

# Amusing algorithms and data-structures that power Lucene and Elasticsearch

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# Agenda

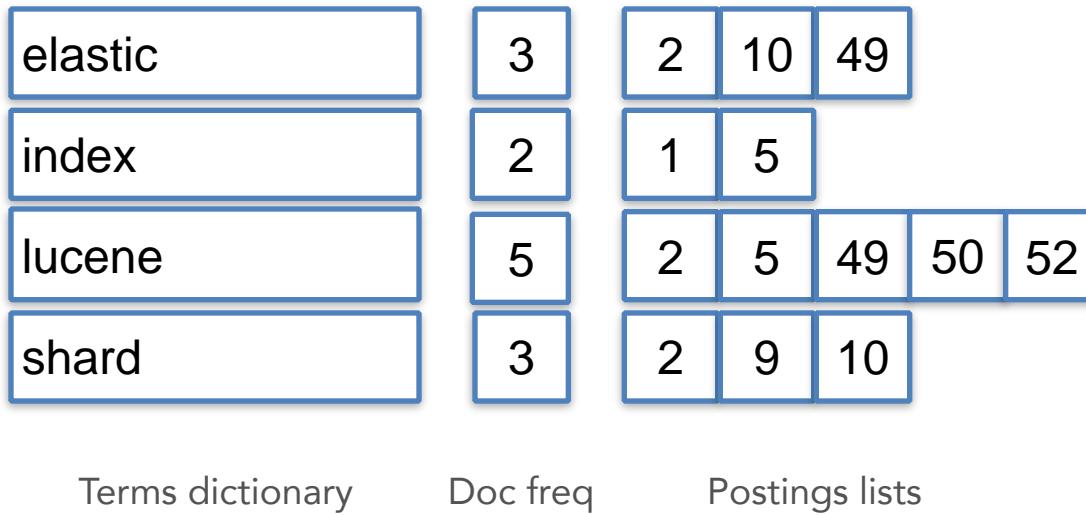
- conjunctions
- regexp queries
- numeric doc values compression
- cardinality aggregation



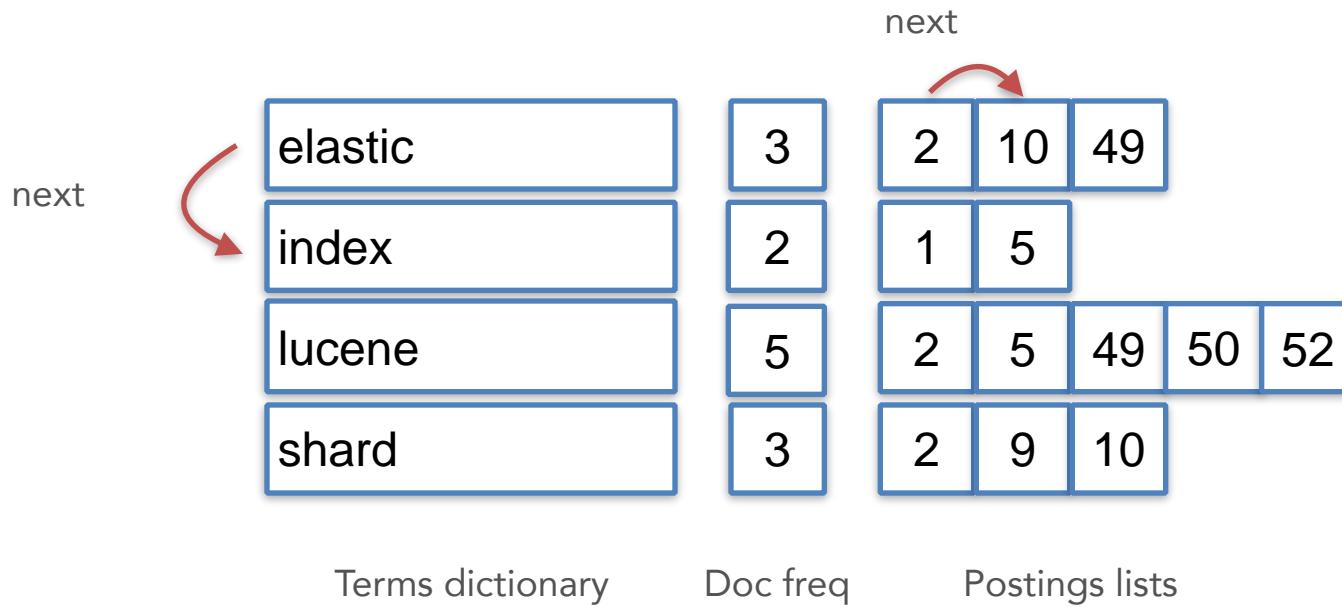
# How are conjunctions implemented?



