Frequency Estimators
Outline for Today

- **Randomized Data Structures**
  - Our next approach to improving performance.

- **Count-Min Sketches**
  - A simple and powerful data structure for estimating frequencies.

- **Count Sketches**
  - Another approach for estimating frequencies.
Randomized Data Structures
Tradeoffs

- Data structure design is all about tradeoffs:
  - Trade preprocessing time for query time.
  - Trade asymptotic complexity for constant factors.
  - Trade worst-case per-operation guarantees for worst-case aggregate guarantees.
Randomization

- Randomization opens up new routes for tradeoffs in data structures:
  - Trade worst-case guarantees for average-case guarantees.
  - Trade exact answers for approximate answers.
- Over the next few lectures, we'll explore two families of data structures that make these tradeoffs:
  - Today: *Frequency estimators*.
  - Next Week: *Hash tables*. 
Preliminaries: *What is a Hash Function?*
Hashing in Practice

• In most programming languages, each object has “a” hash code.
  • C++: std::hash
  • Java: Object.hashCode
  • Python: __hash__

• To store objects in a hash table, you just go and implement the appropriate function or type.

• In other words, hash functions are intrinsic properties of objects.
Hashing in Theoryland

- In Theoryland, a hash function is a function from some domain called the \textit{universe} (typically denoted \( \mathcal{U} \)) to some codomain.
- The codomain is usually a set of the form \{0, 1, 2, 3, ..., \( m - 1 \)\}, which we’ll denote \([m]\).
- We often will grab lots of different hash functions from the same universe \( \mathcal{U} \) to some codomain, and we’ll assume we have access to as many of them as we need.
- In other words, hash functions are \textit{extrinsic} to objects, and it’s possible to have multiple different hash functions available at the same time.
Families of Hash Functions

- A **family** of hash functions is a set $\mathcal{H}$ of hash functions with the same domain and codomain.

- The data structures we’ll explore will assume that we have access to certain families of hash functions with nice properties.

- We’ll then sample uniformly-random choices $h \in \mathcal{H}$ to use as needed.
Sampling Random Functions

- Here's a family of hash functions $\mathcal{H}$ from $\mathbb{N}$ to $[137]$:
  \[
  \mathcal{H} = \{ f(n) = (an + b) \mod 137 \mid a, b \in [137] \}
  \]

- In Theoryland, we'd model picking a uniformly-random hash function from $\mathcal{H}$ as just that – sampling some $h \in \mathcal{H}$ uniformly.

- In The Real World, we'd probably model picking such a function like this:

  ```
  int a = rand() % 137;
  int b = rand() % 137;

  int hash(int value) {
      return (a * value + b) % 137;
  }
  ```
Characterizing Hash Functions

- Different algorithms and data structures require different guarantees from their hash functions.

- In CS161, you explored *universal hash functions* in the context of chained hash tables.

- For what we’ll be doing in CS166, we’re going to need hash functions with slightly stronger probabilistic guarantees.
Pairwise Independence

- Let $\mathcal{H}$ be a family of hash functions from $\mathcal{U}$ to some set $\mathcal{C}$.
- We say that $\mathcal{H}$ is a 2-independent family of hash functions if, for a uniformly-random choice of $h \in \mathcal{H}$, the following is true for all distinct $x, y \in \mathcal{U}$:

  \[
  h(x) \text{ and } h(y) \text{ are uniformly distributed over } \mathcal{C}.
  \]

  \[
  h(x) \text{ and } h(y) \text{ are independent.}
  \]

- 2-independent hash functions are great hash functions when we want a nice distribution over the output space even after fixing some specific element.
3-Independence

- Let $\mathcal{H}$ be a family of hash functions from $\mathcal{U}$ to some set $\mathcal{C}$.
- We say that $\mathcal{H}$ is a **3-independent family of hash functions** if, for a uniformly-random choice of $h \in \mathcal{H}$, the following is true for all distinct $x, y, z \in \mathcal{U}$:
  
  - $h(x)$, $h(y)$, and $h(z)$ are uniformly distributed over $\mathcal{C}$.
  - $h(x)$, $h(y)$, and $h(z)$ are independent.

- As you’ll see, in many cases, making stronger assumptions about our hash functions makes it possible to simplify tricky probabilistic expressions.

- (As you can probably guess, this generalizes even further to $k$-independence, which we’ll see on Tuesday.)
Frequency Estimation
Frequency Estimators

- A **frequency estimator** is a data structure supporting the following operations:
  - **increment**($x$), which increments the number of times that $x$ has been seen, and
  - **estimate**($x$), which returns an estimate of the frequency of $x$.

- Using BSTs, we can solve this in space $\Theta(n)$ with worst-case $O(\log n)$ costs on the operations.

- Using hash tables, we can solve this in space $\Theta(n)$ with expected $O(1)$ costs on the operations.
Frequency Estimators

- Frequency estimation has many applications:
  - Search engines: Finding frequent search queries.
  - Network routing: Finding common source and destination addresses.
- In these applications, $\Theta(n)$ memory can be impractical.
- **Goal:** Get *approximate* answers to these queries in sublinear space.
Some Terminology

- Let's suppose that all elements $x$ are drawn from some set $\mathcal{U} = \{ x_1, x_2, \ldots, x_n \}$.

- We can interpret the frequency estimation problem as follows:
  
  Maintain an $n$-dimensional vector $a$ such that $a_i$ is the frequency of $x_i$.

- We'll represent $a$ implicitly in a format that uses reduced space.
Vector Norms

• Let $a \in \mathbb{R}^n$ be a vector.

• The **L₁ norm of $a$**, denoted $\|a\|_1$, is defined as

$$\|a\|_1 = \sum_{i=1}^{n} |a_i|$$

• The **L₂ norm of $a$**, denoted $\|a\|_2$, is defined as

$$\|a\|_2 = \sqrt{\sum_{i=1}^{n} a_i^2}$$
Properties of Norms

• The following property of norms holds for any vector \( a \in \mathbb{R}^n \). It's a good exercise to prove this on your own:

\[
\|a\|_2 \leq \|a\|_1 \leq \Theta(n^{1/2}) \cdot \|a\|_2
\]

• The first bound is tight when exactly one component of \( a \) is nonzero.

• The second bound is tight when all components of \( a \) are equal.
Where We're Going

• Today, we'll see two data frequency estimation data structures.

• Each is parameterized over two quantities:
  • An *accuracy* parameter \( \varepsilon \in (0, 1) \) determining how close to accurate we want our answers to be.
  • A *confidence* parameter \( \delta \in (0, 1] \) determining how likely it is that our estimate is within the bounds given by \( \varepsilon \).
Where We're Going

- The **count-min sketch** provides estimates with error at most $\varepsilon \|a\|_1$ with probability at least $1 - \delta$.
- The **count sketch** provides estimates with an error at most $\varepsilon \|a\|_2$ with probability at least $1 - \delta$.
  - (Notice that lowering $\varepsilon$ and lower $\delta$ give better bounds.)
- Count-min sketches will use less space than count sketches for the same $\varepsilon$ and $\delta$, but provide slightly weaker guarantees.
The Count-Min Sketch
The Count-Min Sketch

• Rather than diving into the full count-min sketch, we'll develop the data structure in phases.

• First, we'll build a simple data structure that on expectation provides good estimates, but which does not have a high probability of doing so.

