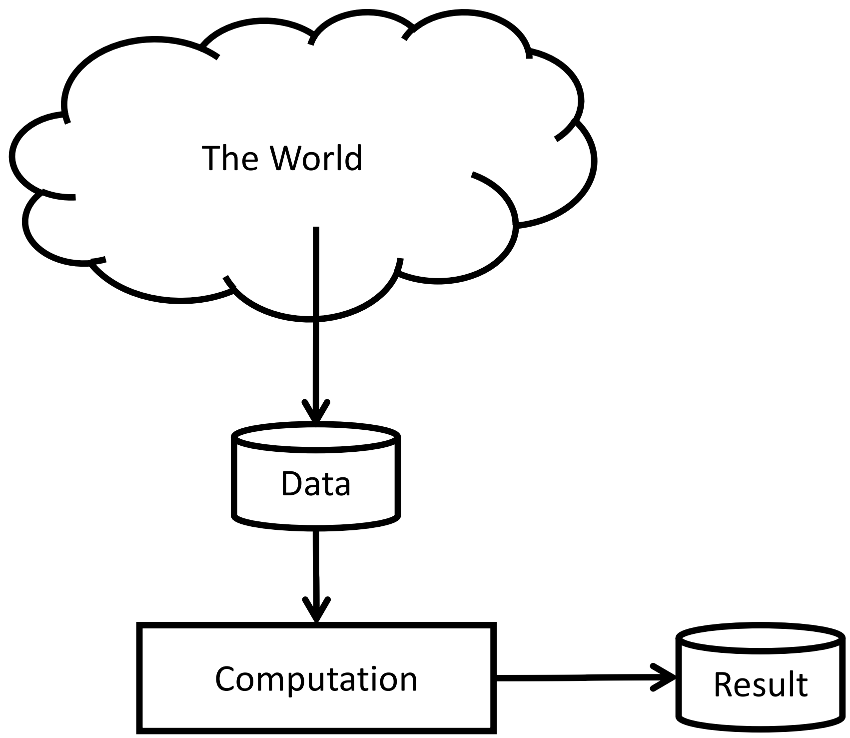
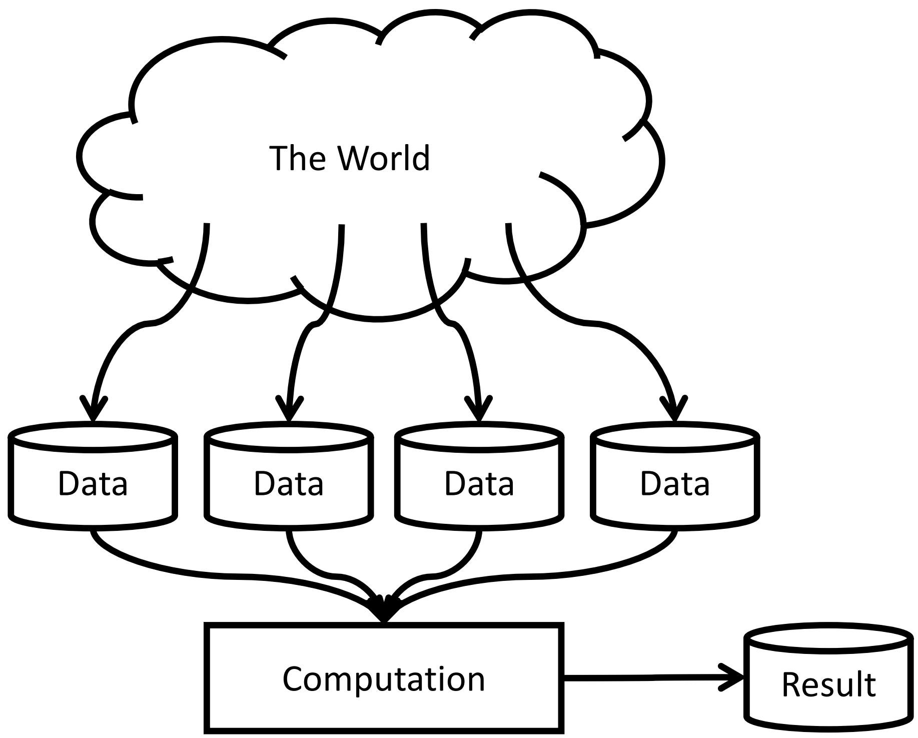
Data Mining Distributed Streams

Edo Liberty
Principal Scientist
Amazon Web Services

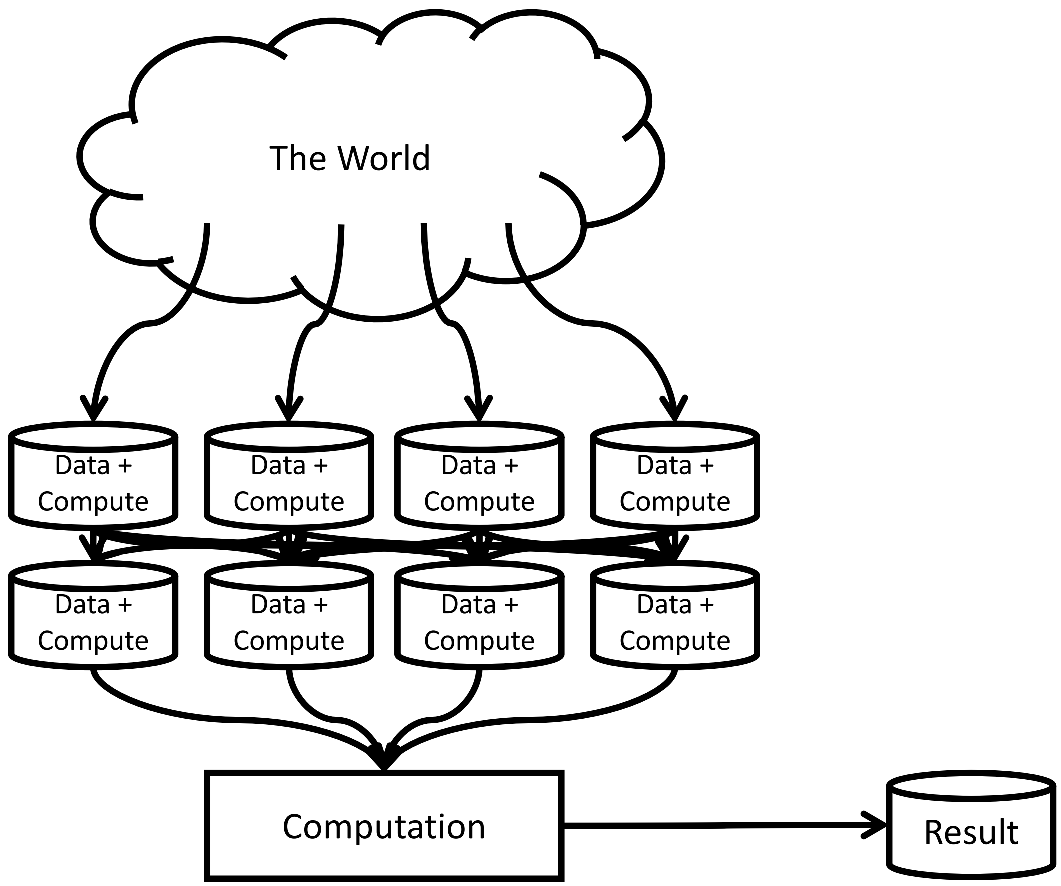
Single machine data processing



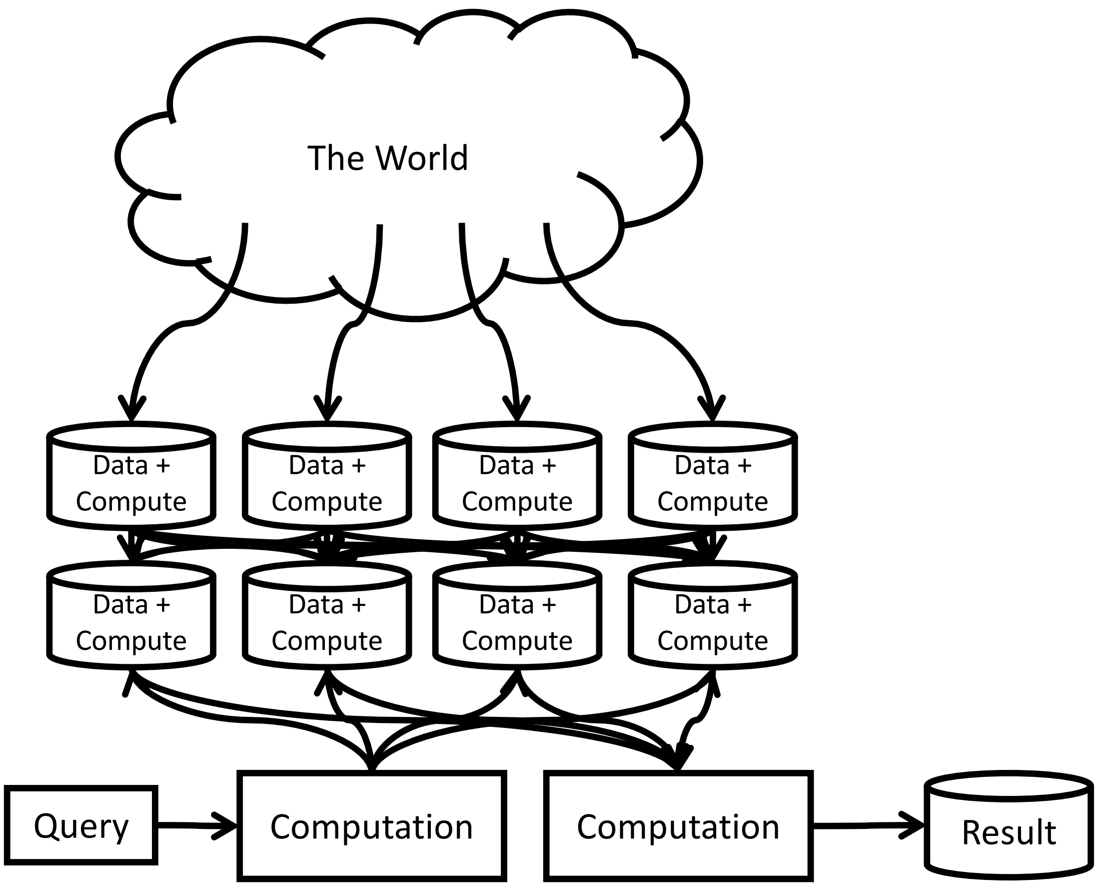
Distributed storage



Distributed compute (map/reduce, MPI, …)

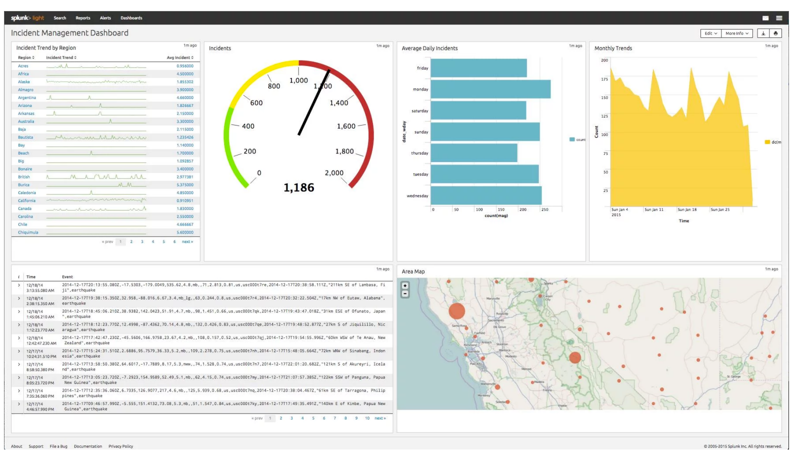


Distributed model (indexes, databases, Spark...)