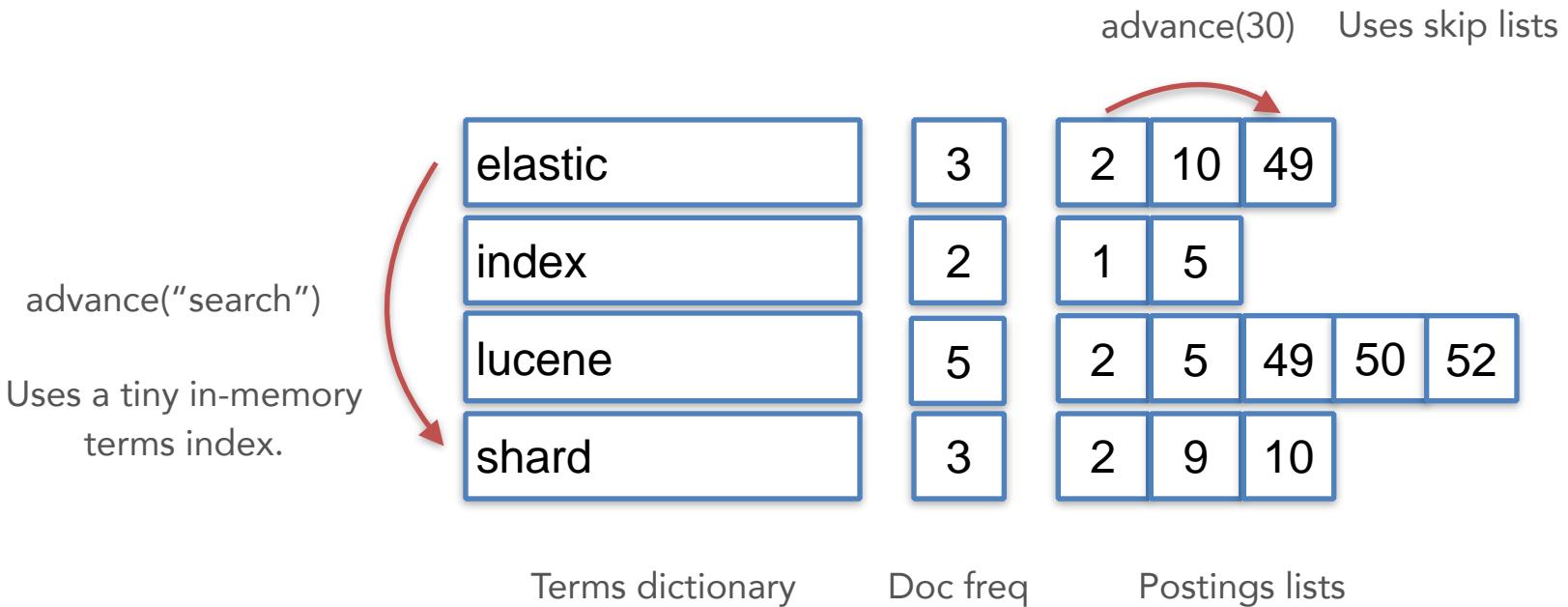
# Inverted index



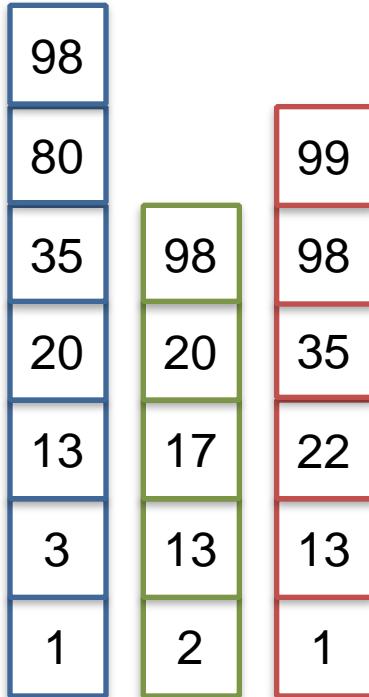
# Inverted index



# Inverted index



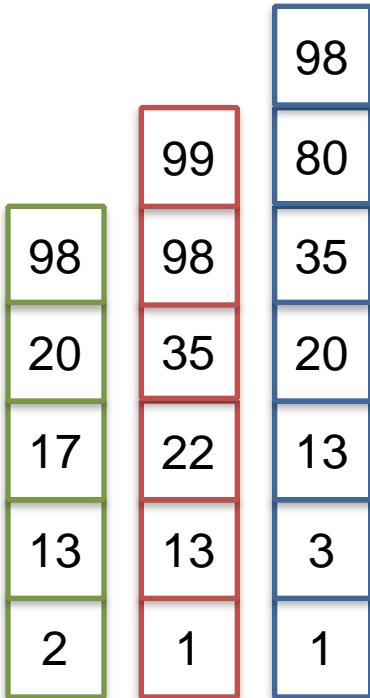
# Conjunctions



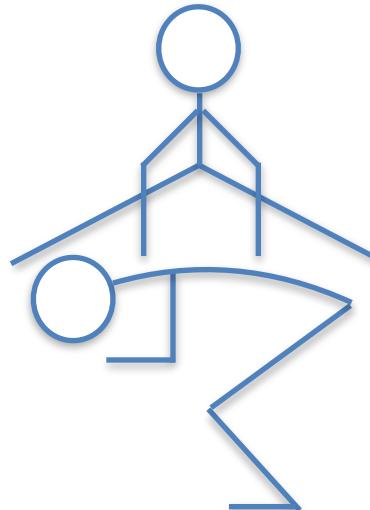
1. Sort by cost



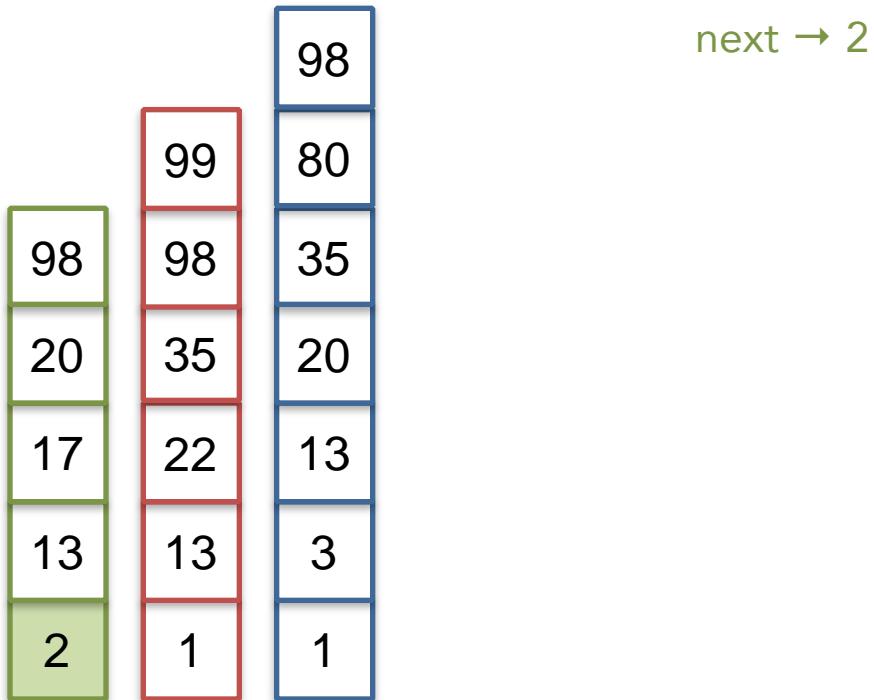
# Conjunctions



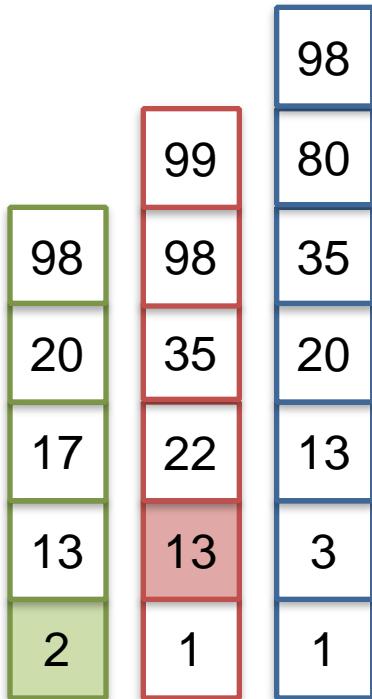
1. Sort by cost
2. Leap frog!



