Techniques for Inverted Index Compression

Giulio Ermanno Pibiri and Rossano Venturini Ca'Foscari University, Universita di Pisa

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This is a survey paper!

Index Compressors

A Single Integer

List Compressors

Many Integers Together (Inverted List)

Index Compressors

Many Lists Together (Whole Invertex Index)

Motivation: A Tour of the Terms

Terms

Forward Index

Doc 1

Set(Term1, Term2)

Doc 2

Set(Term2, Term3)

Doc 3

Set(Term1, Term3)

Inverted Index

Term 1

Doc[1, 3]

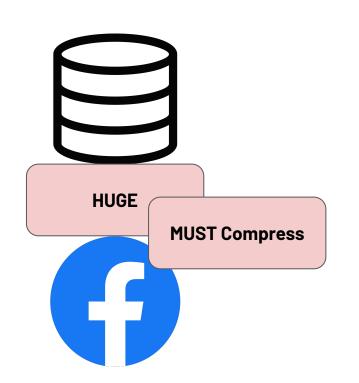
Term 2

Doc[1, 2]

Term 3

Doc[2,3]

Motivation





FIND "chicken sandwich recipes" in DB



FIND friends with pet chickens

Well-Studied Problem

1949	Shannon-Fano [32, 93]
1952	Huffman [43]
1963	Arithmetic [1] ¹
1966	Golomb [40]
1971	Elias-Fano [30, 33]; Rice [87]
1972	Variable-Byte and Nibble
	[101]
1975	Gamma and Delta [31]
1978	Exponential Golomb [99]
1985	Fibonacci-based [6, 37]
1986	Hierarchical bit-vectors [35]
1988	Based on Front Coding [16]
1996	Interpolative [65, 66]
1998	Frame-of-Reference (For) [39];
	modified Rice [2]
2003	SC-dense [11]
2004	Zeta [8, 9]

2005	Simple-9, Relative-10, and Carryover-12 [3];
	RBUC [60]
2006	PForDelta [114]; BASC [61]
2008	Simple-16 [112]; Tournament [100]
2009	ANS [27]; Varint-GB [23]; Opt-PFor [111]
2010	Simple8b [4]; VSE [96]; SIMD-Gamma [91]
2011	Varint-G8IU [97]; Parallel-PFor [5]
2013	DAC [12]; Quasi-Succinct [107]
2014	Partitioned Elias-Fano [73]; QMX [103];
	Roaring [15, 51, 53]
2015	BP32, SIMD-BP128, and SIMD-FastPFor [50];
	Masked-VByte [84]
2017	Clustered Elias-Fano [80]
2018	Stream-VByte [52]; ANS-based [63, 64];
	Opt-VByte [83]; SIMD-Delta [104];
	general-purpose compression libraries [77]
2019	DINT [79]; Slicing [78]

Previous Paper!

Integer Compressors

Inverted Index



Term 3Doc[2, 3]

Goals

- Map each integer to a uniquely-decodable variable-length binary code
 - Assign the smallest codeword possible
- Prefix-Free
- Lexicographic Assignment (same lexicographic order as integers they represent, fast decodability)
- Shannon's Theorem: $|C(x)| = \log_2(1 / P(x))$ where P(x) is the probability of x occurring

Encoding and Decoding Prefix-Free Codes

Table 2. Example Prefix-Free Code for the Integers 1..8, Along with Associated Codewords, Codeword Lengths, and Corresponding Left-Justified, 7-Bit Integers

		(a)			(b)	
x	Codewords	Lengths	Values	Lengths	First	Values
1	0	1	0	1	1	0
2	100	3	64	2	2	64
3	101	3	80	3	2	64
4	11000	5	96	4	4	96
5	11001	5	100		4	96
6	11010	5	104	= 6 < 8 - 5	8	112
7	11011	5	108	7	8	112
8	1110000	7	112	<u>-</u>	9	127
200	<u></u>	<u></u>	127		1	

The codewords are left-justified to better highlight their lexicographic order. In (b), the compact version of the table in (a), used by the encoding/decoding procedures coded in Figure 1. The "values" and "first" columns are padded with a sentinel value (in gray) to let the search be well defined.