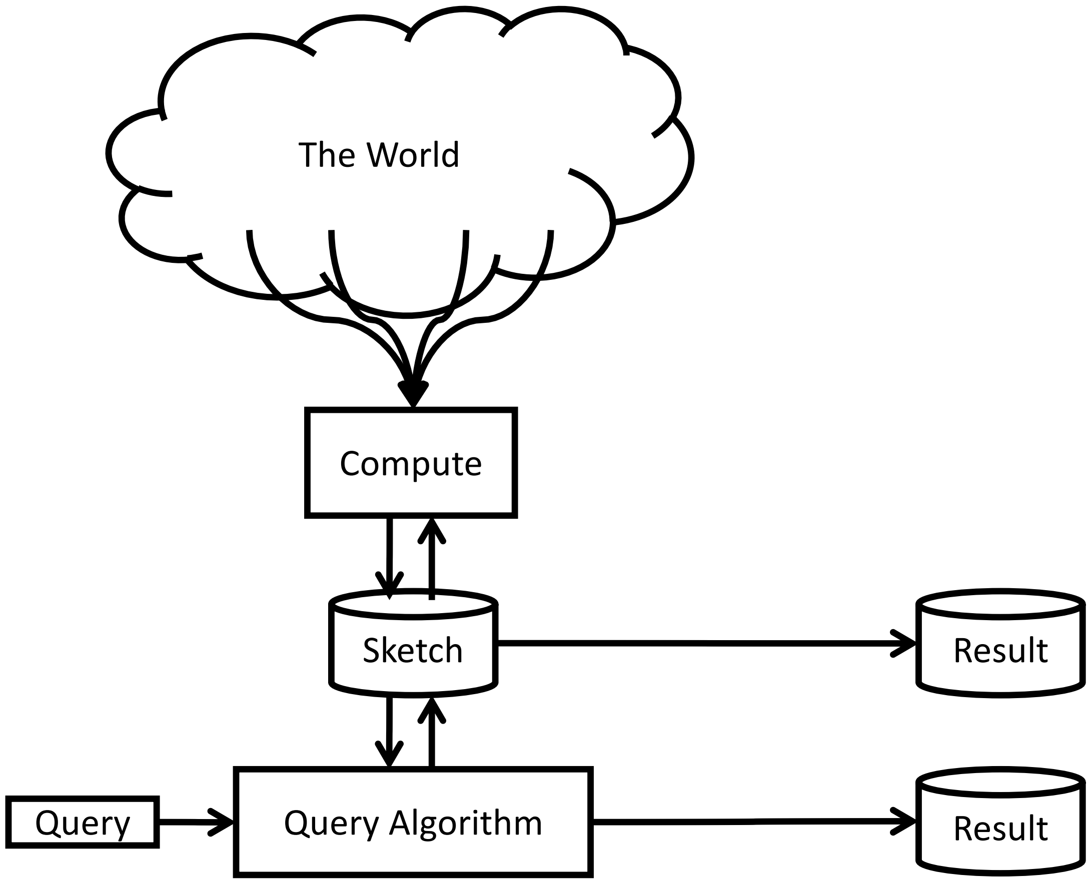


207 big-data infographics (a meta infographic)

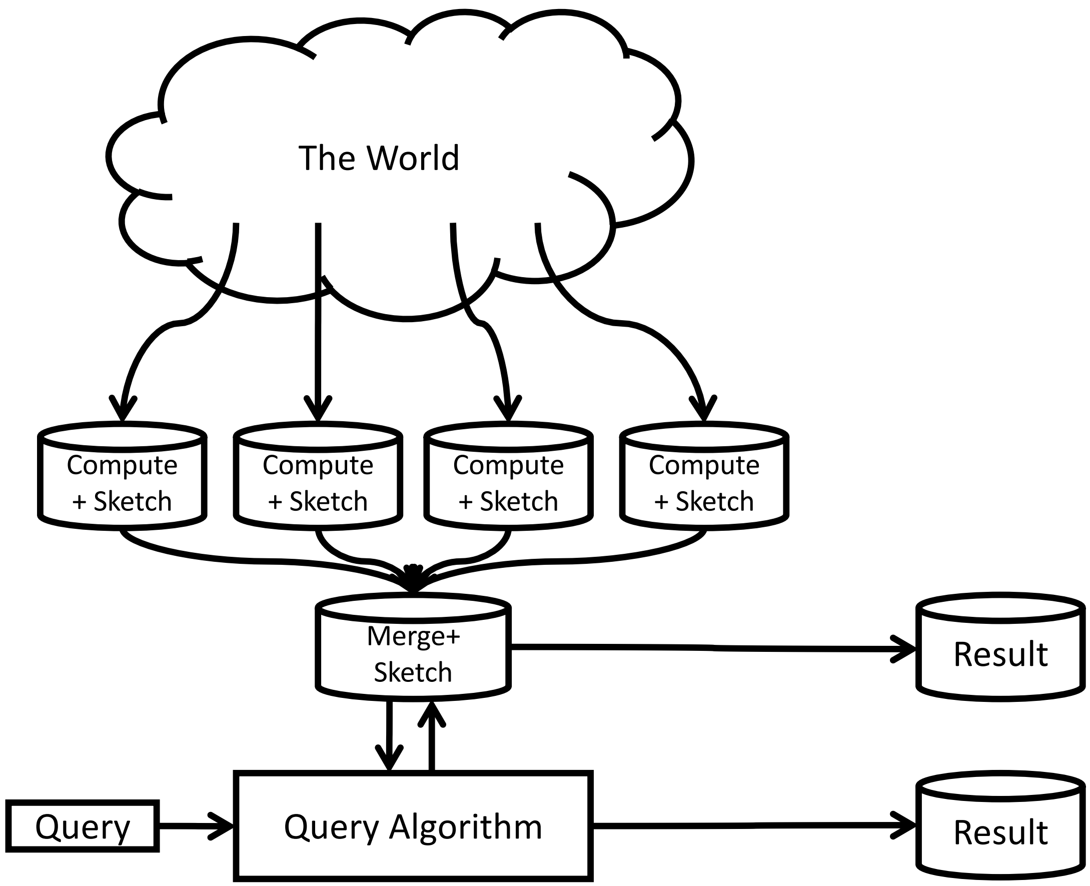
Amazon Kinesis Analytics



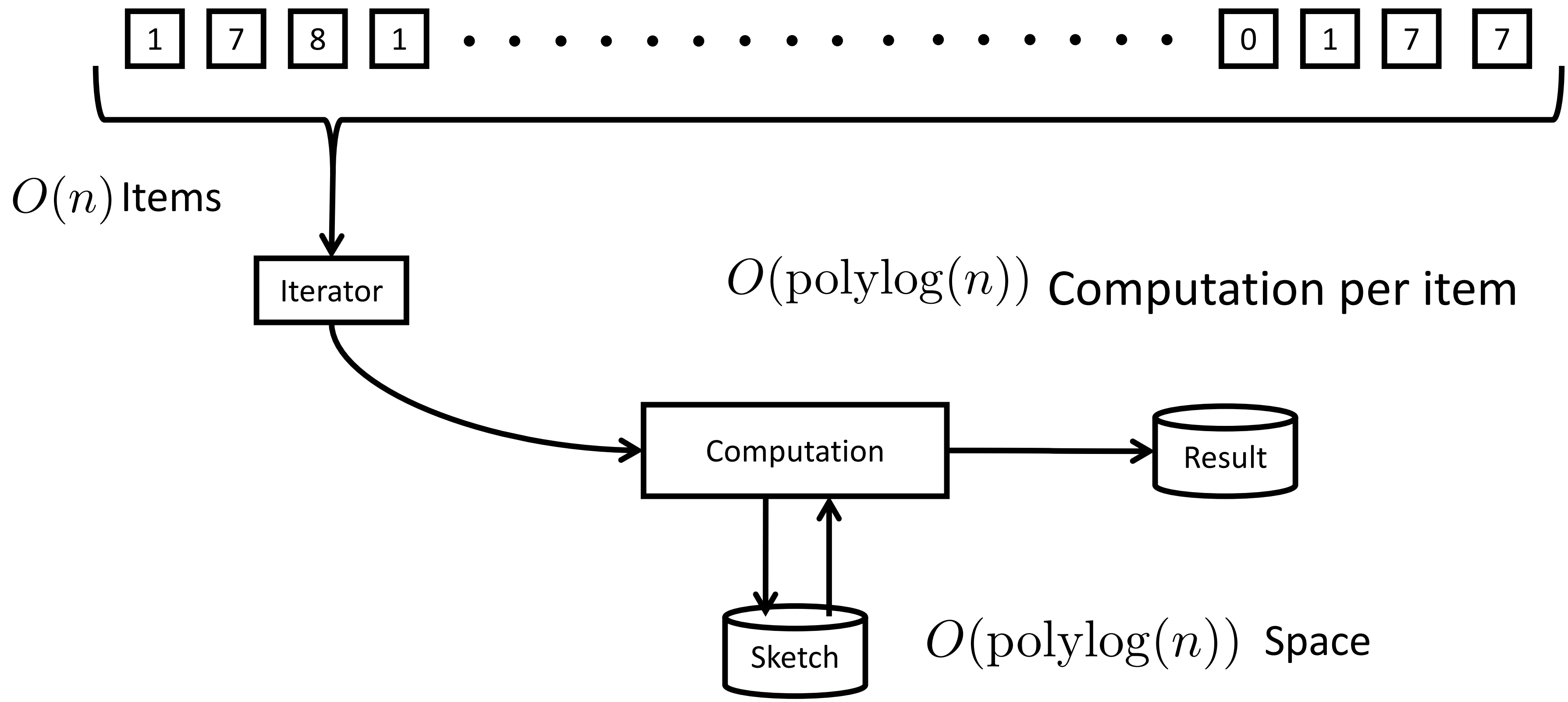
The streaming model



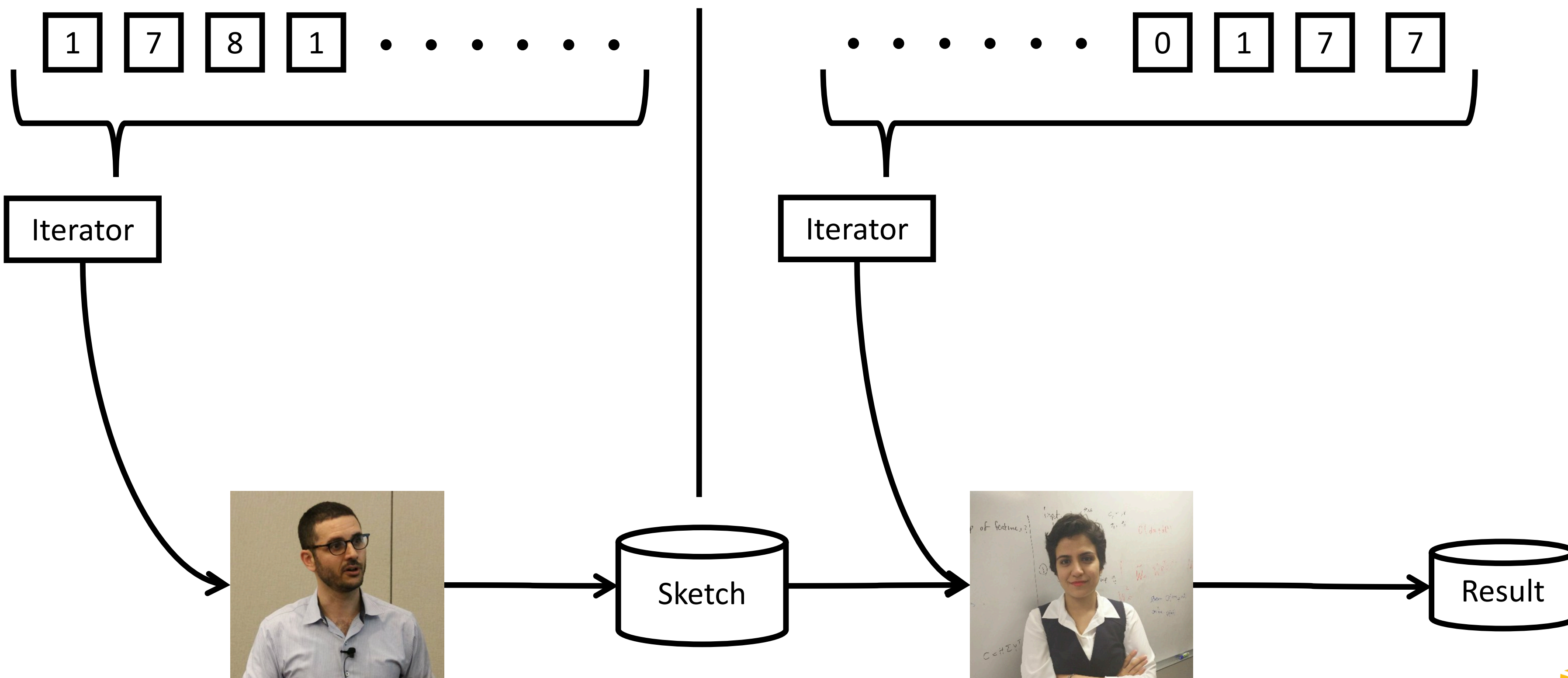
The distributed streaming model



The streaming model (more accurately)



Communication complexity



What Can we do in this model?

Items

(words, IP-addresses, events, clicks,...)

- Item frequencies
- Approximate Quantiles
- Counting distinct elements
- Moment and entropy estimation
- Approximate set operations
- Sampling

Vectors

(text documents, images, example features,...)

- Dimensionality reduction
- Clustering (k-means, k-median,…)
- Linear Regression
- Machine learning (some of it at least)

Matrices

(text corpora, recommendations, ...)

- Covariance estimation matrix
- Low rank approximation
- Sparsification

Graphs*

(social networks, communications, ...)

- Connectivity
- Cut Sparsification
- Weighted Matching

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Frequency Counting

Misra, Gries. Finding repeated elements, 1982.

