Remember: No lecture next Tuesday –
Project group meetings instead

Mining Data Streams
(Part 2)
Today’s Lecture

- More algorithms for streams:
  - (1) Filtering a data stream: **Bloom filters**
    - Select elements with property \( x \) from stream
  - (2) Counting distinct elements: **Flajolet-Martin**
    - Number of distinct elements in the last \( k \) elements of the stream
  - (3) Estimating moments: **AMS method**
    - Estimate std. dev. of last \( k \) elements
(1) Filtering Data Streams
Filtering Data Streams

- Each element of data stream is a tuple
- Given a list of keys $S$
- Determine which tuples of stream are in $S$

- Obvious solution: Hash table
  - But suppose we do not have enough memory to store all of $S$ in a hash table
    - E.g., we might be processing millions of filters on the same stream
Applications

- **Example: Email spam filtering**
  - We know 1 billion “good” email addresses
    - Or, each user has a list of trusted addresses
  - If an email comes from one of these, it is **NOT** spam

- **Publish-subscribe systems**
  - You are collecting lots of messages (news articles)
  - People express interest in certain sets of keywords
  - Determine whether each message matches user’s interest

- **Content filtering:**
  - You want to make sure the user does not see the same ad multiple times

- **Web cache filtering:**
  - Has this piece of content been requested before? Then cache it now.
First Cut Solution (1)

Given a set of keys $S$ that we want to filter

- Create a **bit array $B$** of $n$ bits, initially all **0s**
- Choose a **hash function $h$** with range $[0,n)$
- Hash each member of $s \in S$ to one of $n$ buckets, and set that bit to **1**, i.e., $B[h(s)]=1$
- Hash each element $a$ of the stream and output only those that hash to bit that was set to **1**
  - Output $a$ if $B[h(a)] == 1$
First Cut Solution (2)

- Creates false positives but no false negatives
  - If the item is in $S$ we surely output it, if not we may still output it

Output the item since it may be in $S$. Item hashes to a bucket that at least one of the items in $S$ hashed to.

Drop the item.
It hashes to a bucket set to 0 so it is surely not in $S$. 

Item hashes to a bucket that at least one of the items in $S$ hashed to.

Item hashes to a bucket that at least one of the items in $S$ hashed to.
First Cut Solution (3)

- $|S| = 1$ billion email addresses
  $|B| = 1$GB = 8 billion bits

- If the email address is in $S$, then it surely hashes to a bucket that has the bit set to 1, so it always gets through (no false negatives)

- Approximately $1/8$ of the bits are set to 1, so about $1/8^{th}$ of the addresses not in $S$ get through to the output (false positives)
  - Actually, less than $1/8^{th}$, because more than one address might hash to the same bit
More accurate analysis for the number of false positives

Consider: If we throw \( m \) darts into \( n \) equally likely targets, what is the probability that a target gets at least one dart?

In our case:

- **Targets** = bits/buckets
- **Darts** = hash values of items
Analysis: Throwing Darts (2)

- We have \( m \) darts, \( n \) targets
- What is the probability that a target gets at least one dart?

\[
1 - (1 - 1/n) = \frac{n}{n} \cdot \left(1 - \frac{1}{n}\right)
\]

Equals \( 1/e \) as \( n \to \infty \)

Equivalent

\[
1 - e^{-m/n}
\]

1 - (1 - 1/n)

Probability some target \( X \) not hit by a dart

Probability at least one dart hits target \( X \)

Approximation is especially accurate when \( n \) is large
Analysis: Throwing Darts (3)

- Fraction of 1s in the array $B =$
  $= \text{probability of false positive} = 1 - e^{-m/n}$

- Example: $10^9$ darts, $8 \cdot 10^9$ targets
  - Fraction of 1s in $B = 1 - e^{-1/8} = 0.1175$
  - Compare with our earlier estimate: $1/8 = 0.125$
Bloom Filter

- Consider: $|S| = m, |B| = n$
- Use $k$ independent hash functions $h_1, \ldots, h_k$
- Initialization:
  - Set $B$ to all 0s
  - Hash each element $s \in S$ using each hash function $h_i$, set $B[h_i(s)] = 1$ (for each $i = 1, \ldots, k$)
- Run-time:
  - When a stream element with key $x$ arrives
    - If $B[h_i(x)] = 1$ for all $i = 1, \ldots, k$ then declare that $x$ is in $S$
    - That is, $x$ hashes to a bucket set to 1 for every hash function $h_i(x)$
    - Otherwise discard the element $x$
What fraction of the bit vector B are 1s?

