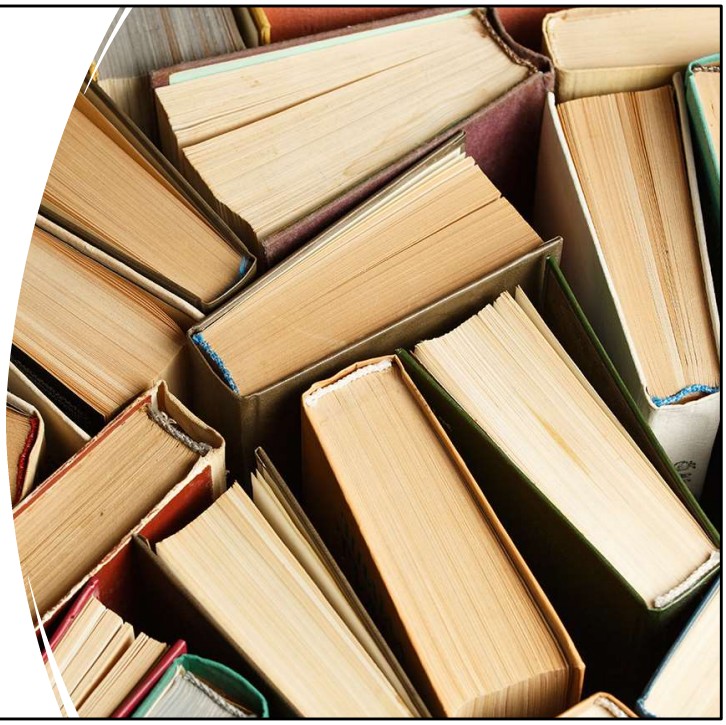
Data-Intensive Distributed Computing CS431/451/631/651

Module 4 – Analysing Text



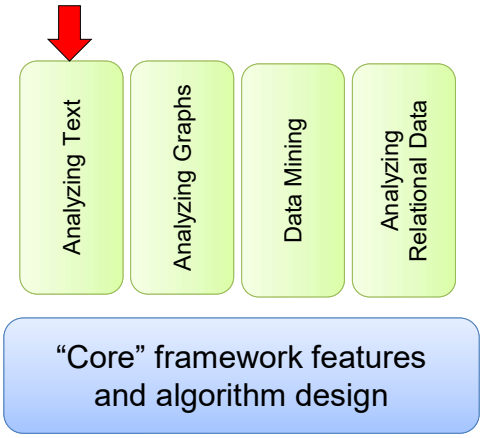
This Module's Agenda

Language Models

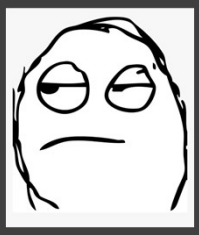
Natural Language Processing

Information Retrieval / Search

Structure of the Course



This all seems LAME!



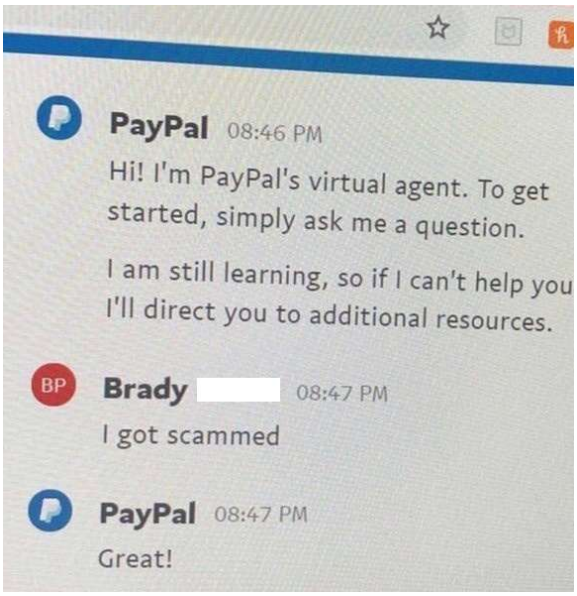
First of all, how dare you

Walk before you run

Language Models are about so much more than Word Counts and PMI!

Natural Language Processing

NLP for short



Probabilistic Model

$P(w_1,w_2,\ldots,w_k)$

– The probability of encountering the sentence $w_1\ w_2\ \ldots\ w_k$

What good is this?

- Machine Translation
  P("High winds expected") > P("Large winds expected")
- Spell Checker that's not fooled by homophones
  P("Waterloo is a great city!") > P("Waterloo is a grate city!")
- Speech Recognition
  P("I saw a van") > P("Eyes awe of an")

We want to be able to take a sentence with k words, and assign a probability to it. This lets us rank alternatives. Of course this doesn't tell us WHERE those alternatives even came from, but one step at a time!

Probabilistic Model

$P(w_1,w_2,\ldots,w_k)$

– The probability of encountering the sentence $w_1\ w_2\ \ldots\ w_k$

How LLMs work*:

1. Given $w_1w_2\ldots w_{k-1}$ obtain probability distribution for w_k
2. Sample word from distribution
3. Repeat until you generate the special “stop” word.

* Basically

The tricky part is generating the probability distribution, of course! And…there are a lot of different sampling techniques to choose from.

Again, not an AI course so we won’t get into too much detail

Probabilistic Model

$P(w_1,w_2,\ldots,w_k)$ =

$P(w_1)$ x $P(w_2,\ldots,w_k|w_1)$ =

…

$P(w_1)$ x $P(w_2 \mid w_1)$ x … x $P(w_k|w_1, w_2, \ldots, w_{k-1})$

P("I saw a van") = P("I") x P("saw" | "I") x P("a" | "I saw") x P("van" | "I saw a")

Q: Can we actually use this?

Chain rule – P(A, B) = P(B) x P(A | B) – Like with PMI

Question: Is this reasonable? How long is a typical sentence? 15-20 words in modern writing. 70+ in ye olden times. PMI took us two passes, will this take 20-70 passes?

A: No

- The size of a sentence is unbounded (even if we might assume a reasonable maximum length)
- "Intractable" is the best word to use
- Let's say we set the sentence length to max of 20
- Let's say there are 100k commonly used English words
- $100k^{20} = 10^{100}$

Fun language quirk: The dictionary says tractable means easy, so intractable means not easy. In a bit of coy understatement, "intractable" in Mathematics actually means "impossible"

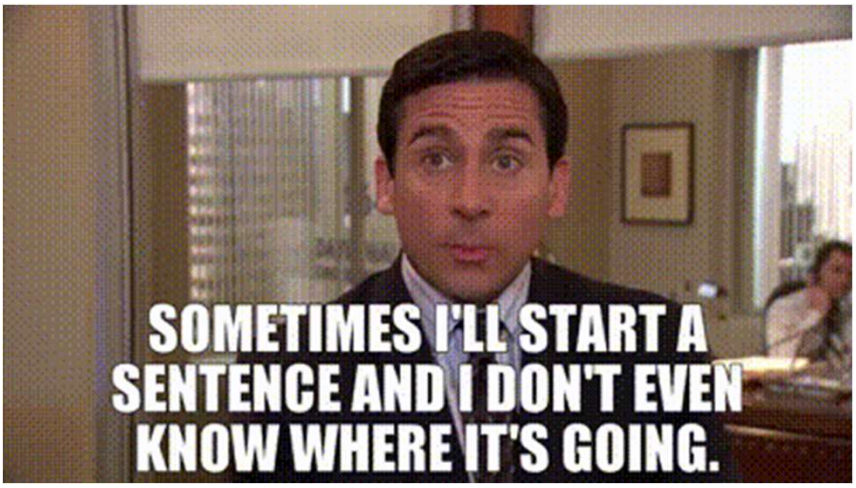
Both of those assumptions are underestimates!