# Conjunctions



# Conjunctions



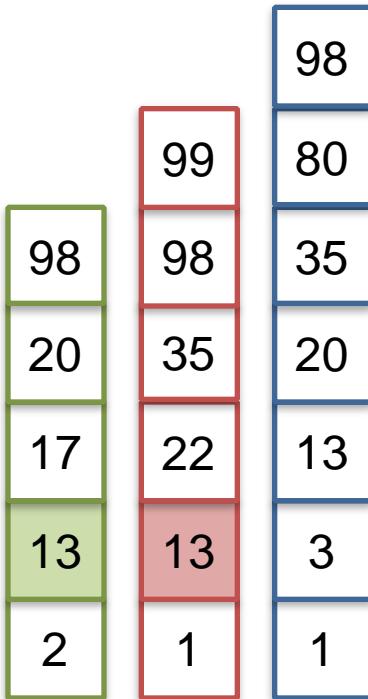
next → 2

advance(2) → 13

TOO FAR



# Conjunctions



next → 2

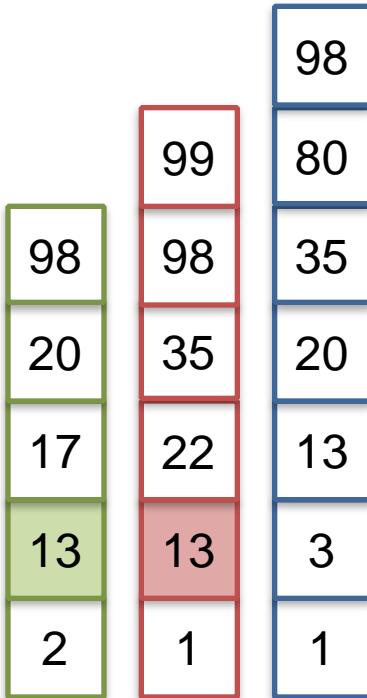
advance(2) → 13

TOO FAR

advance(13) → 13



# Conjunctions



next → 2

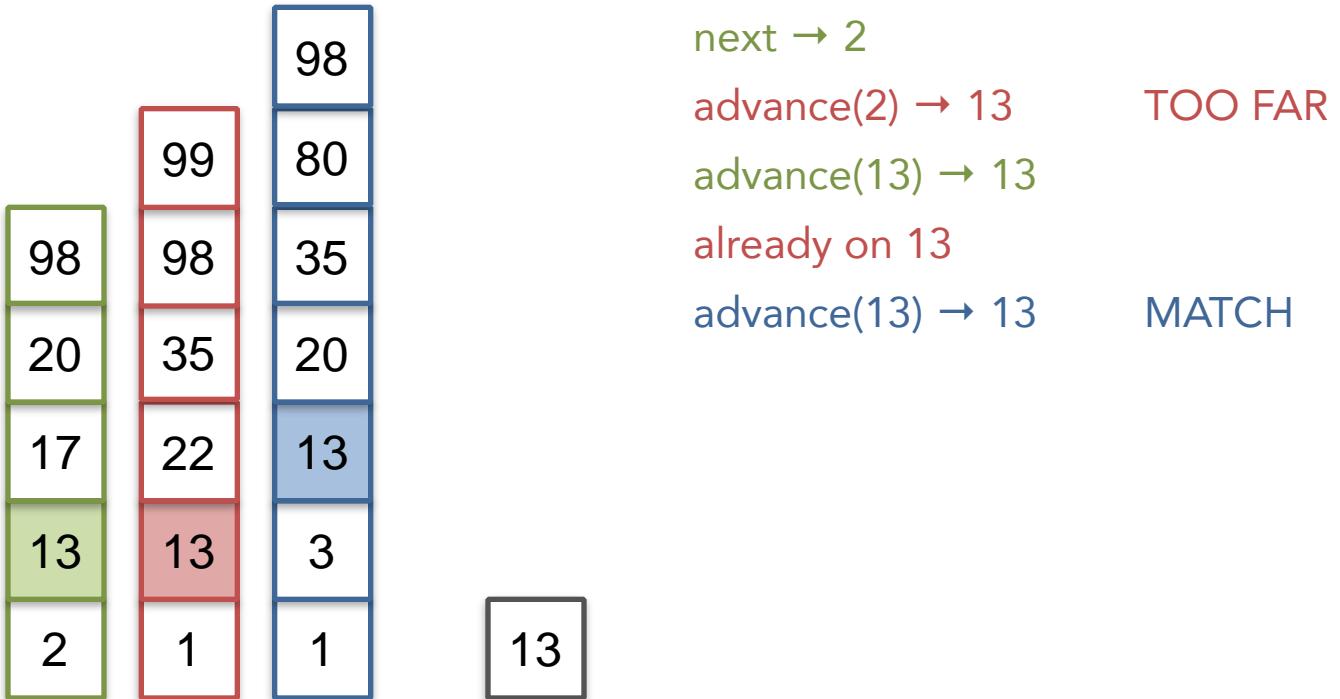
advance(2) → 13      TOO FAR

advance(13) → 13

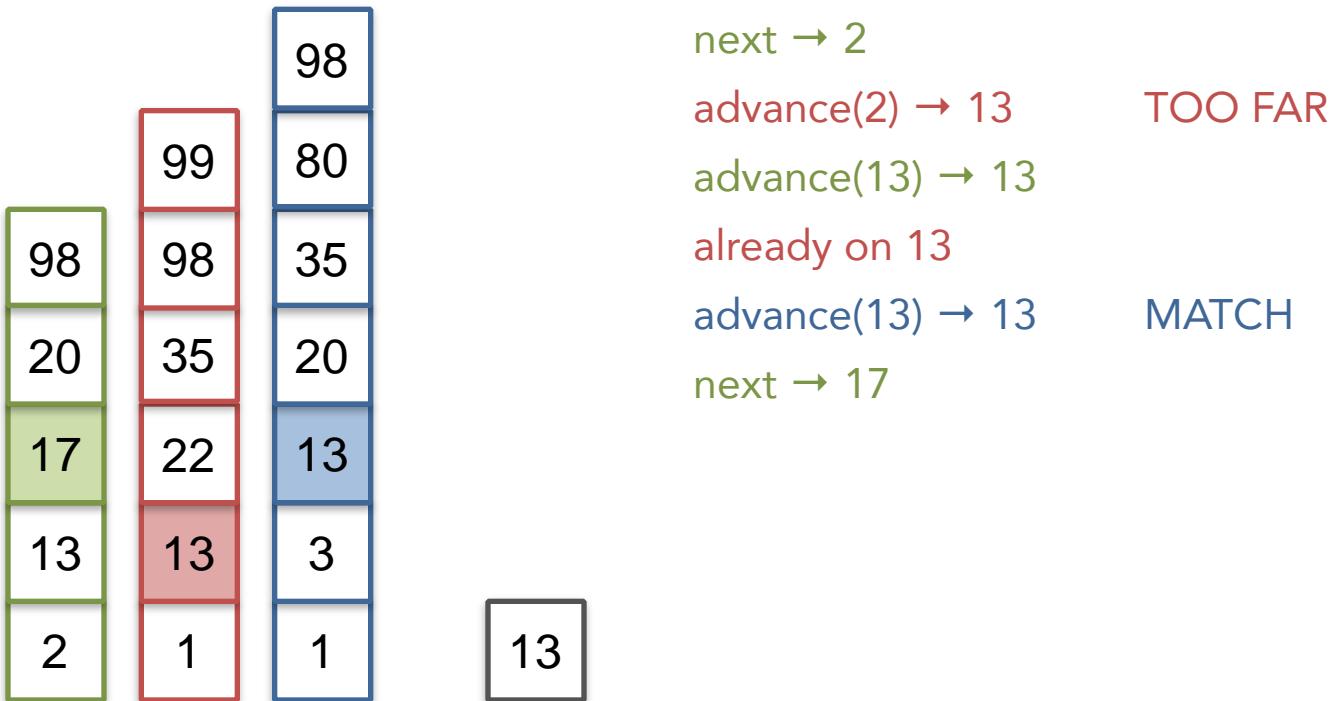
already on 13



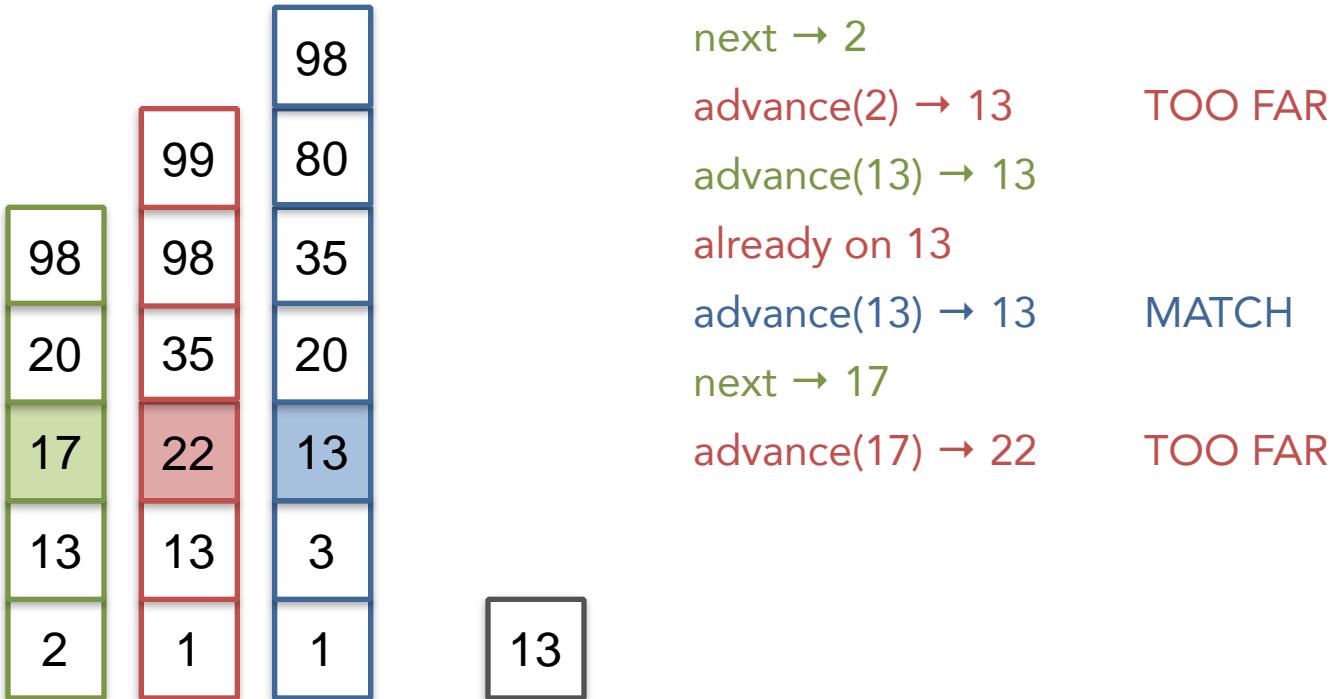
# Conjunctions



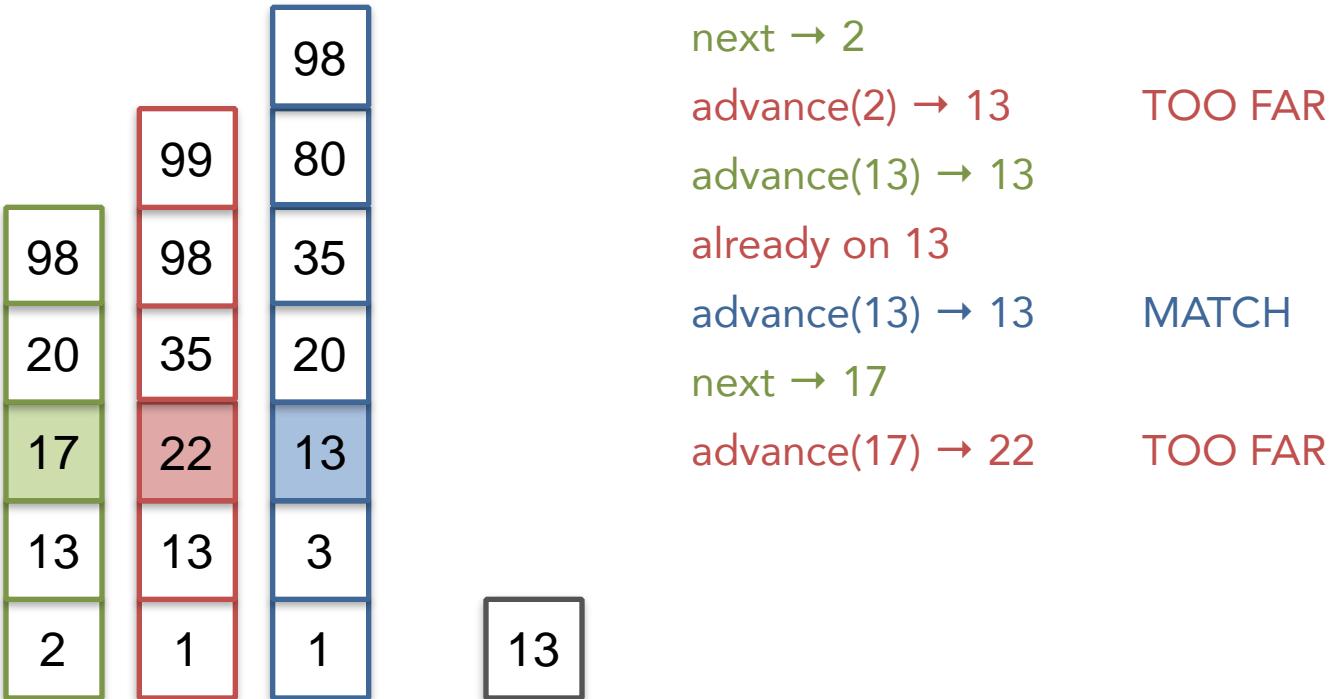
# Conjunctions



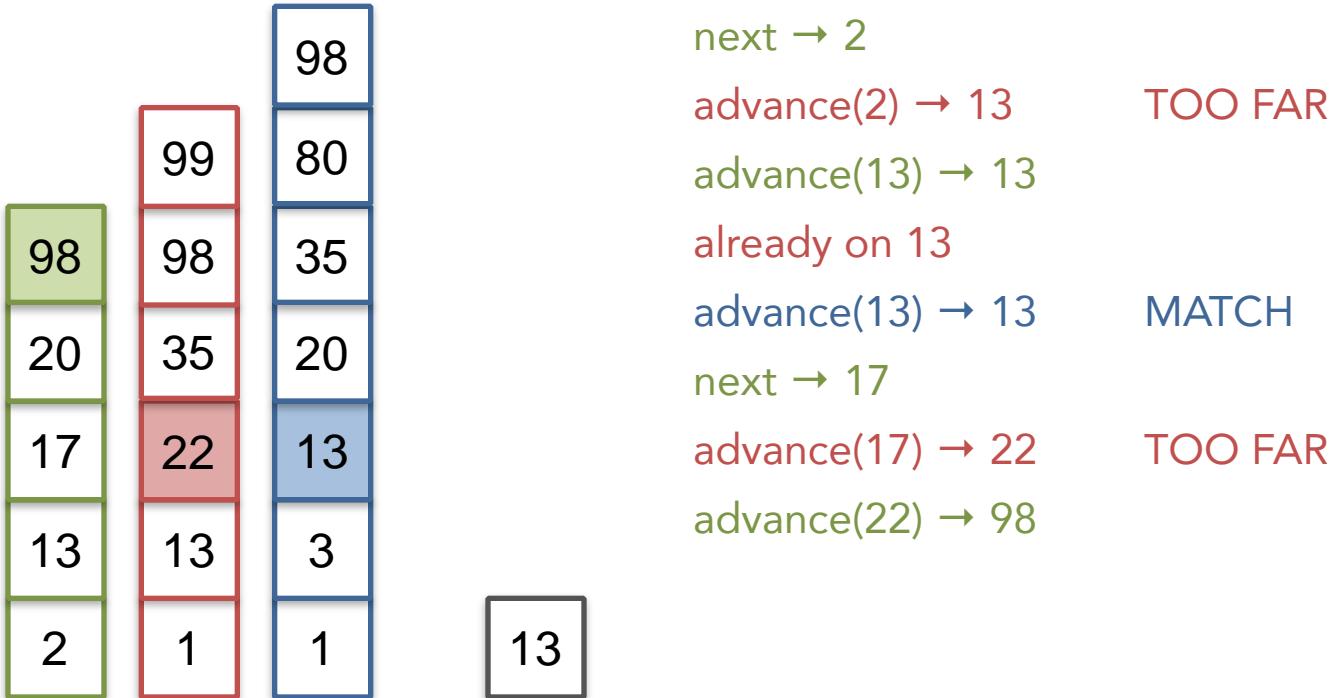
# Conjunctions



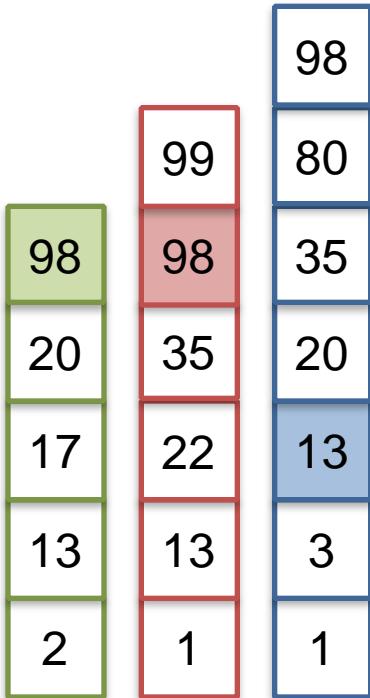
# Conjunctions



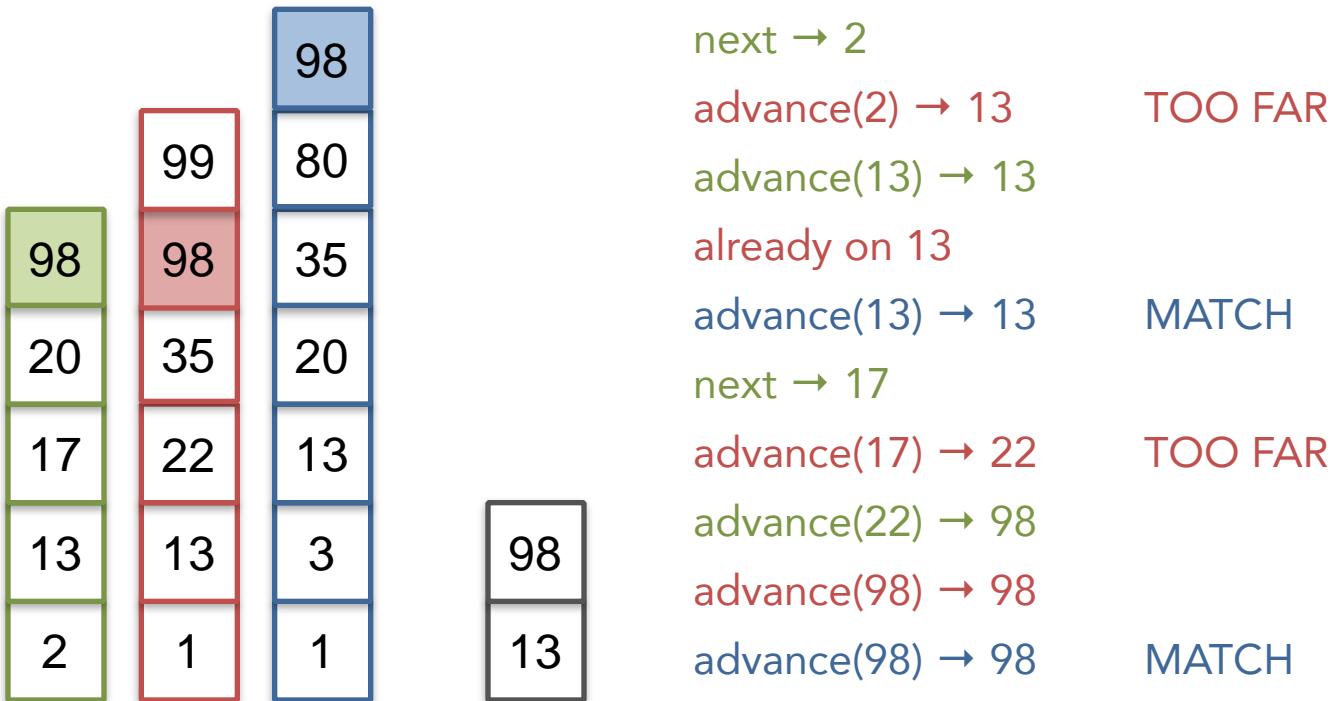
# Conjunctions



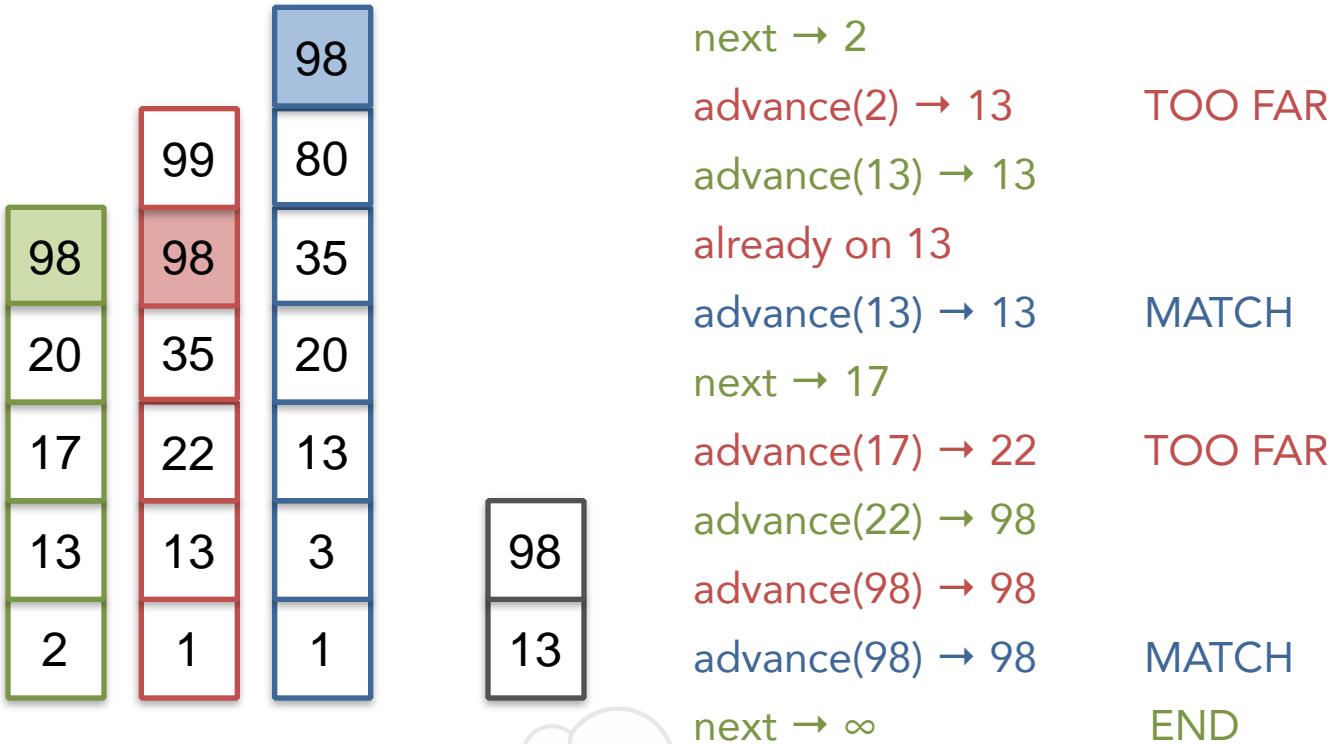
