

COMMONWEALTH OF AUSTRALIA

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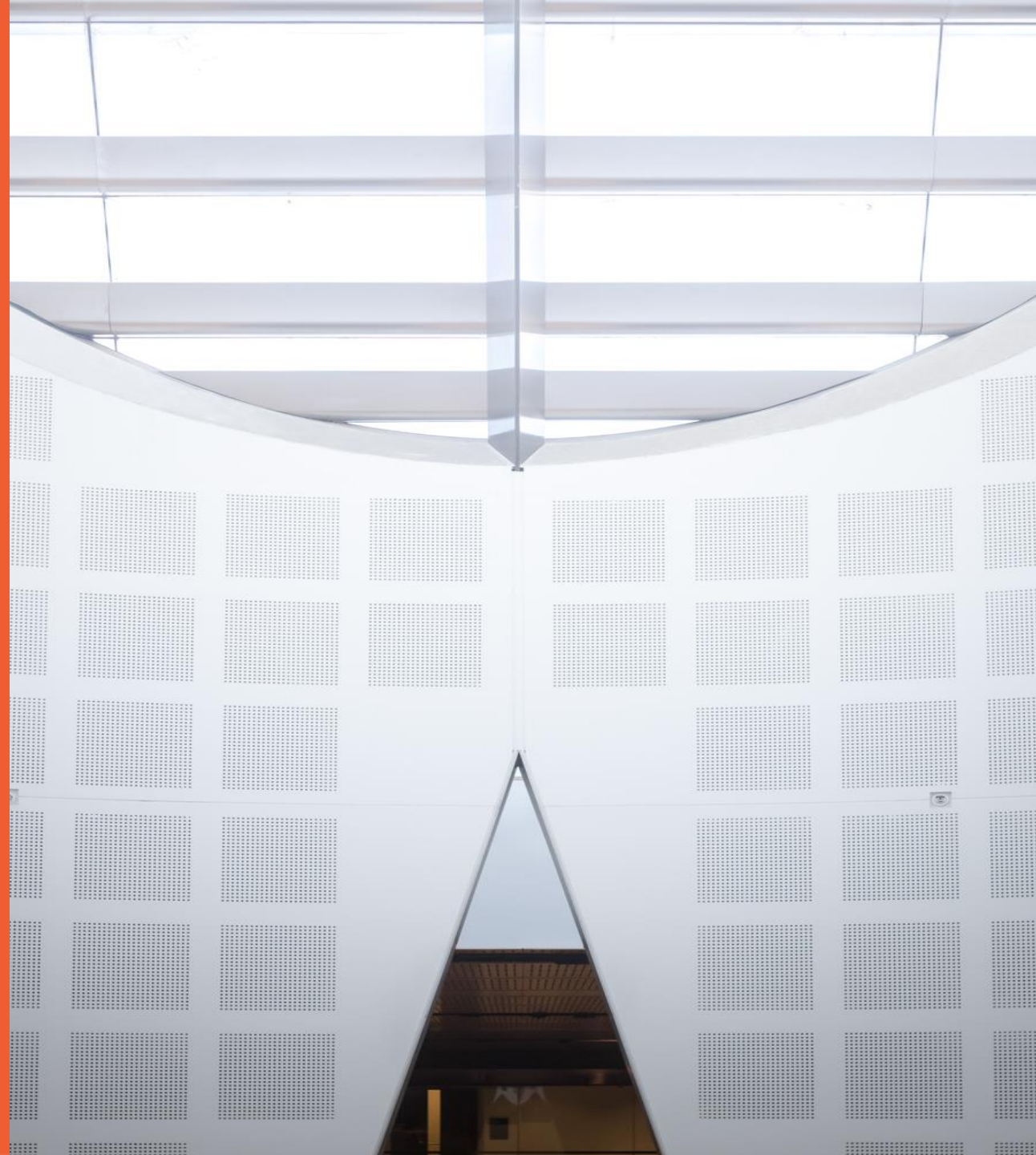
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COMPx270: Randomised and
Advanced Algorithms
Lecture 9: Streaming and
Sketching II

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THE UNIVERSITY OF
SYDNEY



A question

You design a streaming algorithm **A** to solve some problem. The stream of data arrives.

A question

You design a streaming algorithm **A** to solve some problem. The stream of data arrives.

628, 516, 163, 509, 15, 499, 772, 588, 737, 439, 79, 866, 186, 18,
854, 459, 146, 518, 748, 737, 685, 188, 939, 724, 27, 719, 263, 795,
120, 573, 853, 132, 522, 3, 298, 123, 932, 993, 180, 674, 1, 619, 989,
142, 496, 178, 191, 524, 716, 501, 677, 712, 452, 768, 591, 551, 439,
397, 229, 214, 43, 639, 353, 610, 737, 203, 933, 279, 877, 30, 513,
518, 616, 714, 633, 804, 422, 731, 867, 184, 124, 881, 595, 193, 254,
240, 4, 260, 303, 319, 757, 723, 309, 365, 278, 512, 658, 233, 393,
875

A question

You design a streaming algorithm **A** to solve some problem. The stream of data arrives. **A** outputs its answer:

21.5

A question

Oh, no! That wasn't the end. More data arrives.