Smaller Limit: N-Gram

- Basic Idea: Probability of next word only depends on the previous (N – 1) words
- $P(w_k|w1,w2,\ldots w_{k-1}) \approx P(w_k|w_{k-N+1,}\, w_{k-N+2},\ldots,w_{k-1})$
- N = 1 : Unigram Model- $P(w_1,w_2,w_3,\ldots) = P(w_1)\, P(w_2) \ldots P(w_k)$
- N = 2 : Bigram Model- $P(w_1,w_2,w_3,\ldots) = P(w_1)\, P(w_2|w_1) \ldots P(w_k|w_{k-1})$

Google uses N-Grams for Suggestions (N is small)

The meme is intentionally deep fried. I'm told you Zoomers like that



People also use N-grams. Not really. Maybe. It's classified.

Do it with Hadoop!

- Unigram: $P(w) = C(w) / N$
- Bigram: $P(w_i, w_j) = C(w_i, w_j) / N$

  $P(w_j | w_i) = P(w_i,w_j) / P(w_i) = C(w_i,w_j) / C(w_i)$

You can probably figure out trigrams yourself.

Seem Familiar?

If it's not, I'm sorry about your mark on A1 ☹
State of the art rarely goes above 5-grams (call them that not penta-grams)

Example: Bigrams

"Training Corpus"

^ I am Sam $

^ Sam I am $

^ I do not like green eggs and ham $

Counts

Note: We never cross sentence boundaries

(^, I) = 2
(^, Sam) = 1
(I, am) = 2
…

Probabilities

P(I | ^) = 2/3
P(Sam | ^) = 1/3
P(am | I) = 2/3
P($ | Sam) = 1/2
….

The probability P(a | b) = C(b, a) / C(b, *)
Recall that C(b,*) means "count of all pairs that start with b"

Example: Bigrams

P(I like ham)

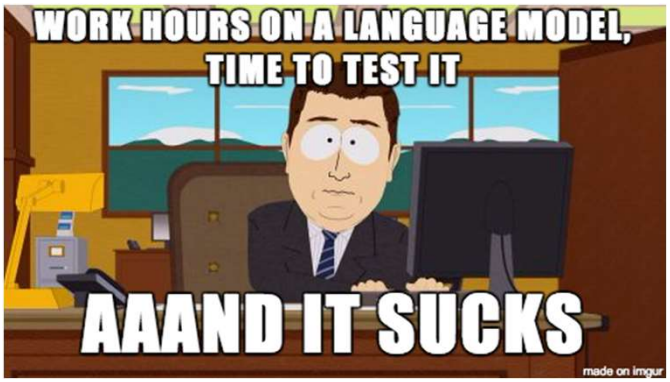
= P(I | ^) P(like | I) P(ham | like) P($ | ham)

= 0

Thoughts?

Probabilities

P(I | ^) = 2/3
P(Sam | ^) = 1/3
P(am | I) = 2/3
P($ | Sam) = ½
….


WORK HOURS ON A LANGUAGE MODEL,
TIME TO TEST IT
AAAND IT SUCKS
made on imgur

No More Zeros

P(s) = 0 means “sentence s is impossible”.
Not true (probably).

“The pirate was purple and wanted eleven candy ants.”

Your language model didn’t think anybody would say that.
Take THAT, computer!

Playing it Smooth

If a single n-gram in the sentence has never been seen, P = 0

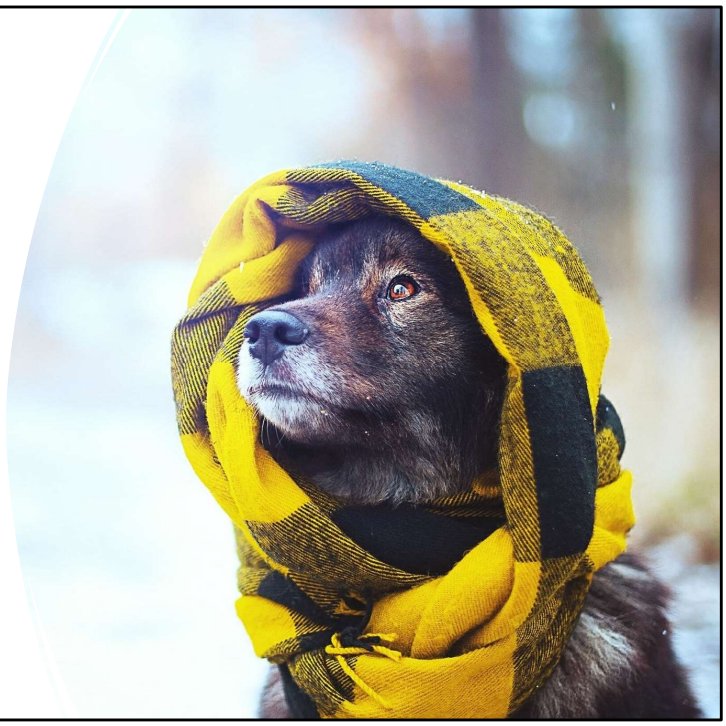
Just one unusual word takes a sentence from “likely” to “impossible”
That’s a “discontinuity”

Removing 0s makes the distribution “smooth”
How can we remove 0s?

Robin Hood

"Take from the rich, give to the poor"

(Or, maybe, universal basic income? Every n-gram gets a non-zero probability)



I picked this picture from Office's suggestions because it's hilariously bad. I might be training it to give bad suggestions. Or funny suggestions.
Oh, also, my Robin Hood is the furry Disney Robin Hood. Pretty sure he put a scarf on his head at one point in that movie. So I guess it's related after all. Spooky.

Laplace Smoothing

Start each count at 1, not 0.

Time tested and simple

Counts

(^, I) = 2
(ham, $) = 1
(I, like) = 0
(like, ham) = 0
…

Counts (Smooth)

(^, I) = 3
(ham, $) = 2
(I, like) = 1
(like, ham) = 1
…

Laplace Smoothing (bigram probabilities)

$$\mathrm{P}(A,B) = \frac{C(A,B)}{N} \rightarrow P_L(A,B) = \frac{C(A,B)+1}{N+V^2}$$

What's V? Vocabulary size. Since every pair of words (A,B) has a +1, we need to add V^2 to N.

You can imagine how to apply this to trigrams, 4-grams, etc.

