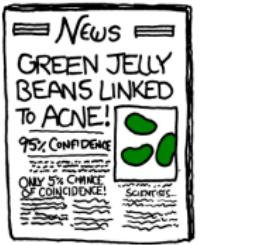
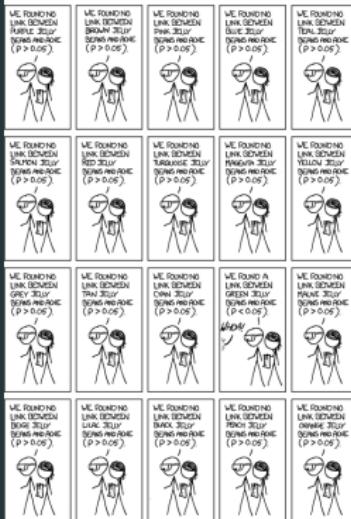


class poll: does this xkcd comic make sense?

- (a) always did . . .
 - (b) not really - is it that jelly beans don't come in 20 different colors?
 - (c) ooh I get it now!



confidence intervals: definition

Each random expt results in 3 outputs
 1) sample mean \bar{X}_n , 2) lower CI A, 3) upper CI B

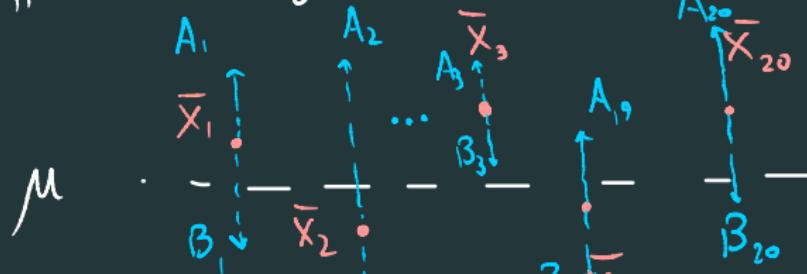
(ideally, smallest)

an random interval $[A, B]$ (computed from data/experiments) is called a 95% confidence interval for some (deterministic) quantity μ if

$$\mathbb{P}[A \leq \mu \leq B] \geq 0.95$$

$\overline{\mu}$ ARE RANDOM
 IS NOT $\frac{1}{n} \sum x_i$; it is the 'truth'

20 different students doing the same expt



We will say $[A, B]$

is a valid 1-d CI if $\mathbb{P}[A \leq \mu \leq B] \geq 1 - \alpha$

$$\bar{X}_i = \frac{1}{n} \sum_{j=1}^n x_{ij}$$

(i.e., i^{th} person's estimate)

Interpretation - On average, $\mu \in [A_i, B_i]$ for

19 out of 20 students

(moreover, $\mathbb{I}[\mu \in [A_i, B_i]] \sim \text{Ber}(\rho \geq 0.95)$)

class poll: abusing CI (?) (Explanation)

in a homework assignment in Simulation, students were asked to do a Monte Carlo simulation to compute π up to 2 decimal places

there were 100 homework submissions, and *all* submissions reported 95% CIs which included 3.14

the probability that this happened 'by chance' is approximately

(a) 0.4

By defn of a valid CI

(b) 0.05

$$\text{P}[\text{student } i \text{ has 3.14 in the CI}] \approx 0.95$$

(c) 0.006

$$\Rightarrow \text{P}[\text{ALL students have 3.14 in CI}] = (0.95)^{100}$$

(d) 0.0007

'Should be'

(e) 0

- All of these are examples of 'p-hacking'
- student assignments are independent
 - The CIs are 'overcalibrated' (i.e., >0.95 chance of success)
 - Experimenter 'selectively reveals' the CI

confidence intervals as a social contract

FREQUENTIST CI

a random interval $[A, B]$ (computed from data/experiments) is a 95% confidence interval for some unknown μ if before the experiment is done

$$\mathbb{P}[A \leq \mu \leq B] \geq 0.95$$



P-hacking - run code multiple times until you 'think CIs are correct'

Alternate : BAYESIAN Interval



confidence intervals for population mean

Define a CI taking the CLT to be literally true

X_1, X_2, \dots are i.i.d. rvs with $\mathbb{E}[X_1] = \mu$ and $\text{Var}(X_1) = \sigma^2 < \infty$; $\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$

