Concentration of Measure: Markov's, Chebyshev's and Hoeffding's Inequalities

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(Partially based on Yevgeny Seldin's Slides)

Outline

Motivation: Supervised Learning

- A finite hypothesis class $\mathcal{H}$
- A sample $S = ((X_1, Y_1), \ldots, (X_n, Y_n))$, with elements independently drawn from a fixed (but unknown) distribution.
- $\ell(h(X), Y)$ is the loss of $h \in \mathcal{H}$ on (X, Y)
- $L(h) = \mathbb{E}[\ell(h(X), Y)]$ is unknown.
- Empirical loss of h:

$$\widehat{L}(h, S) = \frac{1}{n} \sum_{i=1}^{n} \ell(h(X_i), Y_i)$$

- $\widehat{L}(h, S)$ is an unbiased estimator of $L(h)$: $\mathbb{E}[\widehat{L}(h, S)] = L(h)$

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What can be said about $L(h)$?

Motivation: Bernoulli Trials

Assume a certain treatment is successful with probability p, and failing otherwise.

- p is unknown, but is fixed for all subject patients.
- Let $X_1, \ldots, X_n$ be the realized outcomes on n patients.
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How close is $\widehat{p}_n$ to p for a given n?
How much patients do we need to try so that $\widehat{p}_n$ is not farther than p by some ε?

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Recap: Independence

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- X and Y are independent $\Longrightarrow \mathbb{E}[XY] = \mathbb{E}[X]\mathbb{E}[Y]$.
- A collection of r.v.'s $X_1, \ldots, X_n$ are independent if every pair in the collection is independent.
- If $X_1, \ldots, X_n$ are independent and have identical distribution (i.e., $F_{X_1} = \ldots = F_{X_n}$), then they are called independent identically distributed (i.i.d.) r.v.'s.

Recap: Asymptotic Convergence Results

Consider i.i.d. r.v.'s $X_1, \ldots, X_n$, with $\mathbb{E}[X_1] = \mu$ and $\mathrm{Var}(X_1) = \sigma^2 < \infty$.

- Sample mean:

$$\overline{X}_n = \frac{1}{n} \sum_{i=1}^{n} X_i$$

- $\overline{X}_n$ is an unbiased estimate of μ:

$$\mathbb{E}[\overline{X}_n] = \mu$$

- By the Central Limit Theorem (CLT), $\overline{X}_n$ asymptotically converges to μ in distribution:

$$\sqrt{n}(\overline{X}_n - \mu) \xrightarrow{\text{distribution}}_{n\to\infty} \mathcal{N}(0, \sigma^2)$$

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- By the Strong Law of Large Numbers (SLLN), $\overline{X}_n$ asymptotically converges to μ almost surely:

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Most often, concentration inequalities provide upper bounds on

$$\mathbb{P}\Big(f(X_1, \ldots, X_n) > \varepsilon\Big)$$

for a finite set of (conditionally) independent r.v.'s $X_1, \ldots, X_n$.

Outline

Markov's Inequality

Theorem (Markov's Inequality)

Suppose X is a non-negative r.v. Then for all $\varepsilon > 0$,

$$\mathbb{P}(X \geq \varepsilon) \leq \frac{\mathbb{E}[X]}{\varepsilon}$$

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Proof. Define $Y = \mathbb{I}(X \geq \varepsilon) = \begin{cases} 1 & X \geq \varepsilon \\ 0 & \text{otherwise} \end{cases}$. Y is a Bernoulli r.v. and $\mathbb{E}[Y] = \mathbb{P}(Y = 1)$. Thus,

$$\mathbb{P}(X \geq \varepsilon) = \mathbb{P}(Y = 1) = \mathbb{E}[Y] \leq \mathbb{E}\left[\frac{X}{\varepsilon}\right]$$

Markov's Inequality: Examples

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- $\mathbb{P}(X \geq \varepsilon) = \mathbb{P}(e^X \geq e^\varepsilon) \leq e^{-\varepsilon}\mathbb{E}[e^X]$
- For $X_1, \ldots, X_n$ i.i.d. with mean μ,

$$\mathbb{P}(\mu - \overline{X}_n > \varepsilon) \leq \frac{1-\mu}{\varepsilon + 1 - \mu} \leq \frac{1}{\varepsilon + 1}$$

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Theorem (Markov's Inequality)

Suppose X is a non-negative r.v. and f is a monotonically increasing function. Then for all $\varepsilon > 0$,

$$\mathbb{P}(X \geq \varepsilon) \leq \frac{\mathbb{E}[f(X)]}{f(\varepsilon)}$$

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$$\begin{aligned}
\mathbb{P}(|X - \mathbb{E}[X]| \geq \varepsilon) &= \mathbb{P}(|X - \mathbb{E}[X]|^2 \geq \varepsilon^2) \\
&\leq \frac{\mathbb{E}[|X - \mathbb{E}[X]|^2]}{\varepsilon^2} \qquad \text{(Markov's inequality)} \\
&= \frac{\mathrm{Var}(X)}{\varepsilon^2}
\end{aligned}$$