Other Smoothing Techniques

- Good-Turing – Used by Good and Turing as part of cracking Enigma
- Katz backoff – "backoff" means "if n-gram says 0, try (n-1)-gram"
- Jelinek Mercer – Interpolate between n-grams and unigrams
  - $P_{JM}(A,B) = \lambda P(A,B) + (1 - \lambda)P(A)P(B)$
- Dirichlet Smoothing, Witten-Bell – Ways to pick λ
- Kneser-Ney – Current Best Practice
  - Google (used to?) use this for Google Translate, implemented on their MapReduce framework

Hidden Markov Model (Hmm)

Used a lot in Bioinformatics

Also used a lot in NLP

Popular with Witchers

This slide is here for 3 reasons

1. The Hmm meme
2. I used them a fair bit in Bioinformatics
3. The fact that it's somewhat relevant (weak third place)

HMM and NLP

Phoneme Recognition	• Turn an audio stream into a word stream
Part-of-Speech (PoS) tagging	• Doesn't REPLACE N-grams, but helps add context to words • Buffalo buffalo Buffalo buffalo buffalo buffalo Buffalo buffalo

Buffalo is an animal, a city, and a verb that means, essentially, to intimidate. That means the above nonsense is technically grammatical and means:
"Buffalo from Buffalo that are intimidated by other buffalo from Buffalo intimidate a third group of buffalo from Buffalo."

Hadoop HMM

- We don't use HMM on any assignments
  - Grads, feel free for your projects!
- The textbook discusses how to adapt HMM training for MapReduce
  - Surprise! Highly parallelizable
- It's iterative, which means Spark is a good alternative!

Transformers (More than Meets the Eye)

Q: Hey, I saw that ChatGPT can do 8K, 16K, even 64K context…how is it not all zeros???

A1: It's a Transformer Neural Network, not a table of n-gram counters. Words will have latent probability – no smoothing needed

A2: "Self-Attention" – In a context of 4000 words, only some words are important.

Topic Shift: Searching! ("Information Retrieval")

The Central Problem in Search

Concepts

Query Terms

"tragic love story"

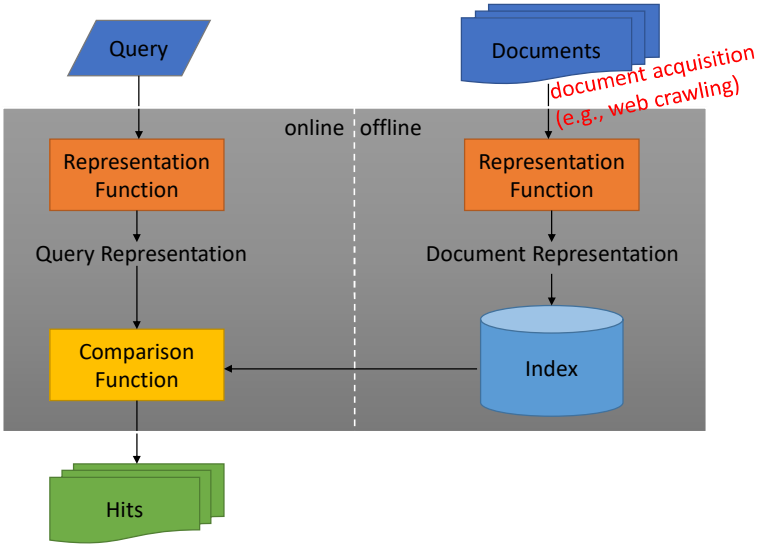
Concepts

Document Terms

"fateful star-crossed romance"

These two things should match! They don't look similar though, do they? No words in common. Language is hard!

Abstract IR Architecture



Representation Matters

Computers can't "understand" (or can they?)

We need to tell them what "relevant" means.

Simple form: "Bag of Words"

Assumptions: terms are independent, relevance is irrelevant, the concept of a "word" is well defined

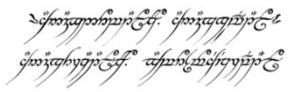
All of those assumptions are obviously wrong. However, so what? "First let's assume a spherical cow" etc.

What's a word?

天主教教宗若望保祿二世因感冒再度住進醫院。這是他今年第二度因同樣的病因住院。

الناطق باسم -وقال مارك ريجيف
إن شارون قبل -الخارجية الإسرائيلية
الدعوة وسيقوم للمرة الأولى بزيارة
تونس، التي كانت لفترة طويلة المقر
.1982الرسمي لمنظمة التحرير الفلسطينية بعد خروجها من لبنان عام

Выступая в Мещанском суде Москвы экс-глава ЮКОСа заявил не совершал ничего противозаконного, в чем обвиняет его генпрокуратура России.



भारत सरकार ने आर्थिक सर्वेक्षण में वित्तीय वर्ष 2005-06 में सात फ़ीसदी विकास दर हासिल करने का आकलन किया है और कर सुधार पर ज़ोर दिया है

日米連合で台頭中国に対処…アーミテージ前副長官提言

조재영 기자= 서울시는 25일 이명박 시장이 `행정중심복합도시'' 건설안에 대해 `군대라도 동원해 막고싶은 심정''이라고 말했다는 일부 언론의 보도를 부인했다.

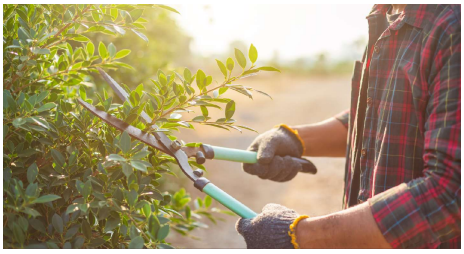
These are all news blurbs. Top to bottom – Chinese, Arabic, Russian, Hindi, Japanese, Korean

Oh, there's also the inscription from The One Ring. The script is elvish, but the words are in the black tongue of Mordor, which I shall not utter here.

Stick to English

What words does the document contain?

