# EECS 440 System Design of a Search Engine Winter 2021

Lecture 14: Ranking

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# Agenda

- 1. Course details.
- 2. HW6 and 7 Hashing
- 3. Ranking.

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### details

 A few teams have made good progress (one finished) on the hashtable and top 10. No one has started the hashblob and hashfile.

#### 2. Reading:

- a. My paper on dynamic ranking.
- b. Brian Fung, "<u>Here's what we know about Google's mysterious</u> search engine", The Washington Post, August 28, 2018.
- c. Look at (no need to read in any detail) Google's <u>Page Quality</u> <u>Rating Guidelines</u>.
- d. Marc Najork and Allan Heydon, "<u>Mercator</u>", September 26, 2001.

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In Homework 6, you will build a conventional hash table. If you build it with -DVerbose, you get timing information. I also give you some sample input.

```
tcsh-31% make verbose
g++ -DVerbose Top10.cpp Common.cpp TopN.cpp -o Top10
g++ -DVerbose HashTable.cpp Common.cpp -o HashTable
g++ -DVerbose HashBlob.cpp Common.cpp -o HashBlob
g++ -DVerbose HashFile.cpp Common.cpp -o HashFile
tcsh-32% wc BigJunkHtml.txt
  62001 215994 2209965 BigJunkHtml.txt
tcsh-33%
```

In Homework 6, you will build a conventional hash table. If you build it with -DVerbose, you get timing information. I also give you some sample input.

```
tcsh-33% ./HashTable BigJunkHtml.txt
Number of tokens = 215994
Total characters = 1782086
Average token length = 8.25063 characters
Building HashTable
Elapsed time = 14759200 ticks
Optimizing HashTable
Elapsed time = 591300 ticks
Enter search words:
hello world how are you
88
    hello
    world
43
91
    how
650
    are
675
     you
Elapsed time = 7696912200 ticks
tcsh-34%
```

#### Here's the top 10.

```
tcsh-34% ./Top10 BigJunkHtml.txt
Number of tokens = 215994
Total characters = 1782086
Average token length = 8.25063 characters
     <a
11931
6605
     the
3314
     ≺a
3144
     to
3088
2223
     and
2059
     of
1930 C
1837 is
1768
     tcsh-36%
```

In HW7, you will build a HashBlob in memory and then search it.

```
tcsh-35% ./HashBlob BigJunkHtml.txt
Number of tokens = 215994
Total characters = 1782086
Average token length = 8.25063 characters
Building HashTable
Elapsed time = 14677300 ticks
Optimizing HashTable
Elapsed time = 575700 ticks
Building HashBlob
Elapsed time = 2503900 ticks
HashBlob size = 942840 bytes
Enter search words:
hello world how are you
   hello
88
43
   world
91
    how
650
    are
675
    you
Elapsed time = 6315604700 ticks
```

You will also build a HashBlob in as a mapped file.

```
tcsh-36% ./HashBlob BigJunkHtml.txt Blob.bin < /dev/null
Number of tokens = 215994
Total characters = 1782086
Average token length = 8.25063 characters
Building HashTable
Elapsed time = 14835000 ticks
Optimizing HashTable
Elapsed time = 637600 ticks
Building HashFile = Blob.bin
Elapsed time = 18153000 ticks
HashBlob size = 942840 bytes
Elapsed time = 24100 ticks
tcsh-37%
```

You will then search the HashBlob in as a mapped file. (The elapsed time reflects that I typed the input search words!)

```
tcsh-37% ./HashFile Blob.bin
Loading HashBlob from Blob.bin
Elapsed time = 105200 ticks
HashBlob size = 942840 bytes
Enter search words:
hello world how are you
    hello
88
    world
43
91
    how
650
    are
675
    you
Elapsed time = 72123829500 ticks
tcsh-38%
```

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# Ranking

Objective is to order pages the same way a human would do using software.

Do a calculation based on what's known about:

- 1. All the documents and words in the index.
- 2. That page.
- 3. Match between the query and the page.

# Ranking

- 1. The rank value should obey the desired ordering relationship, that a better page will get a better score.
- 2. Since search engines typically broadcast a query to a large number of machines with differing fractions of the web and then combine the results, the calculation should be consistent even though the samples might be a little different.
- 3. Beyond ordering, the value is otherwise meaningless: If page A's rank is twice that of page B, it does not mean that A is twice as good as B.

#### Only two ways to get better at ranking:

- 1. Have more or better information.
- 2. Make better use of it.

### Static vs. dynamic rank

#### Static

Quality of the page independent of the query, e.g., PageRank, length of the URL, title or page, domain (.gov or .edu vs. .biz), whether it contains images, pornographic content, etc.

#### **Dynamic**

Quality of a page as possible result for a specific query considering both static rank and the quality of the match between the query and the page.

### Static rank

Some pages are just better than others before you know anything about the query.

#### Static rank

Some domains are better than others, e.g., .gov or .edu over .biz.

Short URLs are better.

Short titles are probably better.

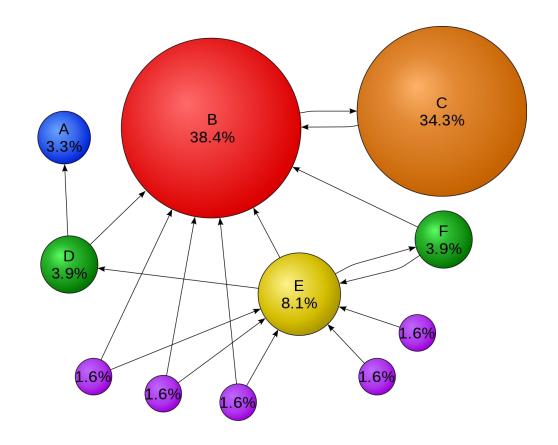
Some pages may be obvious spam.

Some pages may have lots of other pages pointing to them.

# PageRank

A detour into the world's most famous link-analysis algorithm.

