Space- and Time-Efficient Data Structures for Massive Datasets

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Rossano Venturini

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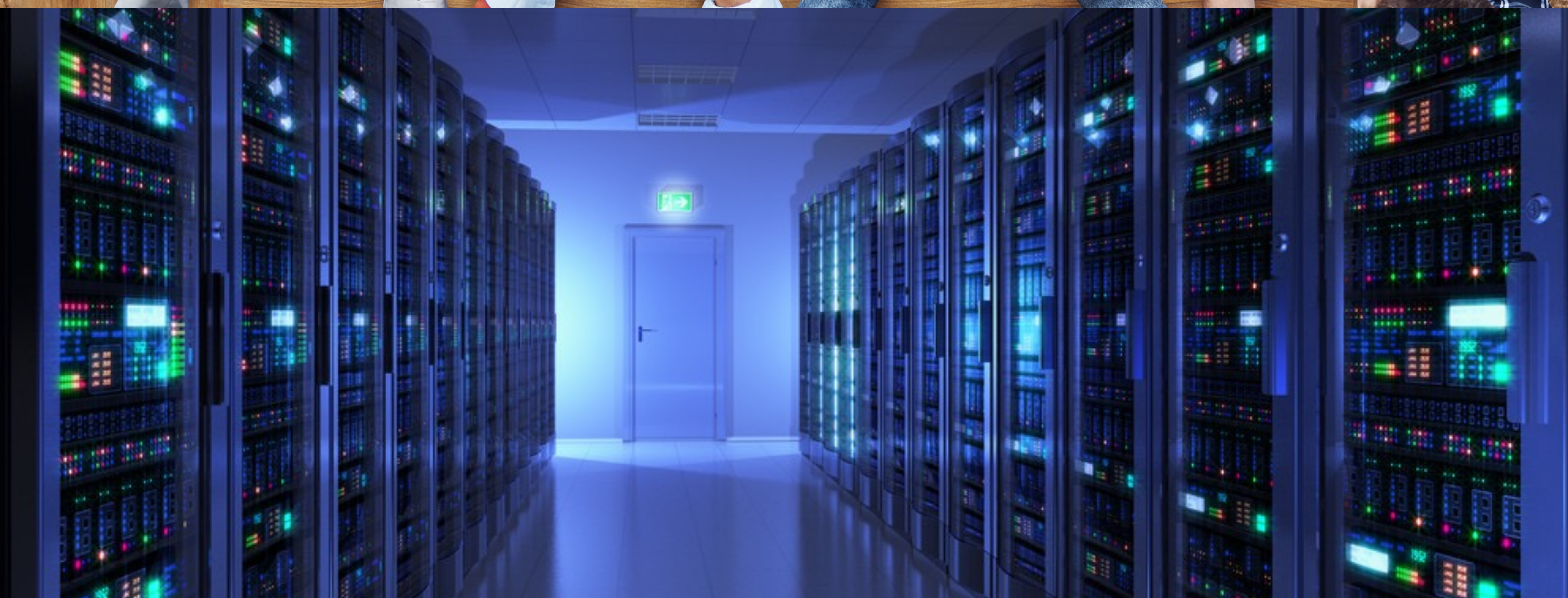
University of Pisa

15/11/2018


Statistics
Progress
Growth & Decline
Statistical
Analysis


Evidence

The increase of information
does **not** scale with technology.

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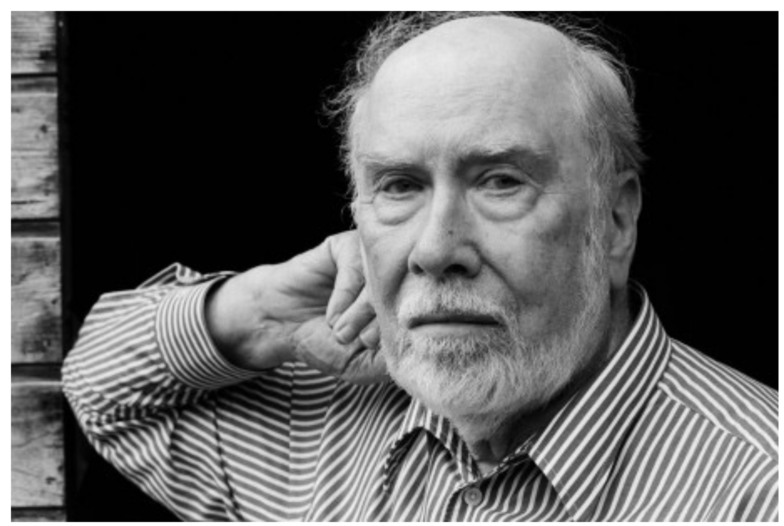

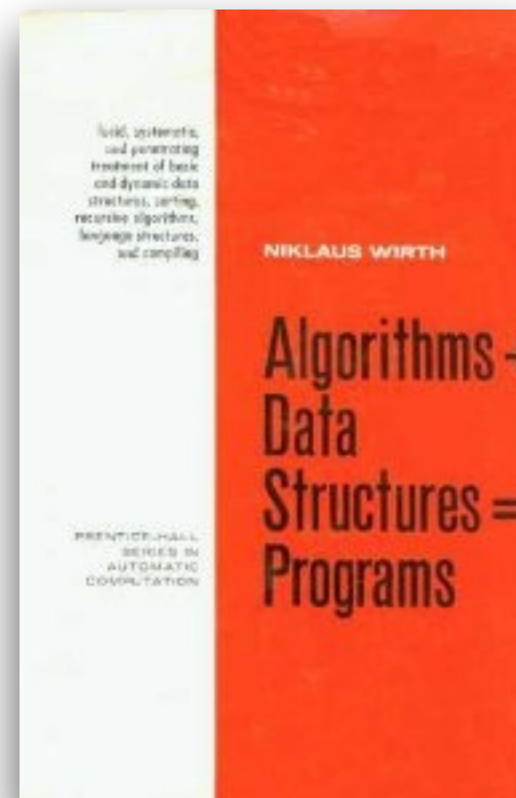

“Software is getting slower more rapidly than hardware becomes faster.”

Niklaus Wirth, A Plea for Lean Software

Evidence

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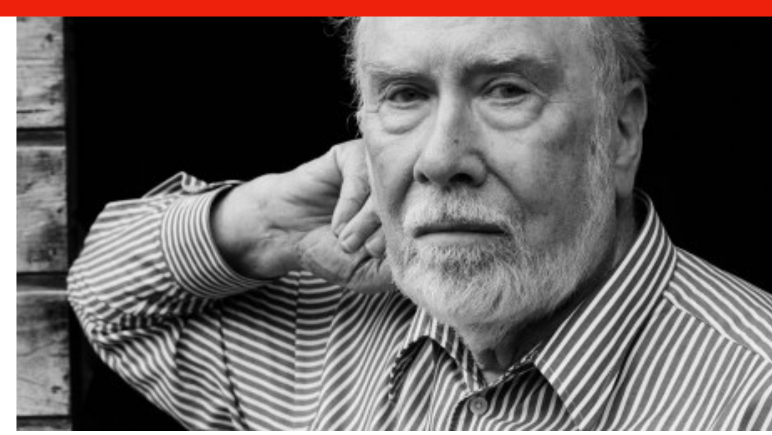
Even more relevant today!



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Scenario

Data structures

PERFORMANCE

how quickly a program does its work - **faster** work

time ✓
✗ space

↔

Algorithms

EFFICIENCY

how much work is required by a program - **less** work

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Data compression

✓ space
time ✗

The dichotomy problem

Small vs. fast?

The dichotomy problem

Small vs. fast?

Choose one.

The dichotomy problem

Small vs. fast?

Choose one.

NO

High level thesis

Data Structures + Data Compression ➡ Fast Algorithms

Design **space-efficient** *ad-hoc* data structures,
both from a theoretical *and* practical perspective,
that support **fast data extraction**.

Data Compression & Fast Retrieval *together*.

Achieved results

Clustered Elias-Fano Indexes
Giulio Ermanno Pibiri and Rossano Venturini
ACM Transactions on Information Systems (TOIS)
Full paper, 34 pages, 2017.

Journal paper

Dynamic Elias-Fano Representation
Giulio Ermanno Pibiri and Rossano Venturini
Annual Symposium on Combinatorial Pattern Matching (CPM)
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Variable-Byte Encoding is Now Space-Efficient Too
Giulio Ermanno Pibiri and Rossano Venturini
arXiv (CoRR), April 2018.
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Giulio Ermanno Pibiri, Matthias Petri and Alistair Moffat
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Efficient Data Structures for Massive N-Gram Datasets
Giulio Ermanno Pibiri and Rossano Venturini
ACM Conference on Research and Development in Information Retrieval (SIGIR)
Full paper, 10 pages, 2017.

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Handling Massive N-Gram Datasets Efficiently
Giulio Ermanno Pibiri and Rossano Venturini
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integer sequences

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short strings

Problem 1

Consider a sorted integer sequence.

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How to represent it as a bit-vector where each original integer is uniquely-decodable, using **as few as possible** bits?

How to maintain **fast decompression speed**?

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This is a difficult problem that has been studied since the the '60.

Applications

Inverted indexes

Databases

RDF indexing

E-Commerce

Geo-spatial data

Graph-compression

Applications

Inverted indexes

Google YAHOO!

bing

Databases

IBM Dropbox

ORACLE

RDF indexing

ontotext

E-Commerce

ebay amazon

Geo-spatial data

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Graph-compression

facebook

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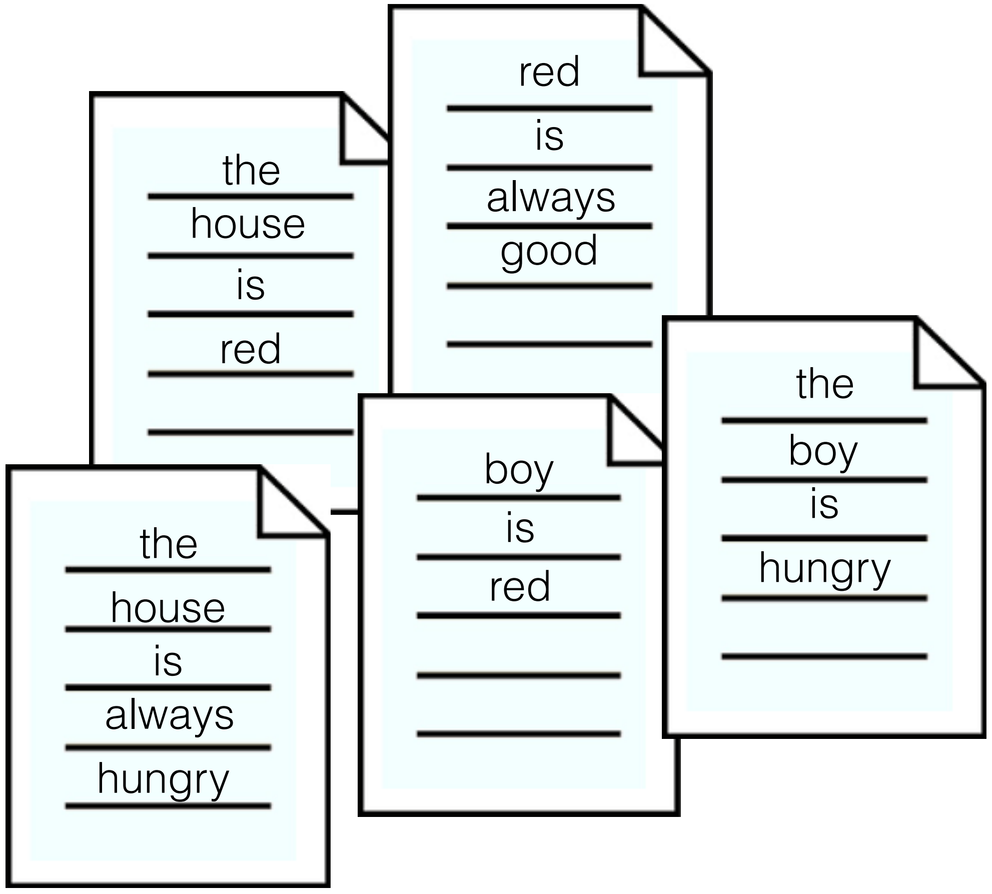

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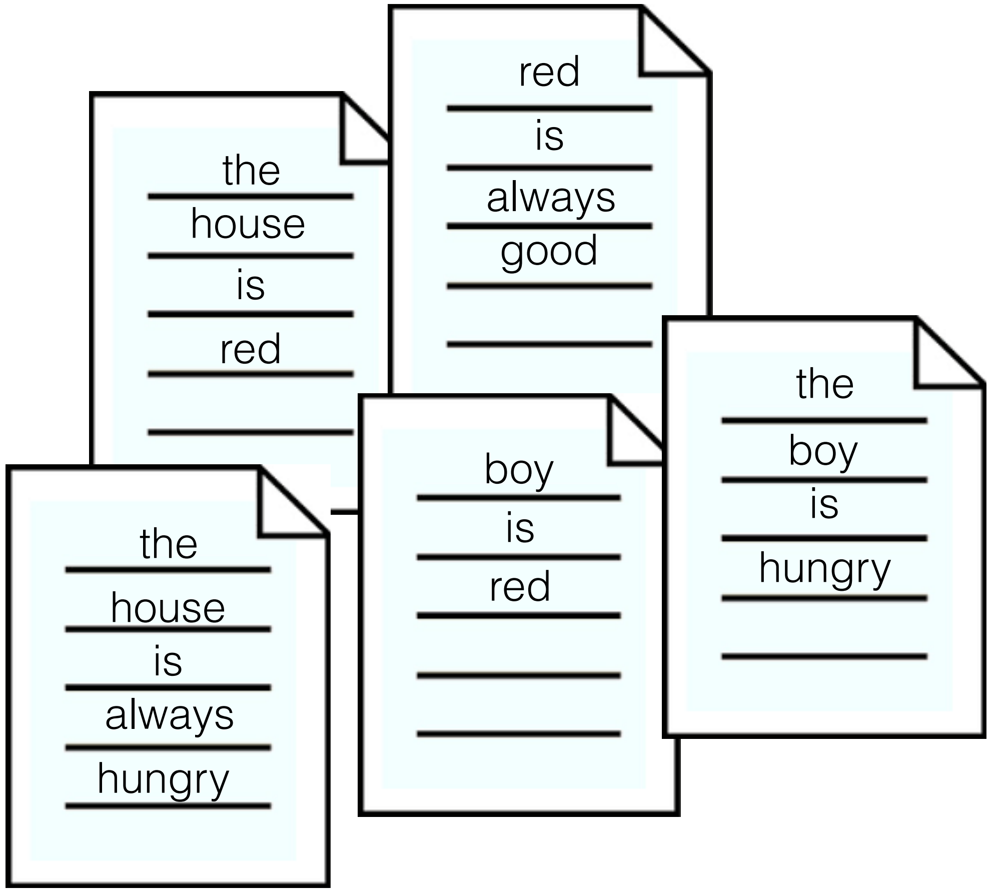

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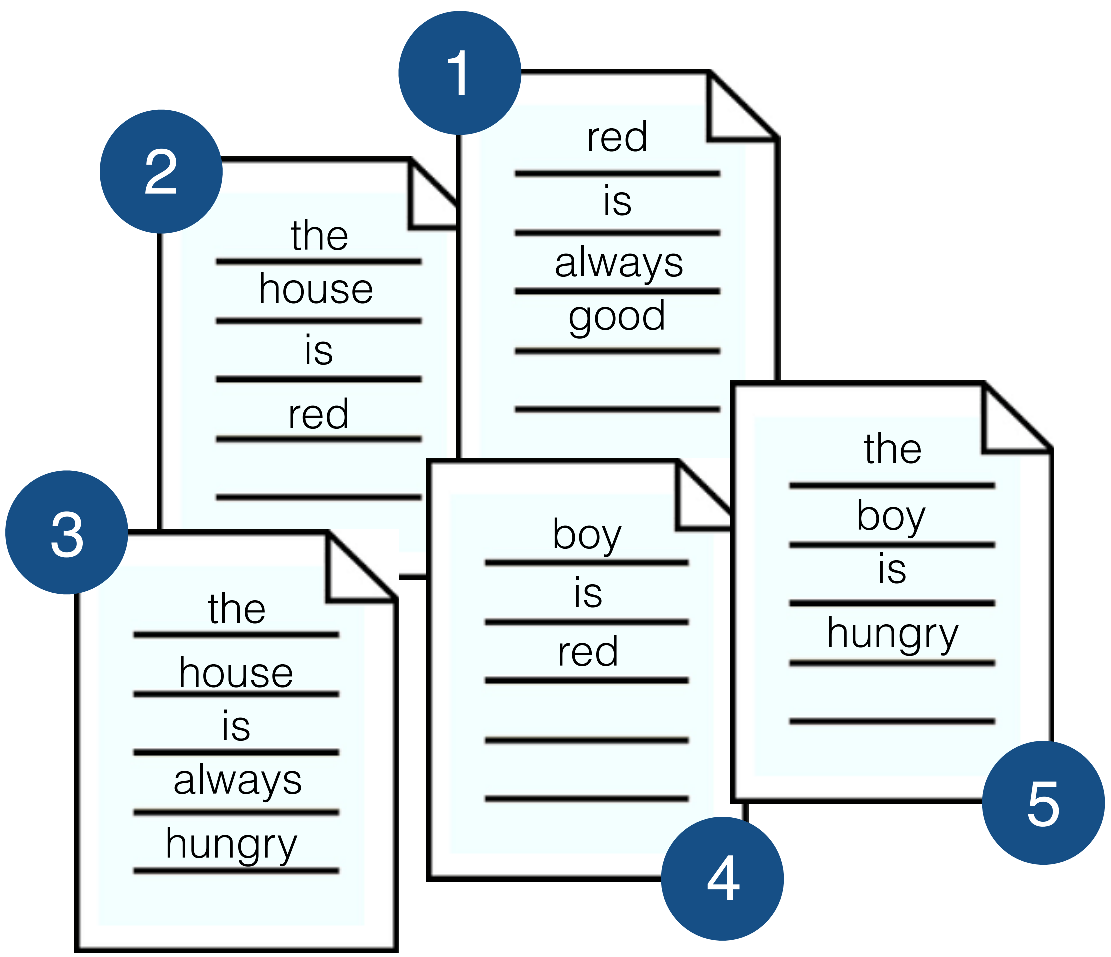

