

Mehrdad Pazooki

TranQuant

Business Management and Big Data Consulting.

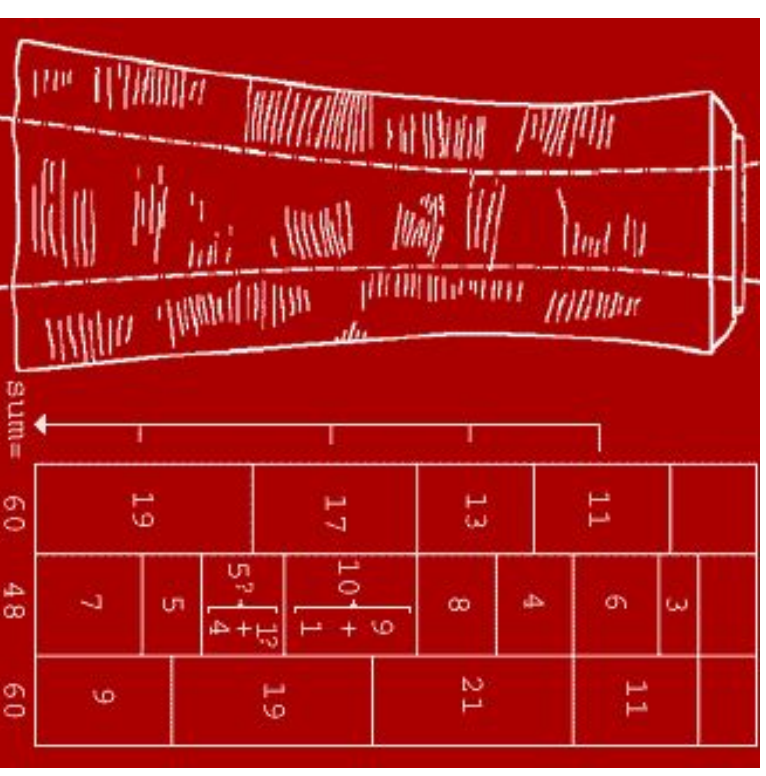
Twitter: [@mepazooki](https://twitter.com/mepazooki)

Email: mehrdad@tranquant.com

Slides: <https://github.com/pazooki/presentations>

Counting

Ishango Bone (20,000 Years Old!)



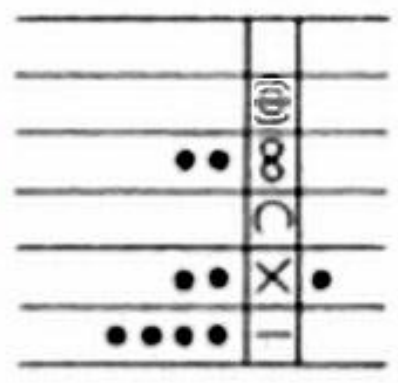
Ancient Counting Devices (500 BCE - 500 CE)