The basic idea: The more and better links to a page, the more likely it should rank higher.



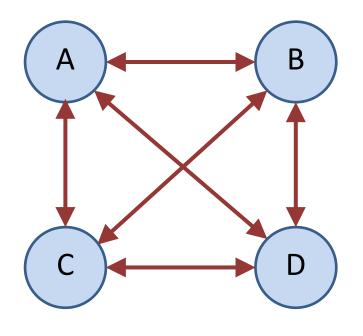
### PageRank random surfer

The model was that people surfed the web, somewhat randomly either clicking on one of the links on the page or going somewhere else.

If an important page pointed to yours, some of that importance should bleed onto yours.

### Basic PR algorithm

- 1. PR output is a vector of probabilities that a person randomly clicking links will arrive at a particular page.
- 2. Initially all probabilities usually assumed equal (or maybe not!)
- 3. Links from a page to itself are ignored.
- 4. Multiple links from one page to another are treated as a single link.
- 5. The PR transferred from one page to another is its PR divided by number of pages it links to.
- 6. At each iteration, the new PR of a given page is calculated as the sum of the PRs transferred to it.
- 7. Repeat until it settles.

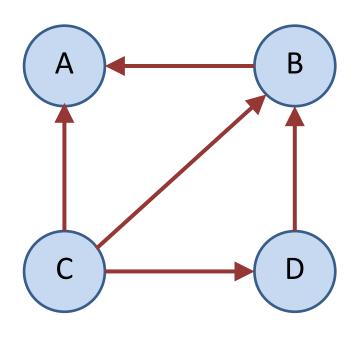


$$PR(A) = \frac{PR(B)}{3} + \frac{PR(C)}{3} + \frac{PR(D)}{3}$$

$$PR(B) = \frac{PR(A)}{3} + \frac{PR(C)}{3} + \frac{PR(D)}{3}$$

$$PR(C) = \frac{PR(A)}{3} + \frac{PR(B)}{3} + \frac{PR(D)}{3}$$

$$PR(D) = \frac{PR(A)}{3} + \frac{PR(B)}{3} + \frac{PR(C)}{3}$$

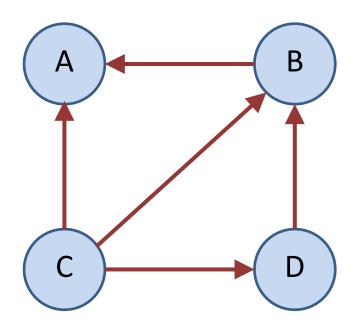


$$PR(A) = \frac{PR(B)}{1} + \frac{PR(C)}{3}$$

$$PR(B) = \frac{PR(C)}{3} + \frac{PR(D)}{1}$$

$$PR(C) = 0$$

$$PR(D) = \frac{PR(C)}{1}$$



$$PR(u) = \sum_{u \in B_u} \frac{PR(v)}{L(v)}$$

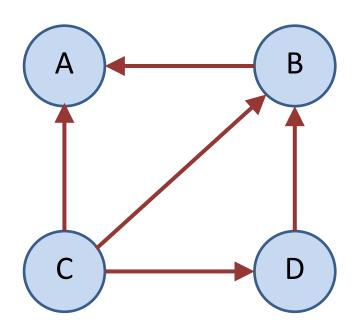
#### Where

u is a page, PR(u) is is the PageRank of page u,  $B_u$  is the set of all pages that link to u, L(v) is the number pages linked from v.

### Damping factor

But in this basic version, PR sinks could happen, where at every iteration, a site just got more and rank.

They solved this by adding the notion that their imaginary surfer randomly clicking links will eventually stop clicking and simply start over at some other random page. This became a damping factor in PageRank.



$$PR(u) = \frac{1-d}{N} + d\sum_{v \in B_u} \frac{PR(v)}{L(v)}$$

#### Where

u is a page, PR(u) is is the PageRank of page u,  $B_u$  is the set of all pages that link to u, L(v) is the number pages linked from v, d is the damping factor, typically ~0.85.

# PageRank

It obviously did work and Google got better results.

It also gave halo of special legitimacy to their results, that they were scientific and unbiased.

#### At Microsoft

We gamely expected our version of PageRank to represent about half the overall rank value, largely based on the hype around it.

Turned out it was very expensive to calculate and represented only a small part of the final rank score.

Mark Najork of Mercator fame argued for lumping whole domains together in something called DomainRank. But it hadn't yet worked when I left.

### Ranking process

- 1. Compile the query.
- Search the index for matching pages.
- 3. Return a list of the n best with scores indicating estimated quality.
- 4. May also return debug information to allow the scoring calculation to be examined.

### Question

- 1. How should you find the n best?
- 2. Should you get the entire list and then sort?

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- 2. Should you get the entire list and then sort?

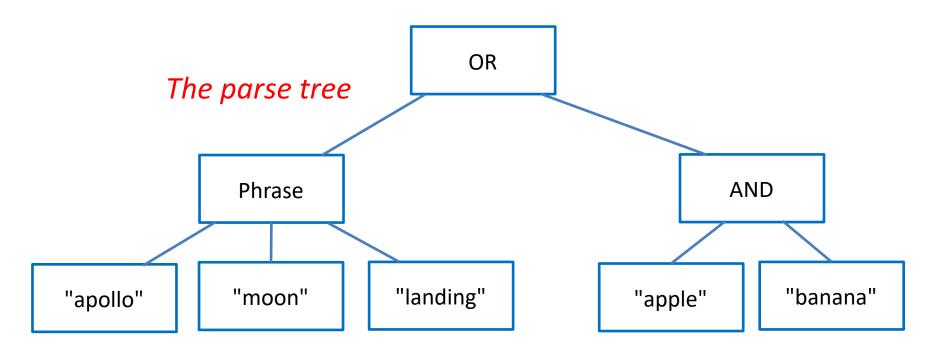
No, you should probably insertion sort into array of n elements.