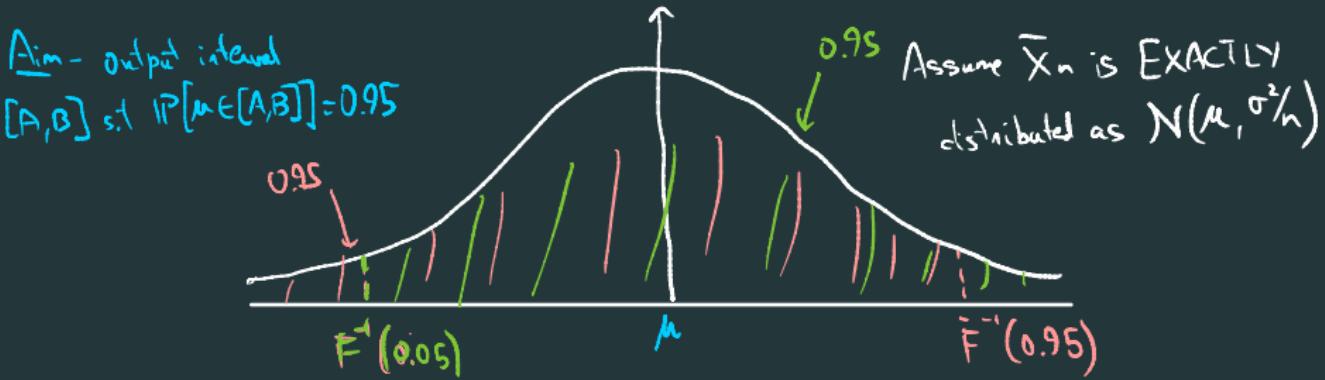
Sample mean

- from the central limit theorem:

$$\sqrt{n}(\bar{X}_n - \mu) \xrightarrow[\substack{\text{H of replications} \\ \text{pretend}}]{\substack{\text{Truth} \\ D}} \sigma \mathcal{N}(0, 1) = \mathcal{N}(0, \sigma^2)$$

- from the inverse cdf of $\mathcal{N}(0, 1)$, we can compute

$$\mathbb{P}\left[-\bar{X}_n + \bar{F}^{-}(0.95) \leq \mathcal{N}(0, 1) \leq \bar{X}_n + \bar{F}^{-}(0.95)\right] \geq 0.95.$$



confidence intervals for population mean

Define a CI taking the CLT to be literally true

X_1, X_2, \dots are i.i.d. rvs with $\mathbb{E}[X_1] = \mu$ and $\text{Var}(X_1) = \sigma^2 < \infty$; $\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$

Sample mean

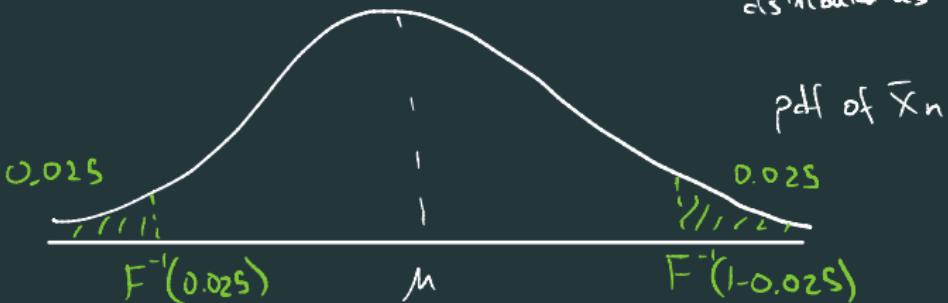
- from the central limit theorem:

$$\sqrt{n}(\bar{X}_n - \mu) \xrightarrow[\substack{\text{H of replications} \\ \text{pretend}}]{\substack{\text{Truth} \\ D}} \sigma \mathcal{N}(0, 1) = \mathcal{N}(0, \sigma^2)$$

- from the inverse cdf of $\mathcal{N}(0, 1)$, we can compute the **SMALLEST** interval s.t

$$\mathbb{P}\left[\underbrace{-1.96}_{\Phi^{-1}(0.025)} \leq \mathcal{N}(0, 1) \leq \underbrace{1.96}_{\approx 2}\right] \geq 0.95.$$

Aim - output interval $[A, B]$ s.t $\mathbb{P}[u \in [A, B]] = 0.95$ $\Phi^{-1}(0.025) \leq \mathcal{N}(0, \sigma^2) \leq \Phi^{-1}(0.975)$ Assume \bar{X}_n is EXACTLY distributed as $\mathcal{N}(\mu, \sigma^2/n)$



confidence intervals (Gaussian approximation for CI)

want to measure $\mu = \mathbb{E}[X_1]$ from simulations Assumption - CLT is literally true

- from the central limit theorem: $\sqrt{n}(\bar{X}_n - \mu) \xrightarrow{D} \sigma \mathcal{N}(0, 1)$
- from the cdf of $\mathcal{N}(0, 1)$, we have $\mathbb{P}[-1.96 \leq \mathcal{N}(0, 1) \leq 1.96] \geq 0.95$

putting these together, we have:

$$\mathbb{P}\left[-1.96\sigma \leq \sqrt{n}(\bar{X}_n - \mu) \leq 1.96\sigma\right] = 0.95$$

$$\Rightarrow \mathbb{P}\left[\bar{X}_n - \frac{1.96\sigma}{\sqrt{n}} \leq \mu \leq \bar{X}_n + \frac{1.96\sigma}{\sqrt{n}}\right] = 0.95$$

where $\bar{X}_n = \frac{1}{n} \sum_{i=1}^n \hat{x}_i$, $\sigma^2 = \text{Var}_n(x_i)$

confidence intervals: problems

- the confidence interval is approximate because

$$\frac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma} \text{ is only approximately } N(0,1)$$