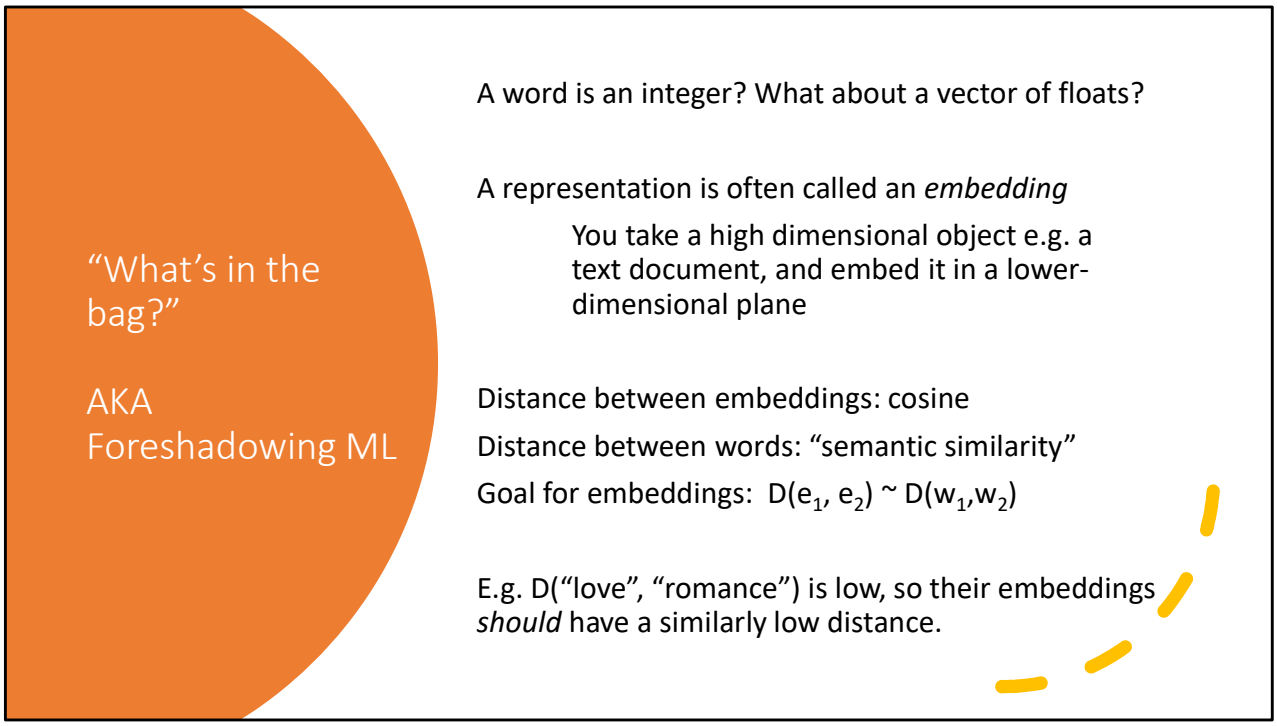
- Tokenizer (remove punctuation)
- Case Folding (treat things as lower case, put Unicode into canonical form)
  - Bush vs bush



Unicode issue: é is a single character. Or it's e followed by the "acute" combining diacritics. Unicode defines a canonical form, the "standard" way to represent a string that may have many equivalent forms.

The thing I did with coöp vs co-op vs coop is also relevant! How'd'ya like that setup? The long game.
Capitalization is not important, except when it is.

We will continue to depend on Jimmy's tokenizer and not worry about confusing Jack Black with a darkly coloured device for lifting cars.



Guess what my friends? PMI is a great way to estimate the "semantic similarity" of words. PMI gives similarity measures similar to cosine similarity! PMI 0 => terms are uncorrelated aka orthogonal. Cos 0 => terms are uncorrelated aka orthogonal

Bag of Words

Word Count (A0)

Current Topic

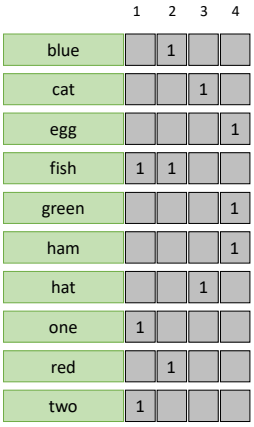
We're ignoring syntax, semantics, knowledge of language, meanings of words, etc – however, BOW is often used with vector embeddings (e.g. word2vec)

Doc 1 one fish, two fish

Doc 2 red fish, blue fish

Doc 3 cat in the hat

Doc 4 green eggs and ham

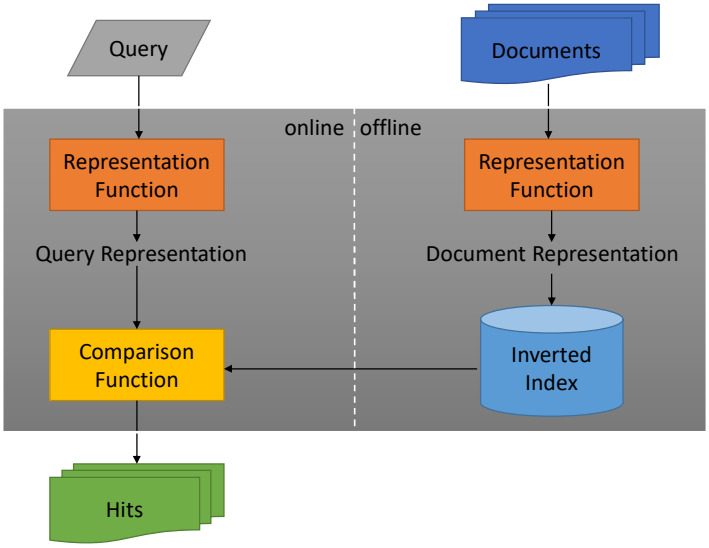


What goes in each cell?

- boolean
- count
- positions

Cs451 – Terminology – Inverted Index. Maps context to documents. Forward Index. Maps documents to context. (Seems strange to me, so a book's index is "inverted"?)

Abstract IR Architecture



Scaling Assumptions

- Queries are small
- Postings are not
  - There are a LOT of documents (100M? 1B? 10B?)
  - 1B docs * 1 bit = 120MB / unique word
- How many unique words?

Vocabulary Size: Heaps' Law

$$M = kT^b$$

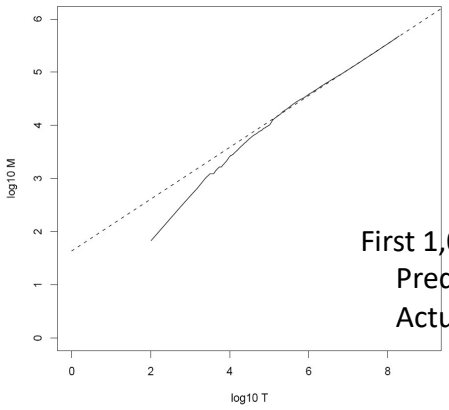
M is vocabulary size
T is collection size (number of documents)
k and *b* are constants

Typically, *k* is between 30 and 100, *b* is between 0.4 and 0.6

Heaps' Law: linear in log-log space

Surprise: Vocabulary size grows unbounded!

Heaps' Law for RCV1



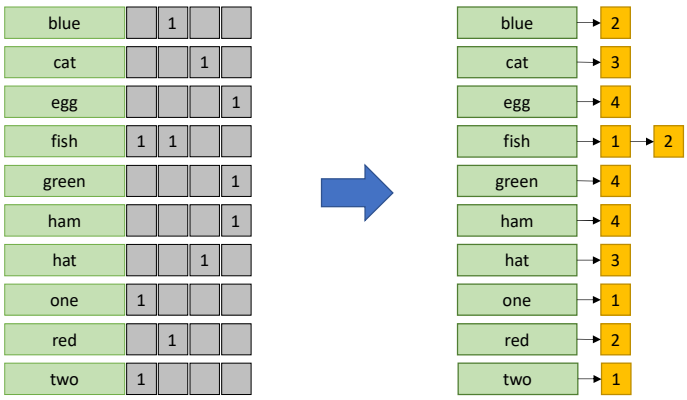
k = 44
b = 0.49

First 1,000,020 terms:
Predicted = 38,323
Actual = 38,365

Reuters-RCV1 collection: 806,791 newswire documents (Aug 20, 1996-August 19, 1997)

Manning, Raghavan, Schütze, Introduction to Information Retrieval (2008)

Saving Space, Postings List



This saves a lot of space because most terms do not appear in most documents (so most rows are mostly 0s). Most? Not all?