#### Simple search engine query language

```
<Constraint>
                   ::= <BaseConstraint> { <OrOp> <BaseConstraint> }
                   ::= 'OR' | '|' | '||'
<0r0p>
<BaseConstraint> ::= <SimpleConstaint> { [ <AndOp> ] <SimpleConstraint> }
                   ::= 'AND' | '&' | '&&'
<AndOp>
<SimpleConstraint> ::= <Phrase> | <NestedConstraint> |
                       <UnaryOp> <SimpleConstraint> |
                       <SearchWord>
                   ::= '+' | '-' | 'NOT'
<UnaryOp>
                 ::= '"' { <SearchWord> } '"'
<Phrase>
<NestedConstraint> ::= '(' <Constraint> ')'
```

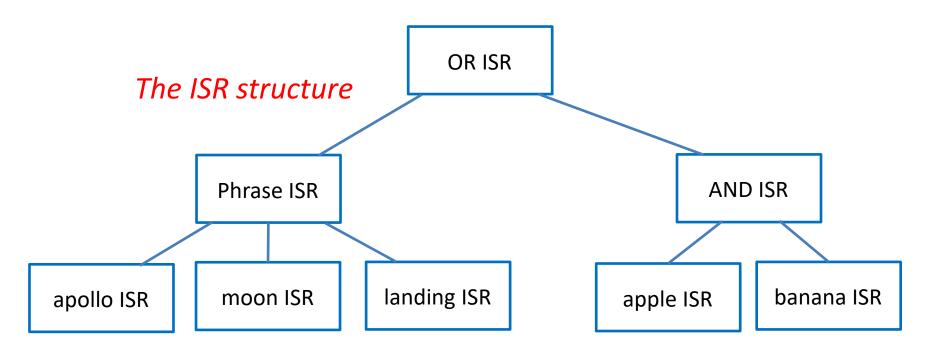
#### The query language and the ISRs can be recursive

"apollo moon landing" | ( apple banana )



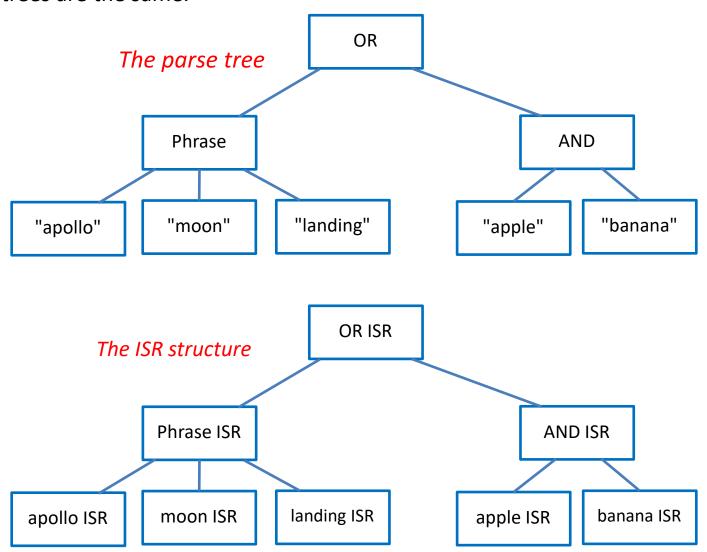
#### The query language and the ISRs can be recursive

"apollo moon landing" | ( apple banana )



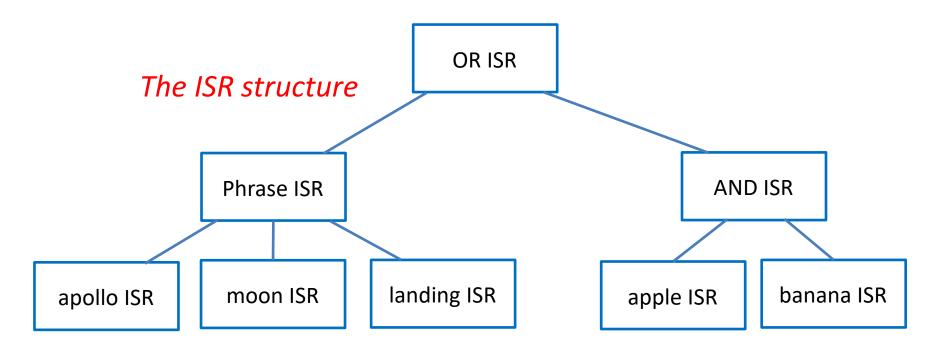
"apollo moon landing" | ( apple banana )

The trees are the same.



#### Technically, is this correct?

"apollo moon landing" | ( apple banana )



How many ISRs does it really take to do this?

## Decorating

Add characters that get stripped out during HTML parsing to indicate special characteristics or types of posts, e.g.,

amazon amazon in the body text

#amazon amazon only in the URL

@amazon amazon only in the title

\$amazon only in the anchor text

% End-of-document token.

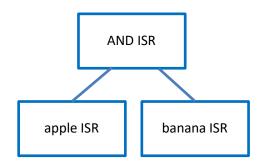
Might also be used for *stemming*:

swim\* swims, swimming, etc.