- the confidence interval is 'exact' when

$$\bar{X}_n \text{ is exactly Gaussian} \iff X_i \sim N(\mu, \sigma^2)$$

- the confidence interval above requires knowledge of σ^2

In some cases, can upper bound σ^2 - If $X_i \sim \text{Ber}(\mu)$
Then $\text{Var}(X_i) = \mu(1-\mu) \leq \frac{1}{4}$

In practice, often replace σ^2 by Empirical Variance $\hat{S}_n = f(X_1, X_2, \dots, X_n)$
 $\text{s.t. } E[\hat{S}_n] = \sigma^2$

confidence intervals: problems

- the confidence interval is approximate because

- ~~the confidence interval is 'exact' when~~

Notes

- S_n^2 is built in to most packages (np.var = std-dev, -1 specified via input)
- $\frac{1}{n}$ vs $\frac{1}{n-1}$ makes little diff for large n
- the confidence interval above requires knowledge of σ^2

can replace σ^2 with its sample estimator

$$S_n^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X}_n)^2. \quad \Rightarrow E[S_n^2] = \sigma^2$$

Random Variable

(fn of random X_1, \dots, X_n)

fixed sample-size: recipe for CI

approximate $100(1 - \alpha)\%$ Gaussian CI for $\mathbb{E}X$

1. select a sample size N
2. generate N i.i.d. samples X_1, X_2, \dots, X_N of X
3. compute the estimators \bar{X}_N, s_N^2

$$\bar{X}_N = \frac{1}{N} \sum_{n=1}^N X_n, \quad s_N^2 = \frac{1}{N-1} \sum_{n=1}^N (X_n - \bar{X}_N)^2$$

4. look up the value of $z_{\alpha/2}$ such that



$$\mathbb{P}[-z_{\alpha/2} \leq N(0, 1) \leq z_{\alpha/2}] = 1 - \alpha$$

$$\mathbb{E}[s_N^2] = \text{Var}(\bar{X}_N)$$

5. the approximate $100(1 - \alpha)\%$ CI for $\mathbb{E}X$ is given by

$$\bar{X}_N \pm z_{\alpha/2} \frac{s_N}{\sqrt{N}} = \bar{X}_N + z_{\alpha/2} \text{Var}(\bar{X}_N)$$

selecting the sample size

how large should N be so that the resulting $100(1 - \alpha)\%$ confidence interval will have a pre-specified width? ← interpretable measure of quality of measurement

- CI $\Rightarrow \bar{X}_N \pm z_{\alpha/2} \left(\sigma / \sqrt{N} \right)$
- half-width $\Rightarrow z_{\alpha/2} \frac{\sigma}{\sqrt{N}} \approx z_{\alpha/2} \frac{s_n}{\sqrt{n}} \xrightarrow{\text{Ans}} \leq w$
- ℓ be the desired half-width
- Set $N = \frac{(z_{\alpha/2})^2 \sigma^2}{w^2}$ $\left(\text{ie, for 95\%, } N = \frac{4 \sigma^2}{w^2} \right)$
- How do we know σ^2 ?
 - If Bn , $\sigma^2 \leq \frac{1}{4}$ \Rightarrow choose $N = 1/w^2$
 - more commonly - use 'pilot sims' to estimate σ^2

selecting the sample size

- problem: σ^2 is unknown!
- estimating σ^2 through s_N^2 requires simulation!
- solution: 'pilot runs'
perform k simulation runs to get $[X'_n : n = 1, \dots, k]$ as outcomes
compute

$$\tilde{X}_k = \frac{1}{k} \sum_{n=1}^k X'_n, \quad \underline{\tilde{s}_k^2} = \frac{1}{k-1} \sum_{n=1}^k (X'_n - \tilde{X}_k)^2$$

pilot estimate of σ^2

use \tilde{s}_k^2 to estimate σ^2

for confidence level α , half-width ℓ , set

$$N = \left\lceil \frac{z_{\alpha/2}^2 \tilde{s}_k^2}{\ell^2} \right\rceil$$

basic simulation workflow

- perform **pilot run** of k simulations (sufficient but not large k)
- compute required sample-size N for desired confidence interval
- run N additional simulations \Rightarrow **production runs**
- form fixed-sample confidence intervals from these N samples
- note: final CI may be different than desired, because it is constructed by using s_N^2 (may be larger/smaller than \tilde{s}_k^2)
- for the final confidence interval, discard the information from the trial runs
not a problem, since $N \gg k$ usually

(not important, but good habit to)
avoid 'contamination'

Issues

- S_n^2 is an estimate for σ^2
- \bar{X}_n is not truly Gaussian

In reality, there is some C
s.t. $P\left\{\mu \in \left[\bar{X}_n + C \frac{S_n}{\sqrt{N}}\right]\right\} \leq 0.95$