Demaine, Lopez-Ortiz, Munro. Frequency estimation of internet packet streams with limited space, 2002

Karp, Shenker, Papadimitriou. A simple algorithm for finding frequent elements in streams and bags, 2003

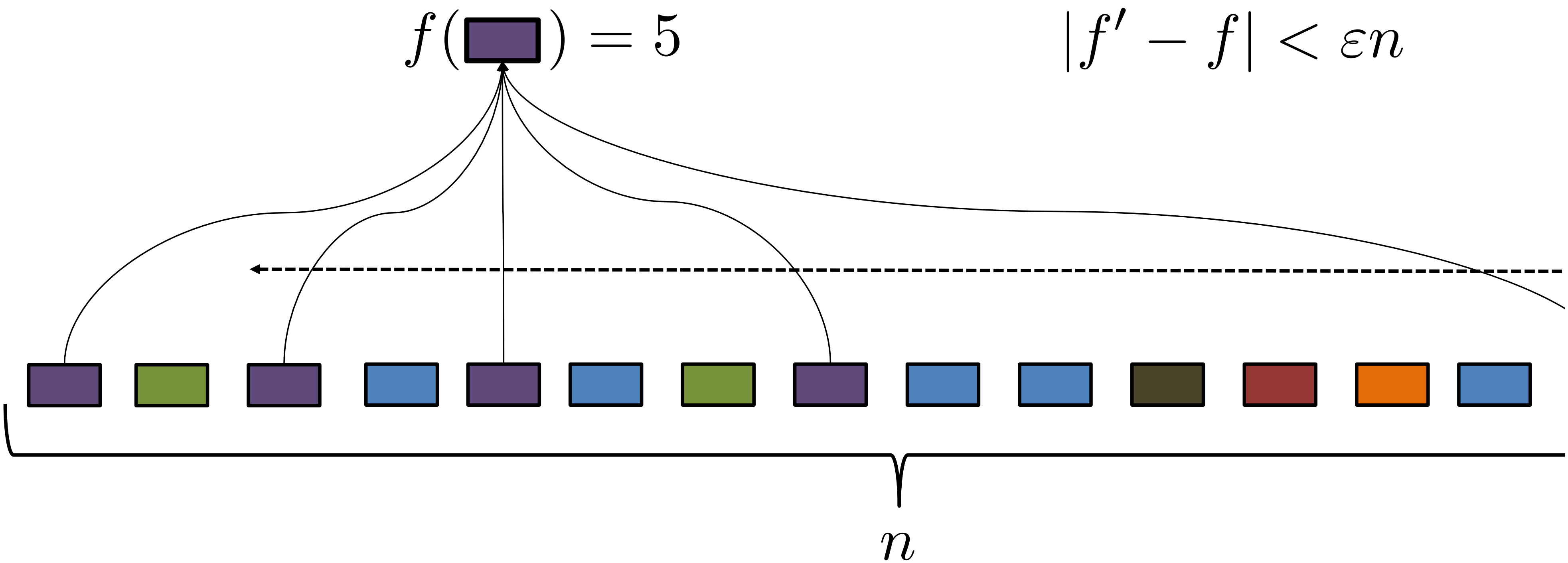
The name ``Lossy Counting" was used for a different algorithm by Manku and Motwani, 2002

Metwally, Agrawal, Abbadi, Efficient Computation of Frequent and Top-k Elements in Data Streams, 2006

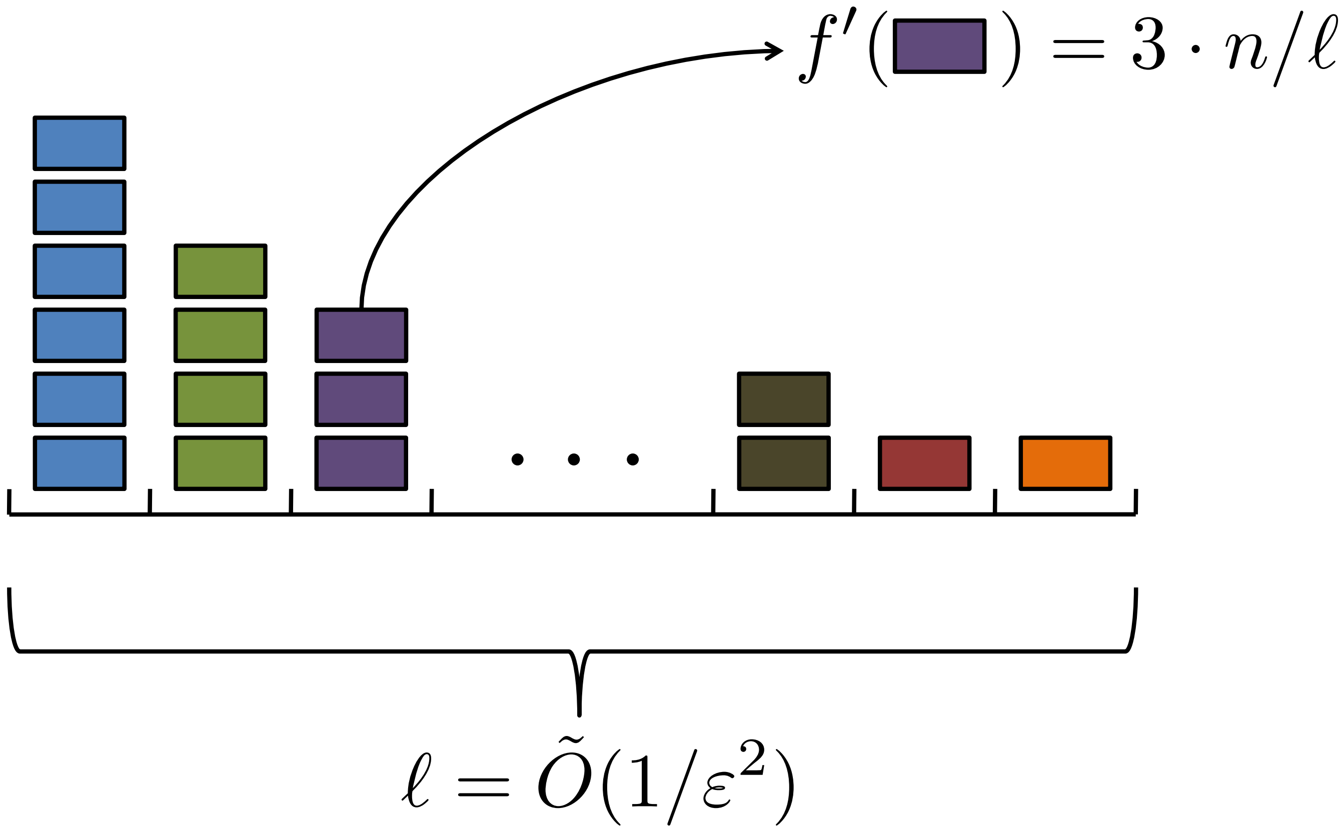
Charikar, Chen, Farach-Colton, Finding frequent items in data streams, 2002

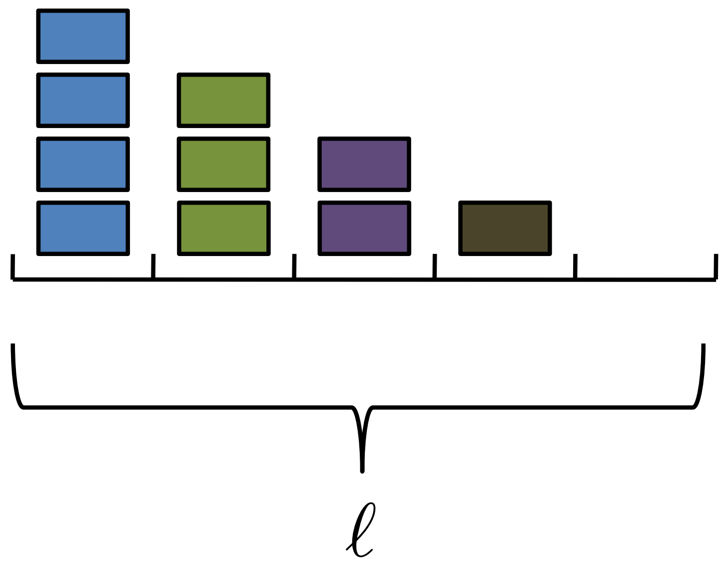
Cormode, Muthukrishnan, An Improved Data Stream Summary: The Count-Min Sketch and its Applications.

Problem Definition



Can we do better than sampling?





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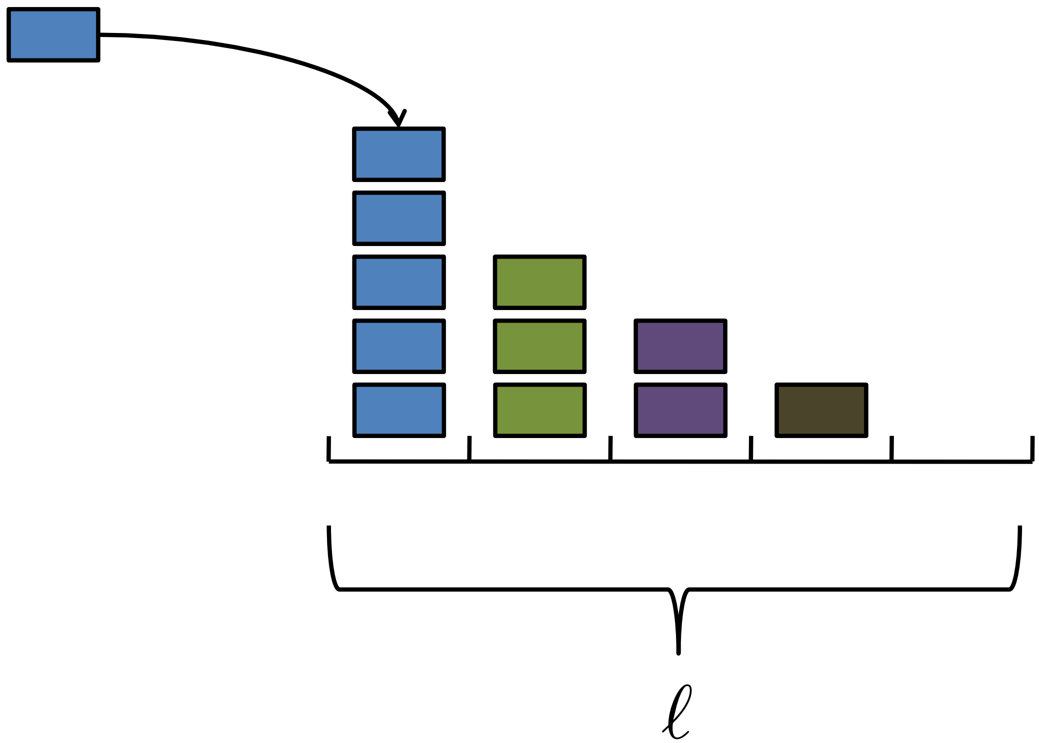
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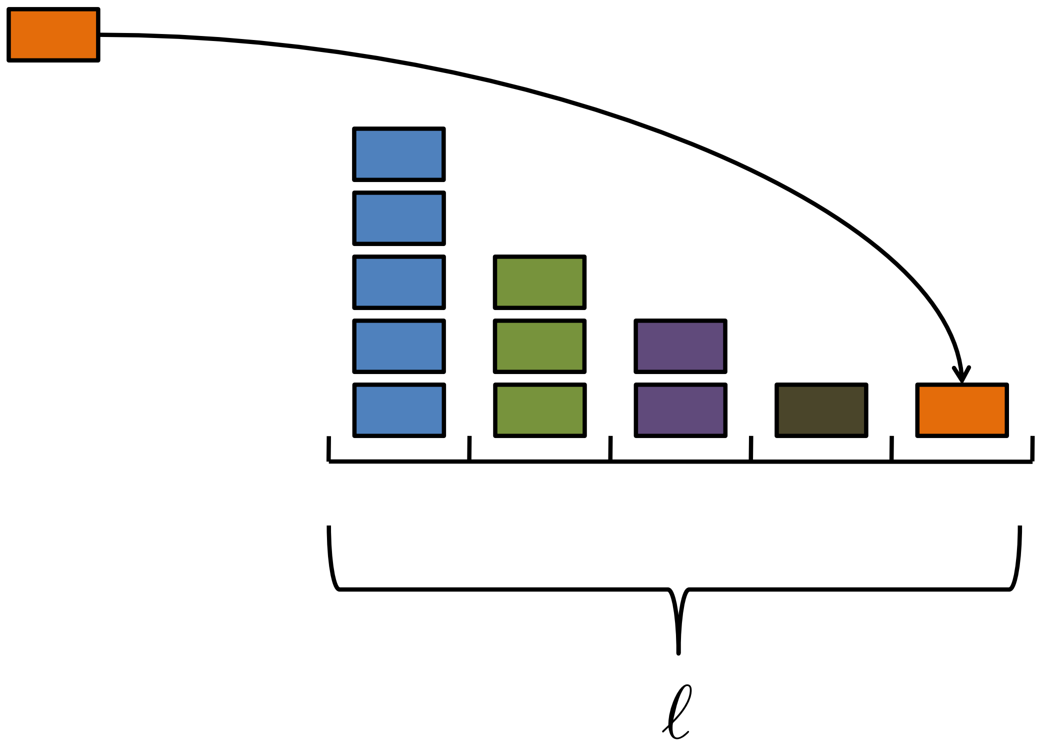
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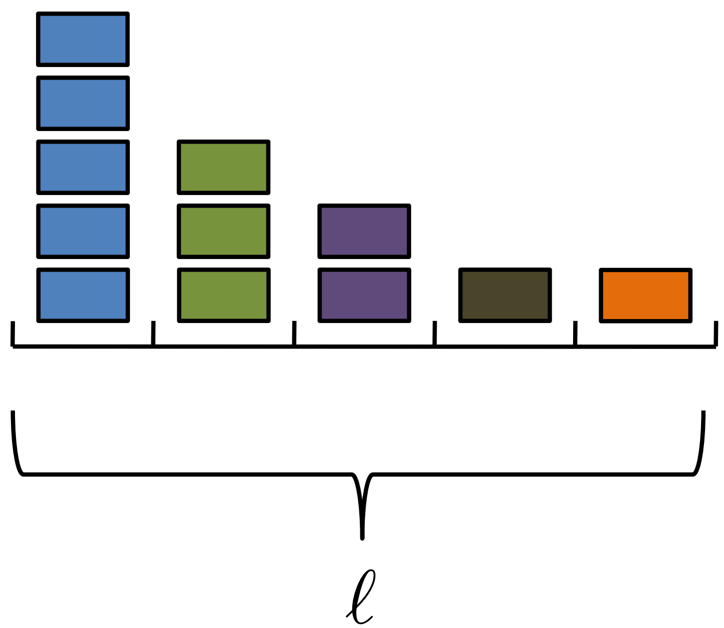
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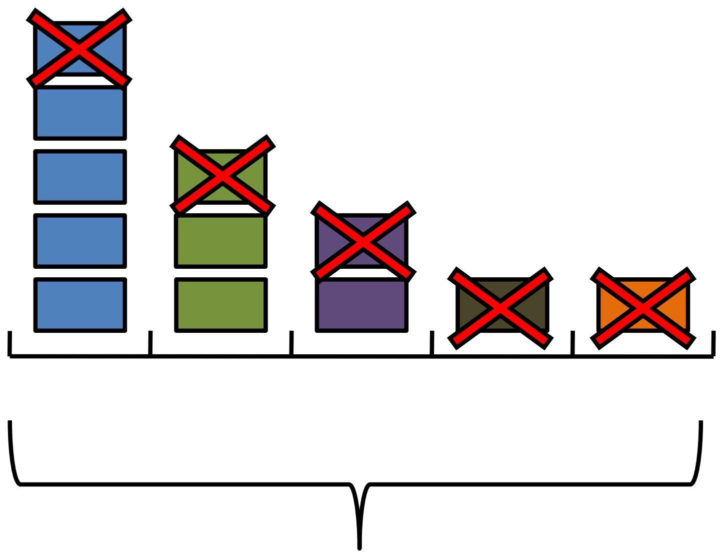

