Introduction to Information Retrieval

Lecture 5: Index Compression

Last lecture – in truction

- Sort-based indexing
  - Naïve in-memory inversion
  - Blocked Sort-Based Indexing
    - Merge sort ng (avoid seeks!)
- Single-Pass In
  - No global dictionary
    - Generate separate dictionary for each block
  - Don't sort postings
    - Accumulate postings in postings lists as they occur
- Distributed indexing using MapReduce
- Dynamic indexing: Multiple indices, logarithmic merge

Today

- Collection statistics in mo _ with RCV1)
  - How big will the dictionary and postings be?
- Dictionary compression
- Postings compression

Why compressio neral)?

- Use less disk space
  - Saves a little money
- Keep more stuff in memory
  - Increases sp
- Increase speed of data tran isk to memory
  - [read compressed data | dec faster than [read uncompressed data]
  - Premise: Decompression algorithms are fast
    - True of the decompression algorithms we use

Why compression erted indexes?

- Dictionary
  - Make it small enough to keep in main memory
  - Make it so small that you can keep some postings lists in main memor
- Postings file(s)
  - Reduce disk space needed
  - Decrease time needed to read postings lists from disk
  - Large search engines keep a significant part of the postings in memory.
    - Compression lets you keep more in memory
- We will devise various IR-specific compression schemes

Recall Reuters R

symbol	statistic	value
N	documents	800,000
L	avg	200
M	ter	~400,000
	avg. # bytes per t (incl. spaces/punct.)	
	avg. # bytes per token (without spaces/punct.)	4.5
	avg. # bytes per term	7.5
	non-positional postings	100,000,000

Index hat we index

(details *IIR* Table 5.1, p.

size of	word types (terms)			non-positional postings			positional postings		
	dictionary			non-positional index			positional index		
	Size (K)	Δ				mul	Size (K)	Δ %	cumul %
Unfiltered	484			109,9			197,879		
No numbers	474	-2	-2	100,6		8	179,158	-9	-9
Case folding	392	-17	-19	96,969	-3	-12	179,158	0	-9
30 stopwords	391	-0	-19	83,390	-14	-24	121,858	-31	-38
150 stopwords	391	-0	-19	67,002	-30	-39	94,517	-47	-52
stemming	322	-17	-33	63,812	-4	-42	94,517	0	-52

Exercise: give intuitions for all the '0' entries. Why do some zero entries correspond to big deltas in other columns?

Lossless vs. lossy ession

- Lossless compression: All information is preserved.
  - What we mostly do in IR.

- Lossy compression: Discard some information
- Several of the https://eduassistpro.github.io/ an be viewed as lossy compression: case fol words, stemming, number elimina

- Chap/Lecture 7: Prune postings entries that are unlikely to turn up in the top *k* list for any query.
  - Almost no loss quality for top *k* list.

Vocabulary vs. c size

- How big is the term vocabulary?
  - That is, how many distinct words are there?
- Can we assume an upper bound?
  - Not really: A t words of length 20
- In practice, the vocabulary rowing with the collection size
  - Especially with Unicode ☺

Vocabulary vs. c size

- Heaps' law: $M = kT^b$
- M is the size of the vocabulary, T is the number of tokens in the collection

- Typical values https://eduassistpro.github.io/ 0.5
- In a log-log plot of vocabula s. T, Heaps' law predicts a line with slo

  - It is the simplest possible relationship between the two in log-log space
  - An empirical finding ("empirical law")

Heaps' Law 81

For RCV1, the dashed line

$\log_{10} M = 0.49 \log_{10} T + 1.64$

is the best least squares fit.

Thus, $M = 10^{1.64} T^{0.49}$ s

$10^{1.64} \approx 44$ and $b = 0.4$

Good empirical fit for Reuters RCV1 !

For first 1,000,020 tokens,

law predicts 38,323 terms;

actually, 38,365 terms

Exercises

- What is the effect of including spelling errors, vs. automatically correcting spelling errors on Heaps' law?

- Compute the this scenario:

  - Looking at a collection of we find that there are 3000 different terms in t 00 tokens and 30,000 different terms in the first 1,000,000 tokens.

  - Assume a search engine indexes a total of 20,000,000,000 (2×10^{10}) pages, containing 200 tokens on average
  - What is the size of the vocabulary of the indexed collection as predicted by Heaps' law?

Zipf's law

- Heaps' law gives the vocabulary size in collections.
- We also study the relative frequencies of terms.

- In natural la w very frequent terms and v ms.

- Zipf's law: The ith most fr m has frequency proportional to $1/i$.