Chebyshev's Inequality: Examples

Example 1: A fair coin is tossed 20 times. Let $X_1, \ldots, X_{20}$ be the realized outcomes. Then,

$$\mathbb{P}(|\overline{X}_{20} - \mu| \geq 0.2) \leq \frac{\mathrm{Var}(\overline{X}_{20})}{0.2^2} = \frac{\frac{1}{20}\mathrm{Var}(X_1)}{0.04} = \frac{\frac{1}{20} \cdot \frac{1}{4}}{0.04}$$

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Example 2: A fair die is rolled 60 times. Let $X_1, \dots, X_{20}$ be the realized outcomes. Upper bound

$$\mathbb{P}(|\sum_i X_i - 210| \geq 20)$$

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Example 2: A fair die is rolled 60 times. Let $X_1, \dots, X_{20}$ be the realized outcomes. Upper bound

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- $\mathbb{E}[X_1] = \frac{7}{2}$. Hence, $\mathbb{E}[\sum_i X_i] = 210$.
- $\mathrm{Var}(\sum_i X_i) = \frac{35}{12}$
- $\mathbb{P}(|\sum_i X_i - 210| \geq 20) \leq \frac{175}{20^2}$

Chebyshev's Inequality

Theorem (Chebyshev's Inequality for I.I.D. Variables)

Let $X_1, \ldots, X_n$ be i.i.d. r.v.'s. Then, for all $\varepsilon > 0$,

$$\mathbb{P}(|\overline{X}_n - \mu| \geq \varepsilon) \leq \frac{\mathrm{Var}(X_1)}{\varepsilon^2}$$

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$$\mathbb{P}(|\overline{X}_n - \mu| \geq \varepsilon) \leq \frac{\mathrm{Var}(X_1)}{\varepsilon^2}$$

Chebyshev's inequality provides a result that decays at a rate $\frac{1}{n}$.

Outline

Hoeffding's Inequality

Theorem (Hoeffding's Inequality)

Let $X_1, \ldots, X_n$ be independent r.v.'s with support $[0, 1]$. Then, for all $\varepsilon > 0$,

$$\text{(i)} \quad \mathbb{P}\left(\sum_{i=1}^n X_i - \mathbb{E}\left[\sum_{i=1}^n X_i\right] \geq \varepsilon\right) \leq e^{-2\varepsilon^2/n}$$

$$\text{(ii)} \quad \mathbb{P}\left(\sum_{i=1}^n X_i - \mathbb{E}\left[\sum_{i=1}^n X_i\right] \leq -\varepsilon\right) \leq e^{-2\varepsilon^2/n}$$

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- Using a union bound:

$$\mathbb{P}\left(\left|\sum_{i=1}^{n} X_i - \mathbb{E}\left[\sum_{i=1}^{n} X_i\right]\right| \geq \varepsilon\right) \leq 2e^{-2\varepsilon^2/n}$$

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- Also, $\mathbb{P}\left(\Big|\frac{1}{n}\sum_{i=1}^n X_i - \frac{1}{n}\mathbb{E}\Big[\sum_{i=1}^n X_i\Big]\Big| \geq \varepsilon\right) \leq 2e^{-2n\varepsilon^2}$
- If X_i's are i.i.d. with mean μ: $\mathbb{P}\left(\Big|\frac{1}{n}\sum_{i=1}^n X_i - \mu\Big| \leq \varepsilon\right) \geq 2e^{-2n\varepsilon^2}$.

  Hoeffding's bound decays exponentially fast in n.

Hoeffding's Inequality: Alternative Form

If X_i's are i.i.d. with mean μ: $\mathbb{P}\left(\frac{1}{n}\sum_{i=1}^n X_i - \mu \geq \varepsilon\right) \leq \underbrace{e^{-2n\varepsilon^2}}_{=\delta}$

Solving $\delta = e^{-2n\varepsilon^2}$ yields $\varepsilon = \sqrt{\frac{1}{2n}\log\left(\frac{1}{\delta}\right)}$ Hence,

$$\mathbb{P}\left(\frac{1}{n}\sum_{i=1}^n X_i - \mu \geq \sqrt{\frac{1}{2n}\log\left(\frac{1}{\delta}\right)}\right) \leq \delta$$

or alternatively:

$$\frac{1}{n}\sum_{i=1}^n X_i - \mu \leq \sqrt{\frac{1}{2n}\log\left(\frac{1}{\delta}\right)} \qquad \text{with probability at least } 1-\delta$$

For $X_1, \ldots, X_n$ i.i.d., it holds that for all $\delta \in (0,1)$,

$$\left|\frac{1}{n}\sum_{i=1}^n X_i - \mu\right| \leq \sqrt{\frac{1}{2n}\log\left(\frac{2}{\delta}\right)} \qquad \text{with probability at least } 1-\delta$$

Hoefdding's Inequality: Proof

The proof of Hoeffding's inequality relies on the following lemma:

Lemma (Hoeffding's Lemma)

Let X be a r.v. supported on $[a, b]$. Then,

$$\mathbb{E}[e^{\lambda(X-\mathbb{E}[X])}] \leq \frac{\lambda^2(b-a)^2}{8}, \quad \forall\lambda \in \mathbb{R}$$

For proof, see Yevgeny's lecture notes.