Enc(6)

$$L = 5$$

Offset =
$$6 - First[L] = 6 - 4 = 2$$

$$Jump = (M - L) = 9 - 5 = 4$$

Encoding and Decoding Prefix-Free Codes

Table 2. Example Prefix-Free Code for the Integers 1..8, Along with Associated Codewords, Codeword Lengths, and Corresponding Left-Justified, 7-Bit Integers

x	Codewords	Lengths	Values
1	0	1	0
2	100	3	64
3	101	3	80
4	11000	5	96
5	11001	5	100
6	11010	5	104
7	11011	5	108
8	1110000	7	112
200	_	_	127

Lengths	First	Values
1	1	0
2	2	64
3	2	64
4	4	96
5	4	96
6	8	112
7	8	112
_	9	127

(b)

Encode(x):

The codewords are left-justified to better highlight their lexicographic order. In (b), the compact version of the table in (a), used by the encoding/decoding procedures coded in Figure 1. The "values" and "first" columns are padded with a sentinel value (in gray) to let the search be well defined.

determine ℓ such that $first[\ell] \le x < first[\ell+1]$ offset = $x - first[\ell]$ $jump = 1 \ll (M - \ell)$ Write(($values[\ell] + offset \times jump$) $\gg (M - \ell), \ell$) Decode():

determine ℓ such that $values[\ell] \le buffer < values[\ell + 1]$ $offset = (buffer - values[\ell]) \gg (M - \ell)$ $buffer = ((buffer \ll \ell) \& MASK) + Take(\ell)$ **return** $first[\ell] + offset$

Encodings

Table 3. Integers 1..8 as Represented with Several Codes

x	U(x)	B(x)	$\gamma(x)$	$\delta(x)$	$G_2(x)$	$ExpG_2(x)$	$Z_2(x)$
1	0	0	0.	0.	0.0	0.00	0.0
2	10	1	10.0	100.0	0.1	0.01	0.10
3	110	10	10.1	100.1	10.0	0.10	0.11
4	1110	11	110.00	101.00	10.1	0.11	10.000
5	11110	100	110.01	101.01	110.0	10.000	10.001
6	111110	101	110.10	101.10	110.1	10.001	10.010
7	1111110	110	110.11	101.11	1110.0	10.010	10.011
8	11111110	111	1110.000	11000.000	1110.1	10.011	10.1000

The "." symbol highlights the distinction between different parts of the codes and has a purely illustrative purpose: it is not included in the final coded representation.

Unary Encoding

Table 3. Integers 1..8 as Represented with Several Codes

x	U(x)	B(x)	Y			$ExpG_2(x)$	$Z_2(x)$
1	0	0	0.	$U(x)=1^{y}$	^{K-1} 0	0.00	0.0
2	10	1	10.0			0.01	0.10
3	110	10	10.1	100.1	10.0	0.10	0.11
4	1110	11	110.00	101.00	10.1	0.11	10.000
5	11110	100	110.			10.000	10.001
6	111110	101	110.	Con: size is li	near in x	10.001	10.010
7	1111110	110	110.	0011. 0120 10 11	TICAL III X	10.010	10.011
8	11111110	111	1110.00		, , , , , , , , , , , , , , , , , , , ,	10.011	10.1000

The "." symbol highlights the distinction between different parts of the codes and has a purely illustrative purpose: it is not included in the final coded representation.

Binary Encoding

Table 3. Integers 1..8 as Represented with Several Codes

x	U(x)	B(x)	$\gamma(x)$	(()	0 ()	(x)	$Z_2(x)$
1	0	0	0.				0.0
2	10	1	10.0	В(x) = bin(x-1)		0.10
3	110	10	10.1				0.11
4	1110	11	110.00	101.00	10.1	0.11	10.000
5	11110	100	110.01			B	10.001
6	111110	101	110.10	Pro	: Size is log(x)	10.010
7	1111110	110	110.11		, کر	b	10.011
8	11111110	111	1110.000	11000 000	1110 1	10.011	10.1000
			distinction between		uniquely de	codable	ely illustrative

Gamma Encoding

U(|bin(x)|) + (|bin(x)| - 1 LSB of bin(x))

Table 3. Integers 1..8 as Represented w

x	U(x)	B(x)	$\gamma(x)$	$\delta(x)$	$G_2(x)$	$ExpG_2(x)$	$Z_2(x)$	
1	0	0	0.	0.	Pro: Size is log(x) and uniquely			
2	10	1	10.0	100.0	decodable			
3	110	10	10.1	100.1	Optimal for $P = 1/2x^2$			
4	1110	11	110.00	101.00	10			
5	11110	100	110.01	101.01	1	Example: 3		
6	111110	101	110.10	101.10	1	bin(3) = 1 1		
7	1111110	110	110.11	101.11	1	bin(3) = 2		
8	11111110	111	1110.000	11000.000	1	U(2) = 10	(7) 1	
Tl pi	Con: can	get big /alues	ior nia – i	tween different parts d representation.		x) -1 LSB of bi => 10.1	n(3)=1	

