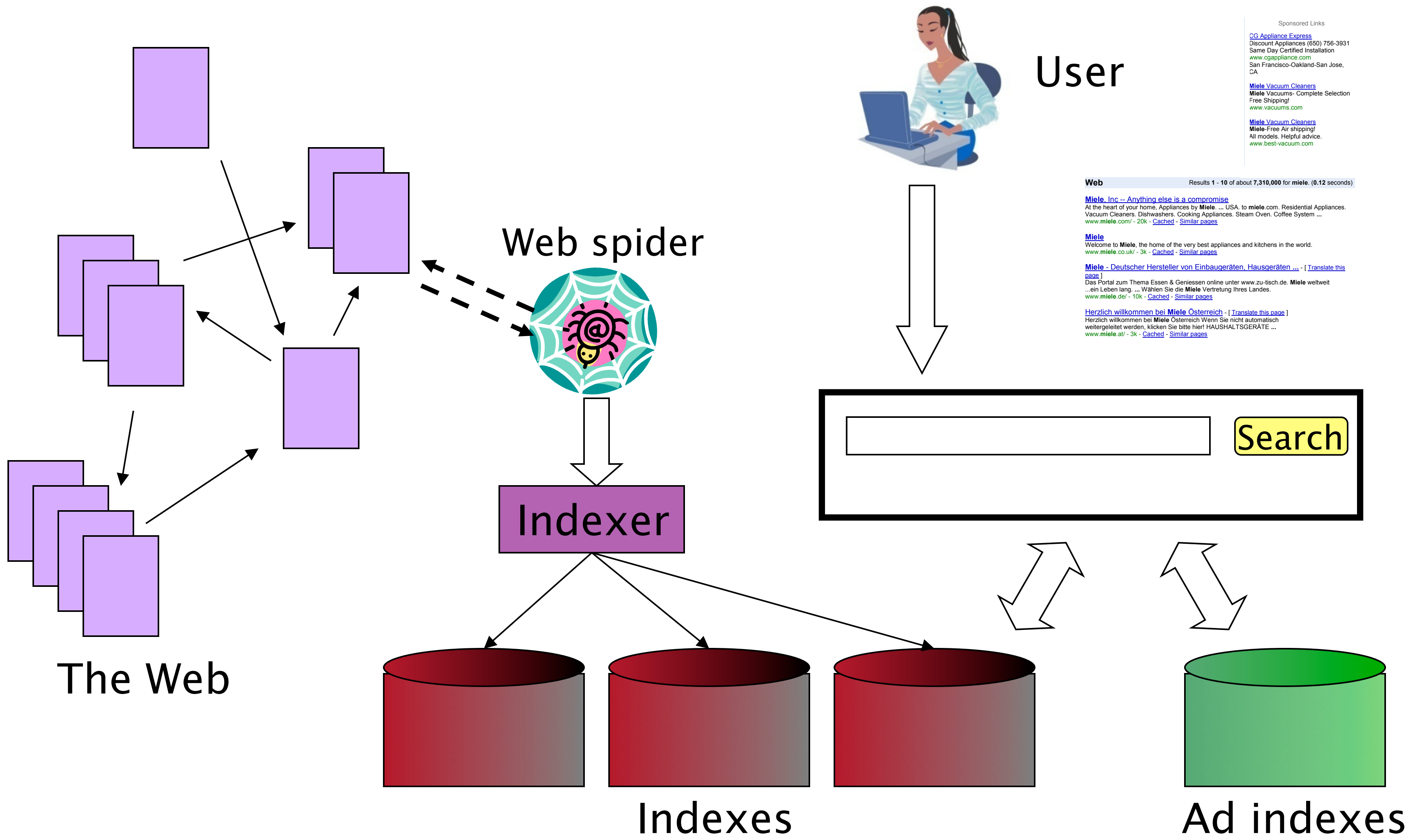
Web search basics



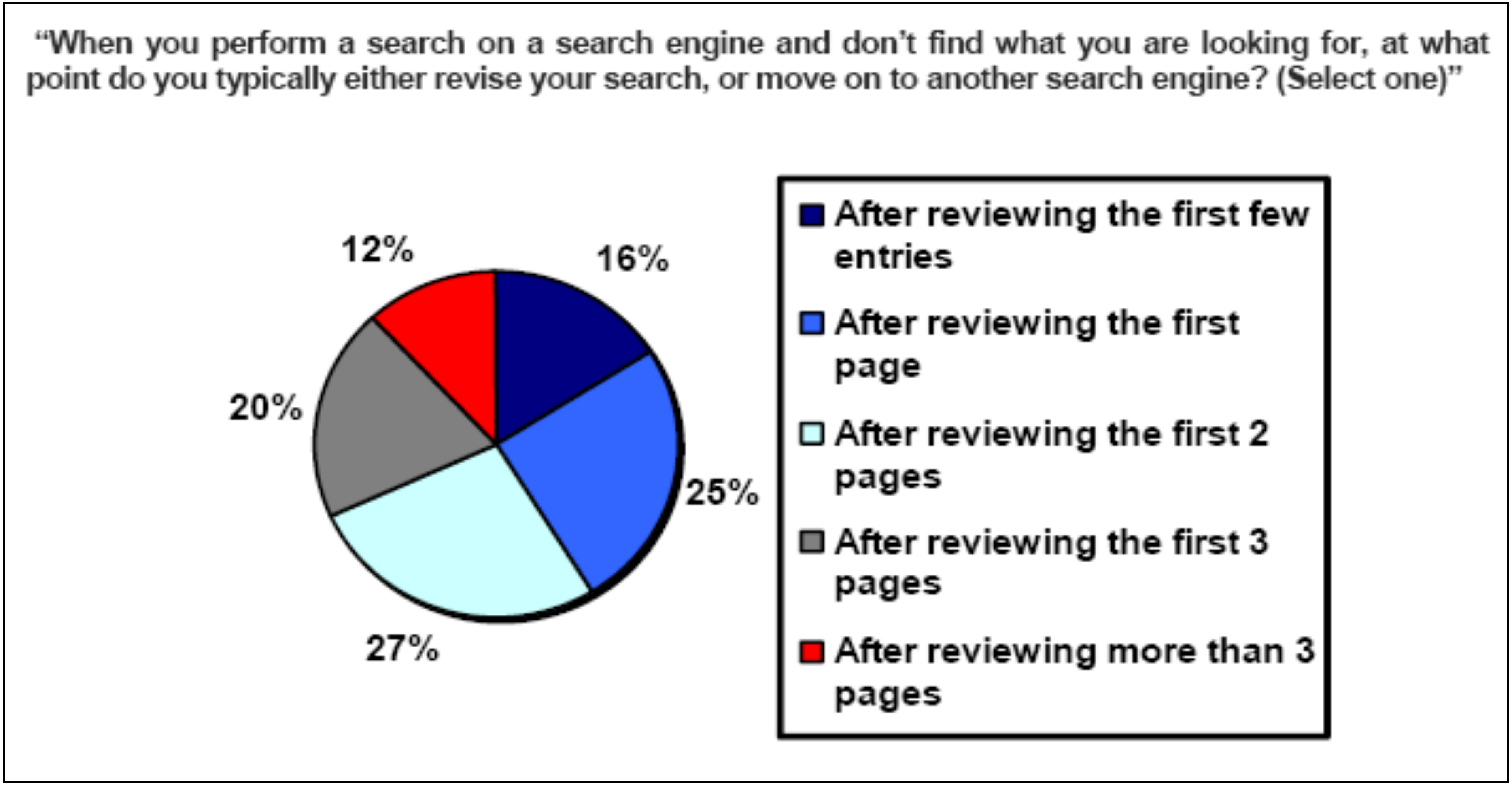
User Needs

- Need [Brod02, RL04]
  - **Informational** – want to learn about something (~40% / 65%)

    `Low hemoglobin`
  - **Navigational** – want to go to that page (~25% / 15%)

    `United Airlines`
  - **Transactional** – want to do something (web-mediated) (~35% / 20%)
    - Access a service — `Seattle weather`
    - Downloads — `Mars surface images`
    - Shop — `Canon S410`
  - **Gray areas**
    - Find a good hub — `Car rental Brasil`
    - Exploratory search "see what's there"

How far do people look for results?



(Source: iprospect.com WhitePaper_2006_SearchEngineUserBehavior.pdf)

Users' empirical evaluation of results

- Quality of pages varies widely
  - Relevance is not enough
  - Other desirable qualities (not traditional IR!!)
    - Content: Trustworthy, diverse, non-duplicated, well maintained
    - Web readability: display correctly & fast
    - No annoyances: pop-ups, etc
- Precision vs. recall
  - On the web, recall seldom matters
- What matters
  - Precision at 1? Precision above the fold?
  - Comprehensiveness – must be able to deal with obscure queries
    - Recall matters when the number of matches is very small
- User perceptions may be unscientific, but are significant over a large aggregate

Users' empirical evaluation of engines

- Relevance and validity of results
- UI – Simple, no clutter, error tolerant
- Trust – Results are objective
- Coverage of topics for polysemic queries
- Pre/Post process tools provided
  - Mitigate user errors (auto spell check, search assist,...)
  - Explicit: Search within results, more like this, refine ...
  - Anticipative: related searches
- Deal with idiosyncrasies
