

CSE 392: Matrix and Tensor Algorithms for Data

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Spring 2024

Lecture 2: Probability Review

Outline

1 Probability review

2 Concentration inequalities

This lecture

Topics to be covered today

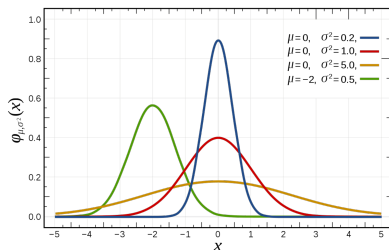
- Probability and properties.
- Concentration measures.
 - ▶ Markov and Chebyshev inequality
 - ▶ CLT and tail bounds

Probability review

Let x be a random variable taking value in some set \mathbb{S} .

For continuous random variable, it might be $\mathbb{S} = \mathbb{R}$.

- **Expectation:** $\mathbb{E}[x] = \sum_{s \in \mathbb{S}} s \cdot \Pr[x = s]$
For continuous case, $\mathbb{E}[x] = \int_{s \in \mathbb{S}} s \cdot \Pr[x = s] ds$
- **Variance:** $\text{Var}[x] = \mathbb{E}[(x - \mathbb{E}[x])^2] = \mathbb{E}[x^2] - \mathbb{E}[x]^2$



Exerise 1: For any scalar α , show that $\mathbb{E}[\alpha x] = \alpha \mathbb{E}[x]$ and $\text{Var}[\alpha x] = \alpha^2 \text{Var}[x]$.

Probability review

Let A and B be random events. Then,

- **Joint Probability:** $\Pr(A \cap B)$ - The probability that both events happen.
- **Conditional Probability:** $\Pr(A \mid B) = \frac{\Pr(A \cap B)}{\Pr(B)}$. Probability A happens conditioned on the event that B happens.
- **Independence:** A and B are independent events if: $\Pr(A \mid B) = \Pr(A)$.
For independent events, we also have that

$$\Pr(A \cup B) = \Pr(A) \cdot \Pr(B)$$

- **Mutually exclusive** events : $\Pr(A \cap B) = 0$.

Probability review

Random sampling can be:

- *with replacement*
- *without replacement*

Question: Which of the above event is independent?

Example: What is the probability that for two independent dice rolls taking values uniformly in $\{1, 2, 3, 4, 5, 6\}$, the first roll comes up even and the second is < 4 ?

Expectation

For random variables x and y ,

- **Linearity of expectation:** For constants $c_1, c_2 \in \mathbb{R}$,

$$\mathbb{E}[c_1x + c_2y] = c_1\mathbb{E}[x] + c_2\mathbb{E}[y].$$

Result holds irrespective of the dependence between x and y .

- **Law of Total Expectation:** If the sample space is the disjoint union of events A_1, A_2, \dots , then

$$\mathbb{E}[x] = \sum_i \mathbb{E}[x \mid A_i] \Pr(A_i).$$

- **Product of expectation:** For any two independent random variables x and y ,

$$\mathbb{E}[x \cdot y] = \mathbb{E}[x] \cdot \mathbb{E}[y]$$

also $\text{Var}[x + y] = \text{Var}[x] + \text{Var}[y]$.

Norms of random variables

- **Moment norm:** For a real random variable x and $p \geq 1$, let

$$\|x\|_p = \mathbb{E}[|x|^p]^{1/p}.$$

We use $\|\cdot\|$ to distinguish from matrix/vector norm.

- For real random variables x, y and $p \geq 1$,
(Minkowski) $\|x + y\|_p \leq \|x\|_p + \|y\|_p$,
and for $\alpha \in \mathbb{R}$, $\|\alpha x\|_p = |\alpha| \|x\|_p$.
- **Centered random variables:** Random variable $x \in \mathbb{R}$ is centered if $\mathbb{E}[x] = 0$.
- **Tail from norms:** For $t > 0$, for centered x ,

$$\Pr\{|x| \geq t\} \leq \|x\|_p^p / t^p$$

- For centered x , $\|x\|_2^2 = \mathbb{E}[x^2] = \text{Var}[x]$. So, $\|x\|_2 = \text{sd}[x]$.
- We know that for two independent random variables x, y ,

$$\text{Var}[x + y] = \text{Var}[x] + \text{Var}[y].$$

So, if they are also centered, then

$$\|x + y\|_2 = \sqrt{\|x\|_2^2 + \|y\|_2^2} \leq \|x\|_2 + \|y\|_2.$$

- **Sub-Gaussian norms:** For a real random variable x ,

$$\|x\|_{\psi_2} \equiv \sup_{p \geq 1} \|x\|_p / \sqrt{p}$$

If $\|x\|_{\psi_2}$ is bounded, we call x *sub-Gaussian*.