Delta Encoding

 $\gamma(|bin(x)|) + (|bin(x)| - 1 LSB)$ of bin(x))

Table 3. Integers 1..8 as Represented w

x	U(x)	B(x)	$\gamma(x)$	$\delta(x)$	$G_2(x)$	$ExpG_2(x)$	$Z_2(x)$
1	0	0	0.	0.	0.0	0.00	0.0
2	10	1	10.0	100.0	0.1	0.01	0.10
3	110	10	10.1	100.1	10.0	0.10	0.11
4	1110	11	110.00	101.00	10		
5	11110	100	110.01	101.01	1	Example:	3
6	111110	101	110.10	101.10	1	$\gamma(x) = 100$	
7	1111110	110	110.11	101.11	1	bin(3) = 11	
			000	11000.000	1 lbin	(x) -1 LSB of b	
	Pro: doesn't d	grow as fa	ast!			100 1	

Optimal for $P(x) = 1/(2x(\log_2 x)^2)$

n between different parts of coded representation.

=> IUU. I

Golomb Encoding

q = floor((x-1) / b) r = x - q*b - 1 G_b = U(q+1) | bin(r)

							ъ -	
		Table 3	Integers 1.8:	as Repr	esented	with Several	Codes	
	11(44)				>	C (w)	EvnC (w)	7 (**)
x	U(x)	_			x)	$G_2(x)$	$ExpG_2(x)$	$Z_2(x)$
1	0		Example: 3			0.0	0.00	0.0
2	10	-	oor((3-1) / 2) =	:1	9	0.1	0.01	0.10
3	110		3 - 1*2 - 1 = 0	• •	1	10.0	0.10	0.11
4	1110	$G_b = U(1)$	+1) bin(0) = 1	0.0	90	10.1	0.11	10.000
5	11110			,	01	110.0	10.000	10.001
6	111110	101	110.10	101.	10	110.1	10.001	10.010
7	1111110	110	110.11	101.	11	1110.0	10.010	10.011
8	11111110	111	1110.000	1100	0.000	1110.1	10.011	10.1000
-								

Pro: Optimal for $P(x) = p(1-p)^{x-1}$

on between different parts of the codes and has a purely illustrative coded representation.

Rice Encoding

Golomb with $b = 2^k$, k > 0

		Table 3	Integers 1.8:	s Repre	sented	with Several	Codes	
${x}$	U(x)				x)	$G_2(x)$	$ExpG_2(x)$	$Z_2(x)$
1	0		xample: 3			0.0	0.00	0.0
2	10	•	oor((3-1) / 2) =	1)	0.1	0.01	0.10
3	110		3 - 1*2 - 1 = 0	1		10.0	0.10	0.11
4	1110	$G_b = U(1)$	+1) bin(0) = 1	0.0	00	10.1	0.11	10.000
5	11110			Je)1	110.0	10.000	10.001
6	111110	TOT	110.10	<u>⊤1</u> 01.1	0	110.1	10.001	10.010
7	1111110	110	110.11	101.1	1	1110.0	10.010	10.011
8	1111111	0 111	1110.000	11000	000	1110.1	10.011	10.1000

The "." symbol highlights the distinction between different parts of the codes and has a purely illustrative purpose: it is not included in the final coded representation.

Exponential Golomb Encoding

10

h = bucket index U(h) | (bin rep of x in range [0, B[h+1] - B[h] - 1])

Buckets

$$B = \left[0, 2^k, \sum_{i=0}^1 2^{k+i}, \sum_{i=0}^2 2^{k+i}, \sum_{i=0}^3 2^{k+i}, \dots\right], \text{ for some } k \ge 0$$

Γ 1	2	3	1	
la ak	k+i	+i $k+i$	C	- 0

0	1	
		_

100.1 00

d with Several Codes

2(00)	- xp - 2(xt)	-2(50)
0.0	0.00	0.0
0.1	0.01	0.10
10.0	0.10	0.11
10.1	0.11	10.000
110.0	10.000	10.001
110.1	10.001	10.010

10.010

10.011

10.011

10.1000

 $\operatorname{ExpG}_{\alpha}(x)$

Example: 3 bucket idx = 0bin rep in bucket = 11 $ExpG_{2} = 0.11$

110

ion between different parts of the codes and has a purely illustrative l coded representation.

1110.0

1110.1

Zeta Encoding

ExpGolomb relative to vector buckets [0, 2^k-1, 2^{2k}-1, ...]

