COMPSCI 514: Algorithms for Data Science

Cameron Musco

University of Massachusetts Amherst. Fall 2022.

Lecture 6

Logistics

- Problem Set 1 is due tomorrow at 11:59pm in Gradescope.
- Quiz 3 is due Monday at 8pm.

Last Time

Last Class:

- Higher moment bounds and exponential concentration bounds
- Bernstein inequality

This Class:

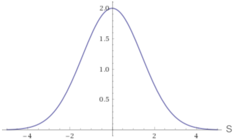
- Connection between exponential concentration bounds and the central limit theorem.
- The Chernoff bound.
- Bloom filters: random hashing to maintain a large set in small space.

Interpretation as a Central Limit Theorem

Bernstein Inequality (Simplified): Consider independent random variables $X_1, \ldots, X_n$ falling in [-1,1]. Let $\mu = \mathbb{E}[\sum X_i]$, $\sigma^2 = \text{Var}[\sum X_i]$, and $s \leq \sigma$. Then:

$$\Pr\left(\left|\sum_{i=1}^{n} X_i - \mu\right| \geq s\sigma\right) \leq 2\exp\left(-\frac{s^2}{4}\right).$$

Can plot this bound for different s:



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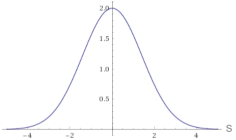

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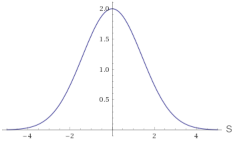

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Exercise: Using this can show that for $X \sim \mathcal{N}(0, \sigma^2)$: for any $s \geq 0$,

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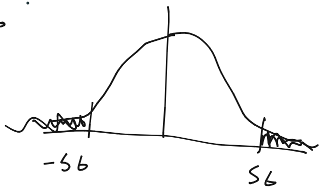

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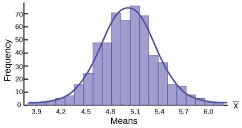
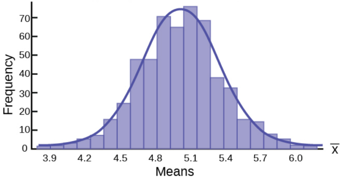
Central Limit Theorem Interpretation: Bernstein's inequality gives a quantitative version of the CLT. The distribution of the sum of *bounded* independent random variables can be upper bounded with a Gaussian (normal) distribution.



Central Limit Theorem

Stronger Central Limit Theorem: The distribution of the sum of *n* *bounded* independent random variables converges to a Gaussian (normal) distribution as *n* goes to infinity.



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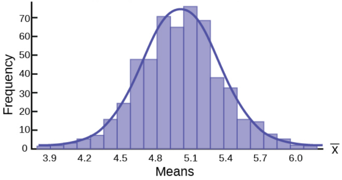

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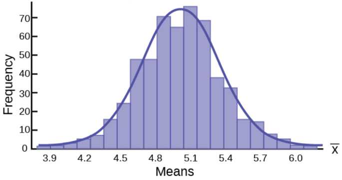

- Why is the Gaussian distribution is so important in statistics, science, ML, etc.?
- Many random variables can be approximated as the sum of a large number of small and roughly independent random effects. Thus, their distribution looks Gaussian by CLT.

A useful variation of the Bernstein inequality for binary (indicator) random variables is:

Chernoff Bound (simplified version): Consider independent random variables $X_1, \ldots, X_n$ taking values in $\{0, 1\}$. Let $\mu = \mathbb{E}[\sum_{i=1}^n X_i]$. For any $\delta \geq 0$

$\sum \mathbb{E} X_i$

$$\Pr\left(\left|\sum_{i=1}^n X_i - \mu\right| \geq \delta\mu\right) \leq 2\exp\left(-\frac{\delta^2\mu}{2+\delta}\right).$$

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As δ gets larger and larger, the bound falls of exponentially fast.

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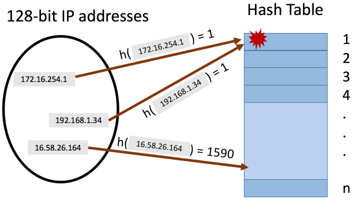

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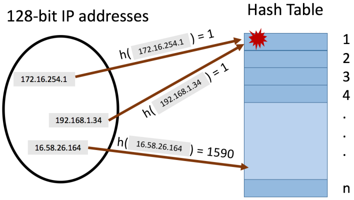

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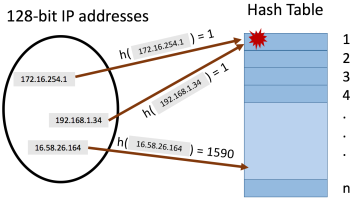

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What will be the maximum number of items hashed into the same location?