• Next, we'll combine several of these data structures together to build a data structure that has a high probability of providing good estimates.
Revisiting the Exact Solution

- In the exact solution to the frequency estimation problem, we maintained a single counter for each distinct element. This is too space-inefficient.

- **Idea:** Store a fixed number of counters and assign a counter to each $x_i \in U$. Multiple $x_i$'s might be assigned to the same counter.

- To **increment**$(x)$, increment the counter for $x$.

- To **estimate**$(x)$, read the value of the counter for $x$. 
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- To **increment**(x), increment the counter for x.

- To **estimate**(x), read the value of the counter for x.
Our Initial Structure

- We can model “assigning each $x_i$ to a counter” by using hash functions.
- Choose, from a family of 2-independent hash functions $\mathcal{H}$, a uniformly-random hash function $h : \mathcal{U} \to [w]$.
- Create an array $\text{count}$ of $w$ counters, each initially zero.
  - We'll choose $w$ later on.
- To $\textbf{increment}(x)$, increment $\text{count}[h(x)]$.
- To $\textbf{estimate}(x)$, return $\text{count}[h(x)]$. 
Analyzing this Structure

- **Recall:** $a$ is the vector representing the true frequencies of the elements.
  - $a_i$ is the frequency of element $x_i$.
- Denote by $\hat{a}_i$ the value of $\text{estimate}(x_i)$. This is a random variable that depends on the true frequencies $a$ (out of our control, but not random) and the hash function $h$ (truly chosen at random.)
- **Goal:** Show that on expectation, $\hat{a}_i$ is not far from $a_i$. 
Analyzing this Structure

• Intuitively, what do we expect $\hat{a}_i$ to be?
• There are $\|a\|_1$ total elements spread out across $w$ buckets.
• Assuming they’re well-distributed, we’d probably expect $\|a\|_1 / w$ of them to be in each bucket.
• So a reasonable guess would be that $\hat{a}_i$ should probably end up being something like $a_i + \|a\|_1 / w$.
• Let’s see if we can formalize this.
Analyzing this Structure

• Let's look at $\hat{a}_i = \text{count}[h(x_i)]$ for some choice of $x_i$.

• For each element $x_j$:
  • If $h(x_i) = h(x_j)$, then $x_j$ contributes $a_j$ to $\text{count}[h(x_i)]$.
  • If $h(x_i) \neq h(x_j)$, then $x_j$ contributes 0 to $\text{count}[h(x_i)]$. 
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To pin this down precisely, let’s define a set of random variables $X_1, X_2, \ldots$, as follows:

$$X_j = \begin{cases} 
1 & \text{if } h(x_i) = h(x_j) \\
0 & \text{otherwise}
\end{cases}$$

Each of these variables is called an \textit{indicator random variable}, since it “indicates” whether some event occurs.
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- The value of $\hat{a}_i$ is then given by

  $\hat{a}_i = \sum_j a_j X_j$
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• The value of $\hat{a}_i$ is then given by

\[
\hat{a}_i = \sum_j a_j X_j = a_i + \sum_{j \neq i} a_j X_j
\]
\[ E[\hat{a}_i] = E[a_i + \sum_{j \neq i} a_j X_j] \]
\[
\mathbb{E}[\hat{a}_i] = \mathbb{E}[a_i + \sum_{j \neq i} a_j X_j] \\
= \mathbb{E}[a_i] + \mathbb{E}[\sum_{j \neq i} a_j X_j]
\]

This follows from \textit{linearity of expectation}. We’ll use this property extensively over the next few days.
\[
E[\hat{a}_i] = E[a_i + \sum_{j \neq i} a_j X_j]
\]

\[
= E[a_i] + E[\sum_{j \neq i} a_j X_j]
\]

\[
= a_i + \sum_{j \neq i} E[a_j X_j]
\]

The actual value of \( a_i \) is not a random variable. The randomness here is in our choice of hash function, not the choice of the data.
\[ E[\hat{a}_i] = E[a_i + \sum_{j \neq i} a_j X_j] \]
\[ = E[a_i] + E[\sum_{j \neq i} a_j X_j] \]
\[ = a_i + \sum_{j \neq i} E[a_j X_j] \]
\[ = a_i + \sum_{j \neq i} a_j E[X_j] \]
\begin{align*}
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  &= E[a_i] + E[\sum_{j \neq i} a_j X_j] \\
  &= a_i + \sum_{j \neq i} E[a_j X_j] \\
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E[X_j] = 1 \cdot \Pr[h(x_i) = h(x_j)] + 0 \cdot \Pr[h(x_i) \neq h(x_j)]
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\[ = 1 \cdot \Pr[h(x_i) = h(x_j)] \]

If \( X \) is an indicator variable for some event \( \mathcal{E} \), then \( E[X] = \Pr[\mathcal{E}] \). This is really useful when using linearity of expectation!
\[ \mathbb{E}[\hat{a}_i] = \mathbb{E}[a_i + \sum_{j \neq i} a_j X_j] \]
\[ = \mathbb{E}[a_i] + \mathbb{E}[\sum_{j \neq i} a_j X_j] \]
\[ = a_i + \sum_{j \neq i} \mathbb{E}[a_j X_j] \]
\[ = a_i + \sum_{j \neq i} a_j \mathbb{E}[X_j] \]

\[ \mathbb{E}[X_j] = 1 \cdot \Pr[h(x_i) = h(x_j)] + 0 \cdot \Pr[h(x_i) \neq h(x_j)] \]
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Any two hash codes from a randomly-chosen 2-independent hash function are independent, uniformly-random variables.
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\[ = \frac{1}{w} \]

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\[ = a_i + \sum_{j \neq i} a_j E[X_j] \]
\[ = a_i + \sum_{j \neq i} \frac{a_j}{w} \]

\[ E[X_j] = 1 \cdot \Pr[h(x_i) = h(x_j)] + 0 \cdot \Pr[h(x_i) \neq h(x_j)] \]
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\[ \mathbb{E}[\hat{a}_i] = \mathbb{E}[a_i + \sum_{j \neq i} a_j X_j] \]

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\[ = a_i + \sum_{j \neq i} \mathbb{E}[a_j X_j] \]

\[ = a_i + \sum_{j \neq i} a_j \mathbb{E}[X_j] \]

\[ = a_i + \sum_{j \neq i} \frac{a_j}{\mathcal{W}} \]

\[ \leq a_i + \frac{\|a\|_1}{\mathcal{W}} \]

\[ \mathbb{E}[X_j] = 1 \cdot \Pr[h(x_i) = h(x_j)] + 0 \cdot \Pr[h(x_i) \neq h(x_j)] \]

\[ = 1 \cdot \Pr[h(x_i) = h(x_j)] \]

\[ = \frac{1}{\mathcal{W}} \]
Interpreting our Analysis

- On expectation, the value of \( \text{estimate}(x_i) \) is at most \( \|a\|_1 / w \) greater than \( a_i \).
  - That matches our intuition from before! Yay!
- From a practical perspective:
  - Increasing \( w \) increases memory usage, but improves accuracy.
  - Decreasing \( w \) decreases memory usage, but decreases accuracy.
One Problem

- We have shown that *on expectation*, the value of \( \text{estimate}(x_i) \) can be made close to the true value.

- However, this data structure may give wildly inaccurate results for most elements.
  - Any low-frequency elements that collide with high-frequency elements will have overreported frequency.