A question

Oh, no! That wasn't the end. More data arrives.

834, 992, 528, 12, 181, 274, 159, 150, 716, 71, 755, 4, 324, 398, 802,
176, 302, 941, 678, 934, 546, 753, 812, 47, 755, 721, 893, 53, 410

A question

Oh, no! That wasn't the end. More data arrives. **A** outputs its answer on this:

18.1

A question

How do you combine 21.5 and 18.1 to get the answer on the whole data stream?

Sketching

Even better: linear sketching



Even better: linear sketching

Frequent Elements (Heavy Hitters)

Theorem 39. *The MISRA-GRIES algorithm is a deterministic one-pass algorithm which, for any given parameter $\varepsilon \in (0, 1]$, provides $\hat{f}_1, \dots, \hat{f}_n$ of all element frequencies such that*

$$f_j - \varepsilon m \leq \hat{f}_j \leq f_j, \quad j \in [n]$$

with space complexity $s = O(\log(mn)/\varepsilon)$. (In particular, it can be used to solve the MAJORITY problem in two passes.)

Frequent Elements (Heavy Hitters): ℓ_1, ℓ_2 , etc.

Frequent Elements (Heavy Hitters): CountSketch (1/5)

Input: Parameters $\varepsilon, \delta \in (0, 1]$

- 1: Set $k \leftarrow O(1/\varepsilon^2)$, and initialize an array \mathbf{C} of size k to zero
- 2: Pick $h: [n] \rightarrow [k]$ from a strongly universal hashing family
- 3: Pick $g: [n] \rightarrow \{-1, 1\}$ from a strongly universal hashing family
- 4: **for all** $1 \leq i \leq m$ **do**
- 5: Get item $a_i = (j, c) \in [n] \times \{-B, \dots, B\}$ \triangleright Assume $B = O(1)$
- 6: $\mathbf{C}[h(j)] \leftarrow \mathbf{C}[h(j)] + c \cdot g(j)$

Output: On query $j \in [n]$, **return** $\hat{f}_j \leftarrow g(j) \cdot \mathbf{C}[h(j)]$

Frequent Elements (Heavy Hitters): CountSketch (2/5)

Input: Parameters $\epsilon, \delta \in (0, 1]$

- 1: Set $k \leftarrow O(1/\epsilon^2)$, and initialize an array \mathbf{C} of size k to zero
- 2: Pick $h: [n] \rightarrow [k]$ from a strongly universal hashing family
- 3: Pick $g: [n] \rightarrow \{-1, 1\}$ from a strongly universal hashing family
- 4: **for all** $1 \leq i \leq m$ **do**
- 5: Get item $a_i = (j, c) \in [n] \times \{-B, \dots, B\}$ ▷ Assume $B = O(1)$
- 6: $\mathbf{C}[h(j)] \leftarrow \mathbf{C}[h(j)] + c \cdot g(j)$

Output: On query $j \in [n]$, **return** $\hat{f}_j \leftarrow g(j) \cdot \mathbf{C}[h(j)]$

Frequent Elements (Heavy Hitters): CountSketch (3/5)

Input: Parameters $\epsilon, \delta \in (0, 1]$

- 1: Set $k \leftarrow O(1/\epsilon^2)$, and initialize an array \mathbf{C} of size k to zero
- 2: Pick $h: [n] \rightarrow [k]$ from a strongly universal hashing family
- 3: Pick $g: [n] \rightarrow \{-1, 1\}$ from a strongly universal hashing family
- 4: **for all** $1 \leq i \leq m$ **do**
- 5: Get item $a_i = (j, c) \in [n] \times \{-B, \dots, B\}$ ▷ Assume $B = O(1)$
- 6: $\mathbf{C}[h(j)] \leftarrow \mathbf{C}[h(j)] + c \cdot g(j)$

Output: On query $j \in [n]$, **return** $\hat{f}_j \leftarrow g(j) \cdot \mathbf{C}[h(j)]$

Frequent Elements (Heavy Hitters): CountSketch (3/5)

Input: Parameters $\epsilon, \delta \in (0, 1]$

- 1: Set $k \leftarrow O(1/\epsilon^2)$, and initialize an array \mathbf{C} of size k to zero
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- 4: **for all** $1 \leq i \leq m$ **do**
- 5: Get item $a_i = (j, c) \in [n] \times \{-B, \dots, B\}$ \triangleright Assume $B = O(1)$
- 6: $\mathbf{C}[h(j)] \leftarrow \mathbf{C}[h(j)] + c \cdot g(j)$

Output: On query $j \in [n]$, **return** $\hat{f}_j \leftarrow g(j) \cdot \mathbf{C}[h(j)]$