- $cf_i \propto 1/i = K/i$ where K is a normalizing constant
- cf_i is collection frequency: the number of occurrences of the term t_i in the collection.

Zipf consequenc

- If the most frequent term (*the*) occurs cf_1 times
  - then the second most frequent term (*of*) occurs $cf_1/2$ times
  - the third mo urs $cf_1/3$ times …
- Equivalent: cf_i malizin so
  - $\log cf_i = \log K - \log i$
  - Linear relationship between $\log cf_i$ and $\log i$
- Another power law relationship

Zipf's law for Re V1

Compression

- Now, we will consider compressing the space for the dictionary and postings

  - Basic Boo
  - No study s, etc.
  - We will consider com schemes

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DICTIONARY COMPRESSION

Why compress t nary?

- Search begins with the dictionary
- We want to keep it in memory

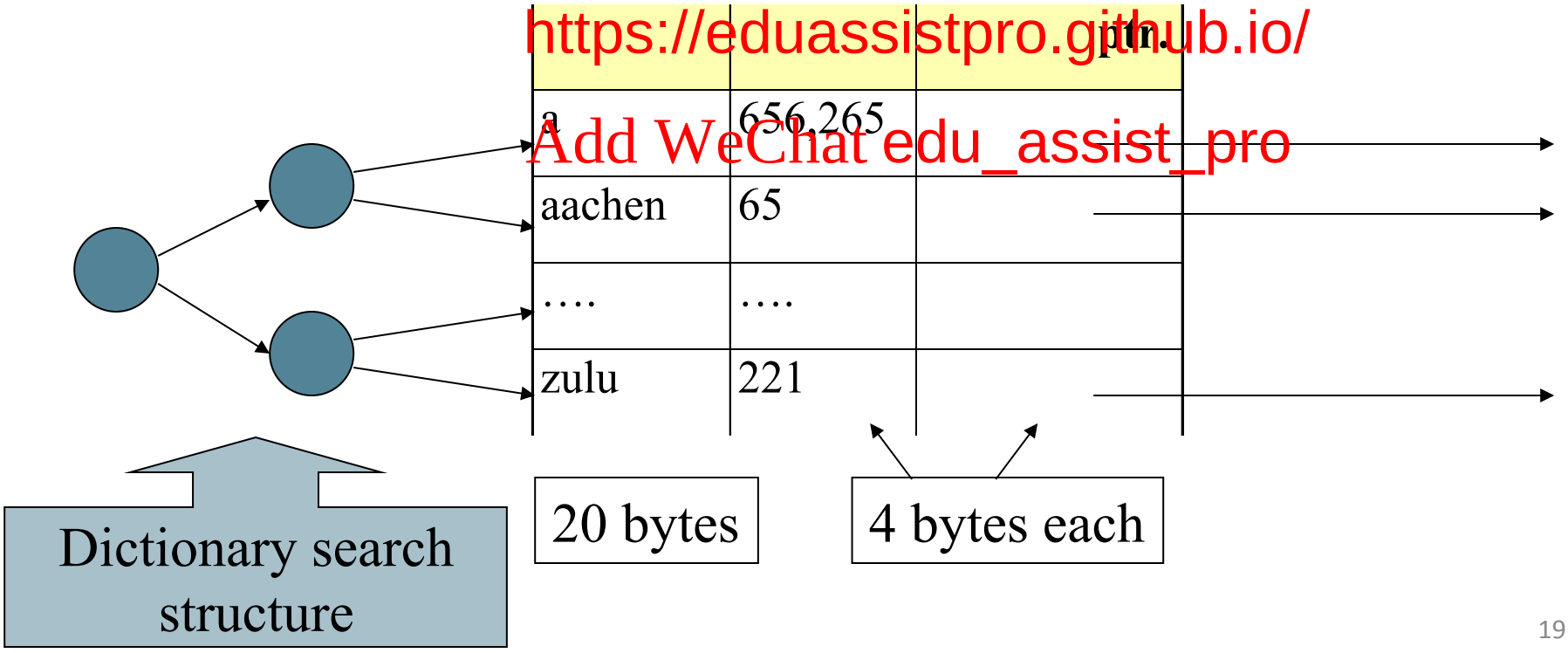
- Memory foot other applications

- Embedded/mobile devices very little memory

- Even if the dictionary isn't in memory, we want it to be small for a fast search startup time
- So, compressing the dictionary is important

Dictionary stora cut

- Array of fixed-width entries
  - ~400,000 terms; 28 bytes/term = 11.2 MB.



