

Confidence Intervals

Christos Dimitrakakis

November 21, 2025

Outline

Hypothesis testing

- Simple Hypothesis Tests

Mean estimation

- Estimating a mean

- Concentration inequalities

Exercises

- Conditional probability

- Hypothesis testing

Simple hypothesis tests

- ▶ Consider n hypotheses, $H_1, \dots, H_n \in \mathcal{H}$
- ▶ Each hypothesis corresponds to a model $P(x|H_i)$ giving a probability value to every possible data $x \in X$.
- ▶ Given specific data x , we want to select the most likely model.

Maximum Likelihood

Pick the model with the highest likelihood:

- ▶ $\hat{H} = \arg \max_{H_i} P(x|H_i)$

Maximum A Posteriori

- ▶ Given prior $P(H_i)$
- ▶ Pick $\hat{H} = \arg \max_{H_i} P(H_i|x)$
- ▶ We use Bayes's theorem to calculate the posterior $P(H_i|x)$.
- ▶ When $P(H_i)$ is uniform, it is the same as maximum likelihood.

The Theorem of Bayes

- ▶ Given some probability space (P, Ω, Σ) .
- ▶ P is a probability measure on Ω
- ▶ Ω is the outcome space.
- ▶ Σ is a collection of subsets of Ω , corresponding to events.
- ▶ Let $\{H_i\}$ be a partition of Ω , i.e.

$$H_i \cup H_j = \emptyset \quad \forall i \neq j, \quad \bigcup_i H_i = \Omega.$$

Then, for any event $A \in \Sigma$, $A \subset \Omega$,

$$P(H_i|A) = \frac{P(A|H_i)P(H_i)}{\sum_j P(A|H_j)P(H_j)}$$

Proof of Bayes's theorem

Note that $P(H_i \cap A) = P(H_i|A)P(A) = P(A|H_i)P(H_i)$. Rearranging,

$$P(H_i|A) = \frac{P(A|H_i)P(H_i)}{P(A)}.$$

Since $\{H_i\}$ is a partition,

$$P(A) = P\left(\bigcup_i A \cap H_i\right) = \sum_i P(A \cap H_i) = \sum_i P(A|H_i)P(H_i)$$

Extensions

- We can use any non-negative scoring function $f_h(x)$:

$$P(h|x) = \frac{f_h(x)P(h)}{\sum_{h' \in \mathcal{H}} f_{h'}(x)P(h')}$$

- For infinite \mathcal{H} we can use this notation:

$$P(B|x) = \frac{\int_B f_h(x) dP(h)}{\int_{\mathcal{H}} f_h(x) dP(h)}, \quad B \subset \mathcal{H}.$$

Null Hypothesis Tests

- ▶ Consider a model H_0 such that $P(x|H_0)$ is known.
- ▶ We need to compare against an **unknown** alternative.
- ▶ We calculate a **statistic** $s : X \rightarrow \mathbb{R}$ to partition X in S_0, S_1 i.e.

$$S_0 = \{x : s(x) \leq \theta\}, \quad S_1 = \{x : s(x) > \theta\}$$

- ▶ Then $P(S_0|H_0) = 1 - \alpha$, $P(S_1|H_0) = \alpha$ for some α
- ▶ We tune θ to achieve the desired α .
- ▶ If $x \in S_0$, we accept H_0 , otherwise we reject it.

Example statistics

- ▶ Likelihood test: $s(x) = P(x|H_0)$,
- ▶ Mean test: $s(x) = |x - \mathbb{E}[x|H_0]|^2$.

Likelihood test

- ▶ We can use $s(x) = P(x|H_0)$.
- ▶ Now we can choose a threshold θ so that:

$$S_1 = \{x : s(x) \geq \theta\}$$

Example: Laplace distribution

- ▶ Density: $f(x|\mu, \lambda) = \frac{1}{2\lambda} e^{-\frac{1}{\lambda}|x-\mu|}$
- ▶ $H_0: x \sim \text{Laplace}(0, 1)$.
- ▶ $f(x|0, 1) \geq \theta$ means $|x| \leq \ln(1/2\theta)$. So

$$P(S_1|H_0) = \int_{-\infty}^{-\ln(1/2\theta)} e^{-x} dx = 1/2\theta.$$

- ▶ Consequently, $\theta = 1/2(1 - \alpha)$, i.e. we accept H_0 if $|x| \leq \ln(4 - 4\alpha)$