Table 3. Integers 1..8 as Represented with Several Codes

x	U(x)	B(x)	Y	(x)	$\delta(x)$	$G_2(x)$	$ExpG_2(x)$	$Z_2(x)$
1	0	0	0.		0.	0.0	0.00	0.0
2	10	1	10.0	9	100.0	0.1	0.01	0.10
3	110	10	10.	1	100.1	10.0	0.10	0.11
			Q	.00	101.00	10.1	0.11	10.000
			`	01	101.01	110.0	10.000	10.001
Example: 3				10	101.10	110.1	10.001	10.010
	bucket_idx = 0			11	101.11	1110.0	10.010	10.011
	bin rep in bucket = 11			000.	11000.000	1110.1	10.011	10.1000
	$Z_2 =$	0.11		ion botu	roon different nort	s of the code	and has a nura	ly illustrative

ion between different parts of the codes and has a purely illustrative al coded representation.

Variable-Byte

- Byte-aligned (simpler and faster to write into memory)
- Bin(x) is divided into the 7-bit sequences. Then you write a continuation bit (1 to continue, 0 to the termination of the sequence) at the start
- Nibble 3 bits instead of 7
- Allows for more SIMD parallelism (ex: Varint-G8IU)

Example: 65790

bin(65790) = 100000000111111110

Chunk into groups of 7: 0000100 | 0000001 | 11111110

Add Control Bits: **0**0000100 | **1**0000001 | **1**11111110

VB(65790) = **0**0000100**1**0000001**1**11111110

SC-Dense

- Variable-Byte but with generalized stoppers

$$\circ$$
 If k(x)=1, the stopper is x-1

$$\circ \qquad y = floor((x-1)/x)$$

$$\circ$$
 $x' = x - sc^{k(x)-1} - s / (c-1)$

- Representation has k(x)-1continuers
- Repeat continuers for k(x)-2times followed by continuer $s + ((y-1) \mod c)$ and final stopper (x'-1) mod s

SC(s, c, x) with k(x) >= 1 such that
$$s \frac{c^{k(x)-1}-1}{c-1} \le x < s \frac{c^{k(x)}-1}{c-1}$$
.

Table 5. Integers 1..20 as Represented by SC (4, 4)- and SC(5, 3)-Dense Codes, Respectively

x	SC(4, 4, x)	SC(5,3,x)	x	SC(4, 4, x)	SC(5,3,x)
1	000	000	11	101.010	110.000
2	001	001	12	101.011	110.001
3	010	010	13	110.000	110.010
4	011	011	14	110.001	110.011
5	100.000	100	15	110.010	110.100
6	100.001	101.000	16	110.011	111.000
7	100.010	101.001	17	111.000	111.001
8	100.011	101.010	18	111.001	111.010
9	101.000	101.011	19	111.010	111.011
10	101.001	101.100	20	111.011	111.100

Overview of the Encoders

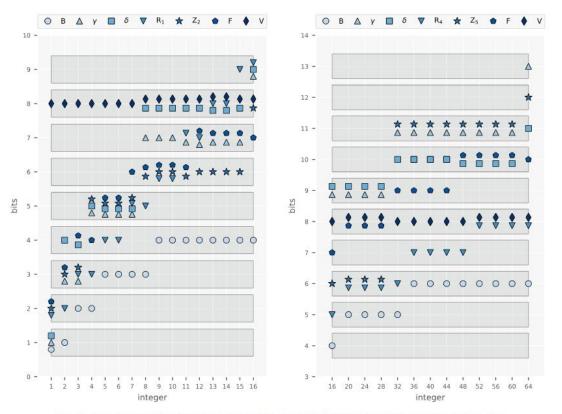
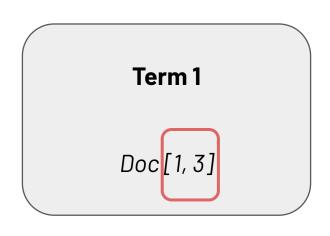


Fig. 3. Comparison between several codes described in Section 2 for the integers 1..64.

List Compressors

Inverted Index



Term 2Doc [1, 2]

Term 3Doc[2, 3]

Binary Packing

- Partition into blocks and encode each block separately
 - o If blocks has clusters of close integers, the values in a block are likely be of similar magnitude
- Binary Packing
 - Use bit width ceil(log₂(max + 1)) of the maximum element then represent all integers in the block with b-bit codewords
- Can also do a variable amount

Simple

- Split the sequence into fixed-memory units and ask how many integers can be packed in a unit
 - 4 bit selector code followed by the integers (for example, in 32-bit word)
- Typically good compression and decoding speed

4-Bit Selector	Integers	Bits per Integer	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