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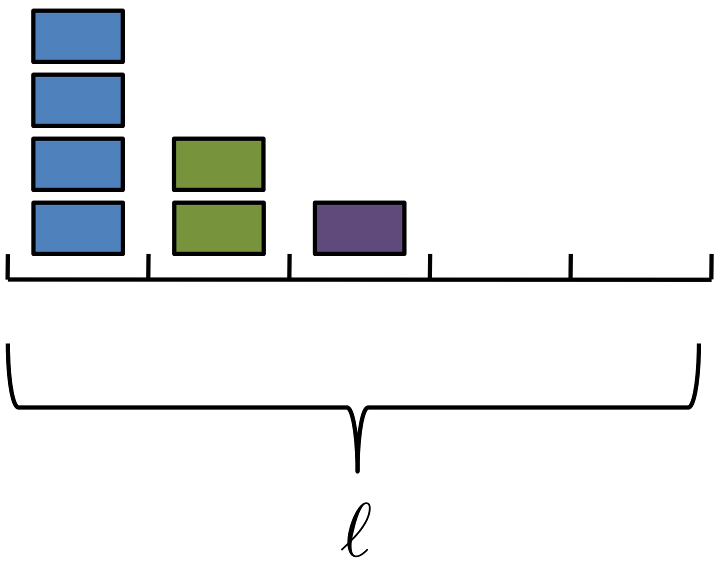

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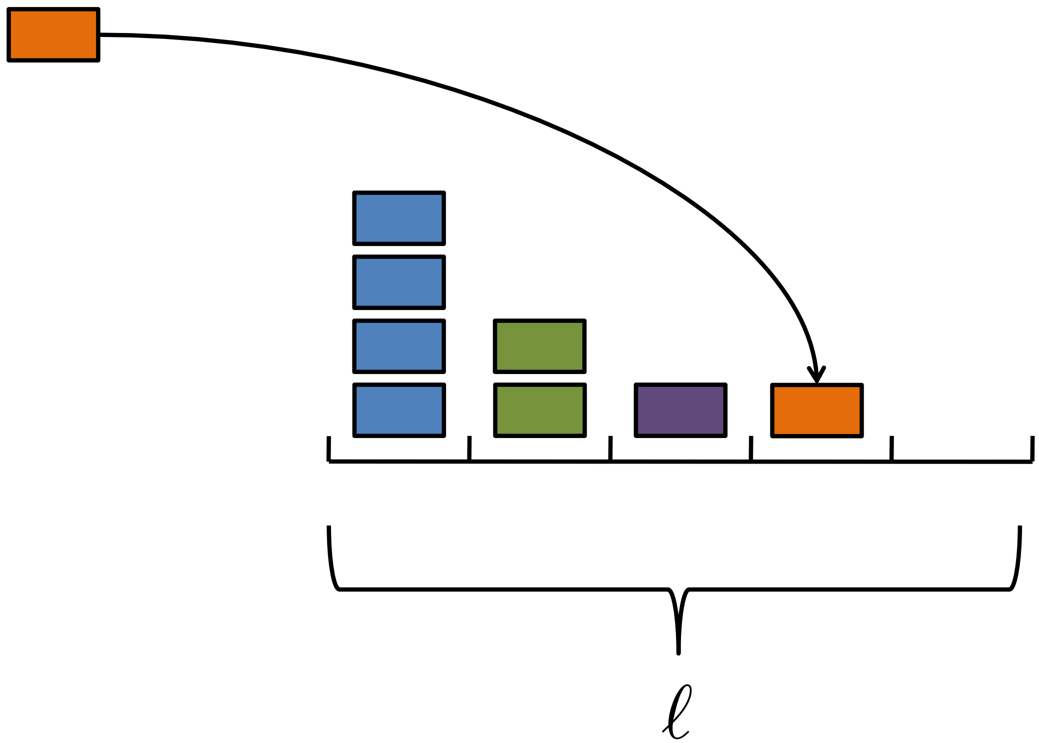
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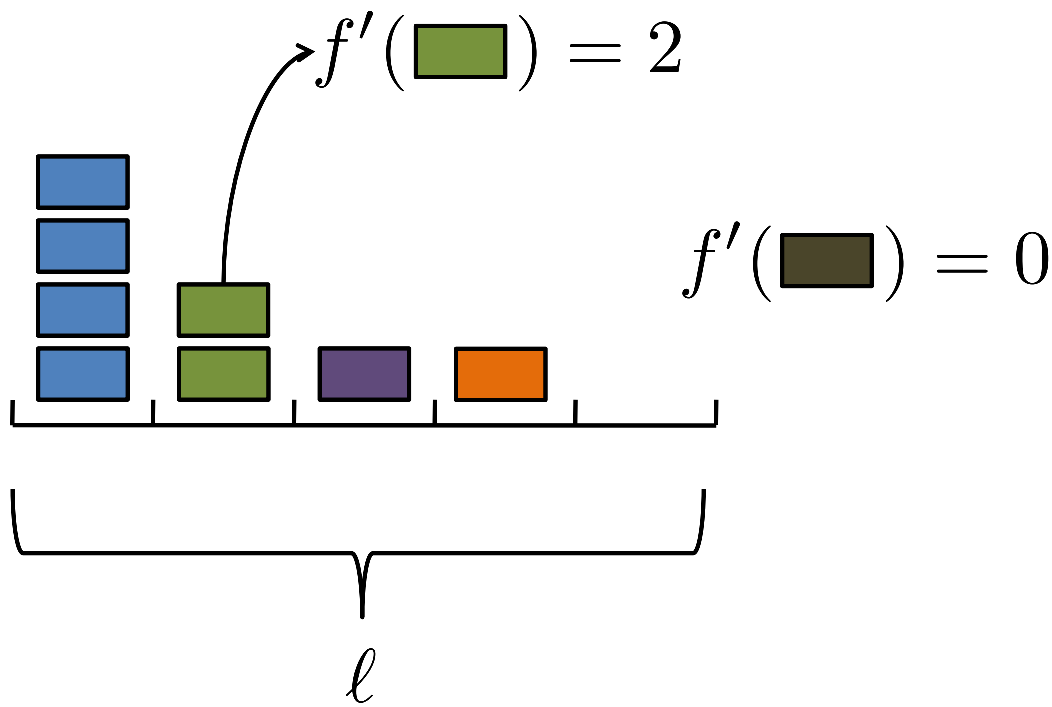
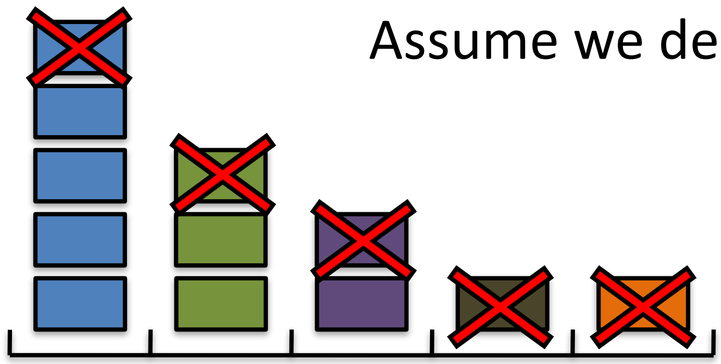

$f'(\ ) = 2$
$f'(\ ) = 0$
ℓ

Analysis

First fact: $f'(x) \leq f(x)$



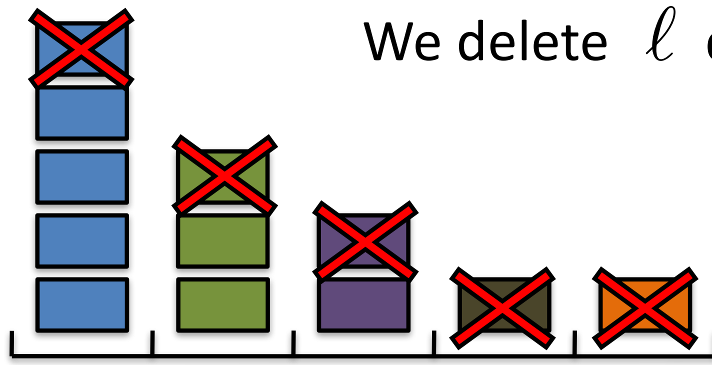
Assume we delete t times

Second fact: $f'(x) \geq f(x) - t$

Therefore: $|f'(x) - f(x)| \leq t$

Analysis

Third fact: $t \leq n/\ell$



We delete ℓ different items every time!

We get that: $|f'(x) - f(x)| < \varepsilon n$

When: $\ell = 1/\varepsilon$ (much better than sampling!)

Analysis

Items' exact probability $p(x) = f(x)/n$

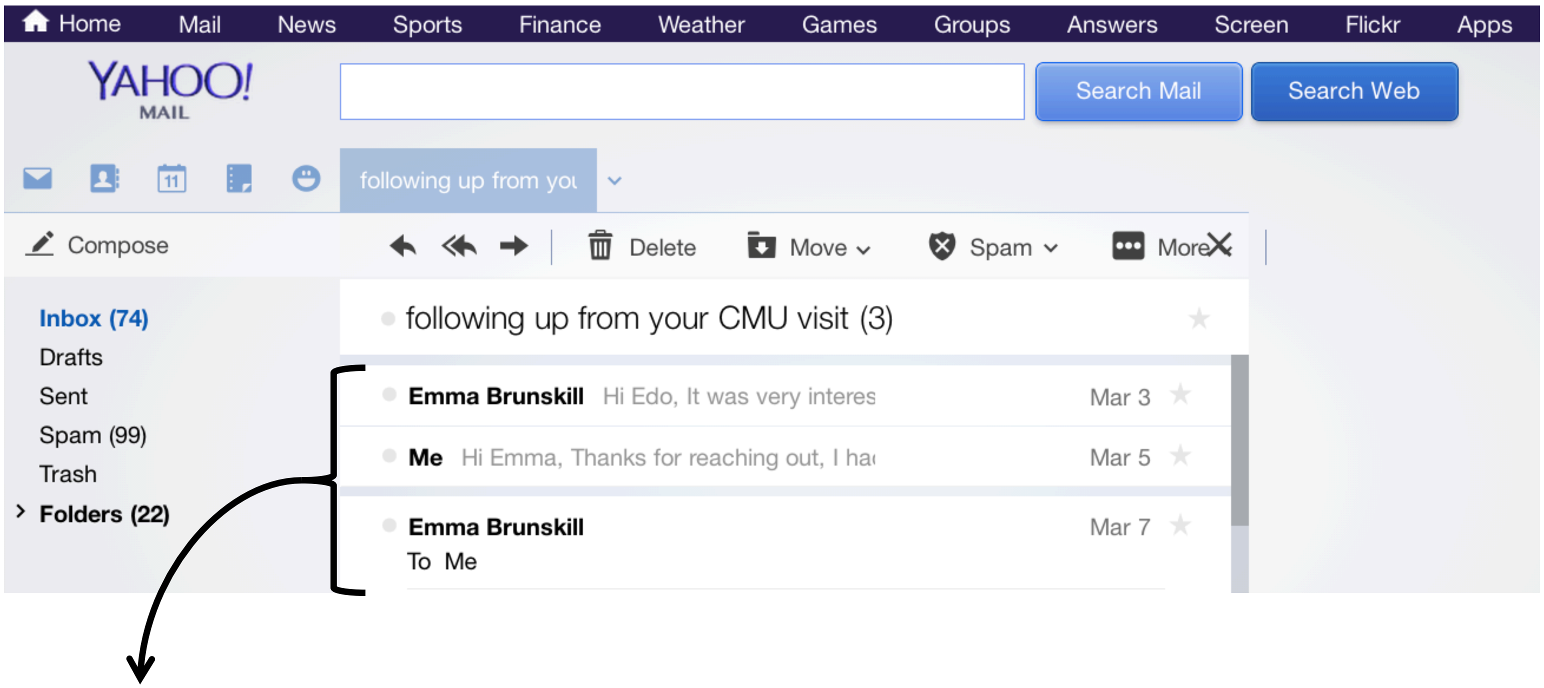
Approximate probability $p'(x) = f'(x)/n$

We get: $|p'(x) - p(x)| \leq 1/\ell$

If $\ell = 10,000$ we get only a 0.01% error in our estimations.