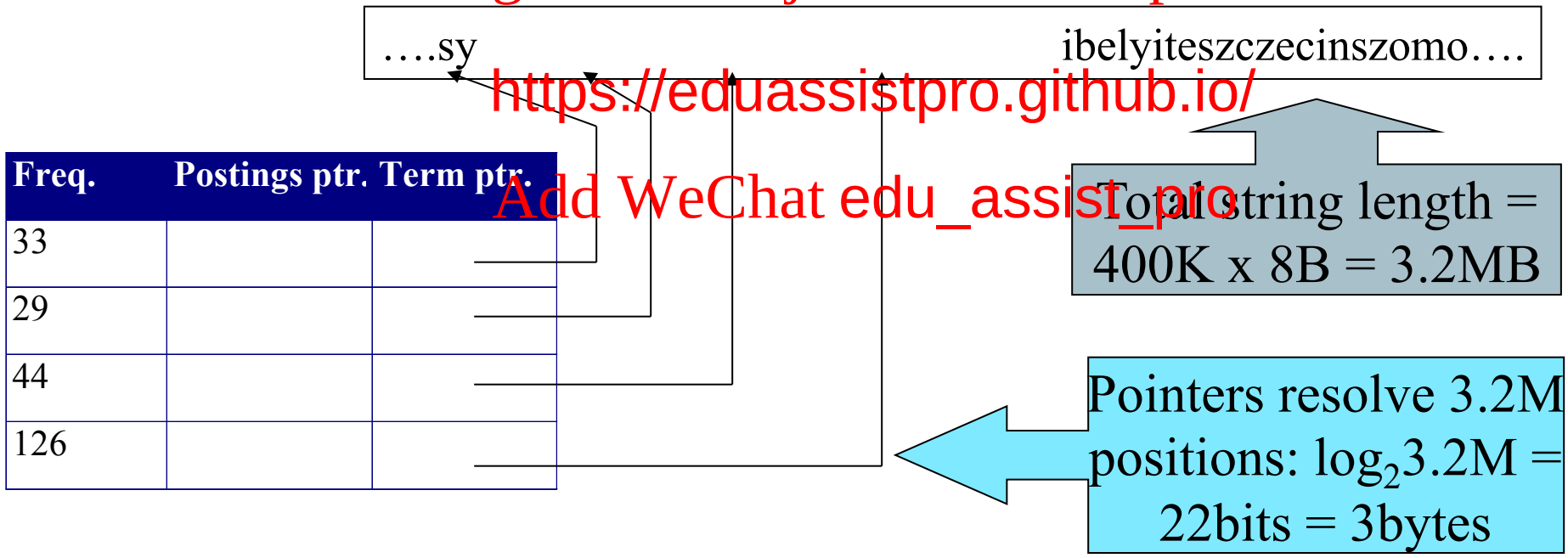
Fixed-width ter asteful

- Most of the bytes in the **Term** column are wasted – we allot 20 bytes for 1 letter terms.
  - And we still can't handle *supercalifragilisticexpialidocious* or *hydrochlorofluo*
- Written Englis cters/word.
  - Exercise: Why is/isn't this the use for estimating the dictionary siz
- Ave. dictionary word in English: ~8 characters
  - How do we use ~8 characters per dictionary term?
- Short words dominate token counts but not type average.

Compre t:

Dictionary-as-a-Str

- Store dictionary as ring of characters:
  - Pointer to next word shows end of current word
  - Hope to save up to 60% of dictionary space.



Space for diction string

- 4 bytes per term for Freq.
- 4 bytes per term for pointer to Postings.
- 3 bytes per te
- Avg. 8 bytes p
- 400K terms x 19 → 7.6 MB 1.2MB for fixed width)

Now avg. 11 bytes/term, not 20.

Blocking

- Store pointers to every *k*th term string.
  - Example below: *k*=4.
- Need to store term lengths (1 extra byte)

Freq.	Postings ptr.	Term ptr.
33		
29		
44		
126		
7		

Save 9 bytes on 3 pointers.

Lose 4 bytes on term lengths.

Net

- Example for block size *k* = 4
- Where we used 3 bytes/pointer without blocking
  - 3 x 4 = 12 bytes,

now we use 3 +

Shaved another ~0.5MB. Thi the size of the dictionary from 7.6 MB to 7.1 MB.
We can save more with larger *k*.

Why not go with larger *k*?

