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Scalable Data Science

Lecture 9: Frequent Elements

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Streaming model revisited

- Data is seen as incoming sequence
 - can be just element-ids, or ids +frequency updates
- Arrival only streams
- Arrival + departure
 - Negative updates to frequencies possible
 - Can represent fluctuating quantities, e.g.



Frequency Estimation

- Given the input stream, answer queries about item frequencies at the end
 - Useful in many practical applications e.g. finding most popular pages from website logs, detecting DoD attacks, database optimization



- Also used as subroutine in many problems
 - Entropy estimation, itemset mining etc
- [Slides courtesy of Graham Cormode]

Frequency estimation

Q1. Can we create a data structure, sketch, sublinear in the data size to answer all frequency queries accurately?



Frequency estimation in one pass

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– No

Q2. Can we create a sketch to estimate frequencies of the “most frequent” elements exactly?



Frequency estimation in one pass

Q1. Can we create a data structure, sketch, sublinear in the data size to answer all frequency queries exactly?

– No

Q2. Can we create a sketch to answer frequencies of the “most frequent” elements exactly?

– No

Q3. Sketch to estimate frequencies of “most frequent” elements approximately?

Frequency estimation in one pass

Q1. Can we create a data structure, sketch, sublinear in the data size to answer all frequency queries exactly?

– No

Q2. Can we create a sketch to answer frequencies of the “most frequent” elements exactly?

– No

Q3. Sketch to estimate frequencies of “most frequent” elements approximately?

– YES!

Approximate Heavy Hitters

- Given an update stream of length m , find out all elements that occur “frequently”
 - e.g. at least 1% of the time
 - cannot be done in sublinear space, one pass
- Find out elements that occur at least ϕm times, and none that appears $< (\phi - \epsilon)m$ times
 - Error ϵ
 - Related question: estimate each frequency with error $\pm \epsilon m$



Starting with a puzzle

[J. Algorithms, 1981] Suppose we have a list of N numbers, representing votes of N processors on result of some computation. We wish to decide if there is a majority vote and what that vote is.

- By J.S. Moore
- Did not talk about streaming solution, but proposed solution is
- Strict majority: $>N/2$



Majority Algorithm

- Arrivals only model
- Start with a counter set to zero
- For each item
 - if counter = 0, pick new item and increment counter
 - else if new item is same as item in hand, increment counter
 - else decrement counter



Majority Algorithm

- Start with a counter set to zero
- For each item
 - if counter = 0, pick new item and increment counter
 - else if new item is same as item in hand, increment counter
 - else decrement counter
- If there is a majority item, it is in hand at the end
- Proof: Since majority occurs $> N/2$ times, not all occurrences can be cancelled out



Frequent [Misra-Gries]

- Keep k counters and items in hand

Initialize:

- Set all counters to 0

Process(x)

- if x is same as any item in hand, increment its counter
- else if number of items $< k$, store x with counter = 1
- else drop x and decrement all counters

Query(q)

- If q is in hand return its counter, else 0

Frequent

- f_x be the true frequency of element x
- At the end, some set of elements is stored with counter values
- If *query* y in hand, $\hat{f}_y = \text{counter value}$, else $\hat{f}_y = 0$



Example



Theoretical Bound

Claim: No element with frequency $> m/k$ is missed at the end



Theoretical Bound

Claim: No element with frequency $> m/k$ is missed at the end

Intuition: Each decrement (including drop) is charged with k arrivals. Therefore, will have some copy of an item with frequency $> m/k$

Stronger Claim

Choose $k = \frac{1}{\epsilon}$. For every item x , with frequency f_x the algo can return an estimate \hat{f}_x such that

$$f_x - \epsilon m \leq \hat{f}_x \leq f_x$$

Stronger Claim

Choose $k = \frac{1}{\epsilon}$. For every item x , with frequency f_x the algo can return an estimate \hat{f}_x such that

$$f_x - \epsilon m \leq \hat{f}_x \leq f_x$$

Same intuition, whenever we drop a copy of item x , we also drop $k - 1$ copies of other items



Summary

- Simple deterministic algorithm to estimate heavy hitters
 - Works only in the arrival model
- Proposed in 1982, rediscovered multiple times with modifications
- Also basis of matrix low rank approximation
- Our next lecture will discuss other algorithms

References:

- Primary references for this lecture
 - Lecture slides by Graham Cormode
<http://dmac.rutgers.edu/Workshops/WGUnifyingTheory/Slides/cormode.pdf>
 - Lecture notes by Amit Chakrabarti: <http://www.cs.dartmouth.edu/~ac/Teach/data-streams-lecnotes.pdf>
 - Sketch techniques for approximate query processing, Graham Cormode.
<http://dimacs.rutgers.edu/~graham/pubs/papers/sk.pdf>



Thank You!!



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