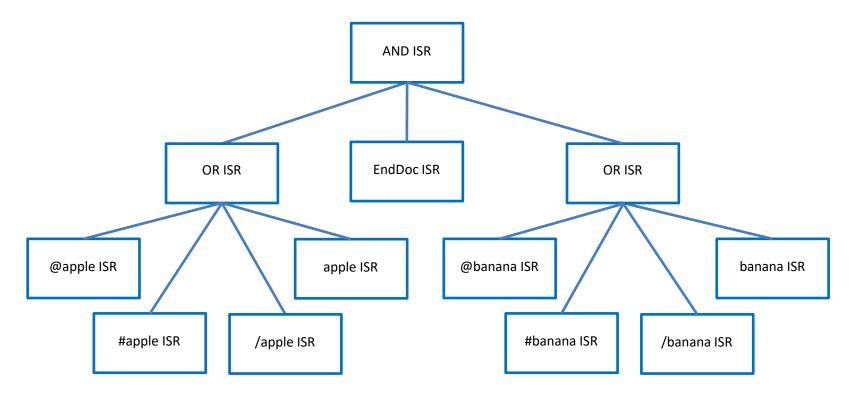
# Decorating vs. attributes

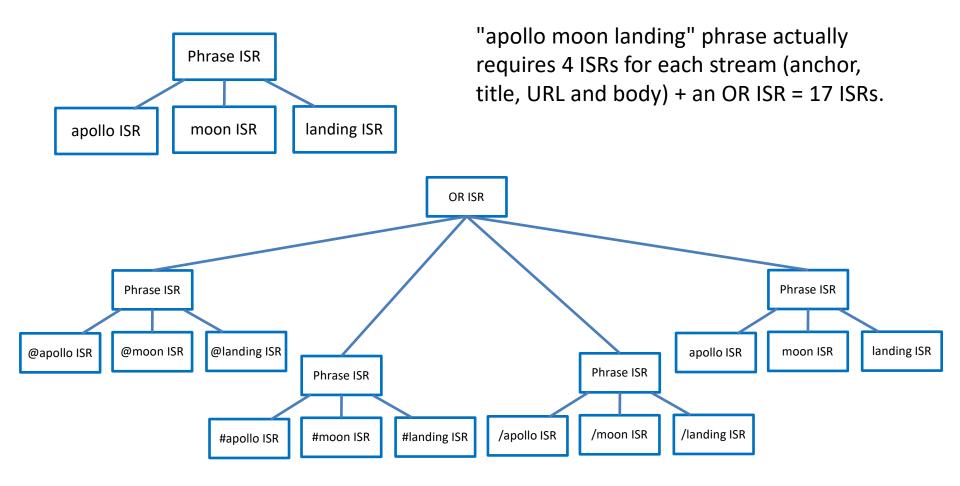
Use decorating when you'd like to use it for searching, to shrink the size of a post or because you'd like to separate the scoring for hits in the title vs. the body for example.

Use attributes when the ranker will want the information about each post and it could be different every time.



The AND of apple and banana might actually take 12 ISRs if the terms are decorated, e.g., @ = anchor, # = title, / = url.

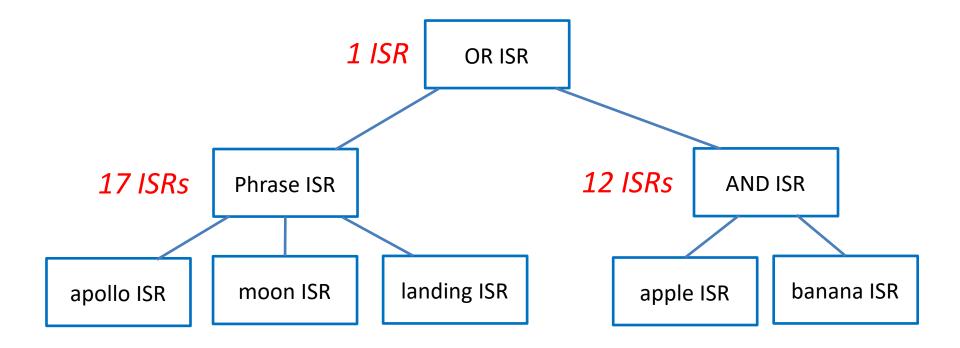




Assume decorations: @ = anchor, # = title, / = url

## Coming back to the question, is this correct?

"apollo moon landing" | ( apple banana )



If the terms are decorated, it could take 30 ISRs.

### Matches in order of importance:

- 1. Anchor text.
- 2. URL.
- 3. Title.
- 4. Body.

Exception is Japan were URL matches are less useful due to mismatch between Kanji or Katakana queries and transliterated URLs.

URLs may need dictionary word-breaking or regex-style matching to be useful. Again, beyond the scope.

Does it matter how many ISRs you use? How much effect will this have on query search time?

What dominates search time?

# Basic ranking

- Matching pages found by the constraint solver but that only finds the page and the static information about the page from the enddoc.
- Queries are flattened. (Very hard to estimate the probability of phrases or other combinations of OR'ing and AND'ing terms.)
- 3. ISRs are reset to the beginning of the document, then advanced through the page, extracting data about where the search words were found.
- 4. Three strategies from there.

# Queries are flattened

These queries all match different sets of pages:

apollo moon landing
( apollo | moon ) landing
"apollo moon landing"

But for scoring, they're all flattened to the same list of search words.

# Three strategies

- 1. Bag of words: The more hits the better.
- 2. Heuristics: Look for exact matches, matches in the right places, hand or machine-tuned.
- 3. Machine learning, typically with a neural net.

Count the number of matches of each of the search words, typically weighted by the frequency of the word within the corpus.

### Two most famous:

- 1. tf-idf
- 2. BM25

## tf-idf

Term-frequency, inverse document frequency.

Bag of words technique. The more occurrences of a rare word, the better.

#### Combined:

- Term weighting based on frequency invented by to Hans Peter Luhn in 1957.
- 2. Statistical interpretation invented by Karen Spärck Jones in 1972.

### Term frequency

$$TF(t) = \frac{Number\ of\ times\ t\ appears\ in\ a\ document}{Total\ number\ of\ terms\ in\ the\ document}$$

Inverse document frequency

$$IDF(t) = \frac{\log_e(Total\ number\ of\ documents\ )}{Number\ of\ documents\ with\ term\ t}$$

Tf-idf is the product. The more the better.

$$Tf - idf(t) = TF(t) * IDF(t)$$

# Okapi BM25

Okapi Best Matching function, a similar bag of words technique.

$$score(D,Q) = \sum_{i=1}^{n} IDF(q) \cdot \frac{f(q_{i},D) \cdot (k_{1}+1)}{f(q_{i},D) + k_{1} \cdot (1-b+b \cdot \frac{|D|}{avgdl})}$$

 $f(q_i, D)$  is  $q_i$ 's term frequency in Document D. |D| is the length of the document in words. avgdl is the average document length.

