

# Lecture 3: Frequency Moments: $F_2$ , Heavy Hitters



# Administrivia, Plan

- Piazza: sign-up!
- PS1 released
- Scriber?
  
- Plan:
  - Frequency Moments
  - Heavy Hitters

# Part 1: Frequency Moments

- Let  $f_i$  be frequency of  $i$ 
  - Lecture 1: count one  $f_i$
  - Lecture 2: count # of non-zeros
- Moment 1:
  - $\sum_i f_i$
  - Estimator with low space?
    - Just count
- Moment 2:
  - $\sum_i f_i^2$



IP	Frequency
1	3
2	2
3	0
4	9
5	0
...	0
$n$	1

$$\sum_i f_i = 15$$

$$\sum_i f_i^2 = 95$$

# 2<sup>nd</sup> Moment: $F_2$

[Alon-Matias-Szegedy 1996]

- **Idea:** *Rademacher* random variables

hash function  $r: [n] \rightarrow \{-1, +1\}$

- **Algorithm (Tug-of-War):**

store  $z = \sum_i r(i) \cdot f_i$

- **Estimator:**

$z^2$

Algorithm TOW ( $F_2$ ):

- Init:  $z = 0$
- when see element  $i$ :  
 $z = z + r(i)$

Estimator:

$z^2$

# Rademacher r.v.

- What if we have  $m$  ones ?  
sum of  $m$  random  $\pm 1$ 's

Algorithm TOW ( $F_2$ ):

- Init:  $z = 0$
- when see element  $i$ :  
 $z = z + r(i)$

Estimator:

$$z^2$$

- How much is  $z = \sum r(i)$  roughly ?
  - Say,  $|z|$  ?
  - $E[z] = 0$
  - $Var[z] = m$
  - Apply Chebyshev:
    - $|z| \leq O(\sqrt{m})$  with constant probability
  - In fact tight

# Analysis

- $E[z^2] = \dots$   
 $= \sum_i f_i^2$
- $Var[z^2] \leq E[z^4] = \dots$   
 $\leq O(\sum f_i^2)^2$
- Randomness?
  - $O(\log n)$  for  $h$  that is 4-wise independent
- Can apply the average trick:
  - Take  $k = O\left(\frac{1}{\epsilon^2}\right)$  counters
  - Obtain:  $1 + \epsilon$  approximation in  $O\left(\frac{1}{\epsilon^2} \log n\right)$  space

Algorithm TOW ( $F_2$ ):

- Init:  $z = 0$
- when see element  $i$ :  
 $z = z + r(i)$

Estimator:

$$z^2$$

# Linearity

- Important property

Algorithm TOW ( $F_2$ ):

- Init:  $z = 0$
- when see element  $i$ :  
 $z = z + r(i)$

Estimator:

$$z^2$$



$z'$



$z''$

$z = z' + z''$  (for  $f = f' + f''$ )

# Similarly for difference!

- Estimate for  $\sum (f_i' - f_i'')^2$   
 $(z' - z'')^2$
- How about  $\sum |f_i' - f_i''|$ ?
  - will see later in the class



IP	Frequency
131.107.65.14	1
18.9.22.69	1
35.8.10.140	1



$z'$



IP	Frequency
131.107.65.14	1
18.9.22.69	2



$z''$



# General streaming model

- At each moment, an update is:  
 $(i, \delta_i)$  : increase  $i^{\text{th}}$  entry by  $\delta_i$  (may be negative!)
- Linear algorithm  $S$  handles easily:
  - $S(f + e_i \delta_i) = S(f) + S(e_i \delta_i)$
  - We'll call  $S$  a *sketch*
- [Nguyen-Li-Woodruff'14]: in fact any algorithm for general streaming might as well be linear!