Read: packs 28 1-bit integers

PForDelta

- Problem with previous implementations: LOTS of wasted space if there's one big value and then rest are small
- Choose k such that >= 90% of integers can be represented using k bits per integer
 - If they do not fit, they are **exceptions** and encoded using another compressor (Variable-Byte or Simple)

Elias-Fano

- Let S(n, U) indicate a sorted sequence S[1..n]
- Break each S[i] into two parts
 - Low bits: L = floor(log₂(U/n))
 - High bits: ceil(log₂U) L
- Low bits are encoded separately with a bit-vector L of n ceil(log₂(U/n)) bits
- High bits are encoded separately with a bit-vector of <= 2n bits by setting the bit in position h_i + i for all i = 1, ..., n
- Concat these two representations

Elias-Fano

Table 7. Example of Elias-Fano Encoding Applied to the Sequence S = [3, 4, 7, 13, 14, 15, 21, 25, 36, 38, 54, 62]

S	3	4	7	13	14	15	21	25	36	38		54	62
	0	0	0	0	0	0	0	0	1	1	1	1	1
high	0	0	0	0	0	0	1	1	0	0	0	1	1
	0	0	0	1	1	1	0	1	0	0	1	0	1
low	0	1	1	1	1	1	1	0	1	1		1	1
	1	0	1	0	1	1	0	0	0	1		1	1
	1	0	1	1	0	1	1	1	0	0		0	0
H		1110 1110			10	10	1	10	0	10	10		
L	01	1.100	0.111	101	.110	.111	101	001	100	.110		110	110

Elias-Fano - Random Access

- Add auxiliary data structures to make this possible
- For Select_b(i), use a bit-vector to get the position of the ith bit set to b
 - o Requires o(n) additional bits
- **0(1)** runtime

Elias-Fano - Successor Queries

- Select_{.b}(x)
- $h_x = high bits of x$
- Binary Search from Select_b(h_x) h_x + 1 to Select_b(h_x +1) h_x
- **0(1+log(U/n))** runtime

Elias-Fano - Partitioning by Universe

- **Roaring:** partition $U(2^{32})$ into chunk spanning 2^{16} values each
 - \circ If a chunk is sparse (less than 2^{12} elements), encode as a sorted array of 16-bit integers.
 - \circ If a chunk is dense (more than 2^{12} elements), encode as a bitmap.
 - \circ If a chunk is full (2¹⁶ elements), encode implicitly.

• **Slicing:** Roaring but continue encoding recursively if the chunk is sparse (at most 28 blocks of 28 elements each)

Interpolative

- Represents a sorted integer sequence without requiring the computation of its gaps
- Exploit the order of the already-encoded elements to compute the number of bits needed to represent the elements that will be encoded next
- Idea: recursively divide, encode middle element with minimum bits

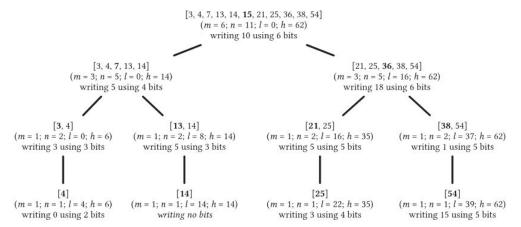


Fig. 4. The recursive calls performed by the Binary Interpolative Coding algorithm when applied to the sequence [3, 4, 7, 13, 14, 15, 21, 25, 36, 38, 54] with initial knowledge of lower and upper bound values l = 0 and h = 62. In bold font, we highlight the middle element being encoded.

Directly-Addressable Codes

- Representation for a list of integers that supports random access to individual integers
 - Problem of random access reduced to one of **ranking over a bitmap**

Entropy Coding

- Huffman \rightarrow too large alphabet (H₀ <= L <= H₀ + 1 where H₀ is the entropy)
- Arithmetic \rightarrow takes nH₀ + 2 bits to encode sequence S of length n with H₀ entropy
- Asymmetric Numeral Systems (ANS) → represent sequence of symbols with a natural number x

Table 8. Two Examples of the ANS Encoding Table with Frame f[1..6] = [aaabbc] and f[1..4] = [caba], Respectively

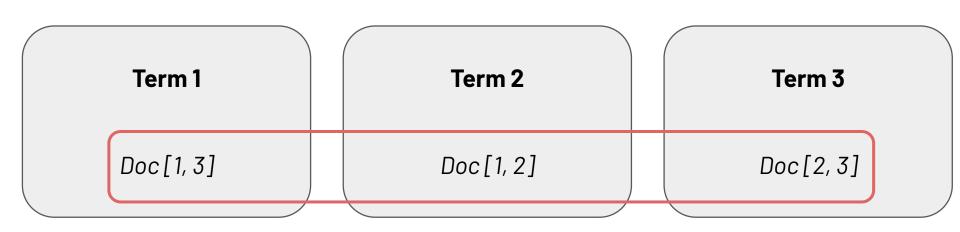
(a) (b)