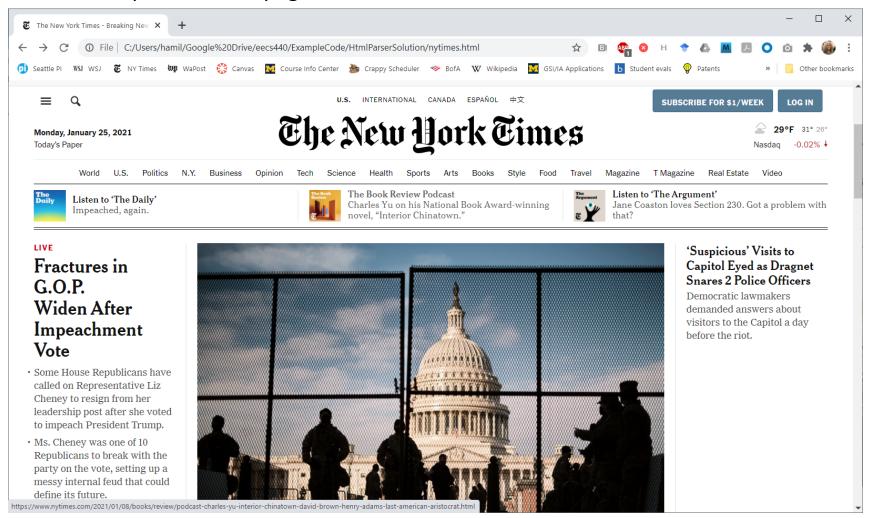
 $k_1$  and b are free parameters you get to choose. Typically

$$k_1 \in [1.2, 2.0]$$
  
 $b = 0.75$ 

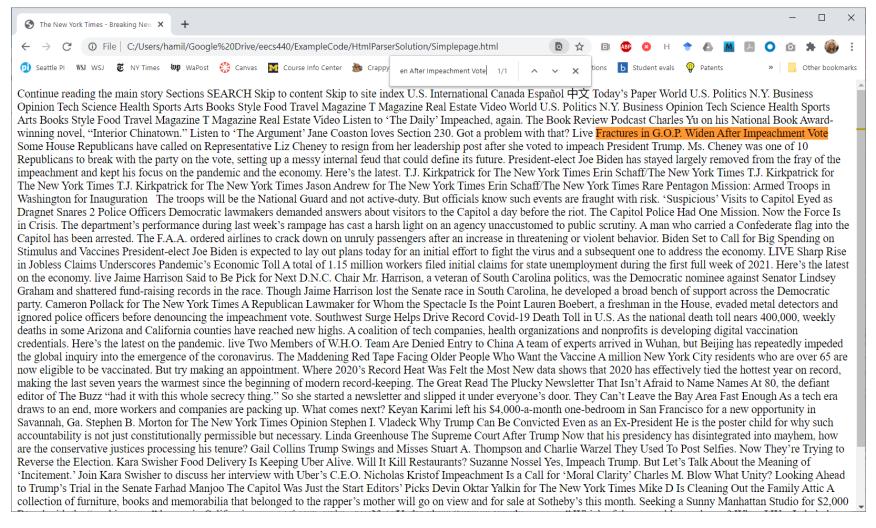
Problem is, bag of words techniques simply don't work very well on the web because they don't do well at distinguishing quality, especially, to find the best match.

They simply cannot distinguish that a page with all the search words in the right order, as an exact phrase, or near the top of the page is better than a page where the words are randomly scattered.

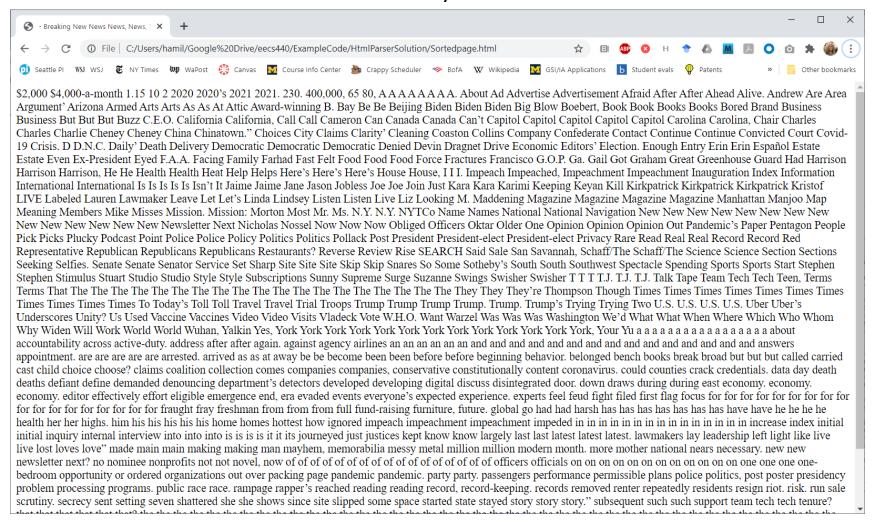
Here's a sample NY Times page from Jan 25, 2021.



#### Here it is stripped of HTML and CSS but the text remains.



Here it is with the words in the title and body sorted. Tf-idf can't tell the difference.



## Heuristics

- Incrementing a flurry of low-level counters, e.g., number of times each word occurred, number of times an exact phrase matching the query was found.
- Large number of cheap heuristics that are expected to provide evidence of the quality of the match.

# Query processing

- 1. Compile the query into a structure of ISRs.
- Pass the ISRs to the constraint solver to find matching pages.
- 3. For each matching page:
  - a. Move the ISRs back to the beginning of the page and scan for hits.
  - b. Calculate a rank value and insertion sort the page into a list of n best.