# Conjunctions



# Conjunctions



# Conjunctions



# How do regexp queries work?



# Regexp queries

elastic	2	10	49
index	1	5	
lucene	2	5	49
search	5	10	
shard	2	9	10

Challenge: find matching terms and merge postings lists

Naive way:

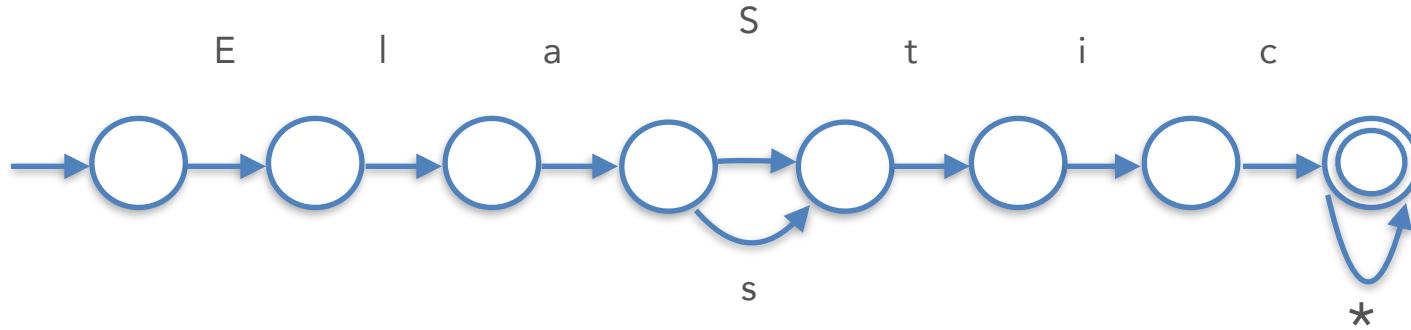
- iterate over terms
- evaluate regexp against every term

SLOWWWWWWW



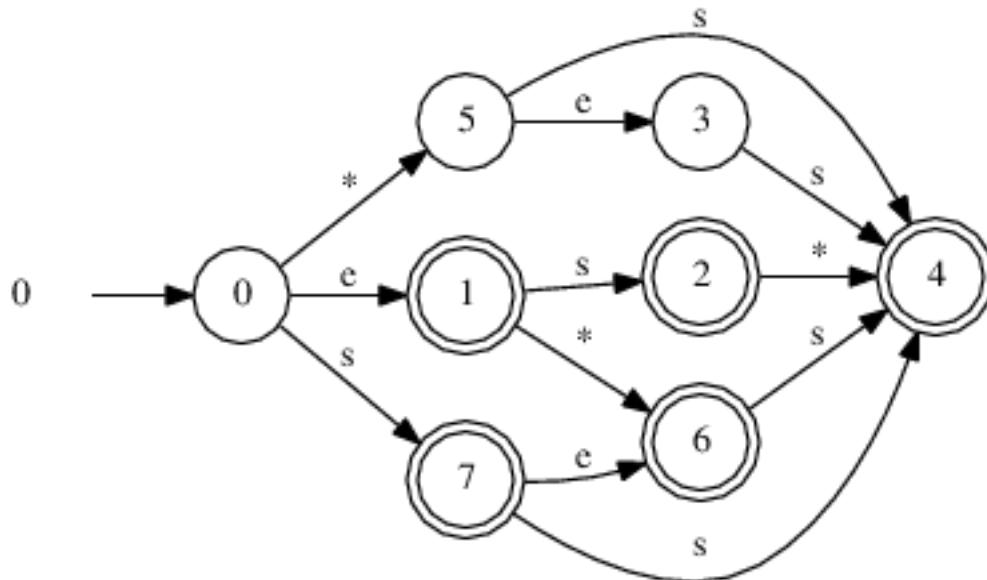
# Regexp queries

Ela[Ss]tic.\*



# Regexp queries

- Not limited to regexps
- Fuzzy queries too!
  - example:  $\text{es} \sim 1$



# How are numeric doc values compressed?



# Aggregation Execution

What is average price of green docs?

"color"	Doc IDs
blue	0
green	<u>1, 4, 5</u>
red	3

(inverted index)



# Aggregation Execution

What is average price of green docs?

