

# CC5212-1

PROCESAMIENTO MASIVO DE DATOS

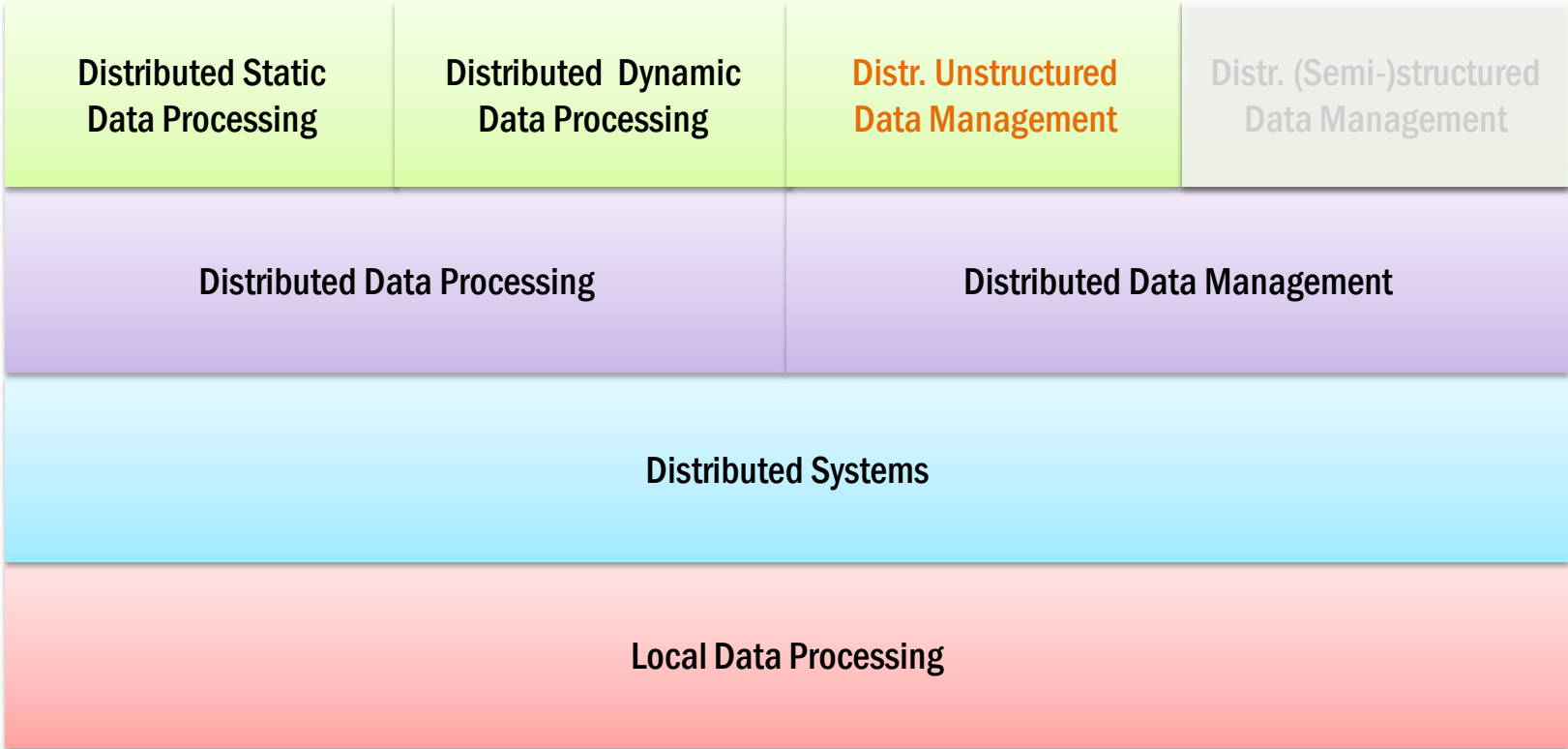
OTOÑO 2023

## Lecture 7

Information Retrieval: Crawling & Indexing

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# MANAGING TEXT DATA

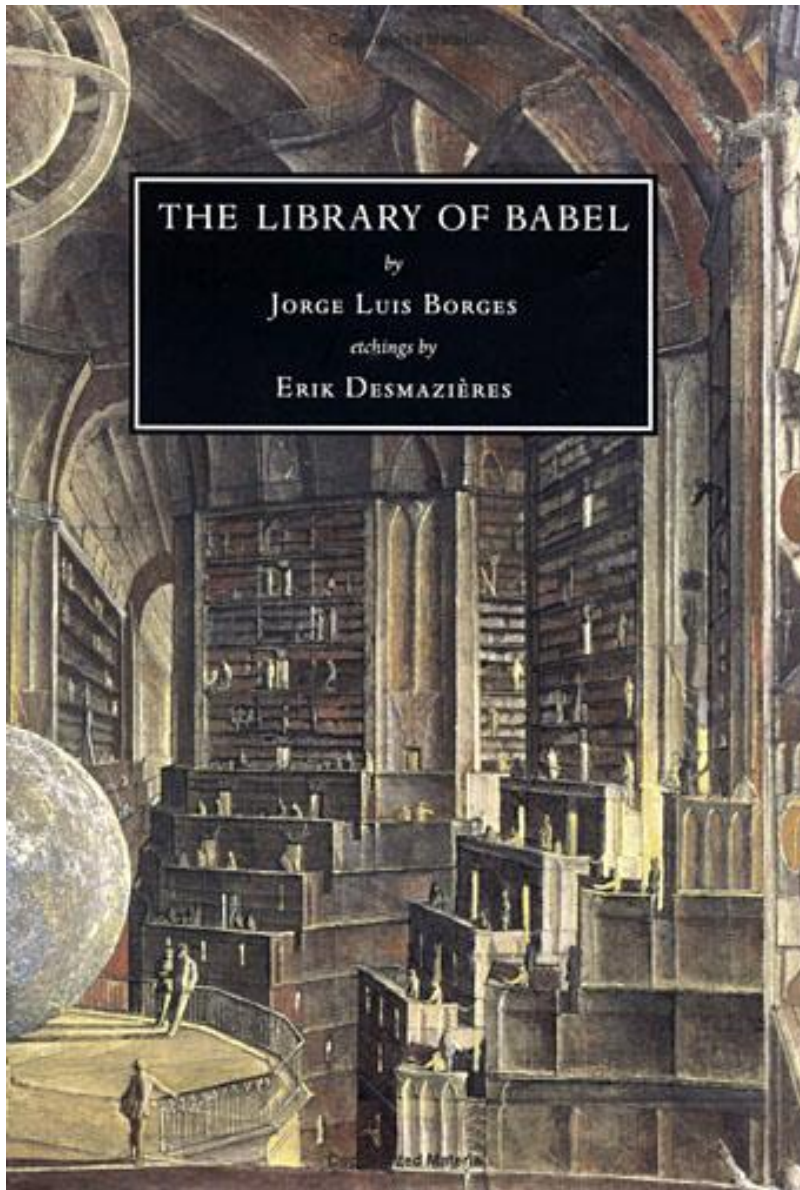
# Information Overload



Getting information off the  
Internet is like taking a  
drink from a fire hydrant.

Mitchell Kapor

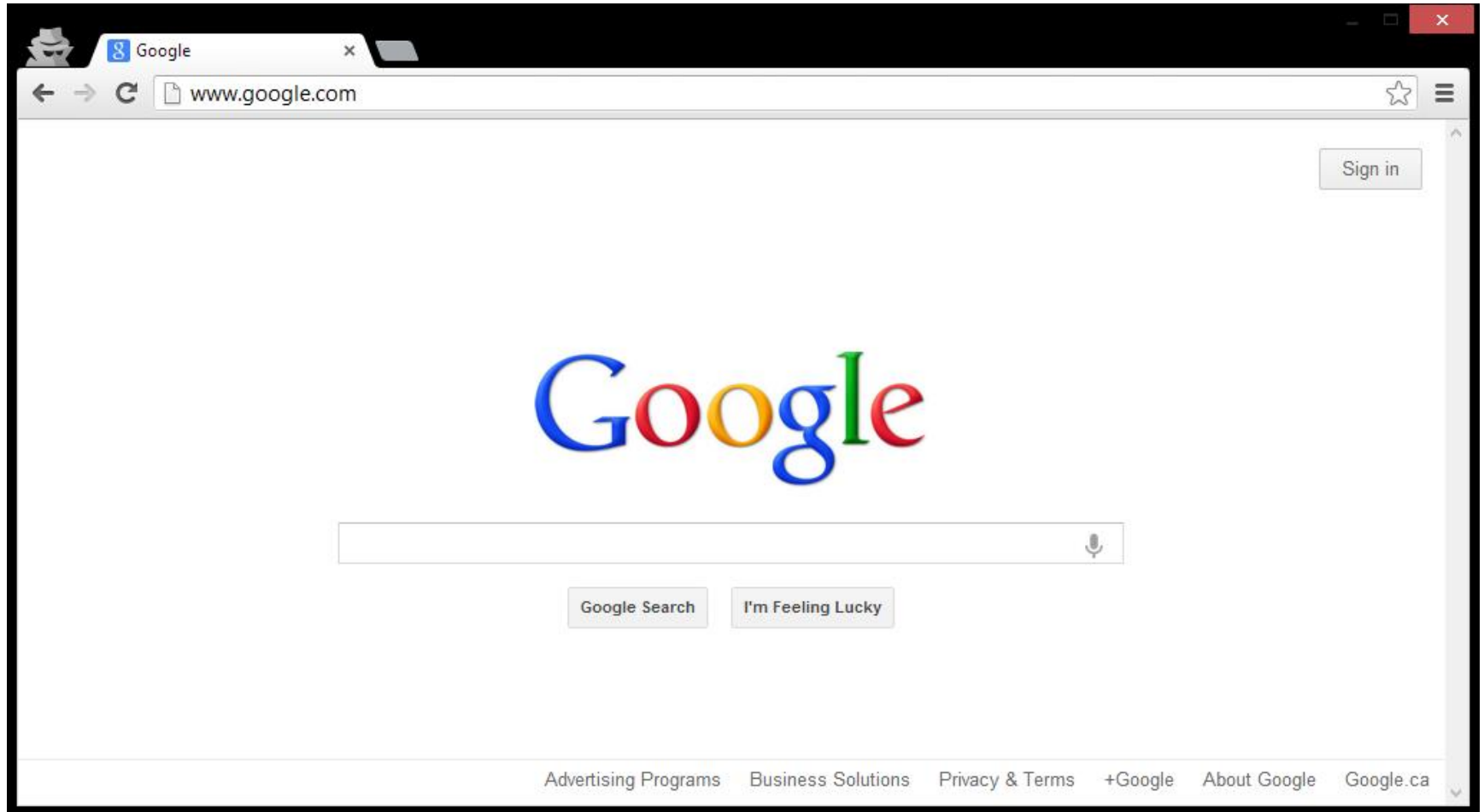
If we didn't have search ...