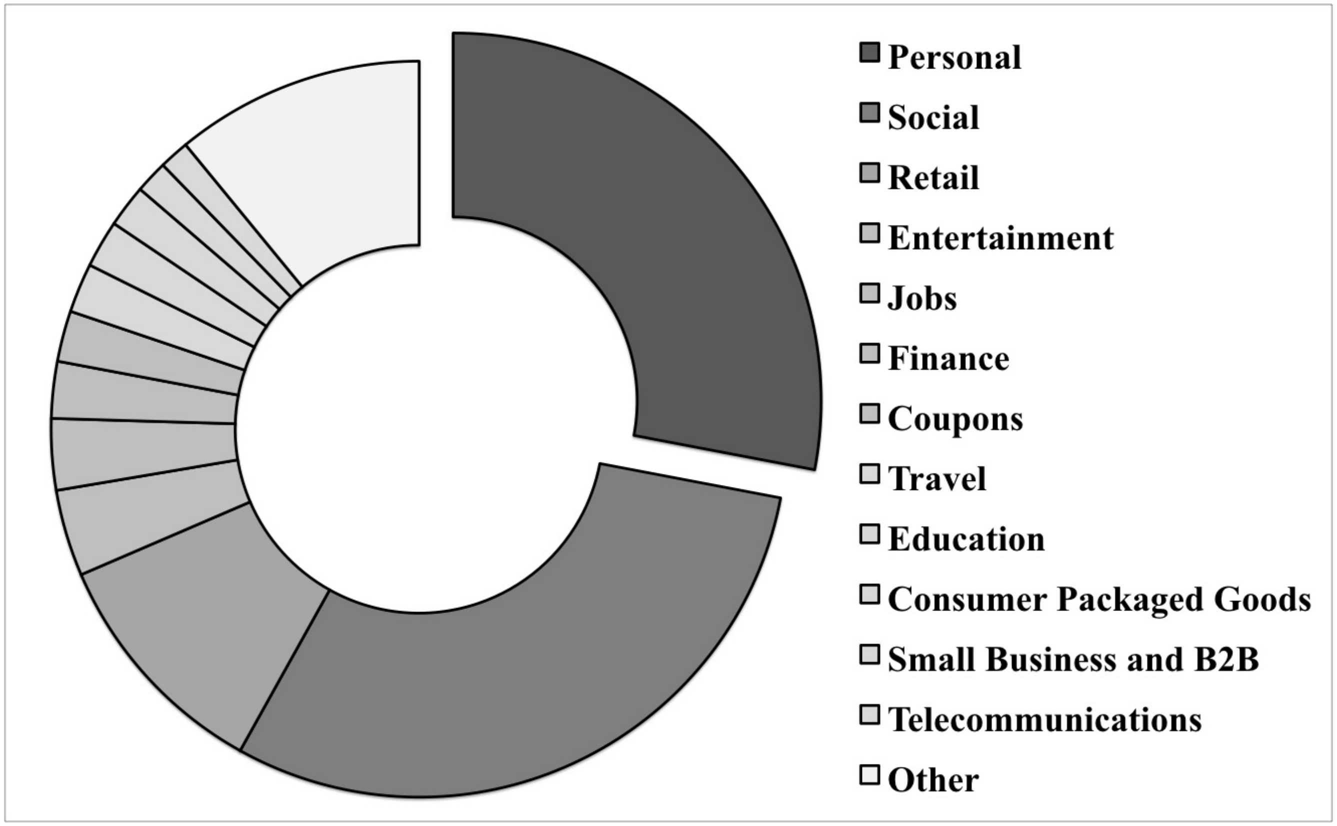
We would need 10 billion samples to get the same accuracy!

Email threads



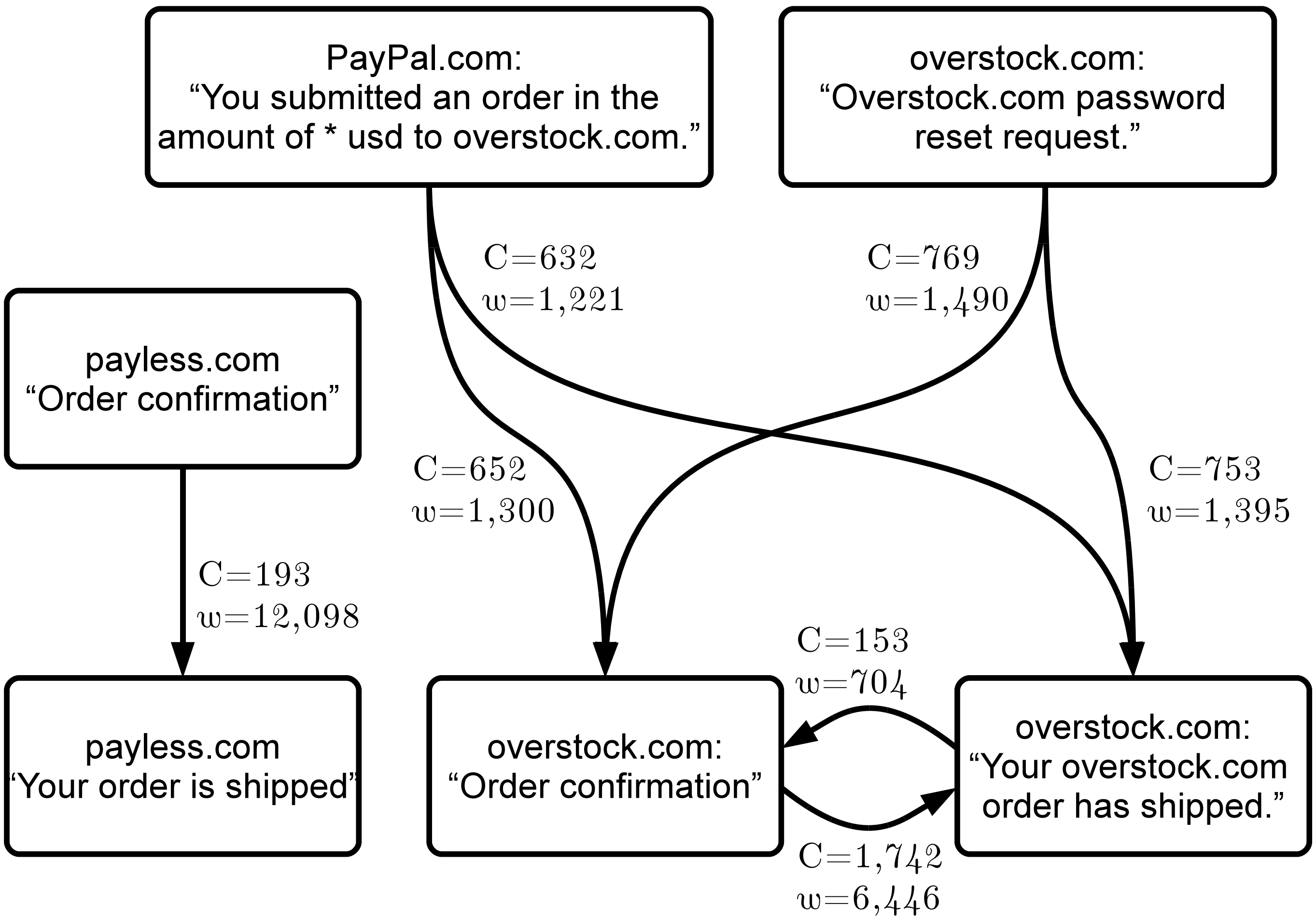
A simple email thread (that's not very hard to do…)