Maximum Load in Randomized Hashing

Let S_i be the number of items hashed into position i and $\mathsf{S}_{i,j}$ be 1 if x_j is hashed into bucket i ($\mathsf{h}(x_j) = i$) and 0 otherwise.

m: total number of items hashed and size of hash table. $x_1, \ldots, x_m$: the items.
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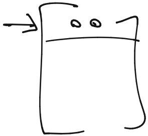

$$\mathbb{E}[\mathsf{S}_i] = \sum_{j=1}^{m} \mathbb{E}[\mathsf{S}_{i,j}] = m \cdot \frac{1}{m} = 1$$

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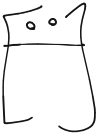

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By the Chernoff Bound: for any $\delta \geq 0$,

$$\Pr(\mathsf{S}_i \geq 1 + \delta) \leq \Pr\left(\left|\sum_{i=1} \mathsf{S}_{i,j} - 1\right| \geq \delta \cdot \mu\right) \leq 2\exp\left(-\frac{\delta^2}{2+\delta}\right)$$

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$\geq 20\log m + 1 \approx 20\log m$

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Apply Union Bound:

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- Using Chebyshev's inequality could only show the maximum load is bounded by $O(\sqrt{m})$ with good probability (good exercise).
- The Chebyshev bound holds even with a pairwise independent hash function. The stronger Chernoff-based bound can be shown to hold with a *k-wise independent hash function* for $k = O(\log m)$.

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Solution: Bloom filters (repeated random hashing). Will use much less space than a hash table.

Bloom Filters

Chose k independent random hash functions $h_1, \ldots, h_k$ mapping the universe of elements $U \to [m]$.

- Maintain an array A containing m bits, all initially 0.
- *insert*(x): set all bits $A[h_1(x)] = \ldots = A[h_k(x)] := 1$.
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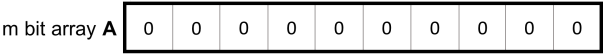

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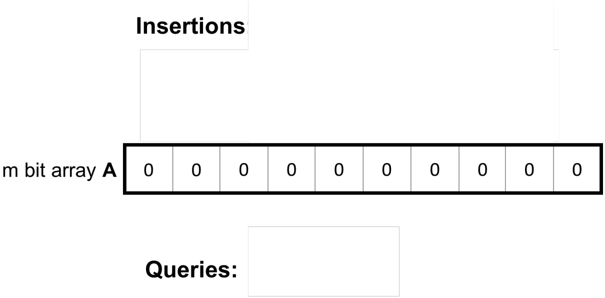

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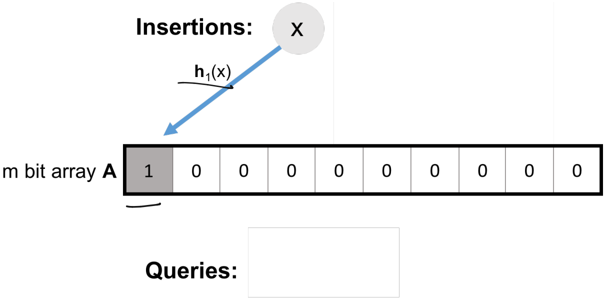

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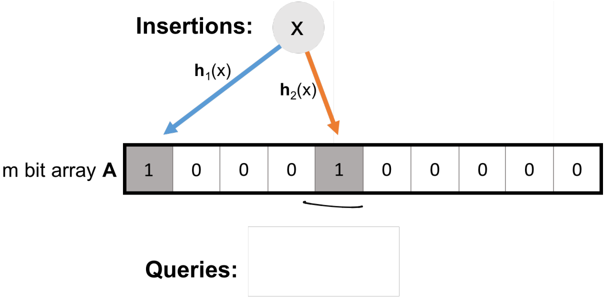

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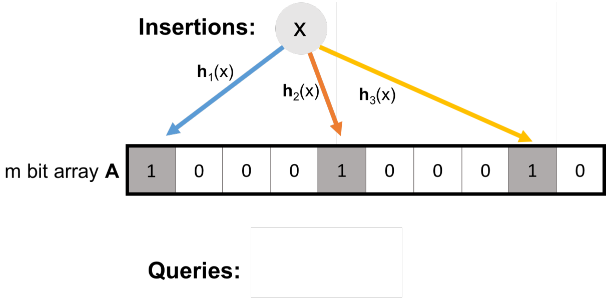