Question: Can we bound the probability that we overestimate the frequency of an element?
One Problem

• We have shown that on expectation, the value of \textit{estimate}(\(x_i\)) can be made close to the true value.

• However, this data structure may give wildly inaccurate results for most elements.
  • Any low-frequency elements that collide with high-frequency elements will have overreported frequency.

• \textbf{Question}: Can we bound the probability that we overestimate the frequency of an element?
A Useful Observation

- Notice that regardless of which hash function we use or the size of the table, we always have $\hat{a}_i \geq a_i$.
- This means that $\hat{a}_i - a_i \geq 0$.
- We have a one-sided error; this data structure will never underreport the frequency of an element, but it may overreport it.
Bounding the Error Probability

• If \( X \) is a nonnegative random variable, then \textit{Markov's inequality} states that for any \( c > 0 \), we have
  \[
  \Pr[ X > c \cdot E[X] ] \leq 1/c
  \]

• We know that
  \[
  E[\hat{a}_i] \leq a_i + \|a\|_1/w
  \]

• Therefore, we see that
  \[
  E[\hat{a}_i - a_i] \leq \|a\|_1/w
  \]

• By Markov's inequality, for any \( c > 0 \), we have
  \[
  \Pr[\hat{a}_i - a_i > \frac{c\|a\|_1}{w}] \leq 1/c
  \]

• Equivalently:
  \[
  \Pr[\hat{a}_i > a_i + \frac{c\|a\|_1}{w}] \leq 1/c
  \]
Bounding the Error Probability

- For any $c > 0$, we know that
  \[ \Pr[\hat{a}_i > a_i + \frac{c\|a\|_1}{w}] \leq \frac{1}{c} \]
- In particular:
  \[ \Pr[\hat{a}_i > a_i + \frac{e\|a\|_1}{w}] \leq \frac{1}{e} \]
- Given an accuracy parameter $\varepsilon$, $\in (0, 1]$, let's set $w = \lceil e / \varepsilon \rceil$. Then we have
  \[ \Pr[\hat{a}_i > a_i + \varepsilon\|a\|_1] \leq \frac{1}{e} \]
- This data structure uses $O(\varepsilon^{-1})$ space and gives estimates with error at most $\varepsilon\|a\|_1$ with probability at least $1 - 1/e$. 
Tuning the Probability

- Right now, we can tune the *accuracy* $\varepsilon$ of the data structure, but we can't tune our *confidence* in that answer (it's always $1 - 1/e$).

- **Goal:** Update the data structure so that for any confidence $0 < \delta < 1$, the probability that an estimate is correct is at least $1 - \delta$. 
Tuning the Probability

● A single copy of our data structure has a decently good chance of providing an estimate that isn’t too far off the true value.

● Intuitively, having lots of copies of this data structure would make it more likely that at least one of them gets a good estimate.

● **Idea:** Combine together multiple copies of this data structure to boost confidence in our estimates.
Running in Parallel

- Let's suppose that we run $d$ independent copies of this data structure. Each has its own independently randomly chosen hash function.
- To $\text{increment}(x)$ in the overall structure, we call $\text{increment}(x)$ on each of the underlying data structures.
- The probability that at least one of them provides a good estimate is quite high.
- **Question:** How do you know which one?

\[
\begin{align*}
&137 & \ldots & 161 & 166 & \ldots & 42 & \ldots & 103 & \ldots & 109 \\
&h_1 & & h_2 & & & & h_d & & & \\
&\downarrow & & \downarrow & & \downarrow & & \downarrow & & \downarrow & & \downarrow \\
&\chi & & \chi & & \chi & & \chi & & \chi & & \chi \\
\end{align*}
\]
Recognizing the Answer

- **Recall:** Each estimate $\hat{a}_i$ is the sum of two independent terms:
  - The actual value $a_i$.
  - Some "noise" terms from other elements colliding with $x_i$.
- Since the noise terms are always nonnegative, larger values of $\hat{a}_i$ are less accurate than smaller values of $\hat{a}_i$.
- **Idea:** Take, as our estimate, the minimum value of $\hat{a}_i$ from all of the data structures.
The Final Analysis

• For each independent copy of this data structure, the probability that our estimate is within $\varepsilon||a||_1$ of the true value is at least $1 - 1/e$.

• Let $\xi_i$ be the event that the $i$th copy of the data structure provides an estimate within $\varepsilon||a||_1$ of the true answer.

• Let $\xi$ be the event that the aggregate data structure provides an estimate within $\varepsilon||a||_1$.

• **Question:** What is $\text{Pr}[\xi]$?
The Final Analysis

• Since we're taking the minimum of all the estimates, if any of the data structures provides a good estimate, our estimate will be accurate.

• Therefore,

\[ \Pr[\mathcal{E}] = \Pr[\exists i. \mathcal{E}_i] \]

• Equivalently:

\[ \Pr[\mathcal{E}] = 1 - \Pr[\forall i. \overline{\mathcal{E}_i}] \]

• Since all the estimates are independent:

\[ \Pr[\mathcal{E}] = 1 - \Pr[\forall i. \overline{\mathcal{E}_i}] \geq 1 - \frac{1}{e^d}. \]
The Final Analysis

- We now have that
  \[ \Pr[\mathcal{E}] \geq 1 - \frac{1}{e^d}. \]
- If we want the confidence to be \(1 - \delta\), we can choose \(\delta\) such that
  \[ 1 - \delta = 1 - \frac{1}{e^d} \]
- Solving, we can choose \(d = \ln \delta^{-1}\).
- If we make \(\ln \delta^{-1}\) independent copies of our data structure, the probability that our estimate is off by at most \(\varepsilon \|a\|_1\) is at least \(1 - \delta\).
The Count-Min Sketch

- This data structure is called the **count-min sketch**.
- Given parameters $\varepsilon$ and $\delta$, choose
  \[
  w = \lceil e / \varepsilon \rceil \quad d = \lceil \ln \delta^{-1} \rceil
  \]
- Create an array `count` of size $w \times d$ and for each row $i$, choose a hash function $h_i : \mathcal{U} \rightarrow [w]$ uniformly and independently from a 2-independent family of hash functions $\mathcal{H}$.
- To **increment** $(x)$, increment `count`[$i$][$h_i(x)$] for each row $i$.
- To **estimate** $(x)$, return the minimum value of `count`[$i$][$h_i(x)$] across all rows $i$. 
The Count-Min Sketch

- Update and query times are $\Theta(d)$, which is $\Theta(\log \delta^{-1})$.
- Space usage: $\Theta(\epsilon^{-1} \cdot \log \delta^{-1})$ counters.
  - This can be significantly better than just storing a raw frequency count!
- Provides an estimate to within $\epsilon \|a\|_1$ with probability at least $1 - \delta$. 
Some Generalizable Ideas

- Many of the techniques and ideas from this analysis will show up in other places.
- First, the idea of using *indicator variables* and *linearity of expectation* to simplify expected value calculations.
- Second, relying on the *independence guarantees* of our hash function to simplify some of the intermediate steps.
- Third, the fact that being good on expectation isn’t the same as being good with high probability and using *concentration inequalities* to quantify spread.
- Finally, the fact that *confidence* and *accuracy* aren’t the same, and running *multiple parallel copies* of a data structure to boost confidence.
Time-Out for Announcements!
Final Project Proposal

• Final project proposals were due today at 2:30PM.