# Part 2: Heavy Hitters

- How about max frequency?
- Impossible to approximate in sublinear space!
- Will settle for an even more modest goal:
  - can detect the max-frequency element if it is *very heavy*

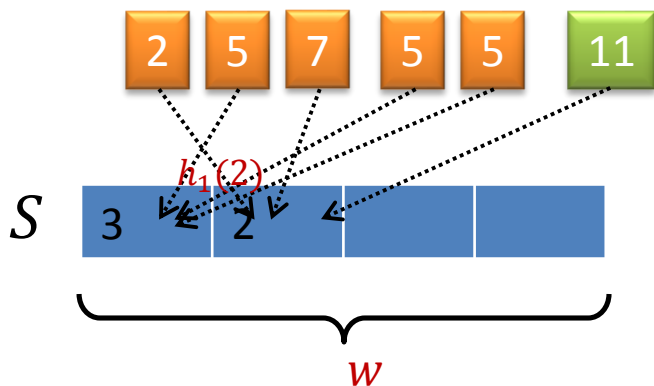


IP	Frequency
1	3
2	2
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5	0
...	0
$n$	1

# Heavy Hitters: Iteration 1

[Charikar-Chen-FarachColton'04, Cormode-Muthukrishnan'05]

- **Definition:**  $i$  is  $\phi$ -heavy if  $f_i \geq \phi \sum_j f_j$
- Will find them in space  $O(1/\phi)$
- **Idea:** hash functions!
  - $h: [n] \rightarrow [w]$  random  $w = O(1/\phi)$
  - Element  $i$  goes to bucket  $h(i)$
  - In a bucket?
    - Sum frequencies there



Estimator for  $f_i$  ?

$$\hat{f}_i = S(h(i))$$

$$\hat{f}_2 = 2$$

$$\hat{f}_5 = 3$$

$$\hat{f}_7 = 2$$

$$\hat{f}_{11} = 2$$

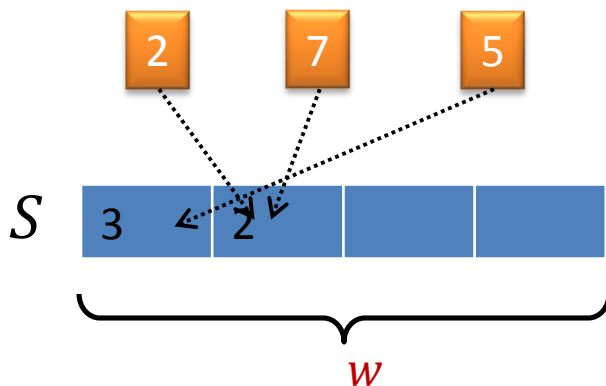
# Iteration 1: analysis

- Let's analyze:
  - Estimator of frequency for element  $i$

$$\begin{aligned}\hat{f}_i &= S(h(i)) \\ &= f_i + \sum_{\{j:h(j)=h(i)\}} f_j\end{aligned}$$

Extra "chaff"

- How much extra "chaff" is there?



# Iteration 1: extra chaff

- $S(h(i)) = f_i + \sum_{\{j:h(j)=h(i)\}} f_j$
- Extra “chaff”:  $C$ 
  - $E[C] = \sum_j \Pr[h(j) = h(i)] \cdot f_j = \frac{\sum_{j \neq i} f_j}{w}$
- Is  $S(h(i))$  an unbiased estimator?
  - No!
  - Bias is at most  $\frac{\sum_j f_j}{w}$  : small for  $f_i \gg \frac{\sum_j f_j}{w}$
- Done?
  - Yes: by Markov  $C \leq \frac{10 \sum_j f_j}{w}$  with 90% prob.

# Iteration 1: really done?

- Estimator:

$$\begin{aligned}\hat{f}_i &= S(h(i)) = f_i + \sum_{\{j:h(j)=h(i)\}} f_j \\ &= f_i + C\end{aligned}$$

where  $C \leq O(\sum_j f_j / w)$  with 90% prob

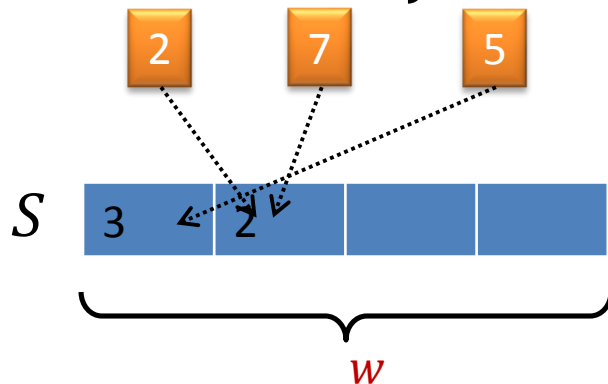
– for  $w = O\left(\frac{1}{\epsilon\phi}\right)$ , and  $f_i \geq \phi \sum_j f_j$

$C \leq \epsilon f_i \Rightarrow \hat{f}_i$  is a  $1 + \epsilon$  approximation!