Frequent Elements (Heavy Hitters): CountSketch (5/5)

Theorem 44. *The (median trick version of the) COUNTSKETCH algorithm is a randomised one-pass sketching algorithm which, for any given parameters $\epsilon, \delta \in (0, 1]$, provides a (succinctly represented) estimate \hat{f} of frequency vector f of the stream such that, for every $j \in [n]$*

$$\Pr \left[\left| \hat{f}_j - f_j \right| \leq \epsilon \|f_{-j}\|_2 \right] \geq 1 - \delta$$

with space complexity

$$s = O \left(\frac{\log(nm)}{\epsilon^2} \log \frac{1}{\delta} \right).$$

Frequent Elements (Heavy Hitters): CountMinSketch (1/4)

Input: Parameters $\epsilon, \delta \in (0, 1]$

- 1: Set $k \leftarrow O(1/\epsilon)$ and $T \leftarrow O(\log(1/\delta))$, and initialize a two-dimensional array C of size $T \times k$ to zero
- 2: Pick $h_1, \dots, h_T: [n] \rightarrow [k]$ independently from a strongly universal hashing family
- 3: **for all** $1 \leq i \leq m$ **do**
- 4: Get item $a_i = (j, c) \in [n] \times \{0, \dots, B\} \triangleright$ Assume $B = O(1)$
- 5: **for all** $1 \leq t \leq T$ **do**
- 6: $C[t][h_t(j)] \leftarrow C[t][h_t(j)] + c$

Output: On query $j \in [n]$, **return** $\hat{f}_j \leftarrow \min_{1 \leq t \leq T} C[t][h_t(j)]$

Frequent Elements (Heavy Hitters): CountMinSketch (2/4)

Input: Parameters $\varepsilon, \delta \in (0, 1]$

- 1: Set $k \leftarrow O(1/\varepsilon)$ and $T \leftarrow O(\log(1/\delta))$, and initialize a two-dimensional array \mathbf{C} of size $T \times k$ to zero
- 2: Pick $h_1, \dots, h_T: [n] \rightarrow [k]$ independently from a strongly universal hashing family
- 3: **for all** $1 \leq i \leq m$ **do**
- 4: Get item $a_i = (j, c) \in [n] \times \{0, \dots, B\}$ \triangleright Assume $B = O(1)$
- 5: **for all** $1 \leq t \leq T$ **do**
- 6: $\mathbf{C}[t][h_t(j)] \leftarrow \mathbf{C}[t][h_t(j)] + c$

Output: On query $j \in [n]$, **return** $\hat{f}_j \leftarrow \min_{1 \leq t \leq T} \mathbf{C}[t][h_t(j)]$

Frequent Elements (Heavy Hitters): CountMinSketch (3/4)

Input: Parameters $\varepsilon, \delta \in (0, 1]$

- 1: Set $k \leftarrow O(1/\varepsilon)$ and $T \leftarrow O(\log(1/\delta))$, and initialize a two-dimensional array \mathbf{C} of size $T \times k$ to zero
- 2: Pick $h_1, \dots, h_T: [n] \rightarrow [k]$ independently from a strongly universal hashing family
- 3: **for all** $1 \leq i \leq m$ **do**
- 4: Get item $a_i = (j, c) \in [n] \times \{0, \dots, B\}$ \triangleright Assume $B = O(1)$
- 5: **for all** $1 \leq t \leq T$ **do**
- 6: $\mathbf{C}[t][h_t(j)] \leftarrow \mathbf{C}[t][h_t(j)] + c$

Output: On query $j \in [n]$, **return** $\hat{f}_j \leftarrow \min_{1 \leq t \leq T} \mathbf{C}[t][h_t(j)]$

Frequent Elements (Heavy Hitters): CountMinSketch (4/4)

Theorem 45. The COUNTMINSKETCH algorithm is a randomised one-pass sketching algorithm which, for any given parameters $\epsilon, \delta \in (0, 1]$, provides a (succinctly represented) estimate \hat{f} of frequency vector f of the stream such that, for every $j \in [n]$

$$\Pr \left[\left| \hat{f}_j - f_j \right| \leq \epsilon \|f\|_1 \right] \geq 1 - \delta$$

with space complexity

$$s = O \left(\frac{\log(nm)}{\epsilon} \log \frac{1}{\delta} \right).$$

(Moreover, \hat{f}_j is always an overestimate: $\hat{f}_j \geq f_j$ for all $j \in [n]$.)

Wait a minute...

This seems **strictly worse** than Misra-Gries!

- Randomised instead of deterministic!
- Uses more space!
- Also in the cash register model!
- Also an ℓ_1 guarantee!



Wait a minute...

This seems **strictly worse** than Misra-Gries!

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- Uses more space!
- Also in the cash register model!
- Also an ℓ_1 guarantee!

Yes, but:

- **Linear** sketch!
- Much **faster** per time step!
- Can be extended to the **strict turnstile** model!



Recap