Σ	P					Co	des				
a	1/2	1	2	3	7	8	9	13	14	15	19
b	1/3	4	5	10	11	16	17	22	23	28	29
C	1/6	6	12	18	24	30	36	42	48	54	60
		0	1	2	3	4	5	6	7	8	9

Σ	P					C	odes	S			
a	1/2	2	4	6	8	10	12	14	16	18	20
b	1/4	3	7	11	15	19	23	27	31	35	39
c	1/4	1	5	9	13	17	21	25	29	33	37
		0	1	2	3	4	5	6	7	8	9

Index Compressors

Inverted Index



Clustered

- Idea: Group lists into clusters and encode from a reference list
- Inverted lists grouped into clusters of similar lists (sharing as many integers as possible)
- Reference List for each cluster → all lists in cluster encoded with respect to the reference list
- Improvement: each intersection can be rewritten in a much smaller universe

ANS Based

- Idea: Preprocessing to reduce alphabet size then apply ANS
- Option 1:
 - Preprocess with Variable-Byte to reduce input list to a sequence of bytes
 - Apply ANS
- Option 2:
 - Preprocess with Simple
 - Apply ANS
- Option 3:
 - Packed processing
 - Apply ANS

Dictionary Based

- Idea: gaps are repetitive, abstract it into a dictionary
- Dictionary stores the most frequent 2^b patterns (b > 0)

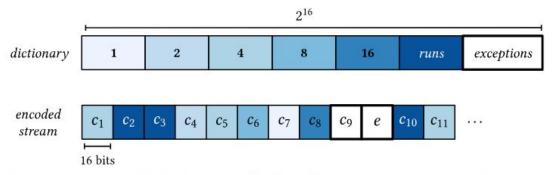


Fig. 6. A dictionary-based encoded stream example, where dictionary entries corresponding to $\{1, 2, 4, 8, 16\}$ -long integer patterns, runs, and exceptions are labeled with different shades. Once provision has been made for such a dictionary structure, a sequence of gaps can be modeled as a sequence of codewords $\{c_k\}$, each being a reference to a dictionary entry, as represented with the *encoded stream* in the picture. Note that, for example, codeword c_9 signals an exception, and therefore the next symbol e is decoded using an escape mechanism.

Experiments!

Metrics

Space Effectiveness

Average number of bits for the representation of a document identifier

Time Efficiency

Time needed to perform sequential decoding, intersection, and union of inverted lists

Experimental Setup

Tests random 1k of each number of queries per intersection/union

(a) Basic Statistics

	Gov2	ClueWeb09	CCNews
Lists	39,177	96,722	76,474
Universe	24,622,347	50,131,015	43,530,315
Integers	5,322,883,266	14,858,833,259	19,691,599,096
Entropy of the gaps	3.02	4.46	5.44
$\lceil \log_2 \rceil$ of the gaps	1.35	2.28	2.99

(b) TREC 2005/06 Queries

		Gov2	ClueWeb09	CCNews
Qı	ueries	34,327	42,613	22,769
2	terms	32.2%	33.6%	37.5%
3	terms	26.8%	26.5%	27.3%
4	terms	18.2%	17.7%	16.8%
5+	terms	22.8%	22.2%	18.4%



Method	Partitioned by	SIMD	Alignment	Description				
VByte	Cardinality	Yes	Byte	Fixed-size partitions of 128				
Opt-VByte	Cardinality	Yes	Bit	Variable-size partitions				
BIC	Cardinality	No	Bit	Fixed-size partitions of 128				
δ	Cardinality	No	Bit	Fixed-size partitions of 128				
Rice	Cardinality	No	Bit	Fixed-size partitions of 128				
PEF Cardinality		No	Bit	Variable-size partitions				
DINT	Cardinality	No	16-bit word	Fixed-size partitions of 128				
Opt-PFor	Cardinality	No	32-bit word	Fixed-size partitions of 128				
Simple 16	Cardinality	No	64-bit word	Ffixed-size partitions of 128				
QMX	Cardinality	Yes	128-bit word	Fixed-size partitions of 128				
Roaring	Universe	Yes	byte	Single span				
Slicing	Universe	Yes	byte	Multi-span				

64 GB RAM DDR4
Linux 5
C++, GCC 9.2.1
Indexes in internal memory,
data structures on disk
Average across three runs

Results (Space + Decoding Time)