- Throwing \( k \cdot m \) darts at \( n \) targets
- So fraction of 1s is \( (1 - e^{-km/n}) \)

But we have \( k \) independent hash functions and we only let the element \( x \) through if all \( k \) hash elements to a bucket of value 1

So, false positive probability = \( (1 - e^{-km/n})^k \)
Bloom Filter – Analysis (2)

- \( m = 1 \) billion, \( n = 8 \) billion
  - \( k = 1 \): \((1 - e^{-1/8}) = 0.1175\)
  - \( k = 2 \): \((1 - e^{-1/4})^2 = 0.0493\)

- What happens as we keep increasing \( k \)?

- Optimal value of \( k \): \( n/m \ln(2) \)
  - In our case: Optimal \( k = 8 \ln(2) = 5.54 \approx 6 \)
  - Error at \( k = 6 \): \((1 - e^{-3/4})^6 = 0.0216\)

**Optimal \( k \):** \( k \) which gives the lowest false positive probability
Bloom Filter: Wrap-up

- Bloom filters allow for filtering / set membership
- **Bloom filters guarantee no false negatives, and use limited memory**
  - Great for pre-processing before more expensive checks
- Suitable for hardware implementation
  - Hash function computations can be parallelized

- Is it better to have 1 big B or k small Bs?
  - It is the same: \((1 - e^{-km/n})^k\) vs. \((1 - e^{-m/(n/k)})^k\)
  - But keeping 1 big B is simpler
(2) Counting Distinct Elements
Counting Distinct Elements

- **Problem:**
  - Data stream consists of a universe of elements chosen from a set of size $N$
  - Maintain a count of the number of distinct elements seen so far

- **Obvious approach:**
  Maintain the set of elements seen so far
  - That is, keep a hash table of all the distinct elements seen so far
Applications

- How many different words are found among the Web pages being crawled at a site?
  - Unusually low or high numbers could indicate artificial pages (spam?)

- How many different Web pages does each customer request in a week?

- How many distinct products have we sold in the last week?
Real problem: What if we do not have space to maintain the set of elements seen so far?

Estimate the count in an unbiased way

Accept that the count may have a little error, but limit the probability that the error is large
Flajolet-Martin Approach

- Pick a hash function $h$ that maps each of the $N$ elements to at least $\log_2 N$ bits
- For each stream element $a$, let $r(a)$ be the number of trailing 0s in $h(a)$
  - $r(a) = \text{position of first 1 counting from the right}$
    - E.g., say $h(a) = 12$, then 12 is 1100 in binary, so $r(a) = 2$
- Record $R = \text{the maximum } r(a) \text{ seen}$
  - $R = \max_a r(a)$, over all the items $a$ seen so far
- Estimated number of distinct elements $= 2^R$
Why It Works: Intuition

- **Rough intuition why Flajolet-Martin works:**
  - $h(a)$ hashes $a$ with equal prob. to any of $N$ values
  - Then $h(a)$ is a sequence of $\log_2 N$ bits, where $2^{-r}$ fraction of all $a$s have a tail of $r$ zeros
    - About 50% of $a$s hash to ***0
    - About 25% of $a$s hash to **00
    - So, if we saw the longest tail of $r=2$ (i.e., item hash ending *100) then we have probably seen about 4 distinct items so far
  - So, it takes to hash about $2^r$ items before we see one with zero-suffix of length $r$
Why It Works: More formally