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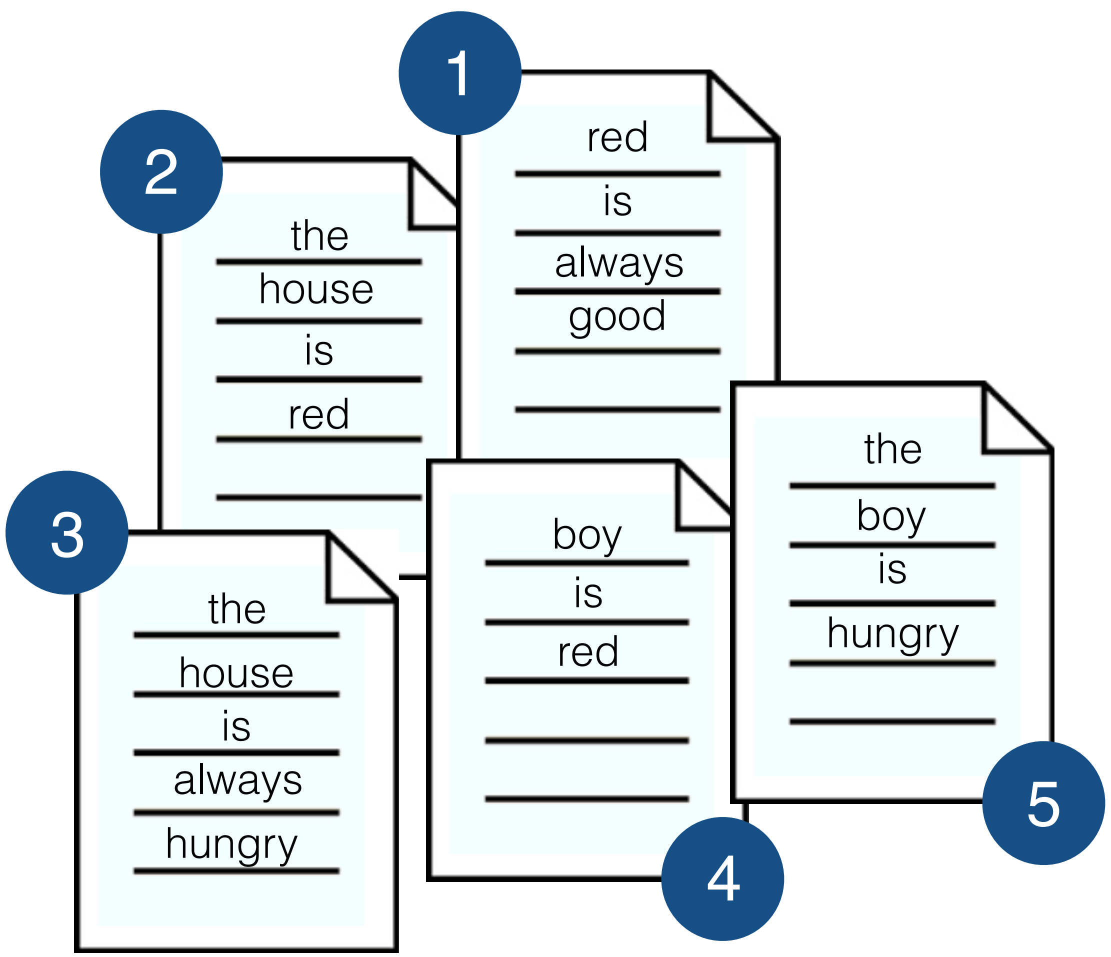

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→

L_{t_1}=[1, 3]
L_{t_2}=[4, 5]
L_{t_3}=[1]
L_{t_4}=[2, 3]
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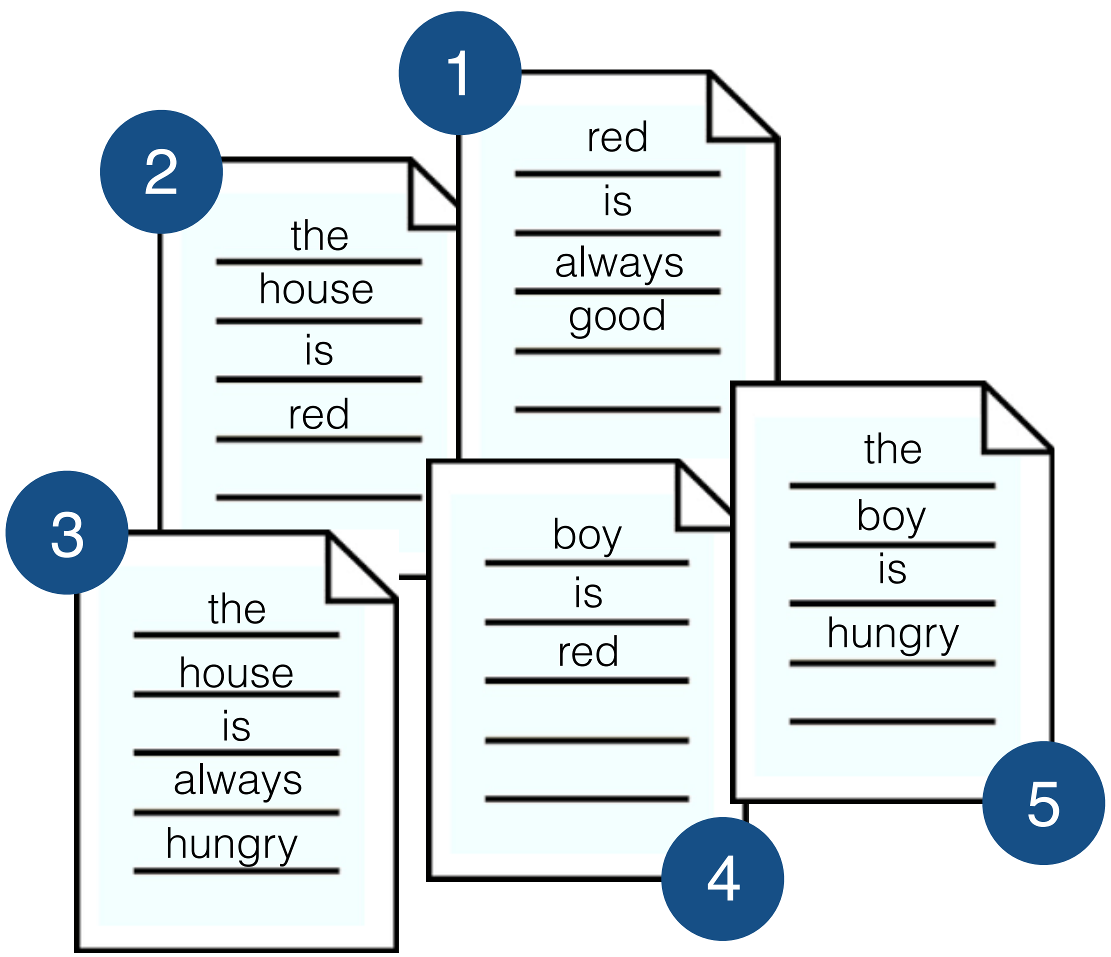

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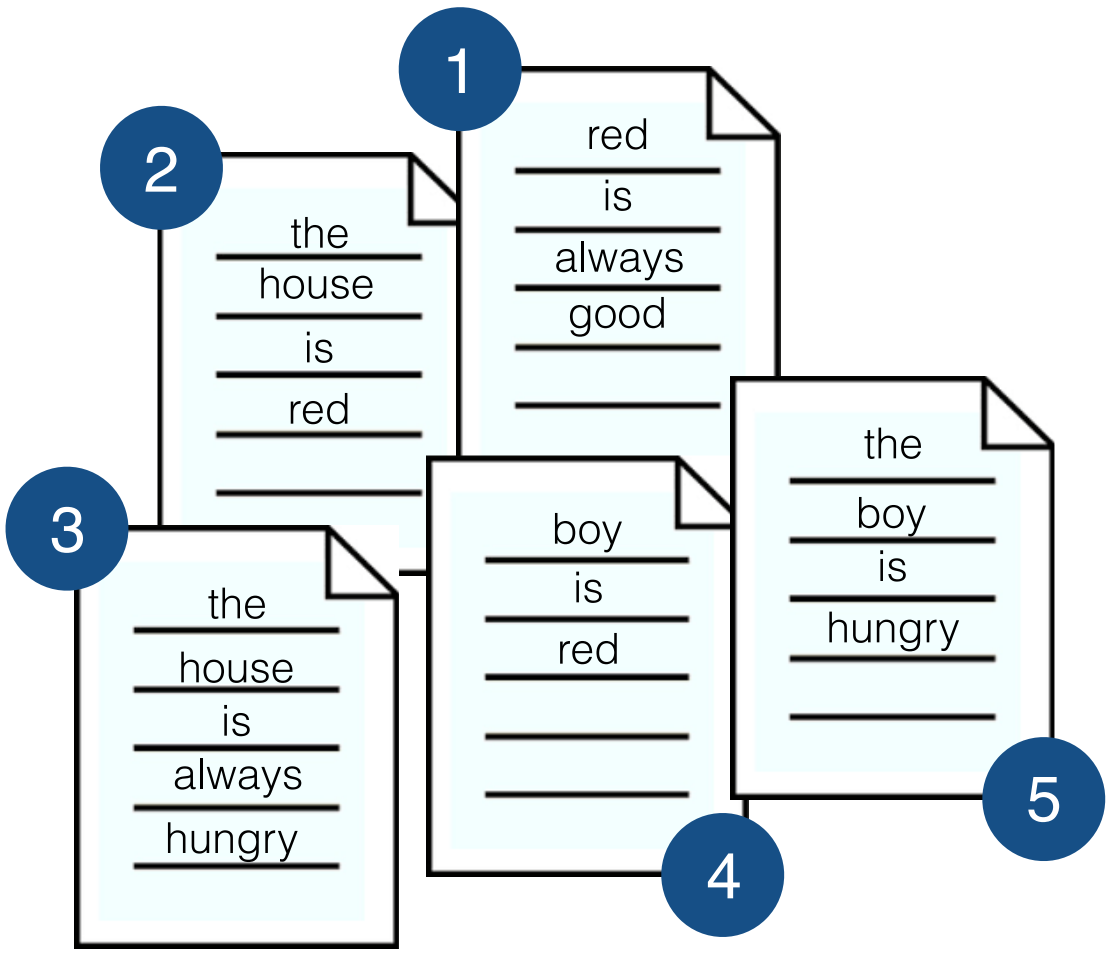

$$\{\overset{t_1}{\text{always}}, \overset{t_2}{\text{boy}}, \overset{t_3}{\text{good}}, \overset{t_4}{\text{house}}, \overset{t_5}{\text{hungry}}, \overset{t_6}{\text{is}}, \overset{t_7}{\text{red}}, \overset{t_8}{\text{the}}\}$$

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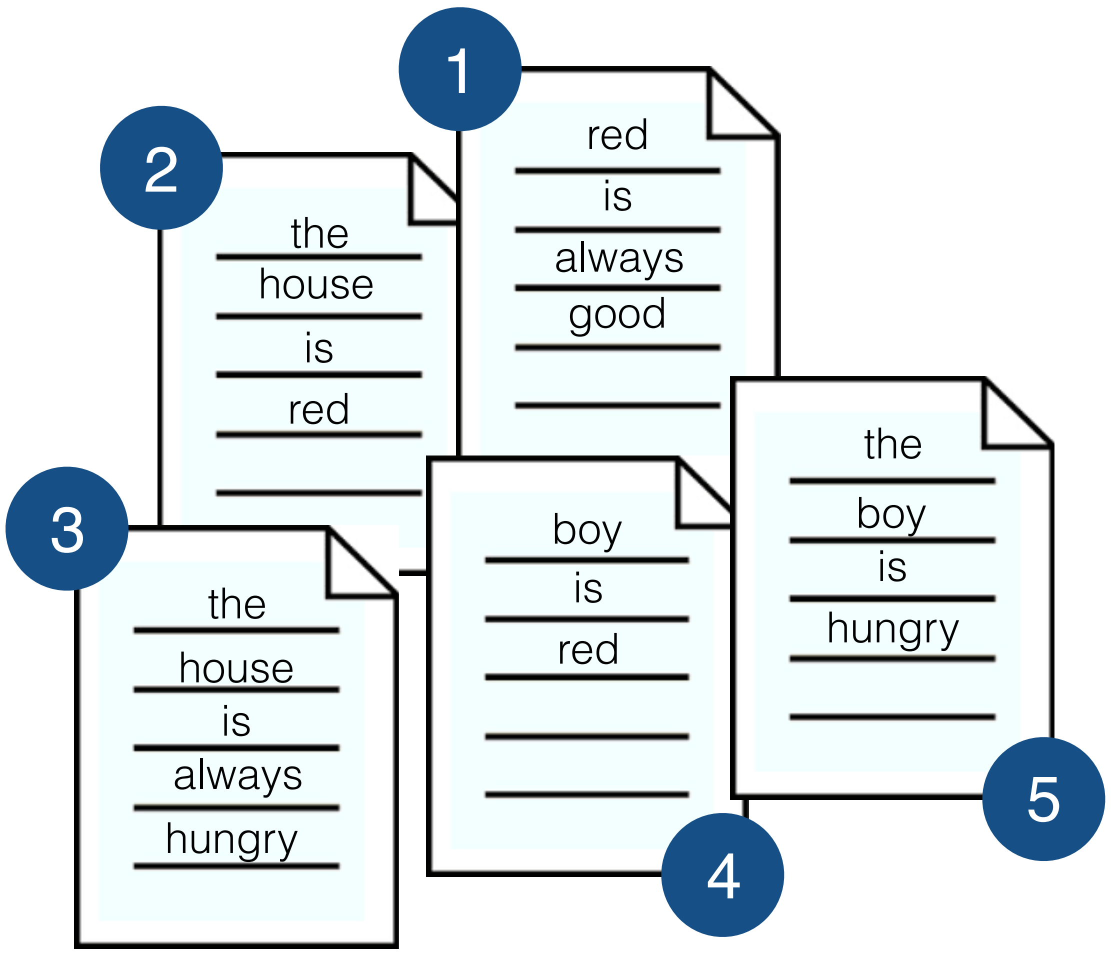

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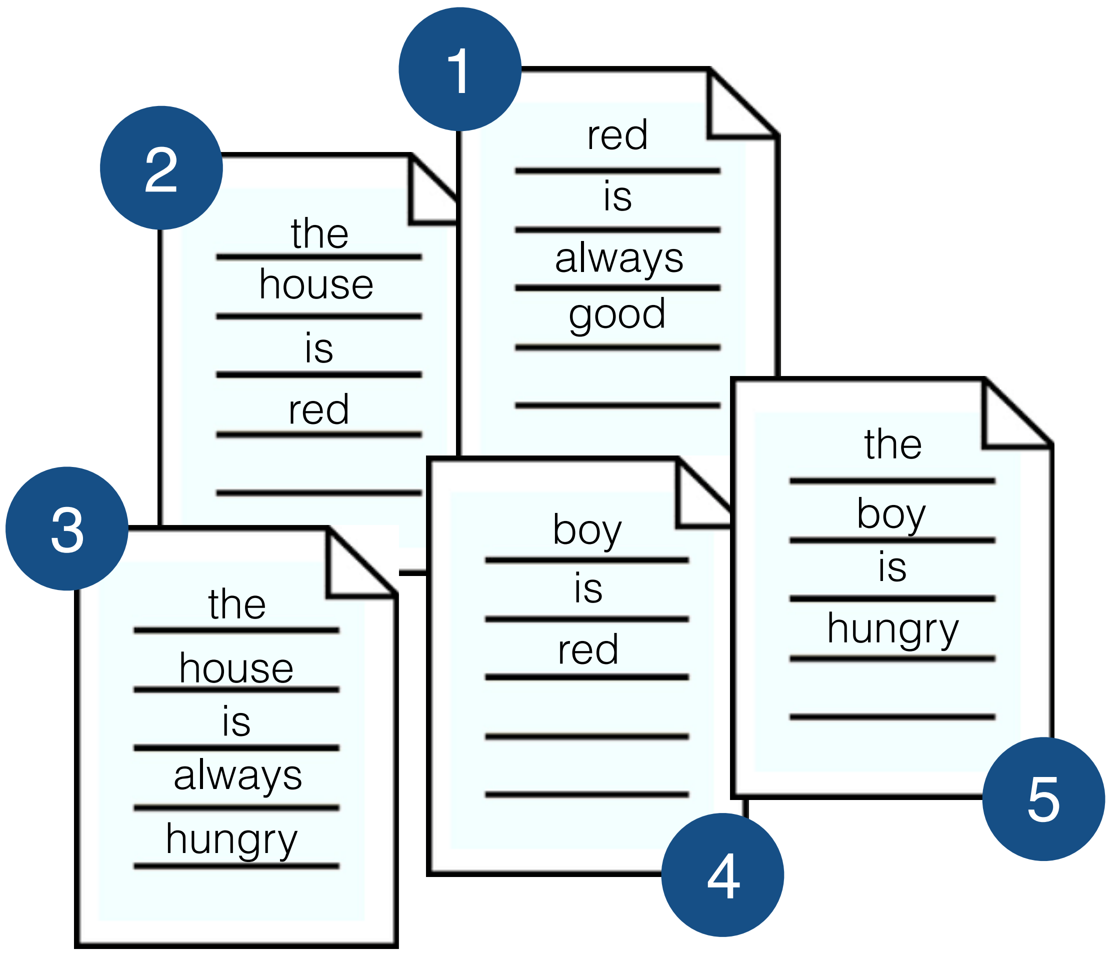

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Many solutions

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

- Elias Gamma and Delta **'70**
- Variable-Byte Family
- Binary Interpolative Coding
- Simple Family
- PForDelta
- QMX
- Elias-Fano
- Partitioned Elias-Fano **2014**

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Space — **Binary Interpolative Coding** — ~**3X** smaller

← Spectrum →

Time — **Variable-Byte Family** — ~**4.5X** faster

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Space | **Time**

Binary Interpolative Coding ← Spectrum → **Variable-Byte Family**

~**3X** smaller | ~**4.5X** faster

Google, Dropbox, amazon, IBM

Key research questions

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Binary Interpolative Coding

← Spectrum →

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1. Is it possible to design an encoding that is **as small as BIC** and **much faster**?

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2. Is it possible to design an encoding that is **as fast as VByte** and **much smaller**?

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3. What about **both** objectives at the same time?!

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Every encoder represents each sequence **individually**.

No exploitation of redundancy.

