On Optimally Partitioning Variable-Byte Index Data

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UNIVERSITY

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Context - Inverted Indexes

We focus on compression effectiveness and retrieval speed in **inverted indexes**.

The inverted index is the *de-facto* data structure at the basis of every large-scale retrieval system.

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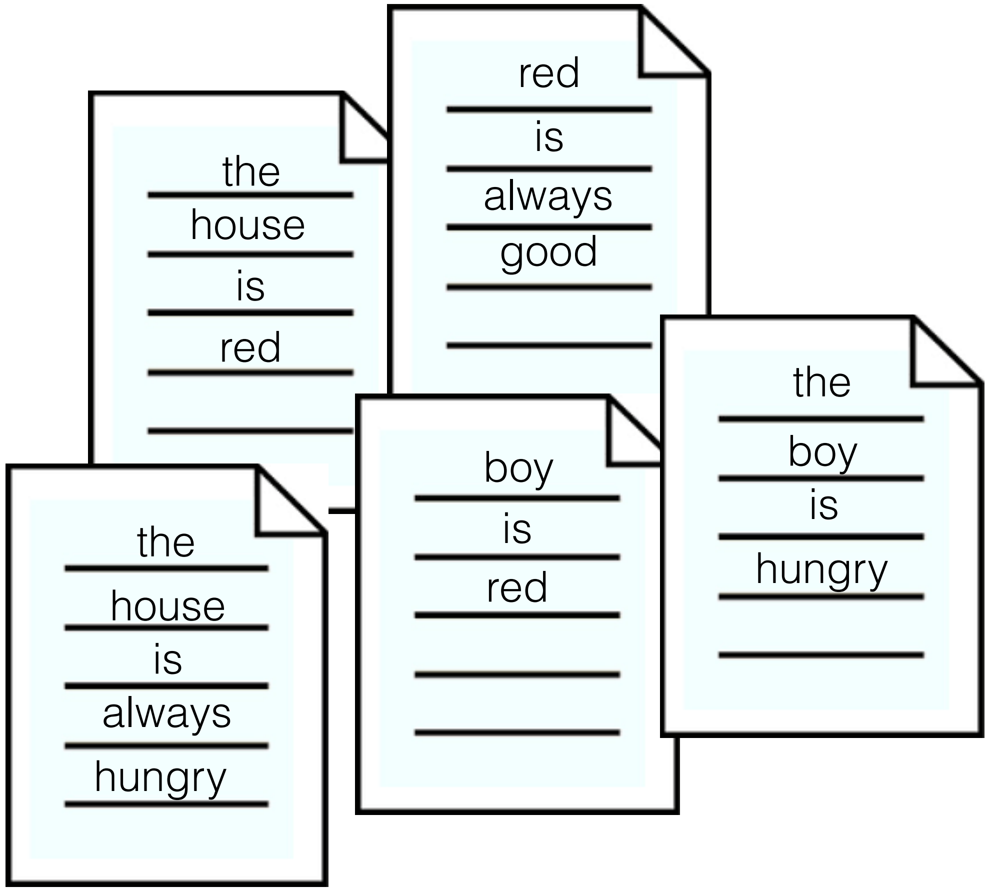

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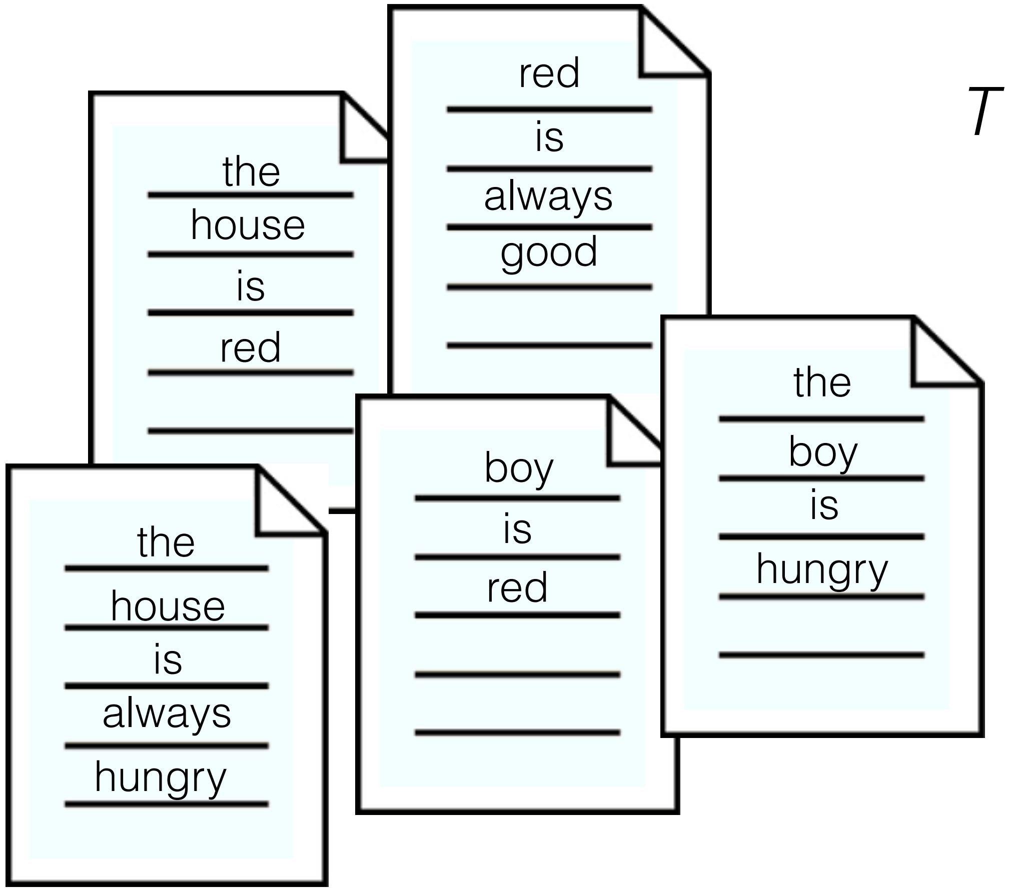

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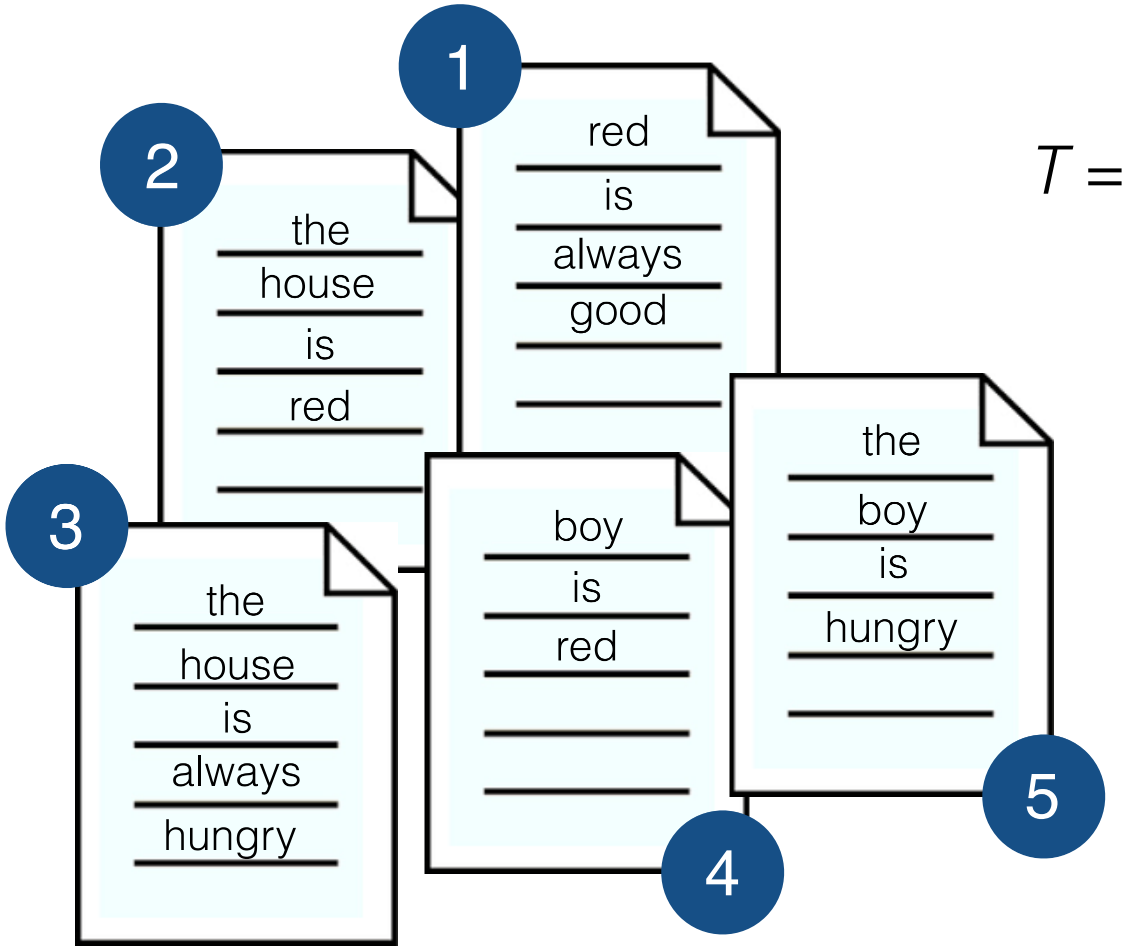

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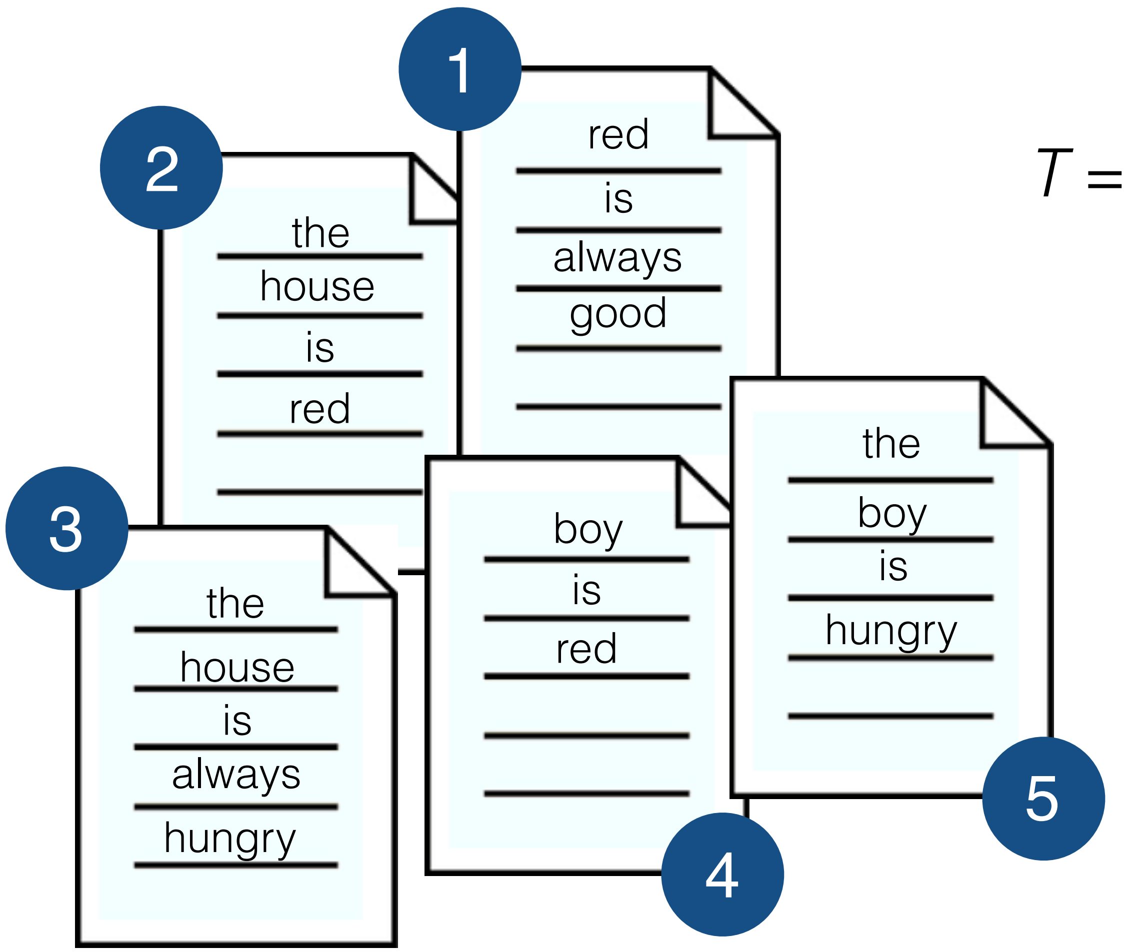

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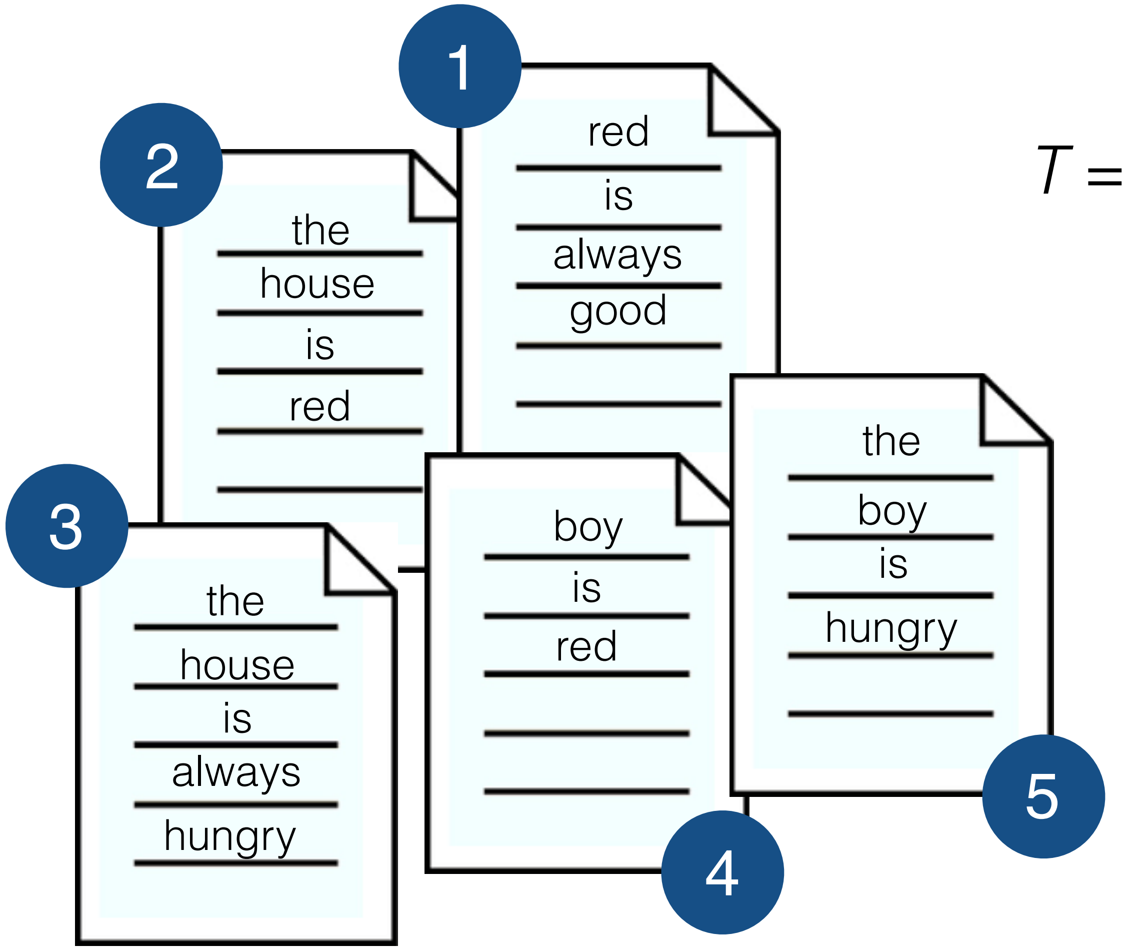

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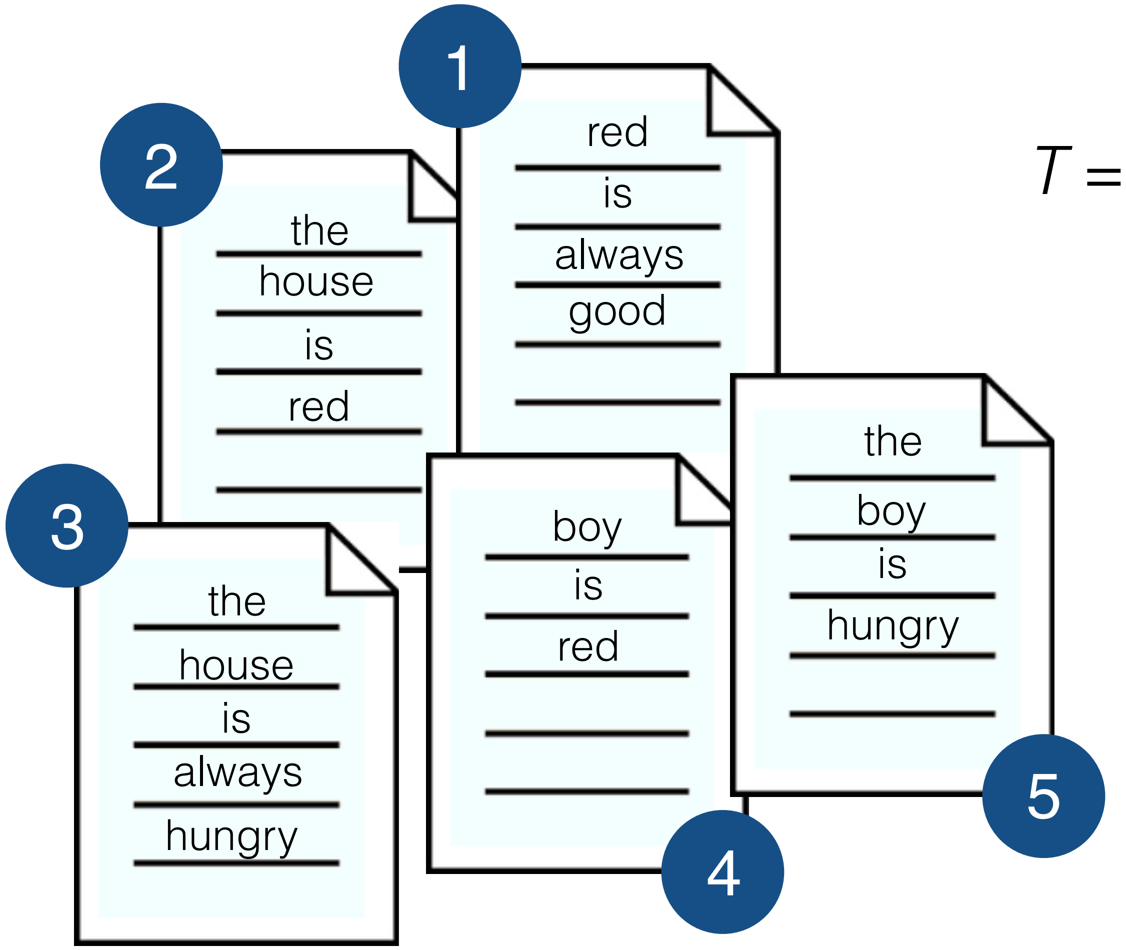

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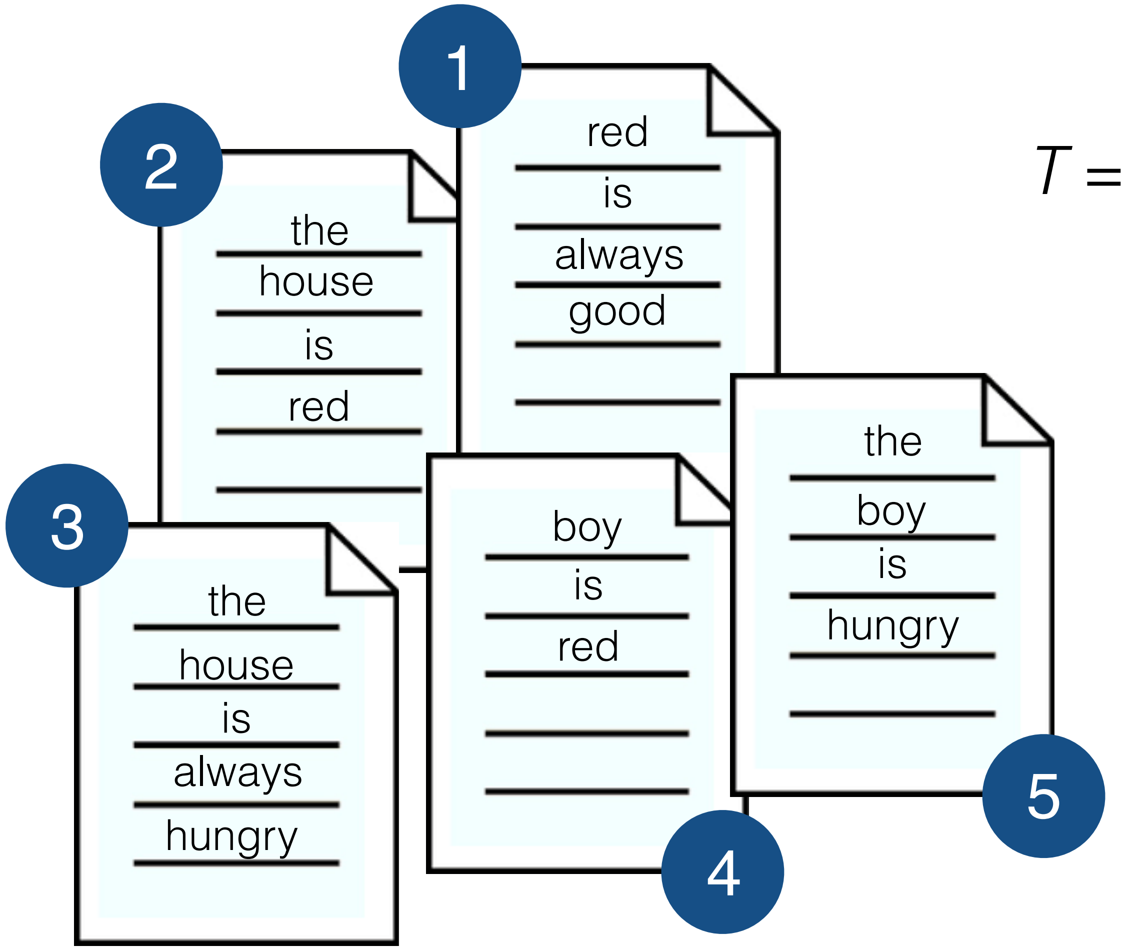

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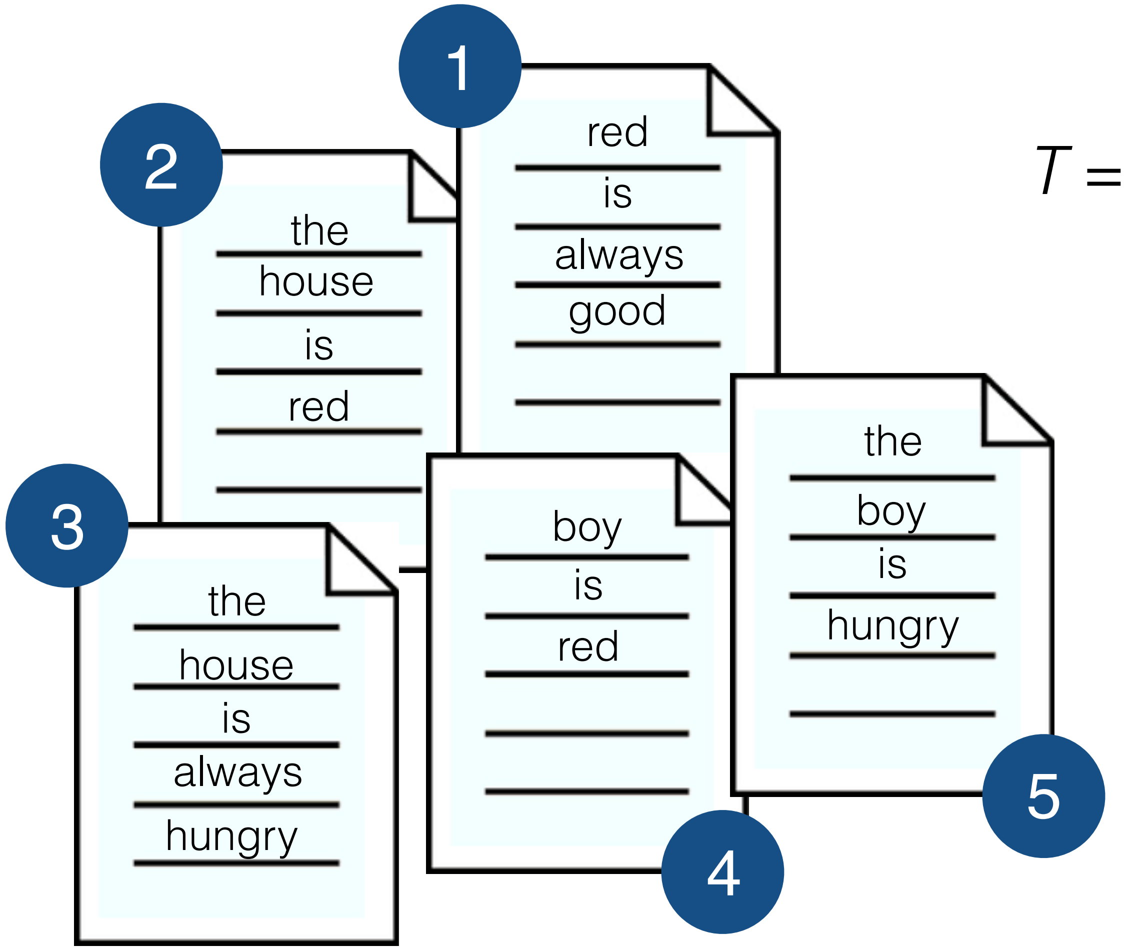

