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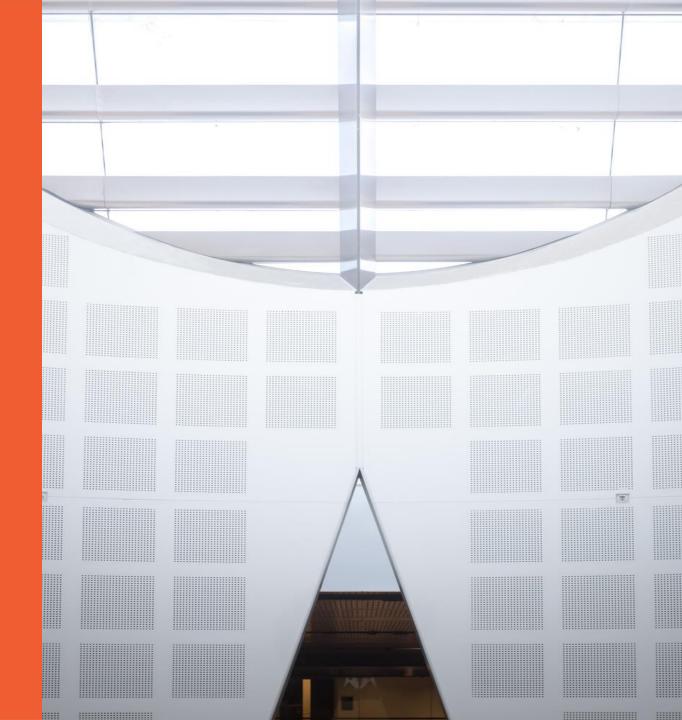
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COMPx270: Randomised and Advanced Algorithms
Lecture 8: Streaming and Sketching I

Clément Canonne School of Computer Science





Some housekeeping

- A2 due tonight
 See Ed+email announcement about Q3.f
- A3 now live, due May 9
- No class next week (semester break!)

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?

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(4,5)

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(3,4)

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(3,6)

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(1,4)

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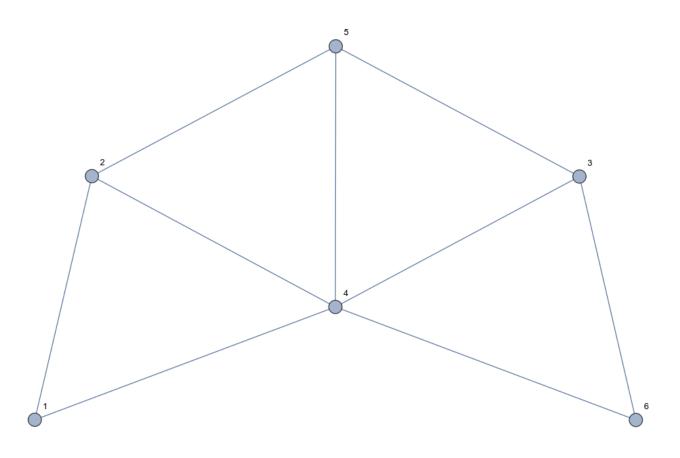
You have a graph, coming one edge at a time, with possible duplicates, and no paper to write anything done, only your memory. What is its average degree?

(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)

A question (an answer)



Streaming algorithms: what? (1/3)

Streaming algorithms: what? (2/3)

Streaming algorithms: what? (3/3)

First example: Majority

First example: Majority (Frequency Estimation)

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

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

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

Second example: Approximate Counting

Second example: Approximate Counting and the Morris Counter

```
1: x \leftarrow 0

2: for all 1 \le i \le m do

3: Get item a_i \in \{0, 1\}

4: if a_i = 1 then

5: r_i \leftarrow \text{Bern}(1/2^x) > Independent of previous choices.

6: x \leftarrow x + r_i

7: return \widehat{d} \leftarrow 2^x - 1
```

Second example: Approximate Counting and the Morris Counter

```
1: C_0 \leftarrow 1

2: for all 1 \le i \le m do

3: Get item a_i \in \{0, 1\}

4: if a_i = 1 then

5: r_i \leftarrow \text{Bern}(1/C_{i-1}) \rightarrow \text{Independent of previous choices.}

6: else r_i \leftarrow 0

7: C_i \leftarrow 2^{r_i}C_{i-1}

8: return \hat{d} \leftarrow C_m - 1
```

Throwback: Law of Total Expectation (and Friends)

Second example: the Morris Counter (1/3)

```
1: C_0 \leftarrow 1

2: for all 1 \le i \le m do

3: Get item a_i \in \{0, 1\}

4: if a_i = 1 then

5: r_i \leftarrow \text{Bern}(1/C_{i-1}) \rightarrow \text{Independent of previous choices.}

6: else r_i \leftarrow 0

7: C_i \leftarrow 2^{r_i}C_{i-1}

8: return \hat{d} \leftarrow C_m - 1
```

Second example: the Morris Counter (2/3)

```
1: C_0 \leftarrow 1

2: for all 1 \le i \le m do

3: Get item a_i \in \{0,1\}

4: if a_i = 1 then

5: r_i \leftarrow \text{Bern}(1/C_{i-1}) \rightarrow \text{Independent of previous choices.}

6: else r_i \leftarrow 0

7: C_i \leftarrow 2^{r_i}C_{i-1}

8: return \hat{d} \leftarrow C_m - 1
```

Second example: the Morris Counter (3/3)

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?