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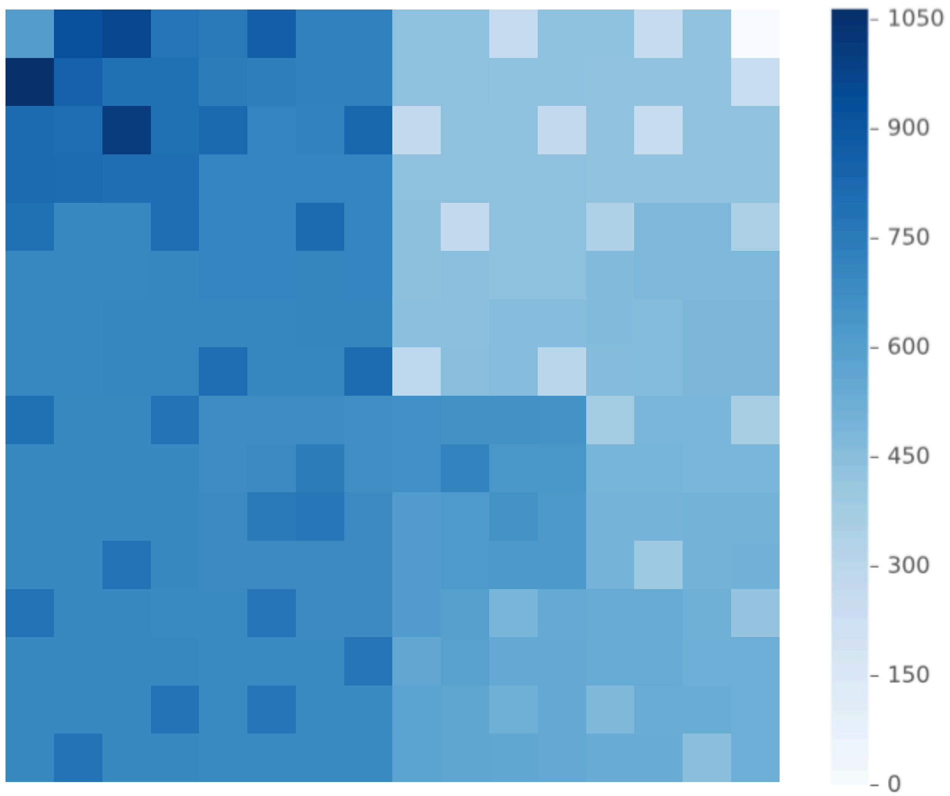

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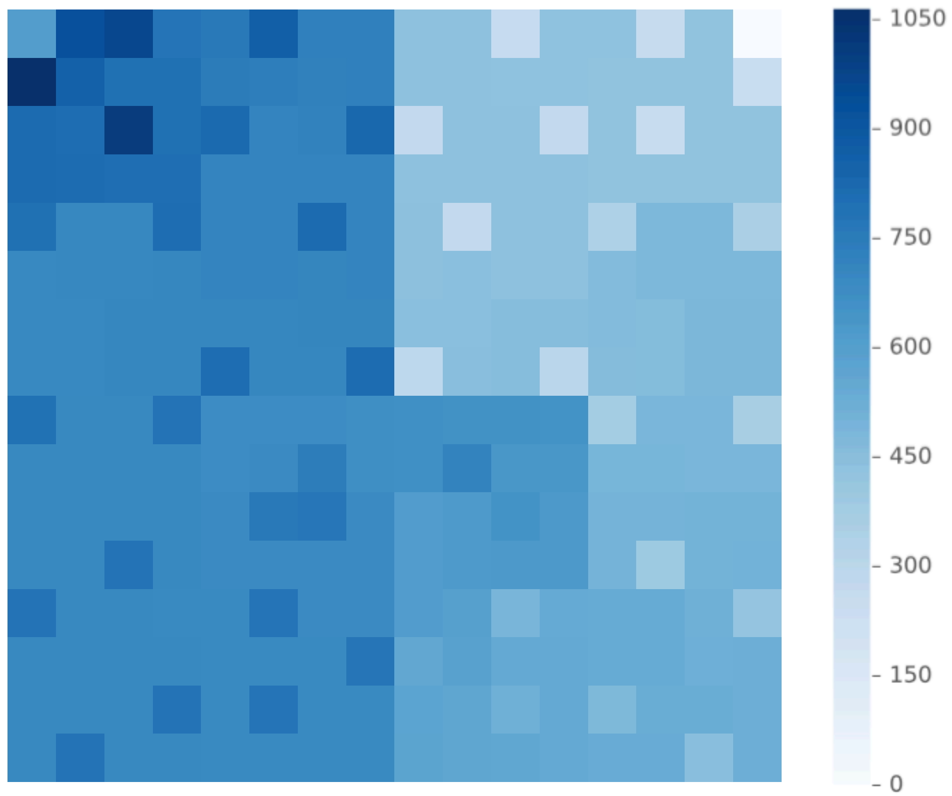

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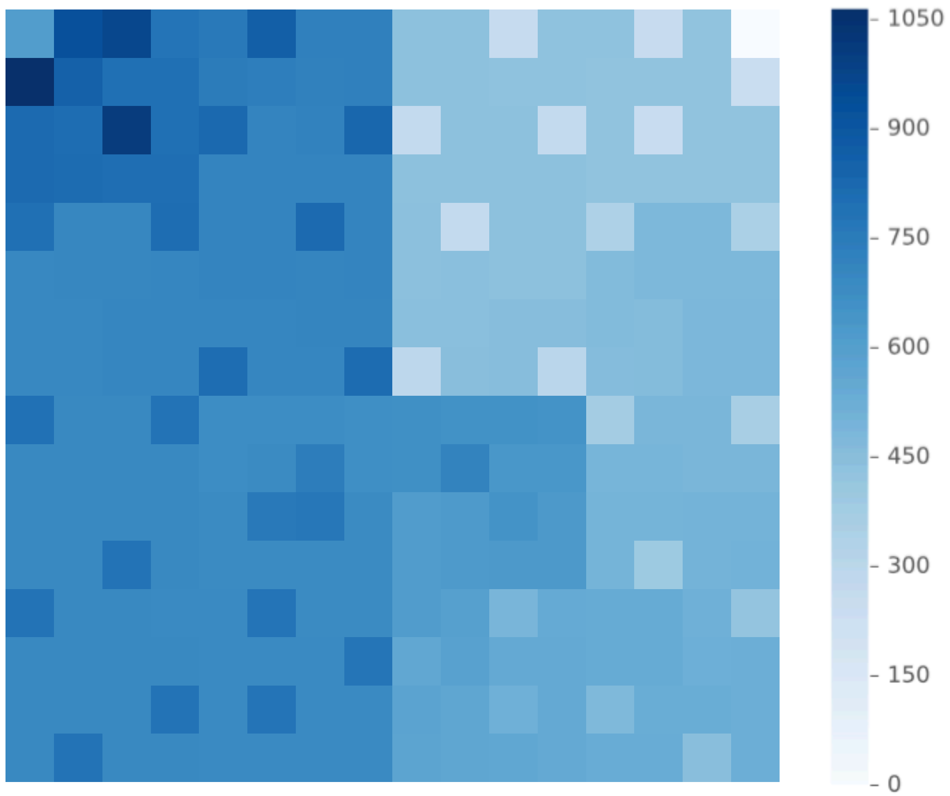

Encode **clusters** of inverted lists.

Space

Always better than PEF (by up to **11%**) and better than BIC (by up to **6.25%**)

← Spectrum →

Time

Much faster than BIC (~103%)
Slightly slower than PEF (~20%)

Idea 2 - Optimally-partitioned VByte (TKDE ’18)

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

VByte needs **at least 8 bits** per integer, that is sensibly far away from bit-level effectiveness (BIC: **3.54**, PEF: **4.1** on Gov2).

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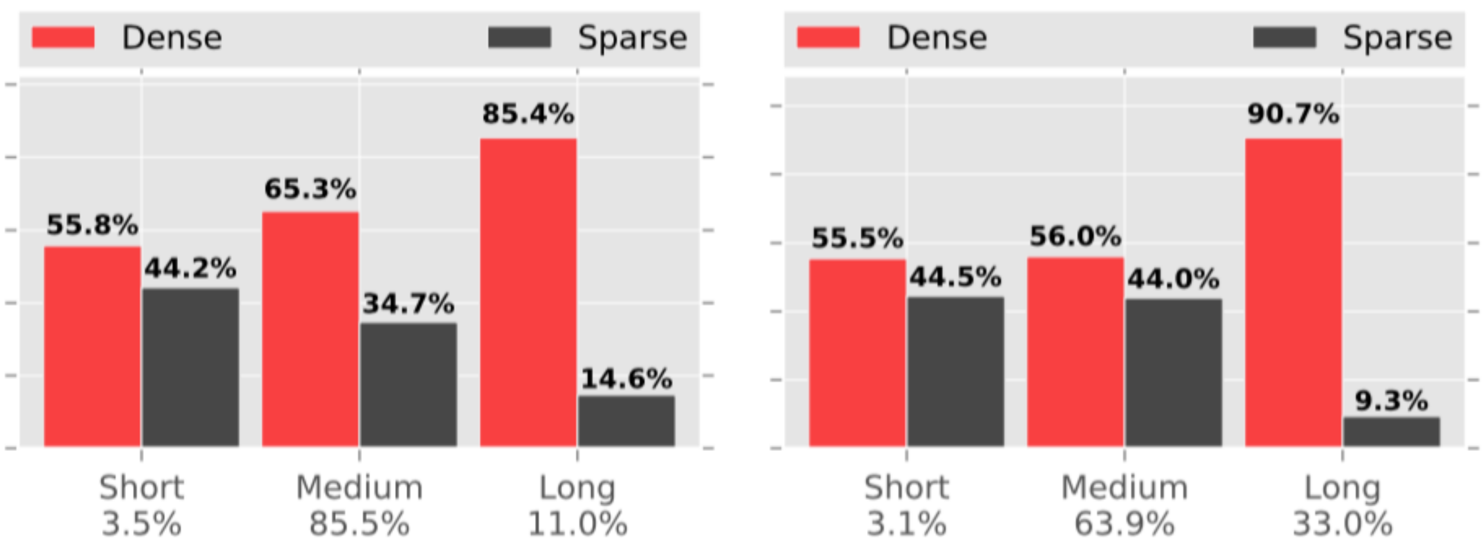

(a) Gov2 (b) ClueWeb09

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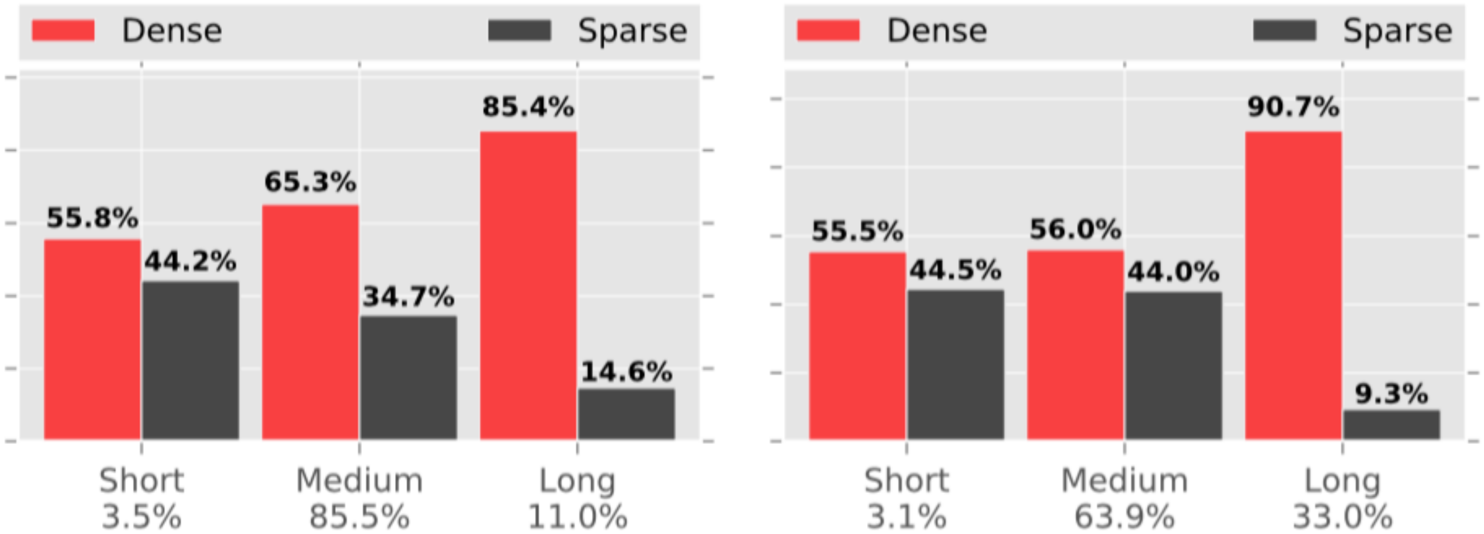

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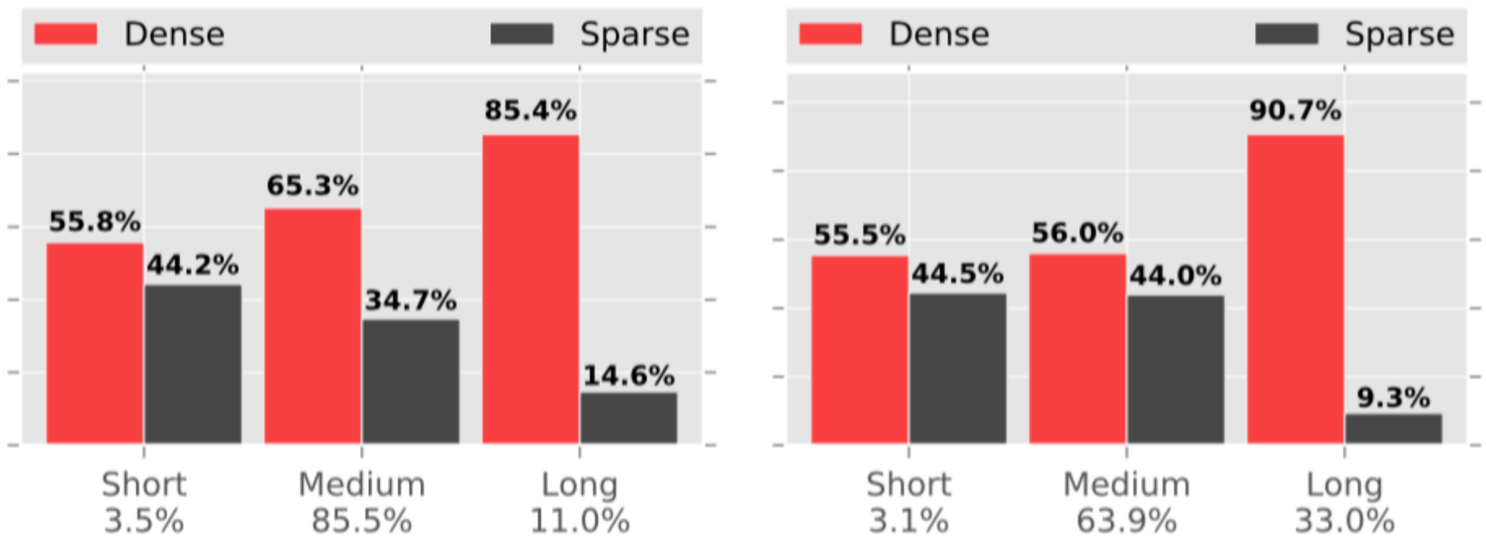

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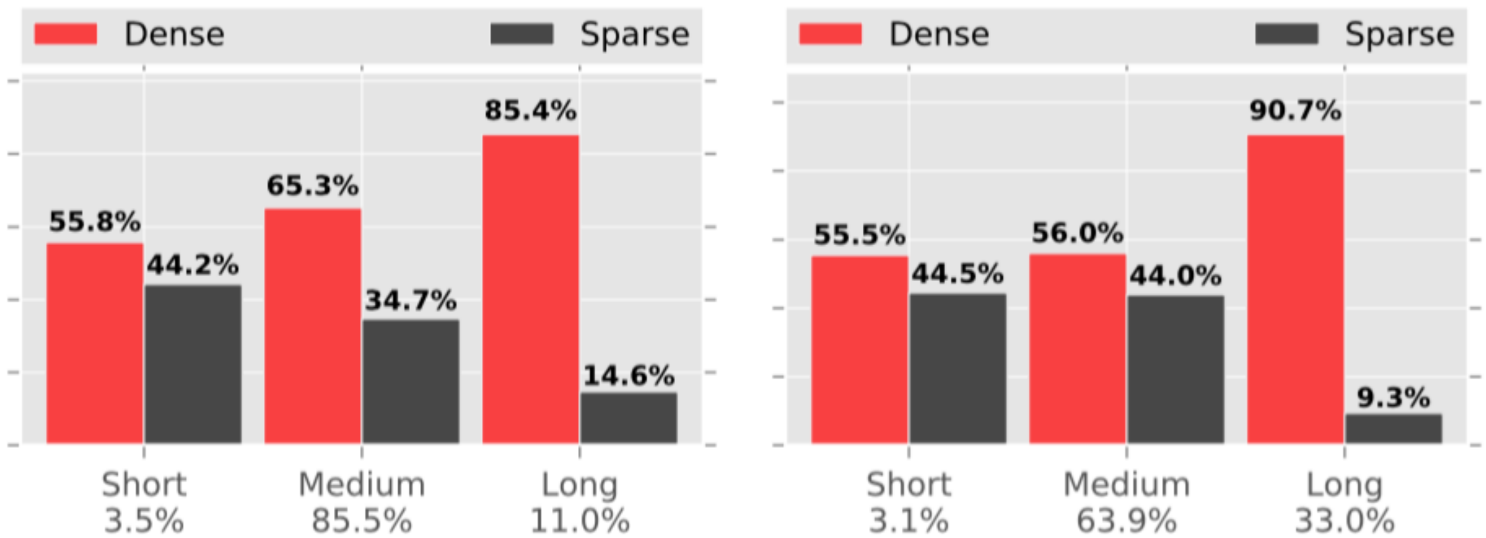

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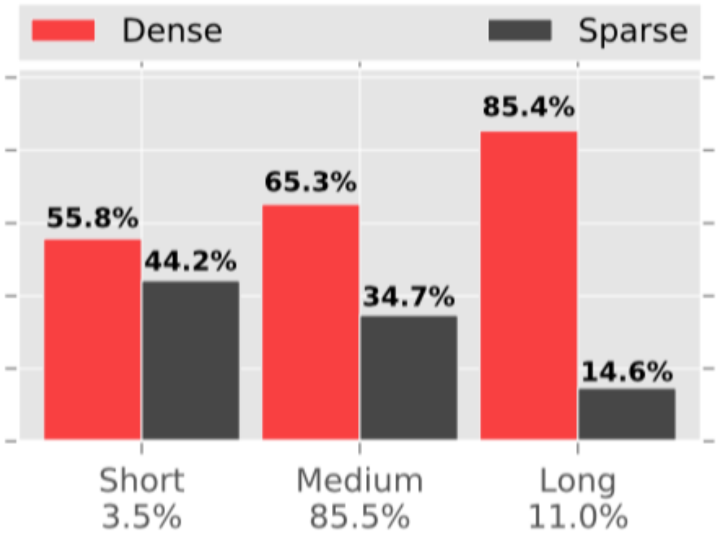

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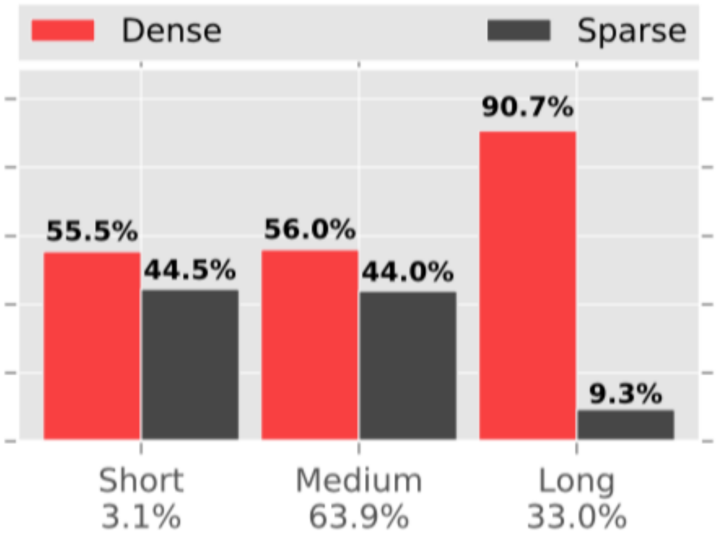

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Compression ratio improves by **2X**.

Query processing speed and sequential decoding **not affected**.