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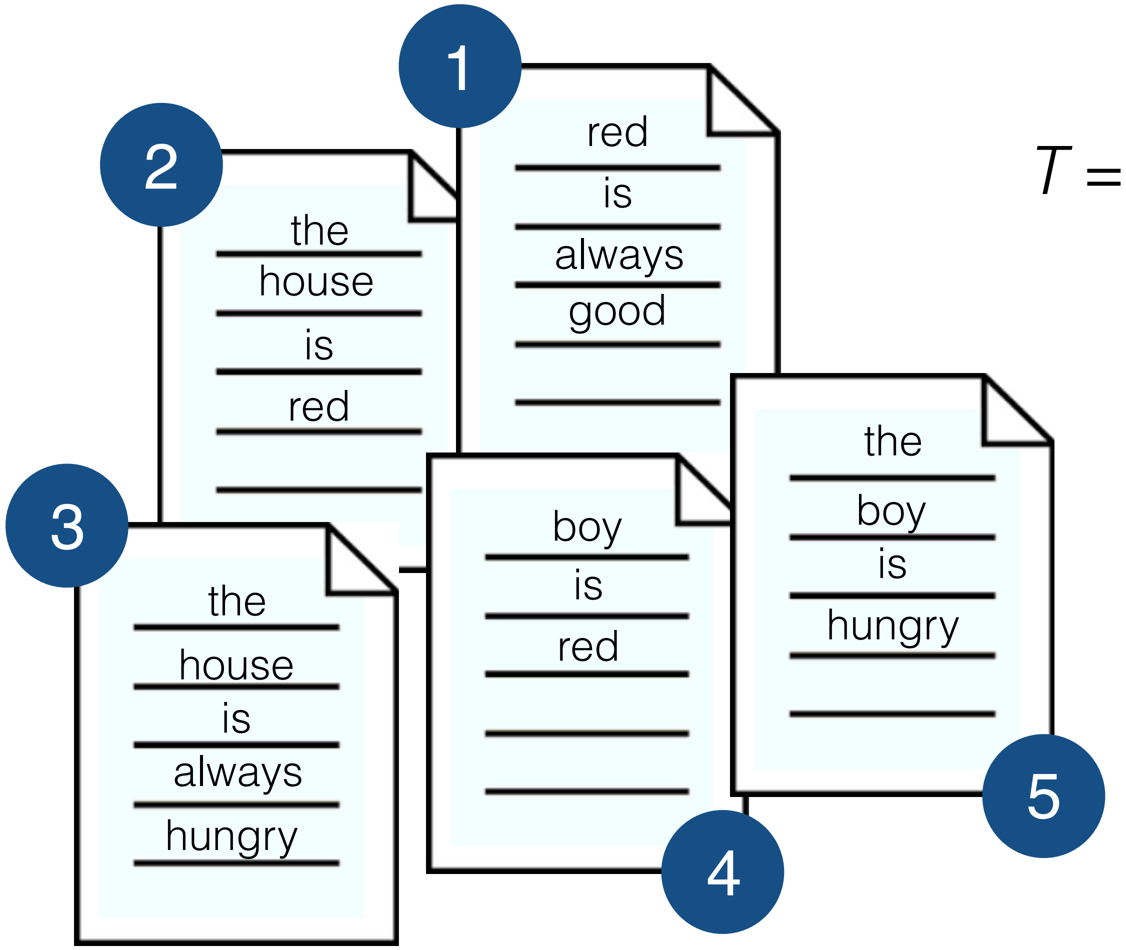

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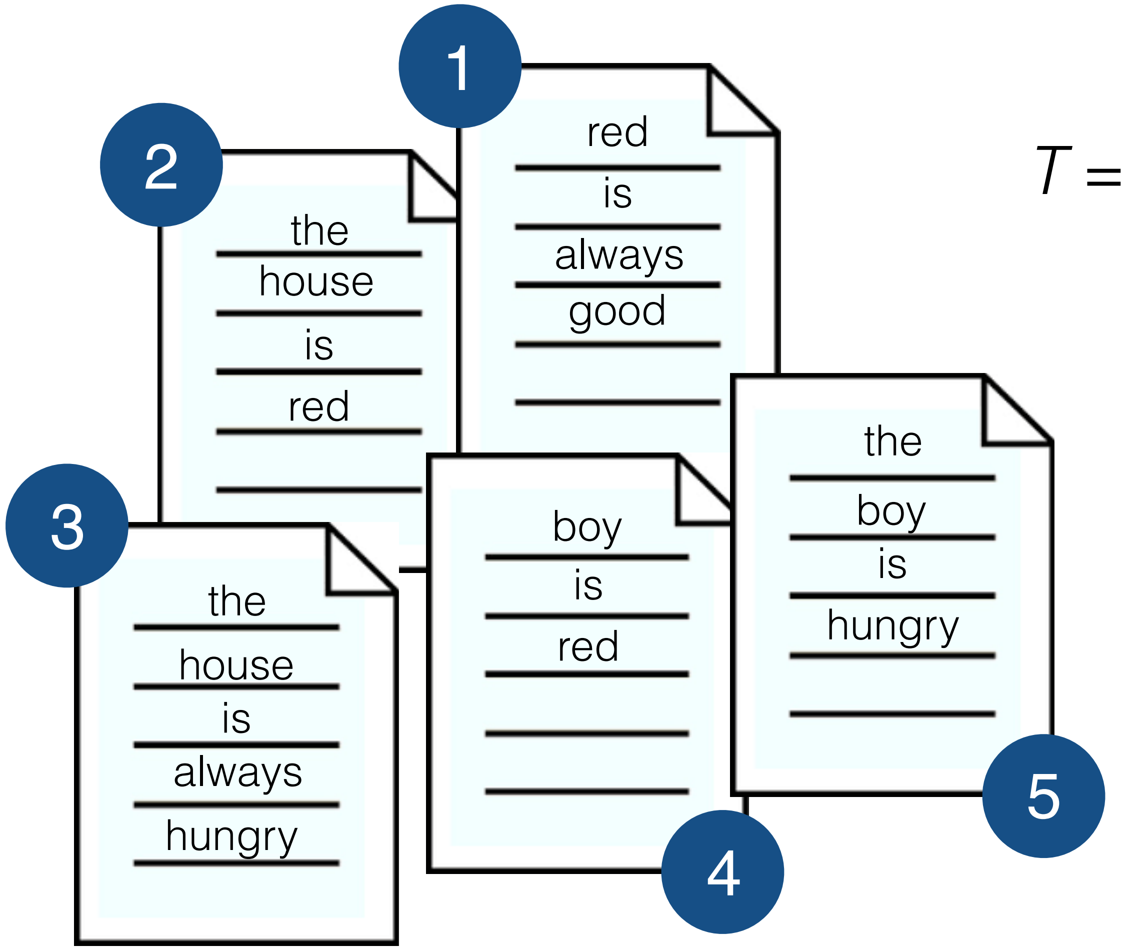

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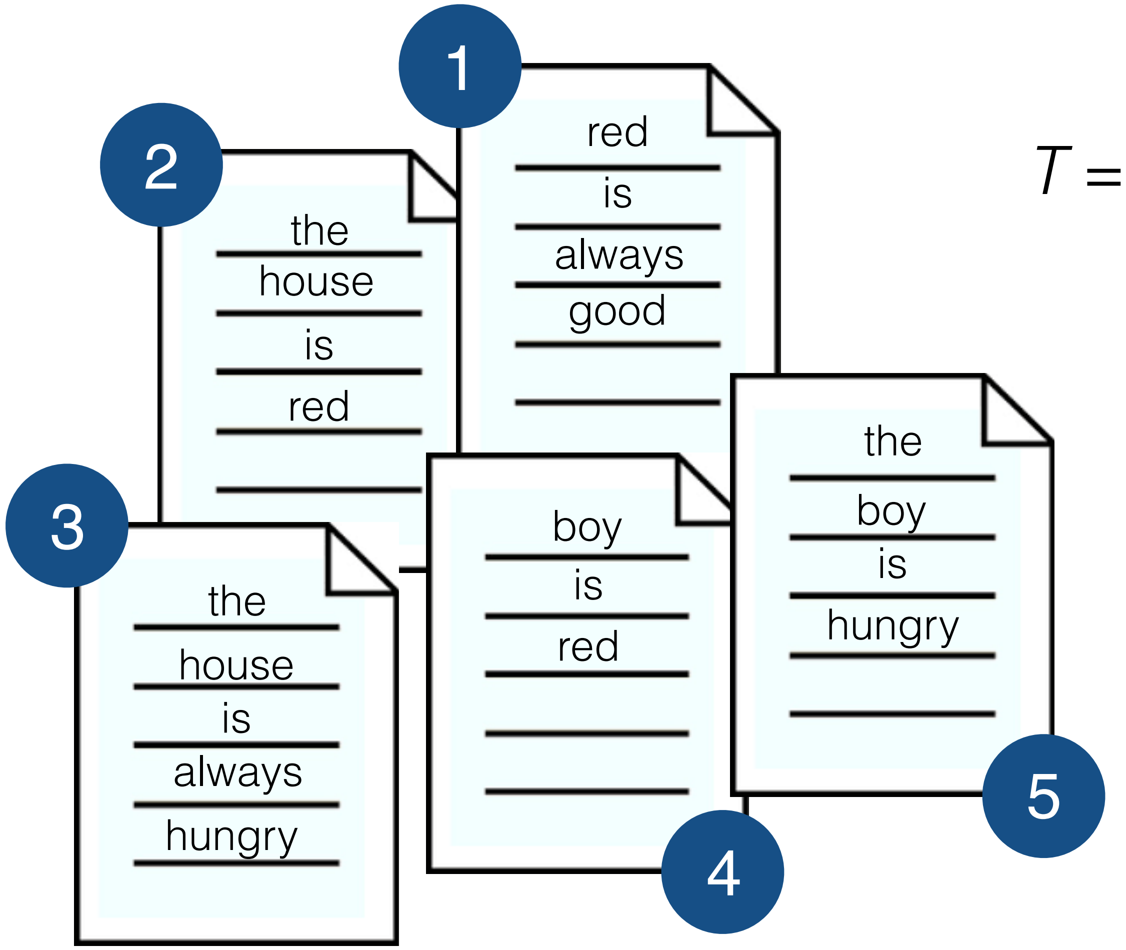

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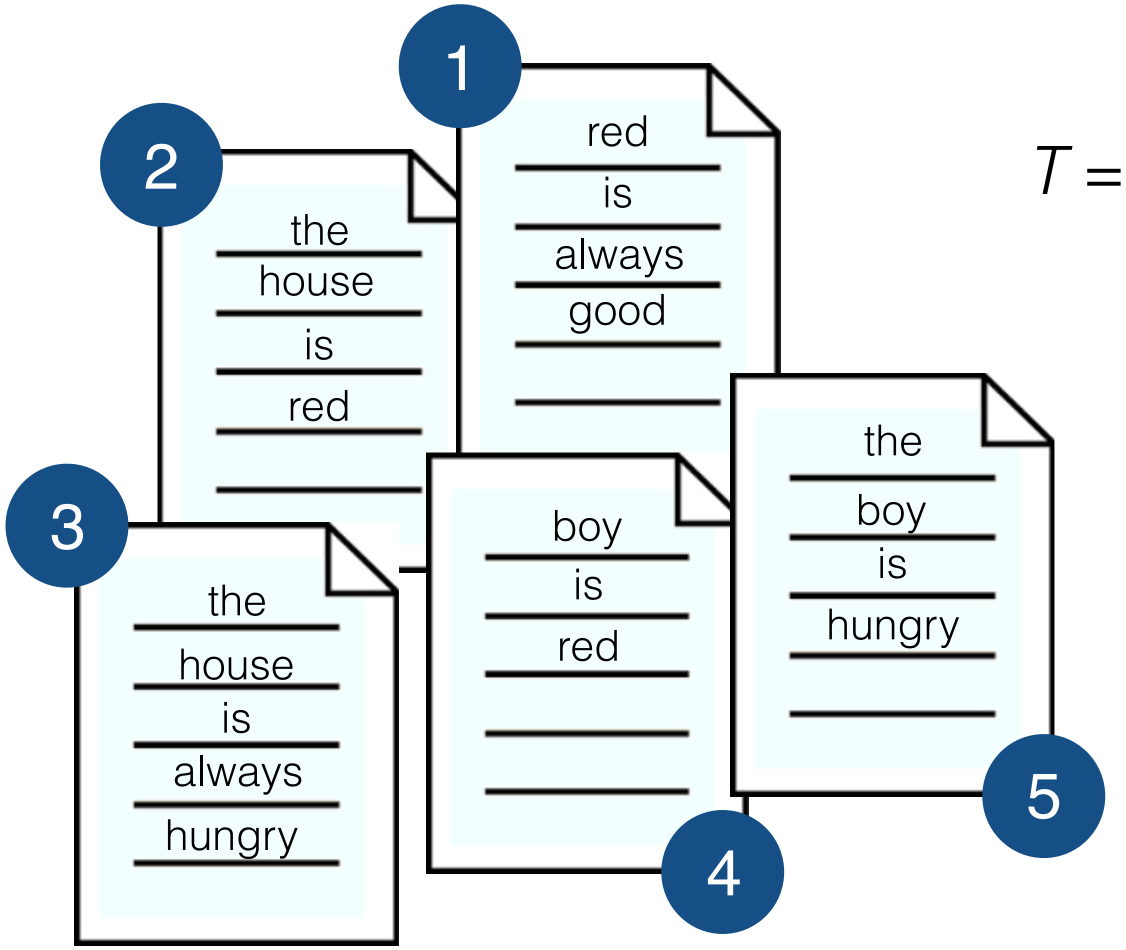

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Huge research corpora describing different **space/time** trade-offs.

- Elias gamma/delta
- Variable-Byte
- Binary Interpolative Coding
- Simple-9/16
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Space

Binary Interpolative Coding

~**3X** smaller

← Spectrum →

Time

Variable-Byte (VByte) Family

~**4.5X** faster

Our research question

Can we improve the space of a VByte-encoded sequence

and

preserve its query processing speed?

Variable-Byte Encoding

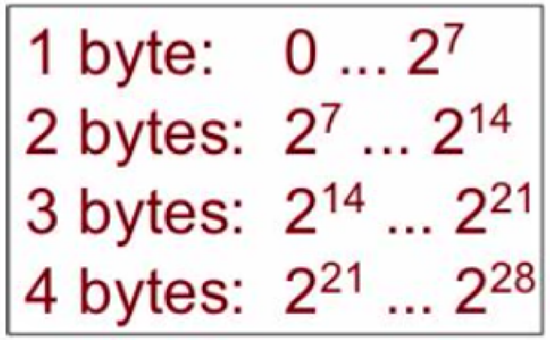
Simple idea: encode each number
using as few bytes as possible.

6 → **1**0000110

127 → **1**1111111

128 → **1**0000001**0**0000000

65790 → **1**0000100**1**0000000**0**1111110



1 byte: 0 ... 2^7
2 bytes: 2^7 ... 2^{14}
3 bytes: 2^{14} ... 2^{21}
4 bytes: 2^{21} ... 2^{28}

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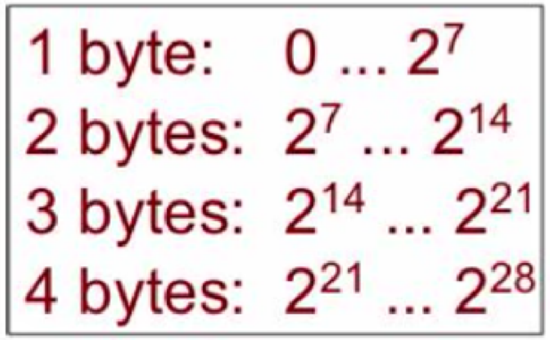

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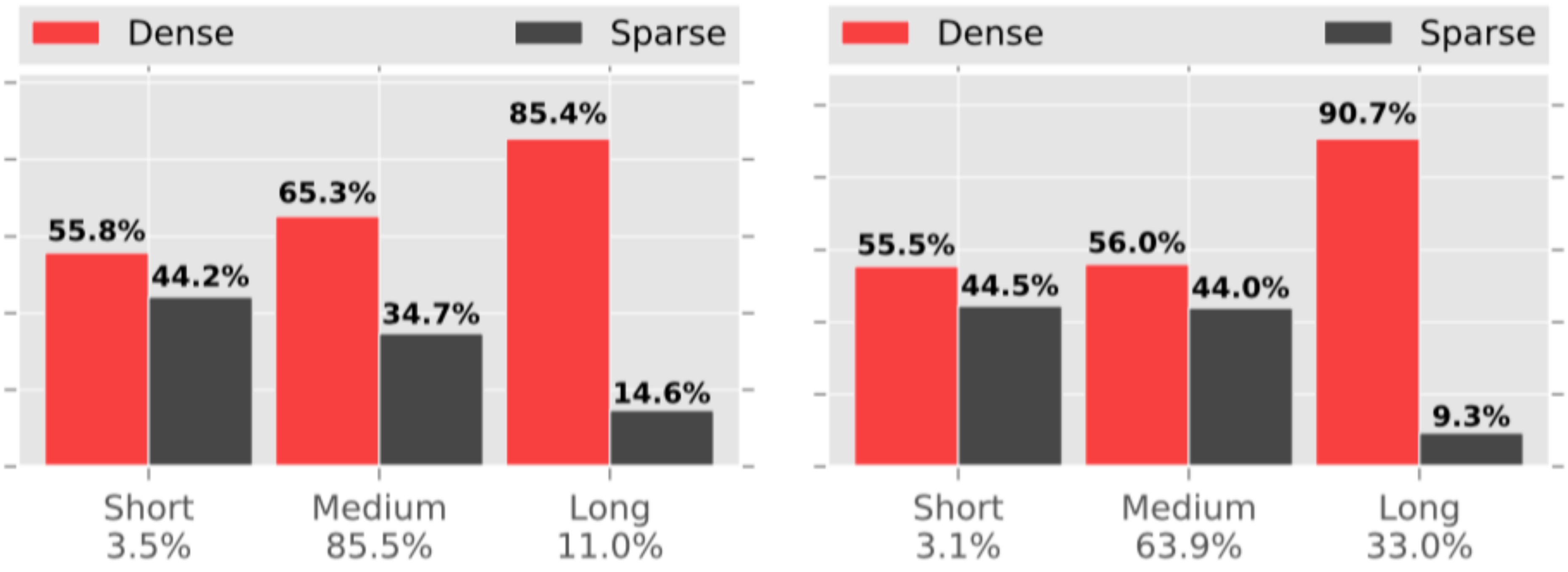
Decoding is **fast**:
keep reading bytes until you hit a value smaller than 128.

SIMD (Single Instruction Multiple Data)

So…what's "wrong" with VByte?



(a) Gov2 (b) ClueWeb09

The majority of values are **small** (*very* small indeed).

VByte needs **at least 8 bits** per integer (bpi).

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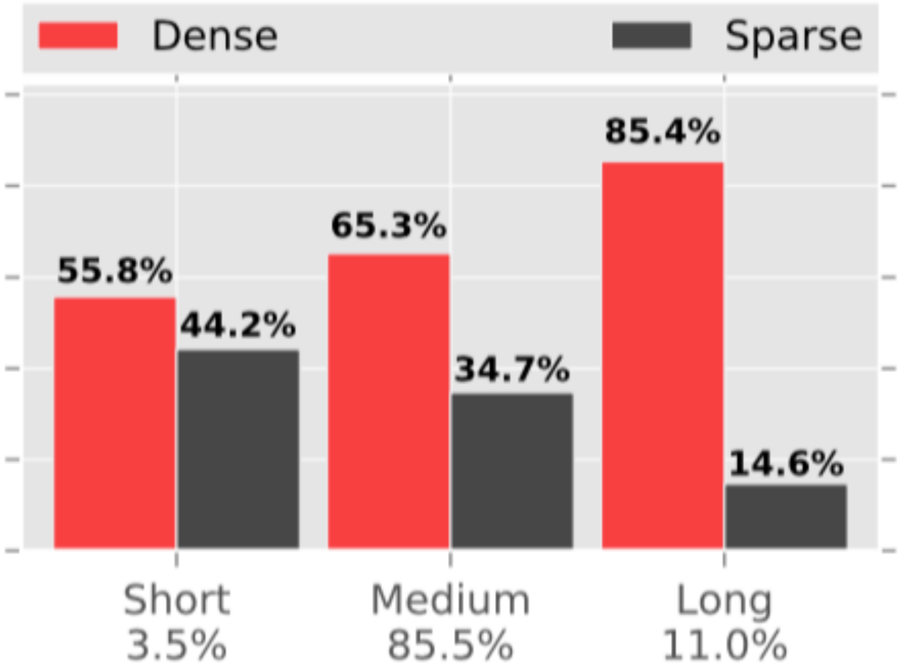

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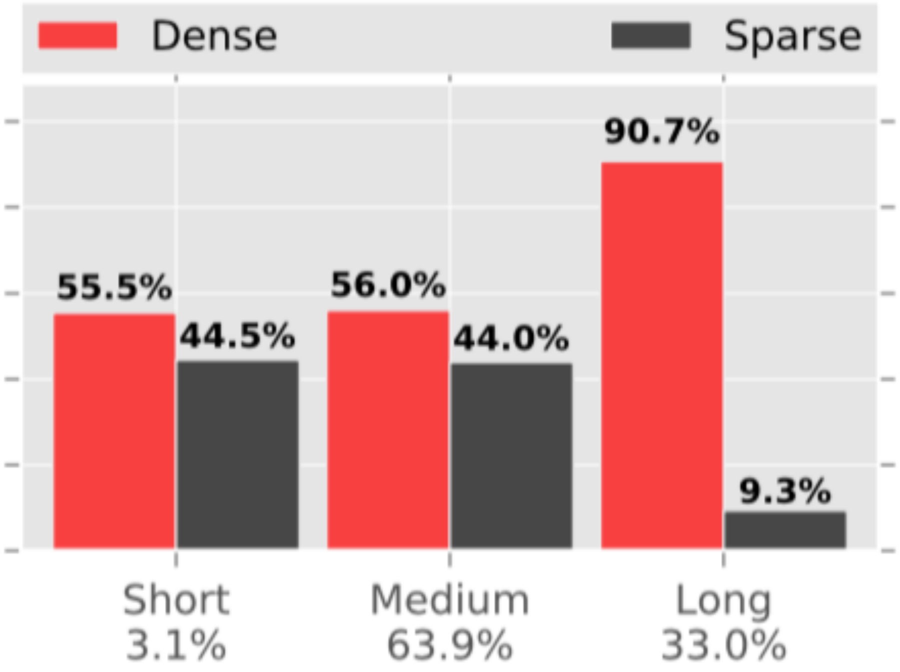

(b) ClueWeb09

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Sensibly far away from bit-level effectiveness.
BIC: **3.8** bpi on Gov2
PEF: **4.1** bpi on Gov2

High-level idea

1. Partition each inverted list into variable-length partitions.
2. Encode *dense* partitions with their **characteristic bitvector**.
3. Encode *sparse* partitions with **VByte**.