Postings Size: Zipf's Law

$$f(k; s, N) = \frac{1/k^s}{\sum_{n=1}^{N}(1/n^s)}$$

N number of elements
k rank
s characteristic exponent

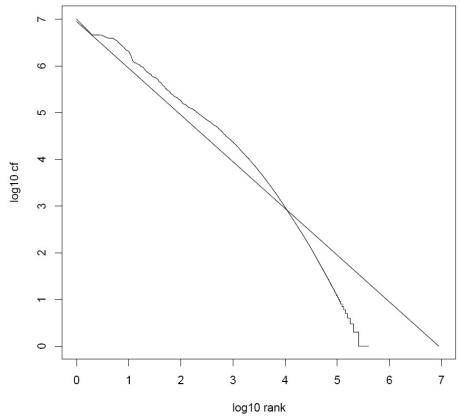
Zipf's Law: (also) linear in log-log space

In other words:

A few elements occur very frequently
Many elements occur very infrequently

https://www.youtube.com/watch?v=fCn8zs912OE&t=253s&ab_channel=Vsauce

Zipf's Law for RCV1

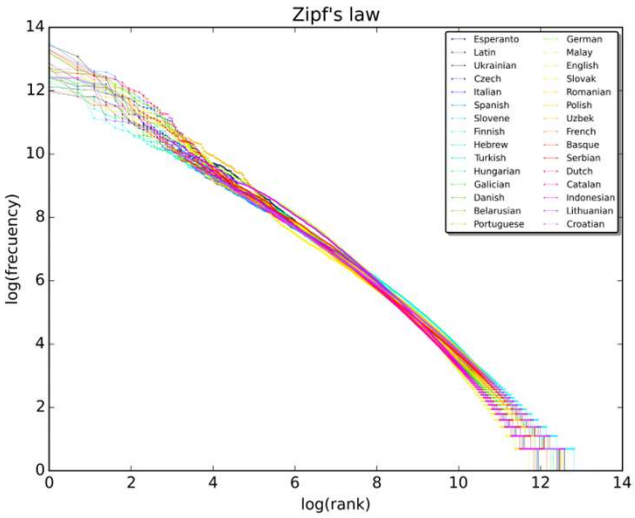


Reuters-RCV1 collection: 806,791 newswire documents (Aug 20, 1996-August 19, 1997)

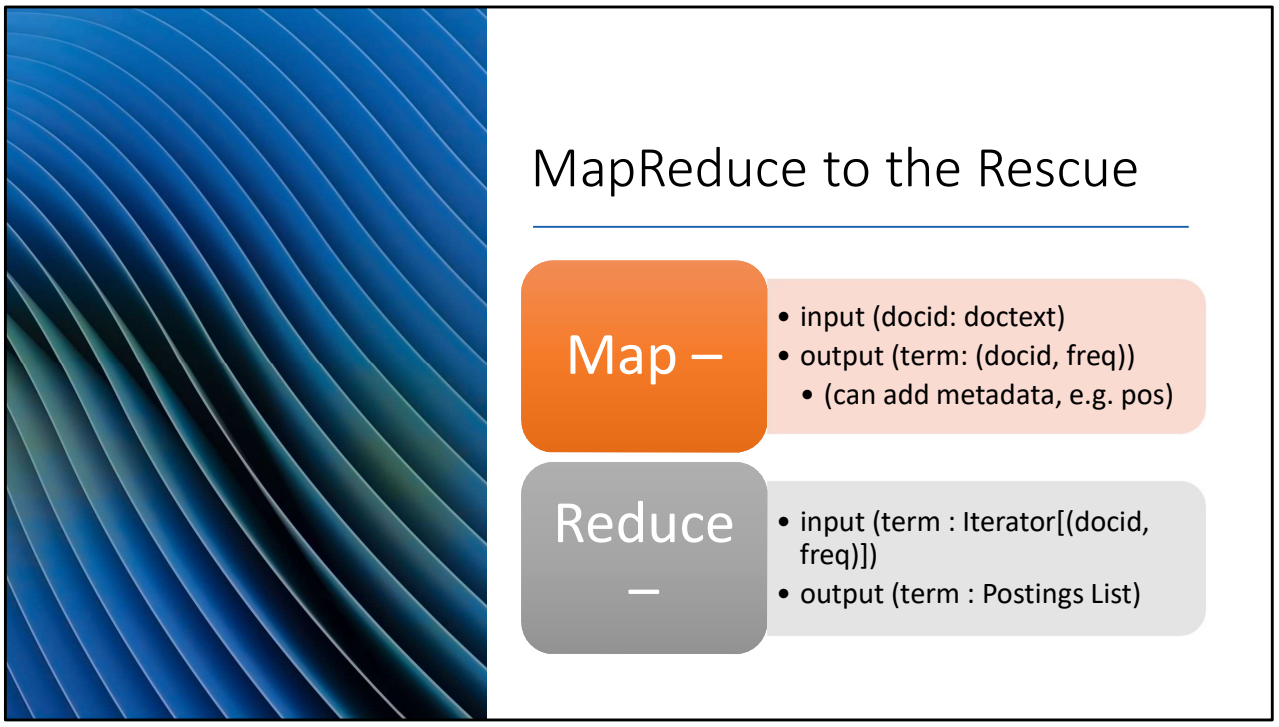
Manning, Raghavan, Schütze, Introduction to Information Retrieval (2008)

Close enough

Zipf's Law for Wikipedia



Rank versus frequency for the first 10m words in 30 Wikipedias (dumps from October 2015)



See any scaling issues?

Pseudo-Code, Mapper

```
def map(docid: Long, doctext: String):
   counts = counter()
   for term in tokenize(doctext):
      counts.add(term)
   for term, freq in counts:
      emit(term, (docid, freq))
```

We can assume each document has only a few million unique terms, so the counter will easily fit in a mapper's memory

Pseudo-code, Reducer

```
def reduce(term: String, postings: Iterator[(Long, Int)]):
    p = list()
    for docid, freq in postings:
        p.append((docid, freq))
    p.sort()
    emit(term, p)
```

Problem? How big is this list going to be???

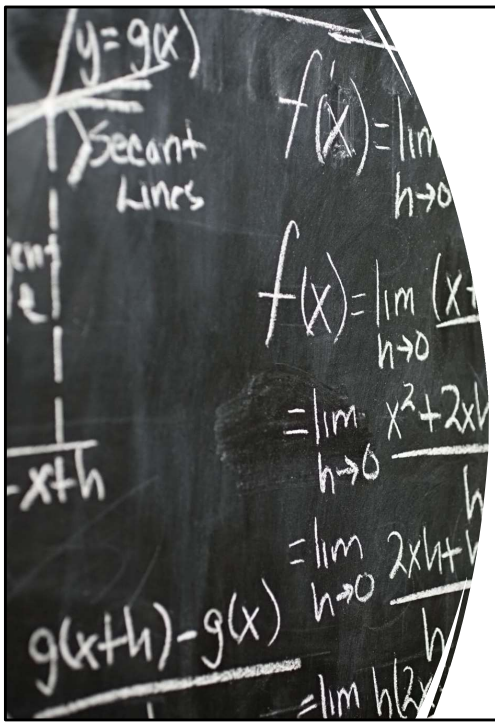
Problem?