Concentration inequalities

One of the key tools in analyzing randomized algorithms.

How likely a random variable x deviates a certain amount from its expectation $\mathbb{E}[x]$.

We will learn three fundamental concentration inequalities:

- **Markov's Inequality** - Applies to *non-negative* random variables.
- **Chebyshev's Inequality** - For random variables with *bounded variance*.
- **Hoeffding/Bernstein/Chernoff bounds** - For *sums of independent* random variables.

Markov's Inequality

For any random variable x which only takes *non-negative* values, and any positive t ,

$$\Pr[x \geq t] \leq \frac{\mathbb{E}[x]}{t}.$$

Equivalently, $\Pr[x \geq \alpha \cdot \mathbb{E}[x]] \leq \frac{1}{\alpha}$.

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Proof: We have to show that $\mathbb{E}[x] \geq t \cdot \Pr[x \geq t]$:

$$\begin{aligned}\mathbb{E}[x] &= \sum_k k \cdot \Pr(x = k) \\ &\geq \sum_{k \geq t} k \cdot \Pr(x = k) \\ &\geq \sum_{k \geq t} t \cdot \Pr(x = k) \\ &= t \cdot \sum_{k \geq t} \Pr(x = k)\end{aligned}$$

Example

A coin is weighted so that its probability of landing on heads is 20%. Suppose the coin is flipped 20 times. Find a bound for the probability it lands on heads at least 16 times.

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Binomial distribution - $n = 20, p = 0.2$

$$\mathbb{E}[x] = n \cdot p = 20 * 0.2 = 4.$$

Let us use **Markov's**:

$$\Pr[x \geq 16] \leq \frac{\mathbb{E}[x]}{16} = 0.25.$$

Is this a good estimate?

Popular applications: k -frequent items, hash functions, and others.

Union Bound

Union Bound

For any random events A_1, \dots, A_k :

$$\Pr[A_1 \cup A_2 \cup \dots \cup A_k] \leq \Pr[A_1] + \Pr[A_2] + \dots + \Pr[A_k]$$

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$$\Pr[A_1 \cup A_2 \cup \dots \cup A_k] \leq \Pr[A_1] + \Pr[A_2] + \dots + \Pr[A_k]$$

Proof: Choose $x_i = \mathbb{1}[A_i]$, and we apply Markov's to $S = \sum_{i=1}^k x_i$.

Hint: Express the union event $A_1 \cup A_2 \cup \dots \cup A_k$ in terms of S . What is $\mathbb{E}[x_i] = ?$

Chebyshev's Inequality

Let x be a random variable, then for any $k > 0$,

$$\Pr(|x - \mathbb{E}[x]| \geq k) \leq \frac{\text{Var}[x]}{k^2}.$$

Chebyshev's Inequality

Let x be a random variable, then for any $k > 0$,

$$\Pr(|x - \mathbb{E}[x]| \geq k) \leq \frac{\text{Var}[x]}{k^2}.$$

Proof: Note that

$$\Pr(|x - \mathbb{E}[x]| \geq k) = \Pr((x - \mathbb{E}[x])^2 \geq k^2).$$

Applying Markov's inequality to the random variable $(x - \mathbb{E}[x])^2$ gives us the result.

- Alternatively, for any $c > 0$,

$$\Pr(|x - \mathbb{E}[x]| \geq c \cdot \sigma_x) \leq \frac{1}{c^2},$$

where $\sigma_x = \sqrt{\text{Var}[x]} = \sqrt{\mathbb{E}[(x - \mathbb{E}[x])^2]}$, is the *standard deviation* of x .

Properties of Chebyshev's inequality

- x need not be non-negative.
- It is a two-sided bound, gives the probability that $|x - \mathbb{E}[x]|$ is large or not.
I.e., x is not too far above or below its expectation.
Markov's only bounded probability that x exceeds $\mathbb{E}[x]$.
- Probability of x being c times away from σ .
- We need a bound on the variance of x .

It is worst case bound, may not be tight in many cases.