- Now we show why Flajolet-Martin works

- Formally, we will show that probability of finding a tail of $r$ zeros:
  - Goes to 1 if $m \gg 2^r$
  - Goes to 0 if $m \ll 2^r$

where $m$ is the number of distinct elements seen so far in the stream

- Thus, $2^R$ will almost always be around $m!$
Why It Works: More formally

- **What is the probability that a given** \( h(a) \) **ends in at least** \( r \) **zeros? It is** \( 2^{-r} \)
  - \( h(a) \) hashes elements uniformly at random
  - Probability that a random number ends in at least \( r \) zeros is \( 2^{-r} \)
- **Then, the probability of NOT seeing a tail of length** \( r \) **among** \( m \) **distinct elements:**

\[
(1 - 2^{-r})^m
\]

- Prob. all \( m \) elements end in fewer than \( r \) zeros.
- Prob. that given \( h(a) \) ends in fewer than \( r \) zeros
Why It Works: More formally

- **Note:** \((1 - 2^{-r})^m = (1 - 2^{-r})^{2^r(m2^{-r})} \approx e^{-m2^{-r}}\)
- **Prob. of NOT finding a tail of length** \(r\) **is:**
  - If \(m << 2^r\), then prob. tends to 1
    - \((1 - 2^{-r})^m \approx e^{-m2^{-r}} = 1\) as \(m/2^r \rightarrow 0\)
    - So, the probability of finding a tail of length \(r\) tends to 0
  - If \(m >> 2^r\), then prob. tends to 0
    - \((1 - 2^{-r})^m \approx e^{-m2^{-r}} = 0\) as \(m/2^r \rightarrow \infty\)
    - So, the probability of finding a tail of length \(r\) tends to 1

- **Thus,** \(2^R\) **will almost always be around** \(m!\)
Why It Doesn’t Work

- **E[2^R]** is actually infinite
  - Observing R has some probability
  - Probability halves when \( R \rightarrow R+1 \), but value doubles
  - Each possible large R contributes to exp. value

- Workaround involves using many hash functions \( h_i \) and getting many samples of \( R_i \)

- How are samples \( R_i \) combined?
  - Average? What if one very large value \( 2^{R_i} \)?
  - Median? All estimates are a power of 2

- Solution:
  - Partition your samples into small groups
  - Take the median of groups
  - Then take the average of the medians
(3) Computing Moments
Generalization: Moments

- Suppose a stream has elements chosen from a set $A$ of $N$ values

- Let $m_i$ be the number of times value $i$ occurs in the stream

- The $k^{th}$ moment is

$$\sum_{i \in A} (m_i)^k$$

This is the same way as moments are defined in statistics. But there one typically “centers” the moment by subtracting the mean.
Special Cases

\[ \sum_{i \in A} (m_i)^k \]

- **0th moment** = number of distinct elements
  - The problem just considered
- **1st moment** = count of the numbers of elements = length of the stream
  - Easy to compute
- **2nd moment** = *surprise number* \( S \) = a measure of how uneven the distribution is
Moments

- Third Moment is Skew:

- Fourth moment: Kurtosis
  - peakedness (width of peak), tail weight, and lack of shoulders (distribution primarily peak and tails, not in between).
Example: Surprise Number

- Measure of how uneven the distribution is
  - Stream of length 100
  - 11 distinct values

- Item counts \( m_i \): 10, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9
  - Surprise \( S = 910 \)

- Item counts \( m_i \): 90, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1
  - Surprise \( S = 8,110 \)
AMS Method

- AMS method works for all moments
- Gives an unbiased estimate
- We will just concentrate on the 2\textsuperscript{nd} moment $S$
- We pick and keep track of many variables $X$:
  - For each variable $X$ we store $X.el$ and $X.val$
    - $X.el$ corresponds to the item $i$
    - $X.val$ corresponds to the count $m_i$ of item $i$
  - Note this requires a count in main memory, so number of $X$s is limited
- Our goal is to compute $S = \sum_i m_i^2$
One Random Variable (X)