GREEK



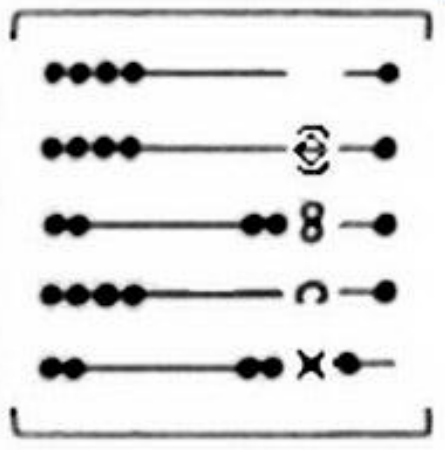
SALAMIS

ROMAN

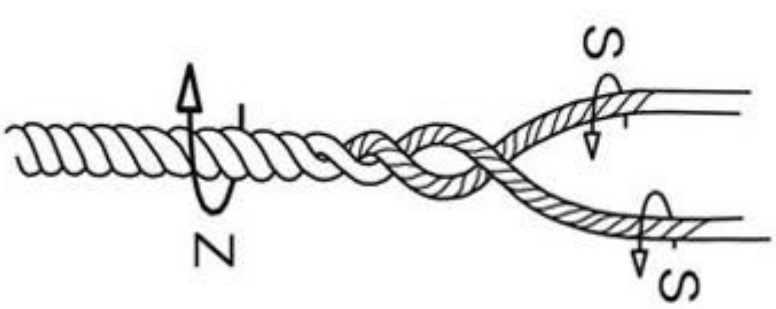
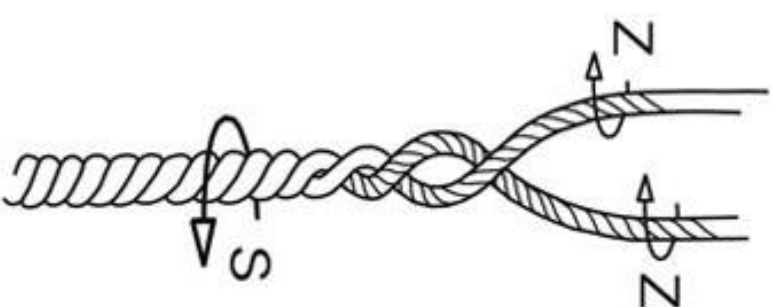
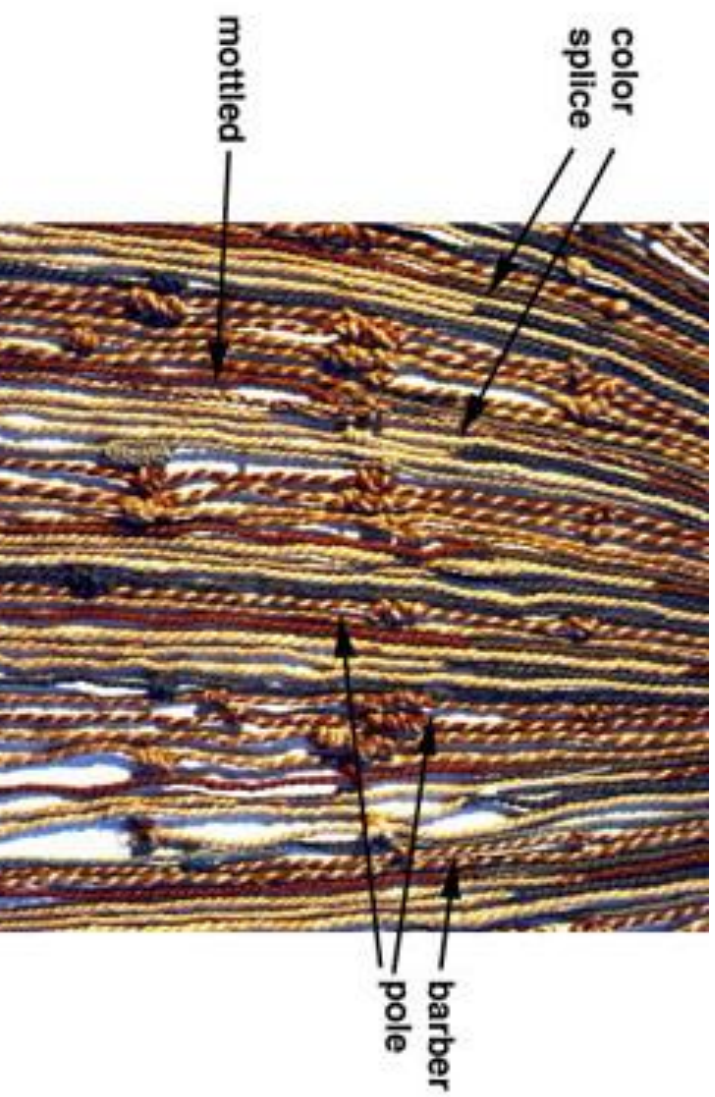