Example phrase query "quick brown fox" and the their 3 posting lists.

Individual search words appear individually many times but there are only two exact phrases. The constraint solver will stop on the first phrase match, then it's up to the ranker to decide what next.

	brown			brown	
	83			83	
	94		quick	94	
	170		62	170	
quick	179		69	179	
62	216		84	216	
69	227		311	227	fox
84	400	fox	421	400	284
311	417	284	430	417	423
421	422	423	559	422	580
430	516	580	619	516	612
559	795	612	794	795	796
619	826	796	952	826	912
794	828	912		828	958
952	957	958		957	

A suggested first step in ranking is to flatten the query, pulling out all the individual ISRs and seeking them to the beginning of the document.

brown		q	uick	brown	fox
83			62	83	284
94			69	94	423
170			84	170	580
179			311	179	612
216			421	216	796
227			430	227	912 958
400	fox		559	400	336
417	284		619	417	
422	423		794	422	
516	580		952	516	
795	612			795	
826	796			826	
828				828	
957	958			957	
•	83 94 170 179 216 227 400 417 422 516 795 826 828	83 94 170 179 216 227 400 fox 417 284 422 423 516 580 795 612 826 796 828 912	83 94 170 179 216 227 400 fox 417 284 422 423 516 580 795 612 826 796 828 912	83 62 94 69 170 84 179 311 216 421 227 430 400 fox 417 284 619 422 423 794 516 580 952 795 612 826 796 828 912	83       62       83         94       69       94         170       84       170         179       311       179         216       421       216         227       430       227         400       fox       559       400         417       284       619       417         422       423       794       422         516       580       952       516         795       612       795         826       796       826         828       912       828

From there, you can move the ISRs any way you like to extract data as long as they only go forward.

Wo	ord counts:	quick	brown	fox
qui	ick 10	62	83	284
bro	own 14	69	94	423
fox	7	84	170	580
		311	179	612
_	o possible strategies:	421	216	796
1.	Simply count the words.	430	227	912
2.	Look for places where the words occur	559	400	958
2	together. Possible combinations of the three words	619	417	
J.	= 10 * 14 * 7 = 980 for a very short	794	422	
	document and will grow with longer	952	516	
	queries.		795	
4.	Not possible to visit all combinations if all		826	
	the ISRs only go forward.		828	
5.	May either read the lists in or process on		957	
	the fly.			

I'm going to show you a simpler strategy I used at Microsoft.



	()30012.74.770.01
States Patent	(10) Patent No.: US 7,254,576 B1 (45) Date of Patent: Aug. 7, 2007
INTING ELECTRONIC	6,523,021 B1 2/2003 Monberg et al. 707:2 6,549,897 B1 4/2003 Kalariya et al. 707:5 6,766,520 B1 7/2004 Wang et al. 707:5 200/2003/1296 A1* 3/2002 Fukushima 382,236
	* cited by examiner
icrosoft Corporation, Redmond, WA	Primary Examiner Uyeu Le (74) Attorney, Agent, or Firm—Shook, Hardy & Bacon, LLP
tent is extended or adjusted under 35	(57) ABSTRACT  A system and a method for locating and presenting electronic documents most-likely of interest to the user. A
/847,598	plurality of search terms to be located in a set of electronic document is received. One of the search terms is selected as
ay 17, 2004	the anchor term, and occurrences of the anchor term are located within the documents. For each located occurrence
sitication Search	of the anchor ferm, a set of search term occurrences is selected. These sets include an occurrence of each search term, and the occurrences are selected by choosing the search term occurrences that are closest to a desired place- ment for the search terms. With each set of search terms, the method associates a value indiceting the cettern to which the selected occurrences vary from the desired placement. The
PATENT DOCUMENTS	accordance with this value. The invention further includes systems and methods for locating and presenting Web pages and for searching the Internet.  40 Claims, 5 Drawing Sheets
DENTIFY 100 SELECT AND 100 SELECT AN	ARCH TERMS  COLUMENTS  CHOCK TERM  MENT NEFORMATION  FERM OCCURRENCE  F P SEARCH TERM NERGOLS  THE PROJECTION  VES  THE PROJECTION  VES  VES  VES
	707/6, 707/3, 707/7, 707/10 sitication Search 707/13, 707/13, 707/13, 707/13, 107/13,

quick	brown	tox
62	83	284
69	94	423
84	170	580
311	179	612
421	216	796
430	227	912
559	400	958
619	417	
794	422	
952	516	
	795	
	826	
	828	
	957	



#### an United States Patent Hamilton

#### US 7,254,576 B1 (10) Patent No.:

(54)	SYSTEM AND METHOD FOR LOCATING
	AND PRESENTING ELECTRONIC
	DOCUMENTS TO A USER

- (75) Inventor: Nicole Ashley Hamilton, Redmond.
- (73) Assignee: Microsoft Corporation. Redmond, WA
- Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 452 days.
- (21) Appl. No.: 10/847,598
- May 17, 2004 (22) Filed:
- G06F 17/30

(2006.01)

- Field of Classification Search
  - See application file for complete search history.

#### (56)References Cited

	U.S	ŝ.	PATENT	DOCUMENTS	
5,983,221	A	۰	11/1909	Christy	707
6,012,053	A	٠	1/2000	Pant et al.	707
6.460.000	10.1		16:3003	Make a second	700

- (45) Date of Patent: Aug. 7, 2007
- 6.523.021 B1 6,549,897 B1 4/2003 Kalariya et al. ..... 707/5 6,766,320 B1 7/2004 Wang et al. ..... 2002/0031269 A1®
- \* cited by examiner

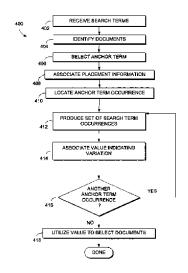
Primary Examiner Uyen Le-

(74) Attorney, Agent, or Firm-Shook, Hardy & Bacon, LLP

ABSTRACT

A system and a method for locating and presenting electrouic documents most-likely of interest to the user. A plurality of search terms to be located in a set of electronic document is received. One of the search terms is selected as the anchor term, and occurrences of the anchor term are located within the documents. For each located occurrence of the anchor term, a set of search term occurrences is selected. These sets include an occurrence of each search term, and the occurrences are selected by choosing the search term occurrences that are closest to a desired placement for the search terms. With each set of search terms, the method associates a value indicating the extent to which the selected occurrences vary from the desired placement. The electronic documents are ranked and presented to the user in accordance with this value. The invention further includes systems and methods for locating and presenting Web pages and for searching the Internet.

