COMMONWEALTH OF AUSTRALIA

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COMPx270: Randomised and Advanced Algorithms Lecture 8: Streaming and Sketching I

Clément Canonne School of Computer Science

Some housekeeping

- A2 due this Friday
- Office Hours (OH) tomorrow, 2:30-3:30pm in J12 402 (+Zoom)
- Preliminary marks for A1 released this evening on Gradescope

You have a graph, coming one edge at a time, with possible duplicates, and no paper to write anything done, only your memory. What is its average degree?

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 $(1,2)$

You have a graph, coming one edge at a time, with possible duplicates, and no paper to write anything done, only your memory. What is its average degree?

 $(2,4)$

You have a graph, coming one edge at a time, with possible duplicates, and no paper to write anything done, only your memory. What is its average degree?

 $(1,2)$

You have a graph, coming one edge at a time, with possible duplicates, and no paper to write anything done, only your memory. What is its average degree?

 $(4, 5)$

You have a graph, coming one edge at a time, with possible duplicates, and no paper to write anything done, only your memory. What is its average degree?

 $(4, 5)$

You have a graph, coming one edge at a time, with possible duplicates, and no paper to write anything done, only your memory. What is its average degree?

(3,4)

You have a graph, coming one edge at a time, with possible duplicates, and no paper to write anything done, only your memory. What is its average degree?

(3,6)

You have a graph, coming one edge at a time, with possible duplicates, and no paper to write anything done, only your memory. What is its average degree?

 $(1,4)$

You have a graph, coming one edge at a time, with possible duplicates, and no paper to write anything done, only your memory. What is its average degree?

(4,6)

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(3,5)

You have a graph, coming one edge at a time, with possible duplicates, and no paper to write anything done, only your memory. What is its average degree?

(3,4)

You have a graph, coming one edge at a time, with possible duplicates, and no paper to write anything done, only your memory. What is its average degree?

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 $(1,4)$

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(4,6)

A question (an answer)

Streaming algorithms: what? (1/3)

\nHow memory: cannot store the whole input.

\nSo, how memory: cannot store the whole input.

\nSo, how many cannot be a a "stream": sequence of long the second way.)

\nNow,
$$
cos x
$$
 is a significant value of the input.

\nSo, $cos x$ is a significant value of the input.

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\nSo, $cos x$ is a significant value of the input.

\nSo, <

Streaming algorithms: what? (2/3)

COLUTION
\nS C Q NITING
\n
$$
S = (a_{11} - a_m) \in [m]
$$
\n
$$
Wj \in [m]
$$
\n
$$
Wj \in [m]
$$
\n
$$
Q \leq \int_{0.3}^{0.5} f(x) \leq m \quad 10^{10} \int_{0^{-1}}^{0.5} f(x) \leq m \quad 10^{10} \int_{0^{-1}}^{0.5
$$

 $\widehat{||\, \widehat{P}||}$

Streaming algorithms: what? (3/3)

MAJORITY (HEAVY HITTERS) \bullet

 $\sqrt{ }$ \overline{a}

$$
\begin{array}{c}\n\begin{array}{ccc}\n\bullet & \bullet & \bullet \\
\hline\n\bullet & \bullet & \bullet\n\end{array}\n\end{array}
$$

First example: Majority

$$
\mu_{\underline{P3}}:\qquad\qquad \text{if } |_{s} \cdot \text{there an element } i^* \in [n] \text{ s.t. } \int_{0}^{s} x \geq \frac{m}{2} \qquad \qquad (at \text{ mod } 2)
$$
\n
$$
\sum_{\underline{E-HH}}:\qquad \text{if } | \underline{0} | \underline{0} \text{ then } \underline{0} \text{ is a } \text{ if } \underline{0} \text{ is a
$$

First example: the Misra-Gries algorithm (1/3)

mple: the Misra-Gries algorithm (1/3)
\n
$$
A \leftarrow n
$$
 zeros
\n $A \leftarrow n$ zeros
\n θ $A[a_{i}] > 0$
\n θ $A[a_{i}] = 0$ θ θ
\n θ $A[a_{i}] = 0$ θ θ
\n θ $A[a_{i}] = 0$ θ θ
\n θ θ θ
\n θ θ
\n<

$$
\mathcal{H}_{\text{unabymel}}^{\text{inthermal}}(m)
$$
\n
$$
\mathcal{H}_{\text{unabym}}^{\text{unabym}}(m)
$$
\n
$$
\mathcal{H}_{\text{out}}^{\text{unabym}},
$$
\n
$$
\leq \frac{1}{2} O(\log n \cdot \log m)
$$
\n
$$
= O(\frac{\log nm}{\epsilon})
$$

