#### cs 677: Big Data Data Sketches: Frequent Items

Lecture 14

# Streaming Big Data

- In many cases, data is produced much faster than we can analyze it
- Batch processing systems like MapReduce let us do analysis offline, after the fact
  - Good: studying long-term trends
  - Bad: reacting quickly...
    - Health monitoring, rerouting traffic, etc.
- We can use a stream processing system, but what happens when that can't handle the workload?

# Sketching

- Rather than storing/processing everything, we can build data sketches of the datasets
- Some information is thrown away...
  - ...but we can store a wider breadth of information.
- These approaches have memory and processing benefits
  - Also well-suited to IoT devices, low-powered cloud instances, etc

# **Counting Events**

- What if we have a lot of elements in a stream and want to know which happen the most frequently?
- These are "Heavy hitters" most popular videos, websites, network users, etc.
- Tracking this in a small amount of space is a challenging problem
  - Simple but inefficient approach: store everything and sort it!
    - Correction: not inefficient. Impossible with big data.

# Majority Sketch

- Imagine we are electing a new US president
  - Whoever receives the majority of votes wins
- We have a data stream of votes
  - Easy! Tally up all the votes for Candidate A and Candidate B and report the winner
- Except it's not really that simple...
  - Many US citizens will be shocked to learn that there are more than two possible presidential candidates
  - In fact, it's possible to write in a vote for whoever you want

# **Tracking Votes**

- Fine. We'll just store **ALL** the votes and see who wins.
  - It's still gonna either be Candidate A or Candidate B!
- Unfortunately, to make matters worse, society has collapsed in an Idiocracy-style dystopia
  - All computing power is devoted to TikTok
- You are able to salvage the original *Apollo Guidance Computer* (AGC) from a museum, but it doesn't have a lot of memory
  - Instead of the actual vote count, can we at least find out who got over 50% of votes?

# Streaming Majority Algorithm

- Enough tomfoolery. Let's look at this algorithm.
- **1.** Initialize a counter to zero. (c = 0)
- **2.** For each element in the stream:
  - If the counter is zero, set majority = element
  - If majority == element, increment counter ( c++ )
    - Else, decrement the counter. ( c-- )
  - When our stream is finished, if c > 0 then we have successfully determined the majority

### Exceptions

- If the final count is 0, then the only thing we know is the last element recorded is **NOT** the majority
- It could have occurred up to  $\frac{n}{2}$  times... (meaning we have a tie) but we don't know for sure
  - Time for a recount!
- If we have three strong candidates, this algorithm won't help
  - We need a situation where knowing what element occurred more than 50% of the time is useful

### Time Wasted?

- Maybe the previous situation doesn't seem very likely or useful
- This algorithm sometimes gets taught in undergrad courses to introduce streams
  - Might be less common now though
- But the algorithm **IS** used in many high-traffic, low computing power situations
  - (determine the destination the majority of packets are being sent to on a network switch)

# A Better Majority Algorithm

- Around 2000 or so, a remixed version of this algorithm caught on
- Massive data streams can make revisiting simple, notso-useful algorithms a bit more interesting
- Frequent Elements Sketch
  - Concerned with "top N" type queries or "iceberg queries"
  - Useful for network monitoring, log analysis, and data mining

# Frequent Elements Sketch [1/2]

- Let's say we want to know the top N YouTube videos based on URL clicks
- Initialize an array with size N and store (URL, count) pairs in the array:

 $egin{aligned} [0] &
ightarrow (URL_1, count) \ [1] &
ightarrow (URL_2, count) \end{aligned}$ 

 $[N] 
ightarrow (URL_N, count)$ 

. . .

# Frequent Elements Sketch [2/2]

- Start reading items from the data stream...
- When an element (URL in our case) comes in:
  - 1. If it's in the sketch already, increment its count
  - 2. If it's not in the sketch, but there's a free space in the array, insert it in the empty slot
  - **3.** If it's not in the sketch and there's no room for it in the array, decrement all counts
  - **4.** If any count drops to 0, remove it from the array, which will free up a slot

# Using the Sketch

- First, sort the array by the element counts
- Boom! Report the results. They are your top N elements.

#### Enhancements

- We can use a map / dictionary / etc. to track the elements instead
  - Easier to test for set membership, increment existing counts
- Track the total number of elements
  - Allows us to calculate the percentage each element represents of the overall dataset

#### Weaknesses

- This algorithm requires us to know  $N\,-\,{\rm how}$  many things we want
  - That is not always possible
- It is susceptible to attacks if we cannot trust the data stream
  - Feeding it with the right (unique or random) inputs will cause frequent elements to be removed
  - The answer will be *technically* right, but since we threw most of the data away we will not be able to detect the attack

### Where to go next

- We have only begun to see the tip of the iceberg when it comes to streaming algorithms
  - Get it?? Get it?? Iceberg queries!!
- If we are willing to throw away more data and use a bit of probability we can make some cool predictions with very little storage space...