"color"	Doc IDs	Doc ID	"price"	
blue	0	0	10	
green	<u>1, 4, 5</u>	1	20	$\frac{(20 + 60 + 20)}{3}$
red	3	2	20	= 33.33
		3	60	
		4	60	
		5	20	

(field data)

# Field Data and Doc Values

## Field Data

- In-memory, lives on JVM Heap
- All-or-nothing
- Lazily constructed at query-time

## Doc Values

- Disk-based, leverages OS FS cache
- Pages in/out of FS cache
- Precomputed at index-time
- Allows better compression



“Allows better compression”

Lots of cool tricks, let's dive in!



# Default strategy

Delta Encoding + bit packing

Doc ID	"price"
0	5
1	2
2	2
3	5
4	9
5	4

## Encoding

- Compute min and max values:
  - min=2
  - max=9
- $\text{max} - \text{min} = 7$ 
  - so deltas require 3 bits per value
- Encode the min value
- Encode deltas on 3 bits per value:
  - [3,0,0,3,7,2] requires 18 bits



# Default strategy

Delta Encoding + bit packing

Doc ID	"price"
0	5
1	2
2	2
3	5
4	9
5	4

## Decoding

- For doc ID  $d$ 
  - Read 3 bits at offset  $d*3$  bits
  - Add the min value



# Less than 256 unique values

## Table encoding

Doc ID	"price"
0	5
1	2
2	2
3	5
4	9
5	4

### Encoding

- Dedup and sort values:
  - [2, 4, 5, 9]
- Encode the table index for every doc:
  - [2, 0, 0, 2, 3, 1]
  - 2 bits per value



# Less than 256 unique values

## Table encoding

Doc ID	"price"
0	5
1	2
2	2
3	5
4	9
5	4

## Decoding

- For doc ID  $d$ :
  - Read 2 bits at offset  $d*2$  bits
  - Gives table index  $t$
  - Read value in table at index  $t$