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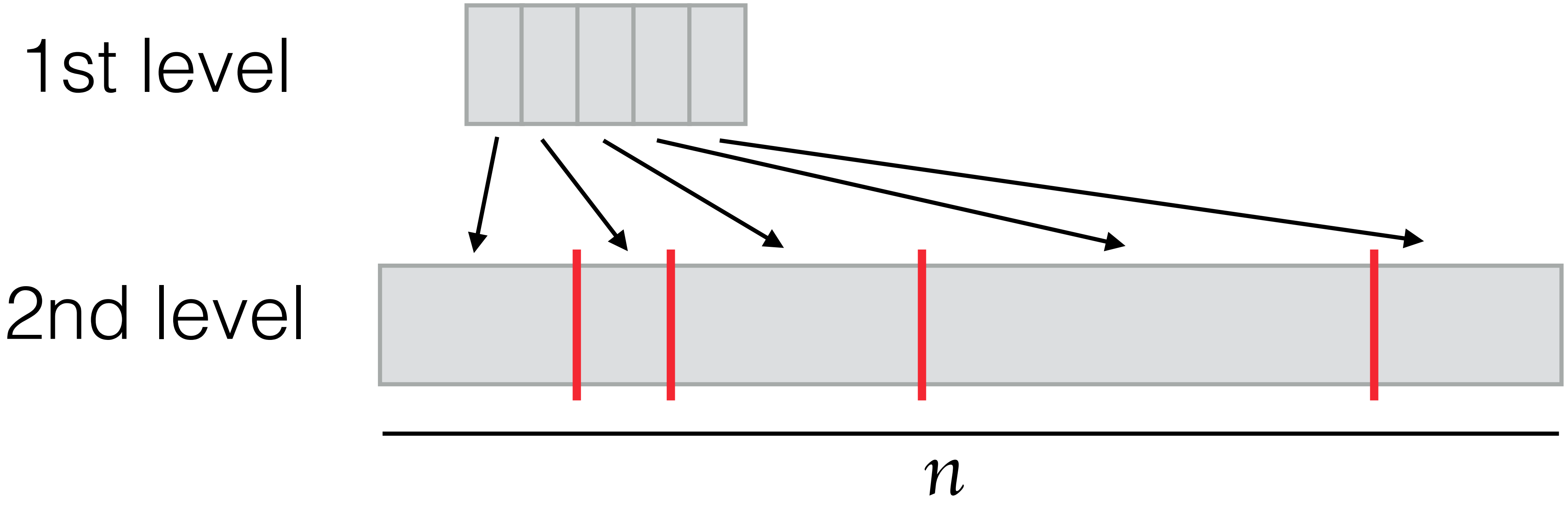
[13, 15, 16, 17, 20, 21, 23, 24]

1	0	**1**	**1**	**1**	0	0	**1**	**1**	0	**1**	**1**
13	14	15	16	17	18	19	20	21	22	23	24

24 - 13 - 1 = 12 bits VS 64 bits (**5.33X**)

Computing an optimal partition



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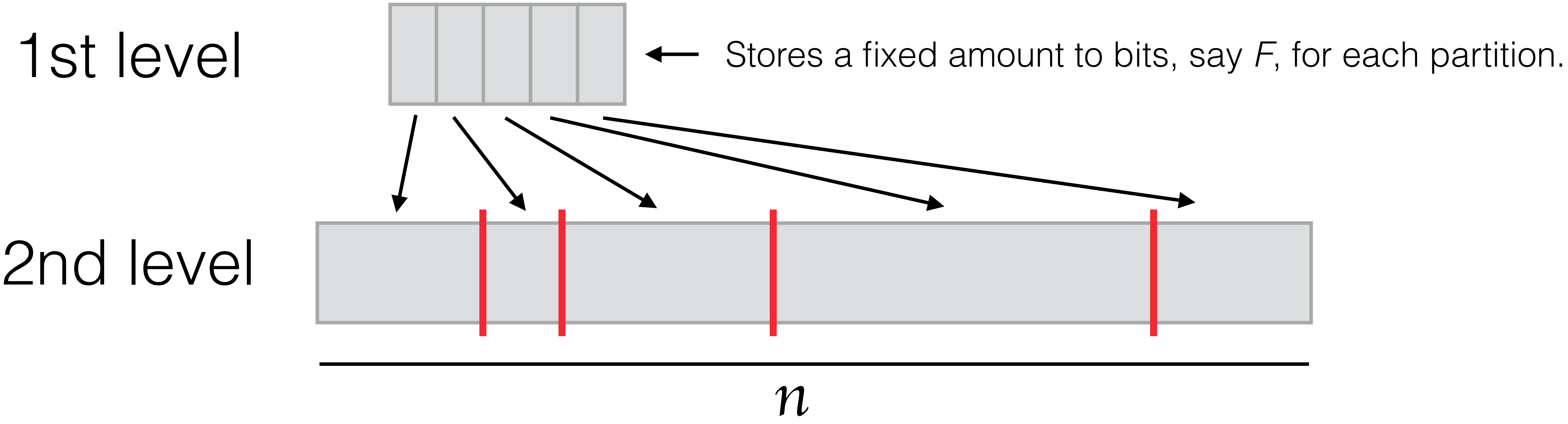

Stores a fixed amount to bits, say *F*, for each partition.

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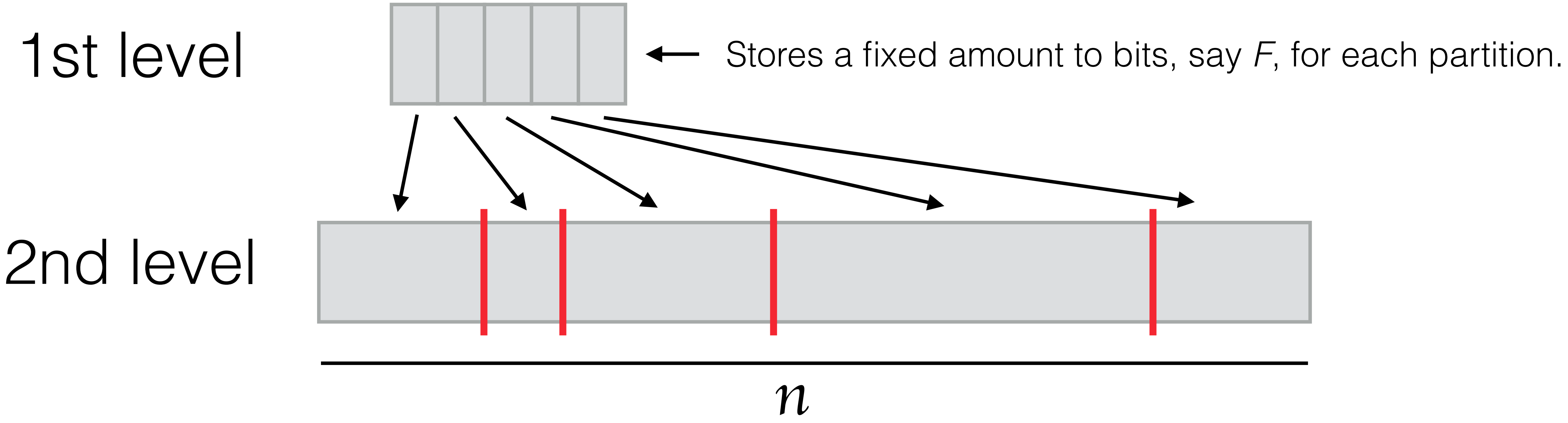

Dynamic Programming (DP)

guarantee

Optimal

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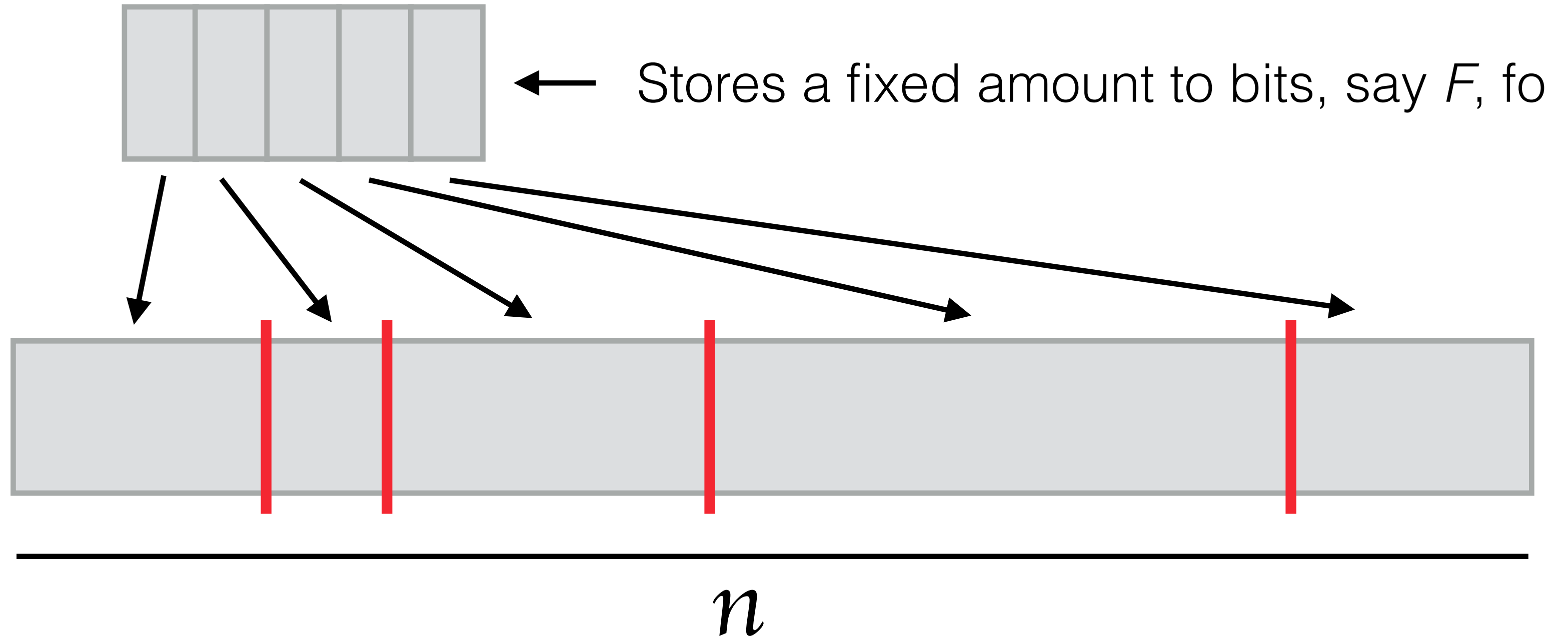

1st level

← Stores a fixed amount to bits, say *F*, for each partition.

2nd level

n

	guarantee	time	space	
Dynamic Programming (DP)	Optimal	$\Theta(n^2)$	$O(n)$	😑

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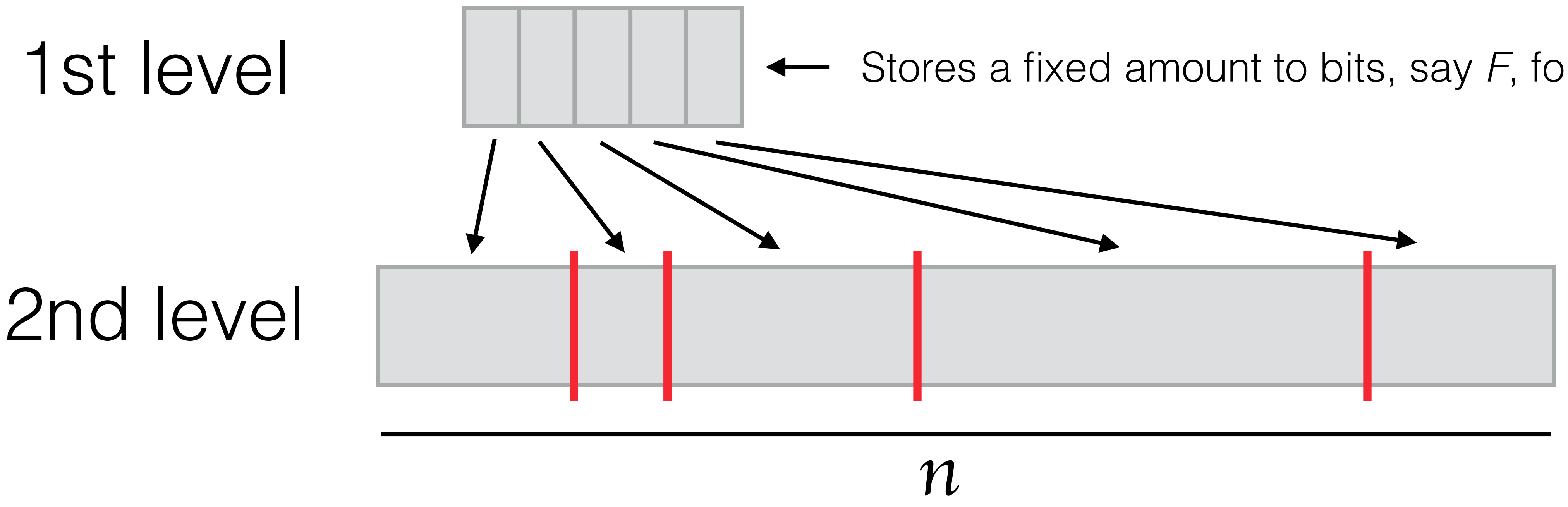

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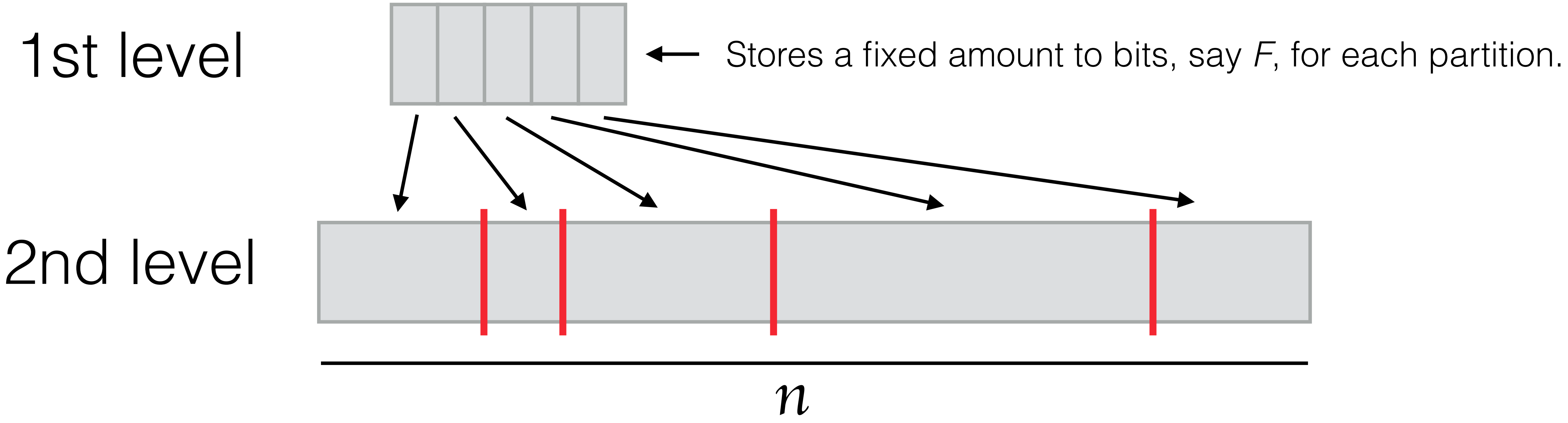

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Our solution	Optimal	$\Theta(n)$	$O(1)$	😍

Computing an optimal partition

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[8, 9, 10, 11, 12, 36, 37, 38, 39, 40]

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splitting	**Elias-Fano**	**VByte**
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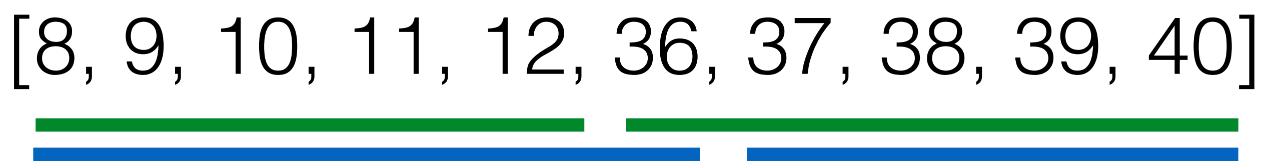

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Costs do NOT change if we consider different splittings.

Our solution - The intuition

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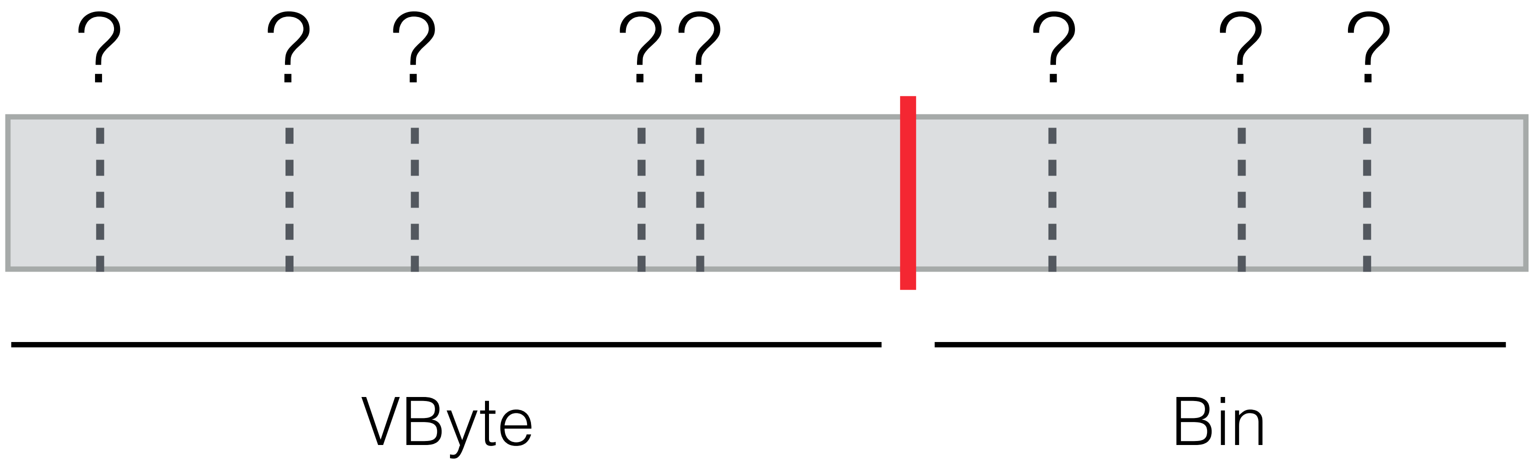

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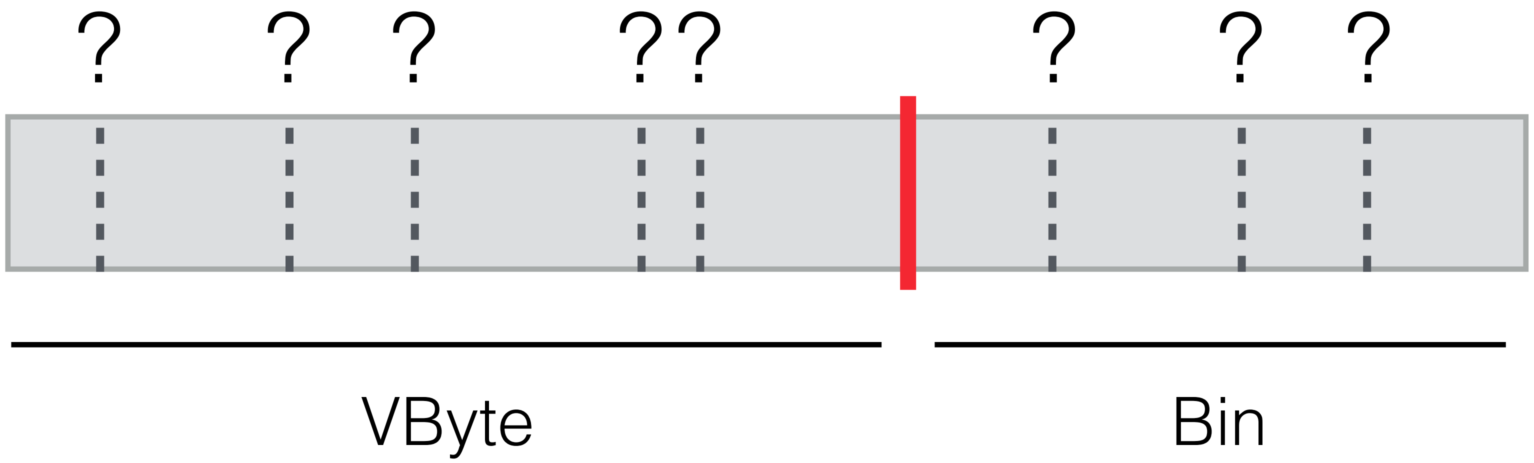

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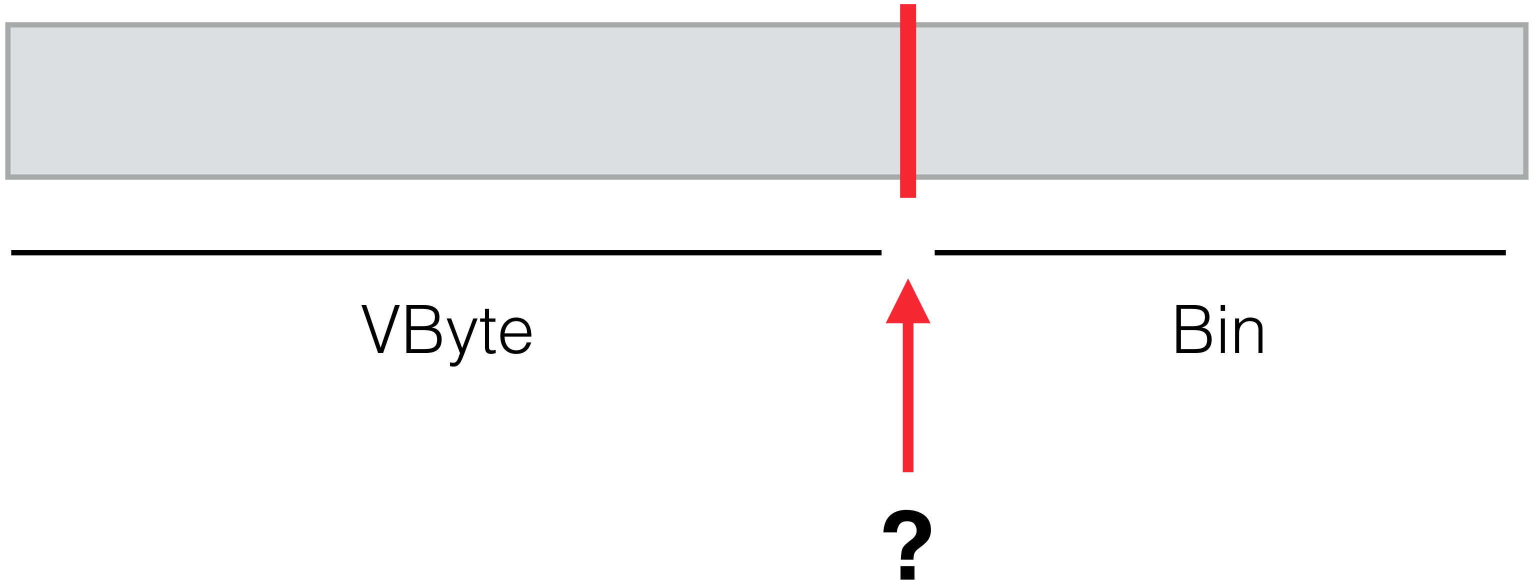

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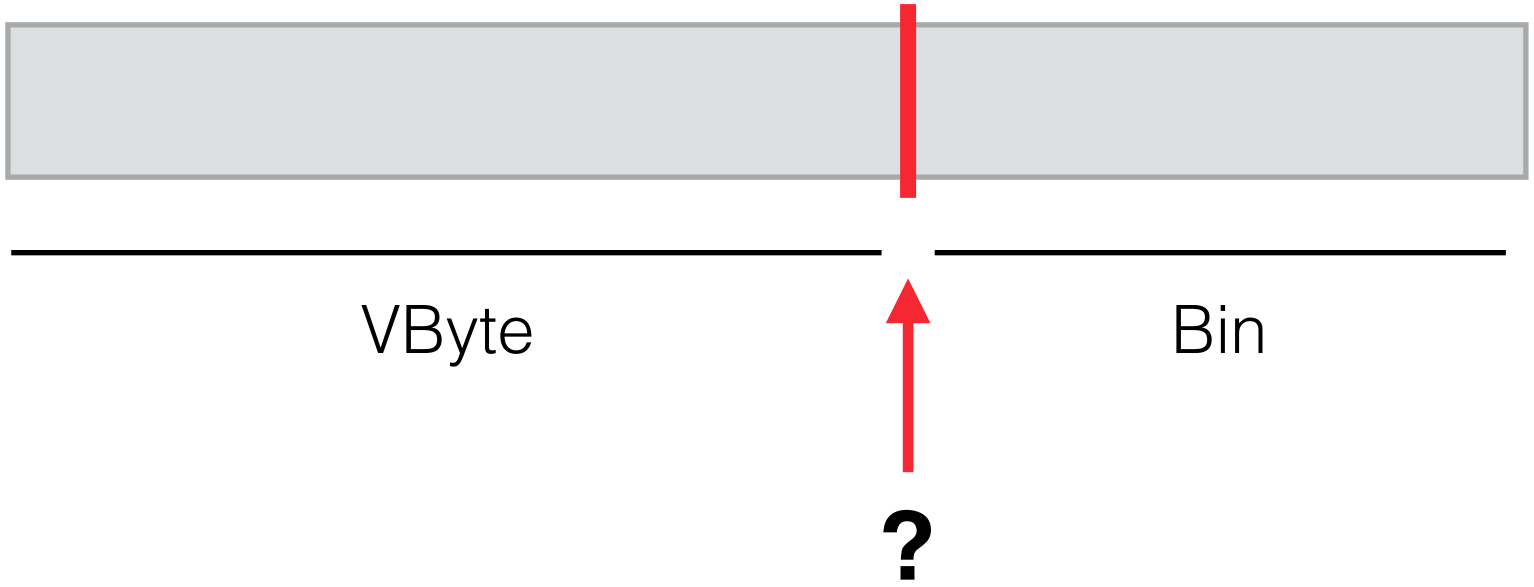