- Contains all books with
  - 25 unique characters
  - 80 characters per line
  - 40 lines per page
  - 410 pages
  - $410 \times 40 \times 80 = 1,312,000$  chars
  - $25^{1,312,000}$  books
- Would contain any book imaginable
  - Including a book with the location of useful books

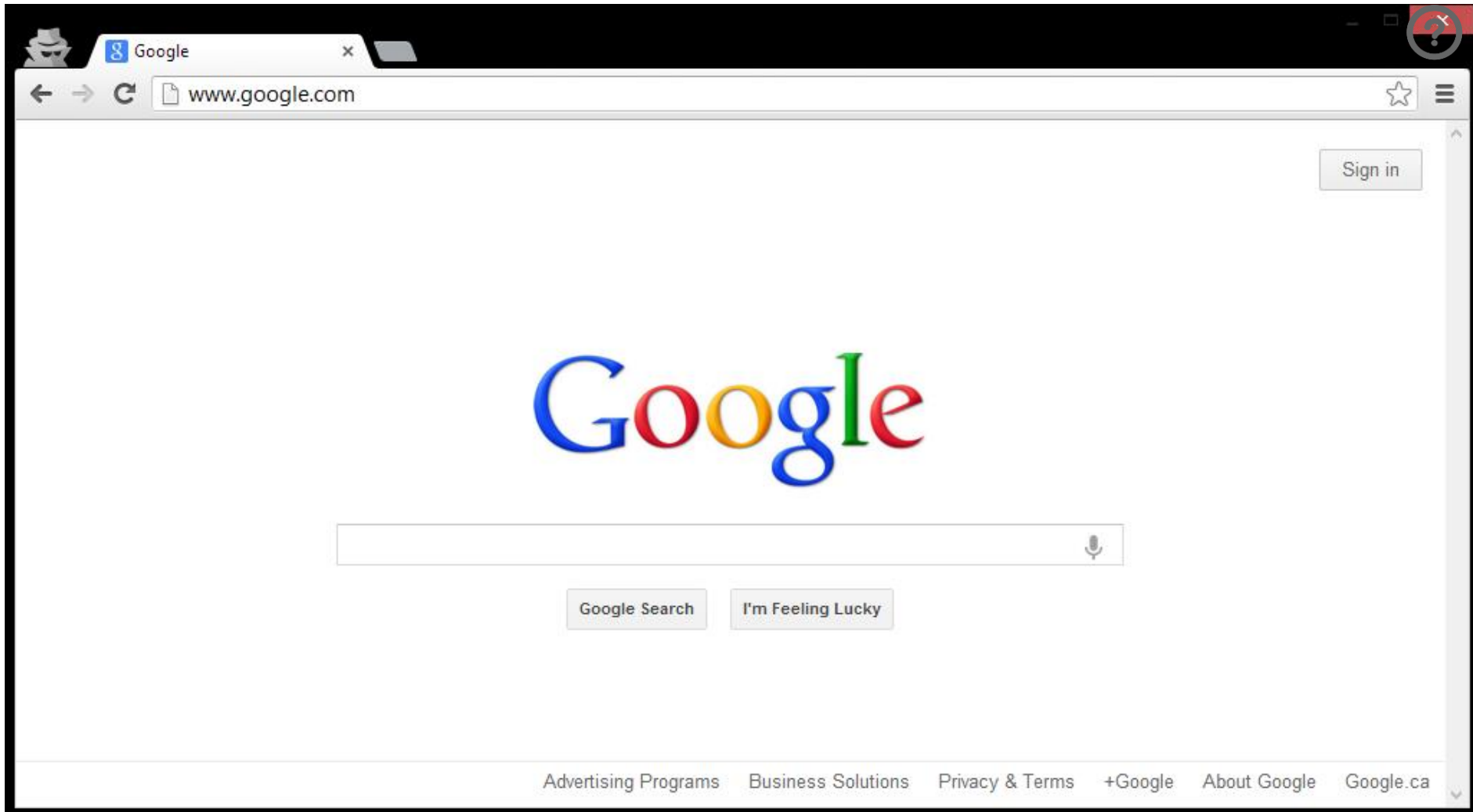
All information = Zero information

# The book that indexes the library



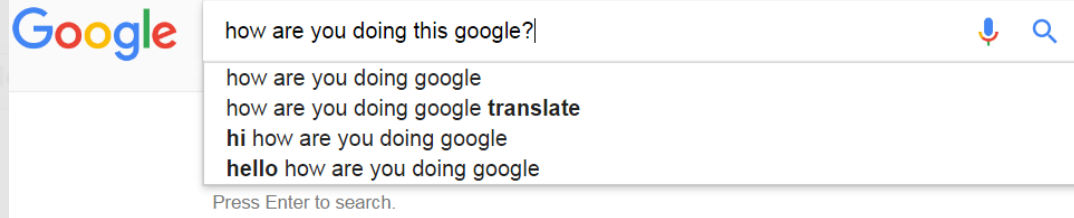
WEB SEARCH/RETRIEVAL

# Building Google Web-search





# Building Google Web-search



What processes/algorithms does Google need to implement Web search?

## Crawling



1. Parse links from webpages
2. Schedule links for crawling
3. Download pages, GOTO 1

## Indexing



1. Parse keywords from webpages
2. Index keywords to webpages
3. Manage updates

## Ranking



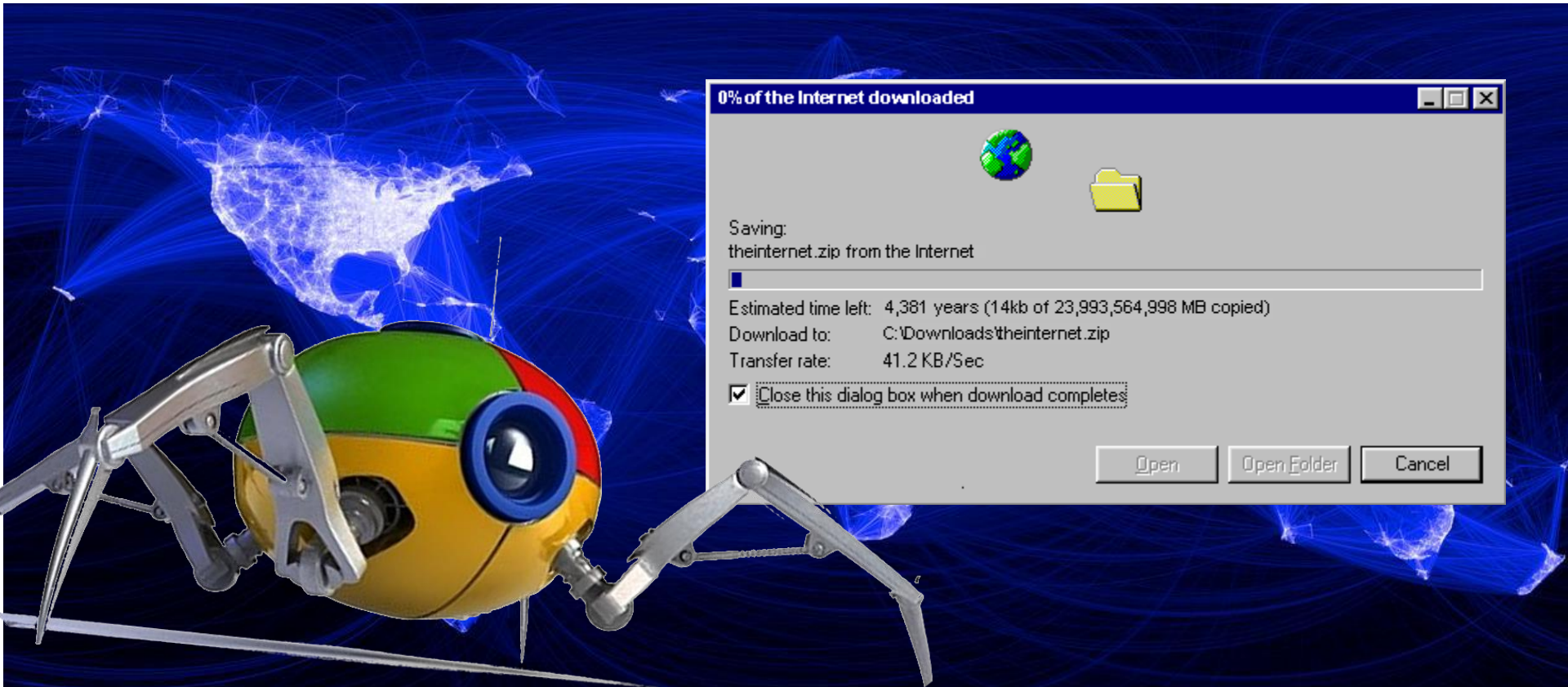
1. How relevant is a page? (TF-IDF)
2. How important is it? (PageRank)
3. How many users clicked it?