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with M. Petri and A. Moffat
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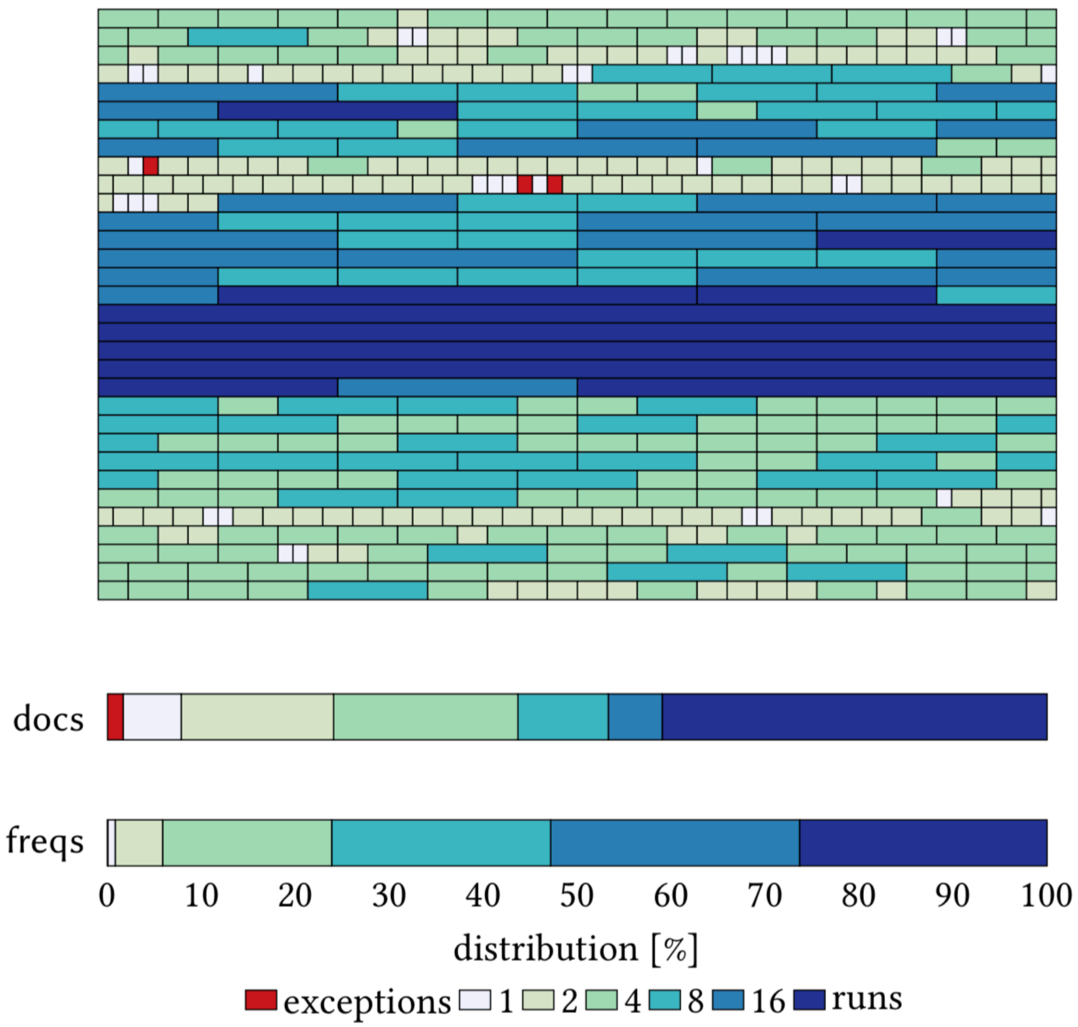

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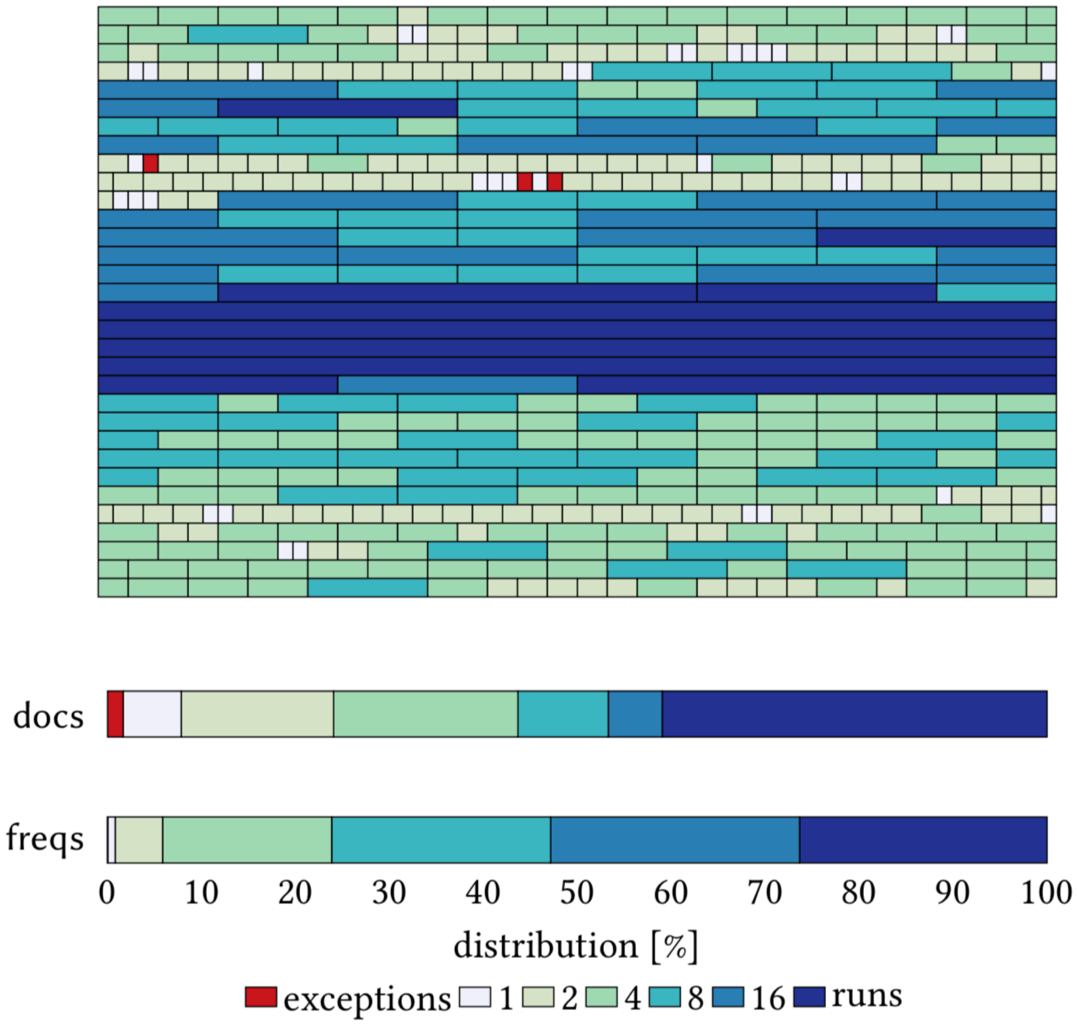

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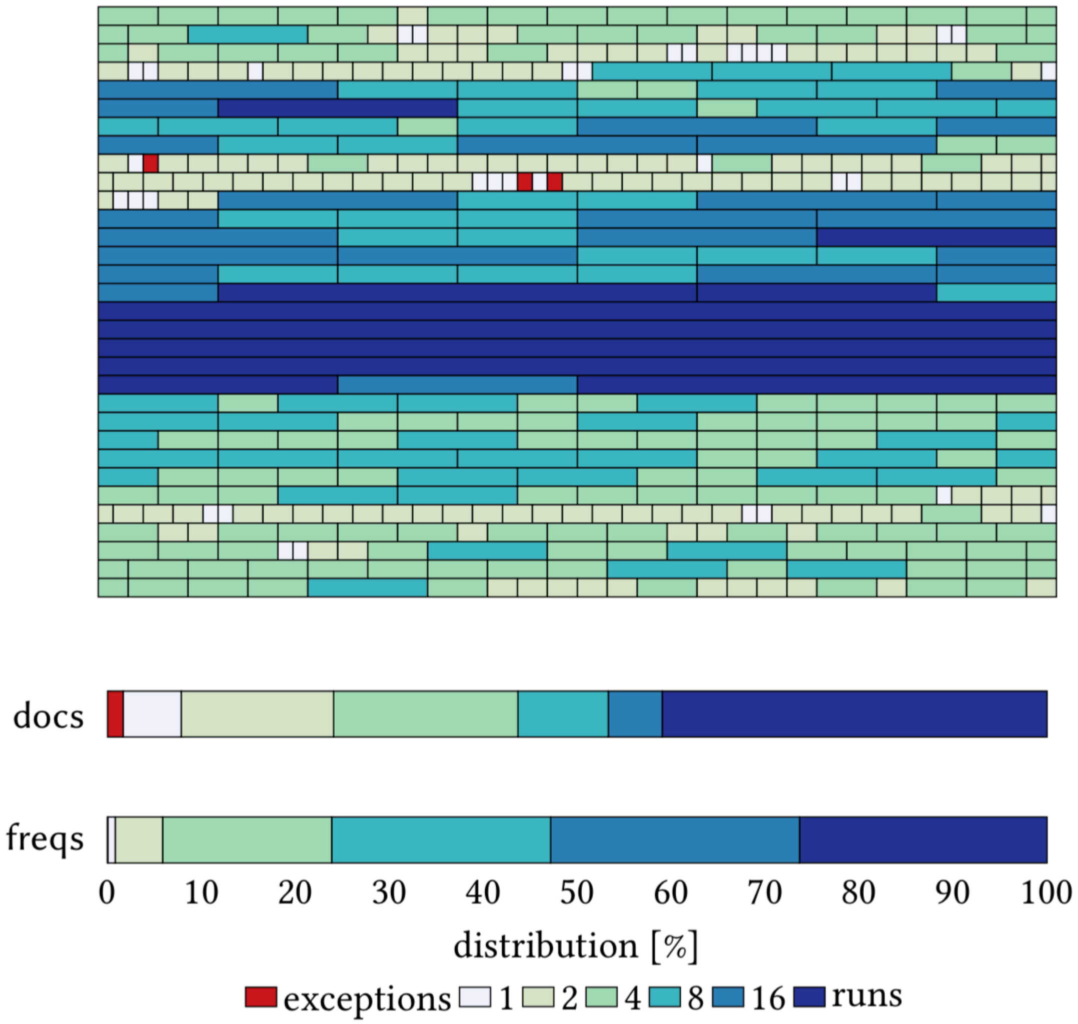

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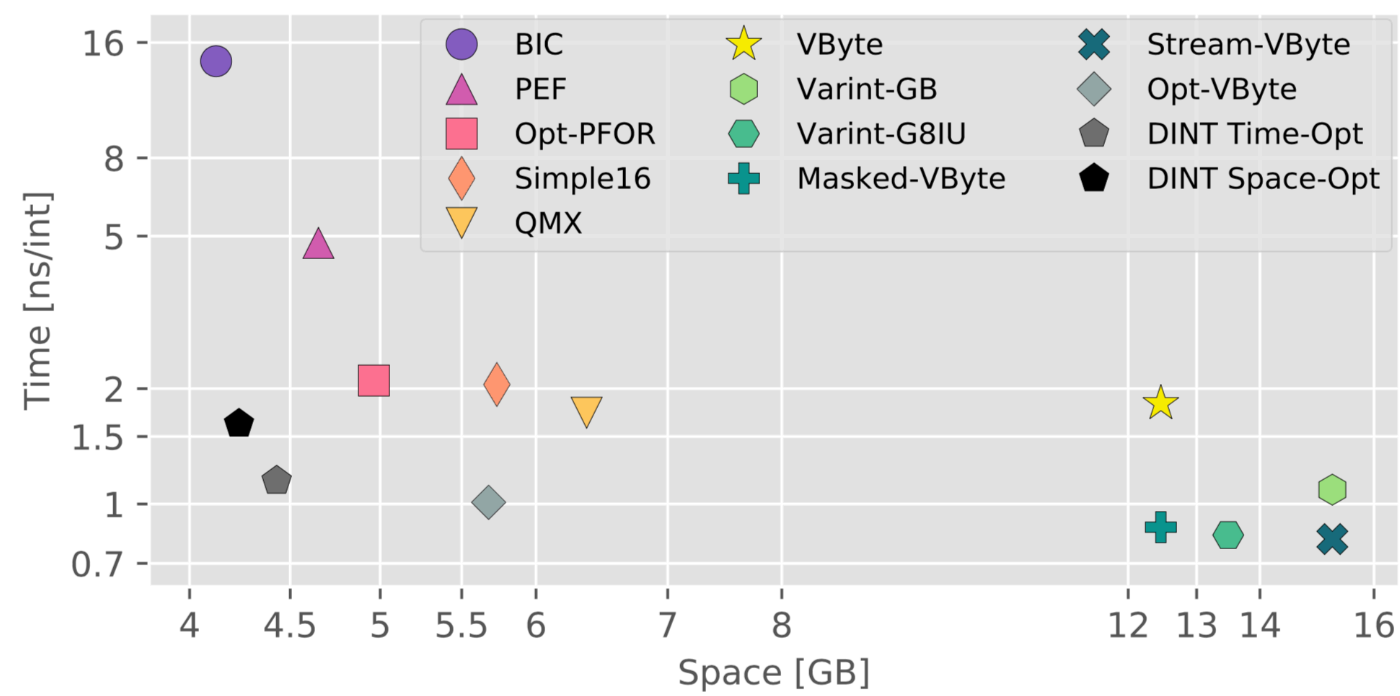
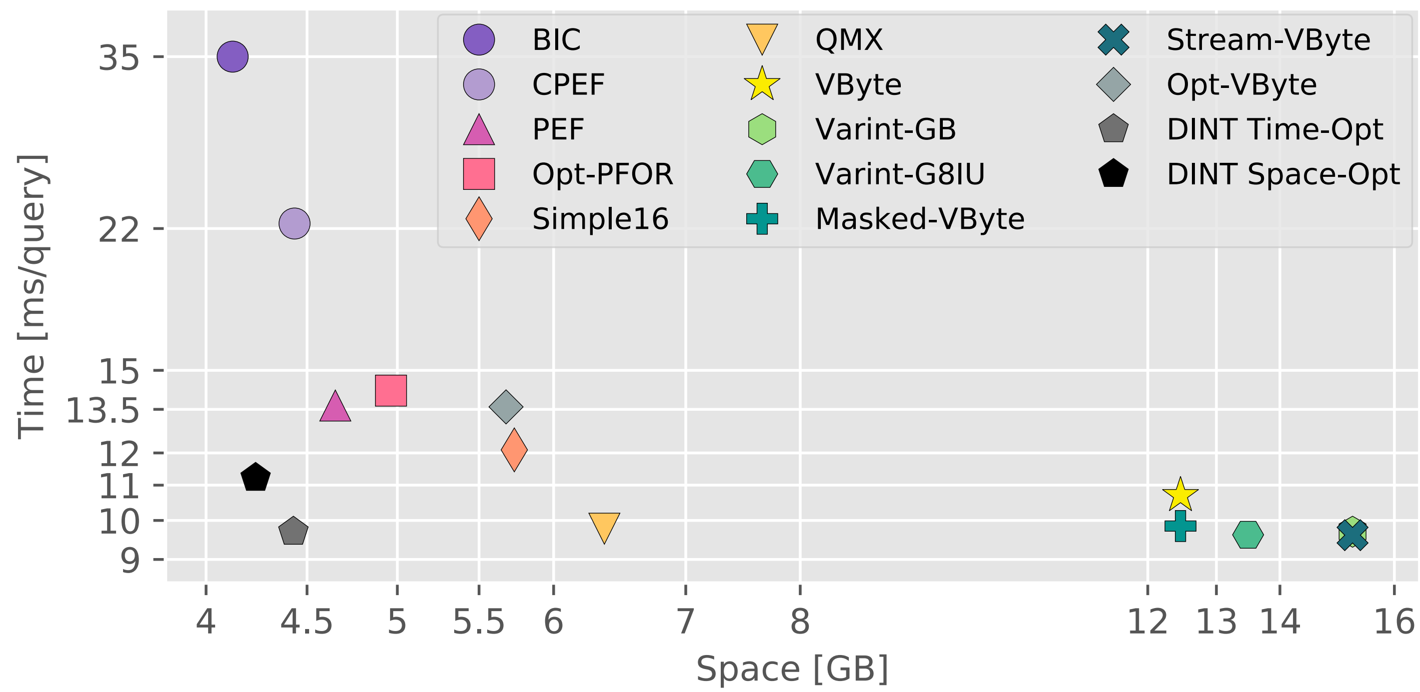
The bigger picture





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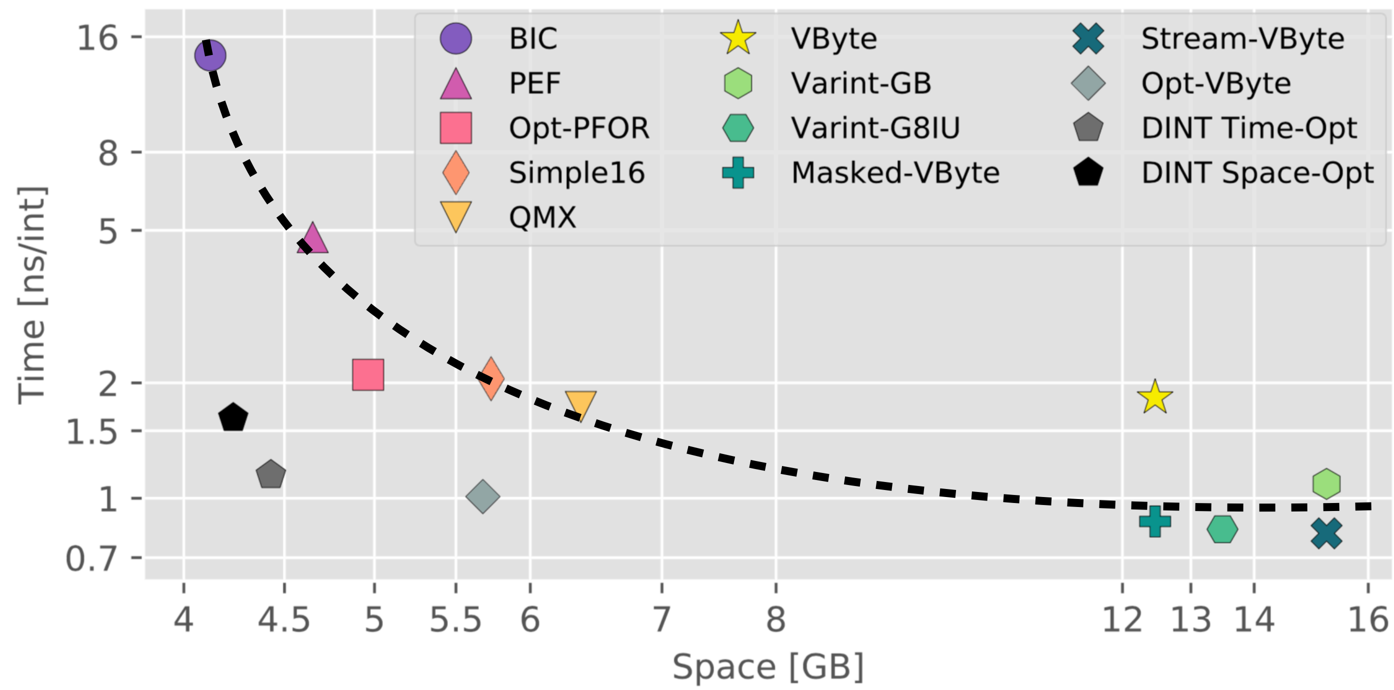