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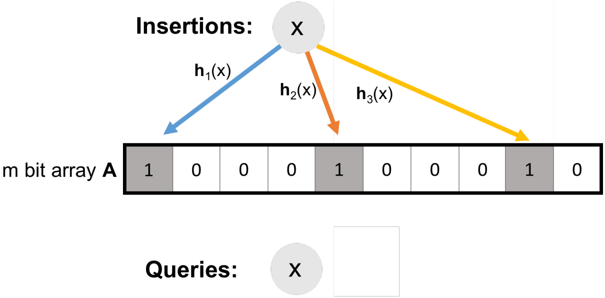

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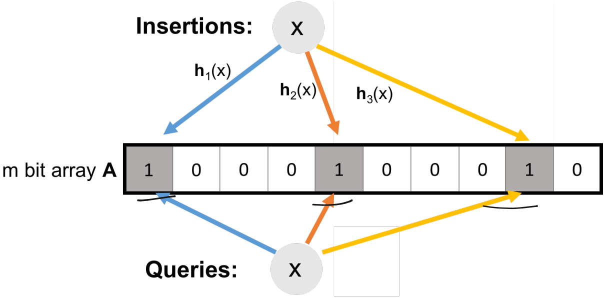

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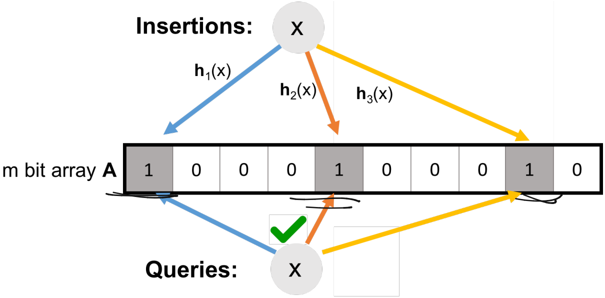

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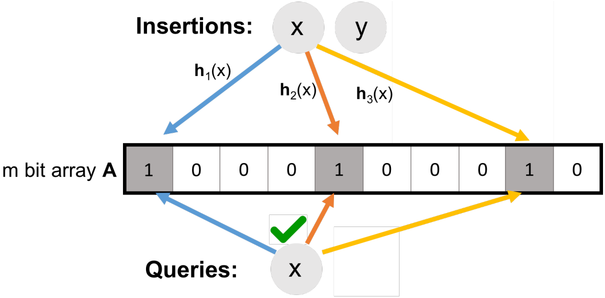

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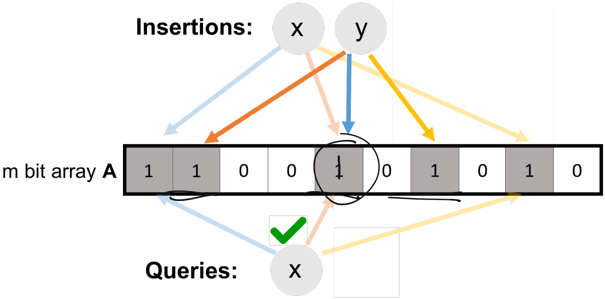

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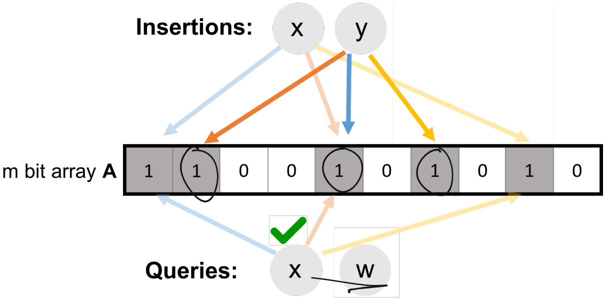

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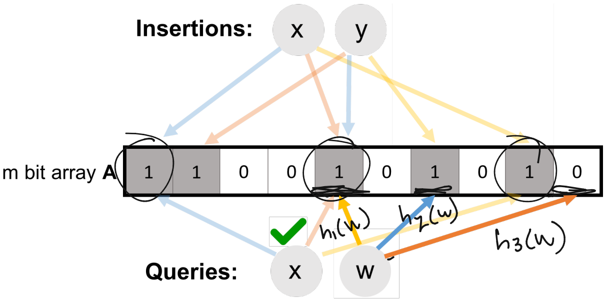