• We’re going to run a matchmaking algorithm soon and get back to everyone with their assigned topics.

• We’re looking forward to seeing what everyone has come up with!
Problem Sets

• Problem Set Four is due next Thursday at 2:30PM.

• Have questions? As always, you can
  • stop by office hours, or
  • ask on Piazza!

• We hope you have fun with this one!
Back to CS166!
An Alternative: Count Sketches
The Motivation

- (Note: This is historically backwards; count sketches came before count-min sketches.)
- In a count-min sketch, errors arise when multiple elements collide.
- Errors are strictly additive; the more elements collide in a bucket, the worse the estimate for those elements.
- **Question**: Can we try to offset the “badness” that results from the collisions?
The Setup

- As before, for some parameter $w$, we'll create an array $\text{count}$ of length $w$.
- As before, choose a hash function $h : \mathcal{U} \rightarrow [w]$ from a family $\mathcal{H}$.
- For each $x_i \in \mathcal{U}$, assign $x_i$ either +1 or -1.
- To $\text{increment}(x)$, go to $\text{count}[h(x)]$ and add $\pm 1$ as appropriate.
- To $\text{estimate}(x)$, return $\text{count}[h(x)]$, multiplied by $\pm 1$ as appropriate.
The Setup

- As before, for some parameter $w$, we'll create an array $\text{count}$ of length $w$.
- As before, choose a hash function $h : \mathcal{U} \rightarrow [w]$ from a family $\mathcal{H}$.
- For each $x_i \in \mathcal{U}$, assign $x_i$ either +1 or -1.
- To $\text{increment}(x)$, go to $\text{count}[h(x)]$ and add $\pm 1$ as appropriate.
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The Setup

- As before, for some parameter $w$, we'll create an array $\text{count}$ of length $w$.
- As before, choose a hash function $h : U \rightarrow [w]$ from a family $\mathcal{H}$.
- For each $x_i \in U$, assign $x_i$ either $+1$ or $-1$.
- To $\text{increment}(x)$, go to $\text{count}[h(x)]$ and add $\pm 1$ as appropriate.
- To $\text{estimate}(x)$, return $\text{count}[h(x)]$, multiplied by $\pm 1$ as appropriate.
The Intuition

• Think about what introducing the ±1 term does when collisions occur.

• If an element \( x \) collides with a frequent element \( y \), we're not going to get a good estimate for \( x \) (but we wouldn't have gotten one anyway).

• If \( x \) collides with multiple infrequent elements, the collisions between those elements will partially offset one another and leave a better estimate for \( x \).
More Formally

- Let’s have $h \in \mathcal{H}$ chosen uniformly at random from a **3-independent** family of hash functions from $\mathcal{U}$ to $\mathcal{W}$.
- Choose $s \in \mathcal{U}$ uniformly randomly and independently of $h$ from a **3-independent** family from $\mathcal{U}$ to $\{-1, +1\}$.
  - (Note: The more traditional analysis uses 2-independence rather than 3-independence. I’m showing you a slightly simplified version.)
- To **increment** $(x)$, add $s(x)$ to $\text{count}[h(x)]$.
- To **estimate** $(x)$, return $s(x) \cdot \text{count}[h(x)]$.
How accurate is our estimation?
Formalizing the Intuition

• As before, define $\hat{a}_i$ to be our estimate of $a_i$.
• As before, $\hat{a}_i$ will depend on how the other elements are distributed. Unlike before, it now also depends on signs given to the elements by $s$.
• Specifically, for each other $x_j$ that collides with $x_i$, the error contribution will be

$$s(x_i) \cdot s(x_j) \cdot a_j$$

• Why?
  • The counter for $x_i$ will have $s(x_j) \cdot a_j$ added in.
  • We multiply the counter by $s(x_i)$ before returning it.
Formalizing the Intuition

• As before, define $\hat{a}_i$ to be our estimate of $a_i$.

• As before, $\hat{a}_i$ will depend on how the other elements are distributed. Unlike before, it now also depends on signs given to the elements by $s$.

• Specifically, for each other $x_j$ that collides with $x_i$, the error contribution will be

$$s(x_i) \cdot s(x_j) \cdot a_j$$

• Or:

  • If $s(x_i)$ and $s(x_j)$ point in the same direction, the terms add to the total.
  • If $s(x_i)$ and $s(x_j)$ point in different directions, the terms subtract from the total.
Formalizing the Intuition

- In our quest to learn more about \( \hat{a}_i \), let’s have \( X_j \) be a random variable indicating whether \( x_i \) and \( x_j \) collided with one another:

\[
X_j = \begin{cases} 
1 & \text{if } h(x_i) = h(x_j) \\
0 & \text{if } h(x_i) \neq h(x_j)
\end{cases}
\]
Formalizing the Intuition

• In our quest to learn more about \( \hat{a}_i \), let’s have \( X_j \) be a random variable indicating whether \( x_i \) and \( x_j \) collided with one another:

\[
X_j = \begin{cases} 
1 & \text{if } h(x_i) = h(x_j) \\
0 & \text{if } h(x_i) \neq h(x_j)
\end{cases}
\]

• We can then express \( \hat{a}_i \) in terms of the signed contributions from the items it collides with:

\[
\hat{a}_i = \sum_j a_j s(x_i) s(x_j) X_j
\]

This is how much the collision impacts our estimate.

We only care about items we collided with.
Formalizing the Intuition

• In our quest to learn more about $\hat{a}_i$, let’s have $X_j$ be a random variable indicating whether $x_i$ and $x_j$ collided with one another:

\[
X_j = \begin{cases} 
1 & \text{if } h(x_i) = h(x_j) \\
0 & \text{if } h(x_i) \neq h(x_j)
\end{cases}
\]

• We can then express $\hat{a}_i$ in terms of the signed contributions from the items it collides with:

\[
\hat{a}_i = \sum_j a_j s(x_i) s(x_j) X_j = a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j
\]

This is how much the collision impacts our estimate.

We only care about items we collided with.
\[ E[\hat{a}_i] = E[a_i + \sum_{j \neq i} a_j s(x_i)s(x_j)X_j] \]
\[
E[\hat{a}_i] = E[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j]
\]

\[
= E[a_i] + E[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j]
\]

Hey, it’s linearity of expectation!
\[
\mathbb{E}[\hat{a}_i] = \mathbb{E}[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j]
\]
\[
= \mathbb{E}[a_i] + \mathbb{E}\left[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j\right]
\]
\[
= a_i + \sum_{j \neq i} \mathbb{E}[a_j s(x_i) s(x_j) X_j]
\]

Remember that \(a_i\) and the like aren’t random variables.
\[ E[\hat{a}_i] = E[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j] \]
\[ = E[a_i] + E[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j] \]
\[ = a_i + \sum_{j \neq i} E[a_j s(x_i) s(x_j) X_j] \]

We chose the hash functions \( h \) and \( s \) independently of one another.

\[ X_j = \begin{cases} 
1 & \text{if } h(x_i) = h(x_j) \\
0 & \text{if } h(x_i) \neq h(x_j) 
\end{cases} \]
\[
E[\hat{a}_i] = E[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j] \\
= E[a_i] + E\left[ \sum_{j \neq i} a_j s(x_i) s(x_j) X_j \right] \\
= a_i + \sum_{j \neq i} E[a_j s(x_i) s(x_j) X_j] \\
= a_i + \sum_{j \neq i} E[s(x_i) s(x_j)] E[a_j X_j]
\]