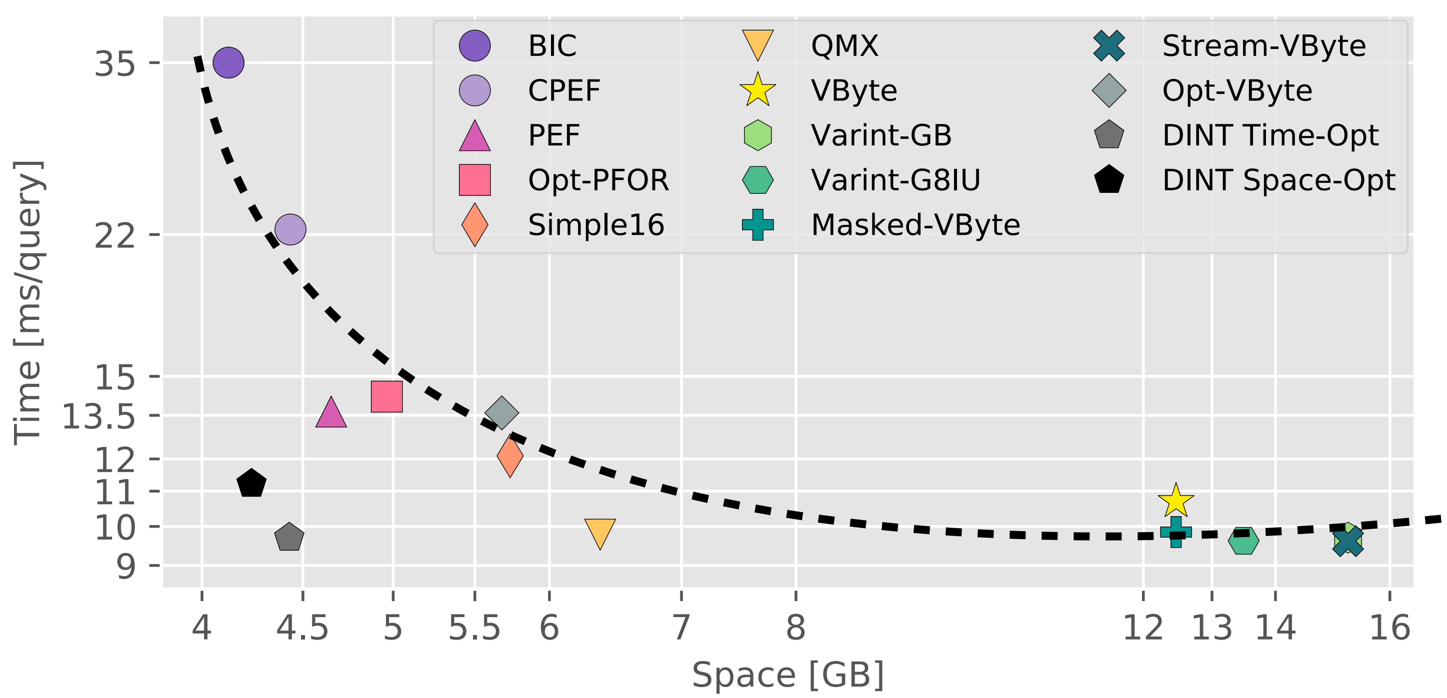

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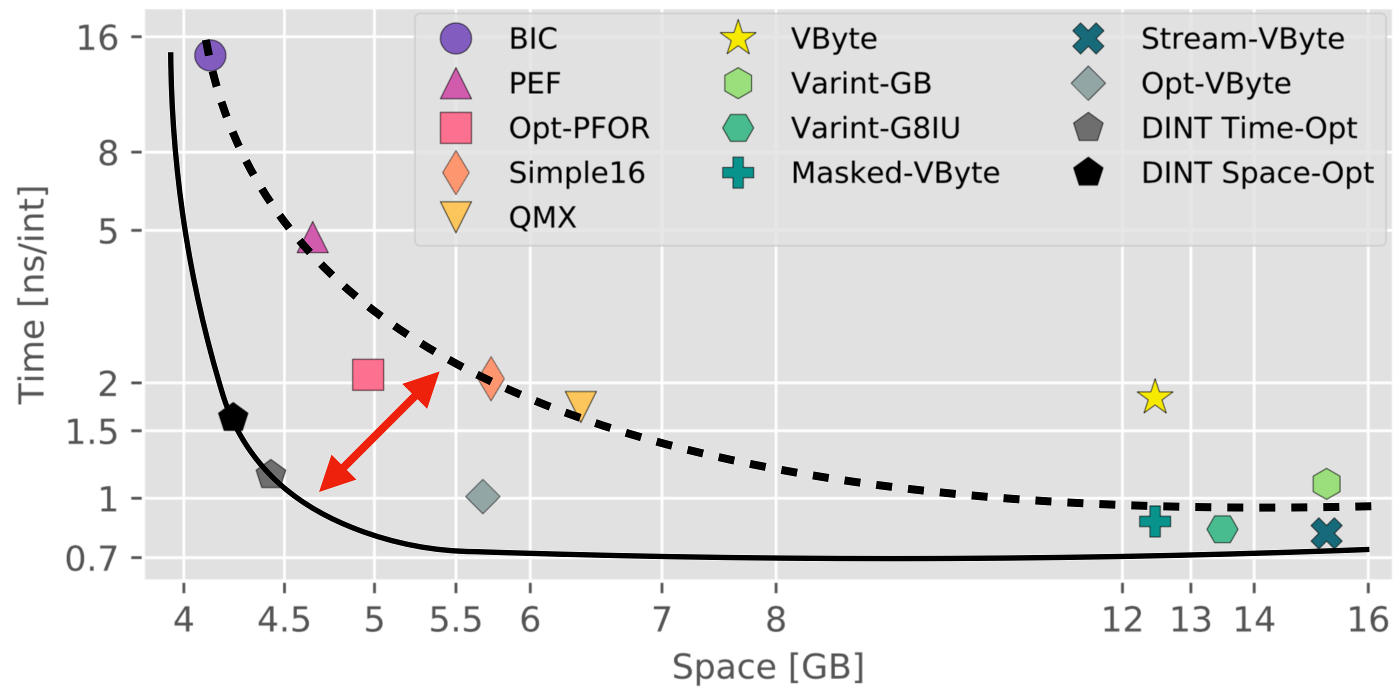

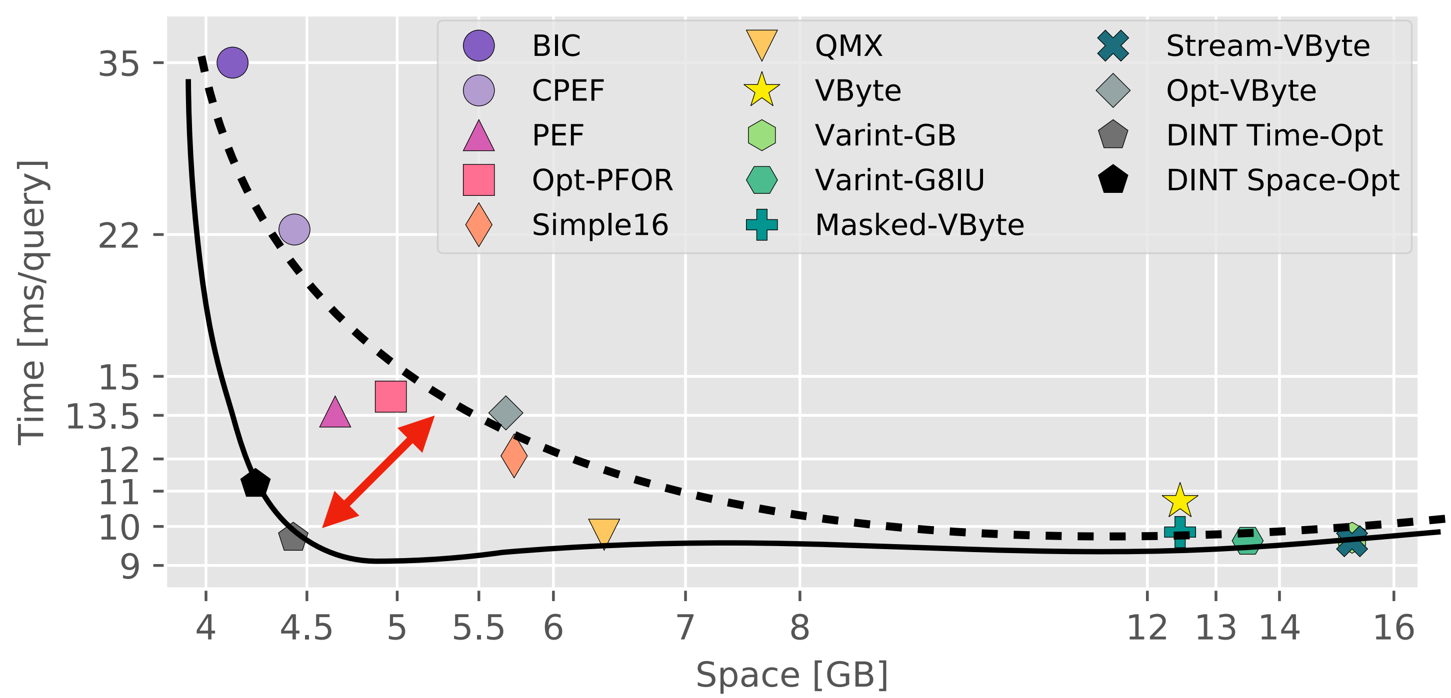

Problem 2

Integer data structures

- van Emde Boas Trees
- X/Y-Fast Tries
- Fusion Trees
- Exponential Search Trees
- …

+ time
- space
+ dynamic

Elias-Fano encoding

- EF($S(n,u)$) = $n \log(u/n) + 2n$ bits to encode a sorted integer sequence S
- O(1) **Access**
- O($1 + \log(u/n)$) **Predecessor**

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+ time
- space
+ dynamic

+ time
+ space
- static

Can we grab the best from both?

Dynamic inverted indexes

Classic solution: use two indexes.
One is big and **cold**; the other is small and **hot**.
Merge them periodically.

Append-only inverted indexes.

Integer dictionaries in succinct space (CPM ’17)

Result 1

For $u = n^\gamma$, $\gamma = \Theta(1)$:

- EF($S(n,u)$) + o(n) bits
- O(1) **Access**
- O(min{1+log(u/n), loglog n}) **Predecessor**

Result 2

- EF($S(n,u)$) + o(n) bits
- O(1) **Access**
- O(1) **Append** (amortized)
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Result 3

- EF($S(n,u)$) + o(n) bits
- O(log n / loglog n) **Access**
- O(log n / loglog n) **Insert/Delete** (amortized)
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Optimal time bounds for all operations using a sublunar redundancy.

Problem 3

Consider a large text.

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How to represent all its substrings of size $1 \leq k \leq N$ words for fixed N (e.g., $N = 5$), using **as few as possible** bits?

Fast **Access** to individual N-grams?

How to **estimate** the probability of occurrence of the patterns under a given probability model?

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Fast **Access** to individual N-grams?

How to **estimate** the probability of occurrence of the patterns under a given probability model?

This is problem is central to applications in IR, ML, NLP, WSE.

Applications

Next word prediction.

Applications

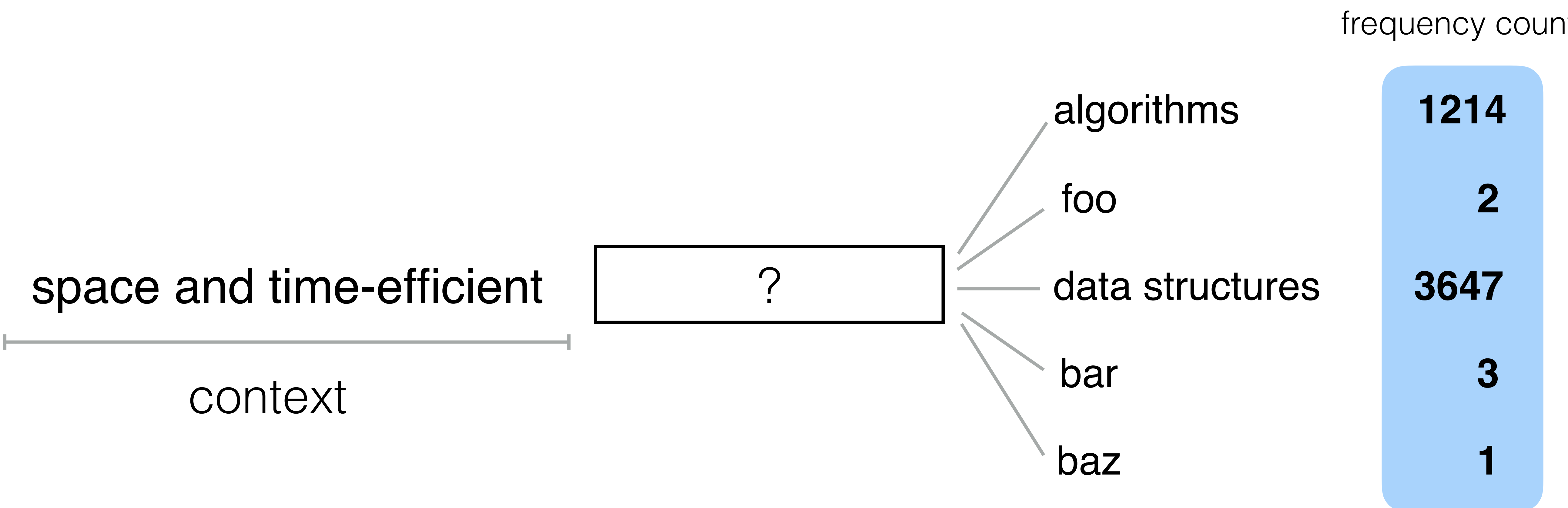
Next word prediction.

space and time-efficient ?

context

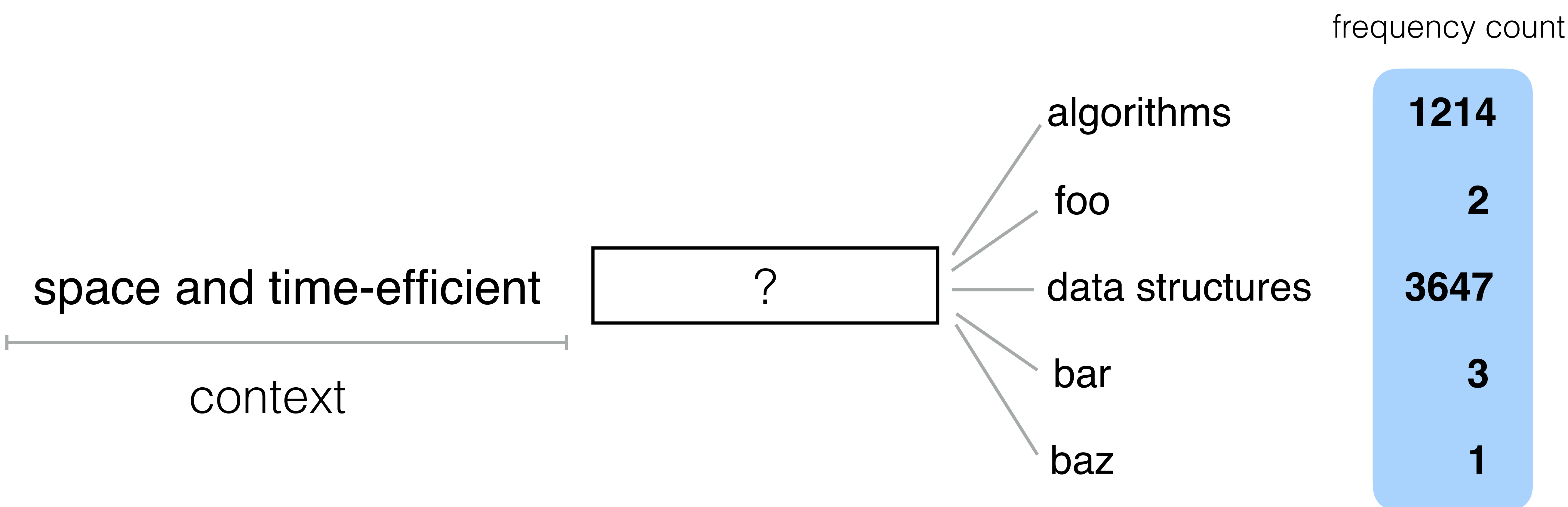
Applications

Next word prediction.



Applications

Next word prediction.



$$\mathcal{P}(\text{“data structures”} \mid \text{“space and time-efficient”}) \approx \frac{f(\text{“space and time-efficient data structures”})}{f(\text{“space and time-efficient”})}$$

What can I help you with?

Siri

Applications

Google Research Blog

The latest news from Research at Google

All Our N-gram are Belong to You

Thursday, August 03, 2006

Posted by Alex Franz and Thorsten Brants, Google Machine Translation Team

Here at Google Research we have been using word n-gram models for a variety of R&D projects, such as statistical machine translation, speech recognition, spelling correction, entity detection, information extraction, and others. While such models have usually been estimated from training corpora containing at most a few billion words, we have been harnessing the vast power of Google's datacenters and distributed processing infrastructure to process larger and larger training corpora. We found that there's no data like more data, and scaled up the size of our data by one order of magnitude, and then another, and then one more - resulting in a training corpus of *one trillion words* from public Web pages.

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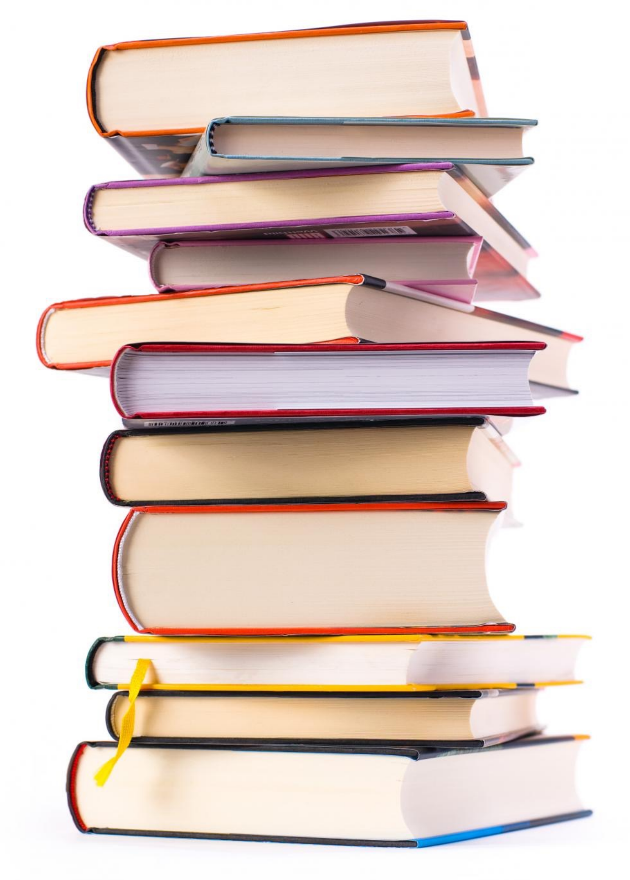
Indexing



Google Books

~6% of the books ever published

n	number of n-grams
1	24,359,473
2	667,284,771
3	7,397,041,901
4	1,644,807,896
5	1,415,355,596

More than 11 billion n-grams.

Idea 1 - Context-based remapped tries (SIGIR '17)

The number of words following a given context is **small**.