...

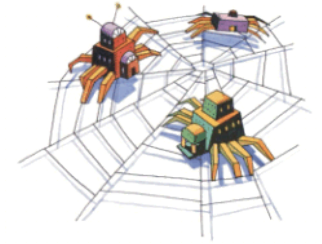


# INFORMATION RETRIEVAL: CRAWLING

# How does Google know about the Web?



# Crawling



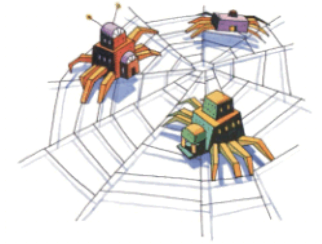
Download the Web. 😊

```
crawl(list seedUrls)
  frontier_i = seedUrls
  while !frontier_i.isEmpty()
    new list frontier_i+1
    for url : frontier_i
      page = downloadPage(url)
      frontier_i+1.addAll(extractUrls(page))
      store(page)
    i++
```

What's missing?



# Crawling: Avoid Cycles



Download the Web. 😊

```
crawl(list seedUrls)
  frontier_i = seedUrls
  new set urlsSeen
  while !frontier_i.isEmpty()
    new list frontier_i+1
    for url : frontier_i
      page = downloadPage(url)
      urlsSeen.add(url)
      frontier_i+1.addAll(extractUrls(page).removeAll(urlsSeen))
      store(page)
  i++
```

Performance?



# Crawling: Performance



Download the Web. 😊

```
C:\Users\Aidan>ping twitter.com

Pinging twitter.com [199.16.156.198] with 32 bytes of data:
Reply from 199.16.156.198: bytes=32 time=118ms TTL=50
Reply from 199.16.156.198: bytes=32 time=120ms TTL=50
Reply from 199.16.156.198: bytes=32 time=120ms TTL=50
Reply from 199.16.156.198: bytes=32 time=125ms TTL=50

Ping statistics for 199.16.156.198:
    Packets: Sent = 4, Received = 4, Lost = 0 (0% loss),
    Approximate round trip times in milli-seconds:
        Minimum = 118ms, Maximum = 125ms, Average = 120ms

C:\Users\Aidan>
```

```
page = downloadPage(url)
```

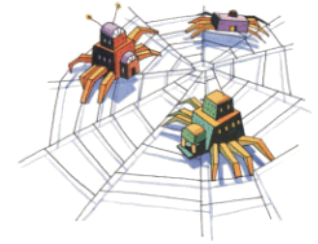
- Majority of time spent waiting for connection
- Disk/CPU usage will be near 0
- Bandwidth will not be maximised



Performance?



# Crawling: Performance



Download the Web. 😊

```
crawl(list seedUrls)
  frontier_i = seedUrls
  new set urlsSeen
  while !frontier_i.isEmpty()
    new list frontier_i+1
    for url : frontier_i
      page = downloadPage(url)
      urlsSeen.add(url)
      frontier_i+1.addAll(extractUrls(page).removeAll(urlsSeen))
      store(page)
  i++
```

Solution?



# Crawling: Multi-threading Important

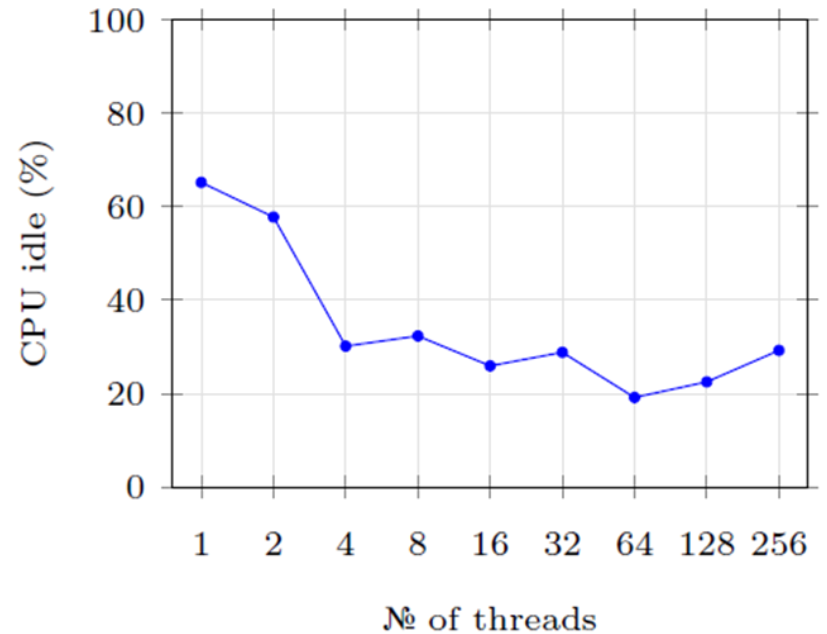
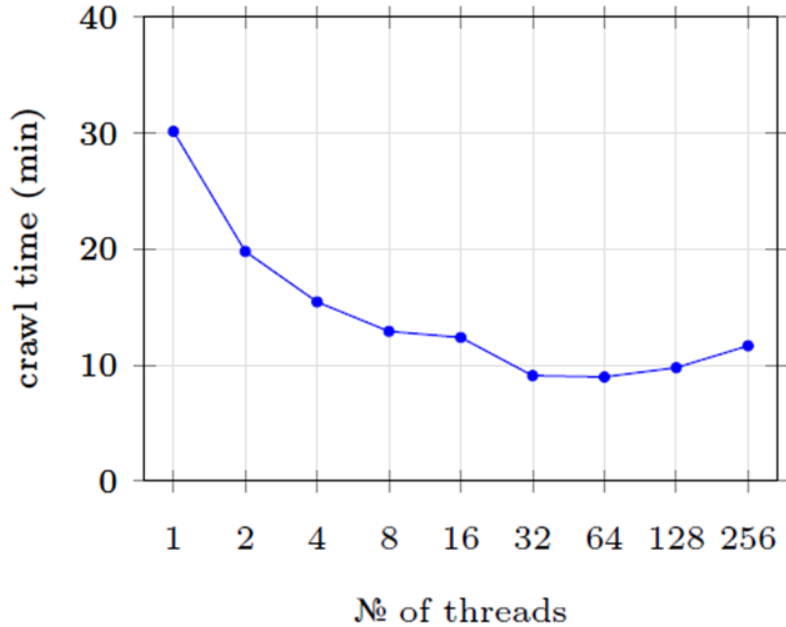
```
crawl(list seedUrls)
  frontier_i = seedUrls
  new set urlsSeen
  while !frontier_i.isEmpty()
    new list frontier_i+1
    new list threads
    for url : frontier_i
      thread = new DownloadThread.run(url,urlsSeen,frontier_i+1)
      threads.add(thread)
    threads.poll()
    i++

DownloadThread: run(url,urlsSeen,frontier_i+1)
  page = downloadPage(url)
  synchronised: urlsSeen.add(url)
  synchronised: frontier_i+1.addAll(extractUrls(page).removeAll(urlsSeen))
  synchronised: store(page)
```



# Crawling: Multi-threading Important

Crawl 1,000 URLs ...



# Crawling: Important to be Polite!

## (Distributed) Denial of Server Attack: (D)DoS

Low Orbit Ion Cannon | U dun goofed | v. 1.1.1.25

Manual Mode (Do it yourself) IRC Mode (HiveMind) IRC server Port Channel Disconnected.  
6667 #loic

1. Select your target

2. Attack options

3. Ready?

Selected target

Attack status

github.com/NewEraCracker/LOIC

# Crawling: Avoid (D)DoSing



- Christopher Weatherhead
- 18 months prison



... more likely your IP range will be banned

# Crawling: Web-site Scheduler

```
crawl(list seedUrls)
  frontier_i = seedUrls
  new set urlsSeen
  while !frontier_i.isEmpty()
    new list frontier_i+1
    new list threads
    for url : schedule(frontier_i) # maximise gap between requests to one site
      thread = new DownloadThread.run(url,urlsSeen,frontier_i+1)
      threads.add(thread)
    threads.poll()
    i++

DownloadThread: run(url,urlsSeen,frontier_i+1)
  page = downloadPage(url)
  synchronised: urlsSeen.add(url)
  synchronised: frontier_i+1.addAll(extractUrls(page).removeAll(urlsSeen))
  synchronised: store(page)
```

# Robots Exclusion Protocol

<http://website.com/robots.txt>

```
User-agent: *
```

```
Disallow: /
```

No bots allowed on the website.

```
User-agent: *
```

```
Disallow: /user/
```

```
Disallow: /main/login.html
```

No bots allowed in /user/ sub-folder or login page.

```
User-agent: googlebot
```

```
Disallow: /
```

Ban only the bot with “user-agent” googlebot.