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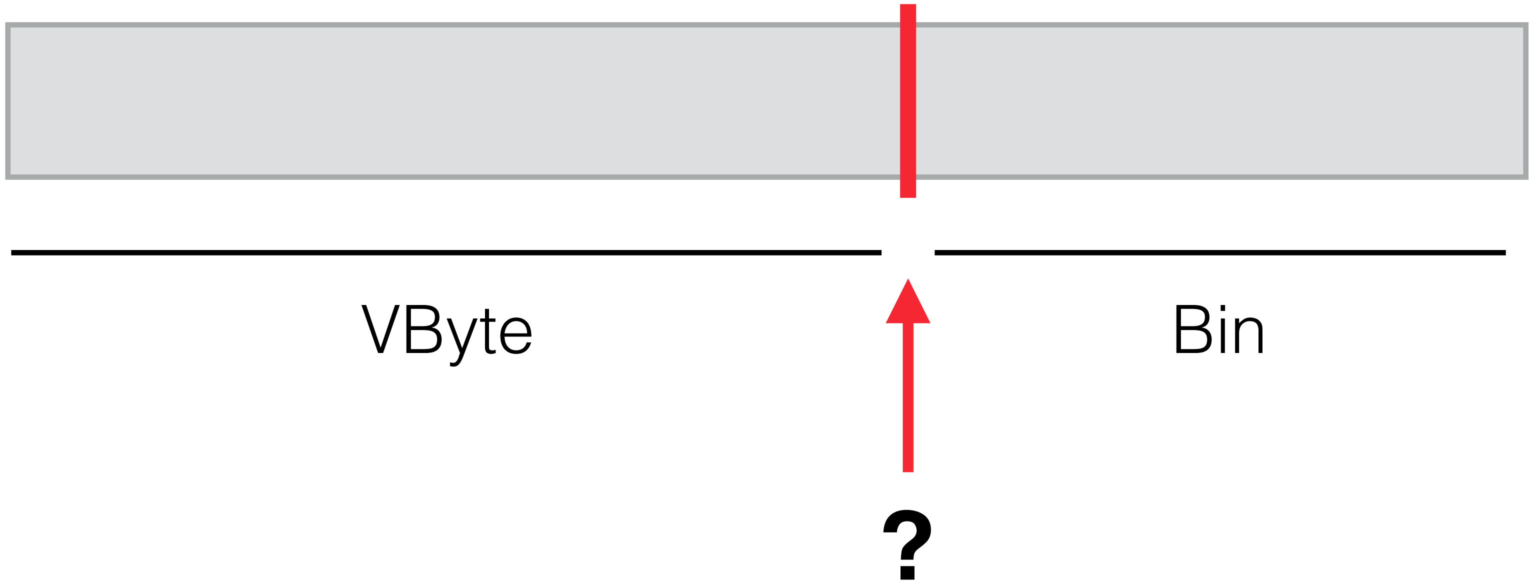

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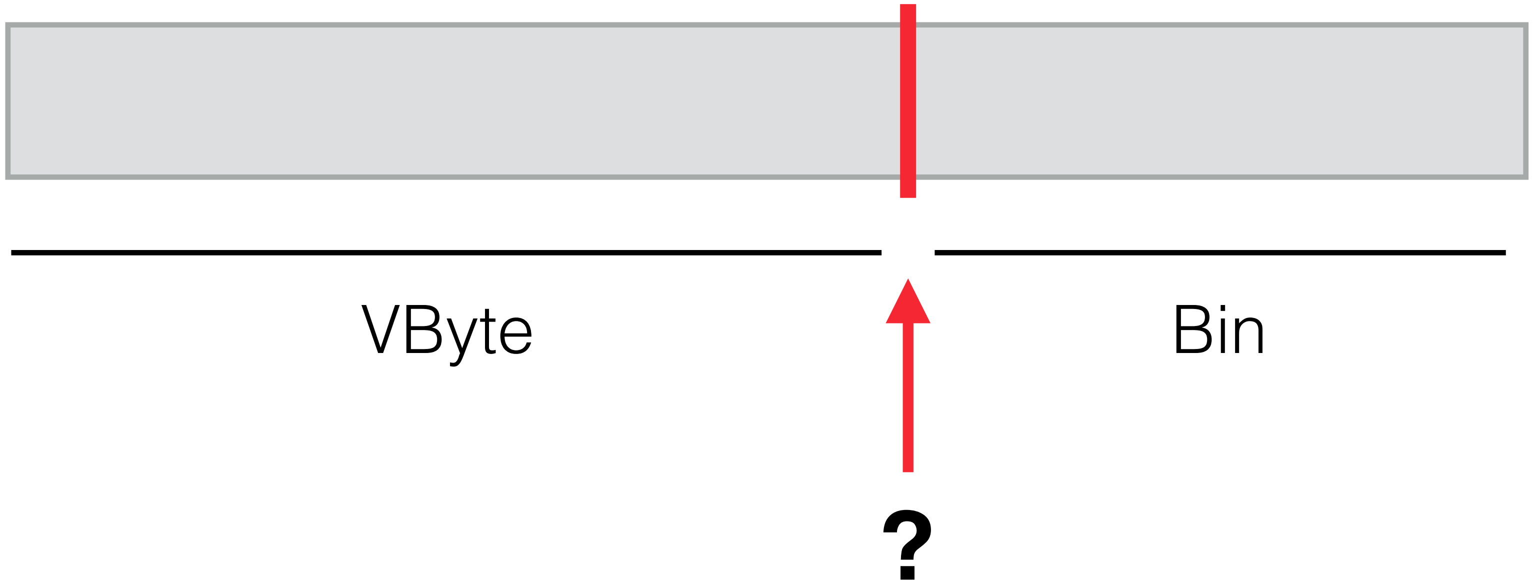

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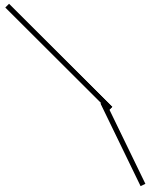
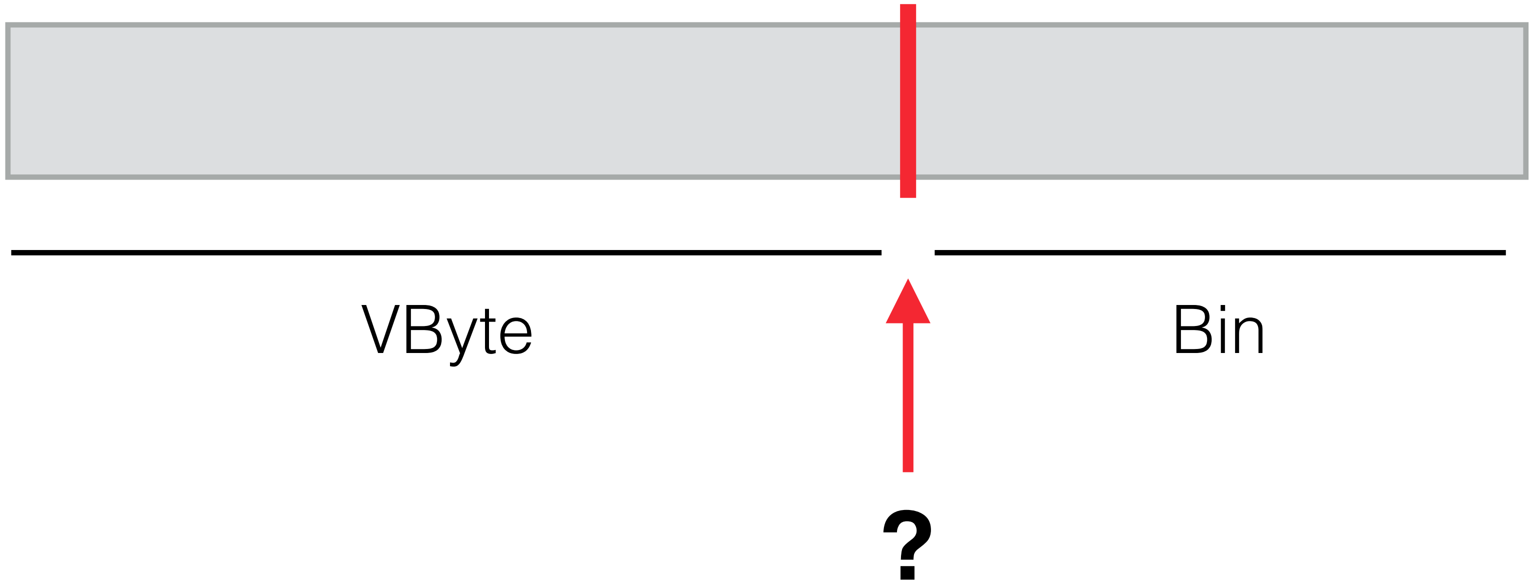


Our solution - The intuition



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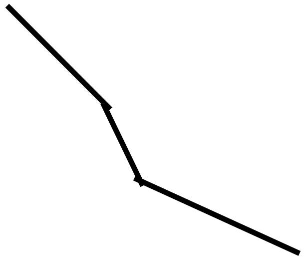

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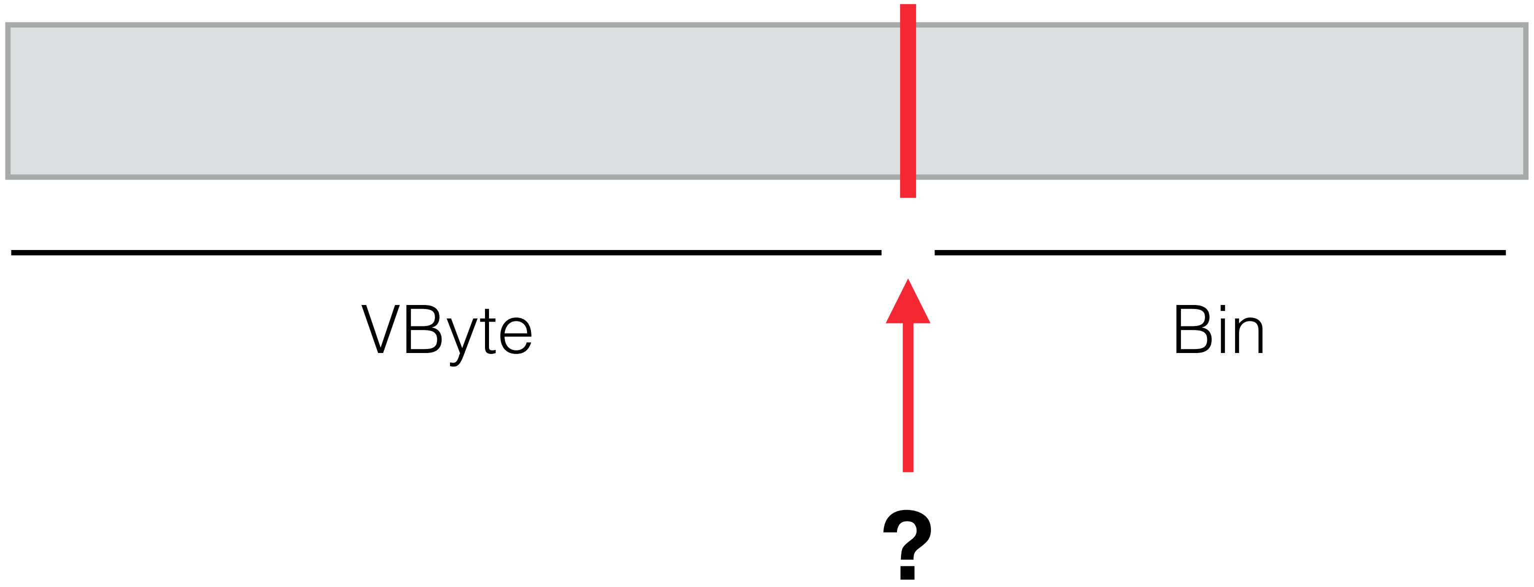

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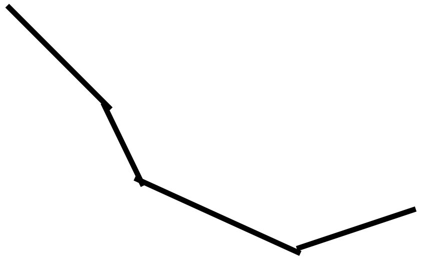

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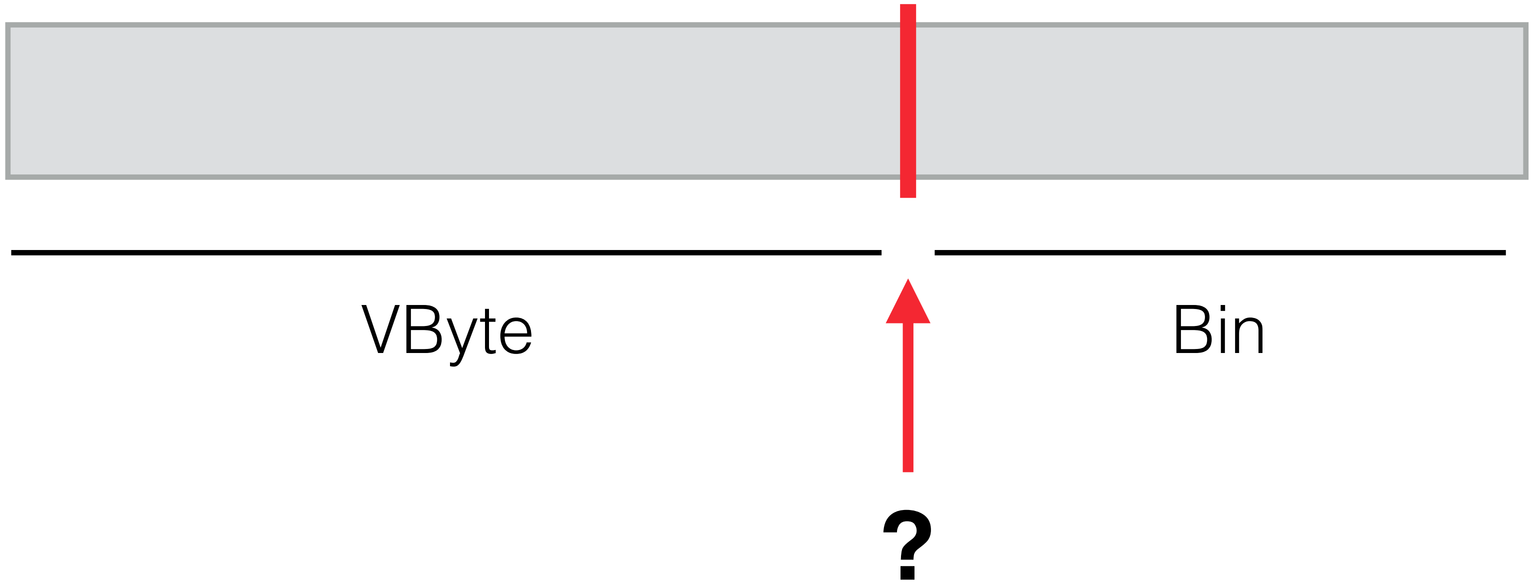

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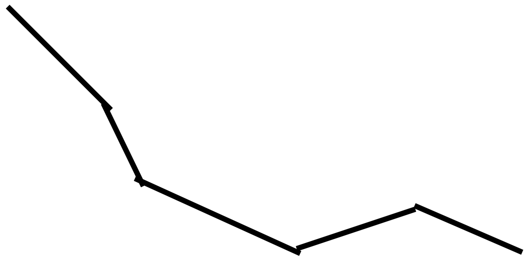

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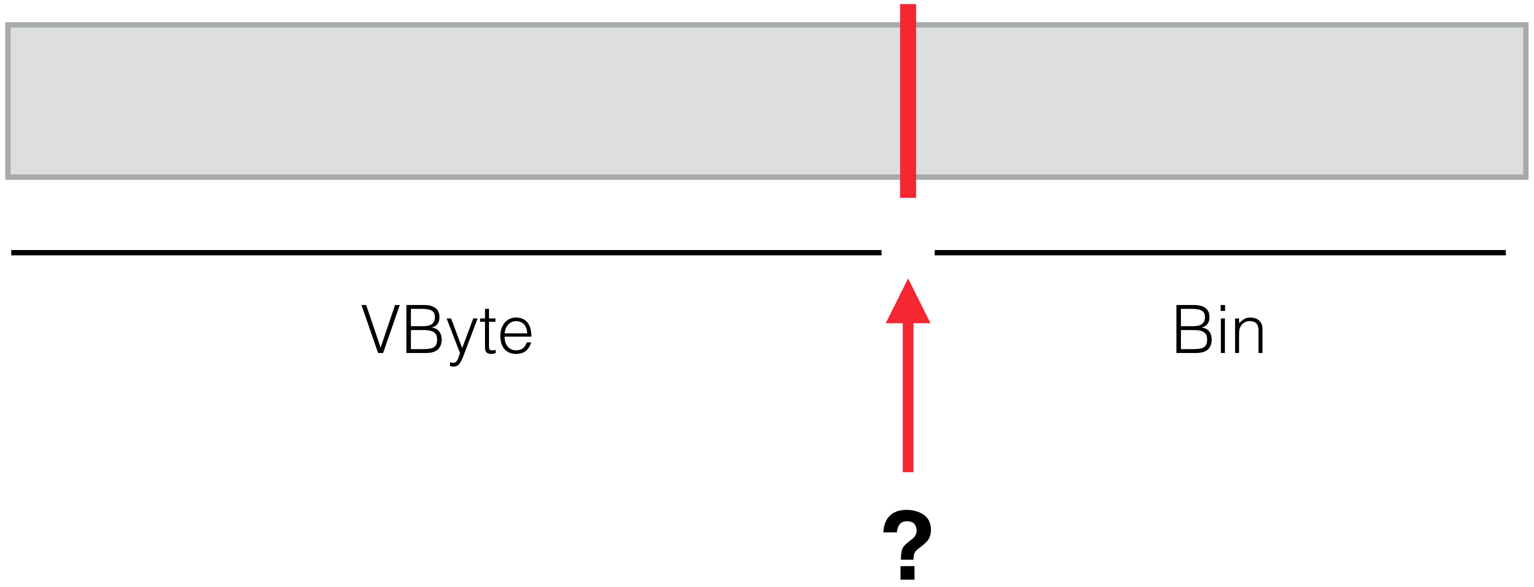

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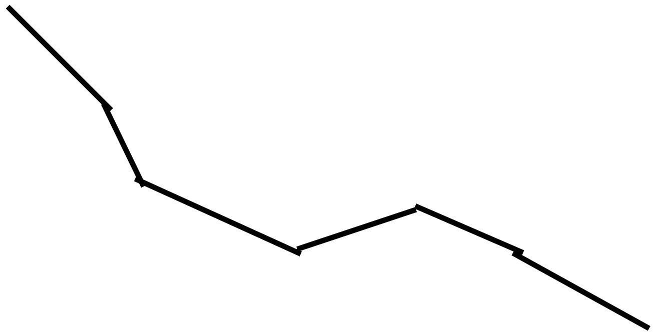

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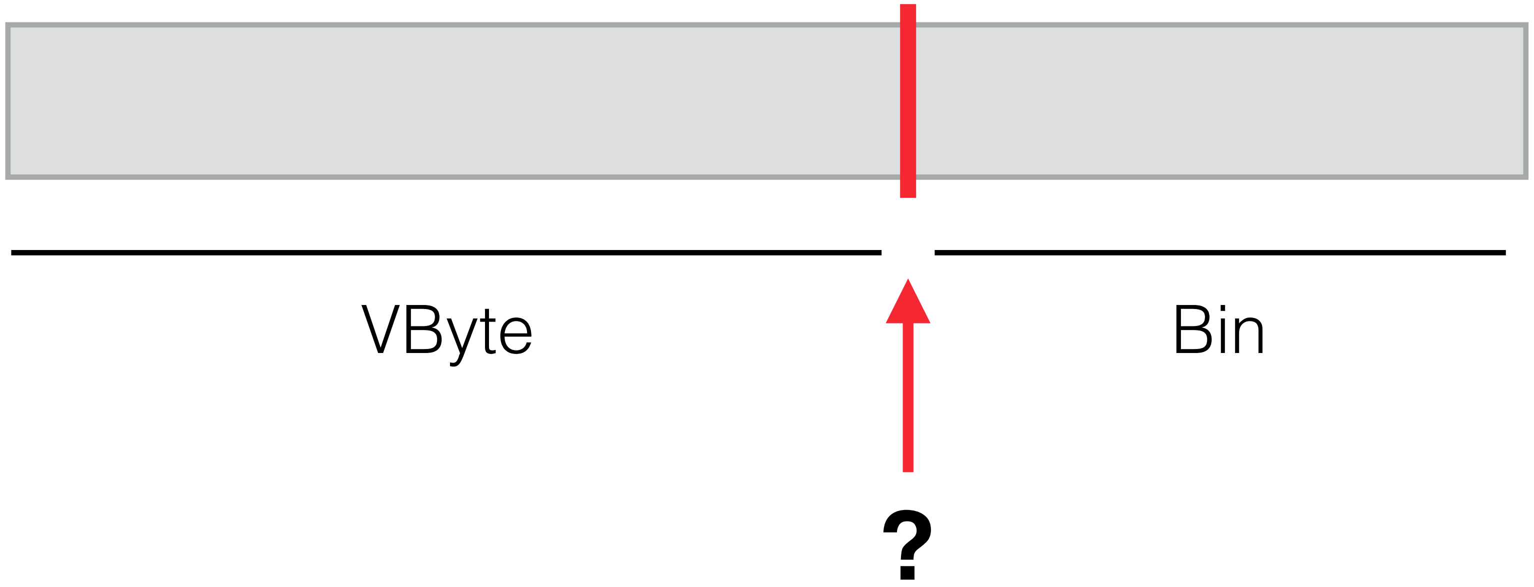

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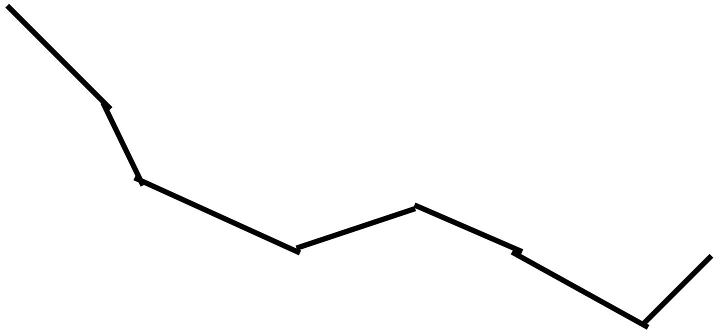
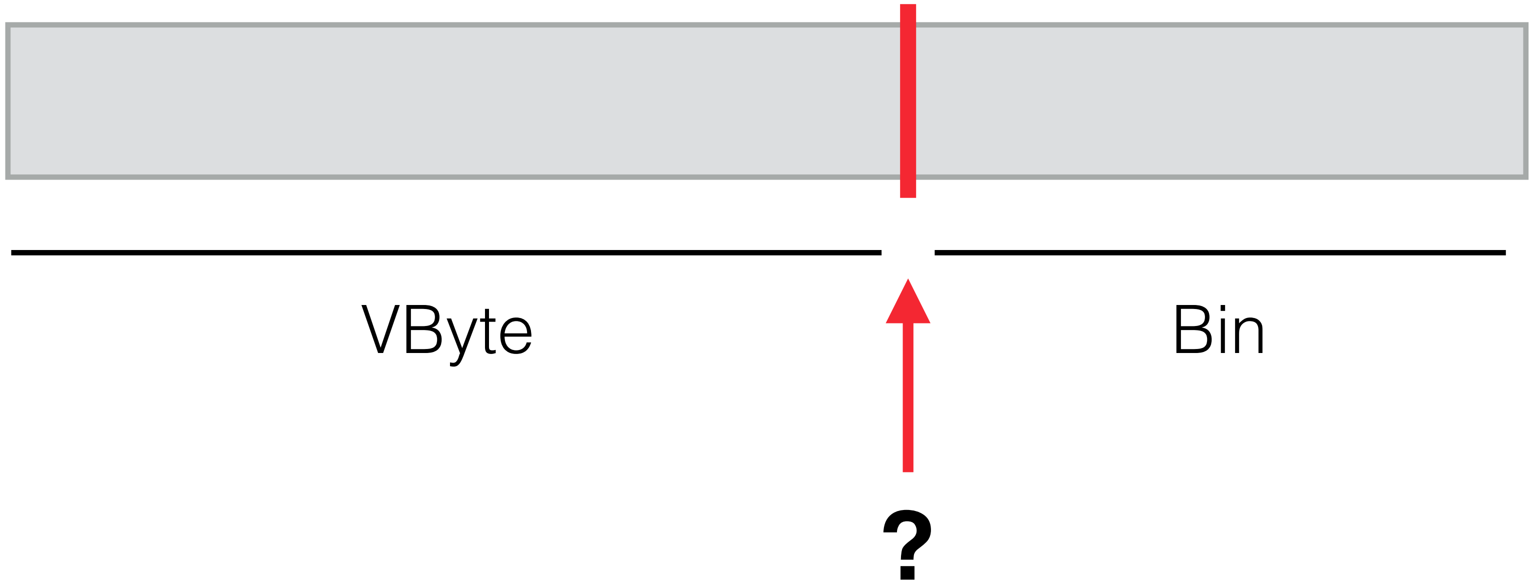


Our solution - The intuition


VByte

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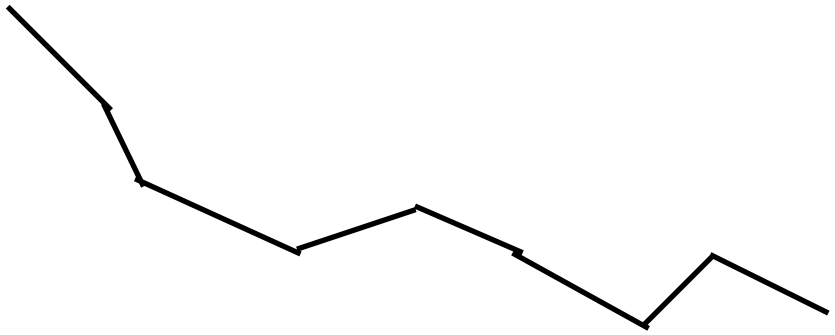