Gaussian concentration

For $x \sim \mathcal{N}(\mu, \sigma^2)$, we have:

$$\Pr[x = \mu \pm x] \sim \frac{1}{\sigma\sqrt{2\pi}} e^{-x^2/2\sigma^2}$$

Gaussian Tail Bound:

For $x \sim \mathcal{N}(\mu, \sigma^2)$,

$$\Pr[|x - \mu| \geq k \cdot \sigma] \leq e^{-k^2/2}$$

Where as, using Chebyshev's inequality we get $\Pr[|x - \mu| \geq k \cdot \sigma] \leq 1/k^2$

Gaussian random variables concentrate *much tighter* around their expectation than what Chebyshev's inequality predicts.

Central limit theorem

Lindeberg–Levy CLT:

Suppose $\{x_1, \dots, x_n\}$ is a sequence of i.i.d. random variables with $\mathbb{E}[x_i] = \mu$ and $\text{Var}[x_i] = \sigma^2 < \infty$. Then, as n approaches infinity, the random variables $\sqrt{n}(\bar{x}_n - \mu)$, where $\bar{x}_n = \sum_{i=1}^n x_i/n$ converge in distribution to a normal $\mathcal{N}(0, \sigma^2)$:

$$\sqrt{n}(\bar{x}_n - \mu) \xrightarrow{a} \mathcal{N}(0, \sigma^2).$$

CLT can be made rigorous to obtain tighter tail bounds than Chebyshev's inequality.

- Chernoff bound
- Bernstein bound
- Hoeffding bound

Different assumptions on random variables (e.g. binary vs. bounded), different forms (additive vs. multiplicative error), etc.

Chernoff Bound

Chernoff Bounds

Let $X = \sum_{i=1}^n x_i$, where $x_i = 1$ with probability p_i and $x_i = 0$ with probability $1 - p_i$, and all x_i are independent. Let $\mu = \mathbb{E}(X) = \sum_{i=1}^n p_i$. Then

- **Upper Tail:** $\Pr(X \geq (1 + \delta)\mu) \leq e^{-\frac{\delta^2}{2+\delta}\mu}$ for all $\delta > 0$;
- **Lower Tail:** $\Pr(X \leq (1 - \delta)\mu) \leq e^{-\frac{\delta^2}{2}\mu}$ for all $0 < \delta < 1$;

Idea of proof:

Based on applying Markov's inequality to moment generating function $\mathbb{E}[e^{s|X - \mathbb{E}[X]|}]$.

Bernstein Inequality

Bernstein Inequality

Let x_1, \dots, x_k be independent random variables with each $x_i \in [-1, 1]$. Let $\mathbb{E}[x_i] = \mu_i$ and $\text{Var}[x_i] = \sigma_i^2$. Let $\mu = \sum_i \mu_i$ and $\sigma^2 = \sum_i \sigma_i^2$. Then, for $k \leq \frac{1}{2}\sigma$, $S = \sum_i x_i$ satisfies

$$\Pr[|S - \mu| \geq k \cdot \sigma] \leq 2e^{-k^2/4}.$$

Idea of proof:

Based on applying Markov's inequality to $e^{\lambda \sum_i x_i}$ for suitable choice of the parameter $\lambda > 0$.

Hoeffding Inequality

Hoeffding Inequality

Let x_1, \dots, x_k be independent random variables with each $x_i \in [a_i, b_i]$. Let $\mathbb{E}[x_i] = \mu_i$ and $\text{Var}[x_i] = \sigma_i^2$. Let $\mu = \sum_i \mu_i$ and $\sigma^2 = \sum_i \sigma_i^2$. Then, for any $\alpha > 0$, $S = \sum_i x_i$ satisfies

$$\Pr[|S - \mu| \geq \alpha] \leq 2e^{-\frac{\alpha^2}{\sum_i (a_i - b_i)^2}}.$$

Idea of proof: Similar to Chernoff bounds. We use that for a real random variable $x \in [a, b]$ almost surely,

$$\mathbb{E} \left[e^{s(x - \mathbb{E}[x])} \right] \leq \exp \left(\frac{1}{8} s^2 (b - a)^2 \right).$$

Example

Coin flip application

We are given a biased coin which lands heads with probability p . How many k times should we flip to ensure

$$\Pr[|\#heads - p \cdot k| \geq \epsilon k] \leq \delta.$$

Setup: Let $x_i = \mathbb{1}[i^{th} \text{ flip is heads}]$. We want bound probability that $S = \sum_{i=1}^k x_i$ deviates from the expectation.

Using Chebyshev: $k \geq ?$

Using Chernoff: $k \geq ?$

Recommended reading:

A good reference for introduction and proofs of the various concentration inequalities, see Dr. Karthik Sridharan's article:

A Gentle Introduction to Concentration Inequalities.

Questions?