# Robots Exclusion Protocol (non-standard)

```
User-agent: googlebot
```

```
Crawl-delay: 10
```

Tell the googlebot to only crawl a page from this host no more than once every 10 seconds.

```
User-agent: *
```

```
Disallow: /
```

```
Allow: /public/
```

Ban everything but the /public/ folder for all agents

```
User-agent: *
```

```
Sitemap: http://example.com/main/sitemap.xml
```

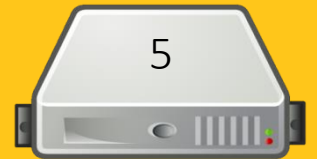
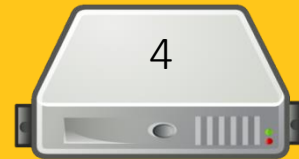
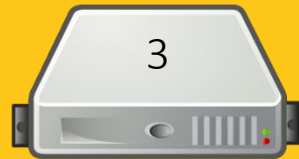
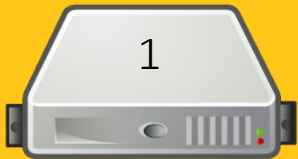
Tell user-agents about your *site-map*

# Crawling: Distribution

How might we implement a distributed crawler?



```
for url : frontier_i-1  
  map(url, count)
```



Similar benefits to multi-threading

What will be the bottleneck as machines increase?



Bandwidth or politeness delays

# Apache Nutch

- Open-source crawling framework!
- Compatible with Hadoop!



<https://nutch.apache.org/>



# INFORMATION RETRIEVAL: INVERTED INDEXING

# Inverted Index

- **Inverted Index**: A map from words to documents
  - “Inverted” because usually documents map to words

Examples of applications?



Google Search

I'm Feeling Lucky

Buscar

Show all Only English Only from Chile

Find Movies, TV shows, Celebrities and more...

All

Movies, TV & Showtimes Celebs, Events & Photos News & Community Watchlist

## WIKIPEDIA

**English**

*The Free Encyclopedia*  
4 501 000+ articles

**日本語**

フリー百科事典  
906 000+ 記事

**Русский**

Свободная энциклопедия  
1 108 000+ статей

**Italiano**

*L'enciclopedia libera*  
1 117 000+ voci

**Polski**

*Wolna encyklopedia*  
1 042 000+ haseł

**Español**

*La enciclopedia libre*  
1 096 000+ artículos

**Deutsch**

*Die freie Enzyklopädie*  
1 712 000+ Artikel

**Français**

*L'encyclopédie libre*  
1 499 000+ articles

**Português**

*A enciclopédia livre*  
825 000+ artigos

**中文**

自由的百科全书  
764 000+ 條目



English



# Inverted Index: Example

1



## *Fruitvale Station*

From Wikipedia, the free encyclopedia

*Fruitvale Station* is a 2013 American [drama film](#) written and directed by [Ryan Coogler](#).

### Inverted index:

Term List	Posting List
a	(1, 2, ...)
american	(1, 5, ...)
and	(1, 2, ...)
by	(1, 2, ...)
directed	(1, 2, ...)
drama	(1, 16, ...)
...	...

# Inverted Index: Example Search

american drama

- **AND**: Intersect posting lists
- **OR**: Union posting lists
- **PHRASE**: ???

How should we implement **PHRASE**?



Inverted index:

Term List	Posting List
a	(1, 2, ...)
american	(1, 5, ...)
and	(1, 2, ...)
by	(1, 2, ...)
directed	(1, 2, ...)
drama	(1, 16, ...)
...	...

# Inverted Index: Example

1



## *Fruitvale Station*

From Wikipedia, the free encyclopedia

1      10      18 21 23      28      37      43      48      56      60      69 72      77

*Fruitvale Station* is a 2013 American [drama film](#) written and directed by [Ryan Coogler](#).

### Inverted index:

Term List	Posting List
a	(1, [21, 96, 103, ...]), (2, [...]), ...
american	(1, [28, 123]), (5, [...]), ...
and	(1, [56, 139, ...]), (2, [...]), ...
by	(1, [69, 157, ...]), (2, [...]), ...
directed	(1, [60, 212, ...]), (4, [...]), ...
drama	(1, [37, 87, ...]), (16, [...]), ...
...	...

# Inverted Index: Flavours

## Record-level inverted index:

Maps words to documents without positional information

Term List	Posting List
a	(1,2,...)
american	(1,5,...)
and	(1,2,...)
by	(1,2,...)
directed	(1,2,...)
drama	(1,16,...)
...	...

## Word-level inverted index:

Additionally maps words with positional information

Term List	Posting List
a	(1,[21,96,103,...]), (2,[...]), ...
american	(1,[28,123]), (5,[...]), ...
and	(1,[56,139,...]), (2,[...]), ...
by	(1,[69,157,...]), (2,[...]), ...
directed	(1,[60,212,...]), (4,[...]), ...
drama	(1,[37,87,...]), (16,[...]), ...
...	...

# Inverted Index: Word Normalisation

drama america

How can we solve this problem?



Inverted index:

Term List	Posting List
a	(1, [21, 96, 103, ...]), (2, [...]), ...
american	(1, [28, 123]), (5, [...]), ...
and	(1, [56, 139, ...]), (2, [...]), ...
by	(1, [69, 157, ...]), (2, [...]), ...
directed	(1, [60, 212, ...]), (4, [...]), ...
drama	(1, [37, 87, ...]), (16, [...]), ...
...	...

# Inverted Index: Word Normalisation

drama **america**

How can we solve this problem?



Normalise words:

Stemming cuts the ends off of words using generic rules:

{ **America** , **American** , **americas** , **americanise** } → { **america** }

Inverted index:

Term List	Posting List
a	(1, [21, 96, 103, ...]), (2, [...]), ...
<b>american</b>	(1, [28, 123]), (5, [...]), ...
and	(1, [56, 139, ...]), (2, [...]), ...
by	(1, [69, 157, ...]), (2, [...]), ...
directed	(1, [60, 212, ...]), (4, [...]), ...
drama	(1, [37, 87, ...]), (16, [...]), ...
...	...



# Inverted Index: Word Normalisation

drama **america**

How can we solve this problem?



Normalise words:

Stemming cuts the ends off of words using generic rules:

{ **America** , **American** , **americas** , **americanise** } → { **america** }

Lemmatisation uses knowledge of the word to normalise:

{ **better** , **goodly** , **best** } → { **good** }

Inverted index:

Term List	Posting List
a	(1, [21, 96, 103, ...]), (2, [...]), ...
<b>american</b>	(1, [28, 123]), (5, [...]), ...
and	(1, [57, 139, ...]), (2, [...]), ...
by	(1, [70, 157, ...]), (2, [...]), ...
directed	(1, [61, 212, ...]), (4, [...]), ...
drama	(1, [38, 87, ...]), (16, [...]), ...
...	...

# Inverted Index: Word Normalisation

drama america

How can we solve this problem?



Normalise words:

Stemming cuts the ends off of words using generic rules:

{ America , American , americas , americanise } → { america }

Lemmatisation uses knowledge of the word to normalise:

{ better , goodly , best } → { good }

Synonym expansion  
{ film , movie } → { movie }

Inverted index:

and	(1, [57, 139, ...]), (2, [...]), ...
by	(1, [70, 157, ...]), (2, [...]), ...
directed	(1, [61, 212, ...]), (4, [...]), ...
drama	(1, [38, 87, ...]), (16, [...]), ...
...	...

# Inverted Index: Word Normalisation

drama **america**

How can we solve this problem?



Normalise words:

Stemming cuts the ends off of words using generic rules:

{ **America** , **American** , **americas** , **americanise** } → { **america** }

Lemmatisation uses knowledge of the word to normalise:

{ **better** , **goodly** , **best** } → { **good** }

Synonym expansion

{ **film** , **movie** } → { **movie** }

➤ Language specific!

➤ Use same normalisation on query and document!




directed	(1, [61, 212, ...]), (4, [...]), ...
drama	(1, [38, 87, ...]), (16, [...]), ...
...	...

# Inverted Index: Space

## Record-level inverted index:

Maps words to documents without positional information


Term List	Posting List
a	(1,2,...)
american	(1,5,...)
and	(1,2,...)
by	(1,2,...)
directed	(1,2,...)
drama	(1,16,...)
...	...