Second example: the Morris Counter, careful version (1/2)

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

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

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

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 (1/5)

```
1: Pick h: [n] \to [n] from a strongly universal hashing family
2: z \leftarrow 0
3: for all 1 \le i \le m do
4: Get item a_i \in [n]
5: if zeros(h(a_i)) \ge z then
6: z \leftarrow zeros(h(a_i))
7: return \sqrt{2} \cdot 2^z
```

Third example: Distinct Elements, the Tidemark (AMS) algorithm (2/5)

```
1: Pick h: [n] \rightarrow [n] from a strongly universal hashing family
2: z \leftarrow 0
3: for all 1 \le i \le m do
4: Get item a_i \in [n]
5: if zeros(h(a_i)) \ge z then
6: z \leftarrow zeros(h(a_i))
7: return \sqrt{2} \cdot 2^z
```

Third example: Distinct Elements, the Tidemark (AMS) algorithm (3/5)

```
1: Pick h: [n] \to [n] from a strongly universal hashing family

2: z \leftarrow 0

3: for all 1 \le i \le m do

4: Get item a_i \in [n]

5: if zeros(h(a_i)) \ge z then

6: z \leftarrow zeros(h(a_i))

7: return \sqrt{2} \cdot 2^z
```

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

```
1: Pick h: [n] \to [n] from a strongly universal hashing family

2: z \leftarrow 0

3: for all 1 \le i \le m do

4: Get item a_i \in [n]

5: if zeros(h(a_i)) \ge z then

6: z \leftarrow zeros(h(a_i))

7: return \sqrt{2} \cdot 2^z
```

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

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,

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

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)

```
Input: Parameter \varepsilon \in (0,1]
 1: Set k \leftarrow O(\log^2 n/\varepsilon^4), T \leftarrow \Theta(1/\varepsilon^2)
 2: Pick h: [n] \rightarrow [n] from a strongly universal hashing family
 3: Pick g: [n] \to [k] from a strongly universal hashing family
 4: z \leftarrow 0, B \leftarrow \emptyset
 5: for all 1 \le i \le m do
       Get item a_i \in [n]
       if zeros(h(a_i)) \ge z then
              B \leftarrow B \cup \{(g(a_i), \operatorname{zeros}(h(a_i)))\}
             while |B| \geq T do
 9:
                  z \leftarrow z + 1
10:
                   Remove every (a, b) with b < z from B
11:
12: return |B| \cdot 2^z
```

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

```
Input: Parameter \varepsilon \in (0,1]

1: Set k \leftarrow O(\log^2 n/\varepsilon^4), T \leftarrow \Theta(1/\varepsilon^2)

2: Pick h: [n] \rightarrow [n] from a strongly universal hashing family

3: Pick g: [n] \rightarrow [k] from a strongly universal hashing family

4: z \leftarrow 0, B \leftarrow \emptyset

5: for all 1 \le i \le m do

6: Get item a_i \in [n]

7: if zeros(h(a_i)) \ge z then

8: B \leftarrow B \cup \{(g(a_i), zeros(h(a_i)))\}

9: while |B| \ge T do

10: z \leftarrow z + 1

11: Remove every (a, b) with b < z from B

12: return |B| \cdot 2^z
```

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

```
Input: Parameter \varepsilon \in (0,1]

1: Set k \leftarrow O(\log^2 n/\varepsilon^4), T \leftarrow \Theta(1/\varepsilon^2)

2: Pick h: [n] \rightarrow [n] from a strongly universal hashing family

3: Pick g: [n] \rightarrow [k] from a strongly universal hashing family

4: z \leftarrow 0, B \leftarrow \emptyset

5: for all 1 \le i \le m do

6: Get item a_i \in [n]

7: if zeros(h(a_i)) \ge z then

8: B \leftarrow B \cup \{(g(a_i), zeros(h(a_i)))\}

9: while |B| \ge T do

10: z \leftarrow z + 1

11: Remove every (a, b) with b < z from B

12: return |B| \cdot 2^z
```

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 ε , $\delta \in (0,1]$, provides an estimate \hat{d} of the number d of distinct elements of the stream such that, for some absolute constant C > 0,

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

with space complexity

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

... Can we do better?