- **How to set X.val and X.el?**
  - Assume stream has length \( n \) (we relax this later)
  - Pick some random time \( t \) \((t<n)\) to start, so that any time is equally likely
  - Let at time \( t \) the stream have item \( i \). **We set X.el = i**
  - Then we maintain count \( c \) \((X.val = c)\) of the number of \( i \)s in the stream starting from the chosen time \( t \)
  - **Then the estimate of the 2\(^{nd}\) moment \((\sum_i m_i^2)\) is:**
    \[
    S = f(X) = n \cdot (2 \cdot c - 1)
    \]
  - Note, we will keep track of multiple Xs, \((X_1, X_2, ... X_k)\)
    and our final estimate will be \( S = 1/k \sum_j^k f(X_j) \)
2nd moment is \( S = \sum_i m_i^2 \)

- \( c_t \) ... number of times item at time \( t \) appears from time \( t \) onwards \((c_1=m_a, c_2=m_a-1, c_3=m_b)\)

\[
E[f(X)] = \frac{1}{n} \sum_{t=1}^{n} n(2c_t - 1) = \frac{1}{n} \sum_i n (1 + 3 + 5 + \cdots + 2m_i - 1)
\]
Expectation Analysis

\[ E[f(X)] = \frac{1}{n} \sum_i n (1 + 3 + 5 + \cdots + 2m_i - 1) \]

- Little side calculation: \( (1 + 3 + 5 + \cdots + 2m_i - 1) = \sum_{i=1}^{m_i} (2i - 1) = 2 \frac{m_i(m_i+1)}{2} - m_i = (m_i)^2 \)

- Then \( E[f(X)] = \frac{1}{n} \sum_i n (m_i)^2 \)

- So, \( E[f(X)] = \sum_i (m_i)^2 = S \)

- We have the second moment (in expectation)!
Higher-Order Moments

- For estimating $k^{th}$ moment we essentially use the same algorithm but change the estimate $f(X)$:
  - For $k=2$ we used $n (2 \cdot c - 1)$
  - For $k=3$ we use: $n (3 \cdot c^2 - 3c + 1)$ (where $c=X.val$)

- Why?
  - For $k=2$: Remember we had $(1 + 3 + 5 + \cdots + 2m_i - 1)$ and we showed terms $2c-1$ (for $c=1,...,m$) sum to $m^2$
    - $\sum_{c=1}^{m} (2c - 1) = \sum_{c=1}^{m} c^2 - \sum_{c=1}^{m} (c - 1)^2 = m^2$
    - So: $2c - 1 = c^2 - (c - 1)^2$
  - For $k=3$: $c^3 - (c-1)^3 = 3c^2 - 3c + 1$

- Generally: Estimate $f(X) = n \left( c^k - (c - 1)^k \right)$
Combining Samples

- **In practice:**
  - Compute $f(X) = n(2c - 1)$ for as many variables $X$ as you can fit in memory
  - Average them in groups
  - Take median of averages

- **Problem: Streams never end**
  - We assumed there was a number $n$, the number of positions in the stream
  - But real streams go on forever, so $n$ is a variable – the number of inputs seen so far
 Streams Never End: Fixups

- **(1)** The variables $X$ have $n$ as a factor – keep $n$ separately; just hold the count in $X$
- **(2)** Suppose we can only store $k$ counts. We must throw some $X$s out as time goes on:
  - **Objective:** Each starting time $t$ is selected with probability $k/n$
  - **Solution:** (fixed-size / reservoir sampling!)
    - Choose the first $k$ times for $k$ variables
    - When the $n^{th}$ element arrives ($n > k$), choose it with probability $k/n$
    - If you choose it, throw one of the previously stored variables $X$ out, with equal probability
Problems on Data Streams

- **Filtering a data stream**
  - Select elements with property $x$ from the stream

- **Counting distinct elements**
  - Number of distinct elements in the last $k$ elements of the stream

- **Estimating moments**
  - Estimate avg./std. dev. of elements in stream

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