Space?   $\sum_{d \in D} U(d)$  (sum of unique words in all docs)

## Word-level inverted index:

Additionally maps words with positional information

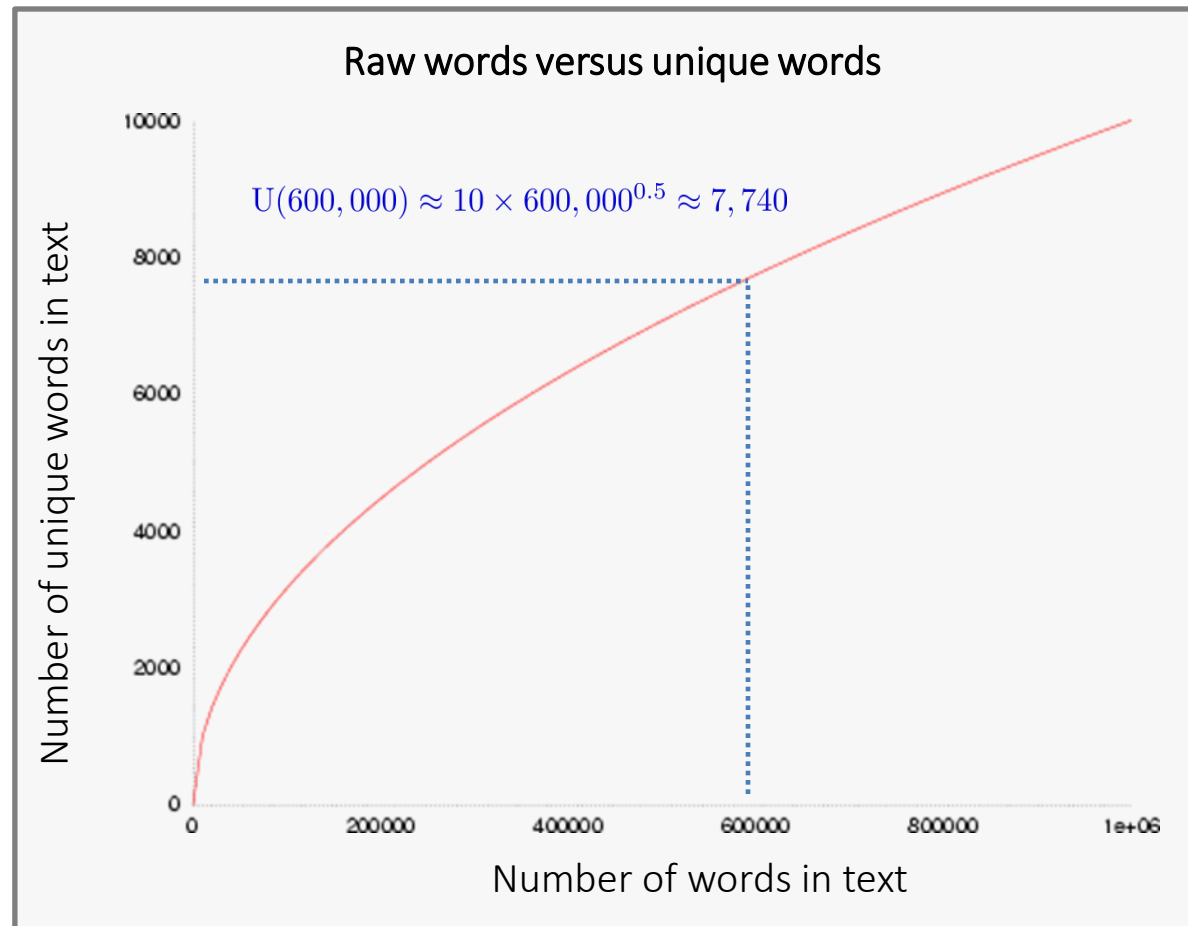
Term List	Posting List
a	(1,[21,96,103,...]), (2,[...]), ...
american	(1,[28,123]), (5,[...]), ...
and	(1,[56,139,...]), (2,[...]), ...
by	(1,[69,157,...]), (2,[...]), ...
directed	(1,[60,212,...]), (4,[...]), ...
drama	(1,[37,87,...]), (16,[...]), ...
...	...

Space?   $\sum_{d \in D} W(d)$  (sum of all word occurrences in all docs)

# Inverted Index: Unique Words

Not so many unique words ...

- Heap's law:  $U(n) \approx Kn^\beta$
- English text
  - $K \in [10,100]$
  - $\beta \in [0.4,0.6]$



# Inverted Index: Space


$$U(d) \approx K \times W(d)^\beta$$



## Record-level inverted index:

Maps words to documents without positional information


Term List	Posting List
a	(1,2,...)
american	(1,5,...)
and	(1,2,...)
by	(1,2,...)
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Space?   $\sum_{d \in D} U(d)$  (sum of unique words in all docs)

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Term List	Posting List
a	(1,[21,96,103,...]), (2,[...]), ...
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drama	(1,[37,87,...]), (16,[...]), ...
...	...

Space?   $\sum_{d \in D} W(d)$  (sum of all word occurrences in all docs)

# Inverted Index: Common Words

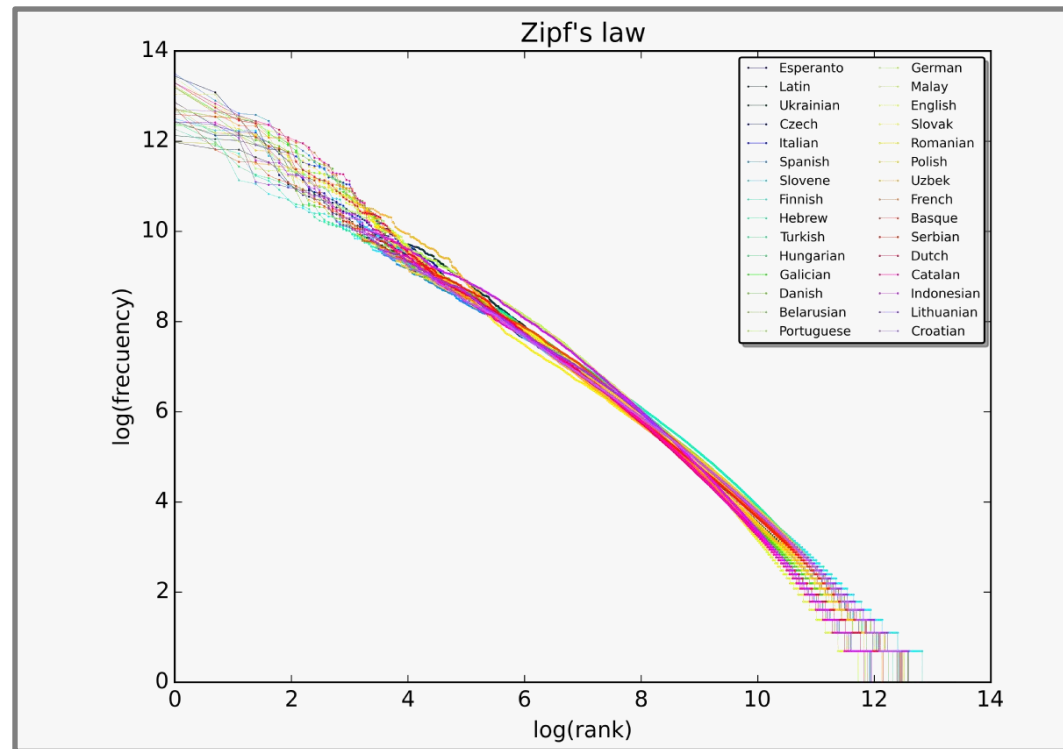
Many occurrences of few words

/ Few occurrences of many words

– Zipf's law

– In English text:

- “the” 7%
- “of” 3.5%
- “and” 2.7%
- 135 words cover half of all occurrences



**Zipf's law:** *the most popular word will occur twice as often as the second most popular word, thrice as often as the third most popular word, n times as often as the n-most popular word.*

# Inverted Index: Common Words

Many occurrences of few words

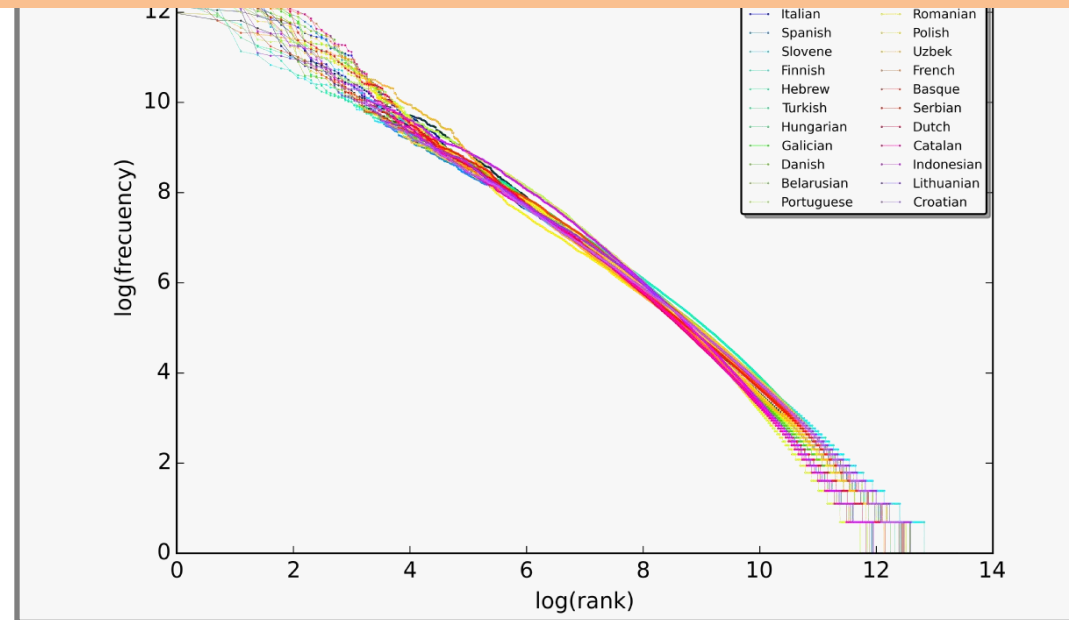
/ Few occurrences of many words

Expect **long posting lists** for common words



— IN ENGLISH TEXT.