We chose the hash functions \( h \) and \( s \) independently of one another.

\[
X_j = \begin{cases} 
1 & \text{if } h(x_i) = h(x_j) \\
0 & \text{if } h(x_i) \neq h(x_j)
\end{cases}
\]
\[
\mathbb{E}[\hat{a}_i] = \mathbb{E}[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j]
\]

\[
= \mathbb{E}[a_i] + \mathbb{E}\left[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j\right]
\]

\[
= a_i + \sum_{j \neq i} \mathbb{E}[a_j s(x_i) s(x_j) X_j]
\]

\[
= a_i + \sum_{j \neq i} \mathbb{E}[s(x_i) s(x_j)] \mathbb{E}[a_j X_j]
\]

\[
= a_i + \sum_{j \neq i} \mathbb{E}[s(x_i)] \mathbb{E}[s(x_j)] \mathbb{E}[a_j X_j]
\]

Remember that \(s\) is drawn from a 3-independent family of hash functions, so \(s(x_i)\) and \(s(x_j)\) are independent random variables.
\[
E[\hat{a}_i] = E\left[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j\right]
\]

\[
= E[a_i] + E\left[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j\right]
\]

\[
= a_i + \sum_{j \neq i} E\left[a_j s(x_i) s(x_j) X_j\right]
\]

\[
= a_i + \sum_{j \neq i} E[s(x_i)] E[s(x_j)] E[a_j X_j]
\]

\[
E[s(x_i)] = \frac{1}{2} \cdot (-1) + \frac{1}{2} \cdot (+1) = 0
\]
\[
\begin{align*}
\mathbb{E}[\hat{a}_i] &= \mathbb{E}[a_i + \sum_{j \neq i} a_j s(x_i)s(x_j)X_j] \\
&= \mathbb{E}[a_i] + \mathbb{E}\left[\sum_{j \neq i} a_j s(x_i)s(x_j)X_j\right] \\
&= a_i + \sum_{j \neq i} \mathbb{E}[a_j s(x_i)s(x_j)X_j] \\
&= a_i + \sum_{j \neq i} \mathbb{E}[s(x_i)s(x_j)]\mathbb{E}[a_j X_j] \\
&= a_i + \sum_{j \neq i} \mathbb{E}[s(x_i)]\mathbb{E}[s(x_j)]\mathbb{E}[a_j X_j]
\end{align*}
\]

\[
\mathbb{E}[s(x_i)] = \frac{1}{2}
\]

\[s\text{ is drawn from a 3-independent family of hash functions.}\]
\[
E[\hat{a}_i] = E[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j]
= E[a_i] + E[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j]
= a_i + \sum_{j \neq i} E[a_j s(x_i) s(x_j) X_j]
= a_i + \sum_{j \neq i} E[s(x_i) s(x_j)] E[a_j X_j]
= a_i + \sum_{j \neq i} E[s(x_i)] E[s(x_j)] E[a_j X_j]
\]

\[
E[s(x_i)] = 0
\]

\[
s \text{ is drawn from a 3-independent family of hash functions.}
\]
\[
s(x_i) \text{ is uniform over \{-1, +1\}}
\]
\[ E[\hat{a}_i] = E[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j] \]

\[ = E[a_i] + E[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j] \]

\[ = a_i + \sum_{j \neq i} E[a_j s(x_i) s(x_j) X_j] \]

\[ = a_i + \sum_{j \neq i} E[s(x_i)] E[s(x_j)] E[a_j X_j] \]

\[ E[s(x_i)] = \frac{1}{2} \cdot (-1) + \frac{1}{2} \cdot (+1) = 0 \]

---

\( E[s(x_i)] = \)

\( s \) is drawn from a 3-independent family of hash functions.

\( s(x_i) \) is uniform over \{-1, +1\}

\( \Pr[s(x_i) = -1] = \frac{1}{2} \quad \Pr[s(x_i) = +1] = \frac{1}{2} \)
\[ E[\hat{a}_i] = E[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j] \]
\[ = E[a_i] + E[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j] \]
\[ = a_i + \sum_{j \neq i} E[a_j s(x_i) s(x_j) X_j] \]
\[ = a_i + \sum_{j \neq i} E[s(x_i)] E[s(x_j)] E[a_j X_j] \]

\[ E[s(x_i)] = \frac{1}{2} \cdot (-1) + \frac{1}{2} \cdot (+1) \]  

\[ s \] is drawn from a 3-independent family of hash functions.  
\[ s(x_i) \] is uniform over \{-1, +1\}  
\[ \Pr[s(x_i) = -1] = \frac{1}{2} \quad \Pr[s(x_i) = +1] = \frac{1}{2} \]
\[ E[\hat{a}_i] = E[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j] \]
\[ = E[a_i] + E[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j] \]
\[ = a_i + \sum_{j \neq i} E[a_j s(x_i) s(x_j) X_j] \]
\[ = a_i + \sum_{j \neq i} E[s(x_i)] E[s(x_j)] E[a_j X_j] \]

\[ E[s(x_i)] = \frac{1}{2} \cdot (-1) + \frac{1}{2} \cdot (+1) = 0 \]

- \(s\) is drawn from a 3-independent family of hash functions.
- \(s(x_i)\) is uniform over \([-1, +1]\)
- \(Pr[s(x_i) = -1] = \frac{1}{2}\)
- \(Pr[s(x_i) = +1] = \frac{1}{2}\)
\[
E[\hat{a}_i] = E[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j]
\]
\[
= E[a_i] + E[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j]
\]
\[
= a_i + \sum_{j \neq i} E[a_j s(x_i) s(x_j) X_j]
\]
\[
= a_i + \sum_{j \neq i} E[s(x_i)] E[s(x_j)] E[a_j X_j]
\]
\[
= a_i + \sum_{j \neq i} 0
\]

\[
E[s(x_i)] = \frac{1}{2} \cdot (-1) + \frac{1}{2} \cdot (+1) = 0
\]

s is drawn from a 3-independent family of hash functions.

s(x_i) is uniform over \{-1, +1\}

\[
Pr[s(x_i) = -1] = \frac{1}{2} \quad Pr[s(x_i) = +1] = \frac{1}{2}
\]
\[
\begin{align*}
\mathbb{E}[\hat{a}_i] &= \mathbb{E}[a_i + \sum_{j \neq i} a_j s(x_i)s(x_j)X_j] \\
&= \mathbb{E}[a_i] + \mathbb{E}\left[\sum_{j \neq i} a_j s(x_i)s(x_j)X_j\right] \\
&= a_i + \sum_{j \neq i} \mathbb{E}[a_j s(x_i)s(x_j)X_j] \\
&= a_i + \sum_{j \neq i} \mathbb{E}[s(x_i)] \mathbb{E}[s(x_j)] \mathbb{E}[a_j X_j] \\
&= a_i + \sum_{j \neq i} 0 \\
&= a_i
\end{align*}
\]

\[
\mathbb{E}[s(x_i)] = \frac{1}{2} \cdot (-1) + \frac{1}{2} \cdot (+1) = 0
\]

\(s\) is drawn from a 3-independent family of hash functions.