Table 11. Space Effectiveness in Total GiB and Bits per Integer, and Nanoseconds per Decoded Integer

Method	(1)	Gov2		(ClueWeb()9	Sa. Maria	CCNews				
Method	GiB	Bits/int	ns/int	GiB	Bits/int	ns/int	GiB	bits/int	ns/int			
VByte	5.46	8.81	0.96	15.92	9.20	1.09	21.29	9.29	1.03			
Opt-VByte	2.41	3.89	0.73	9.89	5.72	0.92	14.73	6.42	0.72			
BIC	1.82	2.94	5.06	7.66	4.43	6.31	12.02	5.24	6.97			
δ	2.32	3.74	3.56	8.95	5.17	3.72	14.58	6.36	3.85			
Rice	2.53	4.08	2.92	9.18	5.31	3.25	13.34	5.82	3.32			
PEF	1.93	3.12	0.76	8.63	4.99	1.10	12.50	5.45	1.31			
DINT	2.19	3.53	1.13	9.26	5.35	1.56	14.76	6.44	1.65			
Opt-PFor	2.25	3.63	1.38	9.45	5.46	1.79	13.92	6.07	1.53			
Simple16	2.59	4.19	1.53	10.13	5.85	1.87	14.68	6.41	1.89			
QMX	3.17	5.12	0.80	12.60	7.29	0.87	16.96	7.40	0.84			
Roaring	4.11	6.63	0.50	16.92	9.78	0.71	21.75	9.49	0.61			
Slicing	2.67	4.31	0.53	12.21	7.06	0.68	17.83	7.78	0.69			

Simpler, byte-aligned code, bitmaps, SIMD instructions

Results (Time for AND Queries)

Table 12. Milliseconds Spent per AND Query by Varying the Number of Query Terms

Mada d	Gov2						CI	ueWel	009		CCNews					
Method	2	3	4	5+	avg.	2	3	4	5+	avg.	2	3	4	5+	avg.	
VByte	2.2	2.8	2.7	3.3	2.8	10.2	12.1	13.7	13.9	12.5	14.0	22.4	19.7	21.9	19.5	
Opt-VByte	2.8	3.1	2.8	3.2	3.0	12.2	13.3	14.0	13.6	13.3	16.0	23.2	19.6	20.3	19.8	
BIC	6.8	9.7	10.4	13.2	10.0	31.7	44.2	51.5	53.8	45.3	45.6	79.7	76.9	88.8	72.8	
δ	4.6	6.3	6.5	8.2	6.4	20.9	28.3	33.5	34.5	29.3	28.6	50.9	48.0	55.6	45.8	
Rice	4.1	5.6	5.8	7.3	5.7	19.2	25.7	30.2	31.1	26.6	26.5	46.5	43.5	50.1	41.6	
PEF	2.5	3.1	2.8	3.2	2.9	12.3	13.5	14.4	13.8	13.5	17.2	24.6	21.0	21.9	21.2	
DINT	2.5	3.3	3.3	4.1	3.3	11.9	14.6	16.5	17.1	15.0	16.9	27.3	24.6	28.1	24.2	
Opt-PFor	2.6	3.5	3.5	4.3	3.5	12.8	15.9	18.0	18.3	16.3	16.6	27.2	24.3	27.1	23.8	
Simple 16	2.8	3.7	3.7	4.6	3.7	12.8	16.3	18.4	18.9	16.6	17.6	28.8	26.3	29.5	25.5	
QMX	2.0	2.6	2.5	3.0	2.5	9.6	11.5	13.0	13.1	11.8	13.3	21.5	18.8	20.8	18.6	
Roaring	0.3	0.5	0.7	0.8	0.6	1.5	2.5	3.1	4.3	2.9	1.1	2.0	2.6	4.1	2.5	
Slicing	0.3	1.0	1.2	1.6	1.0	1.5	4.5	5.4	6.7	4.5	1.8	4.3	5.1	6.0	4.3	

Results (Time for OR Queries)