First example: the Misra-Gries algorithm, alternative view (2/3)

$$
\begin{array}{ccc}\n & \beta_{1} & \beta_{2} & \beta_{3} & \beta_{4} \\
 & \beta_{5} & \beta_{6} & \beta_{7} \\
 & \beta_{7} & \beta_{8} & \beta_{9} \\
 & \beta_{8} & \beta_{8} & \beta_{9} & \beta_{1} \\
 & \beta_{9} & \beta_{8} & \beta_{1} & \beta_{1} \\
 & \beta_{10} & \beta_{11} & \beta_{10} & \beta_{10} \\
 & \beta_{11} & \beta_{12} & \beta_{13} & \beta_{13} \\
 & \beta_{11} & \beta_{12} & \beta_{13} & \beta_{13} \\
 & \beta_{11} & \beta_{12} & \beta_{13} & \beta_{13} \\
 & \beta_{12} & \beta_{13} & \beta_{14} & \beta_{15} \\
 & \beta_{13} & \beta_{14} & \beta_{15} & \beta_{16} \\
 & \beta_{15} & \beta_{16} & \beta_{17} & \beta_{18} \\
 & \beta_{16} & \beta_{17} & \beta_{18} & \beta_{19} \\
 & \beta_{18} & \beta_{19} & \beta_{10} & \beta_{11} \\
 & \beta_{10} & \beta_{11} & \beta_{12} & \beta_{13} \\
 & \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} \\
 & \beta_{12} & \beta_{13} & \beta_{14} & \beta_{15} \\
 & \beta_{13} & \beta_{14} & \beta_{15} & \beta_{16} \\
 & \beta_{15} & \beta_{16} & \beta_{17} & \beta_{18} \\
 & \beta_{16} & \beta_{17} & \beta_{18} & \beta_{19} \\
 & \beta_{18} & \beta_{19} & \beta_{10} & \beta_{11} \\
 & \beta_{19} & \beta_{10} & \beta_{11} & \beta_{12} \\
 & \beta_{10} & \beta_{11} & \beta_{12} & \beta_{13} \\
 & \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} \\
 & \beta_{12} & \beta_{13} & \beta_{14} & \beta_{15} \\
 & \beta_{13} & \beta_{14} & \beta_{15} & \beta_{16} \\
 & \beta_{16} & \beta_{17} & \beta_{18} & \beta_{17} \\
 &
$$

 \bullet \bullet

 $\begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix}$

 \vert \vert

~

 \bullet .

First example: the Misra-Gries algorithm (3/3)

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

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

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

Second example: Approximate Counting
\n
$$
n=2
$$
 $a_{i}\in\{0_{i}\}\$
\n \therefore $\bigcap_{i=1}^{n} (a_{i})$
\n \therefore $\bigcap_{i=1}^{n} (a_{i})$
\n \therefore $\bigcap_{i=1}^{n} (a_{i})$
\n \therefore $\bigcap_{i=1}^{n} (a_{i})$
\n \therefore $\bigcap_{i=1}^{n} (a_{i})$
\n $\bigcap_{i=1}^{n$

 $\mathcal{L}_{\mathcal{A}}$

Second example: Approximate Counting and the Morris Counter $\beta\ell\!k$ view.

Second example: the Morris Counter (193)
\n
$$
\mathbb{E}[C_m^2]
$$
\n
$$
\mathbb{E}[C_{i+1}^2] = \mathbb{E}[\mathbb{E}[C_{i+1}^2|C_i^2]]
$$
\n
$$
= \mathbb{E}[\frac{1}{C_i}(\mathcal{E}C_i)^2 + (1-\frac{1}{C_i})C_i^2]
$$
\n
$$
= \mathbb{E}[C_i^2] + (1-\frac{1}{C_i})C_i^2
$$
\n
$$
= \mathbb{E}[C_i^2] + 3 \mathbb{E}[C_i]
$$
\n
$$
= \mathbb{E}[C_i^2] + 3 \mathbb{E}[C_i]
$$
\n
$$
= \mathbb{E}[C_i^2] + 3(2a_i + 1)
$$
\n
$$
\mathbb{E}[C_m] = 1 + 3\frac{d(d+1)}{2} \implies \forall a_1 C_m = \mathbb{E}[C_m^2 - (d+1)^2 \frac{d(d-1)}{2}]
$$