Bernoulli test

- ▶ H_0 : The coin tosses are fair
- ▶ Then the probability of any sequence $x = x_1, \dots, x_T$ is 2^{-T} .
- ▶ The expected number of heads is $T/2$.
- ▶ Statistic $s(x) = \sum_t x_t$.
- ▶ Select interval $S = [cT, (1 - c)T]$.
- ▶ There is some $c \in [0, 1/2]$ so that $P(S|H_0) = 1 - \alpha$
- ▶ To calculate c we can use the inverse CDF of s .

p values

How to use p values

- ▶ First select a significance threshold α .
- ▶ Collect the data, obtain the p value
- ▶ If $p \leq \alpha$, reject the null hypothesis H_0 .
- ▶ This ensures that, if H_0 is true, the probability of rejecting it is exactly α ! (Because p is uniform in $[0, 1]$ under H_0)

Problems with p values

- ▶ They do not measure quality of fit on the data.
- ▶ Not robust to model misspecification.
- ▶ They ignore effect sizes.
- ▶ They do not consider prior information.
- ▶ They do not represent the probability of having made an error
- ▶ The null-rejection error probability is the same irrespective of the amount of data (by design).

Mean estimation

- ▶ Data $D = x_1, \dots, x_T$
- ▶ i.i.d samples $x_t \sim P$
- ▶ Expectation $\mathbb{E}_P(x_t) = \mu$,
- ▶ Empirical mean:

$$\hat{\mu}(D) = \frac{1}{T} \sum_{t=1}^T x_t.$$

The error of the empirical mean

Since the data D is random, what is the probability that our estimate is far away from μ ?

$$\mathbb{P}[|\hat{\mu}(D) - \mu| > \epsilon] \leq \delta.$$

This means that the probability that our error is larger than ϵ is at most δ , with $\epsilon, \delta > 0$.

Two methods:

- ▶ Distribution-specific confidence intervals
- ▶ Concentration inequalities

Distribution-specific intervals

Bernoulli

If $x_t \sim \text{Bernoulli}(\mu)$, then the distribution of $\hat{\mu}$ is given by the Binomial distribution.

Binomial

Let $n_t = \sum_{i=1}^t x_i$, where $x_t \sim \text{Bernoulli}(\mu)$. Then n_t has a binomial distribution with parameter μ and t trials, i.e. $n_t \sim \text{Binomial}(\mu, t)$, and its probability function is

$$\mathbb{P}(n_t = k) = \binom{t}{k} \mu^k (1 - \mu)^{1-k}$$

Markov's Inequality

If $x \geq 0$

$$\mathbb{P}(x \geq u) \leq \frac{\mathbb{E}[x]}{u}$$

Proof

$$\mathbb{E}[x] = \int_0^{\infty} xp(x)dx \quad (1)$$

$$= \int_0^u xp(x)dx + \int_u^{\infty} xp(x)dx \quad (2)$$

$$\geq \int_u^{\infty} up(x)dx \quad (3)$$

$$= u \mathbb{P}(x \geq u) \quad (4)$$

Chernoff bound

$$\mathbb{P}(x - \mu \geq u) = \mathbb{P}(e^{\lambda(x-\mu)} \geq e^{\lambda u}) \leq \frac{\mathbb{E}[e^{\lambda(x-\mu)}]}{e^{\lambda u}}$$

- ▶ This follows directly from Markov's inequality.
- ▶ Tuning λ gives us the tightest bound.

Normal tail bound

Moment generating function

If $x \sim \text{Normal}(\mu, \sigma^2)$ then

$$\mathbb{E}[e^{\lambda x}] = e^{\mu\lambda + \sigma^2\lambda^2/2}$$

Proof

$$\mathbb{E}[e^{\lambda x}] = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{\lambda x} e^{-\frac{|x-\mu|^2}{2\sigma^2}} dx = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{\lambda x - \frac{|x-\mu|^2}{2\sigma^2}} dx \quad (5)$$

$$= \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{\lambda(\sqrt{2}\sigma y + \mu) - y^2} dy \quad (6)$$

where $y = (x - \mu)/(\sqrt{2}\sigma)$, so $x = \sqrt{2}\sigma y + \mu$.