Table 13. Milliseconds Spent per OR Query by Varying the Number of Query Terms

Method		Gov2						lueWel	009		CCNews					
Method	2	3	4	5+	avg.	2	3	4	5+	avg.	2	3	4	5+	avg.	
VByte	6.8	24.4	54.7	131.7	54.4	20.1	71.3	156.0	379.5	156.7	24.4	94.5	178.8	391.4	172.3	
Opt-VByte	11.0	35.7	77.4	176.0	75.0	31.3	101.4	213.4	500.1	211.6	36.4	128.0	232.0	510.4	226.7	
BIC	16.7	50.3	105.0	238.8	102.7	49.9	145.3	290.4	668.2	288.4	64.4	193.8	332.6	692.5	320.8	
δ	12.6	40.8	87.9	202.5	85.9	34.9	112.9	236.7	557.7	235.6	42.2	144.9	263.8	571.3	255.5	
Rice	13.4	43.1	93.3	211.3	90.3	36.8	118.2	248.5	576.6	245.0	43.6	149.3	270.5	585.6	262.2	
PEF	10.2	33.0	71.7	164.2	69.8	31.1	99.7	208.5	492.3	207.9	37.6	127.5	232.6	507.1	226.2	
DINT	8.5	28.5	63.7	147.6	62.1	24.9	84.1	178.8	424.3	178.0	30.6	109.2	200.4	432.7	193.2	
Opt-PFor	8.9	31.1	69.4	161.4	67.7	27.0	90.8	194.0	453.5	191.3	31.3	113.2	209.0	447.2	200.2	
Simple16	7.8	26.2	58.3	138.2	57.6	23.7	78.0	165.5	394.7	165.5	28.7	101.5	185.3	397.8	178.4	
QMX	6.6	23.8	53.4	128.1	53.0	19.7	70.0	153.2	377.9	155.2	24.0	92.6	175.2	382.4	168.6	
Roaring	1.2	2.8	4.3	6.4	3.7	4.7	9.0	12.0	15.7	10.3	3.8	7.6	10.5	15.1	9.2	
Slicing	1.3	4.0	6.3	9.2	5.2	5.0	12.8	18.1	25.3	15.3	5.8	12.9	17.3	23.0	14.8	

Results (Time/Space)

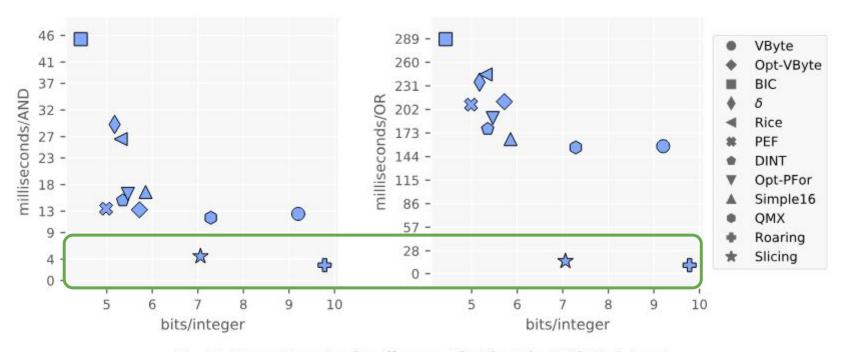
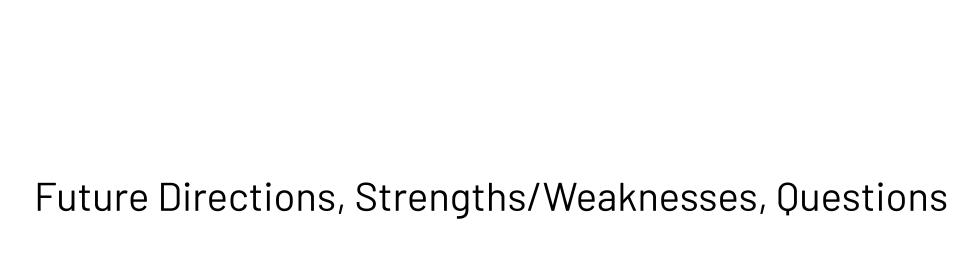


Fig. 7. Space/time trade-off curves for the ClueWeb09 dataset.



The Punchline: Directions for Future Work

 Simpler compression formats that can be decoded with low-latency instructions (bitwise) and few branches

2. Devising **dynamic and compressed representations** for integer sequences that can support additions and deletions

Strengths/Weaknesses

Strengths

Thorough description and evaluation of the different compressors

Weakness

- Nothing really novel contributed except maybe the comparisons(makes sense, it's a survey paper!)
- The evaluation could have explored more realistic queries instead of random queries

Discussion Questions

What are the benefits of these survey papers?

- 2. What are some trends you notice with the algorithms?
 - a. I'm definitely noticing (1) a shift from theoretically how small can the codes be to how can we make it faster (ex: byte-aligned) and (2) over time, the algorithms seems to get more complex

- 3. Which encoding schemes would you use in real-life scenarios (compaction vs. performance)? What are interesting areas these compressions schemes can be used beyond inverted index compression?
 - a. Could some reasonably be used for audio/video/image compression?