Second example: the Morris Counter (2/3)

$$
\begin{array}{ll}\n\text{E}[C_{m}] = d+1 & \sqrt{\text{Var}[C_{m}]} = d(d-1) = O(d^{2}) & \times \\
\text{Bad} & \text{Gdebyther gives} \\
C_{m} = d+1 & \text{Var}[Var_{m}]\n\end{array}
$$
\n
$$
\text{vacuous guarantee} \qquad \qquad \text{C}
$$

Les better prober.

Median - of - means

Second example: the Morris Counter, Median-of-Means

Theorem 40. The medians-of-means version of the MORRIS COUNTER is a randomised one-pass algorithm which, for any given parameters $\varepsilon, \delta \in (0, 1]$, provides an estimate \widehat{d} of the number d of non-zero elements of the stream such that

$$
\Pr\left[(1-\varepsilon)d \le \hat{d} \le (1+\varepsilon)d\right] \ge 1-\delta
$$

with space complexity

$$
s = O\left(\frac{\log \log m}{\varepsilon^2} \cdot \log \frac{1}{\delta}\right)
$$

that is, doubly logarithmic in m.

Did we need to do that?

 $\mathsf{V}\sigma$

Second example: the Morris Counter, careful version (1/3)

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Second example: the Morris Counter, careful version (2/3)

Second example: the Morris Counter, careful version (3/3)

Theorem 41. The "careful" version of MORRIS COUNTER is a randomised one-pass algorithm which, for any given parameters $\varepsilon, \delta \in (0, 1]$, provides an estimate \widehat{d} of the number d of non-zero elements of the stream such that

$$
\Pr\left[(1-\varepsilon)d \leq \hat{d} \leq (1+\varepsilon)d\right] \geq 1-\delta
$$

with space complexity

$$
s = O\left(\log\log m + \log\frac{1}{\varepsilon} + \log\frac{1}{\delta}\right)
$$

that is, doubly logarithmic in m and logarithmic in $1/\varepsilon$.

Third example: Distinct Elements

Third example: Distinct Elements, the Tidemark (AMS) algorithm (1/4)

Third example: Distinct Elements, the Tidemark (AMS) algorithm (2/4)

Third example: Distinct Elements, the Tidemark (AMS) algorithm (3/4)

Third example: Distinct Elements, the Tidemark (AMS) algorithm (4/4)

Third example: Distinct Elements, the Tidemark (AMS) algorithm (5/4?)

Theorem 42. The (median trick version of the) **TIDEMARK** (AMS) algorithm is a randomised one-pass algorithm which, for any given parameter $\delta \in (0,1]$, provides an estimate \widehat{d} of the number d of distinct elements of the stream such that, for some absolute constant $C > 0$,

$$
\Pr\left[\frac{1}{C} \cdot d \le \hat{d} \le C \cdot d\right] \ge 1 - \delta
$$

with space complexity

$$
s = O\!\left(\log n \cdot \log \frac{1}{\delta}\right).
$$

Can we do better?

Third example: Distinct Elements, the BJKST algorithm (1/4)

Third example: Distinct Elements, the BJKST algorithm (2/4)

Third example: Distinct Elements, the BJKST algorithm (4/4)

Theorem 43. The (median trick version of the) BJKST algorithm is a randomised one-pass algorithm which, for any given parameters $\varepsilon, \delta \in$ $(0, 1]$, provides an estimate \widehat{d} of the number d of distinct elements of the stream such that, for some absolute constant $C > 0$,

$$
\Pr\left[\left(1-\varepsilon\right)\cdot d\leq \widehat{d}\leq (1+\varepsilon)d\right]\geq 1-\delta
$$

with space complexity

$$
s = O\bigg(\left(\log n + \frac{\log(1/\varepsilon) + \log\log n}{\varepsilon^2}\right) \cdot \log \frac{1}{\delta}\bigg).
$$

… Can we do better?