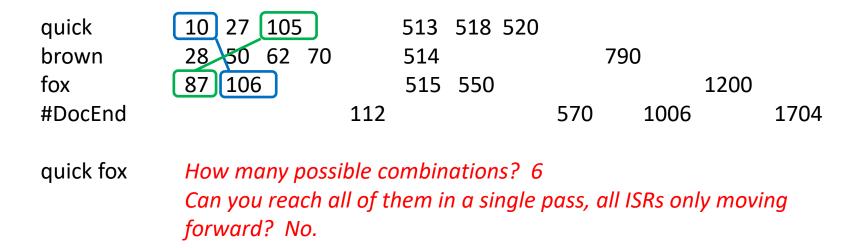
40 Claims, 5 Drawing Sheets



I was very concerned that my ranker would single-handedly blow us out of the water on perf and I wanted something really simple.

It was all integer math and done in a single pass over each page.

### AND'ing streams



Would prefer a technique that allows the ISRs to be moved only in a single pass.

# **Basic strategy**

Choose rarest word as an anchor and advance that ISR through each occurrence in the document.

At each occurrence of the rarest word, advance the other ISRs to position them as close as possible to the desired position in the flattened list.

Requires only one stage of look-ahead.

# Spans

- 1. If there is at least one occurrence of each query term, that's a "span" which can be further distinguished as ordered, short, an exact phrase, etc.
- 2. Only the rarest word is guaranteed to a unique occurrence.
- 3. The other words may be reused.
- 4. Also count doubles and triples, meaning various combinations of just 2 or 3 of the words in the query, one of which must be the rarest.
- 5. Parameterized threshold for short vs. long spans, frequent vs. infrequent, etc.
- 6. Most features are binary and either occur or do not occur unambiguously.

What I did was *pick the rarest word* and *then arrange the other ISRs* to as close as possible to their desired locations in the query relative to each occurrence of the rarest word.

Word counts:		quick	brown	fox	
quick	10	62	83	284	
brown	14	69	94	423	
fox	7	84	170	580	
		311	179	612	
This reduces th	e number of combinations	421	216	796	
to be scored in	this example from 10*14*7	430	227	912	
	can be done a single pass	559	400	958	
with a single st	age of lookahead.	619	417		
	* <b>!</b> *	794	422		
Call each comb	oination a <i>span</i> .	952	516		
			795		
			826		
			828		
			957		

Iterate over the rarest word hits, arranging the other ISRs to as close as they could be to their desired locations in the query. Here are the first 3 *spans*.

	brown			brown			brown	
	83			83			83	
quick	94			94			94	
62	170			170		quick	170	
69	179		quick	179		62	179	
84	216	fox	62	216		69	216	
311	227	284	69	227		84	227	
421	400	423	84	400	fox	311	400	fox
430	417	580	311	417	284	421	417	284
559	422	612	421	422	423	430	422	423
619	516	796	430	516	580	559	516	580
794	795	912	559	795	612	619	795	612
952	826	958	619	826	796	794	826	796
	828		794	828	912	952	828	912
	957		952	957	958		957	958

For each combination, decide if it's an *exact phrase* or all the words *in order*, or *close together*, incrementing an associated counter. Shown here, there is one exact phrase but none of the rest are in order or particularly close together.

	brown			brown			brown	
	83			83			83	
quick	94			94			94	
62	170			170		quick	170	
69	179		quick	179		62	179	
84	216	fox	62	216		69	216	
311	227	284	69	227		84	227	
421	400	423	84	400	fox	311	400	fox
430	417	580	311	417	284	421	417	284
559	422	612	421	422	423	430	422	423
619	516	796	430	516	580	559	516	580
794	795	912	559	795	612	619	795	612
952	826	958	619	826	796	794	826	796
	828		794	828	912	952	828	912
	957		952	957	958		957	958

	brown						brown	
	83						83	
quick	94			brown			94	
62	170			83			170	
69	179		quick	94		quick	179	
84	216		62	170		62	216	
311	227	fov	69	179		69	227	
421	400	fox 284	84	216		84	400	
430	417	423	311	227	four	311	417	£a
559	422	580	421	400	fox 284	421	422	fox 284
619	516	612	430	417	423	430	516	423
794	795	796	559	422	580	559	795	580
952	826	912	<del>619</del>	_516	612	619	826	612
	828	958	794	795	796	794	828	796
	957		952	826	912	952	957	912
				828	958			958
				957				

This last one is *close together* (say, less than 10 words apart) and *in order* but it's *not an exact phrase*.

	brown	
	83	
	94	
	170	
quick	179	
62	216	
69	227	
84	400	fov
311	417	fox 284
421	422	423
430	516	580
559	795	612
619	826	796
794	828	912
952	957	958

Set some thresholds and accumulate some counts,
which can scored at the end.

Thresholds	Values
Max to be short	10
Min to be frequent	?
Min to be most	?
Min to be near the top	?