Threading Machine Generated Email

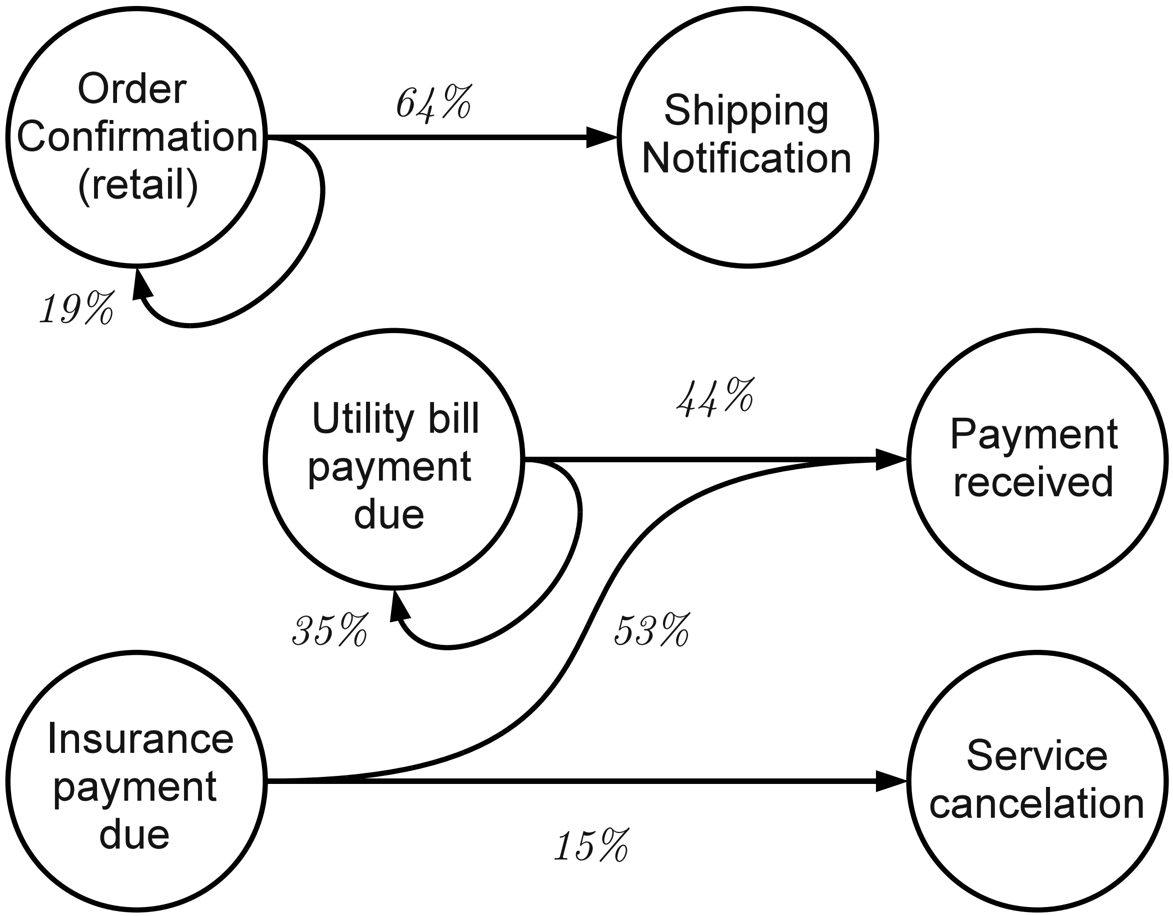


Ailon, Karnin, Maarek, Liberty, Threading Machine Generated Email, WSDM 2013

Threading Machine Generated Email



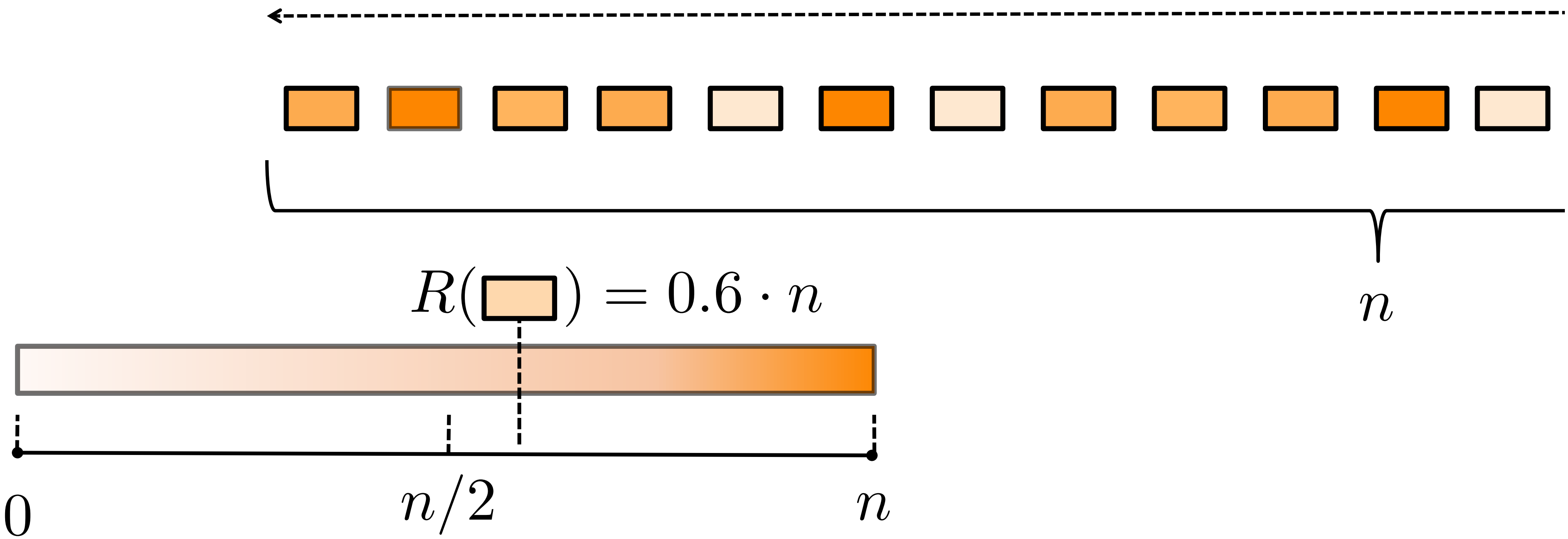
Threading Machine Generated Email



Streaming quantiles

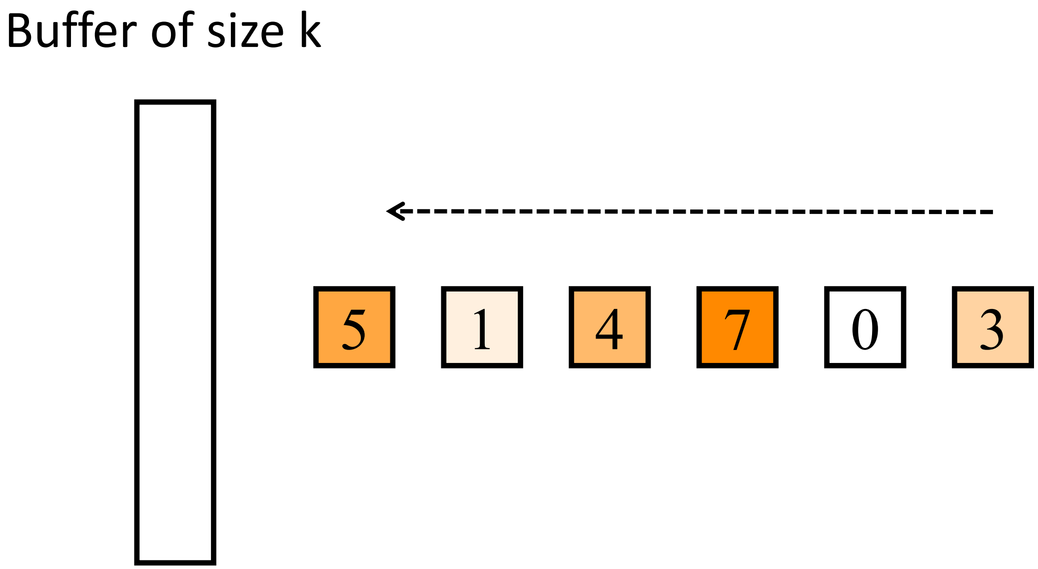
Manku, Rajagopalan, Lindsay. Random sampling techniques for space efficient online computation of order statistics of large datasets.
Munro, Paterson. Selection and sorting with limited storage.
Greenwald, Khanna. Space-efficient online computation of quantile summaries.
Wang, Luo, Yi, Cormode. Quantiles over data streams: An experimental study.
Greenwald, Khanna. Quantiles and equidepth histograms over streams.
Agarwal, Cormode, Huang, Phillips, Wei, Yi. Mergeable summaries.
Felber, Ostrovsky. A randomized online quantile summary in $O((1/\varepsilon)\log(1/\varepsilon))$ words.
Lang, Karnin, Liberty, Optimal Quantile Approximation in Streams.

Problem Definition



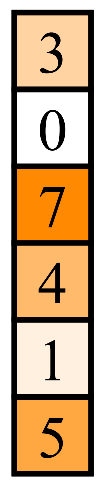
Sampling $\tilde{O}(1/\varepsilon^2)$ values gives $|R' - R| < \varepsilon n$ can we do better?

The basic buffer idea



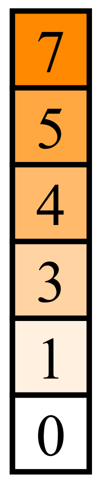
The basic buffer idea

Stores k stream entries



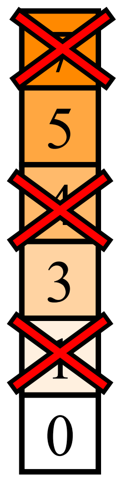
The basic buffer idea

The buffer sorts k stream entries



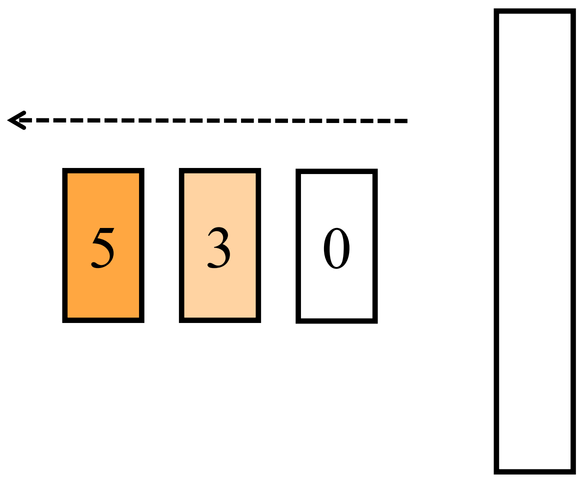
The basic buffer idea

Deletes every other item

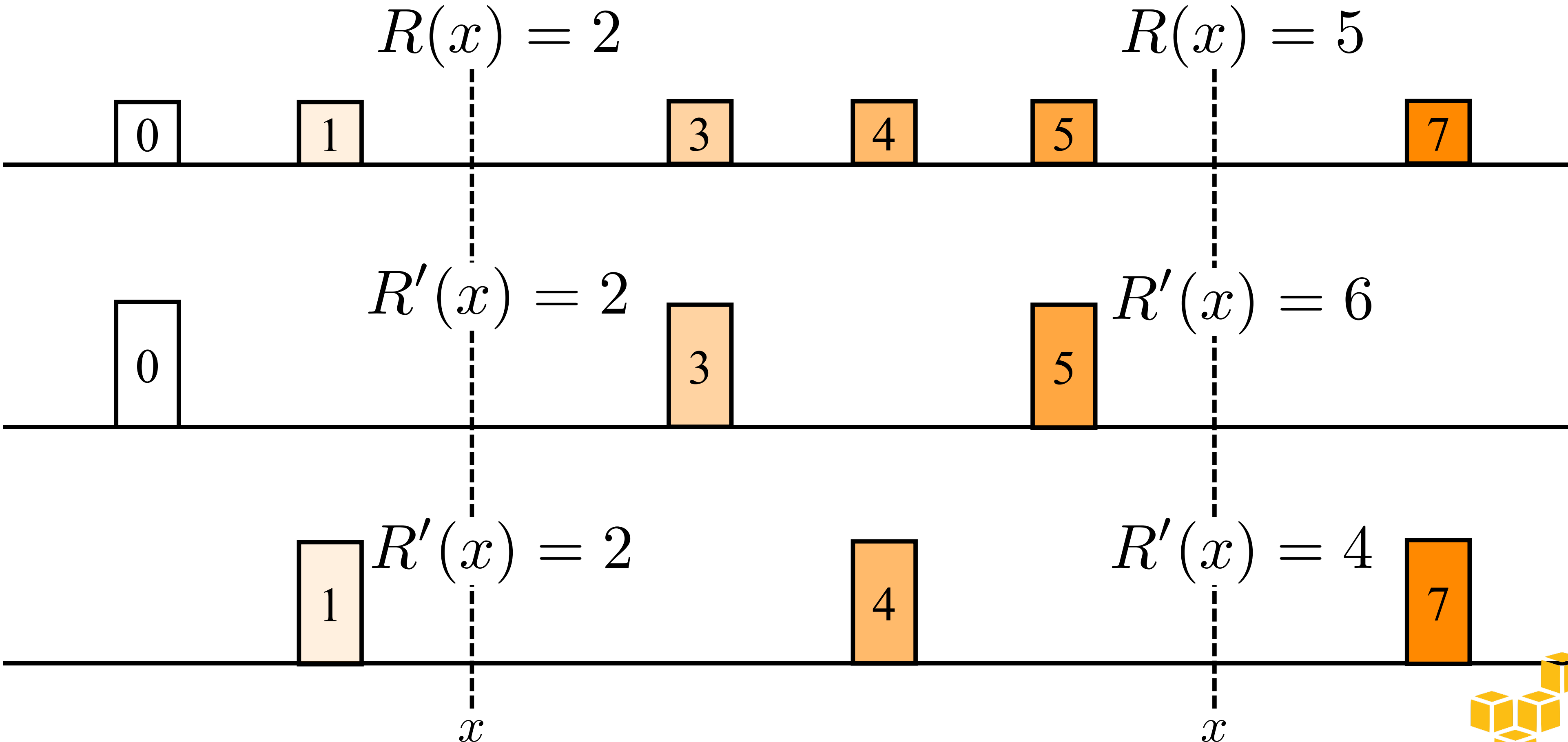


The basic buffer idea

And outputs the rest
with double the weight

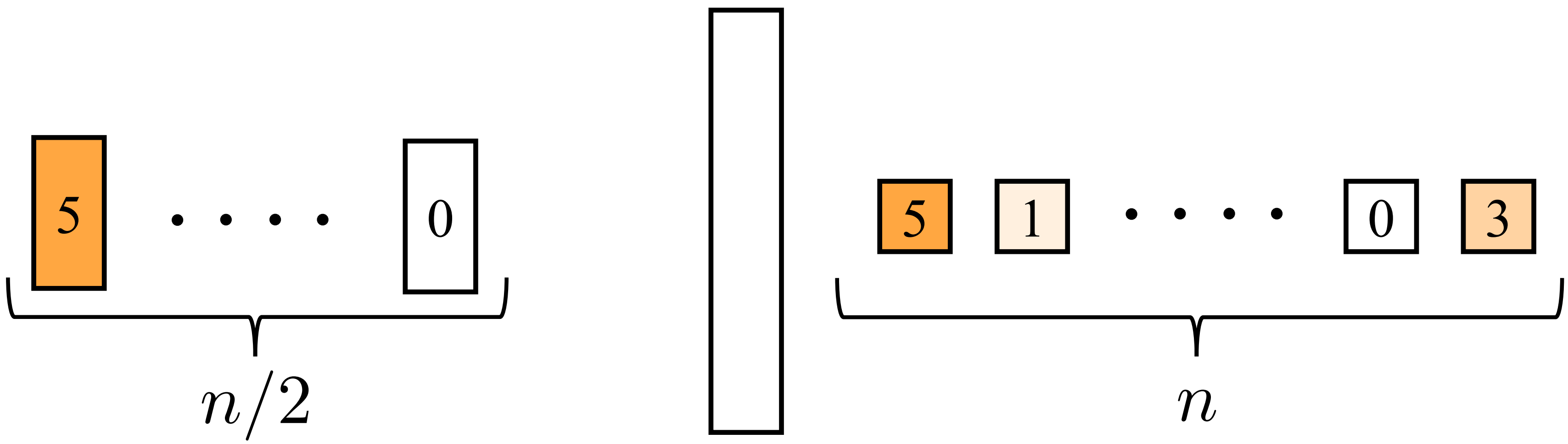


The basic buffer idea



The basic buffer idea

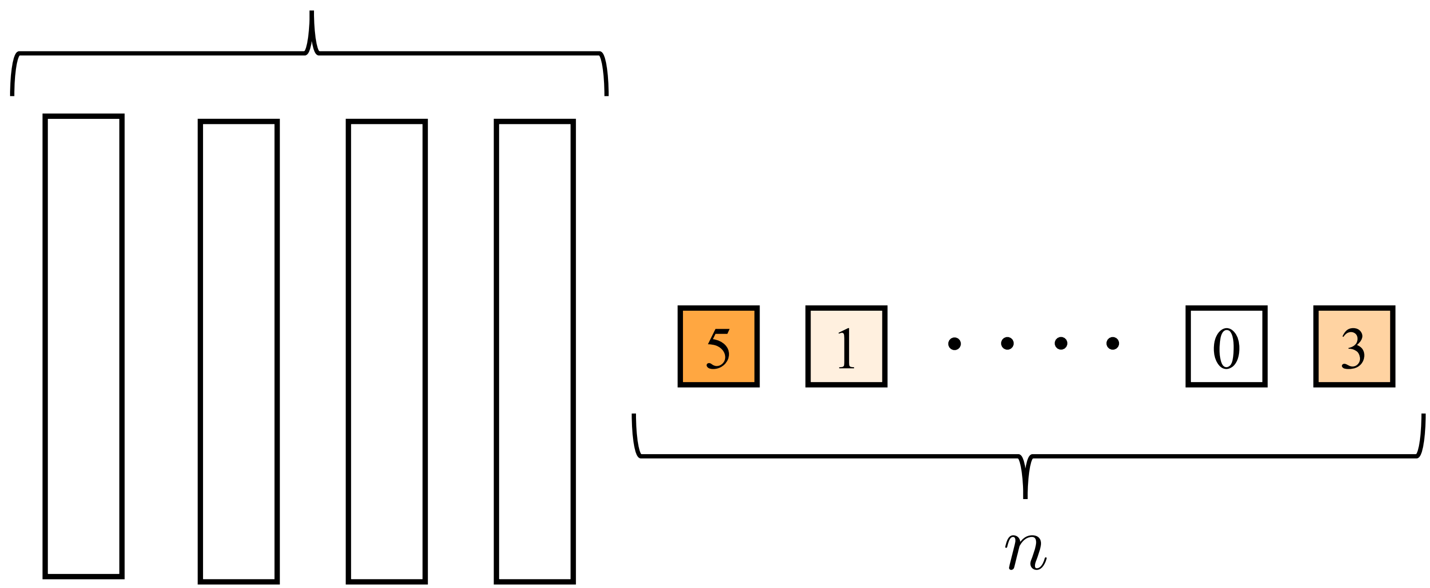
Repeat n/k time until the end of the stream