# Timestamps without full precision

## GCD compression

Doc ID	"price"
0	11
1	31
2	21
3	1
4	71
5	51

### Encoding

- Compute minimum value:
  - 1
- Compute deltas:
  - [10, 30, 20, 0, 70, 50]
- Compute GCD of the deltas:
  - 10
- Encode min value and GCD
- Then encode quotients using bit packing
  - [1,3,2,0,7,5]: 3 bits per value



# Timestamps without full precision

## GCD compression

Doc ID	"price"
0	11
1	31
2	21
3	1
4	71
5	51

### Decoding

- For doc ID  $d$ :
  - Read 3 bits at offset  $d*3$  bits
  - Multiply by the GCD
  - Add the min value



# How does the Cardinality agg work?

bit-pattern observable magic



# Distinct Counts: Naive Solution

Cardinality agg == SELECT Count(Distinct foo)



# Distinct Counts: Naive Solution

Maintain a set of all values

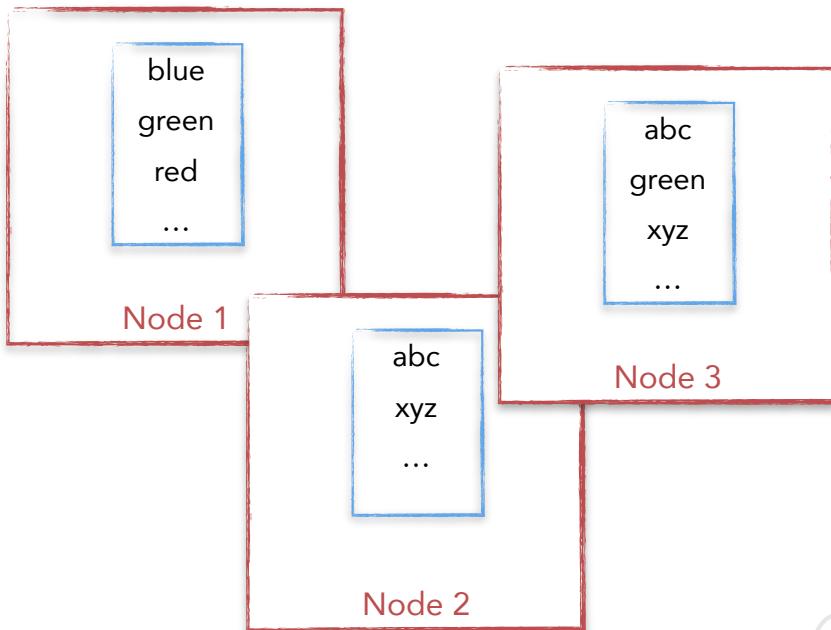
blue  
green  
red  
...

- Cardinality == `set.size()`
- `set.size() == n`
- Memory usage ==  $n * \text{size of each term}$   
*(Ignoring set overhead)*



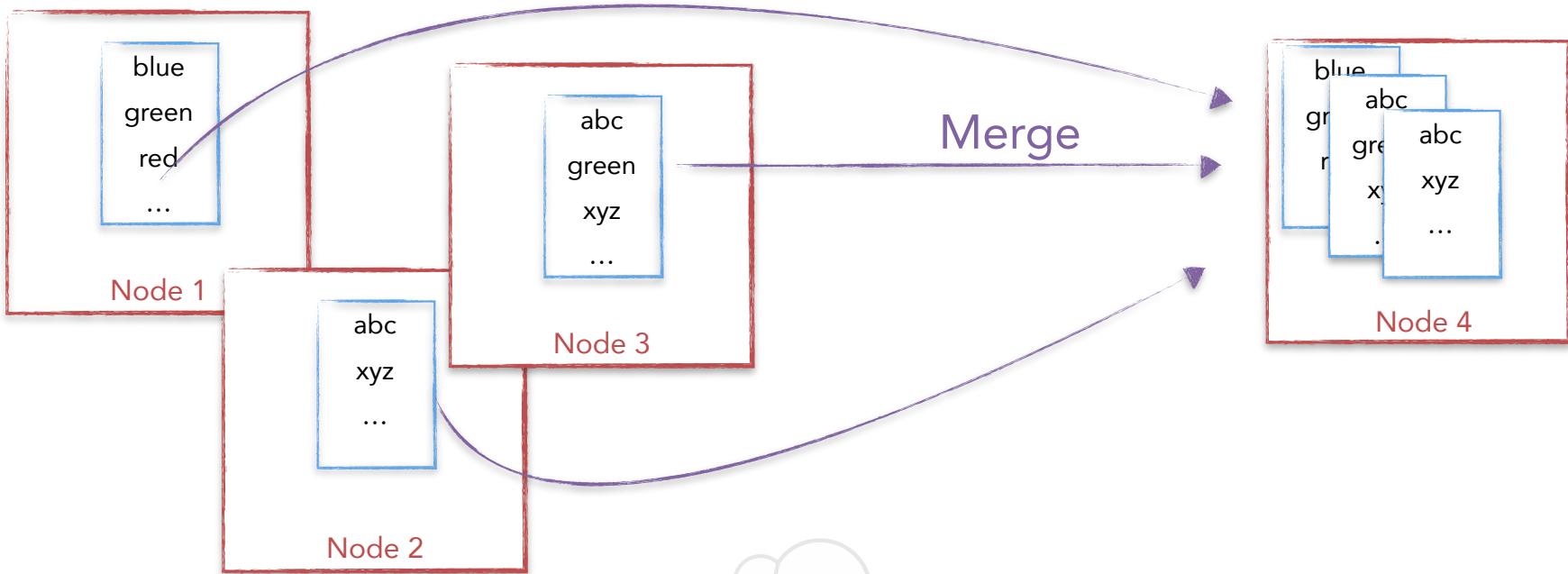
# Distinct Counts: Naive Solution

Gets worse in distributed environment



# Distinct Counts: Naive Solution

Gets worse in distributed environment



# Distinct Counts: HyperLogLog++

Cardinality agg uses HyperLogLog++ instead

- Approximates cardinality
- Uses only a few Kb of memory for billions of distinct values
- Fast!
- Lossless unions



# Bit-Observable Patterns

Let's flip some coins...

Probability of a “run”

$$\frac{1}{2^n}$$



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Probability of a “run”

$$\frac{1}{2^n}$$

5 heads in a row

$$\frac{1}{32}$$



# Bit-Observable Patterns

Let's flip some coins...

Probability of a "run"

$$\frac{1}{2^n}$$

5 heads in a row

$$\frac{1}{32}$$

20 heads in a row

$$\frac{1}{1048576}$$



# Bit-Observable Patterns

Let's flip some coins...

Probability of a "run"

$$\frac{1}{2^n}$$

Could do this in  
one sitting

5 heads in a row

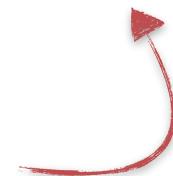
$$\frac{1}{32}$$



20 heads in a row

$$\frac{1}{1048576}$$

Might take  
several days



# Key Insight:

$2^{\text{Length of the run}} \sim = \text{duration of coin flipping}$



# Bit-Observable Patterns

Let's hash values, instead of flipping coins...

$$v = 12345$$

$$h(v) = 1100101111101011010$$

Run of 1 zero



# Bit-Observable Patterns

Let's hash values, instead of flipping coins...

$$v = 12345$$

$$h(v) = 1100101111101011010$$

Set "register" to 1



# Bit-Observable Patterns

Let's hash values, instead of flipping coins...