Heuristic	Count	Weight	Score
Number of short spans	1	5	5
Number of in order spans	1	2	2
Exact phrases	2	10	20
Number of spans near the	top ?	?	?
All word are frequent	?	?	?
Most words are frequent	?	?	?
Some words are frequent	?	?	?

	brown	
	83	
	94	
	170	
quick	179	
62	216	
69	227	
84	400	£
311	417	fox
421	422	284 423
430	516	580
559	795	612
619	826	796
794	828	912
952	957	958

One reason to decorate words as *anchor*, *URL*, *title* or *body* is so they can be separated in to separate *streams* (separate sets of ISRs) and *scored separately* with the same algorithm but different scoring parameters.

Stream	Weight	Score
Anchor	?	?
URL	?	?
Title	?	?
Body	?	?
Total dynamic rank score		?

Each of the streams can start at location 1 relative to the start of the document. The document length is the length of the longest stream.

Not all streams may contain all the words.

	brown	
	83	
	94	
	170	
quick	179	
62	216	
69	227	
84	400	£
311	417	fox 284
421	422	423
430	516	580
559	795	612
619	826	796
794	828	912
952	957	958

We do a similar heuristic calculation of the *static rank*, the quality of the page *independent of the query*.

Heuristic	Weight	Score
Short title	?	?
Nice document length	?	?
Short URL	?	?
Lots of anchor text	?	?
edu/gov/com/etc domain	?	?
PageRank if known	3	5
Total static rank score		?

	brown	
	83	
	94	
	170	
quick	179	
62	216	
69	227	
84	400	<b>C</b>
311	417	fox
421	422	284 423
430	516	580
559	795	612
619	826	796
794	828	912
952	957	958

Combine static and dynamic rank to get a final score.

Component	Weight	Score
Static rank	?	?
Dynamic rank	;	?
Total rank score		?

The result is a *linear combination* of features. We're just adding them up.

You should be able to achieve reasonably good results with a reasonably small number of heuristics and simple *hand-tuning* starting from some rough guesses at, e.g., the relative importance of an exact phrase versus lots of individual hits.

	brown	
	83	
	94	
	170	
quick	179	
62	216	
69	227	
84	400	£
311	417	fox 284
421	422	423
430	516	580
559	795	612
619	826	796
794	828	912
952	957	958

The actual score is calculated as a linear combination of features, which may be thought of as:

$$R = \sum Ci(Q) * Ai(P, Fi) * Si(Fi)$$

#### Where:

R = Overall Rank

Q = The Query and its characteristics, e.g., the number of rare vs. common words in the query.

P = The Page and its characteristics, e.g., the number of words in the URL or title.

Fi = An arbitrary feature observation, e.g., an exact phrase in the title, or a raw value, e.g., raw PageRank.

Si = Scaling for feature Fi from the raw number space of the feature into a nominal 0.0 .. 1.0 range.

Ai = Attribute scaling for feature Fi, possibly dependent on the characteristics of the page P.

Ci = Coefficient for feature Fi, depending on the characteristics of the query Q.

Fi = Ei(Q, P, T)

# Steps to ranking

- Decide what information to collect and how to measure it.
- Decide how to measure the quality of the result.
- 3. Pick a method for scoring a page based on the inputs.
- 4. Tune the system by testing it on sample queries and adjusting parameters, collecting more information or changing the scoring algorithm.

At Microsoft, initially, I just ran queries and eyeballed the results and fiddled with the parameters.

Results were surprisingly good.

We were also collecting labeled pages. We scraped queries and results from several engines and then paid people to rate results on a 0 to 5 scale.

- Definitive result. Unlikely any other page could be a better result for this query, e.g., whitehouse.gov for "whitehouse".
- O Completely deleterious result, e.g., porno, spam, phishing.

This is similar to what Google is doing with their <a href="Page Quality Rating Guidelines">Page Quality Rating Guidelines</a>, creating specificity in the ratings.

Altogether, I think we had about 50K queries and about 150K labeled results.

Next came a tool allowing us to do side-by-side comparison of results with current best parameters in a frame on the left and with a set you could tweak on the right.

If the pages had been labeled, it reported the quality and attempted to score the resulting set.

We ran a competition to see who could come up with the best settings.

Finally, we added a tuner that could adjust the parameters mechanically by gradient descent: Tweak an individual parameter rerun all the searches and measure whether the results got better (more highly ranked pages for each query.)

But we had lots of problems in the methodology of what to do with unlabeled pages.

Initially they were assumed to be "average". Later, a "promising proximity" heuristic was added to the tuner bump the estimate for unlabed pages if the search words were found close together.

The effect was to tune my complex ranker ended up being tuned to behave like the tuner's naïve ranker.

Better strategy would have been to only tune based on labeled results, discarding any unlabeled results.

## Generating labeled results

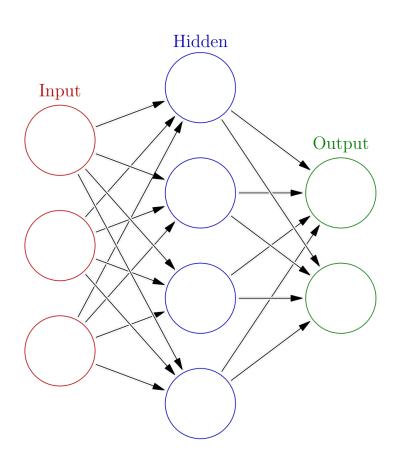
You can't afford to pay people to label results but you might assume that Google is pretty good, so you might simply try to get pages in the same order as Google.

Your ranker won't be as good as Google's, so it might not be able to discern the difference between the top results on the first page, but perhaps it could distinguish between the first result on the first page and the first result on the fifth page.

## How to do better

To do better than heuristics, you will probably need a neural network.

A machine learning strategy would be to simply collect all the lists and pass everything to a neural network, which must be trained. Beyond the scope here.



quick	brown	fox
62	83	284
69	94	423
84	170	580
311	179	612
421	216	796
430	227	912
559	400	958
619	417	
794	422	
952	516	
	795	
	826	
	828	
	957	

Image source: https://en.wikipedia.org/wiki/Artificial\_neural\_network