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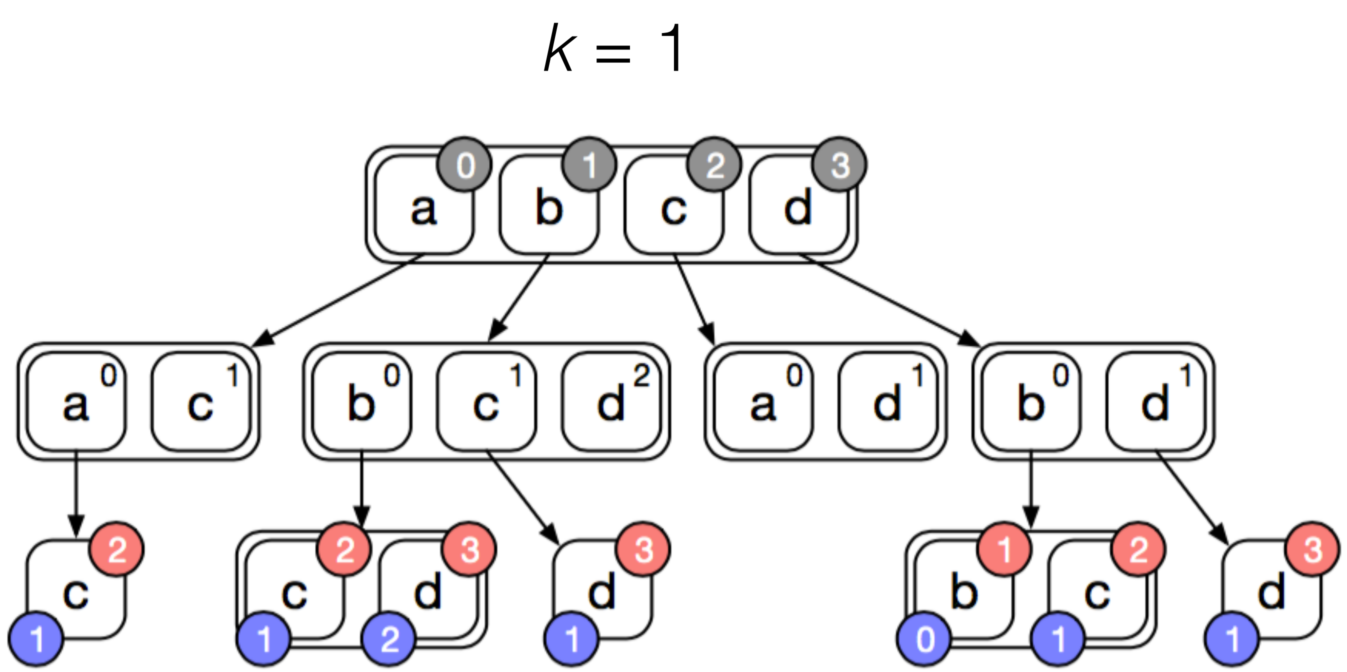

Map a word ID to the **position** it takes within its *sibling* IDs (the IDs following a context of fixed length *k*).

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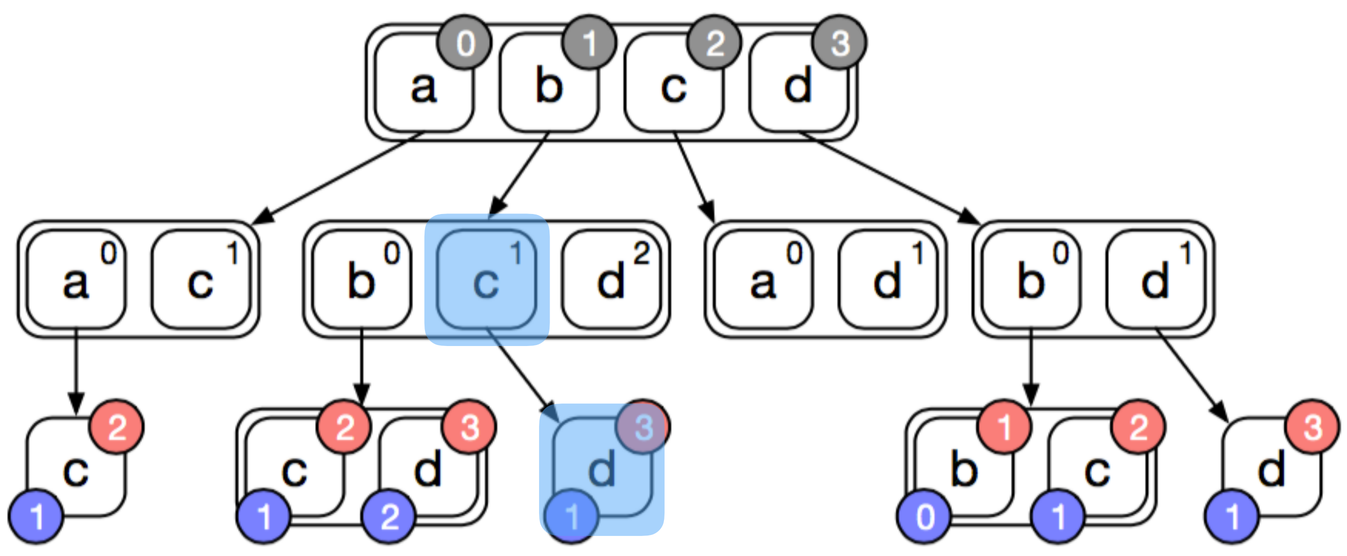
k = 1



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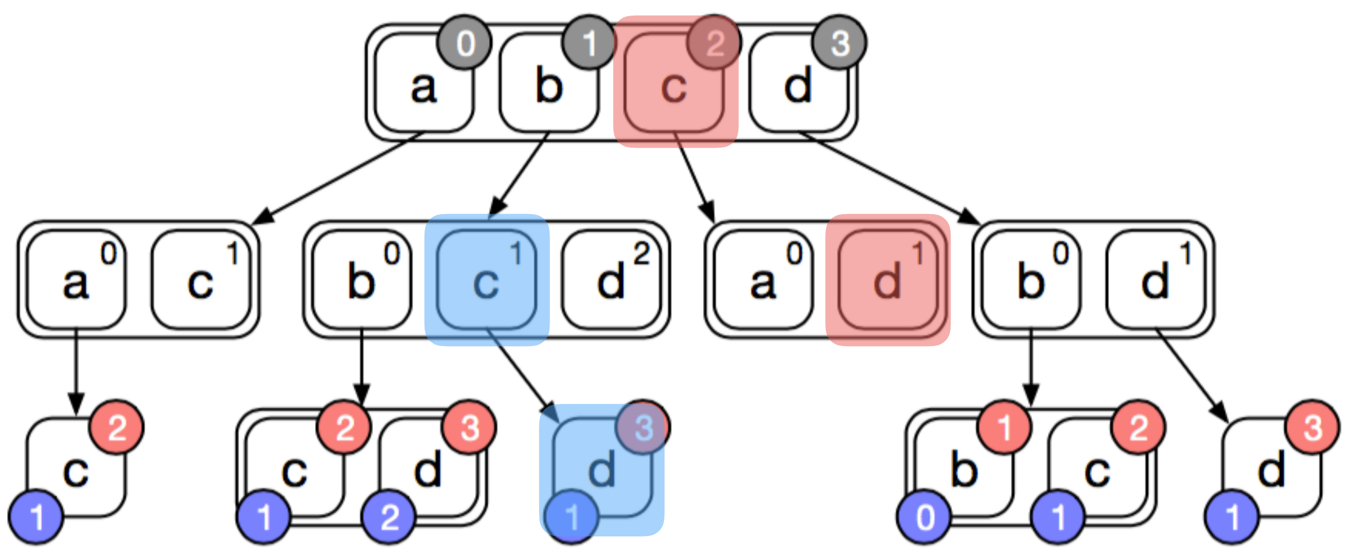

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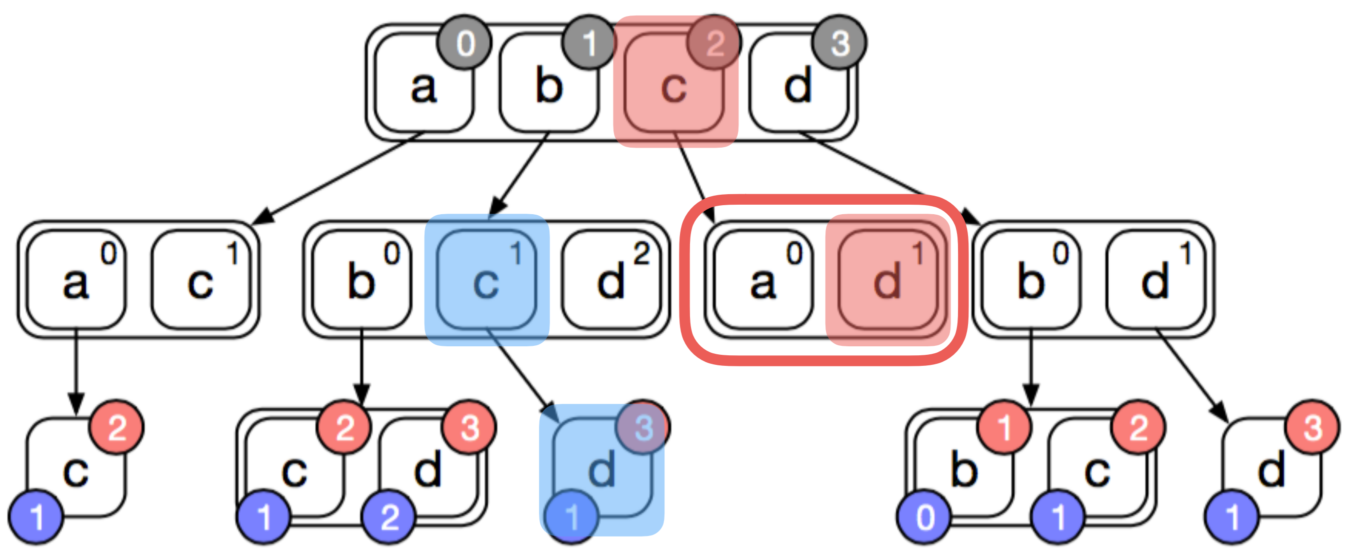

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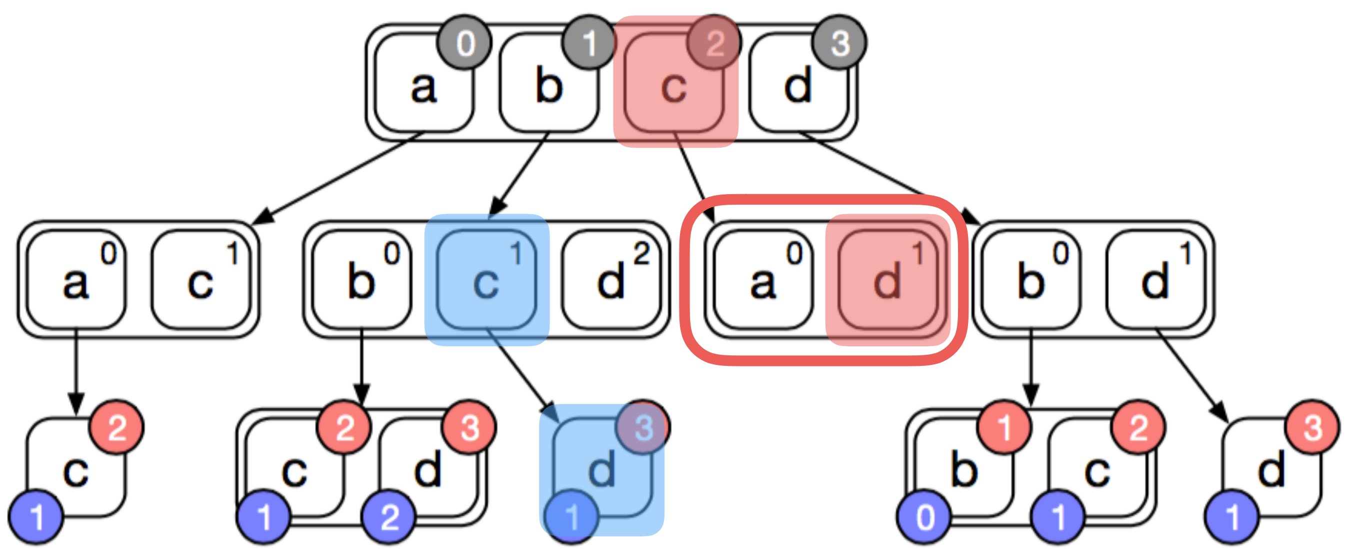

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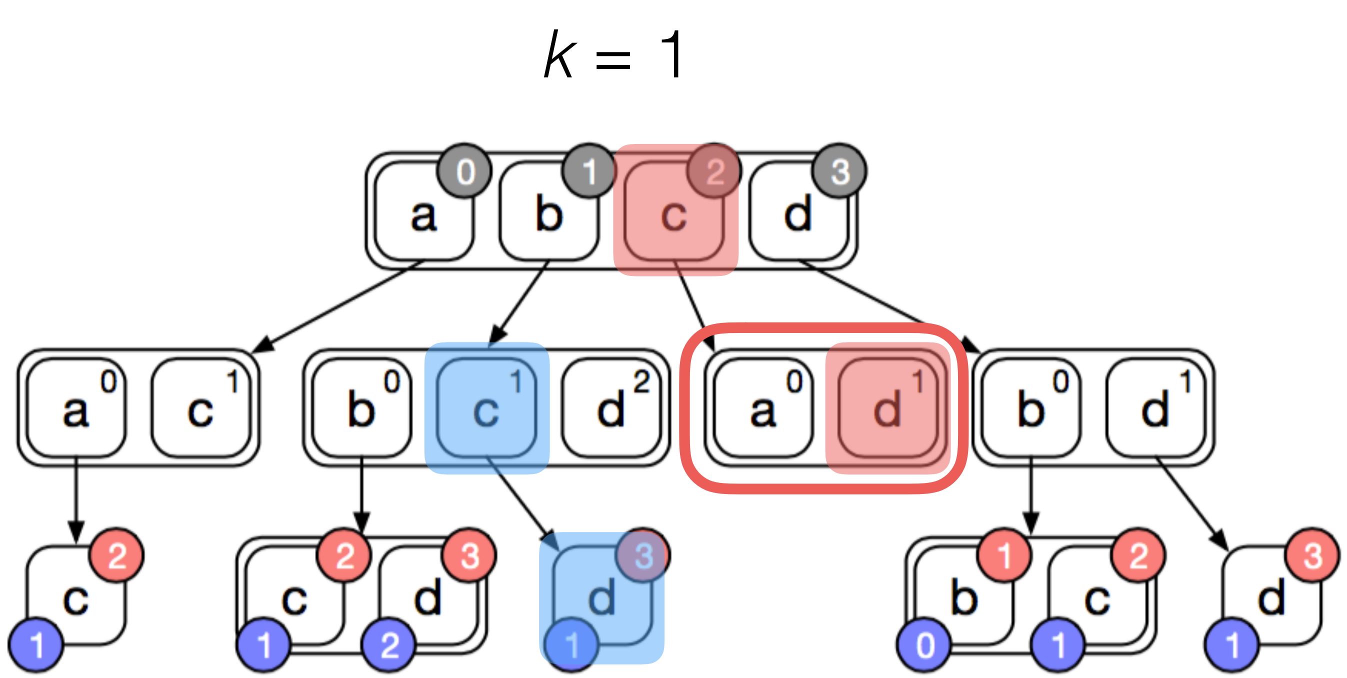

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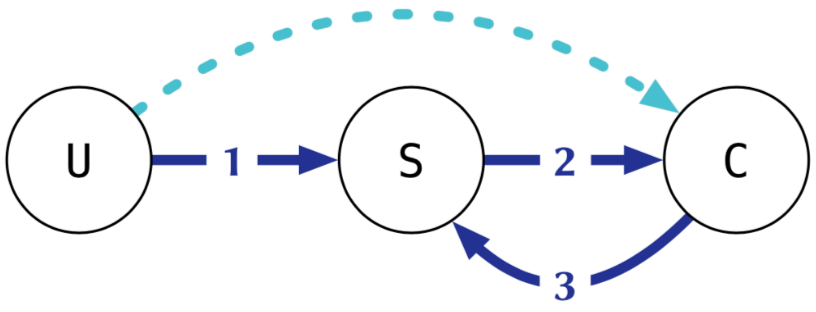
The (Elias-Fano) context-based remapped trie is **even smaller** than the most space-efficient competitors, that are lossy and with false-positives allowed, and up to **5X faster**.

Idea 2 - Fast estimation in external memory (TOIS ’18)

To compute the modified Kneser-Ney probabilities of the n-grams,
the fastest algorithm in the literature uses **3 sorting steps** in external memory.



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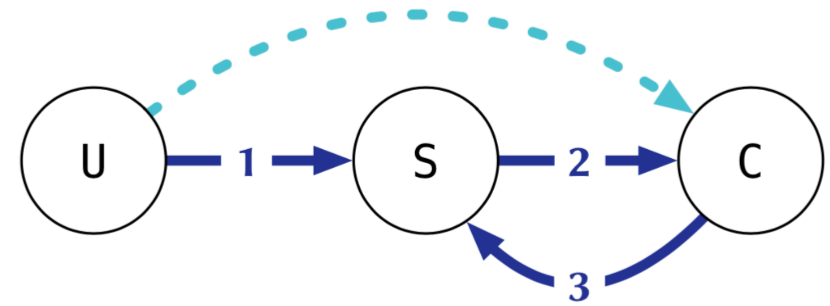

Computing the distinct left extensions.