  - Web specific vocabulary (#lcot, C#, +Chris)
    - Impact on stemming, spell-check, etc.
  - Web addresses typed in the search box

The trouble with paid search ads …

- It costs money. What's the alternative?
- *Search Engine Optimization:*
  - "Tuning" your web page to rank highly in the algorithmic search results for select keywords
    - Alternative to paying for placement
    - Thus, intrinsically a marketing function
- Performed by companies, webmasters and consultants ("Search engine optimizers" -- SEOs) for their clients
- Some perfectly legitimate, some very shady

Simplest forms

- First generation engines relied heavily on *tf-idf*
  - The top-ranked pages for the query **`maui resort`** were the ones containing the most **`maui`**’s and **`resort`**’s
- SEOs responded with dense repetitions of chosen terms
  - e.g., **`maui resort maui resort maui resort`**
  - Often, the repetitions would be in the same color as the background of the web page
    - Repeated terms got indexed by crawlers
    - But not visible to humans on browsers

Pure word density cannot be trusted as an IR signal

Adversarial IR

- Search engines have responded to this in many ways:
  - Quality/spam detection measures on pages
  - Use of other metrics such as link analysis, user votes
- But it's a fundamentally new world:
  - Before, we assumed that the documents just existed independently, and we could build an IR system for them
  - Now, the documents are being changed in ways that attempt to maximize their ranking in search results
- **Adversarial IR**: the unending (technical) battle between SEO's and web search engines
  - For more see: http://airweb.cse.lehigh.edu/

Introduction to

Information Retrieval

Web search

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