CALCULI

HAND-ABACUS



Khipu (1400)



Soroban (1930)

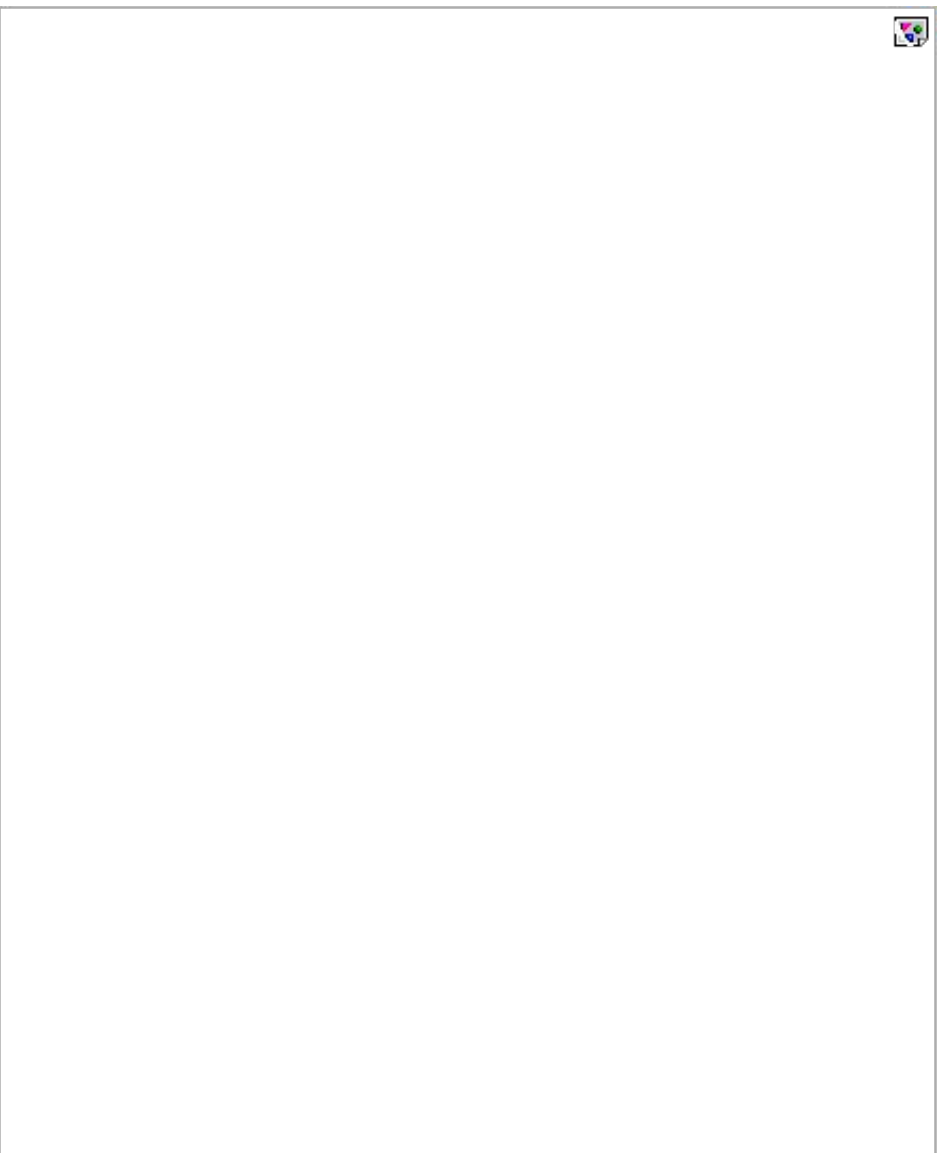