How big does p get? Zipf's law says "usually small, sometimes not small". Sorting is O(n log n). That's not ideal if n is large. Isn't Hadoop good at sorting? (It is.)
Besides which, Hadoop already is sorting (by keys) so really we're sorting twice (even if the second sorts are on a much smaller n, it's still not nothing).

If you did the readings you remember…

- "Secondary Sorting Pattern"
  - (Another "fancy term for simple concept")
- (A : (B, C)) => ((A, B) : C)
  - Remember to make the partitioner send (A, x) to the same partition for all x
- Now it's already sorted by document ID
  - Cool, but how does that save us space?

Why does this make it faster? Well, the mappers are already sorting by key, so now instead of two sort passes through the data, we're only doing one! Additionally, if you have more mappers than reducers (common) you have more machines doing the sort in parallel.



Delta Compression

Zipf's Law works for US now

If a term is rare: There are not many postings

If a term is common: The average delta ($docid_{i+1} - docid_i$) is small

Delta Encoding (AKA Gap Encoding)

If a sequence is ascending, you can instead write down only the "delta" (difference) between elements:

Sequence: `1, 6, 11, 15, 22, 42, 49, 77`

Gaps : `1, 5, 5, 4, 7, 20, 7, 28`

Does that save anything though?

Not if your output is Int.

Thing is, there are more datatypes out there!

VInt

Variable-Width Integer type (There's also VLong)

Uses 1-5 bytes to represent an Int (same range as 4 byte fixed width)

How?

Little Endian: leading bit of each byte is "continue"

Technically Vint and Vlong are exactly the same, writeVInt just passes the int along to writeVLong

VInt Example

```
64 => 0100 0000 [binary]
      1000000  [7-tuples]
      0100 0000   [VarInt, 1 byte]

767 => 0010 1111 1111 [binary]
       0000101 1111111  [7-tuples]
       1111 1111 0000 0101 [VarInt, 2 bytes]
```

Caution: going to be branching on those continue bits (branch mispredicts)

The neat thing about “data intensive” is we can say “meh” when it comes to things like “cache locality” and “branch hazards”

You don’t need to memorize how Vint works.

VInt Compression

Explain!

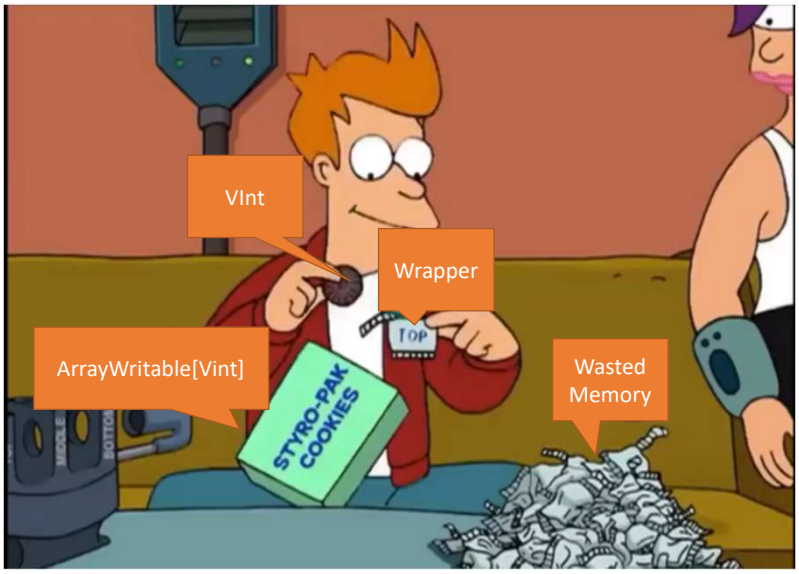
- No
- Array is storing objects (HEAVY)
- Bytes is just a bunch of bytes

ArrayWritable[VInt]

BytesWritable

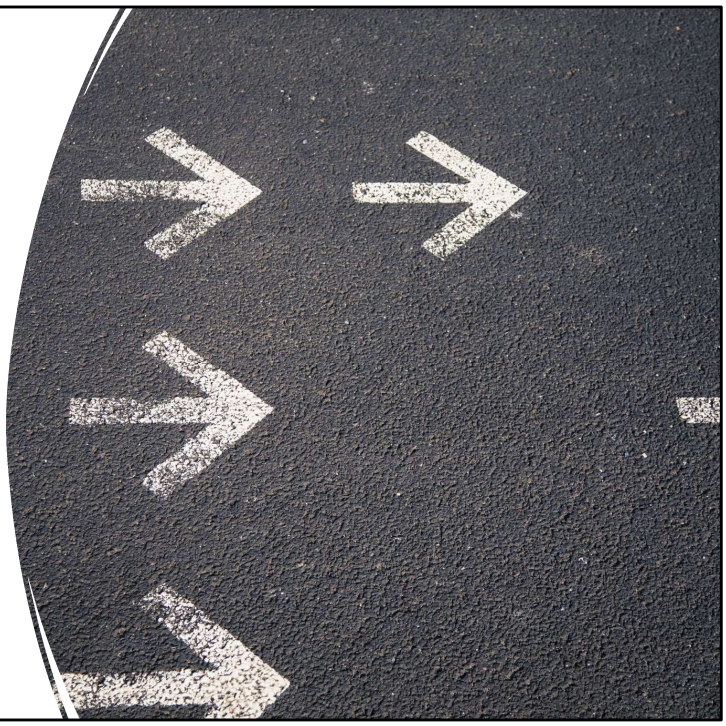
Normalize using the LaForge version of the Drake meme. Levar Burton and LaForge are heros and don't you forget it.

More detailed explanation: Vint saves space when you have many packed together. ArrayWritable doesn't pack them together. You need raw bytes, and to use WritableUtils.writeVInt


VInt
Wrapper
ArrayWritable[Vint]
Wasted Memory
STYRO-PAK COOKIES

Detour! Other Bit-Bashing Methods

- CS451: You don't need to use these, VInt is fine
- CS431: You don't do an indexing assignment at all
  - (Sorry, it's kinda fun)



A few reasons for this difference in courses

1. Spark doesn't sort by key when reducing, so the secondary sort pattern can't be applied.
2. Spark makes Vint etc a bit tricker to use
3. Bespin has a starting point in Hadoop MapReduce, but not in Spark. So it would be a lot more work for 431 students.

Simple-9

How many ways can you divide up 28 bits?