$$|R'(x) - R(x)| < n/k$$

Manku-Rajagopalan-Lindsay (MRL) sketch

$\log_2(n)$ Buffers of size k



$$|R'(x) - R(x)| \leq n \log_2(n)/k$$

Manku-Rajagopalan-Lindsay (MRL) sketch

If we set $k = \log_2(n)/\varepsilon$

We get $|R'(x) - R(x)| \leq \varepsilon n$

And we maintain only $\log_2^2(n)/\varepsilon$ items from the stream!

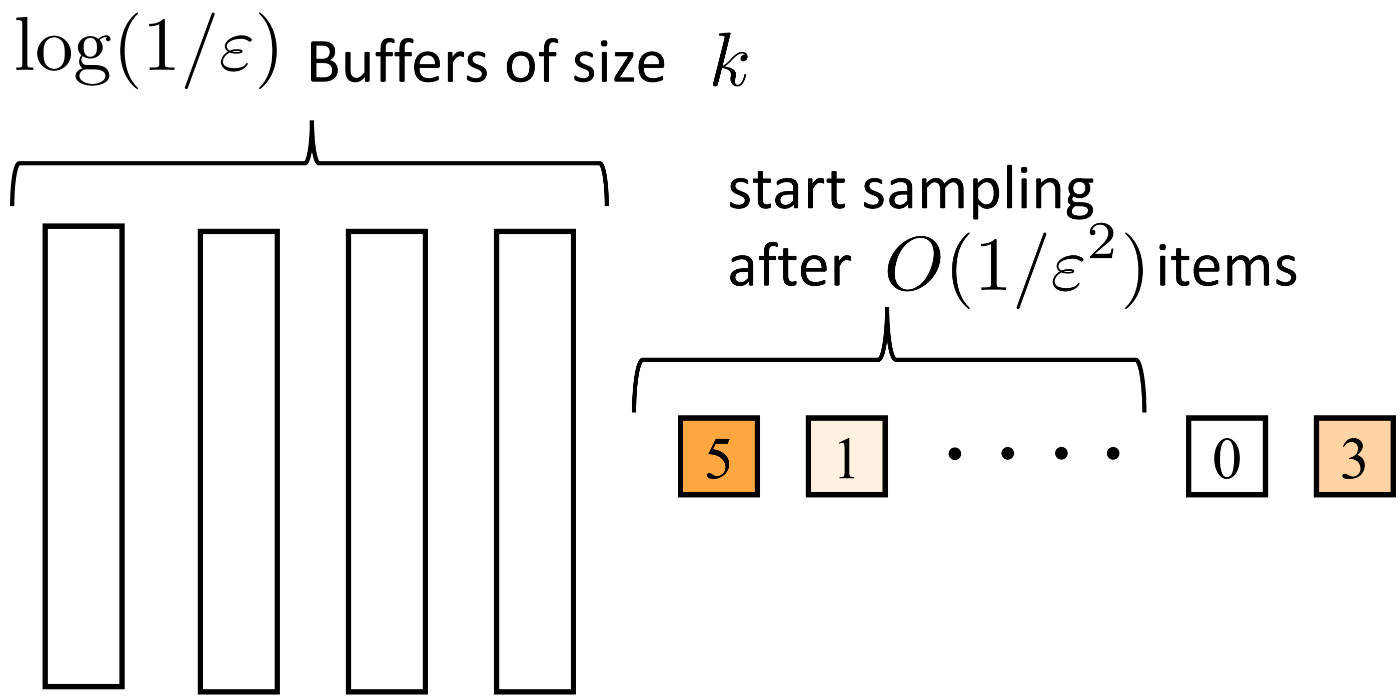
Greenwald-Khanna (GK) sketch

Uses a completely different construction

It gets $|R'(x) - R(x)| \leq \varepsilon n$

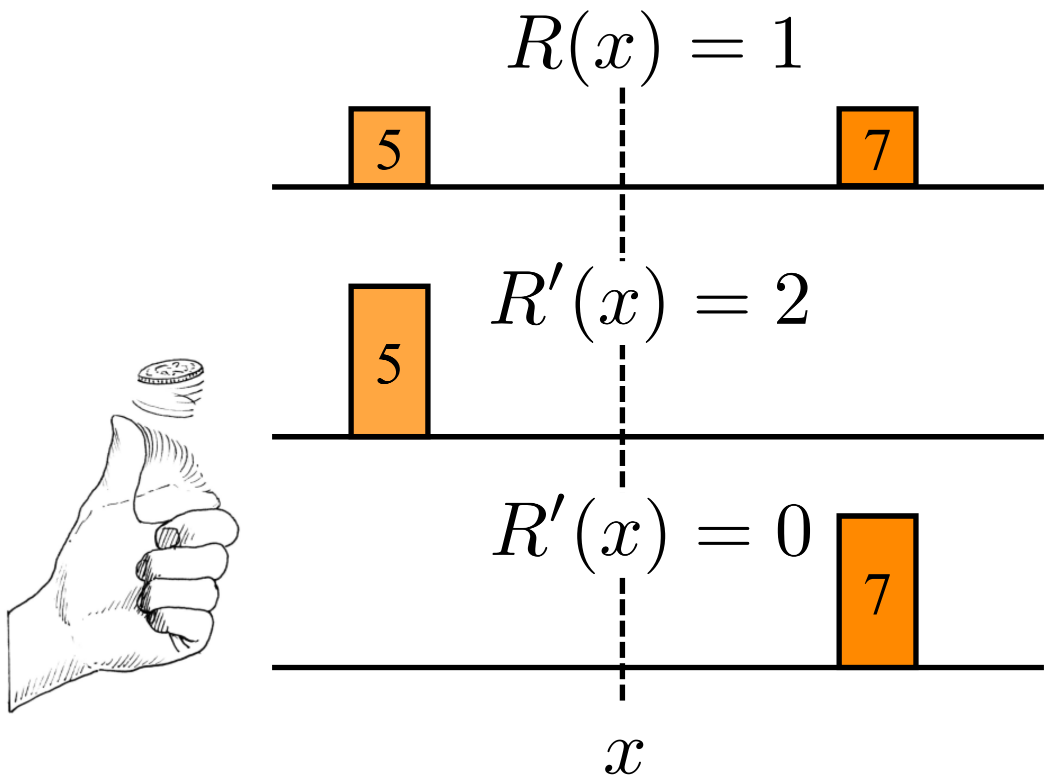
And maintains only $O(\log(n)/\varepsilon)$ items from the stream!

Agarwal, Cormode, Huang, Phillips, Wei, Yi (1)



Reduces space usage to $\log^2(1/\varepsilon)/\varepsilon$ items from the stream.

Agarwal, Cormode, Huang, Phillips, Wei, Yi (2)

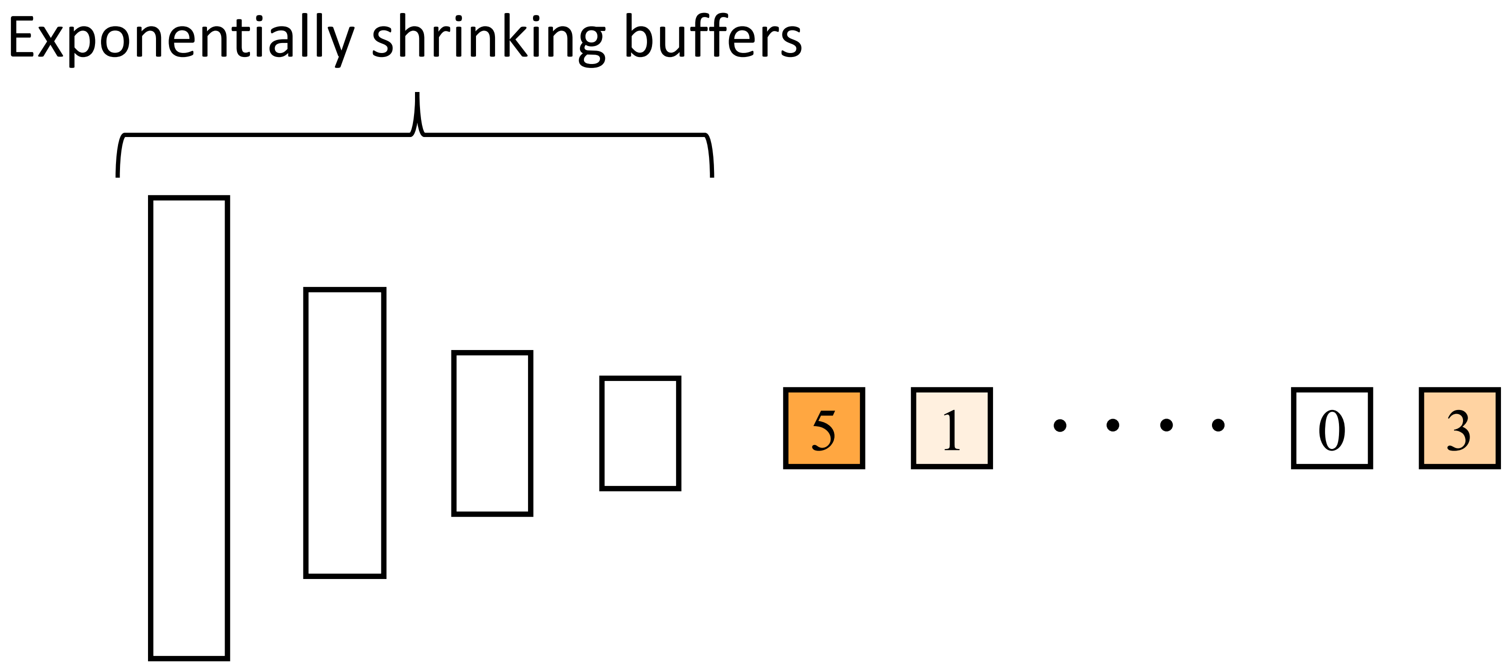


$R'(x)$ is a random variable now and

$$E[R'(x)] = R(x)$$

Reduces space usage to $\log^{3/2}(1/\varepsilon)/\varepsilon$ items from the stream.

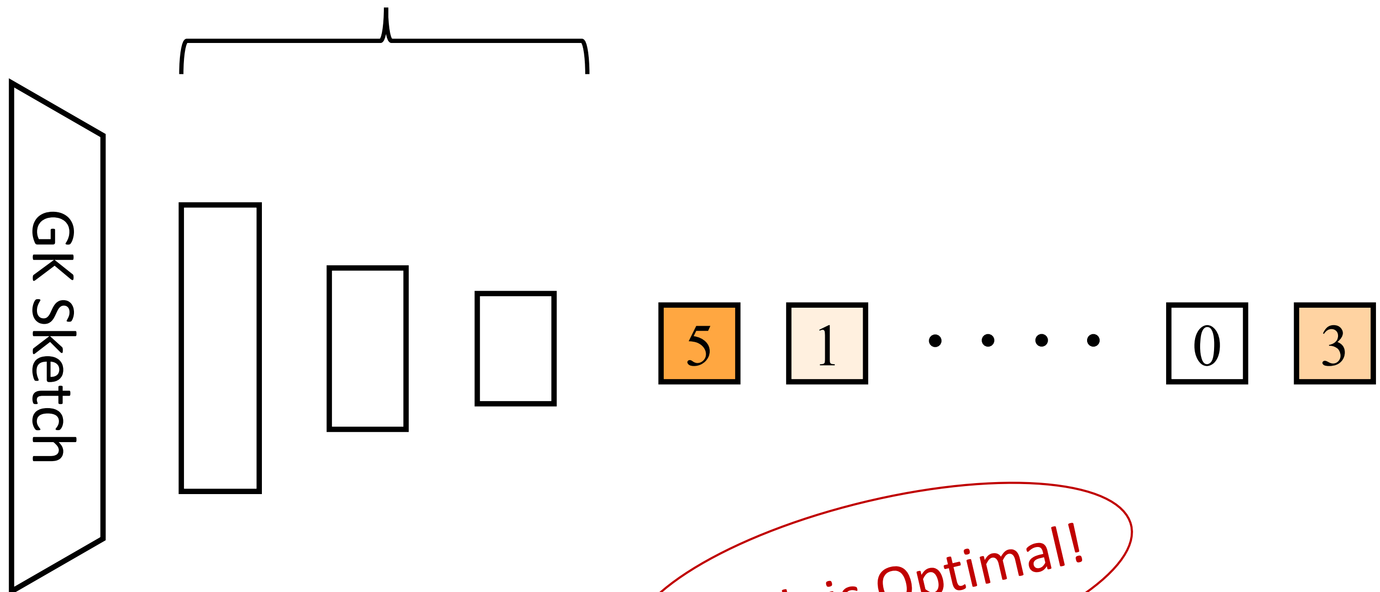
Lang, Karnin, Liberty (1)



Reduces space usage to $\sqrt{\log(1/\varepsilon)}/\varepsilon$ items from the stream.