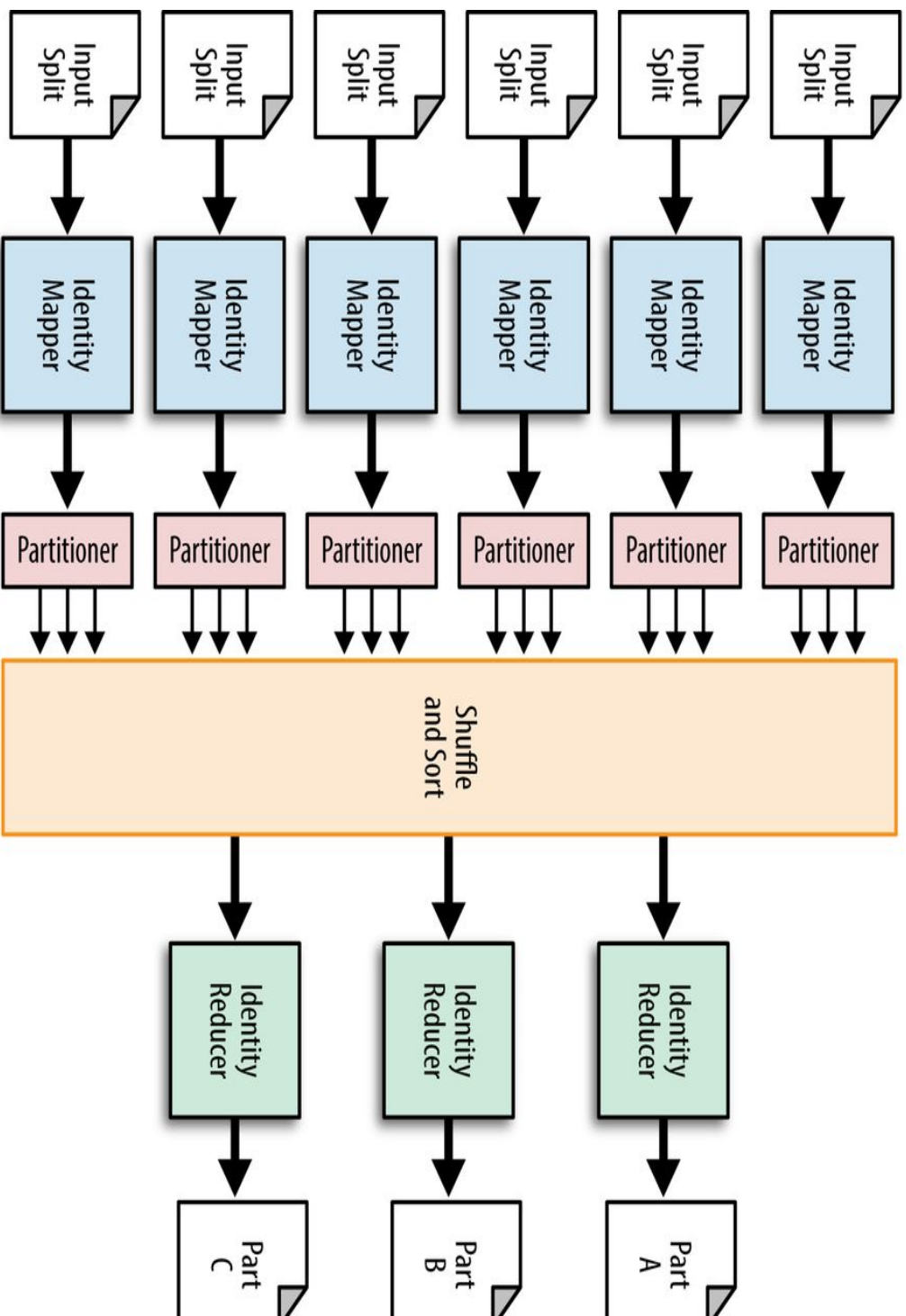
Number of unique users interested in “blue shoes”