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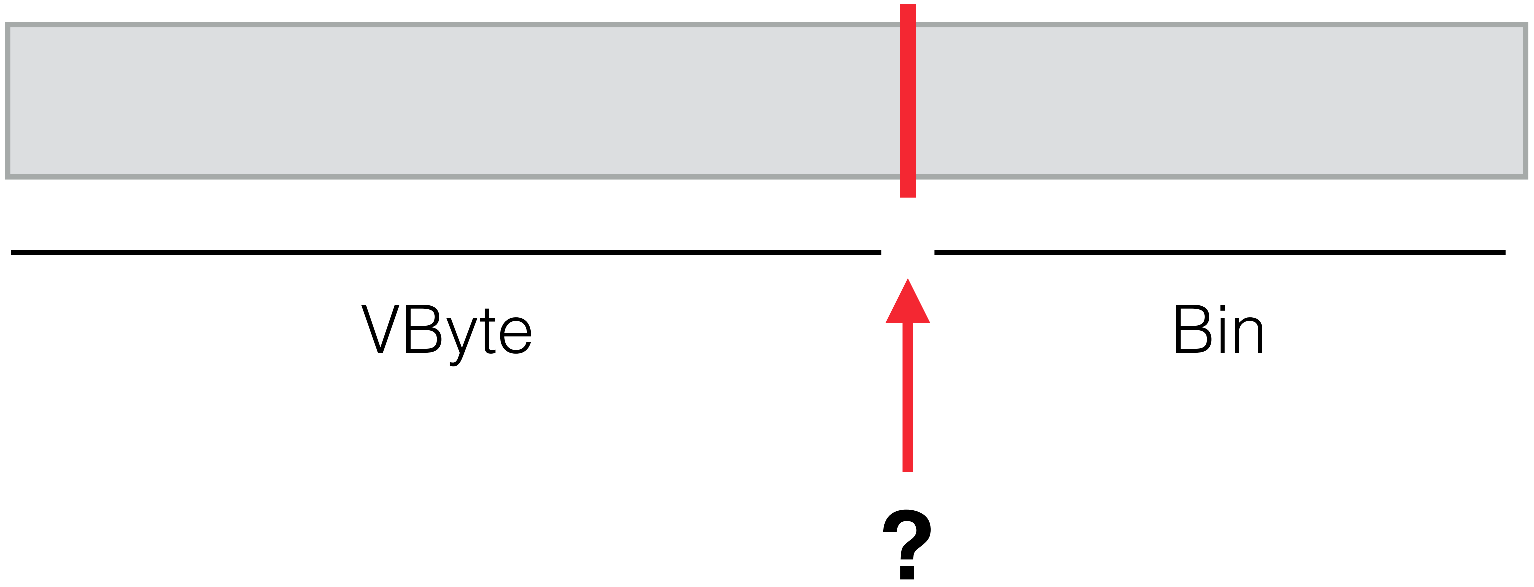

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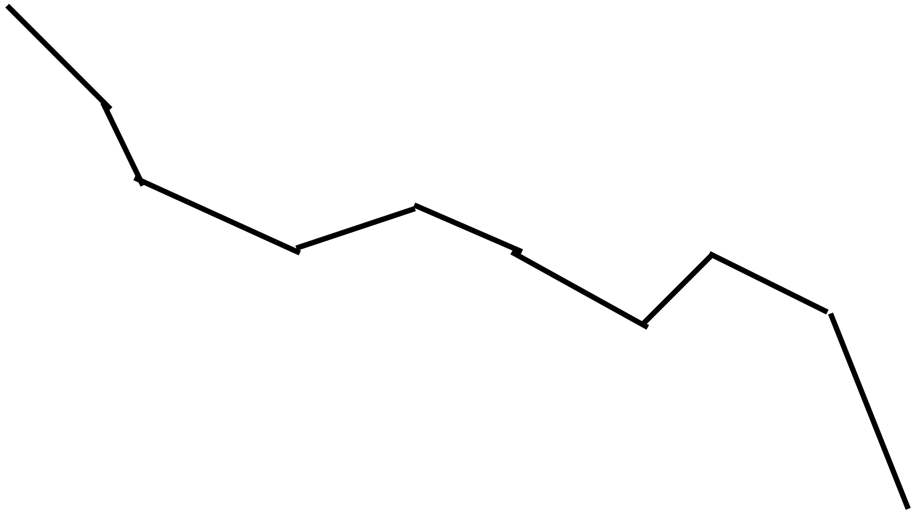

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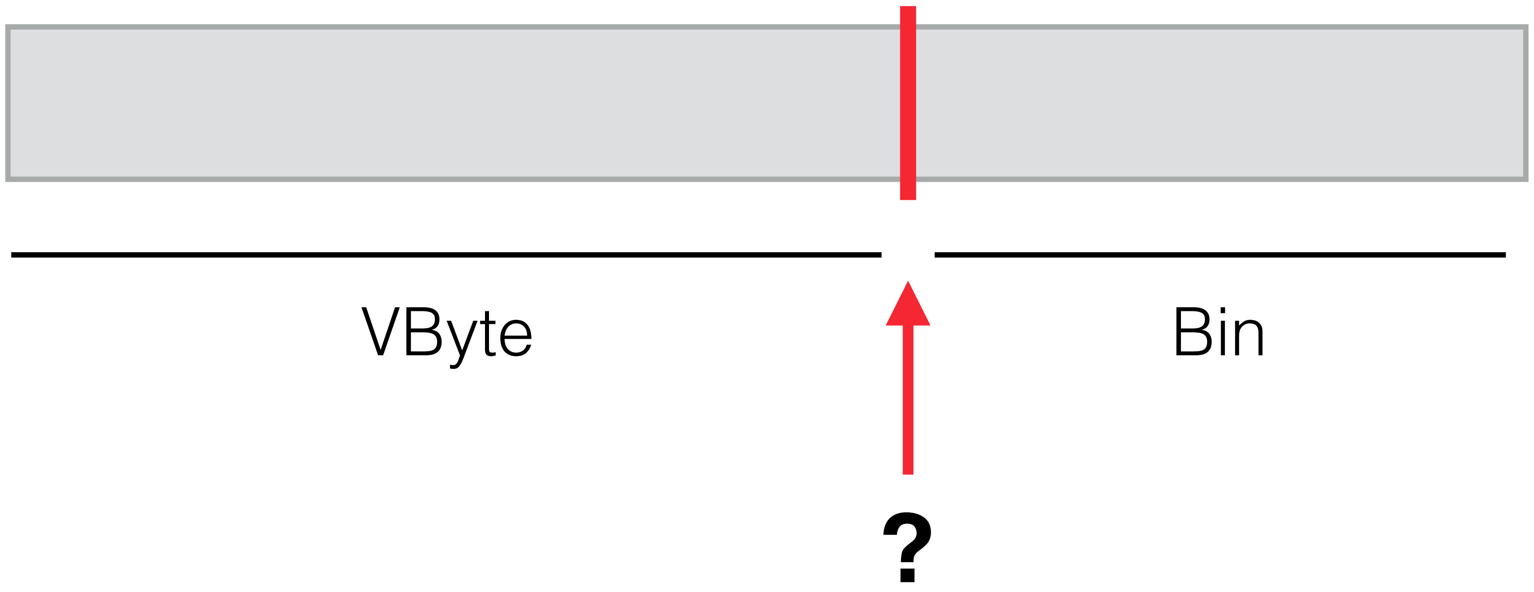

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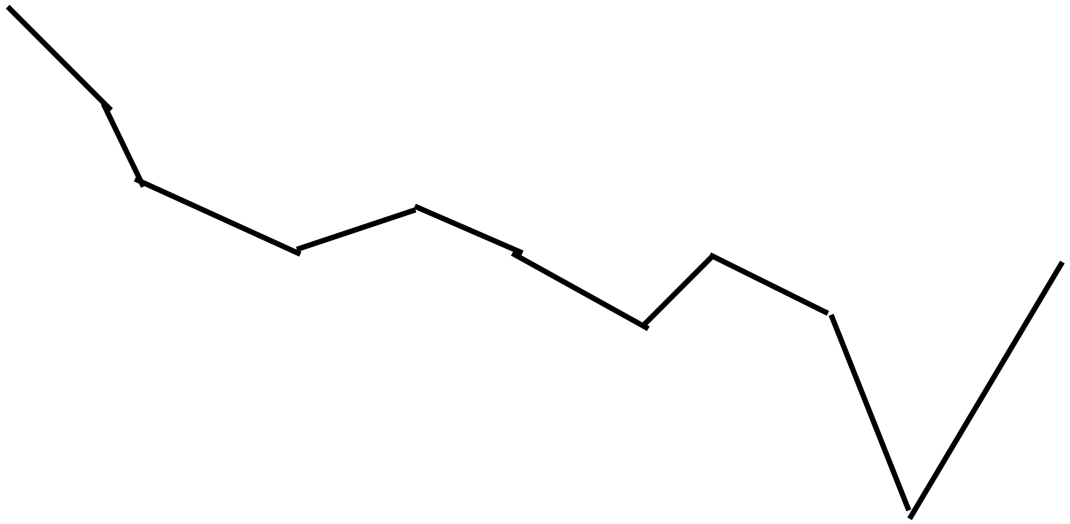

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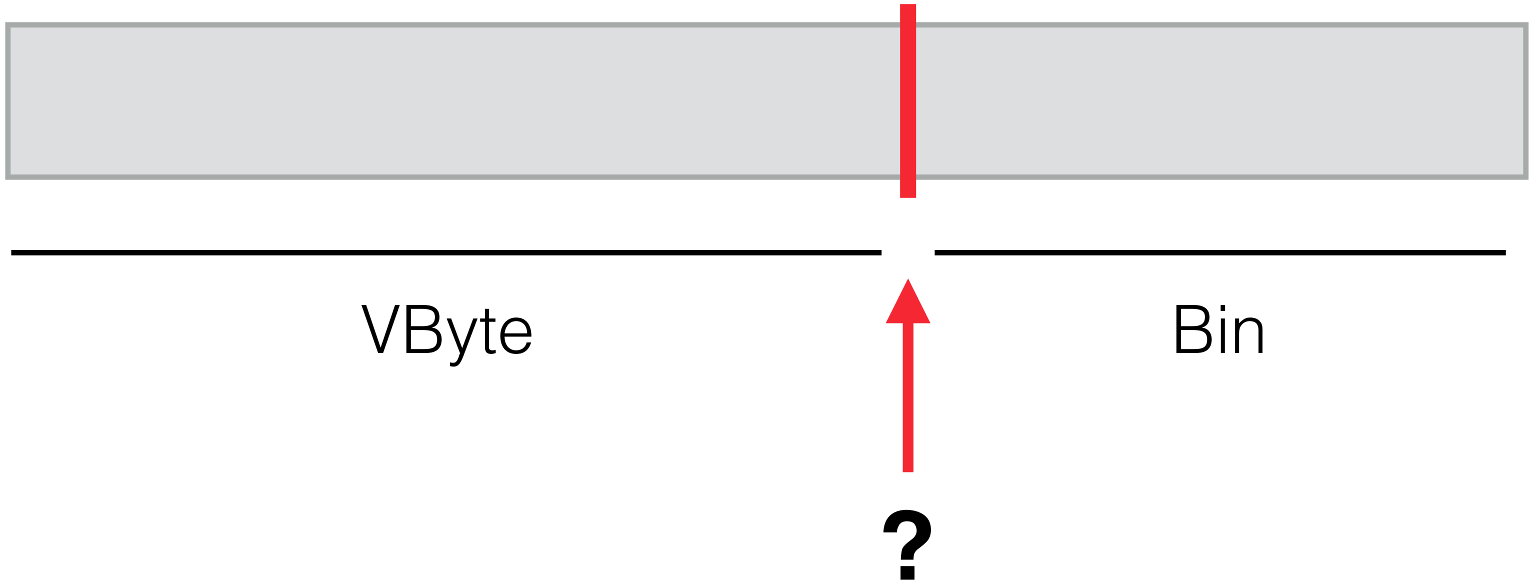

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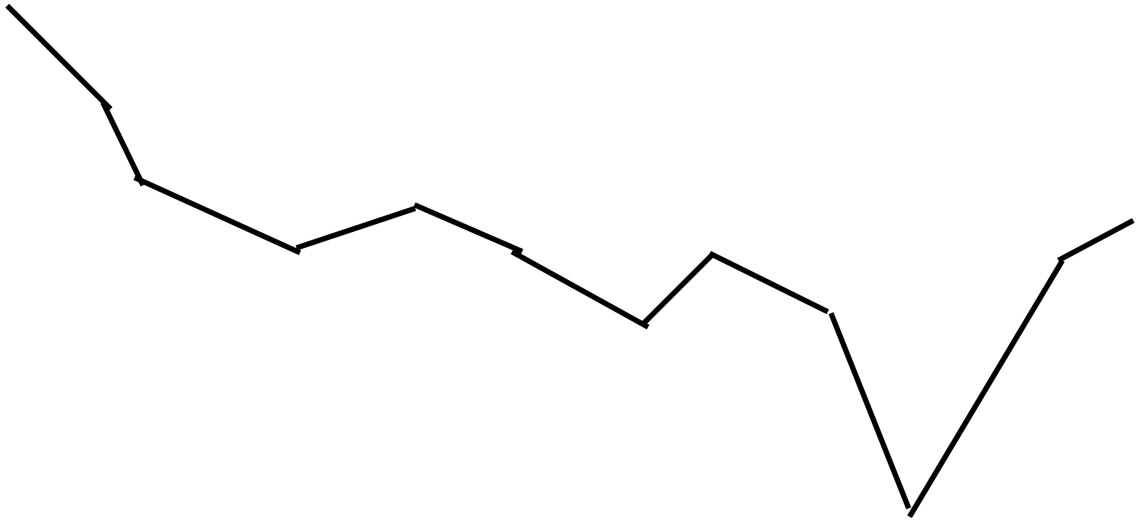

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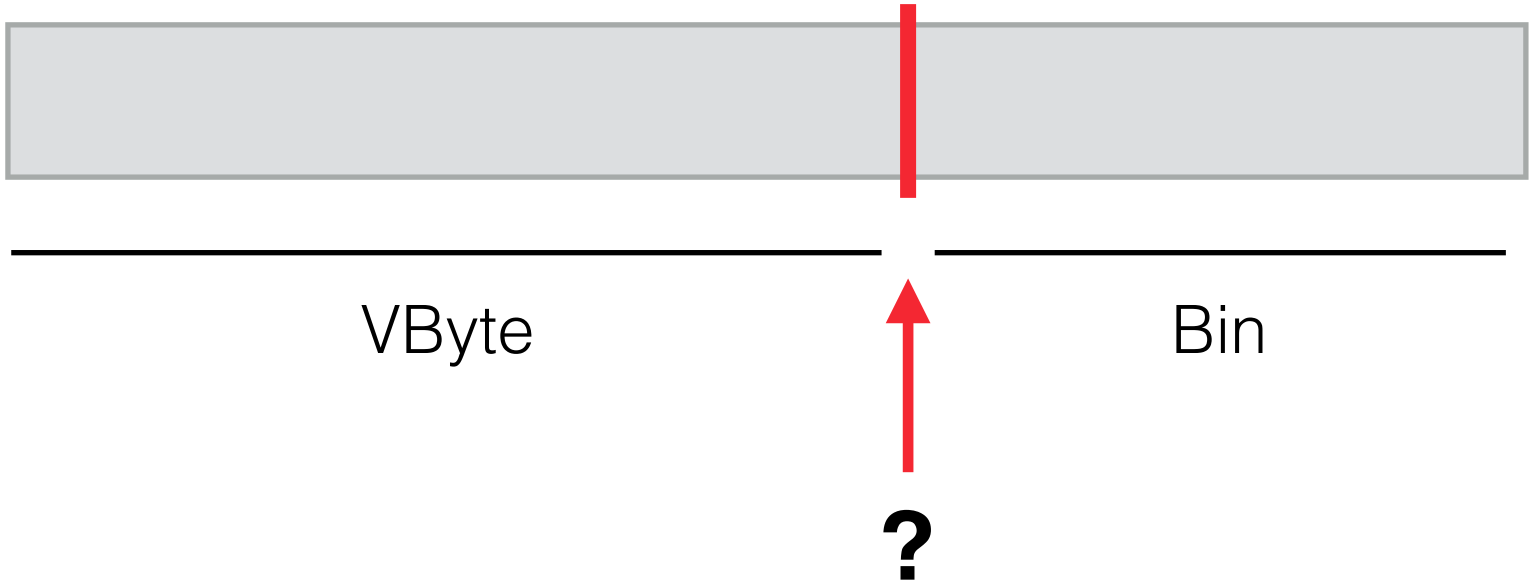

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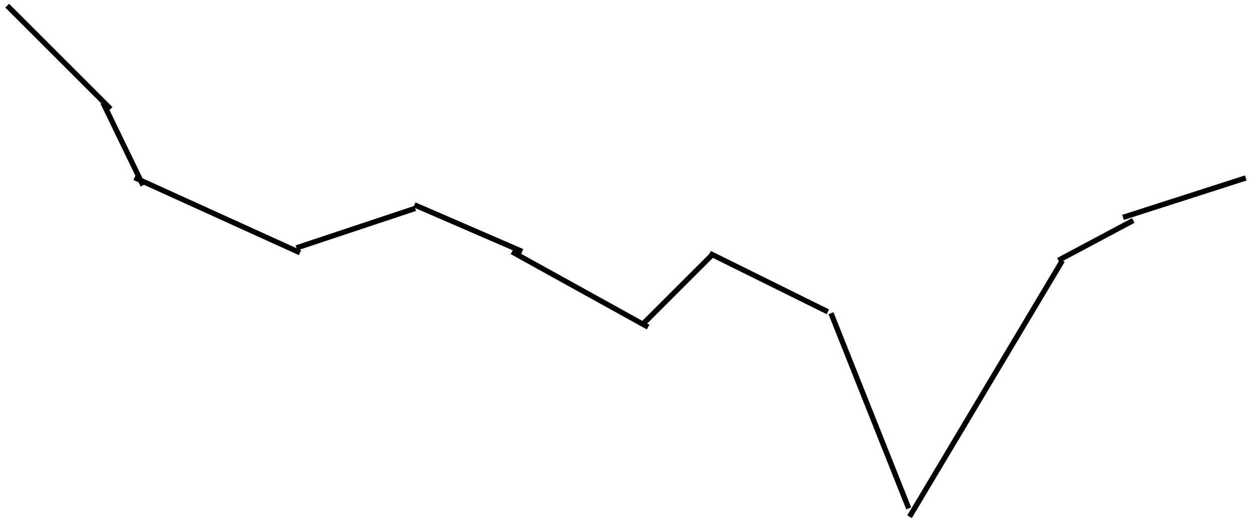

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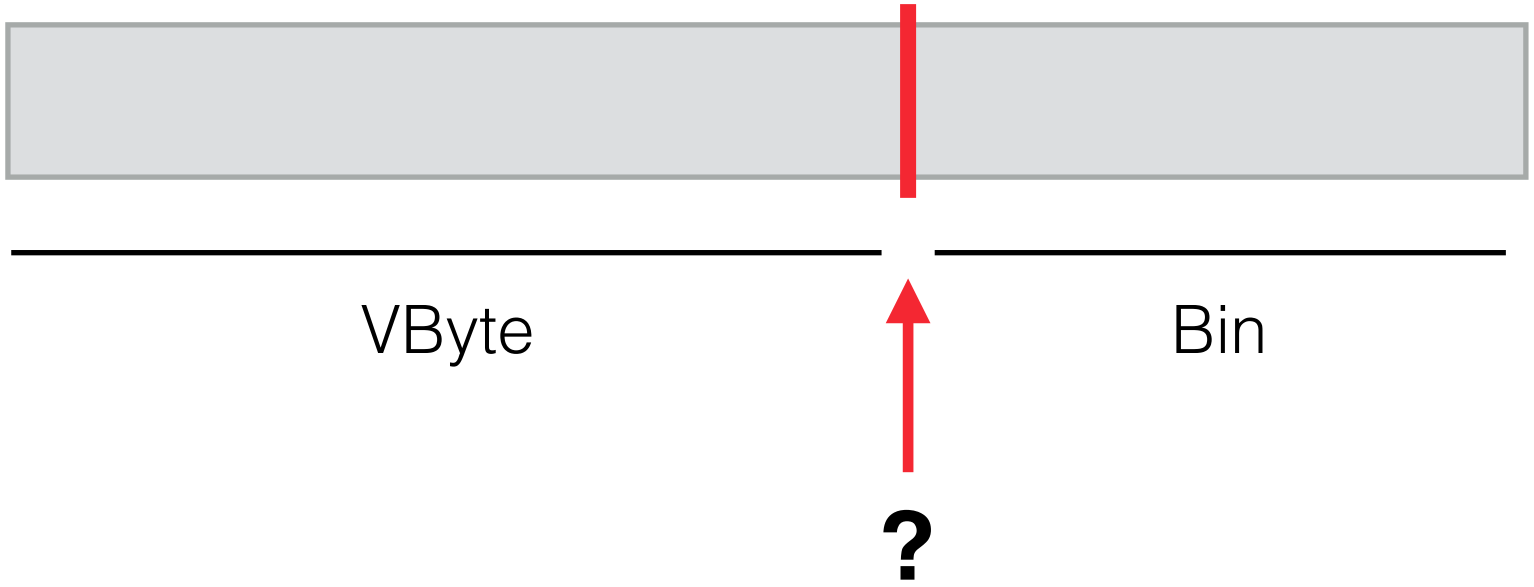

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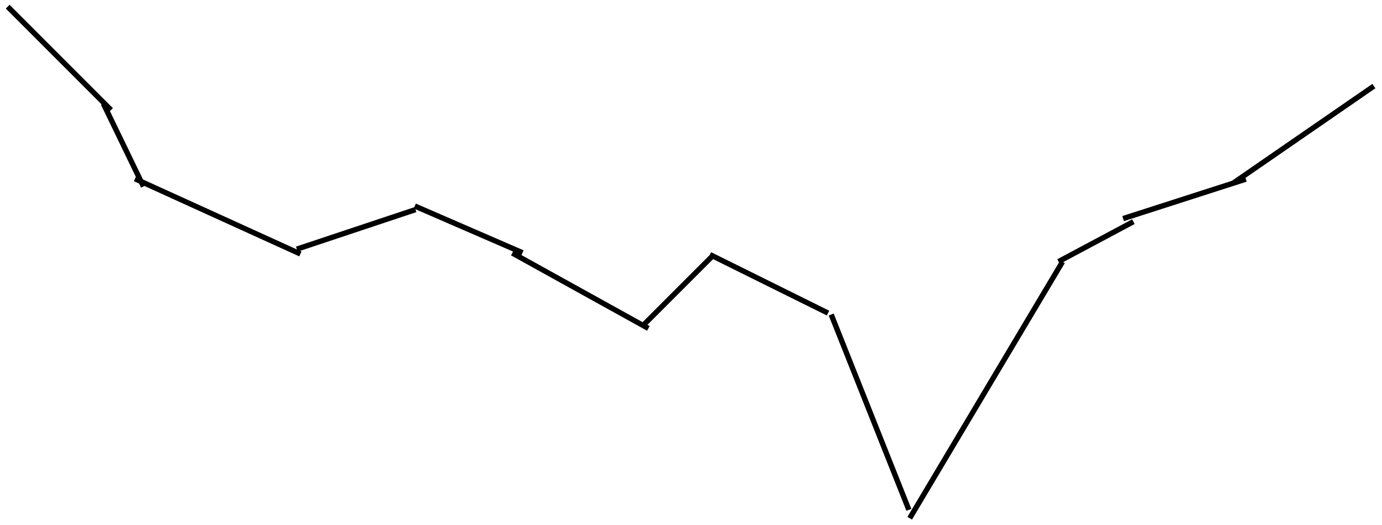

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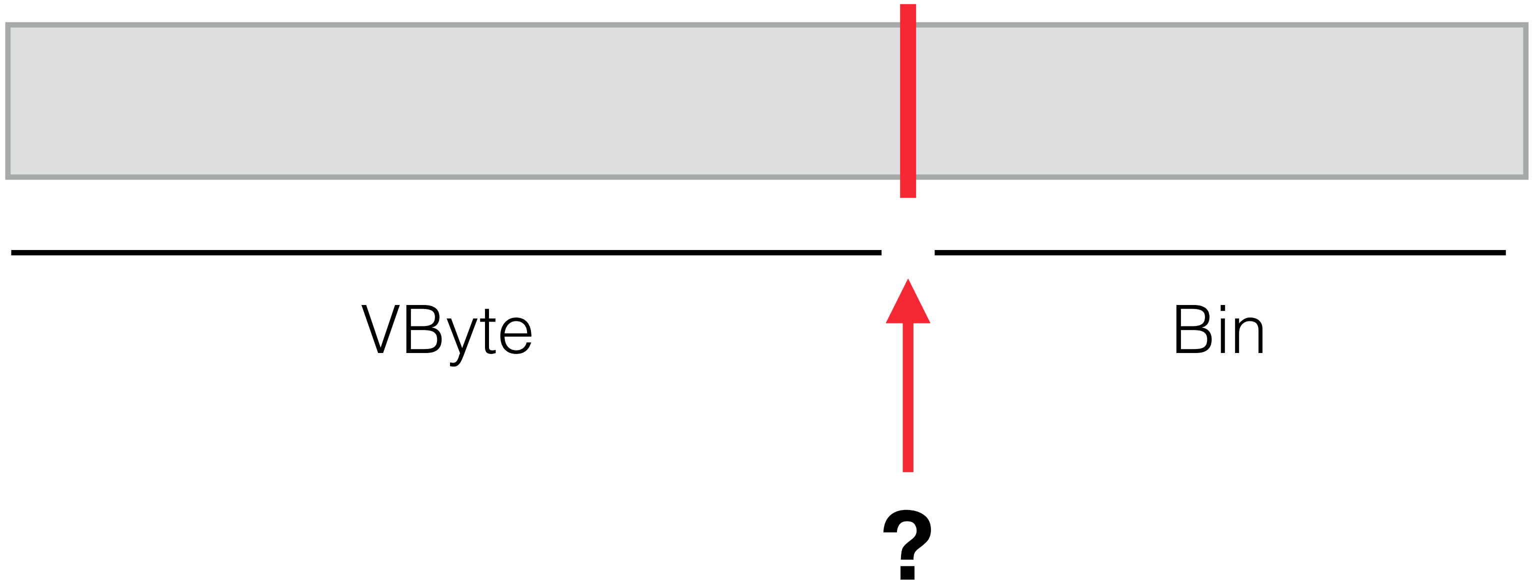