Lang, Karnin, Liberty (2)

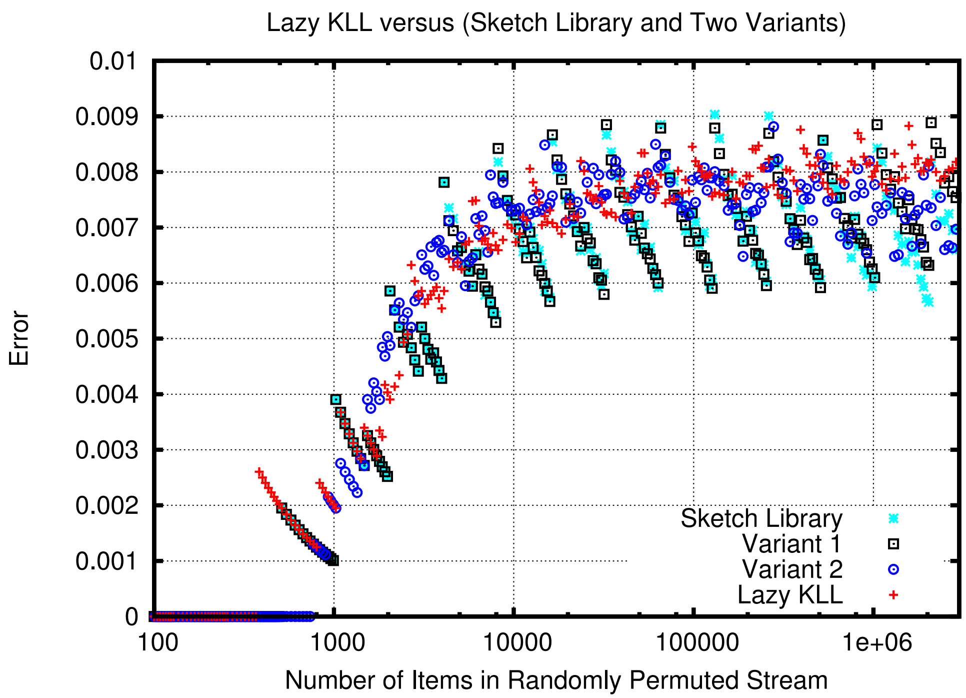
Exponentially decreasing buffer sizes

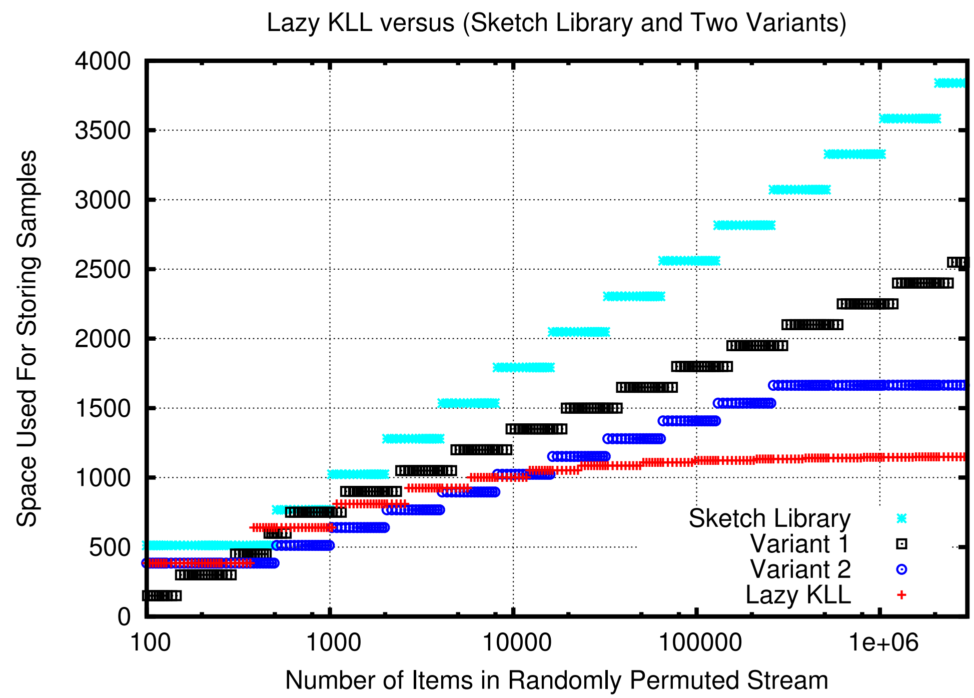


Which is Optimal!

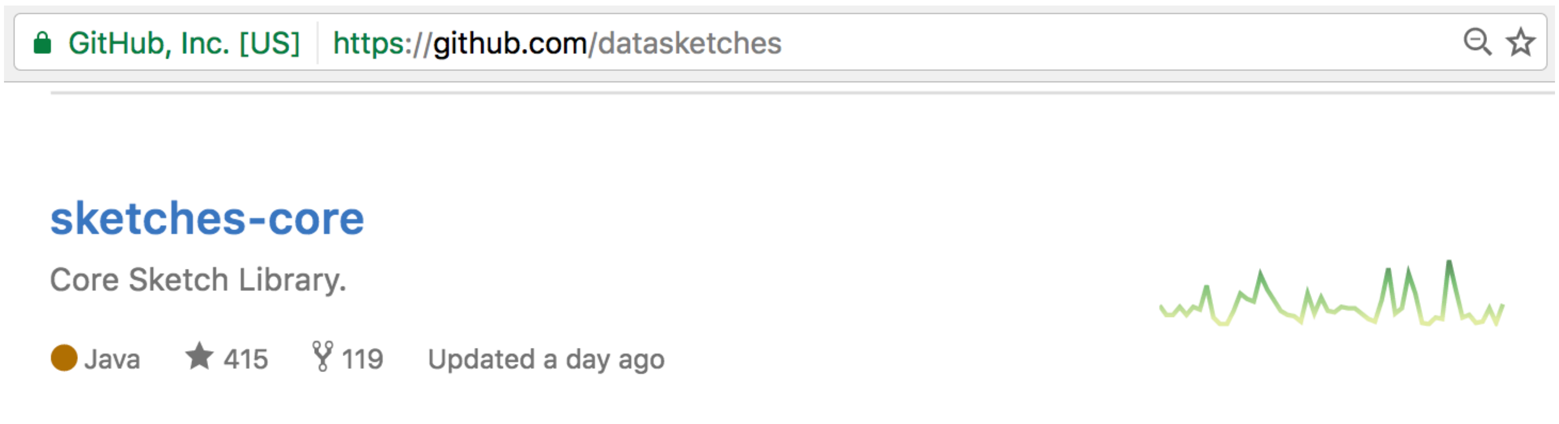
Reduces space usage to $\log\log(1/\varepsilon)/\varepsilon$ items from the stream.

Some experimental results





Count Distinct
(Demo Only)



Assume you need to estimate the number of **unique** numbers in a file

```
>>head data.csv
0
1
0
3
0
2
3
7
3
2
```

In this one, row i tasks a value from [0,i] uniformly at random.

Some stats: there are 10,000,000 such numbers in this ~76Mb file.

```
>>time wc -lc data.csv
 10000000 76046666 data.csv



real 0m0.101s
user 0m0.072s
sys 0m0.021s
```

Reading the file take ~1/10 seconds. We don't foresee IO being an issue.

To count the number of distinct items you might try this:

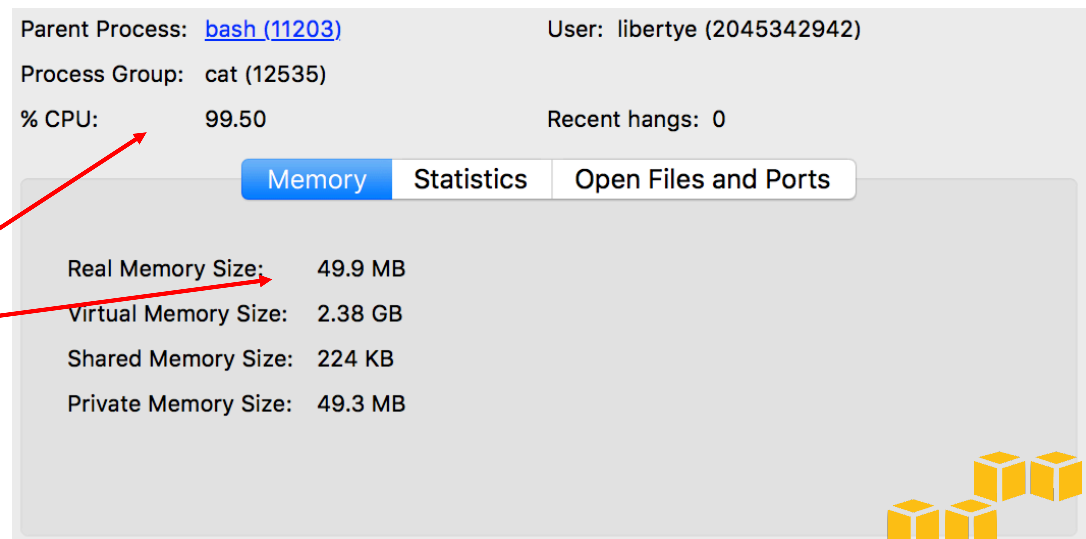
```
>>sort data.csv | uniq | wc -l
```

However, it is faster to have “uniqify” while sorting.

```
>>sort data.csv -u | wc -l
```

```
>>time sort data.csv -u | wc -l
 5001233


real 2m37.071s
user 2m36.587s
sys 0m0.376s
```



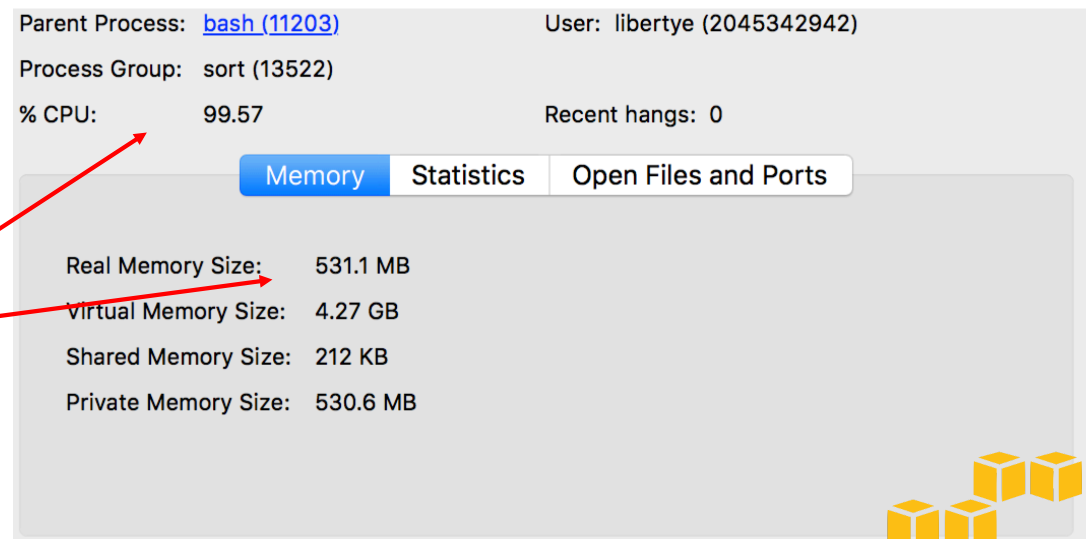
Still, most of the time is spent on comparing strings....

```
>>sort data.csv  -u -n  -S 100% | wc -l
```

This is much better!

```
>>time sort data.csv -u -n | wc -l
 5001233

real 0m11.809s
user 0m11.587s
sys 0m0.228s
```



This is the way to do this with the sketching library

```
>>sketch uniq data.csv
```

```
>>time sketch uniq data.csv
Estimate        : 4974249
Upper Bound : 5116569
Lower Bound : 4835874


real 0m1.527s
user 0m1.506s
sys 0m0.152s
```

Too fast to use the system monitor UI...

It uses ~ 32k of memory!

Thank you!