	A	B	C	D	E	F	G	H	I	J
1	Event_ID	User_ID	Segment	Event_Type						
2	1	26	red shoes	clicked		Segment	Event Type	Total	Uniques	
3	2	3	blue shoes	clicked		blue shoes	clicked	20	5	
4	3	40	green shoes	viewed		blue shoes	viewed	35	10	
5	4	38	green shoes	clicked		green shoes	clicked	20	5	
6	5	4	red shirts	viewed		green shoes	viewed	35	10	
7	6	5	white bags	clicked		red shoes	clicked	20	5	
8	7	2	red shirts	clicked		red shoes	viewed	35	10	
9	8	21	red shoes	clicked		white bags	clicked	20	5	
10	9	23	blue shoes	viewed		white bags	viewed	35	10	
11	10	26	red shoes	clicked		yellow shirts	clicked	20	5	
12	11	13	yellow shirts	clicked		yellow shirts	viewed	35	10	
13	12	24	green shoes	viewed		red shirts	clicked	20	5	
14	13	3	green shoes	viewed		red shirts	viewed	35	10	
15	14	16	red shoes	clicked						
16	15	5	red shirts	viewed						

Distributed Systems



Map/Reduce



Count-distinct Problem

Count-distinct problem in large datasets.

Count-distinct problem

Finding the number of distinct elements in a dataset with repeated elements.

Count-distinct Problem

or

Cardinality Estimation Problem

Probabilistic Data Structures

V/s

Deterministic Data Structures

Deterministic Data Structures

The result of following functions:

- Insert
- Find
- Delete
- Count
- ...

Are always consistent.

Example: Set, Arrays,...

Probabilistic Data Structures

The result of following functions:

- Insert
- Find
- Delete
- Count
- ...

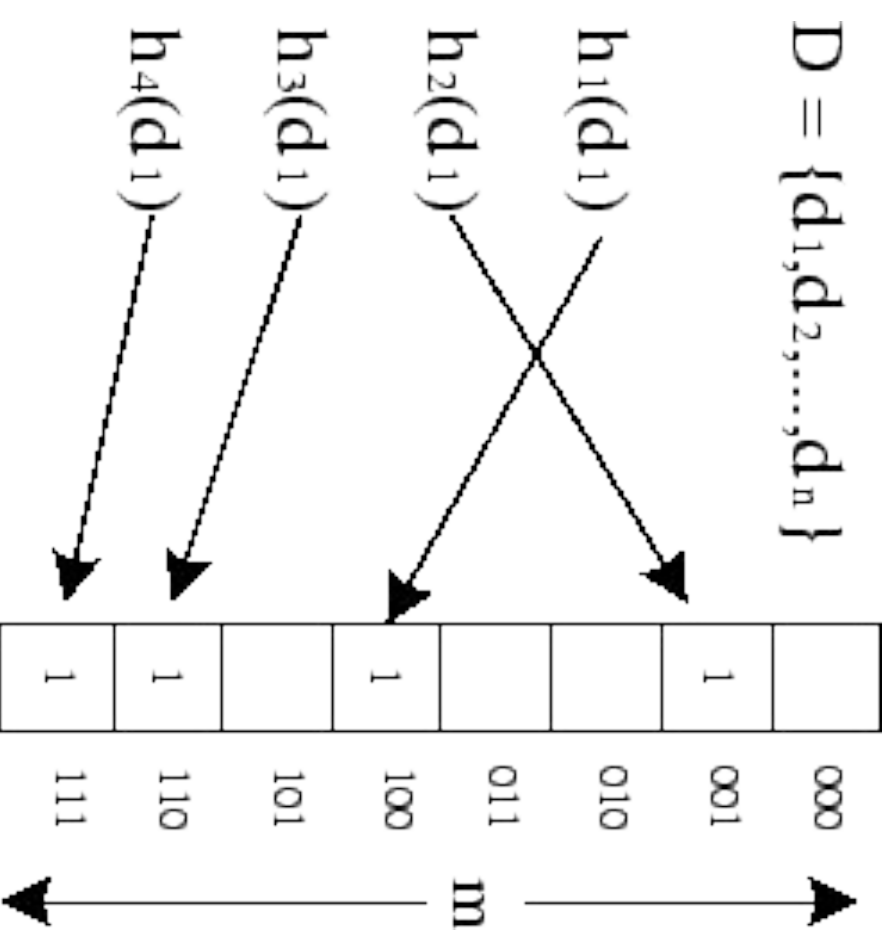
Are not always consistent.