- “the” 7%
- “of” 3.5%
- “and” 2.7%
- 135 words cover half of all occurrences



**Zipf's law:** *the most popular word will occur twice as often as the second most popular word, thrice as often as the third most popular word, n times as often as the n-most popular word.*



# Inverted Index: Common Words

- Perhaps implement **stop-words**?
  - Most common words contain least information

**the** drama **in** america

# Inverted Index: Common Words

- Perhaps implement **stop-words**?
- Perhaps implement **block-addressing**?

*Fruitvale Station* is a 2013 American [drama film](#) written and directed by [Ryan Coogler](#).

## Block 1

What is the effect on phrase search?



Small blocks ~ **okay**  
Big blocks ~ **not okay**

## Block 2

Term List	Posting List
a	(1, [1, ...]), (2, [...]), ...
american	(1, [1, ...]), (5, [...]), ...
and	(1, [2, ...]), (2, [...]), ...
by	(1, [2, ...]), (2, [...]), ...
...	...

# Inverted Index: Common Words

Many occurrences of few words

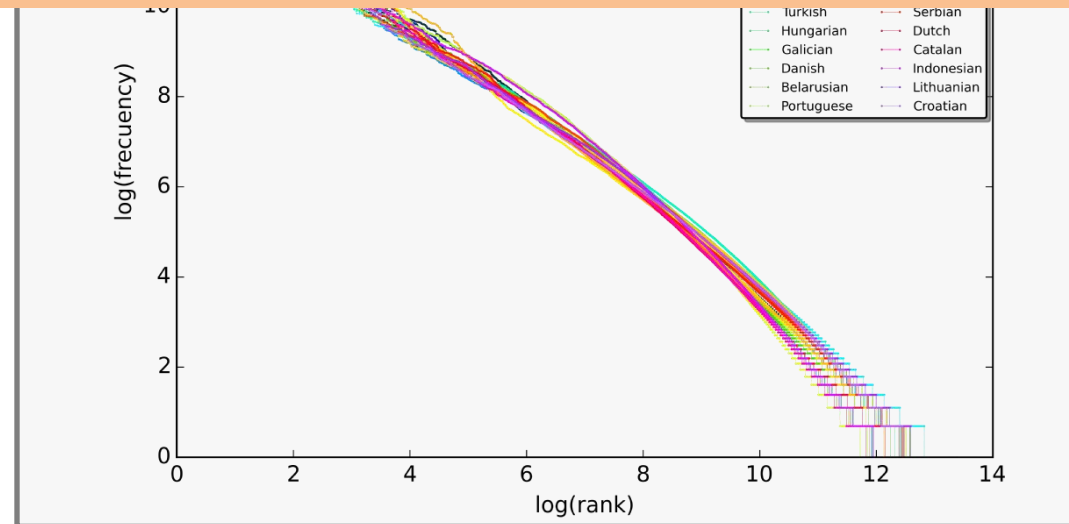
/ Few occurrences of many words

Expect **long posting lists** for common words



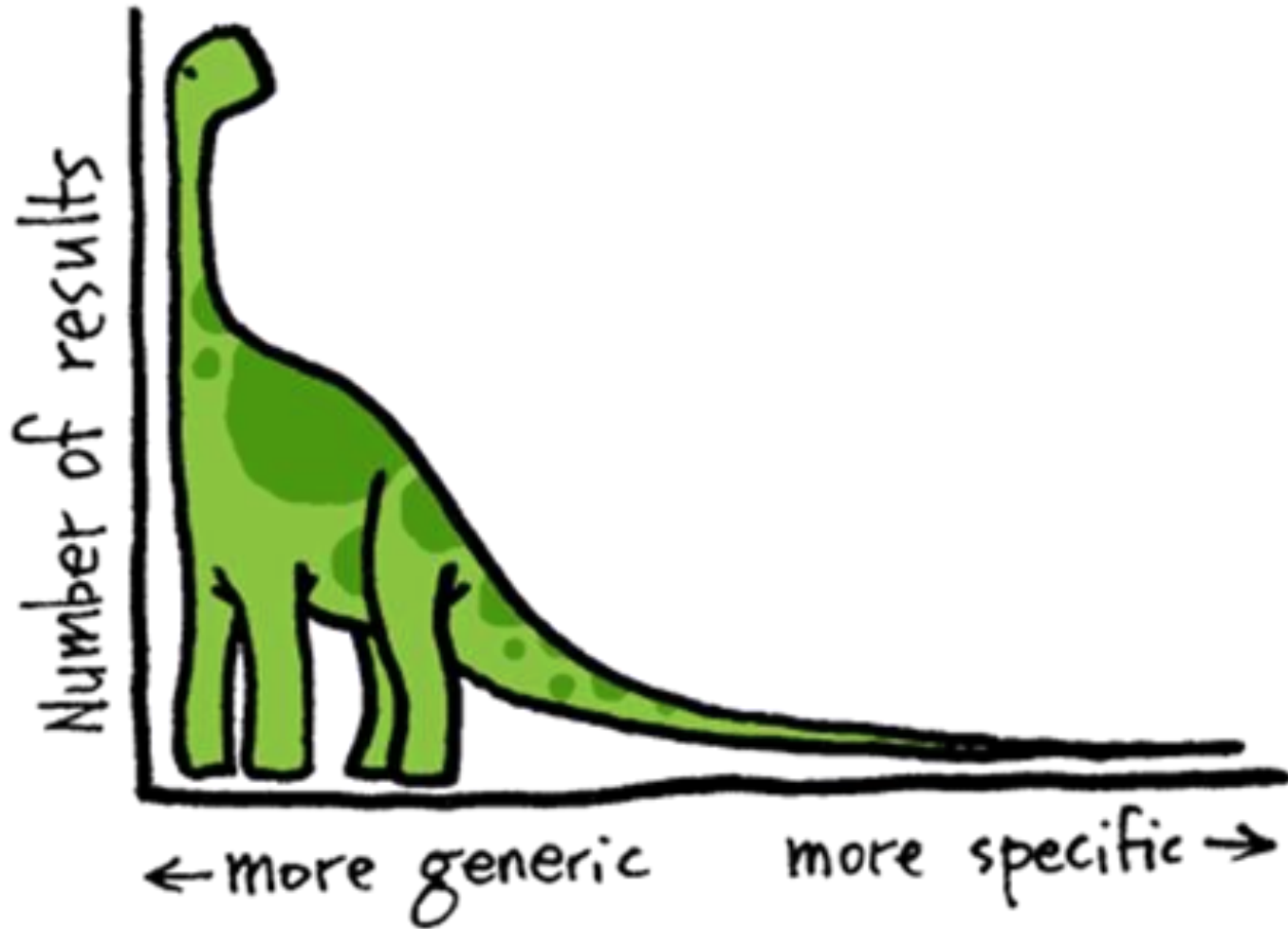
Expect **more queries** with common words