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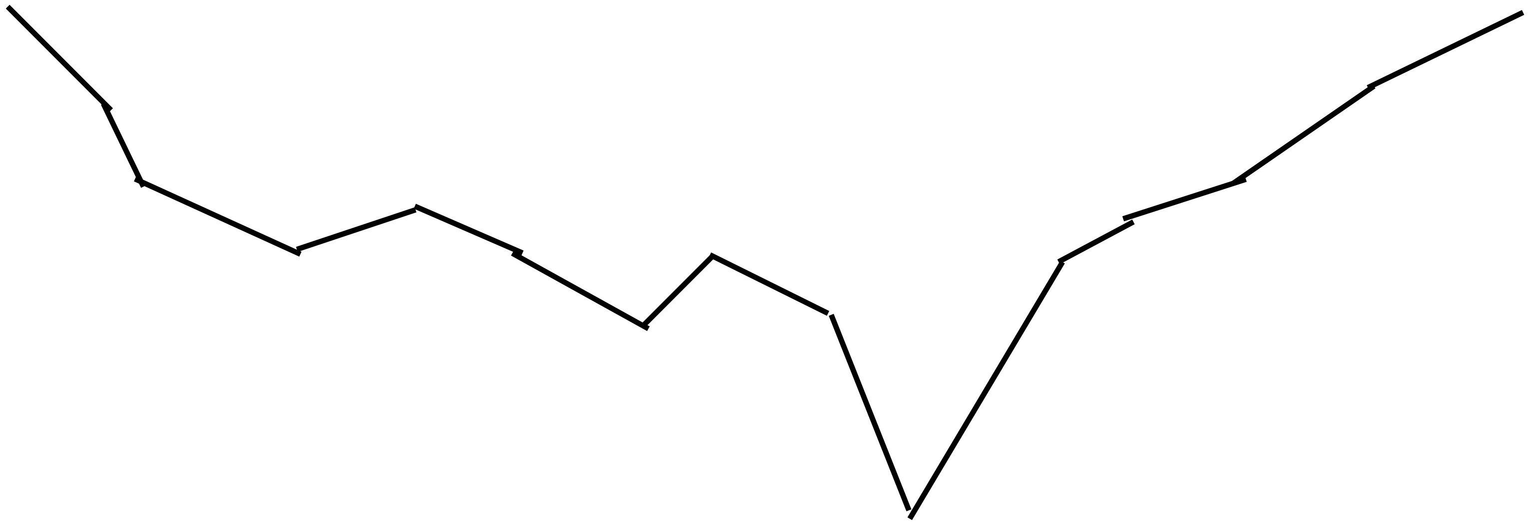

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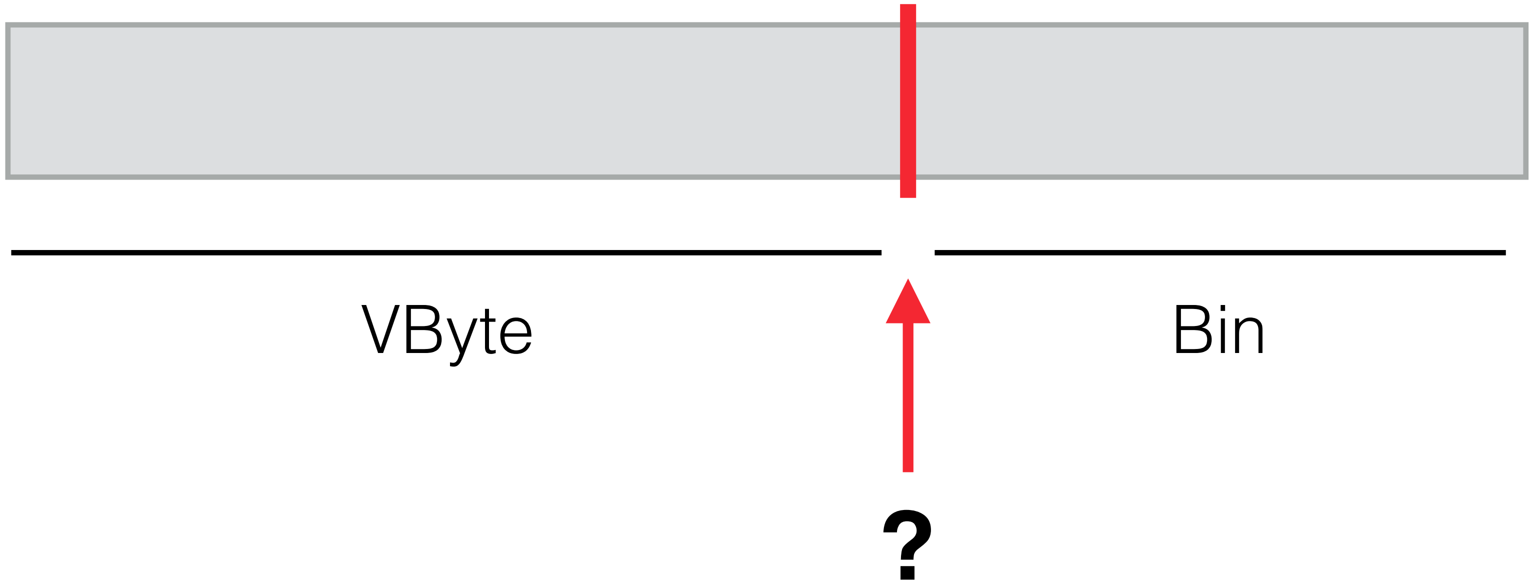

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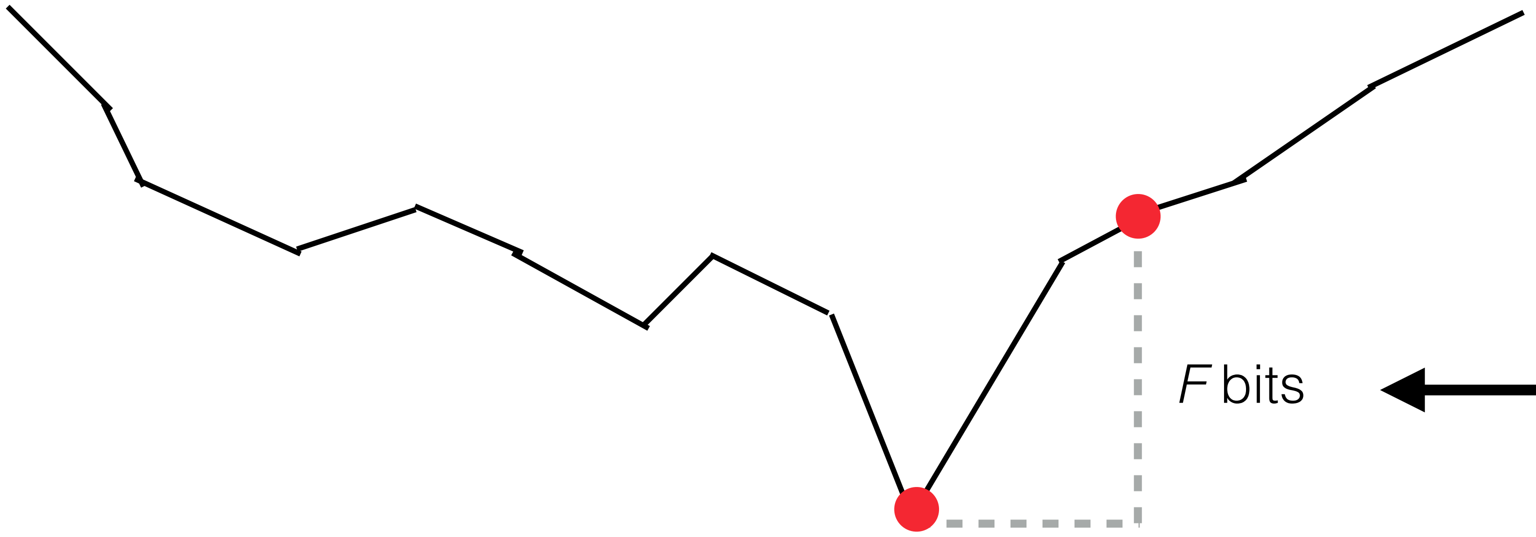
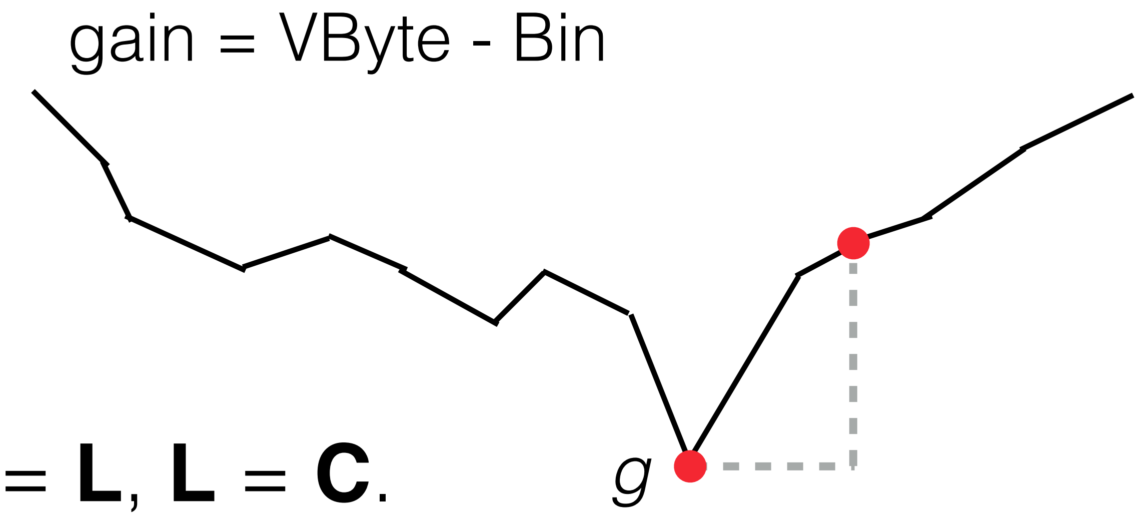


We pay *F* bits for each partition!

Our solution - The algorithm

C := current encoder
L := last encoder

1. Encode first partition.
2. If |**C** - **L**| and *g* are > 2*F*, then encode the current partition with **C** and set **C** = **L**, **L** = **C**.
3. Repeat step (2) until the end of the sequence.
4. Encode last partition.



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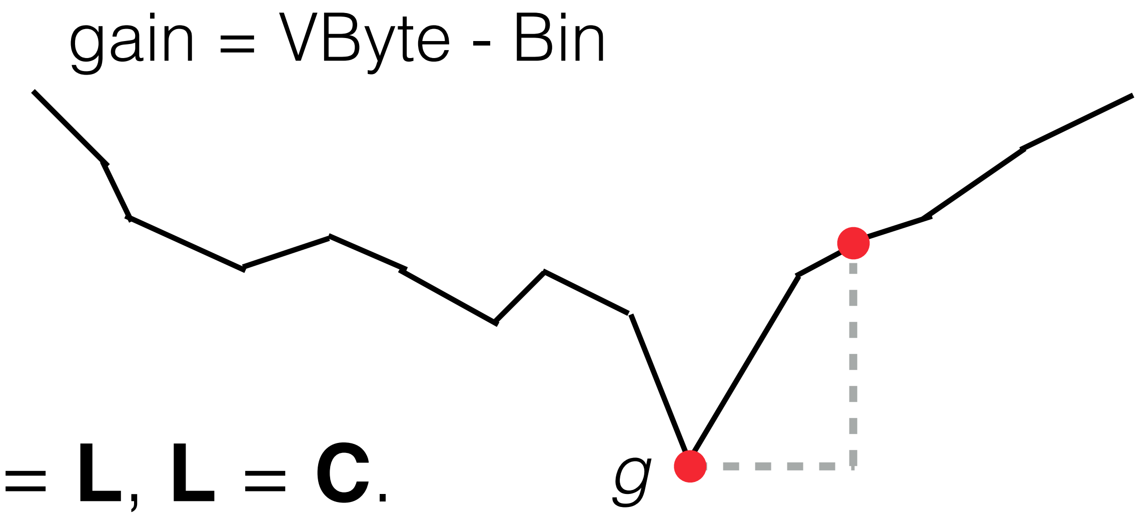

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All details (including proof of optimality), here:
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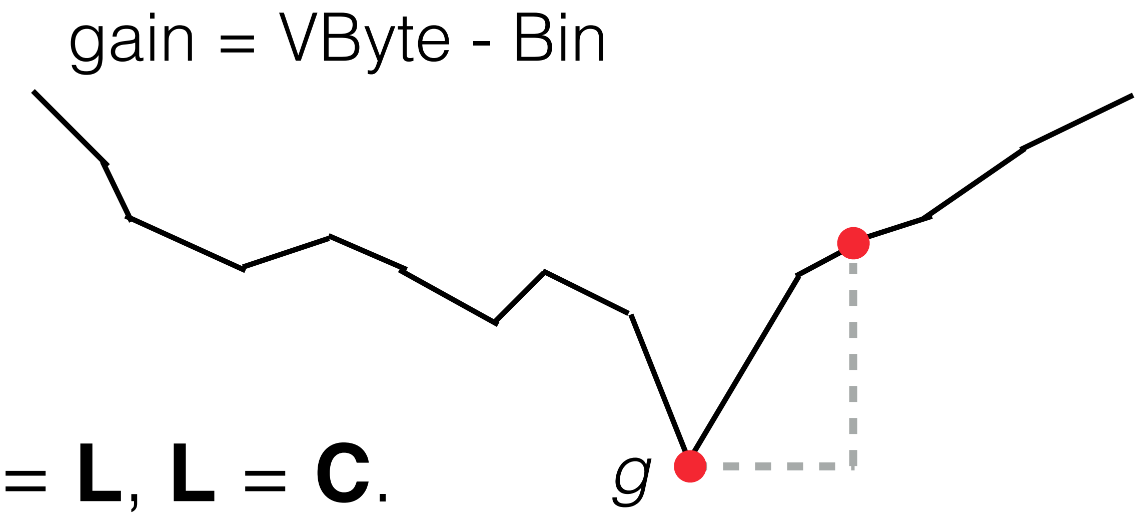

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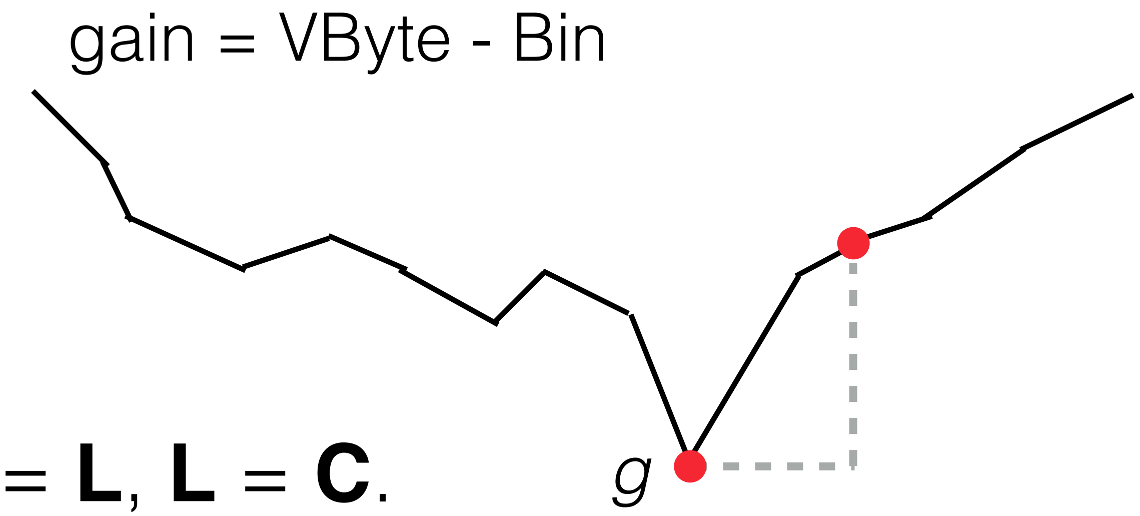

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Valid for ANY *point-wise* encoder.

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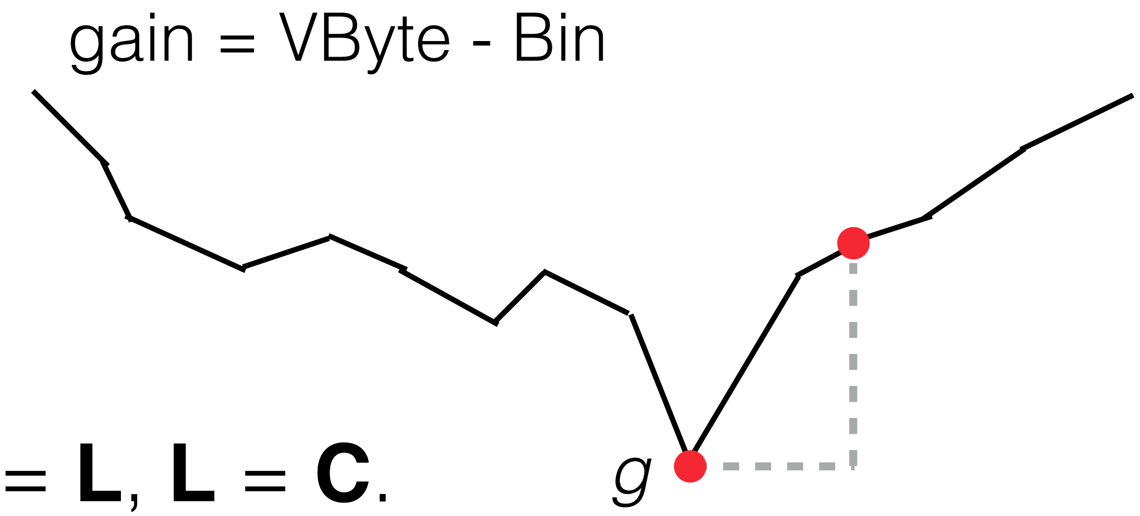

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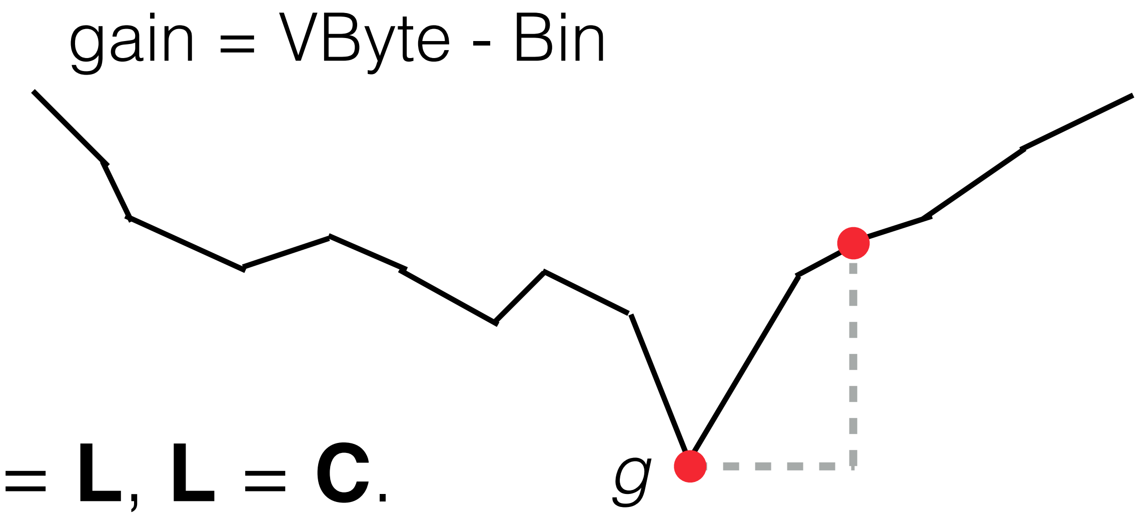

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Optimal.

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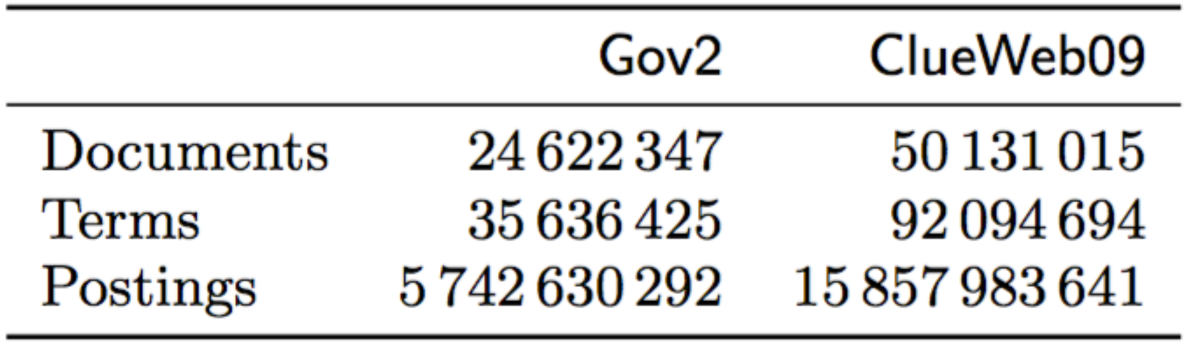
Very low constant factors.

Linear time and constant space.

Experimental Results on Gov2 and ClueWeb09

`C++14` implementation compiled with `gcc` 7.2.0 with highest optimization setting.

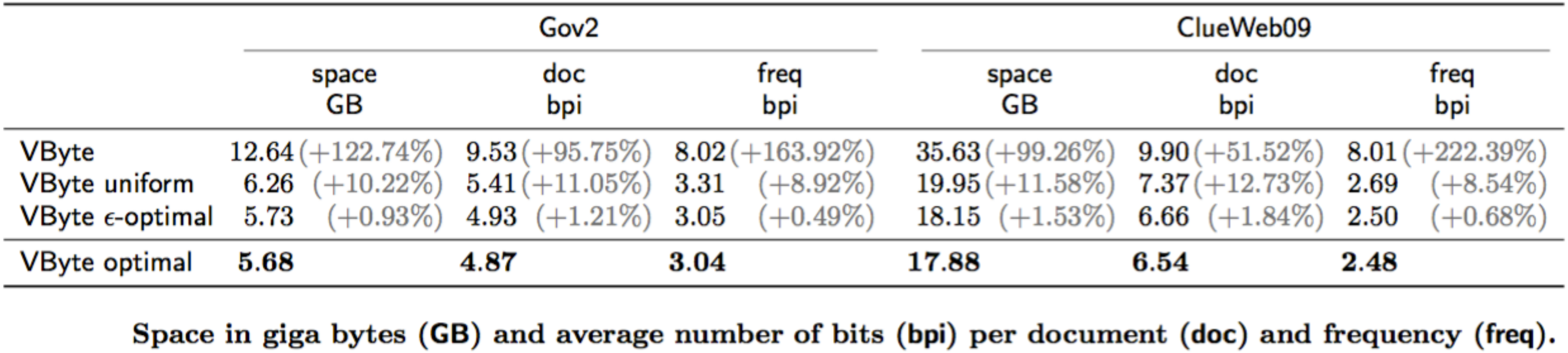


	Gov2	ClueWeb09
Documents	24 622 347	50 131 015
Terms	35 636 425	92 094 694
Postings	5 742 630 292	15 857 983 641

Basic statistics for the tested collections.

Code will be available upon acceptance of the paper.

Partitioned VS. Unpartitioned: Space and Indexing Time



	Gov2			ClueWeb09		
	space GB	doc bpi	freq bpi	space GB	doc bpi	freq bpi
VByte	12.64 (+122.74%)	9.53 (+95.75%)	8.02 (+163.92%)	35.63 (+99.26%)	9.90 (+51.52%)	8.01 (+222.39%)
VByte uniform	6.26 (+10.22%)	5.41 (+11.05%)	3.31 (+8.92%)	19.95 (+11.58%)	7.37 (+12.73%)	2.69 (+8.54%)
VByte ϵ-optimal	5.73 (+0.93%)	4.93 (+1.21%)	3.05 (+0.49%)	18.15 (+1.53%)	6.66 (+1.84%)	2.50 (+0.68%)
VByte optimal	**5.68**	**4.87**	**3.04**	**17.88**	**6.54**	**2.48**

Space in giga bytes (GB) and average number of bits (bpi) per document (doc) and frequency (freq).