\(s(x_i)\) is uniform over \([-1, +1]\)

\(\Pr[s(x_i) = -1] = \frac{1}{2} \quad \Pr[s(x_i) = +1] = \frac{1}{2}\)
Expecting the Unexpected

- We’ve just seen that $\mathbb{E}[\hat{a}_i] = a_i$, so on expectation our estimate is perfectly correct!
- However, we have no idea how likely it is that we’re going to get an estimate like this.
- Let’s see if we can bound the likelihood that we stray far from $a_i$. 
A Hitch

- In the count-min sketch, we used Markov's inequality to bound the probability that we get a bad estimate.
- This worked because we had a one-sided error: the distance $\hat{a}_i - a_i$ from the true answer was nonnegative.
- However, with the count sketch, we have a two-sided error: $\hat{a}_i - a_i$ can be negative in the count sketch because collisions can decrease the estimate $\hat{a}_i$ below the true value $a_i$.
- We'll need to use a different technique to bound the error.
Chebyshev to the Rescue

- **Chebyshev's inequality** states that for any random variable $X$ with finite variance, given any $c > 0$, the following holds:

  $$\Pr\left[ |X - \mathbb{E}[X]| \geq c \sqrt{\text{Var}[X]} \right] \leq \frac{1}{c^2}$$

- Equivalently:

  $$\Pr\left[ |X - \mathbb{E}[X]| \geq c \right] \leq \frac{\text{Var}[X]}{c^2}$$

- If we can get the variance of $\hat{a}_i$, we can bound the probability that we get a bad estimate with our data structure.
Let’s try computing the variance of our estimate $\hat{a}_i$:

$$\text{Var}[\hat{a}_i] = \text{Var}[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j]$$

$$\text{Var}[a + X] = \text{Var}[X]$$
Computing the Variance

• Let’s try computing the variance of our estimate \( \hat{a}_i \):

\[
\text{Var}[\hat{a}_i] = \text{Var}[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j]
\]

\[
= \text{Var}\left[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j\right]
\]

\[\text{Var}[a + X] = \text{Var}[X]\]
Computing the Variance

• Let’s try computing the variance of our estimate $\hat{a}_i$:

$$\text{Var}[\hat{a}_i] = \text{Var}[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j]$$

$$= \text{Var}[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j]$$

• Variance is not a linear operator, but it is linear if the underlying random variables are independent of one another.

• **Claim:** Each term of the sum is independent of the others.
Independence Day

- We want to show that these two terms are independent:

\[
 a_j \, s(x_i) \, s(x_j) \, X_j \quad \quad a_k \, s(x_i) \, s(x_k) \, X_k
\]

- Imagine we know \( a_j \, s(x_i) \, s(x_j) \, X_j \).

- Whether \( a_k \, s(x_i) \, s(x_k) \, X_k = 0 \) depends on whether \( h(x_i) = h(x_k) \).

  - The values \( h(x_i), h(x_j), \) and \( h(x_k) \) are uniformly-random and independent because \( h \) is 3-independent.

  - Knowing whether \( h(x_i) = h(x_j) \) doesn’t impact the probability that \( h(x_i) = h(x_k) \), since all three values are uniform and independent.

- The sign of \( a_k \, s(x_i) \, s(x_k) \, X_k \) depends on \( s(x_i) \cdot s(x_k) \).

  - \( s(x_i), s(x_j), \) and \( s(x_k) \) are uniformly-random and independent because \( s \) is 3-independent.

  - There’s an equal chance that \( s(x_i) \cdot s(x_k) = 1 \) and \( s(x_i) \cdot s(x_k) = -1 \), since even with \( s(x_i) \cdot s(x_j) \) fixed, \( s(x_k) \) is independently and uniformly distributed over \( \{+1, -1\} \).
\[ \text{Var}[\hat{a}_i] = \text{Var}[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j] \]

\[ = \text{Var}\left[ \sum_{j \neq i} a_j s(x_i) s(x_j) X_j \right] \]
\[
\text{Var}[\hat{a}_i] = \text{Var}[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j] \\
= \text{Var}\left[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j\right] \\
= \sum_{j \neq i} \text{Var}[a_j s(x_i) s(x_j) X_j] \\
\]

The “Sum-o’-Var” Samovar!

😊
\[ \text{Var}[\hat{a}_i] = \text{Var}[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j] \]

\[ = \text{Var}[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j] \]

\[ = \sum_{j \neq i} \text{Var}[a_j s(x_i) s(x_j) X_j] \]

\[ \text{Var}[Z] = E[Z^2] - E[Z]^2 \leq E[Z^2] \]
\[
\text{Var}[\hat{a}_i] = \text{Var}[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j] \\
= \text{Var}[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j] \\
= \sum_{j \neq i} \text{Var}[a_j s(x_i) s(x_j) X_j] \\
\leq \sum_{j \neq i} \mathbb{E}[(a_j s(x_i) s(x_j) X_j)^2] \\
\]

\[
\text{Var}[Z] = \mathbb{E}[Z^2] - \mathbb{E}[Z]^2 \\
\leq \mathbb{E}[Z^2]
\]
\[ \text{Var}[\hat{a}_i] = \text{Var}[a_i + \sum_{j \neq i} a_j s(x_i)s(x_j)X_j] \]

\[ = \text{Var}[\sum_{j \neq i} a_j s(x_i)s(x_j)X_j] \]

\[ = \sum_{j \neq i} \text{Var}[a_j s(x_i)s(x_j)X_j] \]

\[ \leq \sum_{j \neq i} \mathbb{E}[(a_j s(x_i)s(x_j)X_j)^2] \]

\[ = \sum_{j \neq i} \mathbb{E}[a_j^2 s(x_i)^2 s(x_j)^2 X_j^2] \]

\[ s(x) = \pm 1, \]

so

\[ s(x)^2 = 1 \]
\[
\text{Var}[\hat{a}_i] = \text{Var}[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j]
\]
\[
= \text{Var}\left[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j\right]
\]
\[
= \sum_{j \neq i} \text{Var}[a_j s(x_i) s(x_j) X_j]
\]
\[
\leq \sum_{j \neq i} \mathbb{E}[\left(a_j s(x_i) s(x_j) X_j\right)^2]
\]
\[
= \sum_{j \neq i} \mathbb{E}[a_j^2 s(x_i)^2 s(x_j)^2 X_j^2]
\]
\[
= \sum_{j \neq i} a_j^2 \mathbb{E}[X_j^2]
\]

\[
\begin{align*}
&\text{s(x) = \pm 1,} \\
&\text{SO} \\
&\text{s(x)^2 = 1}
\end{align*}
\]
\[
\text{Var}[\hat{a}_i] = \text{Var}[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j]
\]
\[
= \text{Var}\left[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j\right]
\]
\[
= \sum_{j \neq i} \text{Var}[a_j s(x_i) s(x_j) X_j]
\]
\[
\leq \sum_{j \neq i} \mathbb{E}\left[(a_j s(x_i) s(x_j) X_j)^2\right]
\]
\[
= \sum_{j \neq i} \mathbb{E}[a_j^2 s(x_i)^2 s(x_j)^2 X_j^2]
\]
\[
= \sum_{j \neq i} a_j^2 \mathbb{E}[X_j^2]
\]

\[
X_j = \begin{cases} 
1 & \text{if } h(x_i) = h(x_j) \\
0 & \text{if } h(x_i) \neq h(x_j)
\end{cases}
\]
\begin{align*}
\text{Var}[\hat{a}_i] &= \text{Var}[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j] \\
&= \text{Var}\left[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j\right] \\
&= \sum_{j \neq i} \text{Var}[a_j s(x_i) s(x_j) X_j] \\
&\leq \sum_{j \neq i} \mathbb{E}\left[\left(a_j s(x_i) s(x_j) X_j\right)^2\right] \\
&= \sum_{j \neq i} \mathbb{E}[a_j^2 s(x_i)^2 s(x_j)^2 X_j^2] \\
&= \sum_{j \neq i} a_j^2 \mathbb{E}[X_j^2]
\end{align*}