Examples: BloomFilter, HyperLogLog, Count-min Sketch, MinHash,...

Number of unique users interested in “blue shoes”

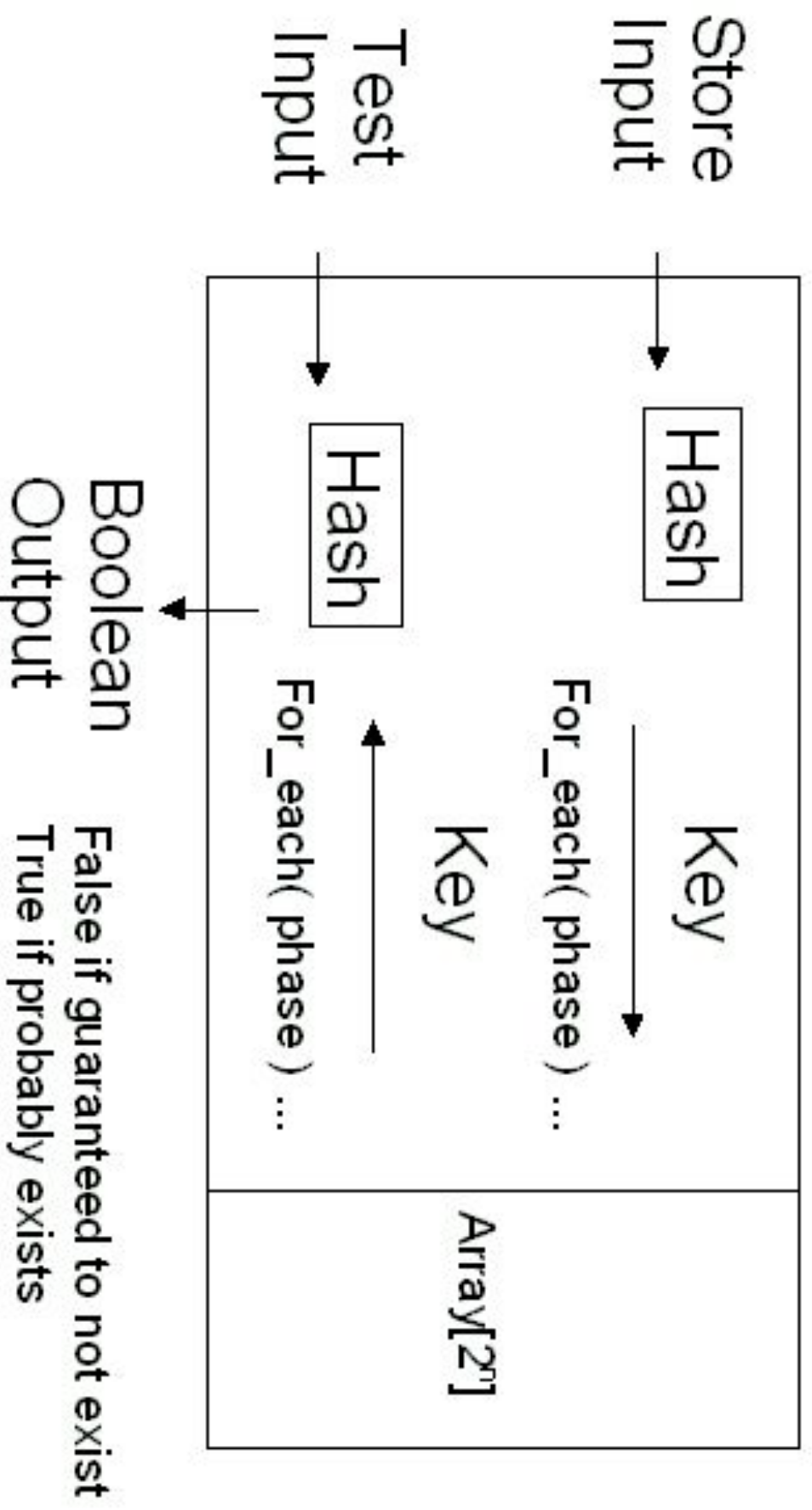
	A	B	C	D	E	F	G	H	I	J
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5	4	38	green shoes	clicked		green shoes	clicked	20	5	
6	5	4	red shirts	viewed		green shoes	viewed	35	10	
7	6	5	white bags	clicked		red shoes	clicked	20	5	
8	7	2	red shirts	clicked		red shoes	viewed	35	10	
9	8	21	red shoes	clicked		white bags	clicked	20	5	
10	9	23	blue shoes	viewed		white bags	viewed	35	10	
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14	13	3	green shoes	viewed		red shirts	viewed	35	10	
15	14	16	red shoes	clicked						
16	15	5	red shirts	viewed						