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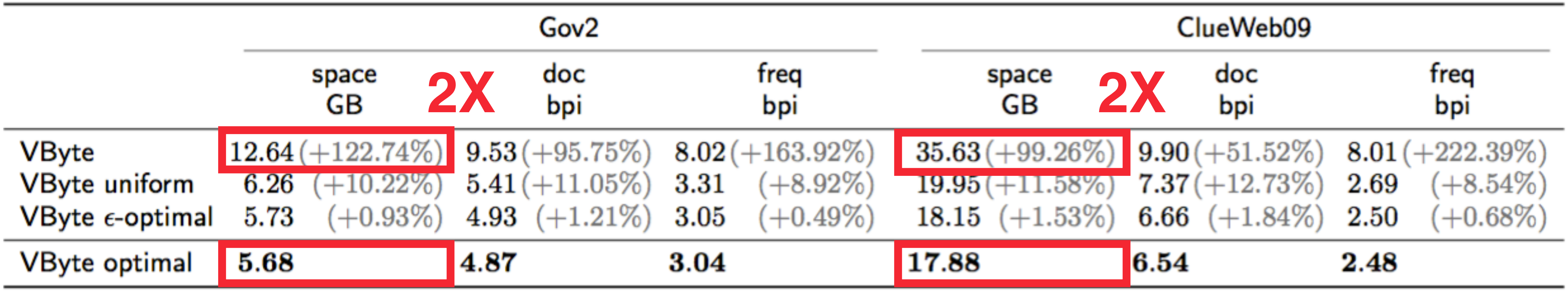

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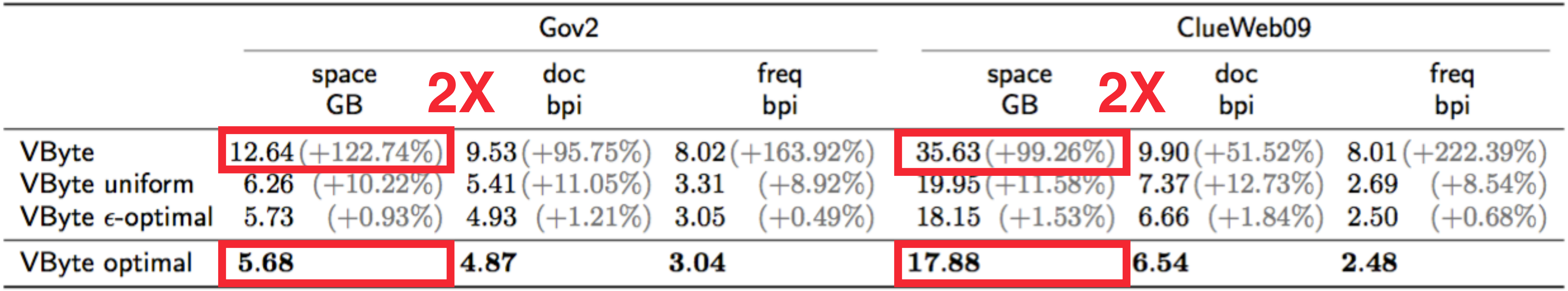

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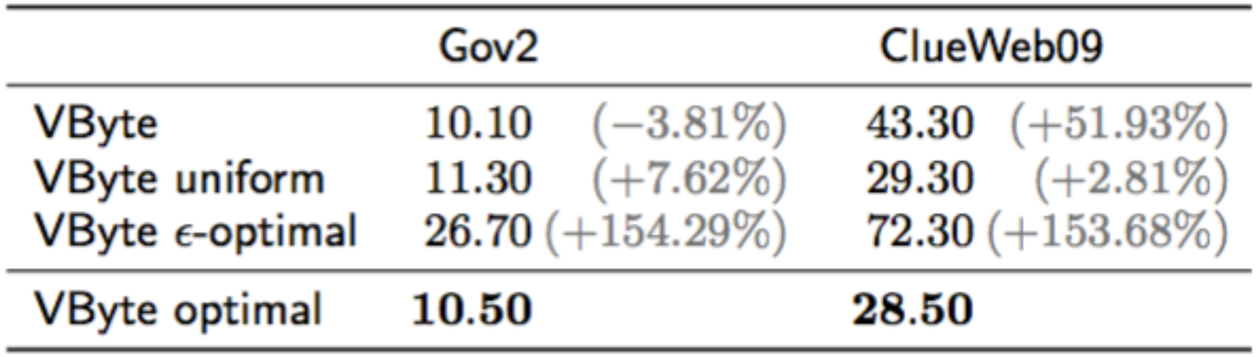
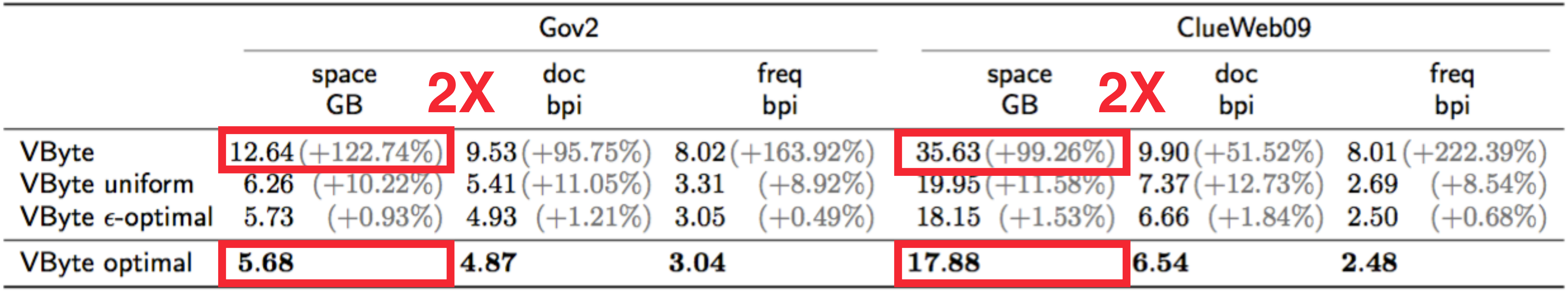


	Gov2	ClueWeb09
VByte	10.10 (−3.81%)	43.30 (+51.93%)
VByte uniform	11.30 (+7.62%)	29.30 (+2.81%)
VByte ϵ-optimal	26.70 (+154.29%)	72.30 (+153.68%)
VByte optimal	**10.50**	**28.50**

Index building timings in minutes.

Partitioned VS. Unpartitioned: Space and Indexing Time



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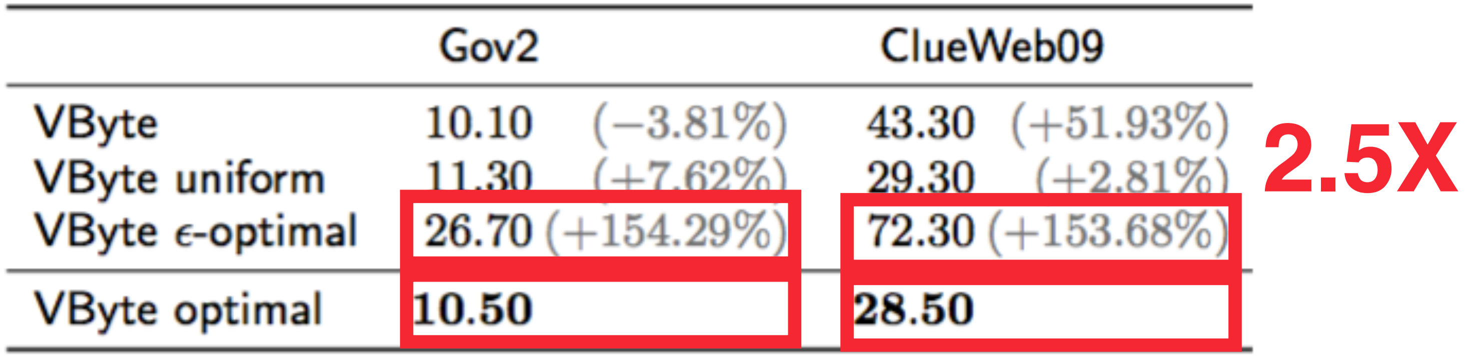

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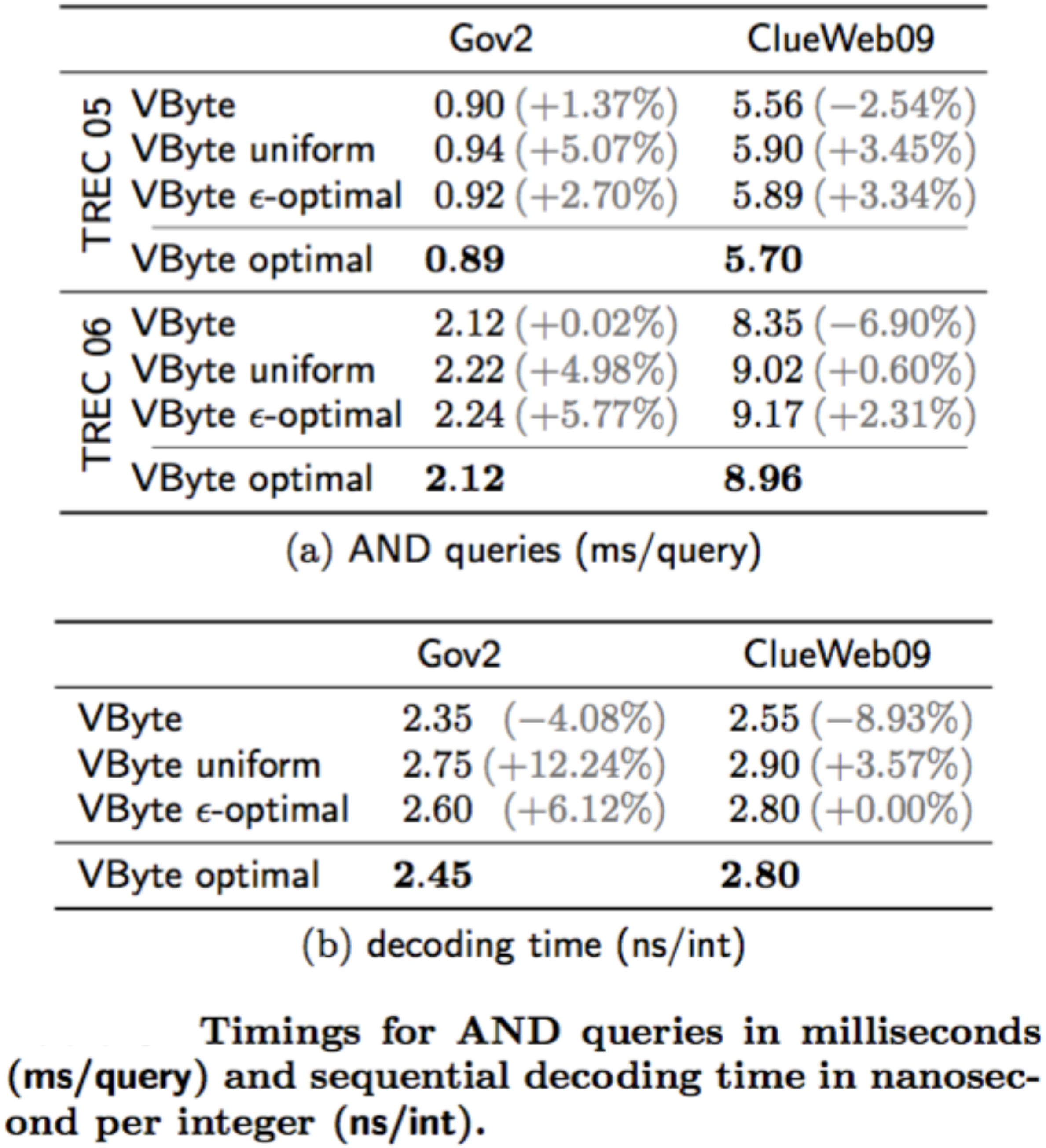
Index building timings in minutes.

Partitioned VS. Unpartitioned: AND queries and decoding



		Gov2	ClueWeb09
TREC 05	VByte	0.90 (+1.37%)	5.56 (−2.54%)
	VByte uniform	0.94 (+5.07%)	5.90 (+3.45%)
	VByte ϵ-optimal	0.92 (+2.70%)	5.89 (+3.34%)
	VByte optimal	**0.89**	**5.70**
TREC 06	VByte	2.12 (+0.02%)	8.35 (−6.90%)
	VByte uniform	2.22 (+4.98%)	9.02 (+0.60%)
	VByte ϵ-optimal	2.24 (+5.77%)	9.17 (+2.31%)
	VByte optimal	**2.12**	**8.96**

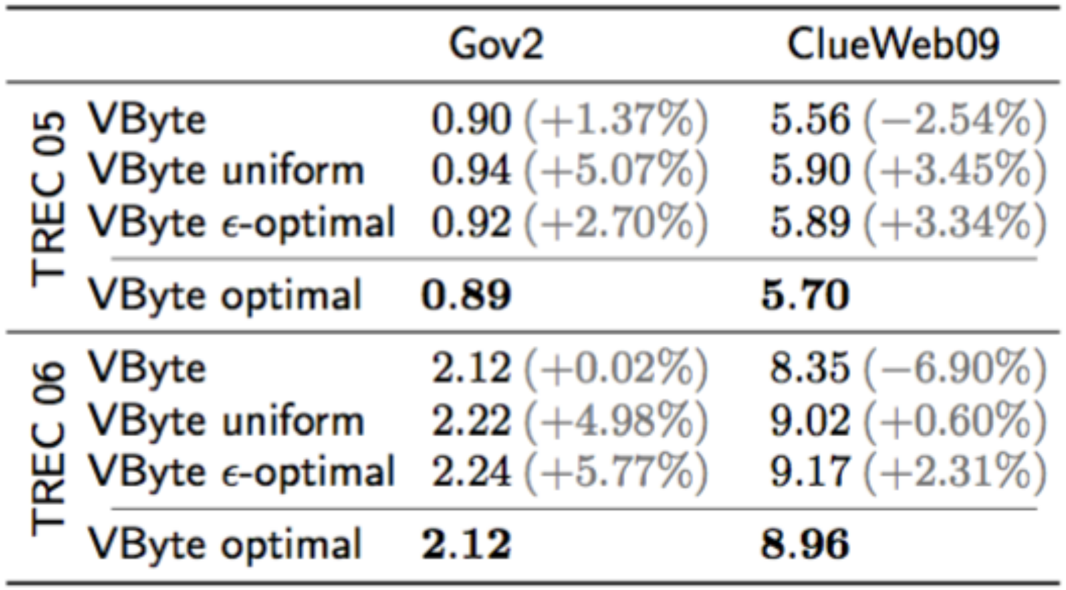
(a) AND queries (ms/query)

	Gov2	ClueWeb09
VByte	2.35 (−4.08%)	2.55 (−8.93%)
VByte uniform	2.75 (+12.24%)	2.90 (+3.57%)
VByte ϵ-optimal	2.60 (+6.12%)	2.80 (+0.00%)
VByte optimal	**2.45**	**2.80**

(b) decoding time (ns/int)

Timings for AND queries in milliseconds (ms/query) and sequential decoding time in nanosecond per integer (ns/int).

Partitioned VS. Unpartitioned: AND queries and decoding



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	VByte optimal	**0.89**	**5.70**
TREC 06	VByte	2.12 (+0.02%)	8.35 (−6.90%)
	VByte uniform	2.22 (+4.98%)	9.02 (+0.60%)
	VByte ϵ-optimal	2.24 (+5.77%)	9.17 (+2.31%)
	VByte optimal	**2.12**	**8.96**

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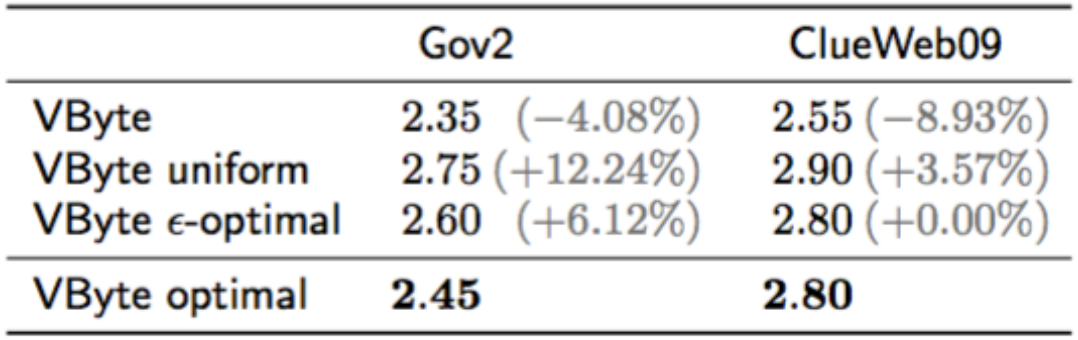

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VByte	2.35 (−4.08%)	2.55 (−8.93%)
VByte uniform	2.75 (+12.24%)	2.90 (+3.57%)
VByte ϵ-optimal	2.60 (+6.12%)	2.80 (+0.00%)
VByte optimal	**2.45**	**2.80**

(b) decoding time (ns/int)

Timings for AND queries in milliseconds (ms/query) and sequential decoding time in nanosecond per integer (ns/int).

Speed NOT affected by partitioning.

Partitioned VS. Unpartitioned: AND queries and decoding

		Gov2	ClueWeb09
TREC 05	VByte	0.90 (+1.37%)	5.56 (−2.54%)
	VByte uniform	0.94 (+5.07%)	5.90 (+3.45%)
	VByte ϵ-optimal	0.92 (+2.70%)	5.89 (+3.34%)
	VByte optimal	**0.89**	**5.70**
TREC 06	VByte	2.12 (+0.02%)	8.35 (−6.90%)
	VByte uniform	2.22 (+4.98%)	9.02 (+0.60%)
	VByte ϵ-optimal	2.24 (+5.77%)	9.17 (+2.31%)
	VByte optimal	**2.12**	**8.96**

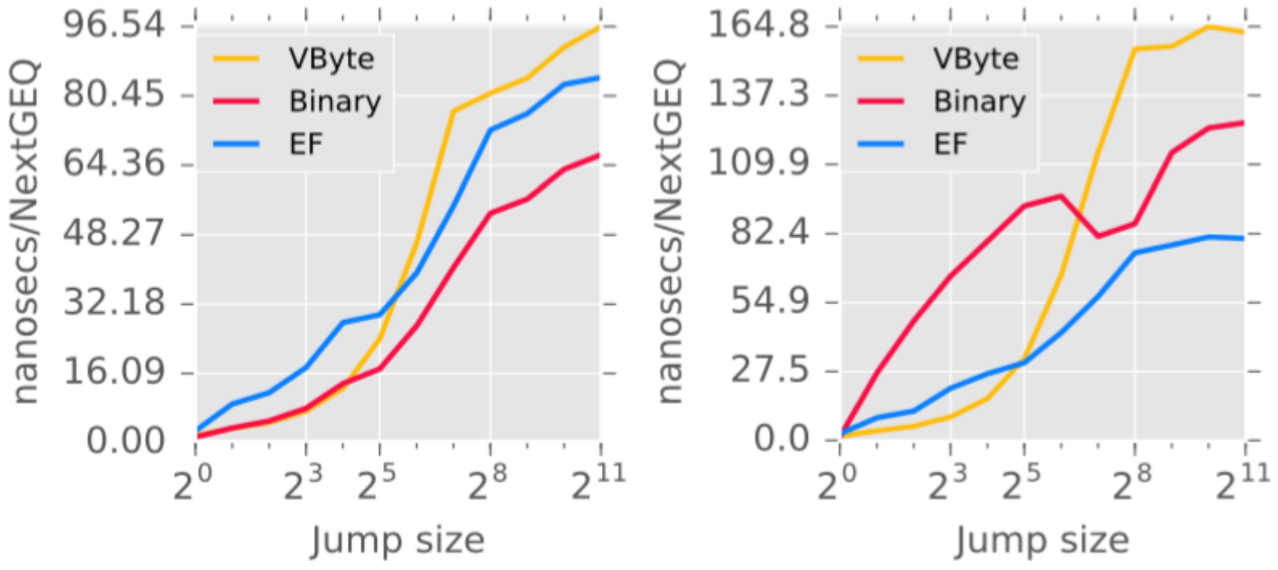
(a) AND queries (ms/query)

	Gov2	ClueWeb09
VByte	2.35 (−4.08%)	2.55 (−8.93%)
VByte uniform	2.75 (+12.24%)	2.90 (+3.57%)
VByte ϵ-optimal	2.60 (+6.12%)	2.80 (+0.00%)
VByte optimal	**2.45**	**2.80**

(b) decoding time (ns/int)

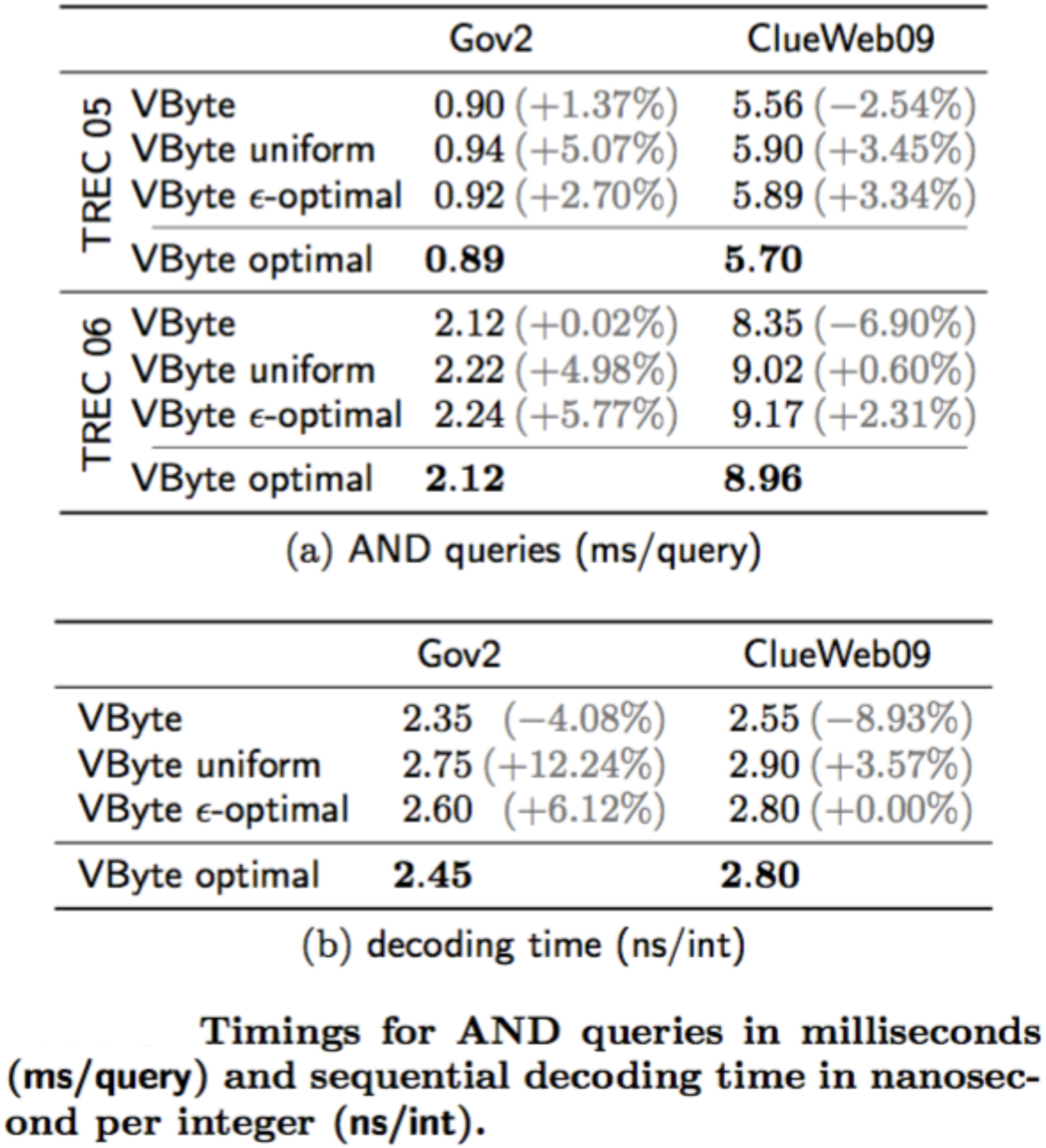
Timings for AND queries in milliseconds (ms/query) and sequential decoding time in nanosecond per integer (ns/int).

Speed NOT affected by partitioning.