**Useful Fact:**
If $X$ is an indicator variable, then $X^2 = X$. 

\[X_j^2 = \begin{cases} 
1 & \text{if } h(x_i) = h(x_j) \\
0 & \text{if } h(x_i) \neq h(x_j) 
\end{cases} \]
\[
\text{Var}[\hat{a}_i] = \text{Var}[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j]
\]

\[
= \text{Var}[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j]
\]

\[
= \sum_{j \neq i} \text{Var}[a_j s(x_i) s(x_j) X_j]
\]

\[
\leq \sum_{j \neq i} \mathbb{E}[(a_j s(x_i) s(x_j) X_j)^2]
\]

\[
= \sum_{j \neq i} \mathbb{E}[a_j^2 s(x_i)^2 s(x_j)^2 X_j^2]
\]

\[
= \sum_{j \neq i} a_j^2 \mathbb{E}[X_j^2]
\]

\[
= \sum_{j \neq i} a_j^2 \mathbb{E}[X_j]
\]

**Useful Fact:**
If \(X\) is an indicator variable, then \(X^2 = X\).
\[ \text{Var}[\hat{a}_i] = \text{Var}[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j] \]

\[ = \text{Var}\left[ \sum_{j \neq i} a_j s(x_i) s(x_j) X_j \right] \]

\[ = \sum_{j \neq i} \text{Var}[a_j s(x_i) s(x_j) X_j] \]

\[ \leq \sum_{j \neq i} E\left[ (a_j s(x_i) s(x_j) X_j)^2 \right] \]

\[ = \sum_{j \neq i} E[ a_j^2 s(x_i)^2 s(x_j)^2 X_j^2 ] \]

\[ = \sum_{j \neq i} a_j^2 E[X_j^2] \]

\[ = \sum_{j \neq i} a_j^2 E[X_j] \]

\[ X_j = \begin{cases} 
1 & \text{if } h(x_i) = h(x_j) \\
0 & \text{if } h(x_i) \neq h(x_j) 
\end{cases} \]
\begin{align*}
\text{Var}[\hat{a}_i] &= \text{Var}[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j] \\
&= \text{Var}\left[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j\right] \\
&= \sum_{j \neq i} \text{Var}[a_j s(x_i) s(x_j) X_j] \\
&\leq \sum_{j \neq i} \mathbb{E}\left[(a_j s(x_i) s(x_j) X_j)^2\right] \\
&= \sum_{j \neq i} \mathbb{E}[a_j^2 s(x_i)^2 s(x_j)^2 X_j^2] \\
&= \sum_{j \neq i} a_j^2 \mathbb{E}[X_j^2] \\
&= \sum_{j \neq i} a_j^2 \mathbb{E}[X_j] \\
&= \sum_{j \neq i} a_j^2 / w \\
X_j &= \begin{cases} 
1 & \text{if } h(x_i) = h(x_j) \\
0 & \text{if } h(x_i) \neq h(x_j) 
\end{cases}
\end{align*}
\[
\begin{align*}
\text{Var}[\hat{a}_i] &= \text{Var}[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j] \\
&= \text{Var}\left[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j \right] \\
&= \sum_{j \neq i} \text{Var}[a_j s(x_i) s(x_j) X_j] \\
&\leq \sum_{j \neq i} \mathbb{E}\left[ (a_j s(x_i) s(x_j) X_j)^2 \right] \\
&= \sum_{j \neq i} \mathbb{E}[a_j^2 s(x_i)^2 s(x_j)^2 X_j^2] \\
&= \sum_{j \neq i} a_j^2 \mathbb{E}[X_j^2] \\
&= \sum_{j \neq i} a_j^2 \mathbb{E}[X_j] \\
&= \sum_{j \neq i} a_j^2 / w \\
\end{align*}
\]
\[\sqrt{\sum_{j} a_j^2} = \|a\|_2\]
$$\text{Var}[\hat{a}_i] = \text{Var}[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j]$$

$$= \text{Var}\left[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j\right]$$

$$= \sum_{j \neq i} \text{Var}[a_j s(x_i) s(x_j) X_j]$$

$$\leq \sum_{j \neq i} \mathbb{E}\left[(a_j s(x_i) s(x_j) X_j)^2\right]$$

$$= \sum_{j \neq i} \mathbb{E}[a_j^2 s(x_i)^2 s(x_j)^2 X_j^2]$$

$$= \sum_{j \neq i} a_j^2 \mathbb{E}[X_j^2]$$

$$= \sum_{j \neq i} a_j^2 \mathbb{E}[X_j]$$

$$= \sum_{j \neq i} a_j^2 / w$$

$$\leq \|a\|_2^2 / w$$

$$\sqrt{\sum_j a_j^2} = \|a\|_2$$
\[
\text{Var}[\hat{a}_i] = \text{Var}[a_i + \sum_{j \neq i} a_j s(x_i) s(x_j) X_j]
\]
\[
= \text{Var}\left[\sum_{j \neq i} a_j s(x_i) s(x_j) X_j\right]
\]
\[
= \sum_{j \neq i} \text{Var}[a_j s(x_i) s(x_j) X_j]
\]
\[
\leq \sum_{j \neq i} E[(a_j s(x_i) s(x_j) X_j)^2]
\]
\[
= \sum_{j \neq i} E[a_j^2 s(x_i)^2 s(x_j)^2 X_j^2]
\]
\[
= \sum_{j \neq i} a_j^2 E[X_j^2]
\]
\[
= \sum_{j \neq i} a_j^2 E[X_j]
\]
\[
= \sum_{j \neq i} a_j^2 / w
\]
\[
\leq \|a\|_2^2 / w
\]

I know this might look really dense, but many of these substeps end up being really useful techniques. These ideas generalize, I promise.
Harnessing Chebyshev

- Chebyshev's Inequality says
\[
\Pr\left[ |X - E[X]| \geq c \sqrt{\text{Var}[X]} \right] \leq 1/c^2
\]

- Applying this to \( \hat{a}_i \) yields
\[
\Pr\left[ |\hat{a}_i - a_i| \geq \frac{c \|a\|_2}{\sqrt{w}} \right] \leq 1/c^2
\]

- Given error parameter \( \varepsilon \), pick \( w = [e / \varepsilon^2] \), so
\[
\Pr\left[ |\hat{a}_i - a_i| \geq \frac{c \varepsilon \|a\|_2}{\sqrt{e}} \right] \leq 1/c^2
\]

- Therefore, choosing \( c = e^{1/2} \) gives
\[
\Pr\left[ |\hat{a}_i - a_i| \geq \varepsilon \|a\|_2 \right] \leq 1/e
\]
The Story So Far

• We now know that, by setting $\varepsilon = (e / w)^{1/2}$, the estimate is within $\varepsilon \|a\|_2$ with probability at least $1 - 1 / e$.

• Solving for $w$, this means that we will choose $w = \lceil e / \varepsilon^2 \rceil$.