BloomFilter



A Bloom Filter that uses 4 hash functions and has a size of $m=8$ bits.

Bloom Filter Process



BloomFilter

- Compact with controllable error rate
- Great for fast filtering (is value V in set S ?)
 - Fraud Detection
 - DDOS Attack Prevention
- ...
- Great for problems not sensitive to false positive results
- Not that great for distinct count of large datasets
- It will be sparse for small datasets
- Dynamic Block-Partitioned BloomFilters

HyperLogLog

Q: How many distinct elements are in an infinite stream of data?

Similar to

Q: How many times the coin is flipped in coin flipping?



Coin Flipping

- Long runs of **heads** in random series are rare
- The longer you look, the more likely you will find one
- Long runs are very rare and are correlated with how many coins you've flipped

Basic HyperLogLog Algorithm

$n = 0$

For each input item:

Hash item into bit string

Count trailing zeros in bit string

if this count $> n$:

Let $n = \text{count}$

Estimated Cardinality (“Count Distinct”) = 2^n

HyperLogLog

- Great for distinct count of large datasets
 - Fixed Memory
- Some set operations:
 - Union
- Higher error ratio
- Limited spectrum for set Intersection operation
- The HyperLogLog algorithm is able to estimate cardinalities of 10^9 with a typical error rate of 2%, using 1.5 kB of memory.