- “of” 3.5%
- “and” 2.7%
- 135 words cover half of all occurrences

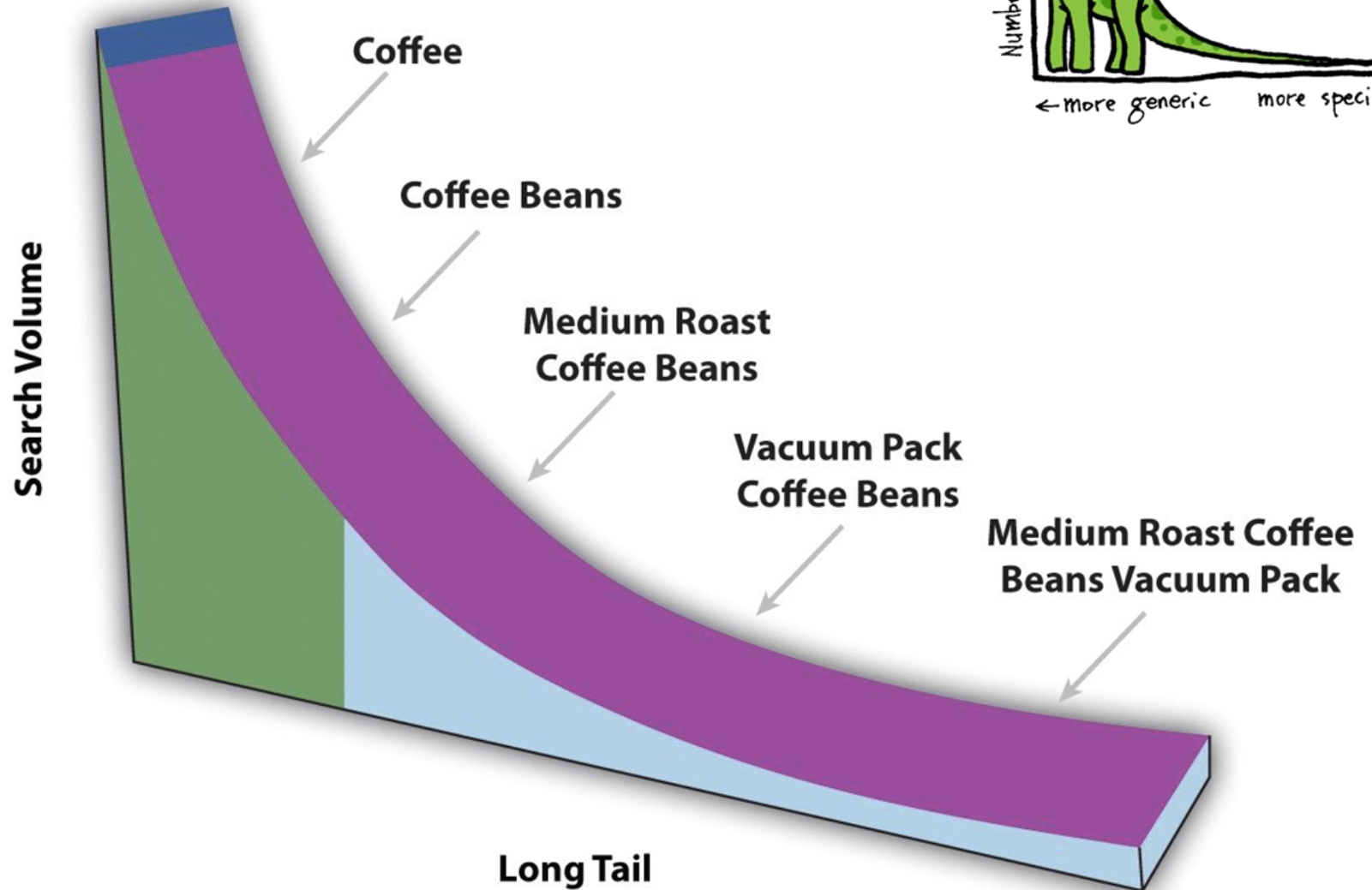


**Zipf's law:** *the most popular word will occur twice as often as the second most popular word, thrice as often as the third most popular word, n times as often as the n-most popular word.*

# The Long Tail of Search



# The Long Tail of Search



How to optimise for this?



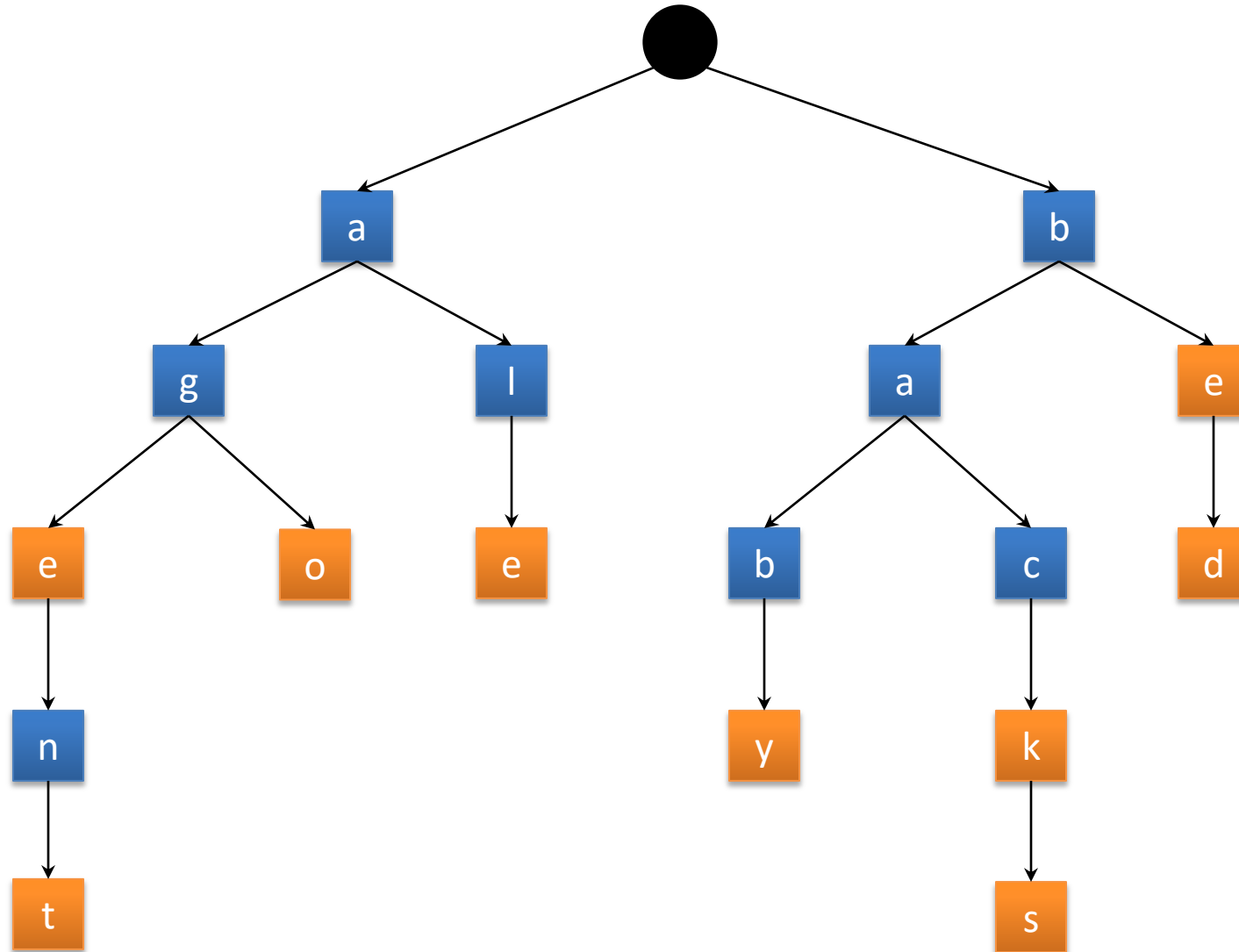
Caching for common queries like "coffee"

# Search Implementation

- Vocabulary keys:
  - Hashing:  $O(1)$  lookups (assuming ideal hashing)
    - no range queries
  - Sorting/B-Tree:  $O(\log(u))$  lookups,  $u$  unique words
    - range queries
  - Tries:  $O(l)$  lookups,  $l$  length of the word
    - range queries, compression



# Trie



# Memory Sizes

- **Term list** (vocabulary keys) small:
  - Often will fit in memory (with compression ...)!
- **Posting lists** larger:
  - On disk / Hot regions cached

Term List	Posting List
a	(1, [21, 96, 103, ...]), (2, [...]), ...
american	(1, [28, 123]), (5, [...]), ...
and	(1, [57, 139, ...]), (2, [...]), ...
by	(1, [70, 157, ...]), (2, [...]), ...
directed	(1, [61, 212, ...]), (4, [...]), ...
drama	(1, [38, 87, ...]), (16, [...]), ...
...	...



# Compression techniques

- **Numeric** compression important

Term List	Posting List
country	(1), (2), (3), (4), (6), (7), ...
...	...

# Compression techniques: High Level

- Interval indexing
  - Example for record-level indexing
    - Could also be applied for block-level indexing, etc.

Term List	Posting List
country	(1), (2), (3), (4), (6), (7), ...
...	...

Term List	Posting List
country	(1-4), (6-7),
...	...

# Compression techniques: High Level

- Gap indexing
  - Example for record-level indexing
    - Could also be applied for block-level indexing, etc.

Term List	Posting List
country	(1), (3), (4), (8), (9), ...
...	...

Term List	Posting Lists
country	(1), 2, 1, 4, 1
...	...

Benefit?



Repeated small numbers easier to compress!

# Compression techniques: Bit Level

- Variable length coding: bit-level techniques
- For example, **Elias  $\gamma$  (gamma) encoding**
  - Assumes many small numbers

$$2\lfloor \log_2(z) \rfloor + 1 \text{ bits}$$

z: integer to encode	$n = \lfloor \log_2(z) \rfloor$ coded in unary	a zero marker	next n binary numbers	final Elias $\gamma$ code
1	0			0
2	1	0	0	100
3	1	0	1	101
4	11	0	00	11000
5	11	0	01	11001
6	11	0	10	11010
7	11	0	11	11011
8	111	0	000	1110000
...	...	...	...	...

Can you decode “01000011000111000011001”?



<1, 2, 1, 1, 4, 8, 5>

# Compression techniques: Bit Level

- Variable length coding: bit-level techniques
- For example, Elias  $\delta$  (delta) encoding
  - Better for some distributions

$$\lfloor \log_2(z) \rfloor + 2\lfloor \log_2(\lfloor \log_2(z) \rfloor + 1) \rfloor + 1 \text{ bits}$$

z: integer to encode	$\lfloor \log_2(z) \rfloor + 1$ coded in Elias $\gamma$	next $\lfloor \log_2(z) \rfloor$ binary numbers	final Elias $\delta$ code
1	0		0
2	100	0	1000
3	100	1	1001
4	101	00	10100
5	101	01	10101
6	101	10	10110
7	101	11	10111
8	11000	000	11000000
...	...	...	...

Can you decode “0110000011001011001001”?