• Space usage is now $O(\varepsilon^{-2})$, but the error bound is now $\varepsilon \|a\|_2$ rather than $\varepsilon \|a\|_1$.

• As before, the next step is to reduce the error probability.
Repetitions with a Catch

• As before, our goal is to make it possible to choose a bound $0 < \delta < 1$ so that the confidence is at least $1 - \delta$.

• As before, we'll do this by making $d$ independent copies of the data structure and running each in parallel.

• Unlike the count-min sketch, errors in count sketches are two-sided; we can overshoot or undershoot.

• Therefore, it's not meaningful to take the minimum or maximum value.

• How do we know which value to report?
Working with the Median

- **Claim:** If we output the median estimate given by the data structures, we have high probability of giving the right answer.
- **Intuition:** The only way we report an answer more than $\varepsilon||a||_2$ is if at least half of the data structures output an answer that is more than $\varepsilon||a||_2$ from the true answer.
- Each individual data structure is wrong with probability at most $1/e$, so this is highly unlikely.
The Setup

- Let $X$ denote a random variable equal to the number of data structures that produce an answer not within $\varepsilon \|a\|_2$ of the true answer.
- Since each independent data structure has failure probability at most $1 / e$, we can upper-bound $X$ with a $\text{Binom}(d, 1 / e)$ variable.
- We want to know $\Pr[X > d / 2]$.
- How can we determine this?
Chernoff Bounds

- The **Chernoff bound** says that if \( X \sim \text{Binom}(n, p) \) and \( p < 1/2 \), then

\[
\Pr[X > n/2] < e^{\frac{-n(1/2-p)^2}{2p}}
\]
Chernoff Bounds

- The **Chernoff bound** says that if $X \sim \text{Binom}(n, p)$ and $p < 1/2$, then

  $$\Pr[X > n/2] < e^{\frac{-n(1/2-p)^2}{2p}}$$

- In our case, $X \sim \text{Binom}(d, 1/e)$, so we know that

  $$\Pr[X > \frac{d}{2}] \leq e^{\frac{-d(1/2-1/e)^2}{2(1/e)}}$$
The \textbf{Chernoff bound} says that if $X \sim \text{Binom}(n, p)$ and $p < 1/2$, then

$$\Pr[X > n/2] < e^{\frac{-n(1/2-p)^2}{2p}}$$

In our case, $X \sim \text{Binom}(d, 1/e)$, so we know that

$$\Pr[X > \frac{d}{2}] \leq e^{\frac{-d(1/2-1/e)^2}{2(1/e)}}$$

$$= e^{-k \cdot d} \quad \text{(for some constant } k)$$
Chernoff Bounds

- The **Chernoff bound** says that if $X \sim \text{Binom}(n, p)$ and $p < 1/2$, then
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- In our case, $X \sim \text{Binom}(d, 1/e)$, so we know that
  $$\Pr[X > d/2] \leq e^{-d(1/2-1/e)^2/2(1/e)}$$
  $$= e^{-k \cdot d} \quad \text{(for some constant } k \text{)}$$

- Therefore, choosing $d = k^{-1} \cdot \log \delta$ ensures that
  $\Pr[X > d/2] \leq \delta$. 
Chernoff Bounds

- The **Chernoff bound** says that if $X \sim \text{Binom}(n, p)$ and $p < 1/2$, then

\[
\Pr[X > n/2] < e^{-\frac{-n(1/2-p)^2}{2p}}
\]

- In our case, $X \sim \text{Binom}(d, 1/e)$, so we know that

\[
\Pr[X > \frac{d}{2}] \leq e^{-\frac{-d(1/2-1/e)^2}{2(1/e)}} = e^{-k \cdot d} \quad \text{(for some constant } k)\]

- Therefore, choosing $d = k^{-1} \cdot \log \delta$ ensures that $\Pr[X > d/2] \leq \delta$.

- Therefore, the success probability is at least $1 - \delta$. 
Chernoff Bounds

- The **Chernoff bound** says that if $X \sim \text{Binom}(n, p)$ and $p < 1/2$, then

  $$\Pr[X > n/2] < e^{\frac{-n(1/2-p)^2}{2p}}$$

  In our case, $X \sim \text{Binom}(i, 1/e)$, so we know that

  $$\Pr[X > i/2] < e^{\frac{-d(1/2-1/e)^2}{2(1/e)}}$$

  The specific constant factor here matters, since it’s an exponent! To implement this data structure, you’ll need to work out the exact value.

- Therefore, choosing $d = k^{-1} \cdot \log \delta$ ensures that $\Pr[X > d / 2] \leq \delta$.

- Therefore, the success probability is at least $1 - \delta$. 
The Overall Construction

- The *count sketch* is the data structure given as follows.
- Given $\varepsilon$ and $\delta$, choose
  \[ w = \lceil \epsilon / \varepsilon^2 \rceil \quad d = \Theta(\log \delta^{-1}) \]
- Create an array `count` of $w \times d$ counters.
- Choose hash functions $h_i$ and $s_i$ for each of the $d$ rows.
- To *increment* $(x)$, add $s_i(x)$ to `count[i][h_i(x)]` for each row $i$.
- To *estimate* $(x)$, return the median of $s_i(x) \cdot \text{count}[i][h_i(x)]$ for each row $i$. 


The Final Analysis

- With probability at least $1 - \delta$, all estimates are accurate to within a factor of $\varepsilon \|a\|_2$.

- Space usage is $\Theta(w \times d)$, which we've seen to be $\Theta(\varepsilon^{-2} \cdot \log \delta^{-1})$.

- Updates and queries run in time $\Theta(\delta^{-1})$.

- Trades factor of $\varepsilon^{-1}$ space for an accuracy guarantee relative to $\|a\|_2$ versus $\|a\|_1$. 
In Practice

- These data structures have been and continue to be used in practice.
- These sketches and their variants have been used at Google and Yahoo! (or at least, there are papers coming from there about their usage).
- Many other sketches exist as well for estimating other quantities; they'd make for really interesting final project topics!
More to Explore

• A **cardinality estimator** is a data structure for estimating how many different elements have been seen in sublinear time and space. They're used extensively in database implementations.

• If instead of estimating $a_i$ terms individually we want to estimate $\|a\|_1$ or $\|a_2\|$, we can use a **frequency moment estimator**.

• You’ll get to play around with at least one of these on Problem Set Five.
Some Concluding Notes
Randomized Data Structures

- You may have noticed that the final versions of these data structures are actually not all that complex – each just maintains a set of hash functions and some 2D tables.
- The analyses, on the other hand, are a lot more involved than what we saw for other data structures.
- This is common – randomized data structures often have simple descriptions and quite complex analyses.
The Strategy

- Typically, an analysis of a randomized data structure looks like this:
  - First, show that the data structure (or some random variable related to it), on expectation, performs well.
  - Second, use concentration inequalities (Markov, Chebyshev, Chernoff, or something else) to show that it's unlikely to deviate from expectation.

- The analysis often relies on properties of some underlying hash function. On Tuesday, we'll explore why this is so important.
Next Time

- **Hashing Strategies**
  - There are a lot of hash tables out there. What do they look like?

- **Linear Probing**
  - The original hashing strategy!

- **Analyzing Linear Probing**
  - ...is way, way more complicated than you probably would have thought. But it's beautiful! And a great way to learn about randomized data structures!