(a) Dense (b) Sparse

Partitioned VS. Unpartitioned: AND queries and decoding



		Gov2	ClueWeb09
TREC 05	VByte	0.90 (+1.37%)	5.56 (−2.54%)
	VByte uniform	0.94 (+5.07%)	5.90 (+3.45%)
	VByte ϵ-optimal	0.92 (+2.70%)	5.89 (+3.34%)
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(a) AND queries (ms/query)

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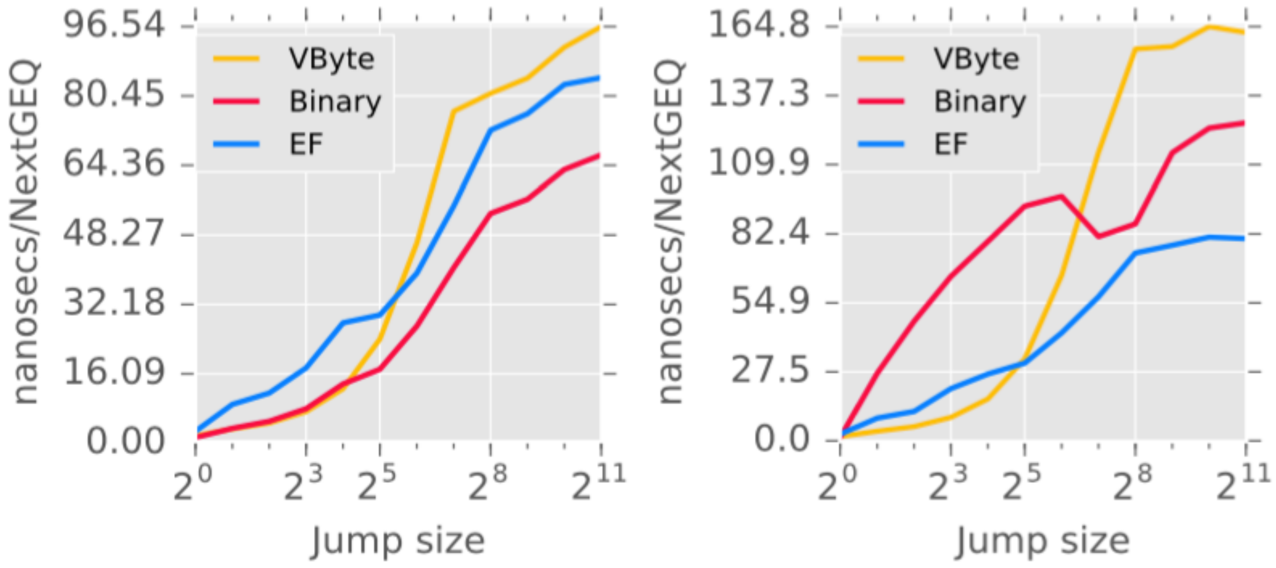
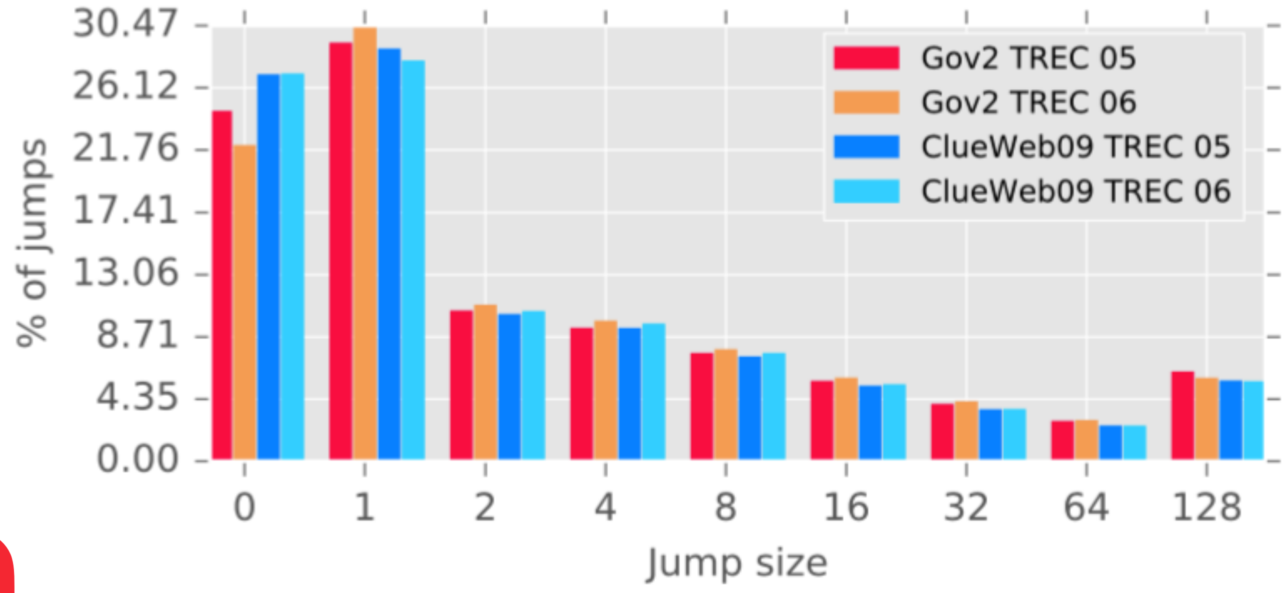
Timings for AND queries in milliseconds (ms/query) and sequential decoding time in nanosecond per integer (ns/int).

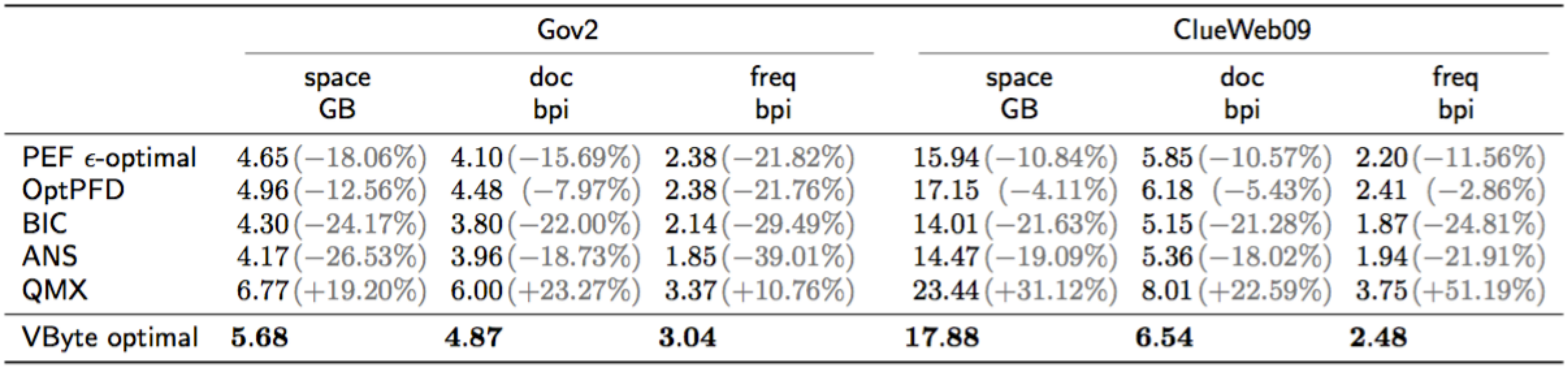


(a) Dense (b) Sparse



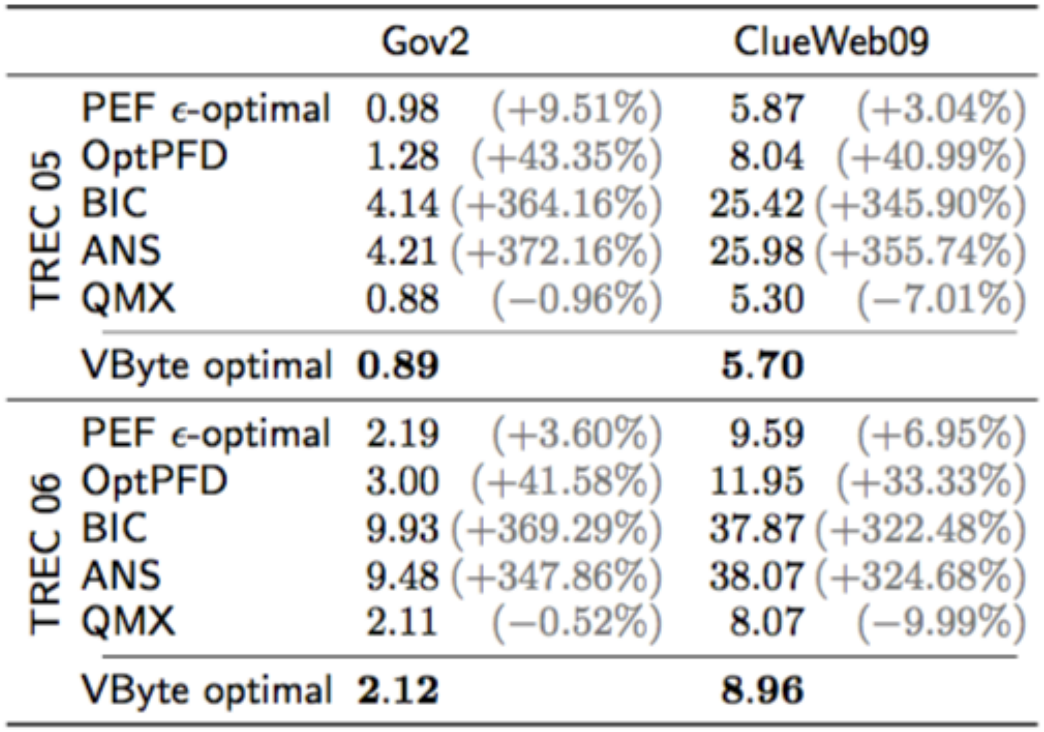
Speed NOT affected by partitioning.

Overall Comparison



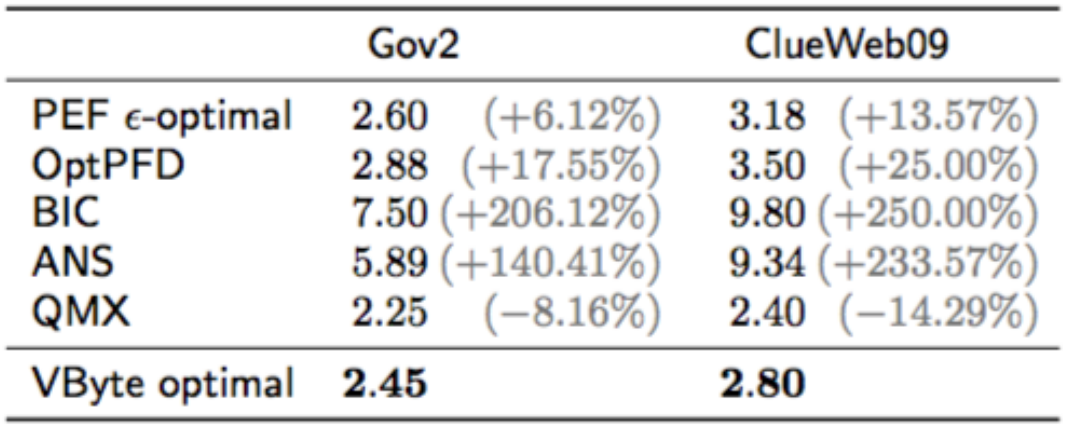
	Gov2			ClueWeb09		
	space GB	doc bpi	freq bpi	space GB	doc bpi	freq bpi
PEF ϵ-optimal	4.65 (−18.06%)	4.10 (−15.69%)	2.38 (−21.82%)	15.94 (−10.84%)	5.85 (−10.57%)	2.20 (−11.56%)
OptPFD	4.96 (−12.56%)	4.48 (−7.97%)	2.38 (−21.76%)	17.15 (−4.11%)	6.18 (−5.43%)	2.41 (−2.86%)
BIC	4.30 (−24.17%)	3.80 (−22.00%)	2.14 (−29.49%)	14.01 (−21.63%)	5.15 (−21.28%)	1.87 (−24.81%)
ANS	4.17 (−26.53%)	3.96 (−18.73%)	1.85 (−39.01%)	14.47 (−19.09%)	5.36 (−18.02%)	1.94 (−21.91%)
QMX	6.77 (+19.20%)	6.00 (+23.27%)	3.37 (+10.76%)	23.44 (+31.12%)	8.01 (+22.59%)	3.75 (+51.19%)
VByte optimal	**5.68**	**4.87**	**3.04**	**17.88**	**6.54**	**2.48**

Space in giga bytes (GB) and average number of bits (bpi) per document (doc) and frequency (freq).



		Gov2	ClueWeb09
TREC 05	PEF ϵ-optimal	0.98 (+9.51%)	5.87 (+3.04%)
	OptPFD	1.28 (+43.35%)	8.04 (+40.99%)
	BIC	4.14 (+364.16%)	25.42 (+345.90%)
	ANS	4.21 (+372.16%)	25.98 (+355.74%)
	QMX	0.88 (−0.96%)	5.30 (−7.01%)
	VByte optimal	**0.89**	**5.70**
TREC 06	PEF ϵ-optimal	2.19 (+3.60%)	9.59 (+6.95%)
	OptPFD	3.00 (+41.58%)	11.95 (+33.33%)
	BIC	9.93 (+369.29%)	37.87 (+322.48%)
	ANS	9.48 (+347.86%)	38.07 (+324.68%)
	QMX	2.11 (−0.52%)	8.07 (−9.99%)
	VByte optimal	**2.12**	**8.96**

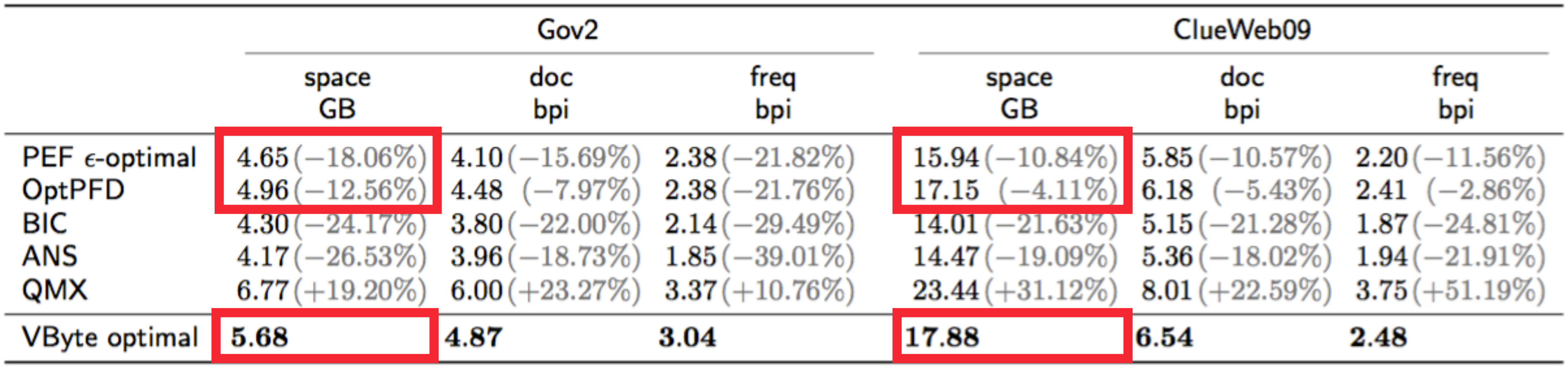
(a) AND queries (ms/query)



	Gov2	ClueWeb09
PEF ϵ-optimal	2.60 (+6.12%)	3.18 (+13.57%)
OptPFD	2.88 (+17.55%)	3.50 (+25.00%)
BIC	7.50 (+206.12%)	9.80 (+250.00%)
ANS	5.89 (+140.41%)	9.34 (+233.57%)
QMX	2.25 (−8.16%)	2.40 (−14.29%)
VByte optimal	**2.45**	**2.80**

(b) decoding time (ns/int)

Overall Comparison



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	space GB	doc bpi	freq bpi	space GB	doc bpi	freq bpi
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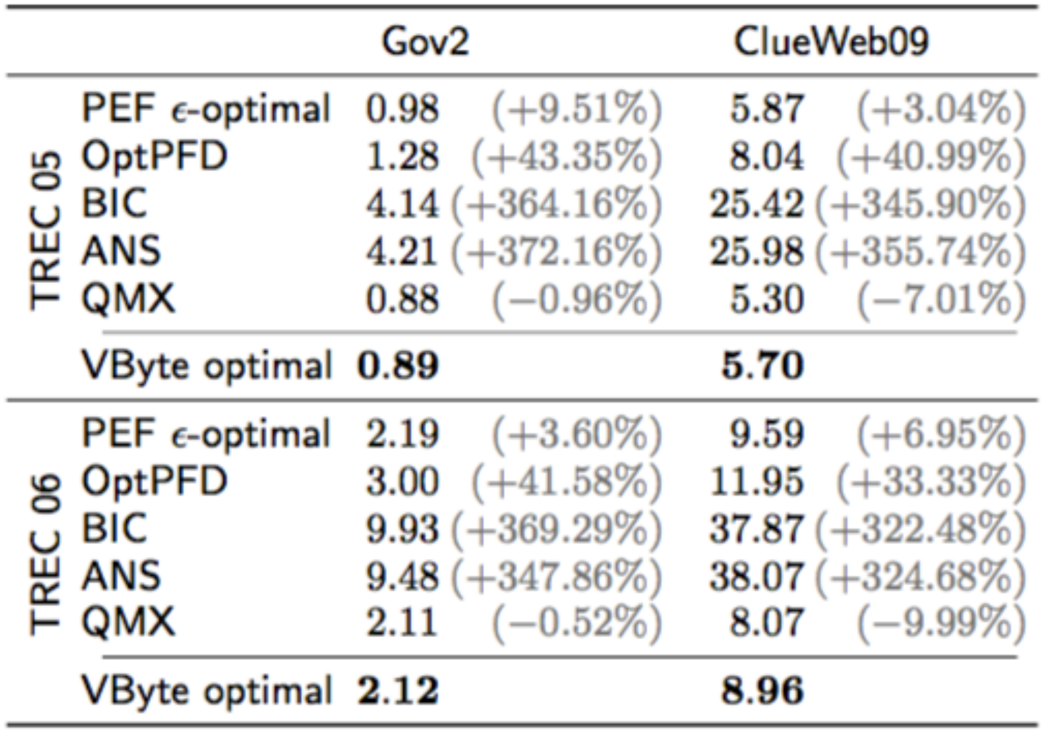

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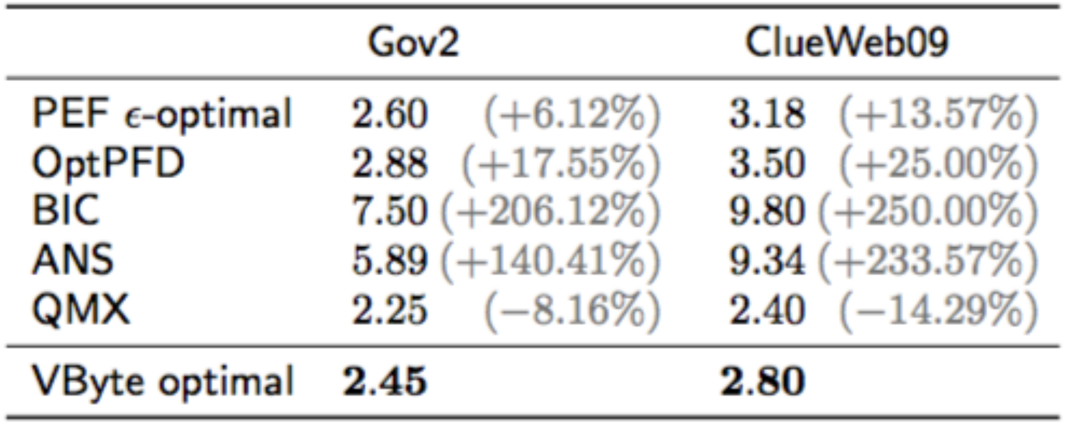

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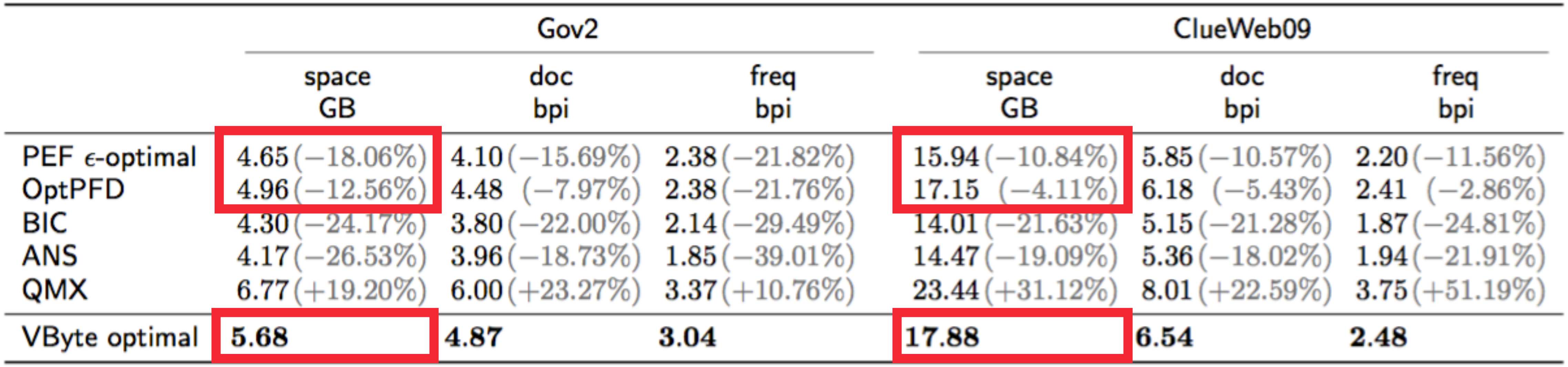

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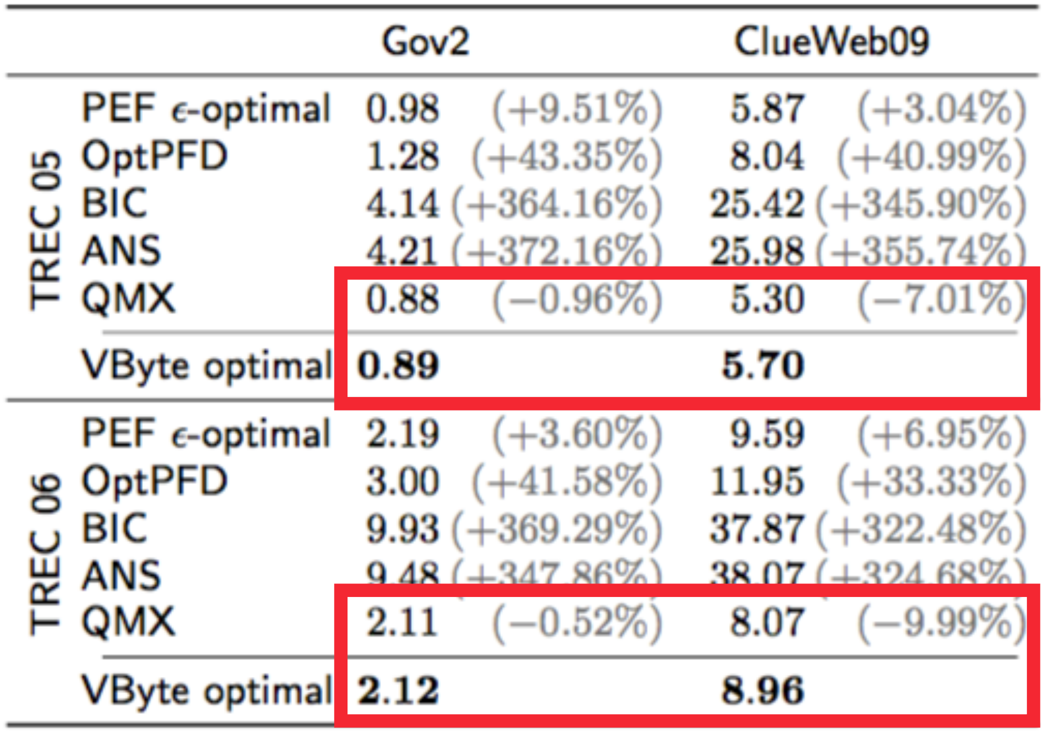

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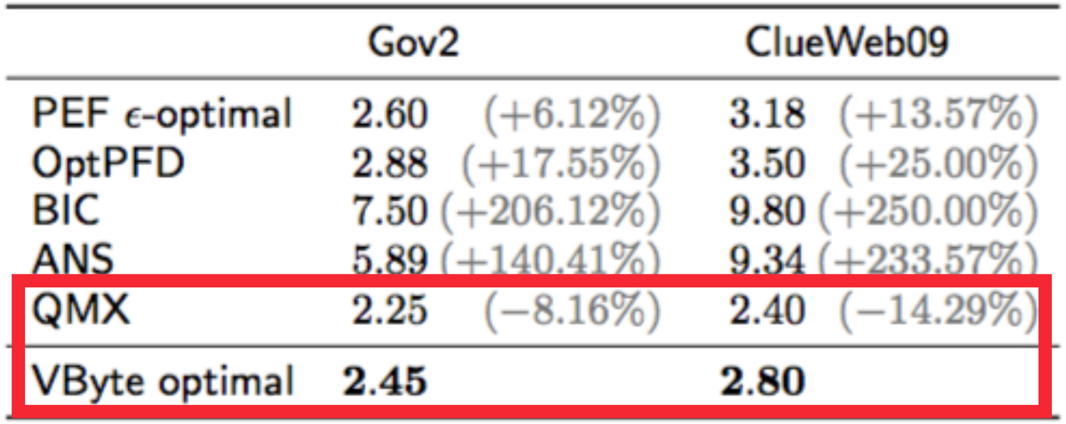

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(b) decoding time (ns/int)

Take-home messages

Just **do not waste space** with VByte:
partition the sequences!

Compression ratio is likely to improve a lot,
without affecting speed.

The partitioning algorithm is **fast**, **optimal**,
and makes indexing even more efficient.

Thanks for your attention, time, patience!

Any questions?

Problem

Scale with the quantity of indexed data.

(Some people would say: “Big Data”.)

Dataset	Uncompressed	Compressed
Gov2	46GB	**4GB (~11X)**
ClueWeb09	128GB	**14GB (~9X)**

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Can we put everything on disk ?

Memory hierarchy!

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See, for example:

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