1

v = 3456

h(v) = 10001101001100111000

Run of 3 zeros



# Bit-Observable Patterns

Let's hash values, instead of flipping coins...

$$v = 3456$$

$$h(v) = 10001101001100111000$$

Set "register" to 3



# Bit-Observable Patterns

Let's hash values, instead of flipping coins...

v = 948

h(v) = 01000111110100110100

3

Don't update register

Run of 2 zeros



# Key Insight:

cardinality

$2^{(\text{Length of the run})} \sim = \cancel{\text{duration of coin flipping}}$

Probability of a “run”

$$\frac{1}{2^n}$$

5 zeros in a row

$$\frac{1}{32}$$

20 zeros in a row

$$\frac{1}{1048576}$$

~32 distinct values

~1048576 distinct values

What if you get unlucky on first value?

v = 938

$h(v) = 0000010000000000$

Run of 10 zeros

oops :(



# Stochastic Averaging

Solution: keep multiple counters

v = 938

h(v) = 0000010000000000



# Stochastic Averaging

Solution: keep multiple counters

$$v = 938$$

$$h(v) = 0000010000000000$$

Use first 2 bits as  
register index



# Stochastic Averaging

Solution: keep multiple counters

v = 938

h(v) = 0000010000000000



# Stochastic Averaging

Solution: keep multiple counters

$$v = 7482$$

$$h(v) = 1001110100111010$$

Use first 2 bits as  
register index



Run of 1 zero



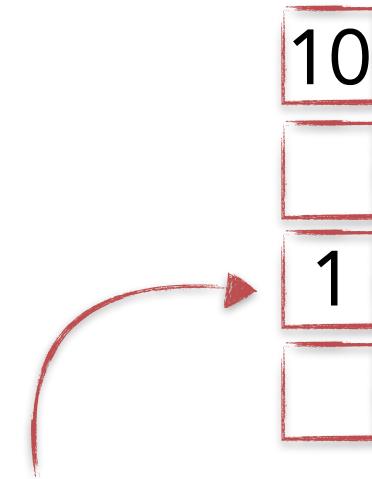
# Stochastic Averaging

Solution: keep multiple counters

$$v = 7482$$

$$h(v) = 1001110100111010$$

---



# Stochastic Averaging

10

$$2^{10} = 1024$$

2

$$2^2 = 4$$

3

$$2^3 = 8$$

1

$$2^1 = 2$$

- Naive approach: sum

- $1024 + 4 + 8 + 2$
  - $= 1038$

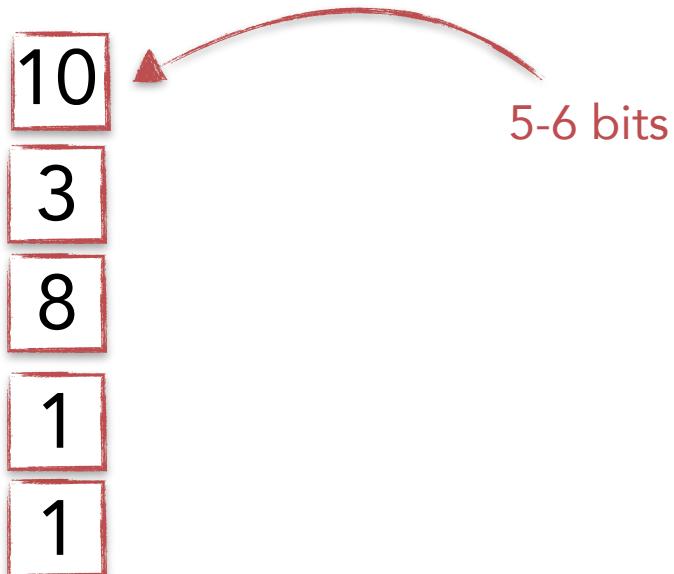
- In practice harmonic mean times number of registers works better:

- $4 * 4 / (1/1024 + 1/4 + 1/8 + 1/2)$
  - $= 18.3$
  - Gives less weight to outliers



# Other neat attributes

Registers are small!



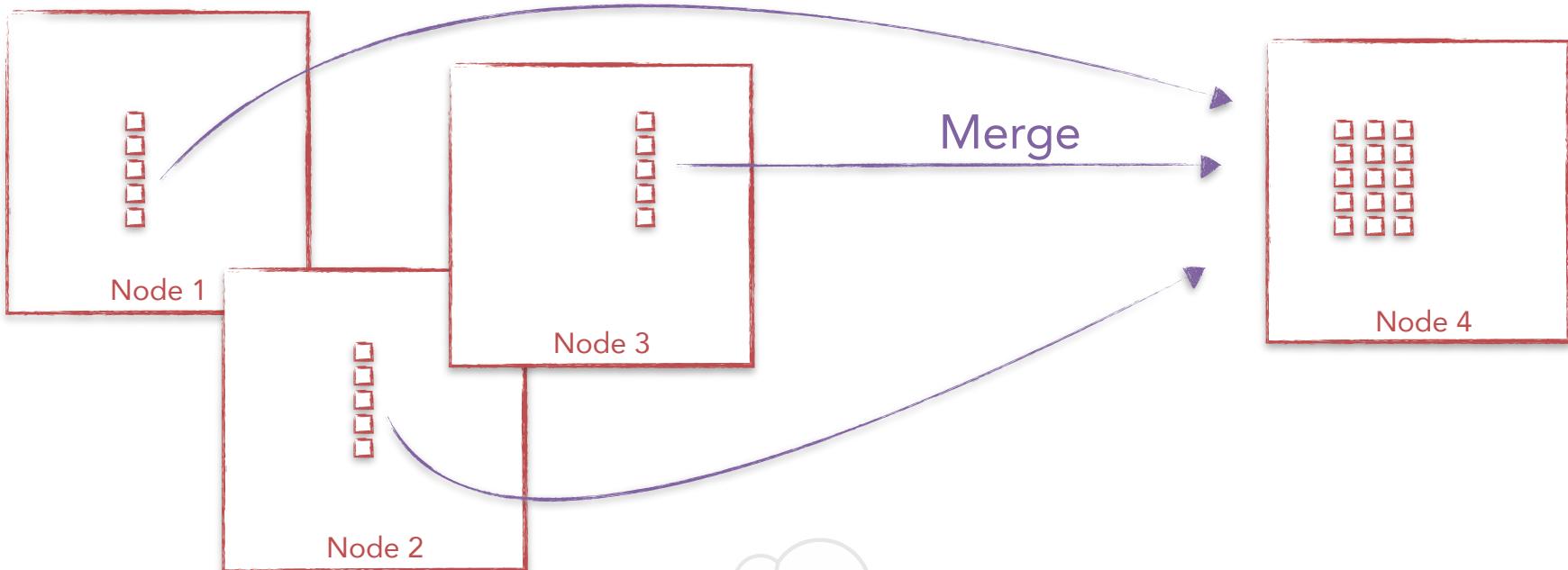
# Other neat attributes

Unions are lossless!



# Other neat attributes

Which is perfect for distributed environments



# In closing...

Stop worrying and learn to love approximate algorithms



# Thank you!

@jpountz