Approximate Count in Apache Spark

`countApproxDistinct(relativeSD=0.05)`

Note: Experimental

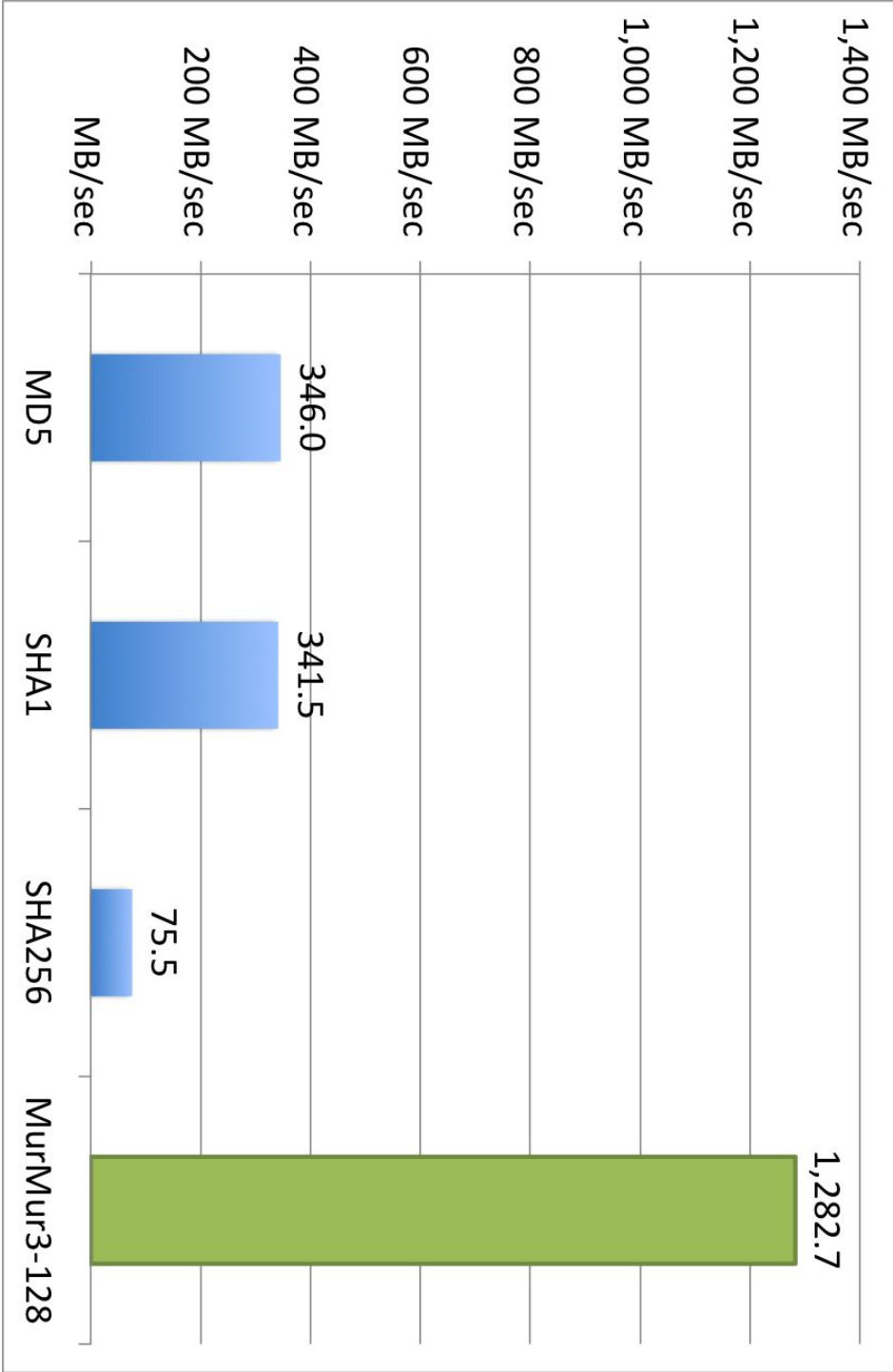
Return approximate number of distinct elements in the RDD.

The algorithm used is based on streamlib's implementation of "**HyperLogLog** in Practice: Algorithmic Engineering of a State of The Art Cardinality Estimation Algorithm", available [here](#).

Parameters: **relativeSD** – Relative accuracy. Smaller values create counters that require more space. It must be greater than 0.000017.

```
>>> n = sc.parallelize(range(1000)).map(str).countApproxDistinct()
>>> 900 < n < 1100
True
>>> n = sc.parallelize([i % 20 for i in range(1000)]).countApproxDistinct()
>>> 16 < n < 24
True
```

Hash Functions



References

- <https://highlyscalable.wordpress.com/2012/05/01/probabilistic-structures-web-analytics-data-mining/>
- https://en.wikipedia.org/wiki/Count-distinct_problem
- https://en.wikipedia.org/wiki/Category:Probabilistic_data_structures
- <http://www.slideshare.net/a235/probabilistic-data-structures-and-approximate-solutions>
- <http://dl.acm.org/citation.cfm?id=2452376.2452456>
- <http://www.ee.ryerson.ca/~elf/abacus/images/fig-antiquity.JPG>
- <https://pdfs.semanticscholar.org/5da8/bf81712187712aed159aed62e38fb012872e.pdf>
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Mehrdad Pazooki

TranQuant

Business Management and Big Data Consulting.

Twitter: [@mepazooki](#)

Email: mehrdad@tranquant.com

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Thank You!