1	2	3	4	5	6	7	8	9	10	11	12
A	**A**	**A**	**A**	**B**	**B**	**C**	**C**	**X**	**X**	**X**	**X**
A	B	B	X	A	C	A	A	C	X	X	X
B	A	C	X	X	A	A	B	A	C	X	X
A	X	A	X	X	A	B	C	B	A	C	X
X	X	A	X	X	B	A	A	C	B	A	C

Suffix order

7	1	8	5	2	3	6	9	10	11	12	4
C	A	C	B	A	A	B	X	X	X	X	A
A	**A**	**A**	**A**	**B**	**B**	**C**	**C**	**X**	**X**	**X**	**X**
A	B	B	X	A	C	A	A	C	X	X	X
B	A	C	X	X	A	A	B	A	C	X	X
A	X	A	X	X	A	B	C	B	A	C	X

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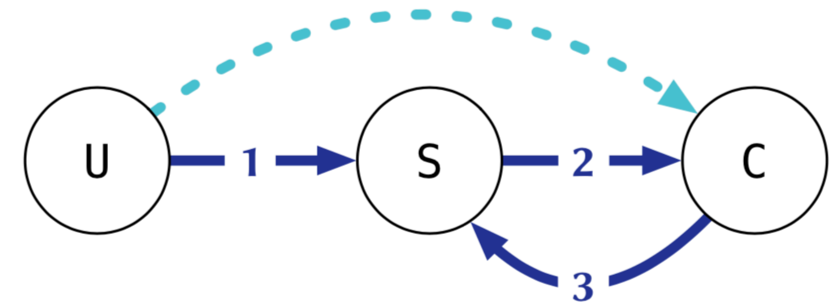

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A	B	B	X	A	C	A	A	C	X	X	X
B	A	C	X	X	A	A	B	A	C	X	X
A	X	A	X	X	A	B	C	B	A	C	X
X	X	A	X	X	B	A	A	C	B	A	C

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C	A	C	B	A	A	B	X	X	X	X	A
A	**A**	**A**	**A**	**B**	**B**	**C**	**C**	**X**	**X**	**X**	**X**
A	B	B	X	A	C	A	A	C	X	X	X
B	A	C	X	X	A	A	B	A	C	X	X
A	X	A	X	X	A	B	C	B	A	C	X

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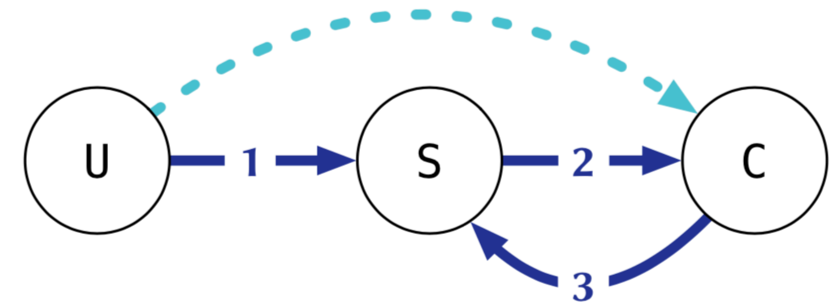

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A	B	B	X	A	C	A	A	C	X	X	X
B	A	C	X	X	A	A	B	A	C	X	X
A	X	A	X	X	A	B	C	B	A	C	X
X	X	A	X	X	B	A	A	C	B	A	C

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A	B	B	X	A	C	A	A	C	X	X	X
B	A	C	X	X	A	A	B	A	C	X	X
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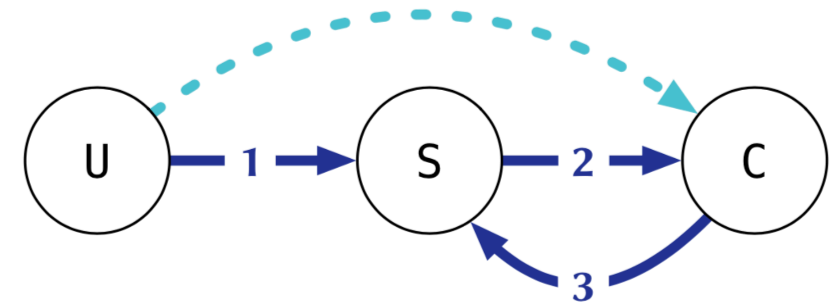

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A	B	B	X	A	C	A	A	C	X	X	X
B	A	C	X	X	A	A	B	A	C	X	X
A	X	A	X	X	A	B	C	B	A	C	X
X	X	A	X	X	B	A	A	C	B	A	C

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A	B	B	X	A	C	A	A	C	X	X	X
B	A	C	X	X	A	A	B	A	C	X	X
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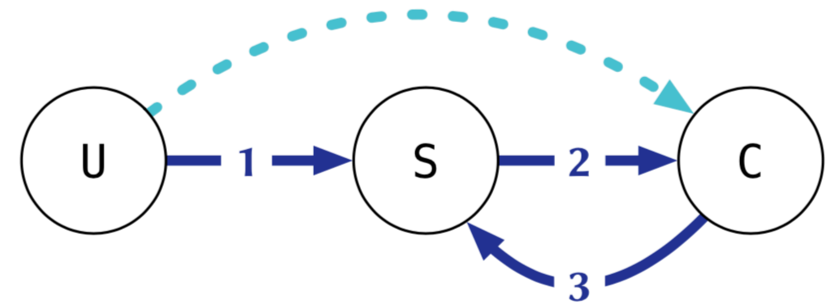

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B	A	C	X	X	A	A	B	A	C	X	X
A	X	A	X	X	A	B	C	B	A	C	X
X	X	A	X	X	B	A	A	C	B	A	C

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A	B	B	X	A	C	A	A	C	X	X	X
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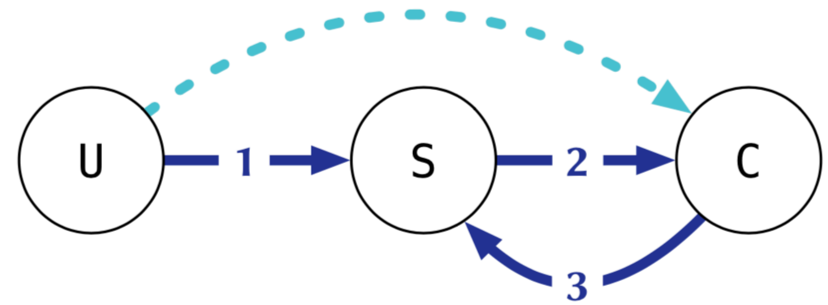

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A	B	B	X	A	C	A	A	C	X	X	X
B	A	C	X	X	A	A	B	A	C	X	X
A	X	A	X	X	A	B	C	B	A	C	X
X	X	A	X	X	B	A	A	C	B	A	C

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A	B	B	X	A	C	A	A	C	X	X	X
B	A	C	X	X	A	A	B	A	C	X	X
A	X	A	X	X	A	B	C	B	A	C	X

Context order

Using a scan of the block and O(|V|) space.

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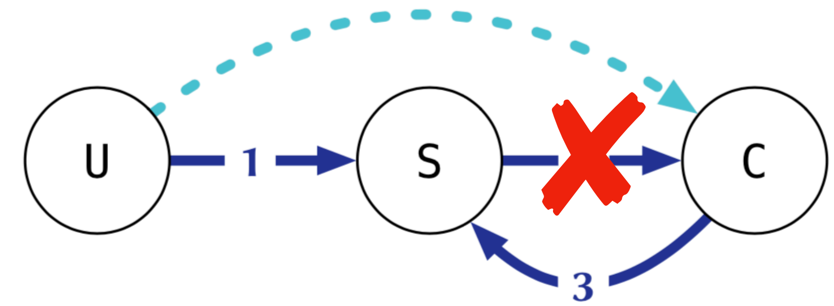

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A	B	B	X	A	C	A	A	C	X	X	X
B	A	C	X	X	A	A	B	A	C	X	X
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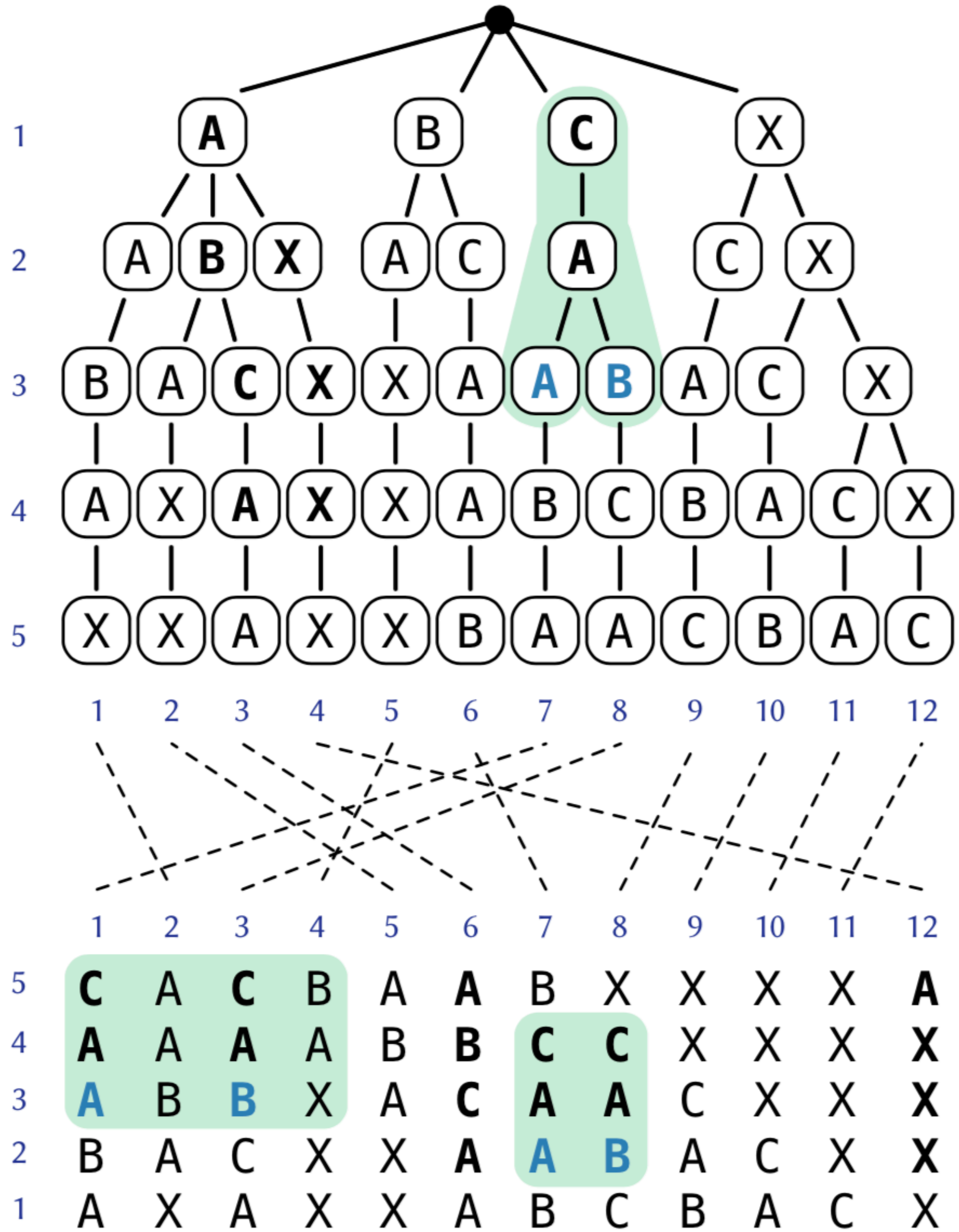

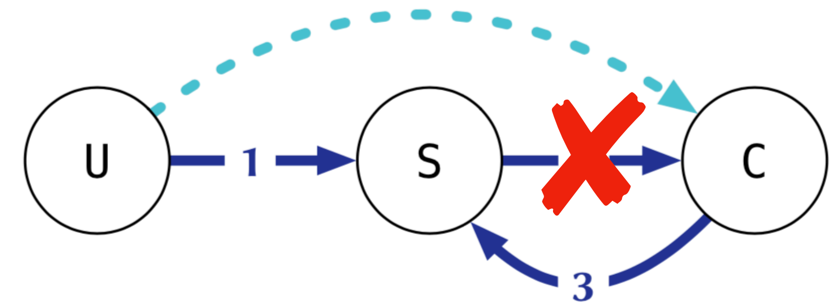

Rebuilding the last level of the trie.

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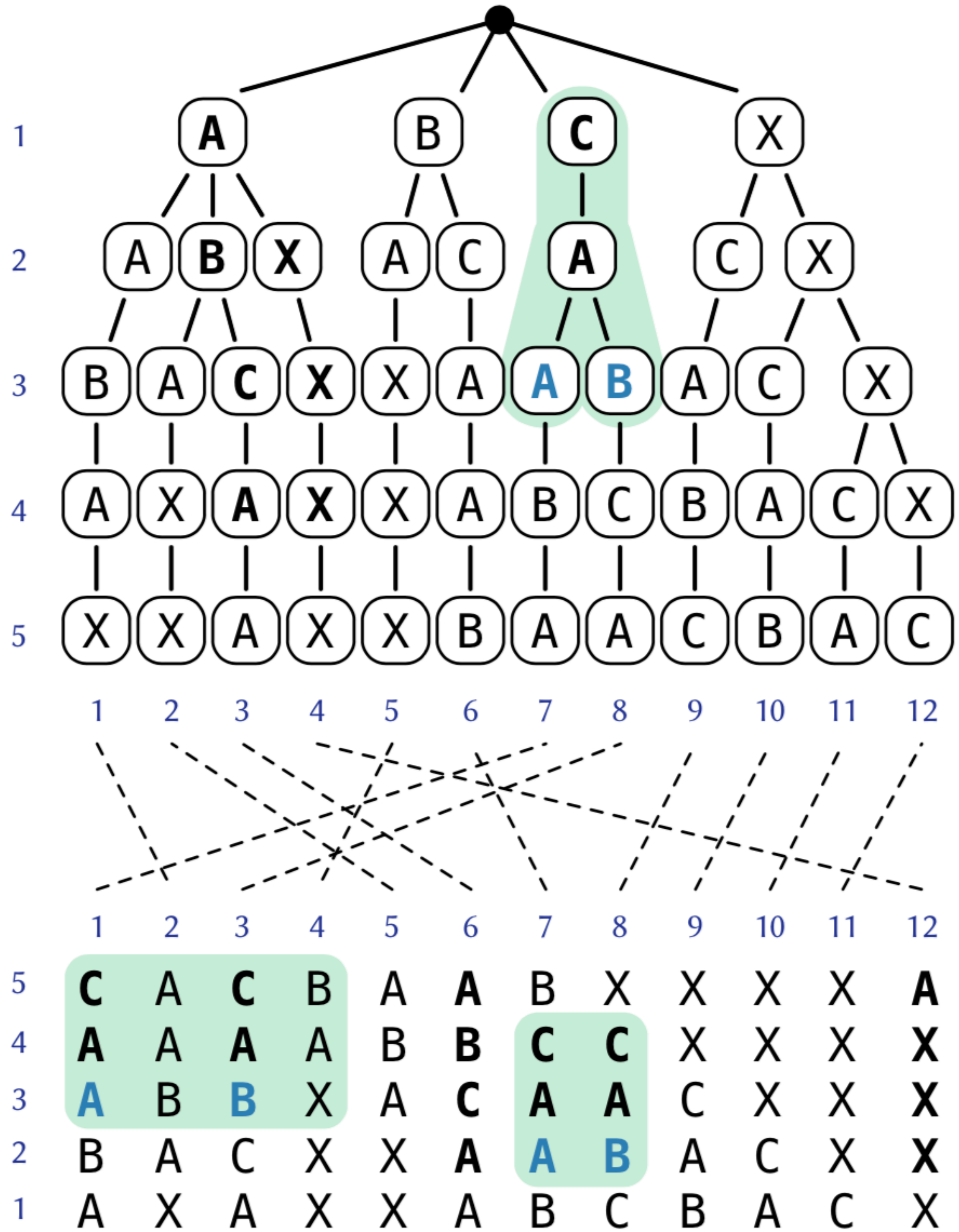

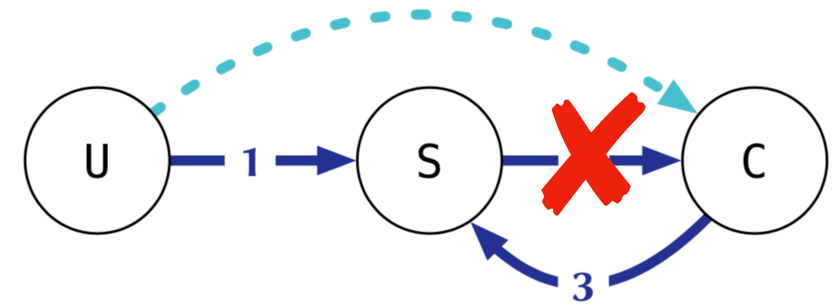

Rebuilding the last level of the trie.

A	4
B	2
C	2
X	4

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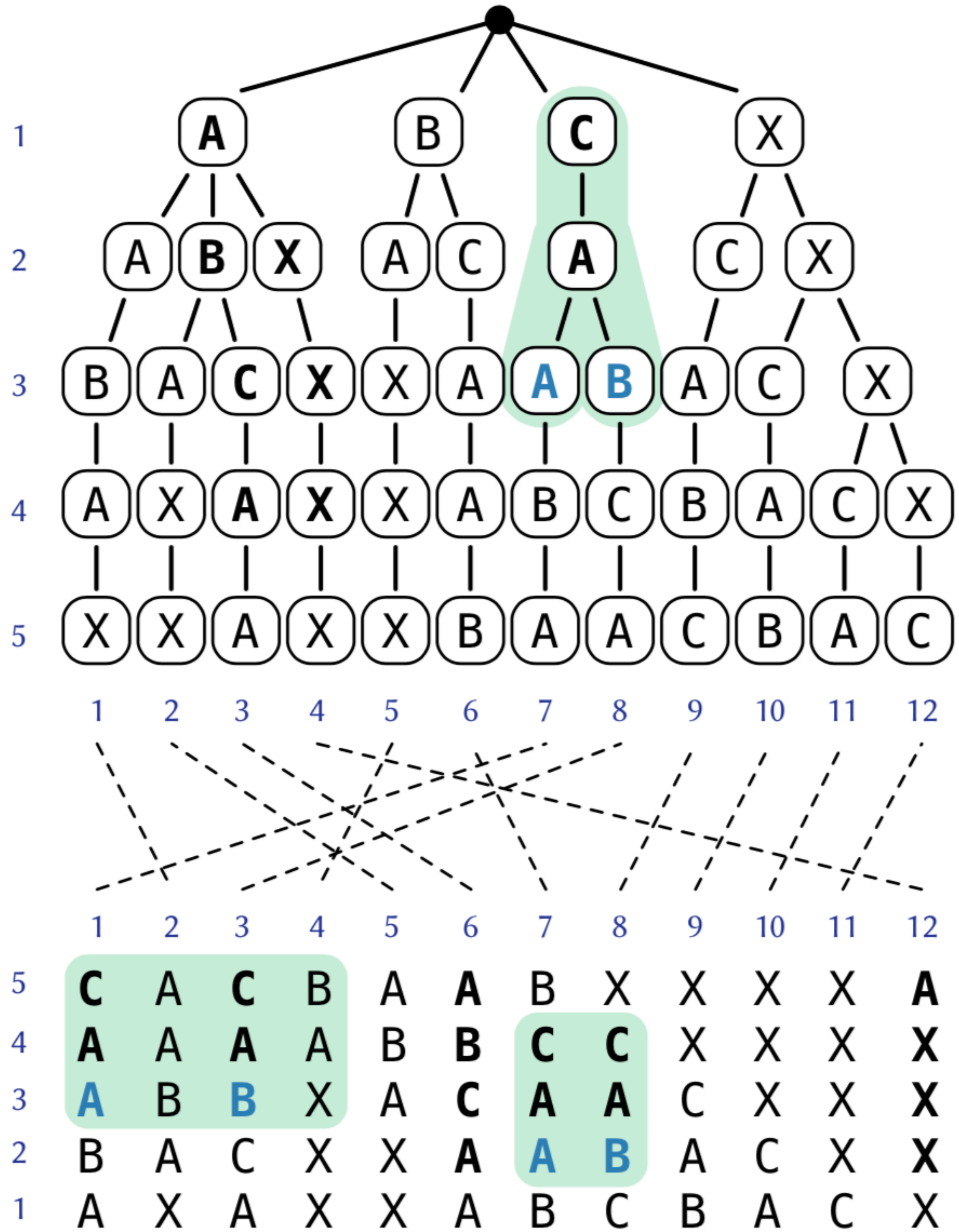
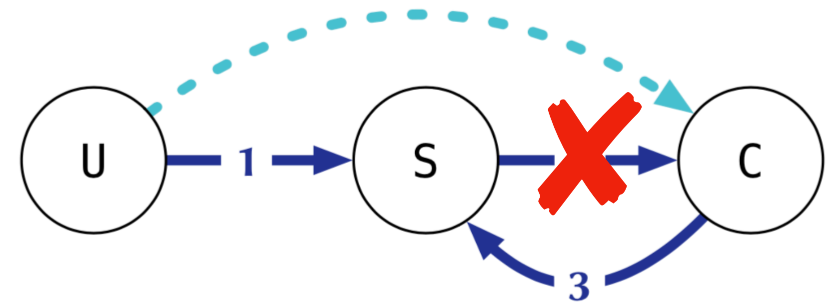