Exercise

- Estimate the space usage (and savings compared to 7.6 MB) with blocking, for block sizes of *k = 4, 8* and *16.*

Dictionary search wit king

- Assuming each dictionary term equally likely in query (not really so in practice!), number of comp = (1+2·2+4·3+4)/8 ~ 2.6

Exercise: what if the frequencies of query terms were non-uniform but known, how would you structure the dictionary search tree?

Dictionary searc locking

- Binary search down to 4-term block;
  - Then linear search through terms in block.
- Blocks of 4 (binary tree), avg. = (1+2·2+2·3+2·4+5)/8 = 3 compares

Exercise

- Estimate the impact on search performance (and slowdown compared to k=1) with blocking, for block sizes of k = 4, 8 and 16.

Front coding

- Front-coding:
  - Sorted words commonly have long common prefix – store differences only
  - (for last *k-1* i

8***automata***8***au***

◇8***automat****a1◇***e***2◇***ic***3

Encodes ***automat***

Extra length beyond ***automat.***

Begins to resemble general string compression.

Front Encoding [Witten, Moffat, Bell]

- Complete front encoding
  - (prefix-len, suffix-len, suffix)
- Partial 3-in-4 front encoding
  - No encoding for 3 in a block of 4 consecutive strings
  - Enables binary search

Assume previous string is "auto"

String	Complete Front Encoding	Partial 3-in-4 Front Encoding
8, automata	4, 4, mata	, 8, automata
8, automate	7, 1, e	7, 1, e
9, automatic	7, 2, ic	7, 2, ic
10, automation	8, 2, on	8, , on

RCV1 dictionary c sion summary

Technique	Size in MB
Fixed width	11.2
Dictionary-as-Strin rm	7.6
Also, blocking $k = 4$	7.1
Also, Blocking + front coding	5.9

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POSTINGS COMPRESSION

Postings compre

- The postings file is much larger than the dictionary, factor of at least 10.

- Key desideratum: store each posting compactly.
- A posting for
- For Reuters (800,000 docu would use 32 bits per docID when using 4 gers.

- Alternatively, we can use $\log_2$ 800,000 ≈ 20 bits per docID.
- Our goal: use a lot less than 20 bits per docID.

Postings: two co forces

- A term like ***arachnocentric*** occurs in maybe one doc out of a million – we would like to store this posting using $\log_2$ 1M ~ 20 bits.

- A term like ***th*** ery doc, so 20 bits/posting is

  - Prefer 0/1 bitmap vector in t

Postings file entr

- We store the list of docs containing a term in increasing order of docID.
  - ***computer***: 33,47,154,159,202 …
- Consequence
  - 33,14,107,5,43 …
- Hope: most gaps can be en ed with far fewer than 20 bits.

Three postings e

Variable length e g

- Aim:
  - For ***arachnocentric***, we will use ~20 bits/gap entry.
  - For ***the***, we will use ~1 bit/gap entry.

- If the average https://eduassistpro.github.io/ e want to use ~$\log_2 G$ bits/ga

- Key challenge: encode ever gap) with about as few bits as needed for that integer.
- This requires a *variable length encoding*
- Variable length codes achieve this by using short codes for small numbers

Variable Byte (V

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

ex(824)=0x0338
Hex(214577)=0x00034631

Example

docIDs	824	829	215406
gaps		5	214577
VB code	10000110 1	10000101	00001101 00001100 10110001

Postings stored as the byte c ion
000001101011100010000010100 1 10010110001

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

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

Other variable u s

- Instead of bytes, we c e a different "unit of alignment": 32 bits (words), 16 bits, 4 bits (nibbles).
- Variable byte alignment wastes space if you have many small g in such cases.
- Variable byte
  - Used by many commercial/ ems
  - Good low-tech blend of variable-length coding and sensitivity to computer memory alignment matches (vs. bit-level codes, which we look at next).
- There is also recent work on word-aligned codes that pack a variable number of gaps into one word (e.g., simple9)

Simple9

- Encodes as many gap le in one DWORD
- 4 bit selector + 28 bit data bits
  - Encodes 9 possible ways to "use" the data bits

Selector	#		Wasted bits
0000	28	1	0
0001	14	2	0
0010	9	3	1
0011	7	4	0
0100	5	5	3
0101	4	7	0
0110	3	9	1
0111	2	14	0
1000	1	28	0

Unary code

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

  11111111111 1111111111110 .
- Unary code for 80 is:

  11111111111111111111111111111111111111111
  11111111111111111111111111111111110

- This doesn't look promising, but….