28 1-bit numbers
14 2-bit numbers
9 3-bit numbers [1 bit wasted]
7 4-bit numbers
5 5-bit numbers [3 bits wasted]
4 7-bit numbers
3 9-bit numbers [1 bit wasted]
2 14-bit numbers
1 28-bit number

- Why 28? 4 bit "selector", 16 options. Only use 9 though.
- Extend to 64-bit
  - 14 ways to divide 60
- Simple
- Works fairly well for gaps

We have to go deeper

Simple-9 (and Simple-14) work at the WORD level

- Different ways to store a variable number of values in a single word

VInt (or VLong) works at the BYTE level

- Store a fixed range of values in a variable number of bytes

What about BIT-level?

- Store a fixed range of values in a variable number of bits

Elias γ Code

Assumptions

- natural numbers with no upper bound
  - like counts, for example
- small numbers are more common than large numbers
  - gaps for common terms, for example
  - term frequency within docs, too?

γ is gamma, fyi

Elias γ Code

Encoding x:

1. Let N = $\lfloor \log_2 x \rfloor$
2. Write N 0s
3. Write x as an N+1-bit number

   This number starts with 1. Trust me

Decoding x:

1. Read 0s until a 1, call this N
2. Interpret next N+1 bits as a binary number

   Including the 1
3. There is no step 3

γ is gamma, fyi

Does γ work well?

Does well for term frequencies (how many times the term appears in the document)

Does OK for gaps, too

Underlying Assumption

The Elias code assumes the values are distributed by a power law

Most numbers should be small, or it doesn't save any space

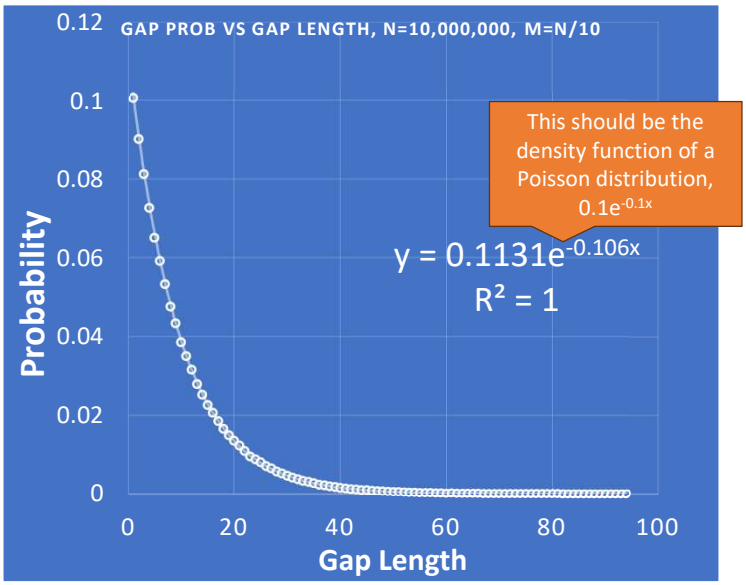
Gap Distribution

What do you think the distribution of gaps looks like if you have N document IDs and a term that matches M documents?

It…has a lot of binomials in it. It's scary.

Unless you remember Stats, in which case it's clearly a Poisson distribution with $\gamma = M/N$

Simulated gaps for 10 million documents



As we all know, the probability density for "waiting time" in a Poisson distribution with parameter γ is $\gamma e^{-\gamma t}$

Here $\gamma = 0.1$ and we can clearly see that the simulated distribution matches quite closely.

TF DF Distribution

The math here is actually the same except that the overall DF can exceed N, and sampling is done with replacement.

TL;DR: Still a Power Law

It's a Polish surname (Gołąb) transliterated to English

Golomb Code

For encoding positive integer x:

- Quotient and remainder when divided by M

q = (x - 1) / M

r = x – qM – 1

q gets encoded in uniary (q 0s, then 1)

r gets encoded in truncated binary

Number of documents containing term

Let z = $\frac{D_T}{D}$ ← Number of documents (total)

Approximate as $\left\lceil \frac{0.69}{z} \right\rceil$ → M = $\left\lceil \frac{\log(2-z)}{-\log(1-z)} \right\rceil$ -- good for gap encoding

Pronunciation key: ł is pronounced mostly as an l, but in some parts of eastern Poland (and polish speaking Ukraine) it's more like a w sound.
ą is pronounced somewhere around w "om" or "am" sound.

However, none of that really matters as Golomb himself said it as "Go-lam" so it doesn't really make any sense to dig deep into exactly what part of Poland we're talking about

That's right, each term gets its own custom encoding scheme! Neat.

Note that this is for situations where we only care about "contains" or "doesn't contain", not the number of times a term appears in a document

Golomb Encoding

Uniary
n is represented as n 0s, then a 1

5 => 000001
0 => 1
(Or you can switch 0s and 1s)

Truncated Binary
For numbers {0, 1, … n-1} :
k = $\lfloor \log_2 n \rfloor$
u = $2^{k+1} - n$

First u codewords:
    First u codes with length k
Last n-u codewords:
    LAST n – u codes with length k+1

Truncated Binary

N = 15 i.e. set = {0, 1, … , 14}

$k = \text{floor}(\log_2 15) = 3$

$u = 2^4 - 15 = 1$

0 => 000

1 => 0010

2 => 0011

3 => 0100

…

14 => 1111

Golomb Code Examples

M = 12 (k=3, u = 4)

x = 52

q = (52 – 1) / 12 = 4 = 00001_u
r = 52 – 12*4 -1 = 3 = 011_t
encoded(x) => 00001011_b

M = 32 (k=5, u = 32)

x =52

q = (52-1) / 32 = 1 = 01_u
r = 52 – 32*1 – 1 = 19 = 10011_t
encoded(x) => 0110011_b

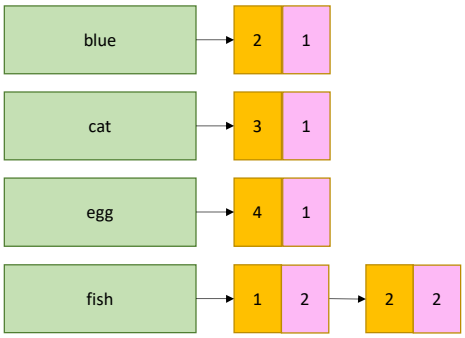
When M is a power of 2, these are also called “Rice codes” – Since u = m, there’s no “truncated” binary, it’s just k-bit binary.

Golomb Code in MapReduce

We can't calculate M without knowing df, but we only know that at the end!

(We solved that already with a special key that sorts first)

What if we also want frequencies?



((blue, *), 1)
((blue, 2), 1)
((cat, *), 1)
((cat, 3), 1)
((egg, *), 1)
((egg, 4), 1)
((fish, *), 4) or 2???
((fish, 1), 2)
((fish, 2), 2)

Orange = docid
Pink = freq (number of times term appears in that document)
(Term, *) = total freq? Or number of documents containing term? If we want to use golomb codes, we need both

ID and Frequency

It's best to treat these as independent

You can encode each with a different approach!