- Issues?

– Only constant probability

– For many indices, it is an overestimate!

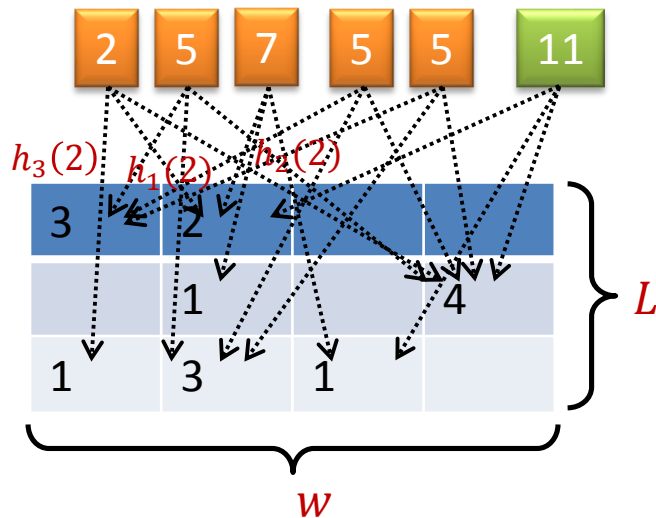


Fundamental issue: if  $i$  and  $j$  collide, can't know if it's  $i$  or  $j$  with high frequency;

but must have many collisions to reduce space

# Iteration 2: CountMin

- Median trick!
  - Use  $L = O(\log n)$  hash tables with hash functions  $h_j$



$$\begin{aligned}\hat{f}_2 &= 2 \\ \hat{f}_5 &= 3 \\ \hat{f}_7 &= 1 \\ \hat{f}_{11} &= 2\end{aligned}$$

Algorithm CountMin:

Initialize( $r, L$ ):

array  $S[L][w]$

$L$  hash functions  $h_1 \dots h_L$ , into  $\{1, \dots, w\}$

Process(int  $i$ ):

for( $j=0; j<L; j++$ )

$S[j][h_j(i)] += 1;$

Estimator:

```
foreach  $i$  in PossibleIP {  
     $\hat{f}_i = \text{median}_j(S[j][h_j(i)]);$   
}
```

# CountMin: analysis

- Consider an index  $i$
- Each table gives
  - $\hat{f}_i = f_i \pm \epsilon\phi$  with 90% probability
- Median is a  $\pm\epsilon\phi$  with  $1 - 1/n^2$  probability
  - Apply union bound over all  $i \in [n]$
  - All are  $\pm\epsilon\phi$ , with  $1 - 1/n$  probability
- Alternative estimator?
  - Take MIN instead of median

Algorithm CountMin:

Initialize( $r, L$ ):

array  $S[L][w]$

$L$  hash functions  $h_1 \dots h_L$ , into  $\{1, \dots, w\}$

Process(int  $i$ ):

for( $j=0$ ;  $j<L$ ;  $j++$ )

$S[j][h_j(i)] += 1$ ;

Estimator:

foreach  $i$  in PossibleIP {

$\hat{f}_i =$ ~~median~~ $_j(S[j][h_j(i)]);$

} **min**





# CountMin: overall

- Iterate over all  $i$ 's
- Heavy hitters:  $\hat{f}_i \geq \phi$ 
  - If  $\frac{f_i}{\sum f_j} \leq \phi(1 - \epsilon)$ , not in the output
  - If  $\frac{f_i}{\sum f_j} \geq \phi(1 + \epsilon)$ , reported as heavy hitter
- Space:  $O\left(\frac{\log^2 n}{\epsilon\phi}\right)$  bits
- Issues?
  - Time: to iterate  $\Omega(n)$

Algorithm CountMin:

Initialize( $r, L$ ):

array  $S[L][w]$

$L$  hash functions  $h_1 \dots h_L$ , into  $\{1, \dots, w\}$

Process(int  $i$ ):

for( $j=0$ ;  $j<L$ ;  $j++$ )

$S[j][h_j(i)] += 1$ ;

Estimator:

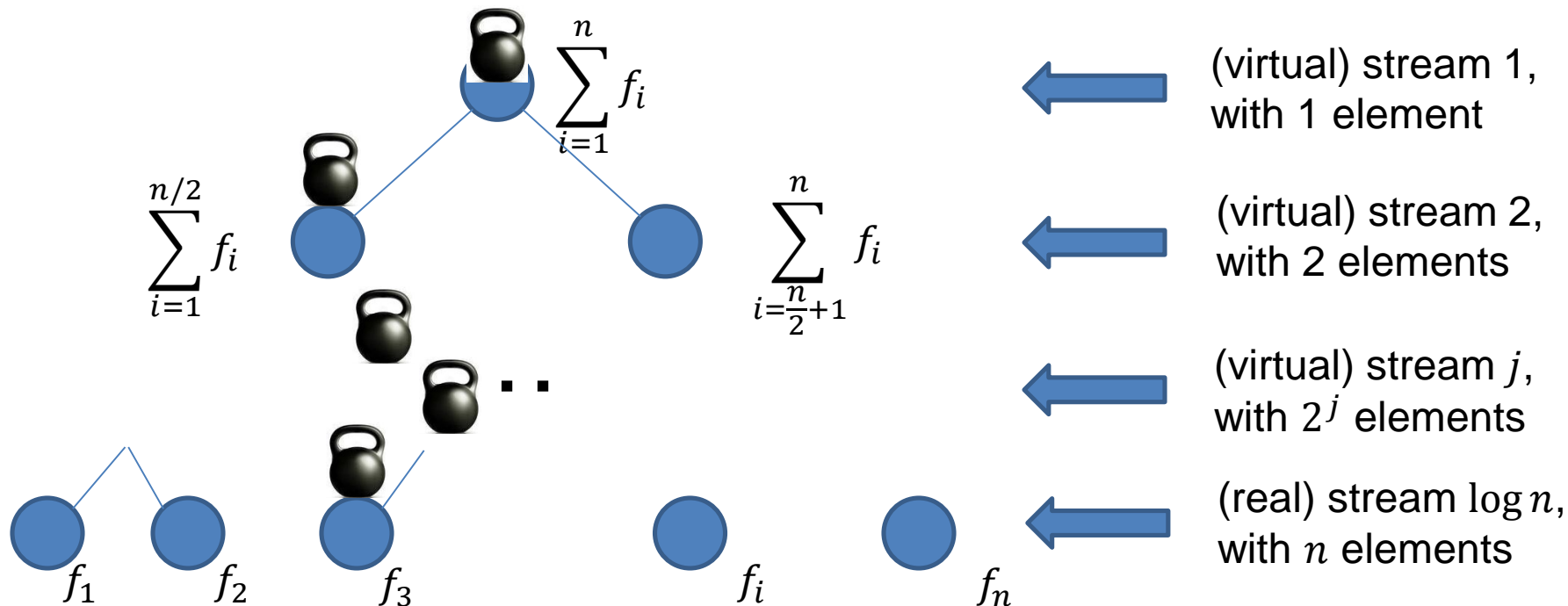
foreach  $i$  in PossibleIP {

$\hat{f}_i =$ ~~median~~ $_j(S[j][h_j(i)]);$

} **min**

# CountMin: time

- Can improve time; space degrades to  $O\left(\frac{\log^3 n}{\epsilon\phi}\right)$  bits
- **Idea:** dyadic intervals
  - Each level with its own sketch
  - Find heavy hitters by following down the tree all the heavy hitters (in intermediary)



# A variant: CountSketch

- Is CountMin linear?
  - CountMin( $f' + f''$ ) from CountMin( $f'$ ) and CountMin( $f''$ ) ?
  - Just sum the two!
    - sum the 2 arrays, assuming we use the same hash function  $h_j$
- What about  $f = f' - f''$  ?
  - “Heavy hitter”: if  $|f_i| \geq \phi \sum_j |f_j| = \phi \cdot \|f\|_1$
  - “min” is an issue
  - But median is still ok
  - Ideas to improve it further?
    - Use Tug of War  $r$  in each bucket => CountSketch
    - Better in certain cases

# Recap

- 2<sup>nd</sup> moment:
  - Tug-Of-War (sum of random  $\pm 1$ 's)
- Linearity:
  - Can add/subtract sketches easily
- Max-frequency:
  - Can only do heavy hitters
  - Hash functions to distribute elements
  - CountMin
    - <https://sites.google.com/site/countminsketch/>
  - CountSketch: CountMedian+TugOfWar