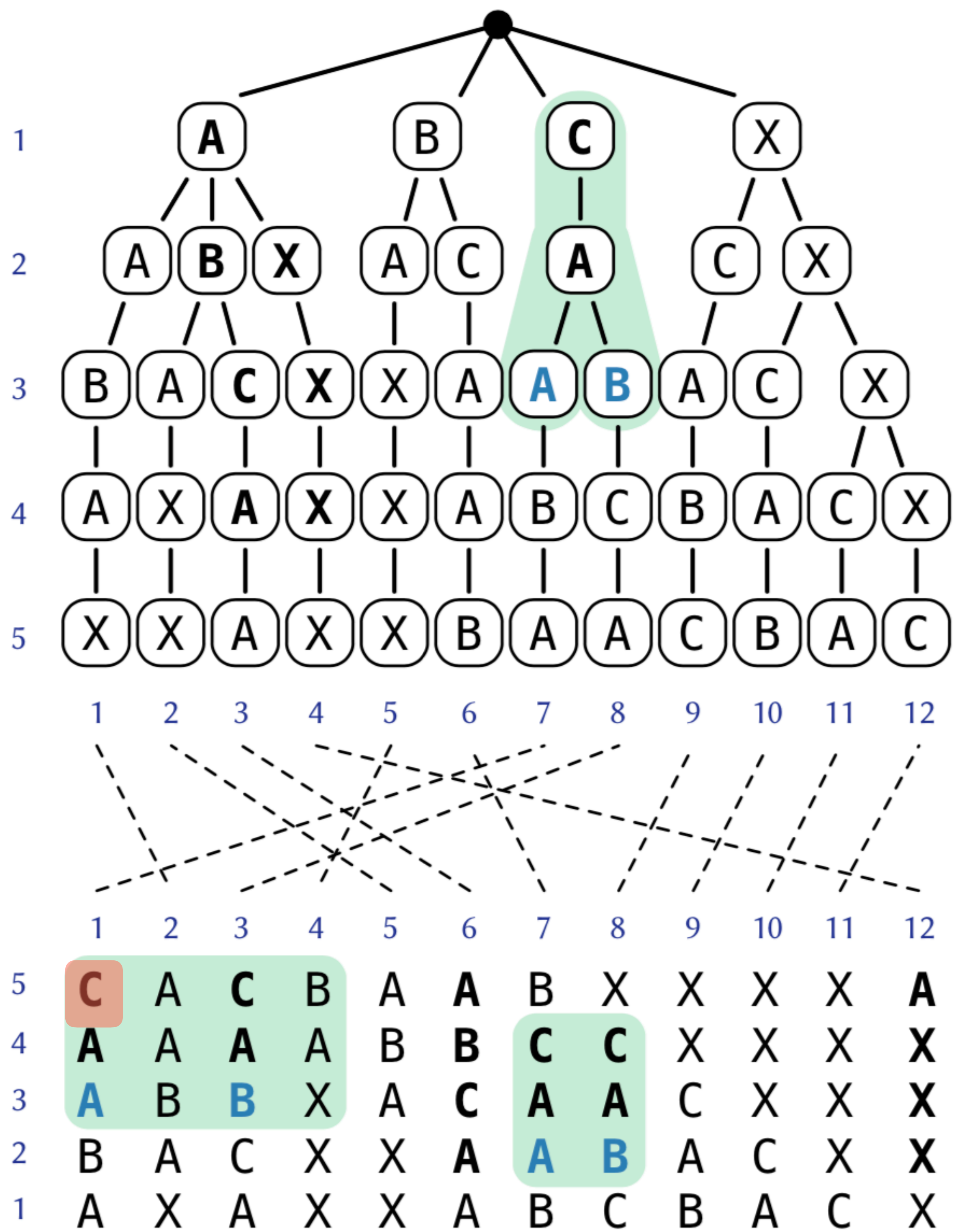
Rebuilding the last level of the trie.

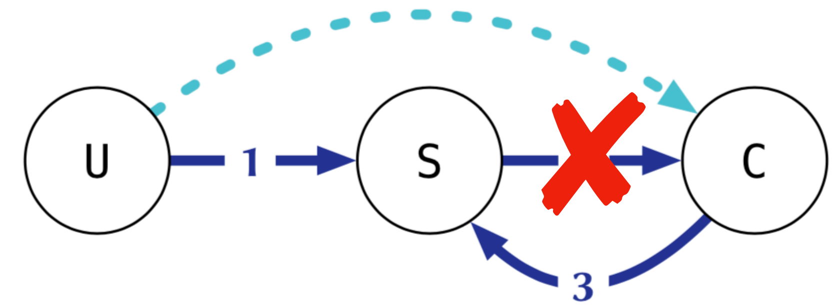
A	4
B	2
C	2
X	4

→

A	1
B	5
C	7
X	9

Idea 2 - Fast estimation in external memory (TOIS ’18)





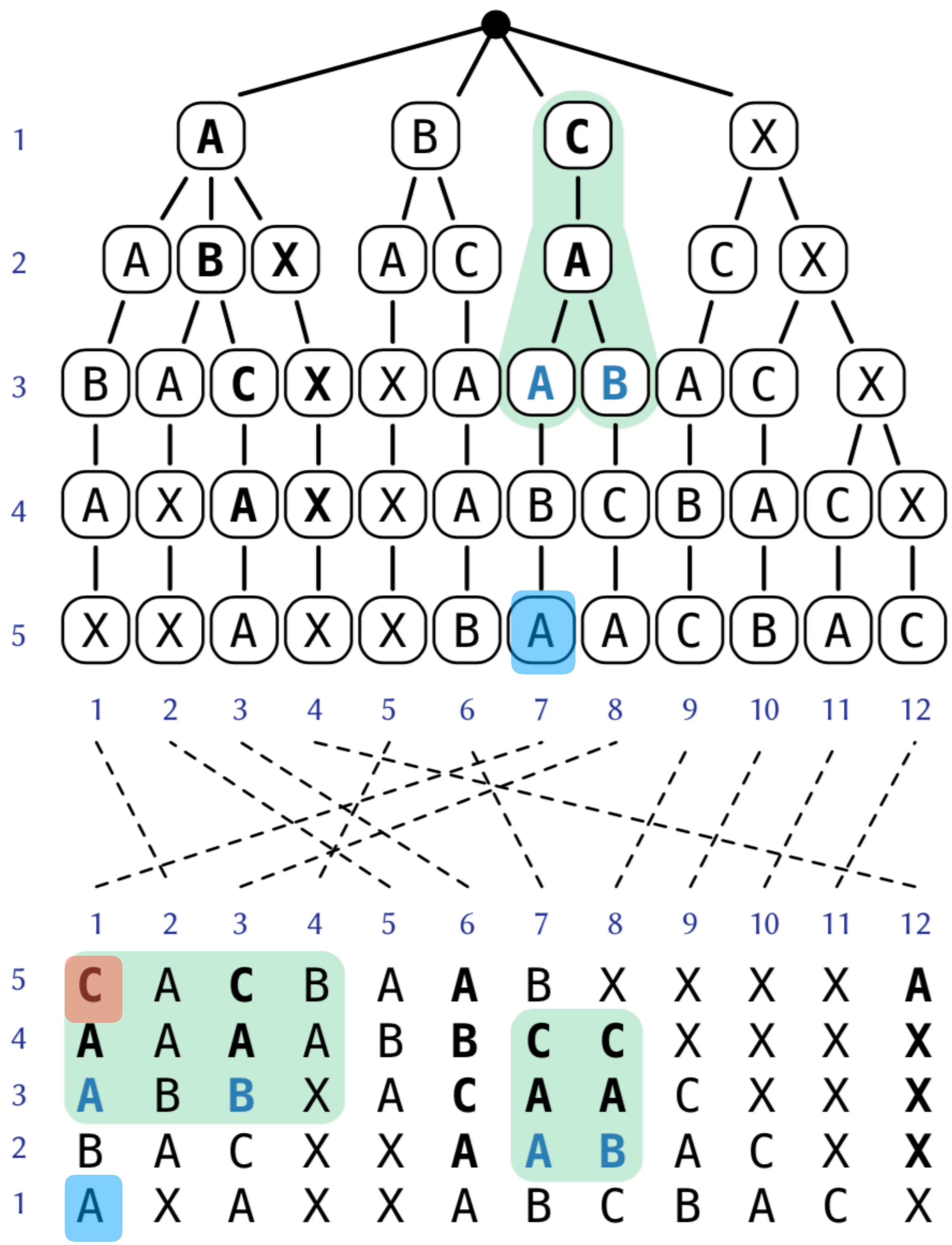
Rebuilding the last level of the trie.

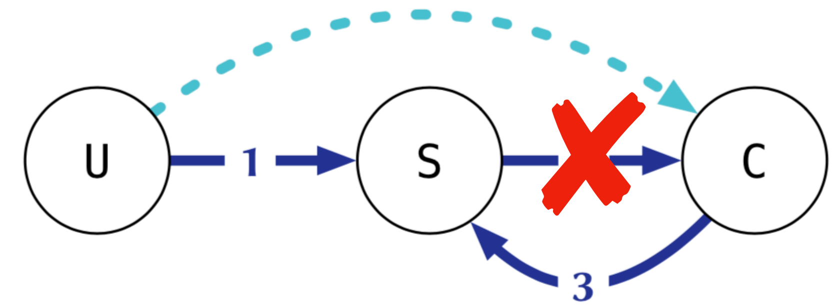
A	4
B	2
C	2
X	4

→

A	1
B	5
C	7
X	9

Idea 2 - Fast estimation in external memory (TOIS '18)





Rebuilding the last level of the trie.

A	4
B	2
C	2
X	4

→

A	1
B	5
C	7
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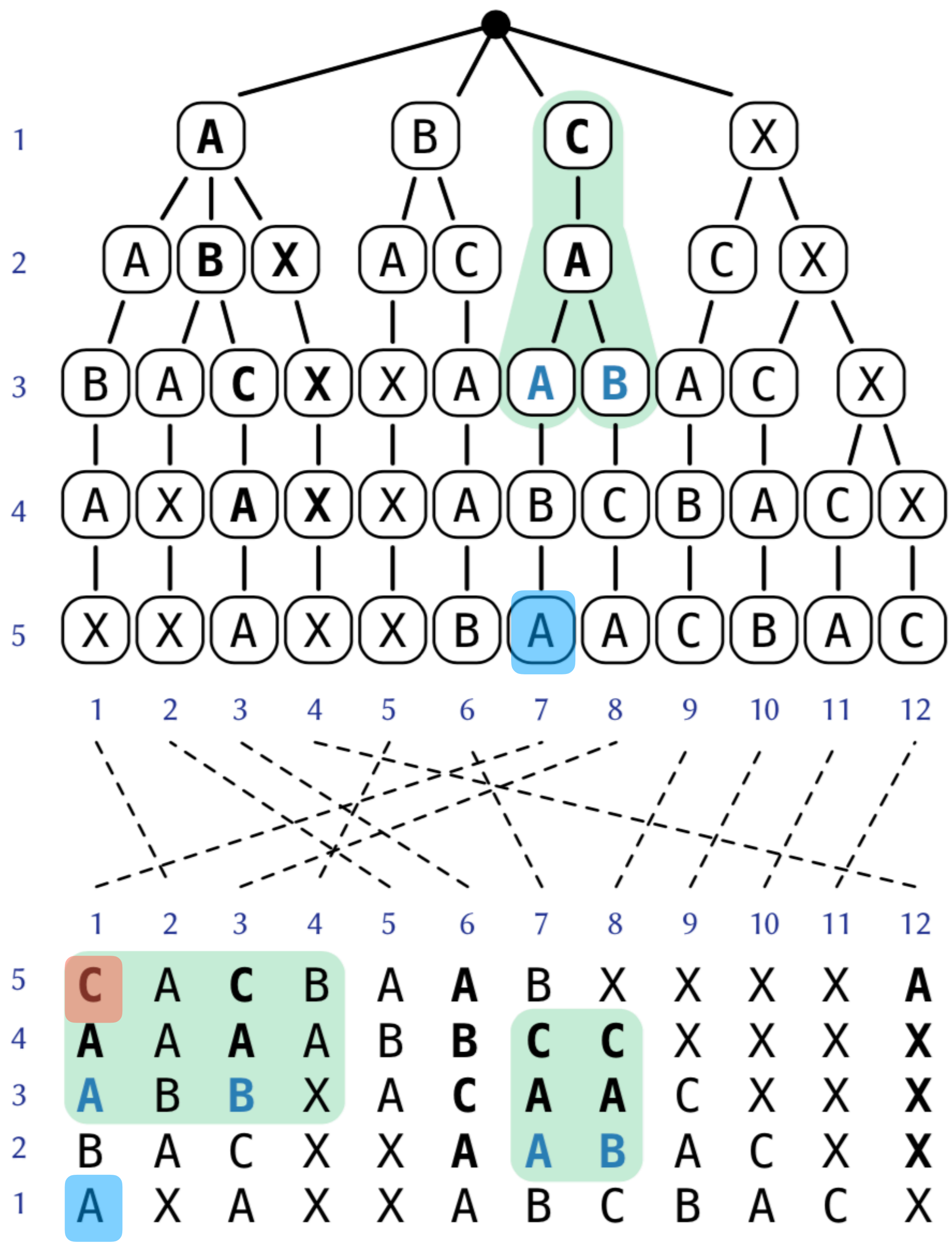
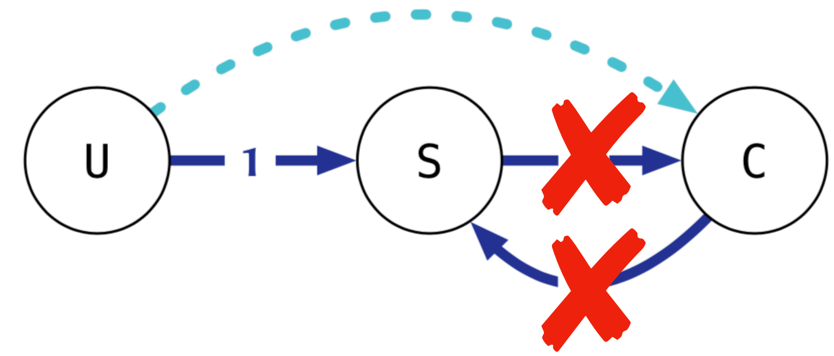
Idea 2 - Fast estimation in external memory (TOIS '18)





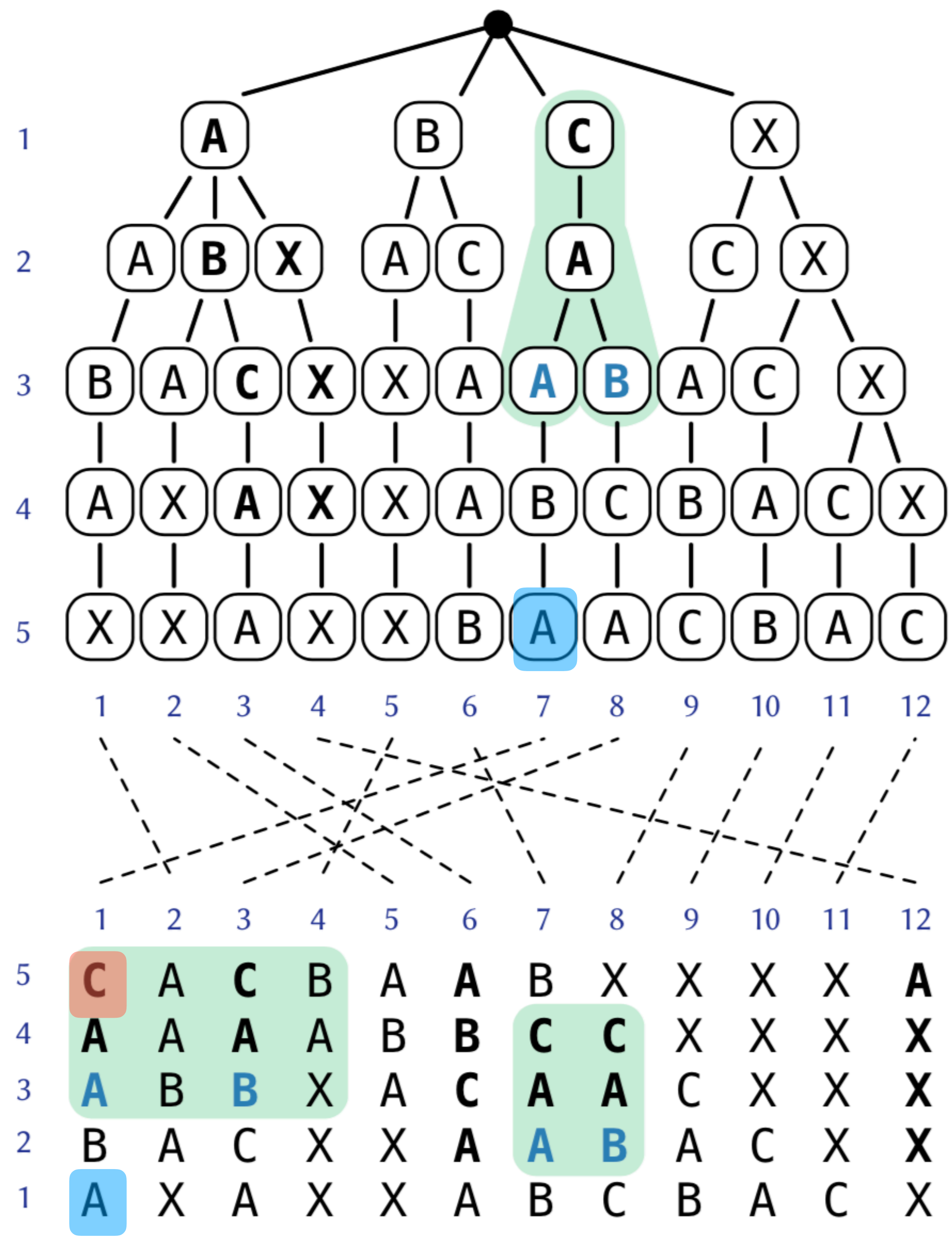
Rebuilding the last level of the trie.

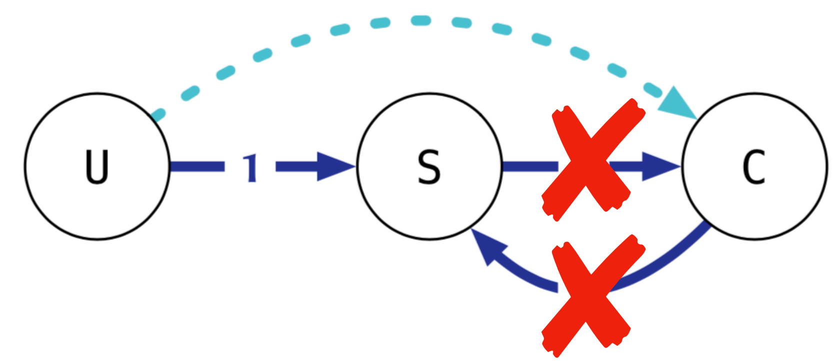
A	4
B	2
C	2
X	4

→

A	1
B	5
C	7
X	9

Idea 2 - Fast estimation in external memory (TOIS '18)





Rebuilding the last level of the trie.

A	4
B	2
C	2
X	4

→

A	1
B	5
C	7
X	9

Estimation runs 4.5X faster with billions of strings.

Thanks for your attention, time, patience!

Any questions?