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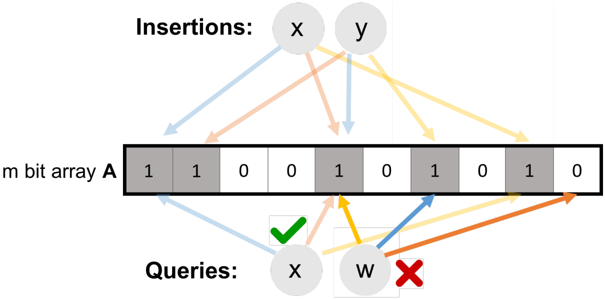

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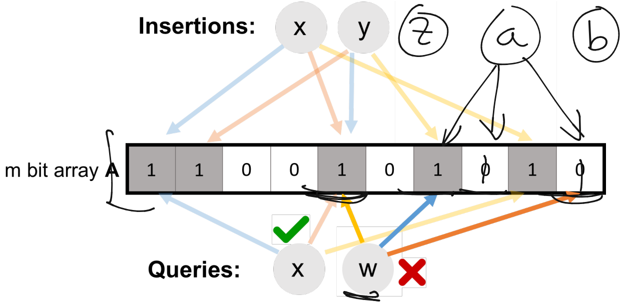
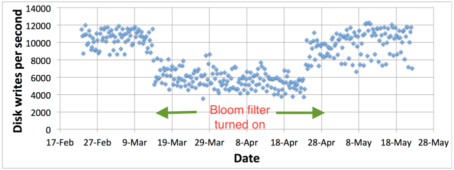


No false negatives. False positives more likely with more insertions.

Applications: Caching

Akamai (Boston-based company serving 15 – 30% of all web traffic) applies bloom filters to prevent caching of 'one-hit-wonders' – pages only visited once fill over 75% of cache.



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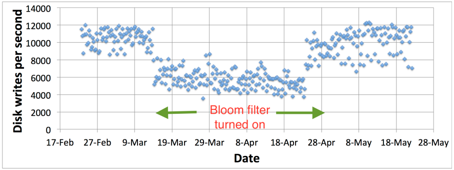

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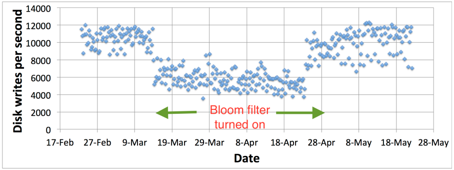

- When url x comes in, if $query(x) = 1$, cache the page at x. If not, run $insert(x)$ so that if it comes in again, it will be cached.
- **False positive:** A new url (possible one-hit-wonder) is cached. If the bloom filter has a false positive rate of $\delta = .05$, the number of cached one-hit-wonders will be reduced by at least 95%.

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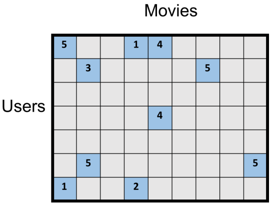

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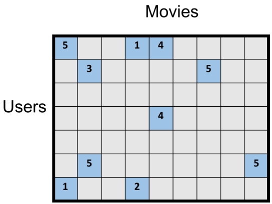

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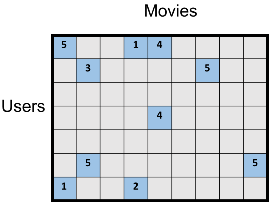

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- **False positive:** A read is made to a possibly empty cell. A $\delta = .05$ false positive rate gives a 95% reduction in these empty reads.

More Applications

- **Database Joins:** Quickly eliminate most keys in one column that don't correspond to keys in another.
- **Recommendation systems:** Bloom filters are used to prevent showing users the same recommendations twice.
- **Spam/Fraud Detection**:
  - Bit.ly and Google Chrome use bloom filters to quickly check if a url maps to a flagged site and prevent a user from following it.
  - Can be used to detect repeat clicks on the same ad from a single IP-address, which may be the result of fraud.
- **Digital Currency:** Some Bitcoin clients use bloom filters to quickly pare down the full transaction log to transactions involving bitcoin addresses that are relevant to them (SPV: simplified payment verification).

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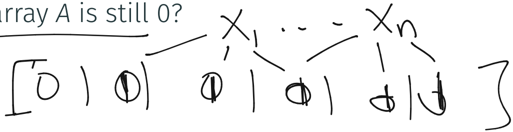

$$\left(\frac{m-1}{m}\right)^{nk}$$

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