(Don't mix something ALIGNED like VInt with something UNALIGNED like Golomb)

Comparison

Indexing 181MB of Wikipedia sentences, including term frequency

It's pretty normal for the index to be larger than the documents being indexed!

Method	Size
Uncompressed (Int)	182MB
VInt	78MB
Gamma (both)	44MB
Golomb (gap) + Gamma (freq)	41.4MB
Golomb (both, different M)	41.2MB

Why is it bigger? Well each term is using 8 bytes per document it appears in, while common words tend to be short! (And the average is about 5 letters). – removing stop words will make it smaller, but means that a user cannot search for stop words even if they really want to! That might be OK but just be aware.

Going from Gamma to Golomb for the frequencies made it slightly smaller, but barely any. Also need to collect both document frequency for terms, and total frequency (how many times the word appears across all documents) – more messages for very little gain

One Last Thing

There's also the "Exponential Golomb Code"

Same thing, except you use an Elias Gamma code to write the quotient instead of using uniary.

It's SLIGHTLY smaller than regular Golomb

MapReduce it?

Perfect for MapReduce!

The indexing problem

- Scalability is critical
- Must be relatively fast, but need not be real time
- Fundamentally a batch operation
- Incremental updates may or may not be important
- For the web, crawling is a challenge in itself

The retrieval problem

- Must have sub-second response time
- For the web, only need relatively few results

Uh… not so good…

Retrieval

Let’s assume everything fits in memory on one machine

Boolean Retrieval

Query is formed using Boolean operators (AND OR NOT)

(either matches or doesn't)

Hits: set of documents for which the query is true

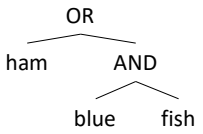
Remember: A set might be sorted by docid, but certainly isn't sorted by relevance to the query. It either matches the query, or doesn't.

Boolean Retrieval

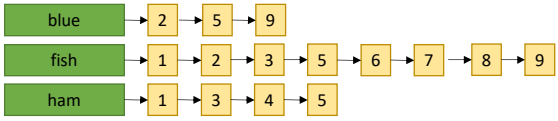
To execute a Boolean query:

Build query syntax tree

(blue AND fish) OR ham



For each clause, look up postings



Traverse postings and apply Boolean operator

Term-At-A-Time

For each term, generate sets of documents

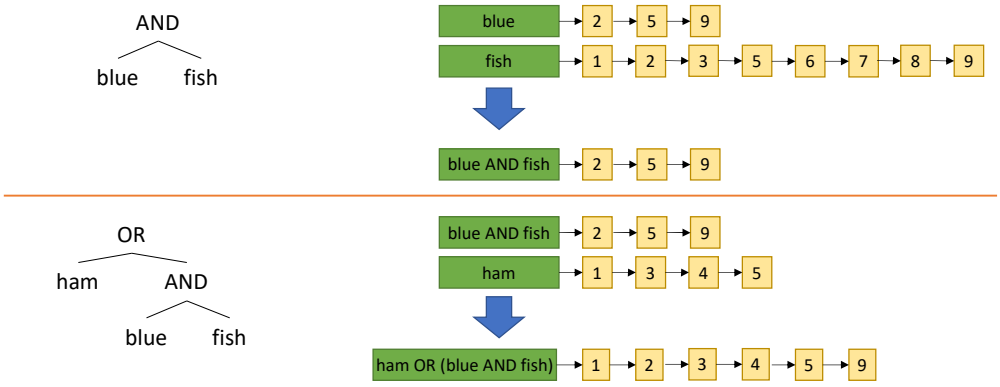
- AND = intersection
- OR = union
- NOT = negate

Analysis?

Not seems bad. Really bad. Not (rare term) => just about the whole internet. We SURE about assuming this fits into memory???

BUT – we only need 2 sets in memory at once. Easy to hold that many in memory (hopefully)

Term-At-A-Time



Since the postings are sorted by docID, AND / OR are modifications of the merge functions from mergesort.
AND – only include a doc if the "next" doc from both postings is equal. OR – if both "next" are equal, only include it once, otherwise same as normal merge

What about not? It's best to have a flag for the set: "Inverted". If an inverted set contains 5, it means the true set does NOT contain 5. (Now you have to modify merge though…)

Document-At-A-Time

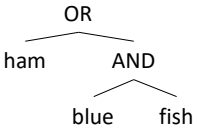
For each document, see if it passes the query

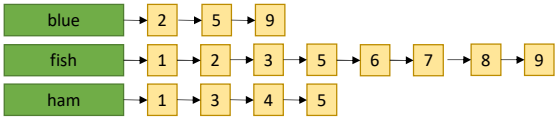
Since documents are in sorted order, modified merge operation will work

Analysis?

Need to have the posting lists for each term in memory simultaneously! (but you can stream them from the FileSystem I'm sure…)
Not makes things a bit awkward again.

Document-At-A-Time





Repeat: for the smallest "next doc" – does it match?

1 – has ham, include and advance "fish" and "ham" lists

2 – no ham, but does have blue and fish. Include.

3, 4, 5 – ham. Include.

6, 7, 8 – no ham, fish but not blue. Exclude

9 – fish and blue. Include

Ummm, unsorted?

A set of hits is fine…but we probably want them sorted by relevance?

That's a different problem: Ranked Retrieval!

Requires: relevance function R(q, d)

Ranked Retrieval

- Can we just do Boolean Retrieval and then sort by relevance?
  - Yes
- Cool, that was easy!
  - O(n log n) where n is the number of hits
- So…you're not going to let me? ☹
  - No, sorry, there might be a lot of hits…

Ranked Retrieval

Simplify the query. It's now only a list of terms (AND)

Need a way to weight a hit

One way to be relevant

- Terms that occur many times in one document should have high weights (for that document)
- Terms that occur in many times in the entire collection should have low weights

We need:

term frequency (times a term is used in a document)

document frequency (number of documents containing the given term)

TF-IDF

(Term Frequency and Inverse Document Frequency)

$$w_{ij} = tfij \ \log \frac{N}{df_i}$$

- w_{ij} – weight (relevance) of term *i* in document *j*
- tf_{ij} – number of occurrences of term i in document j
- df_i – number of documents containing term I
- N – total number of documents

Document-At-A-Time

For each document:

1. Score each query term, and add them all up
2. Accumulate best k hits
    1. A min-heap is good for this

Add the term relevance? Multiply?? Some other function???

PRO: time is O(n log k), memory is O(k) – k probably a constant

CON: can't terminate early, must look at whole document collection

Term-At-A-Time

1. Collect hits and ranking for rarest term into accumulator
2. For each other term in the query:
   1. If a document does NOT have that term, remove from accumulator
   2. Otherwise, add next term's ranking to overall ranking

PRO: Can have early termination heuristics, will not normally need to traverse all documents

CON: uses a lot of memory

Which to use?

Good question. There are tradeoffs. No one correct answer.

Depends a lot on the query, too.

What about synonyms?

1. Use word2vec on your document set and create a table of synonyms:

    if a user searches “love” grab “love” and “romance” postings

2. Use doc2vec to create document embeddings, then…hold that thought until the ML unit