Normal tail bound

If $x_t \sim \text{Normal}(\mu, 1)$, then

$$\mathbb{P}(|x_t - \mu| > \epsilon) \leq 2e^{-\epsilon^2/2}$$

Normal bound

- ▶ $\hat{\mu} \sim \text{Normal}(\mu, 1/T)$.
- ▶ For any $c > 0$, $\mathbb{V}[cx] = c \mathbb{V}[x] \Rightarrow T\hat{\mu} \sim \text{Normal}(T\mu, 1)$. So:

$$\mathbb{P}(|T\hat{\mu} - T\mu| \geq \epsilon) \leq 2e^{-\epsilon^2/2} \quad \text{from the tail bound} \quad (7)$$

$$\mathbb{P}(|\hat{\mu} - \mu| \geq \epsilon/T) \leq 2e^{-\epsilon^2/2} \quad \text{as } a \geq b \Leftrightarrow ca \geq cb \text{ for } c > 0 \quad (8)$$

$$\mathbb{P}(|\hat{\mu} - \mu| \geq u) \leq 2e^{-T^2 u^2/2} \quad \text{where } u = \epsilon/T \quad (9)$$

Subgaussian random variables

Definition (Subgaussianity)

x is σ -subgaussian if

$$\mathbb{E}[\exp(\lambda x)] \leq \exp(\lambda^2 \sigma^2 / 2), \quad \forall \lambda \in \mathbb{R}.$$

Theorem (Subgaussian bound)

If x is σ -subgaussian then, for all $\epsilon \geq 0$,

$$\mathbb{P}(x \geq \epsilon) \leq \exp\left(-\frac{\epsilon^2}{2\sigma^2}\right) \quad (10)$$

The proof is straightforward:

$$\begin{aligned} \mathbb{P}(x \geq 0) &= \mathbb{P}(\exp(\lambda x) \geq \exp(\lambda \epsilon)) \\ &\leq \mathbb{E}[\exp(\lambda x)] \exp(-\lambda \epsilon) \\ &\leq \exp\left(-\frac{\lambda^2 \sigma^2}{2} + \lambda \epsilon\right). \end{aligned}$$

Set $\lambda = \epsilon / \sigma^2$.

Application of subgaussian bounds

- ▶ If x is σ subgaussian then $\mathbb{E}[x] = 0$, $\mathbb{V}[x] \leq \sigma^2$
- ▶ cX is $|c|\sigma$ subgaussian for all $c \in \mathbb{R}$.
- ▶ If x_1, x_2 are σ_1, σ_2 subgaussian then $x_1 + x_2$ is $\sqrt{\sigma_1^2 + \sigma_2^2}$ subgaussian.

Corollary

If $x_t - \mu$ are independent σ subgaussian and

$$\hat{\mu} = \frac{1}{T} \sum_{t=1}^T x_t$$

$$\mathbb{P}(\hat{\mu} \geq \mu + \epsilon) \leq \exp\left(-\frac{n\epsilon^2}{2\sigma^2}\right)$$

Hoeffding bound

Hoeffding Inequality

For any sequence of independent (but not identical) rv's x_1, \dots, x_T , with $x_t \in [a_t, b_t]$, and consider the sum $s_T = \sum_{t=1}^T x_t$, which is also random. Then

$$\mathbb{P}(s_T \geq \mathbb{E}[s_T] + \epsilon) \leq \exp \left(-\epsilon^2 / \sum_t (b_t - a_t)^2 \right).$$

Corollary

For any sequence of independent rv's x_1, \dots, x_T , with $x_t \in [0, 1]$, with expectation $\mathbb{E}[x_t] = \mu$ it holds for the empirical mean $z_T = \frac{1}{T} \sum_{t=1}^T x_t$:

$$\mathbb{P}(|\mu - z_T| \geq \epsilon) \leq 2 \exp(-2n\epsilon^2)$$

Bayesian Reasoning

You are tested for COVID and found negative. The doctor says that the probability of a false positive (i.e. that the probability that the test is positive if you do not have COVID) is $1/10$ and the probability of a negative test if you have COVID is $1/5$. The prevalence of COVID in the population is $1/10$. What is the probability that you actually have COVID?

Exercise

A statistical test

Consider the null hypothesis H_0 that $x_t \sim \text{Bernoulli}(1/2)$ and the sample mean $\hat{\mu}_T = \frac{1}{T} \sum_{t=1}^T x_t$. The probability of making an error of more than ϵ is

$$1 - \sum_{k=T\epsilon} T\epsilon$$