Hoeffding's Inequality: Proof

Proof of (i). Let $Z := \sum_{i=1}^n X_i - \mathbb{E}\left[\sum_{i=1}^n X_i\right]$.

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$$
\begin{aligned}
\mathbb{P}(Z \geq \varepsilon) &= \mathbb{P}(e^{\lambda Z} \geq e^{\lambda\varepsilon}) \\
&\leq e^{-\lambda\varepsilon}\mathbb{E}[e^{\lambda Z}] \quad \text{(Markov's inequality)} \\
&\leq e^{-\lambda\varepsilon}\mathbb{E}\Big[e^{\lambda(\sum_{i=1}^n X_i - \mathbb{E}[\sum_{i=1}^n X_i])}\Big] \\
&\leq e^{-\lambda\varepsilon}\prod_{i=1}^n \mathbb{E}[e^{\lambda(X_i - \mathbb{E}[X_i])}] \\
&\leq e^{-\lambda\varepsilon}\prod_{i=1}^n \mathbb{E}[e^{\lambda^2/8}] = e^{-\lambda\varepsilon + \frac{n\lambda^2}{8}} \quad \text{(Hoeffding's lemma)}
\end{aligned}
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&\leq e^{-\lambda\varepsilon}\mathbb{E}\Big[e^{\lambda(\sum_{i=1}^n X_i - \mathbb{E}\big[\sum_{i=1}^n X_i\big])}\Big] \\
&\leq e^{-\lambda\varepsilon}\prod_{i=1}^n \mathbb{E}[e^{\lambda(X_i - \mathbb{E}[X_i])}] \\
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\end{aligned}$$

Hence, $\mathbb{P}(Z \geq \varepsilon) \leq \min_{\lambda>0} e^{-\lambda\varepsilon + \frac{n\lambda^2}{8}}$ The best bound is attained at $\lambda = 4\varepsilon n^{-1}$:

$$\mathbb{P}(Z \geq \varepsilon) \leq e^{-2\varepsilon^2/n}$$

Hoeffding's Inequality: Generic Ranges

Theorem (Hoeffding's Inequality)

Let $X_1, \dots, X_n$ be independent r.v.'s such that $X_i \in [a_i, b_i]$ almost surely, that is $\mathbb{P}(X_i \in [a_i, b_i]) = 1$. Then, for all $\varepsilon > 0$,

$$\mathbb{P}\Big(\sum_{i=1}^n X_i - \mathbb{E}\Big[\sum_{i=1}^n X_i\Big] \geq \varepsilon\Big) \leq e^{-\frac{2\varepsilon^2}{\sum_{i=1}^n (b_i - a_i)^2}}$$

$$\mathbb{P}\Big(\sum_{i=1}^n X_i - \mathbb{E}\Big[\sum_{i=1}^n X_i\Big] \leq -\varepsilon\Big) \leq e^{-\frac{2\varepsilon^2}{\sum_{i=1}^n (b_i - a_i)^2}}$$

Hoeffding's Inequality: Examples

Example 1 (revisited): A fair coin is tossed 20 times. Let $X_1, \ldots, X_{20}$ be the realized outcomes.

By Hoeffding's inequality,

$$\mathbb{P}\left(\left|\frac{1}{20}\sum_{i=1}^{20} X_i - \frac{1}{2}\right| \geq 0.1\right) \leq 2e^{-2\cdot 20\cdot 0.1^2}$$

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Compare it to the result from Chebyshev's inequality.

Hoeffding's Inequality: Sub-Gaussian Case

Sub-Gaussian Random Variable

A r.v. X is said to be R-sub-Gaussian if

$$\mathbb{E}[e^{\lambda(X-\mathbb{E}[X])}] \leq \frac{\lambda^2 R^2}{2}, \quad \forall \lambda \in \mathbb{R}$$

- A r.v. with range $[a, b]$ is sub-Gaussian with $R = \frac{b-a}{2}$ (by Hoeffding's Lemma)
- A Gaussian r.v. is sub-Gaussian with $R = \sigma$.
- Intuitively, the tail of a sub-Gaussian r.v. decays at least as fast as that of a Gaussian.

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Theorem (Hoeffding's Inequality: Sub-Gaussian Case)

Let $X_1, \ldots, X_n$ be i.i.d. R-sub-Gaussian r.v.'s with mean μ. Then, with probability at least $1 - \delta$,

$$\frac{1}{n}\sum_{i=1}^{n} X_i - \mu \le R\sqrt{\frac{2}{n}\log\left(\frac{2}{\delta}\right)}$$