Bit-Aligned Code

- Breaks between enco ers can occur after any bit position
- *Unary* code
  - Encode *k* by
  - 0 at end mak

Number	Code
0	0
1	10
2	110
3	1110
4	11110
5	111110

Unary and Binar

- Unary is very efficient for small numbers such as 0 and 1, but quickly becomes very expensive
  - 1023 can be bits, but requires 1024 bits in
- Binary is more efficient for bers, but it may be ambiguous

Elias-γ Code

- To encode a number e

unary

binary

- k_d is numb

nary

Elias-δ Code

- Elias-γ code uses no more bits than unary, many fewer for k > 2
  - 1023 takes 19 bits instead of 1024 bits using unary
- In general, ta
- To improve coding of large , use Elias-δ code
  - Instead of encoding k_d in una de $k_d + 1$ using Elias-γ
  - Takes approximately $2 \log_2 \log_2 k + \log_2 k$ bits

Elias-δ Code

- Split (k_d+ 1) into:

$$k_{dd} = \lfloor \log_2(k_d + 1) \rfloor$$

$$k_{dr} = (k_d + 1) - 2^{\lfloor \log_2(k_d+1) \rfloor}$$

  - encode k_{dd} i k_r in binary

Gamma code pr

- G is encoded using 2 log G + 1 bits
  - Length of offset is $\lfloor \log G \rfloor$ bits
  - Length of length is $\lfloor \log G \rfloor + 1$ bits
- All gamma co er of bits
- Almost within a factor of 2 sible, $\log_2 G$

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

Gamma seldom practice

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

Shannon Limit

- Is it possible to derive codes that are optimal (under certain assumptions)?

- What is the optimal average code length for a code that encodes ths) independentl

- Lower bounds on average c : Shannon entropy
  - $H(X) = - \Sigma_{x=1}^{n} Pr[X=x] \log Pr[X=x]$
- Asymptotically optimal codes (finite alphabets): arithmetic coding, Huffman codes

How to design an optimal code for geometric distribution?

Global Bernoulli

- Assumption: term occurrence are Bernoulli events
- Notation:
  - n: # of documents, m: # of terms in vocabulary
  - N: total # of (
- Probability of a term t_i occu cument d_i: p = N/nm
- Each term-document occurrence is an independent event
- Probability of a gap of length x is given by the geometric distribution $\Pr[X = x] = (1-p)^{x-1} \cdot p$

It can also be deemed as a generalization of the unary code.

Golomb Code

- Golomb Code (Golomb 1966): highly efficient way to design optimal Huffman-style code for geometric distribution

  - Parameter b

  - For given x ≥ ent $q = \lfloor (x-1)/b \rfloor$

  - and remainder $r = (x-1) - q \cdot b$
- Assume b = 2^k
  - Encode q in unary, followed by r coded in binary
  - A bit complicated if b != 2^k. See wikipedia.
- First step: (q+1) bits
- Second step: log(b) bits

Golomb Code & de

- How to determine optimal b*?
- Select minimal b such that

$$b^{b+1} \le 1$$

- Result due to rms 1975: generates an optimal prefix eometric distribution
- Small p approximation:

$$b^* \approx \ln 2 / p = 0.69 \cdot avg\_val$$

- Rice code: only allow b = 2^k

Local Bernoulli

- If length of posting lists is known, then a Bernoulli model on each individual inverted list can be used
- Frequent words are coded with smaller b, infrequent words with la
- Term frequency need to be use gamma-code)
- Local Bernoulli outperforms global Bernoulli model in practice (method of practice!)

RCV1 compressi

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

Google's Indexin e

- Index shards partition by doc, multiple replicates
- Disk-resident index

  - Use outer parts of the disk
  - Use different r different fields:

    Rice$_k$ (a speci or gaps, and Gamma
    for positions.

- In-memory index
  - All positions; No docid
    - Keep track of document boundaries
  - Group-variant encoding
    - Fast to decode

Source: Jeff Dean's WSDM 2009 Keynote

Other details

- Gap = $docid_n$ - $docid_{n-1}$ **- 1**
- Freq = freq – 1
- Pos_Gap = po

- C.f., Jiangong Zhang, Xiaoh Torsten Suel: Performance of Compressed Inverted List Caching in Search Engines. WWW 2008.

Index compressi mary

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

Resources for to cture

- *IIR* 5
- *MG* 3.3, 3.4.

- F. Scholer, H. l. 2002. Compression https://eduassistpro.github.io/ Evaluation. *Proc. ACM-SIGI*

  - Variable byte codes
- V. N. Anh and A. Moffat. 2005. Inverted Index Compression Using Word-Aligned Binary Codes. *Information Retrieval* 8: 151–166.
  - Word aligned codes