<1, 9, 3, 1, 17>

# Compression techniques: Bit Level

- Previous methods “non-parametric”
  - Don’t take an input value
- Other compression techniques parametric:
  - for example, Golomb-3 code:

$z$ : integer to encode	$n = \lfloor (z-1)/3 \rfloor$ coded in unary	zero separator	remainder	final Golomb-3 code
1	0		0	00
2	0		10	010
3	0		11	011
4	1	0	0	100
5	1	0	10	1010
6	1	0	11	1011
7	11	0	0	1100
8	11	0	10	11010
...	...		...	...

# Comparison

- Small values

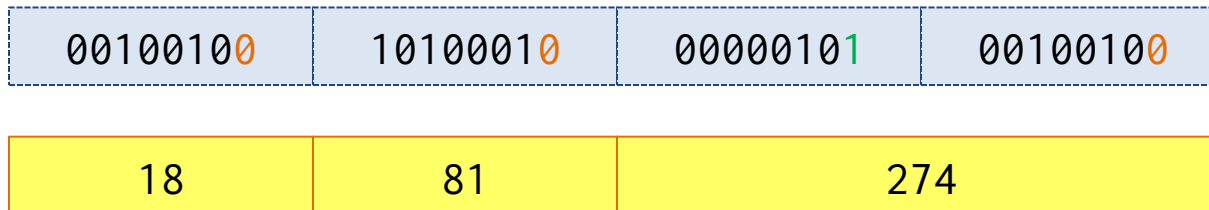
z: input integer	Elias $\gamma$ code	Elias $\delta$ code	Golomb-3 code
1	0	0	00
2	100	1000	010
3	101	1001	011
4	11000	10100	100
5	11001	10101	1010
6	11010	10110	1011
7	11011	10111	1100
8	1110000	11000000	11010

- Larger values

z: input integer	Elias $\gamma$ code	Elias $\delta$ code	Golomb-3 code
100	1111110100100	10110100100	1111111...101
...			...

# Compression techniques: Byte Level

- Use variable length byte codes
- Use last bit of byte to indicate if the number ends
- For example:





## Other Optimisations

- **Top-Doc**: Order posting lists to give likely “top documents” first: good for top- $k$  results
- **Selectivity**: Load the posting lists for the most rare keywords first; apply thresholds
- **Sharding**: Distribute over multiple machines [...]

# Extremely Scalable/Efficient

# When engineered correctly 😊



Google Search

I'm Feeling Lucky

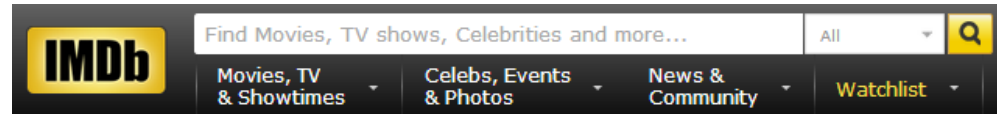
YAH!  
CHILE

Buscar

bing

Beta

Show all Only English Only from Chile



IMDb Find Movies, TV shows, Celebrities and more... All

Movies, TV & Showtimes Celebs, Events & Photos News & Community Watchlist

## WIKIPEDIA

English

The Free Encyclopedia  
4 501 000+ articles

Español

La enciclopedia libre  
1 096 000+ artículos

日本語

フリー百科事典  
306 000+ 記事

Deutsch

Die freie Enzyklopädie  
1 712 000+ Artikel

Русский

Свободная энциклопедия  
1 108 000+ статей

Français

L'encyclopédie libre  
1 499 000+ articles

Italiano

L'enciclopedia libera  
1 117 000+ voci

Português

A enciclopédia livre  
825 000+ artigos

Polski

Wolna encyklopedia  
1 042 000+ haseł

中文

自由的百科全书  
764 000+ 條目



English



# DISTRIBUTING AN INVERTED INDEX

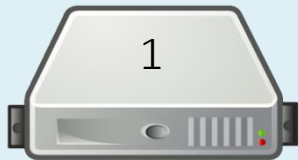
# Inverted Index: Distribution

Term	Posting
and	1, 3, 4, 5, 6
ate	1, 2, 3
cat	3, 4, 6
dog	3, 5, 6, 7
the	1, 2, 3, 4, 5, 6, 7
vet	4

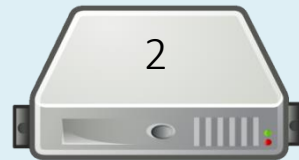
How might we distribute an inverted index?



Split by word



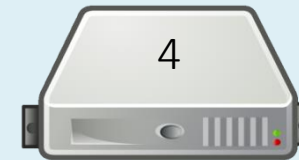
Term	Posting
dog	3, 5, 6, 7



Term	Posting
and	1, 3, 4, 5, 6
vet	4



Term	Posting
ate	1, 2, 3
the	1, 2, 3, 4, 5, 6, 7



Term	Posting
cat	3, 4, 6

Possible disadvantages?



- Complications for load balancing given common words
- AND or PHRASE search within each document involves multiple machines
- Difficult to store statistics, etc., for a document (not usually a big issue)

# Inverted Index: Distribution

Term	Posting
and	1, 3, 4, 5, 6
ate	1, 2, 3
cat	3, 4, 6
dog	3, 5, 6, 7
the	1, 2, 3, 4, 5, 6, 7
vet	4

How might we distribute an inverted index?



Split by document



Term	Posting
ate	2
cat	6
dog	6
the	2, 6

Term	Posting
and	3, 5
ate	3
cat	3
dog	5
the	3, 5

Term	Posting
and	1
ate	1
the	1

Term	Posting
and	4
cat	4
dog	7
the	7
vet	4

Possible disadvantages?




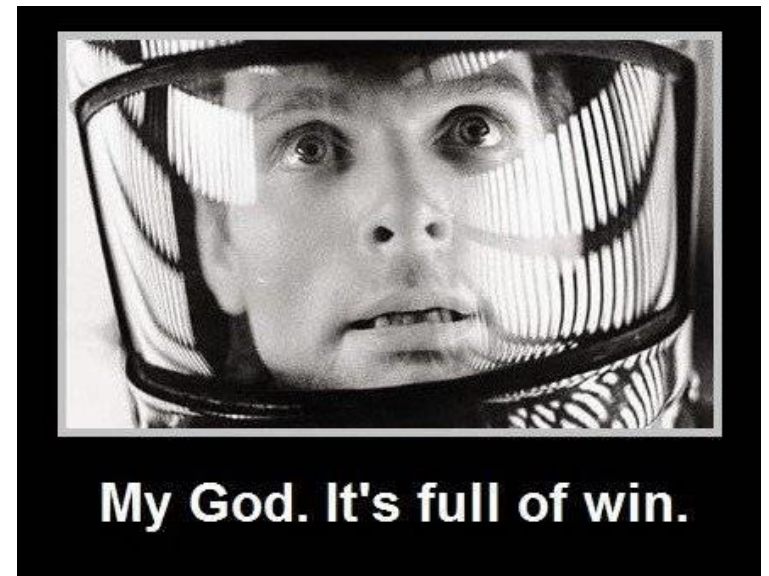
- All searches require unions over multiple machines
- Might be load balancing issues for large documents (not usually a big issue)
- Longer term lists per machine (not usually a big issue)

# LUCENE: TEXT INDEXING

# Apache Lucene



- Inverted Index
  - They built one so you don't have to!
  - Open Source in Java
  - Single machine 





# Doug Cutting (above) & Mike Cafarella (below)







# Apache Solr



- Inverted Index
  - Based on Apache Lucene
  - Higher-level interfaces (and richer features)
  - Distributed by document  ... 

# Elasticsearch



- Inverted Index
  - Based on Apache Lucene
  - Higher-level interfaces (and richer features)
  - Distributed by document  ... 

# Elasticsearch: a word of warning

## Reported Elasticsearch data breaches [\[ edit \]](#)

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- 2018-11-15 AWS Elasticsearch database belonging to **VoxOx** exposed tens of millions of text messages, including password reset links, two-factor codes, shipping notifications and more.<sup>[36]</sup>
- 2018-11-27 Elasticsearch database belonging to **Urban Massage** exposed more than 309,000 user records, including names, email addresses and phone numbers.<sup>[37]</sup>
- 2019-01-12 Elasticsearch server belonging to do-it-yourself chain, **B&Q** exposed personal details of individuals caught or suspected of stealing goods from stores.<sup>[38][39]</sup>
- 2019-01-21 Elasticsearch database belonging to Youth-run agency **AIESEC** exposed over 4 million intern applications including the applicant's name, gender, date of birth, and the reasons why the person was applying for the internship.<sup>[40]</sup>
- 2019-01-23 Elasticsearch database belonging to **Ascension Data and Analytics** exposed 24 million financial and banking documents, representing tens of thousands of loans and mortgages from some of the biggest banks in the U.S.<sup>[41]</sup>
- 2019-09-13 Elasticsearch database belonging to Dealer Leads exposed 198 million car buying records which contained the personal information of customers.<sup>[42]</sup>
- 2019-10-26 Elasticsearch database belonging to **Adobe** exposed 7.5 million customer records which contained email addresses, Adobe member IDs (usernames), country of origin, and what Adobe products they were using.<sup>[43]</sup>
- 2019-11-19 Elasticsearch database belonging to **Conrad Electronic** exposed 14 million customer records which contained postal addresses, in parts fax- and telephone numbers as well as **IBANs** on a fifth of the exposed data-records.<sup>[44]</sup>



Questions?