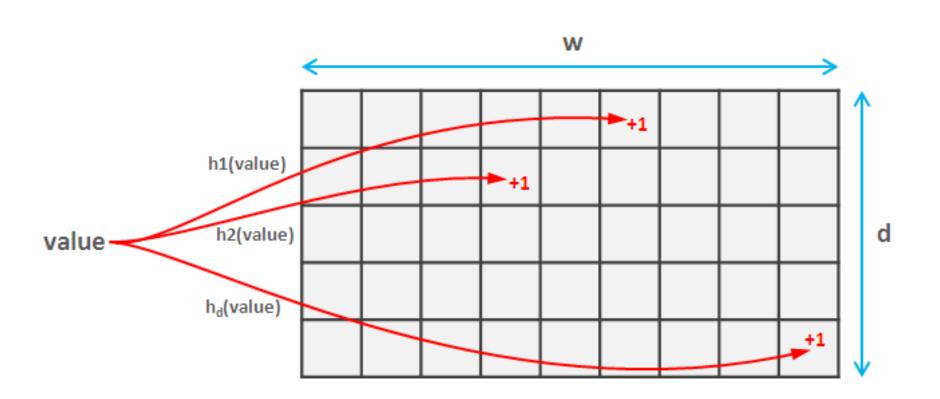
## Data stream statistics

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### Cache and Bloom filters

- Consider you have a proxy that caches web pages. You may want not to cache a page that will be visited only once
  - Solution: use a bloom filter. Once you have a request first check whether it has already be seen.
     If YES cache the page, otherwise NO. ANYWAY add the page to the Bloom filter.

# Estimation of the number of occurrences



## What about computing distributions?

 Given highly skewed data I want to measure the frequency at least of the top elements

#### Facts:

- Counters are expected to be higher because of the contribution of other elements
- CM returns the counter with less noise

#### Idea

Estimate the contribution of noise for a specific counter

## CMM – Count Mean-Min sketch

```
class CountMeanMinSketch {
         // initialization and addition procedures as in CountMinSketch
 3
         // n is total number of added elements
 4
 5
         long estimateFrequency(value) {
             long e[] = new long[d]
             for(i = 0; i < d; i++) {
                 sketchCounter = estimators[i][ hash(value, i) ]
 9
                 noiseEstimation = (n - sketchCounter) / (w - 1)
                 e[i] = sketchCounter - noiseEstimator
10
11
12
             return median(e)
13
```

# Heavy hitters

- All the above data structures allow counting or membership evaluation.
- How to know the most represented keys in a stream?
- Until now:
  - I can count how many keys exist,
  - I can check if a particular key is present
  - I can count the number of its occurrences
  - ...but I can't do anything if I don't know it

### Bad news

- Naïve solution:
  - Sort data

 There is no algorithm that solves the Heavy Hitters problems in one pass while using a sublinear amount of auxiliary space

# A simple algorithm

 Problem: find the elements that occur more than N/k times (N is the stream length, k is a free parameter)

#### Solution:

 Maintain a CM and a max-heap (with k elements) of the top elements

#### Process:

- 1. Add the element in the CM and estimate its frequency
- 2. If frequency >= N/k insert the element in the heap
- Note: the number of elements in the heap must be at most k

# The Space saving algorithm - build

```
Algorithm: Space-Saving(m \text{ counters, stream } S)
begin
  for each element, e, in S{
    If e is monitored,
      increment the counter of e;
    else{
      let e_m be the element with least hits, min
      Replace e_m with e;
      Increment count_m;
      Assign \varepsilon_m the value min;
  }// end for
end;
```

# The Space saving algorithm - query

```
Algorithm: QueryFrequent(m counters, support \phi)
begin
  Bool guaranteed = true;
  Integer i = 1;
  while (count_i > \phi N \text{ AND } i \leq m)
    output e_i;
    If ((count_i - \varepsilon_i) < \phi N)
       guaranteed = false;
    i++;
  }// end while
  return( guaranteed )
end;
```

Note that counts are sorted in descending order in this implementation

## References

- New Estimation Algorithms for Streaming Data: Countmin Can Do More
  - http://citeseerx.ist.psu.edu/viewdoc/download? doi=10.1.1.420.449&rep=rep1&type=pdf
- Efficient Computation of Frequent and Top-k Elements in Data Streams
  - http://citeseerx.ist.psu.edu/viewdoc/download? doi=10.1.1.94.8360&rep=rep1&type=pdf
- PROBABILISTIC DATA STRUCTURES FOR WEB ANALYTICS AND DATA MINING
  - https://highlyscalable.wordpress.com/2012/05/01/ probabilistic-structures-web-analytics-data-mining/

#### **Datasets**

- Free Twitter datasets
  - http://followthehashtag.com/datasets/
- Stackexchange Q&A website
  - https://archive.org/download/stackexchange