



Computer
Science

CSC380: Principles of Data Science

Statistics 4

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Announcement

- Midterm review this Thursday, Feb 29
- Midterm Time: Mar 14, Thursday, 3:30-4:45 pm
- Location: Meinel Optical Sci, Room 410 (same as lecture room)
- What you can bring?
 - Cheat sheet: letter size, double-sided
 - Scientific calculator

Review: Sample Mean for Bernoulli

Sample mean: $\hat{p} = \frac{1}{N} \sum_i X_i$

Expectation: $\mathbf{E}[\hat{p}(X)] = \mathbf{E}\left[\frac{1}{N} \sum_i X_i\right]$
 $\stackrel{(a)}{=} \frac{1}{N} \sum_i \mathbf{E}[X_i]$
 $\stackrel{(b)}{=} \frac{1}{N} Np = p$

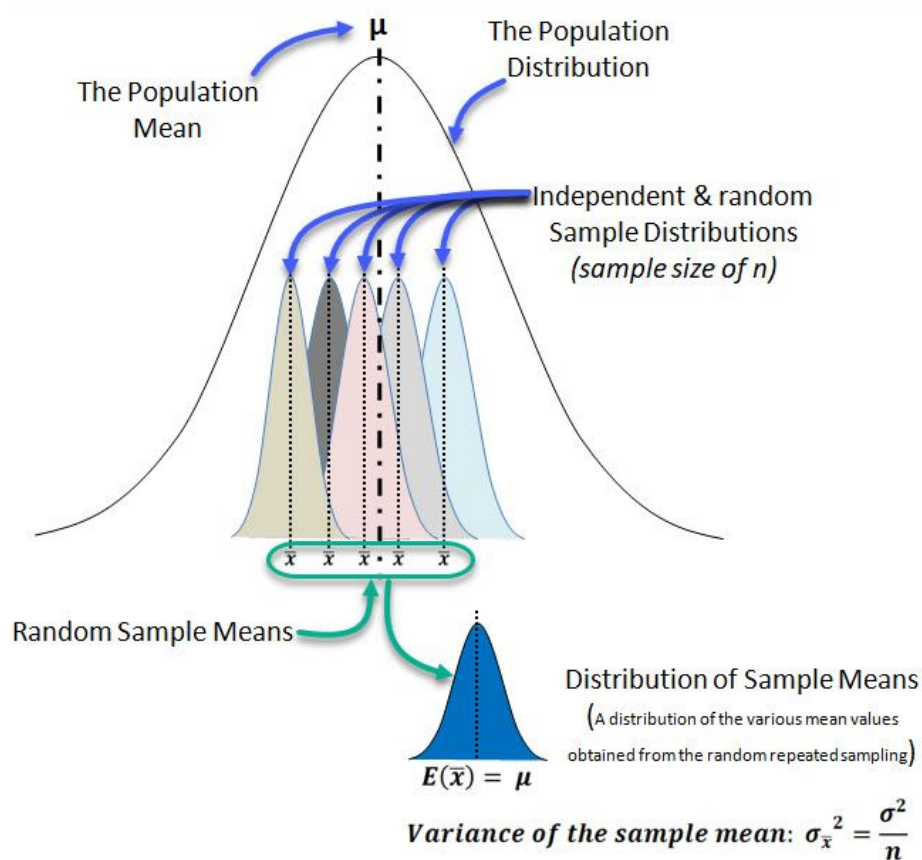
Variance: $\mathbf{Var}(\hat{p}) = \mathbf{Var}\left(\frac{1}{N} \sum_i X_i\right)$
 $\stackrel{(a)}{=} \frac{1}{N^2} \mathbf{Var}\left(\sum_i X_i\right)$
 $\stackrel{(b)}{=} \frac{1}{N^2} \sum_i \mathbf{Var}(X_i)$
 $\stackrel{(c)}{=} \frac{1}{N^2} \sum_i p(1-p) = \frac{1}{N} p(1-p) = \frac{1}{N} \mathbf{Var}(X)$

Review: Sample Mean for Gaussian

(Property of Gaussian: $E[X] = \mu_x$, $Var[X] = \sigma_x^2$)

Expectation:
$$E[\hat{p}(X)] = E\left[\frac{1}{N} \sum_i X_i\right]$$
$$\stackrel{(a)}{=} \frac{1}{N} \sum_i E[X_i]$$


Variance:
$$Var(\hat{p}) = Var\left(\frac{1}{N} \sum_i X_i\right)$$
$$\stackrel{(a)}{=} \frac{1}{N^2} Var\left(\sum_i X_i\right)$$
$$\stackrel{(b)}{=} \frac{1}{N^2} \sum_i Var(X_i)$$
$$= \frac{1}{N} Var(X)$$



Review: Sample Variance

Sample variance: $\hat{\sigma}^2 = \frac{1}{N} \sum_i (X_i - \hat{\mu})^2$

Source of bias:
plug-in mean
estimate



Expectation: $\mathbf{E}[\hat{\sigma}^2] = \frac{1}{N} \sum_i \mathbf{E}[(X_i - \hat{\mu})^2] = \text{boring algebra} = \frac{N-1}{N} \sigma^2$

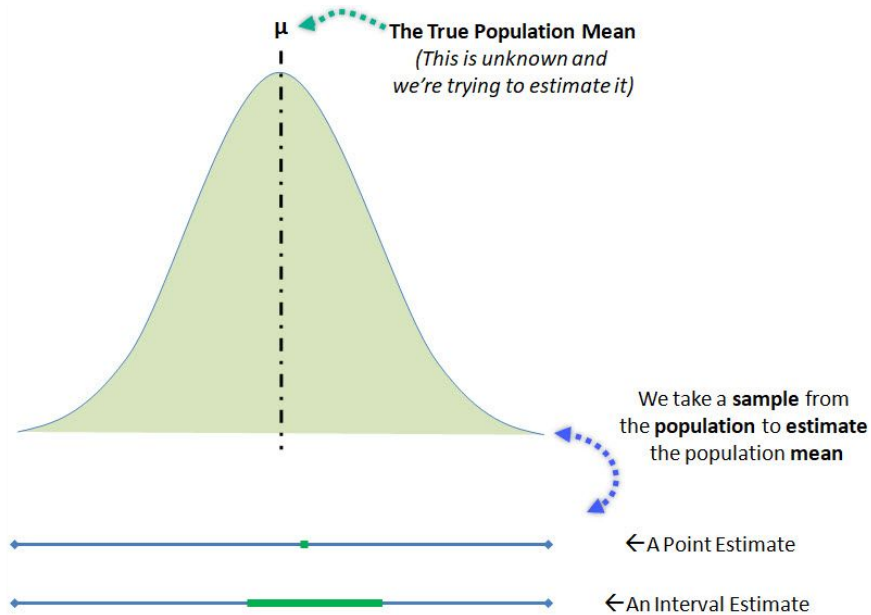
Correcting bias : $\hat{\sigma}_{\text{unbiased}}^2 = \frac{N}{N-1} \hat{\sigma}^2 = \frac{1}{N-1} \sum_i (X_i - \hat{\mu})^2$

$$E[\hat{\sigma}_{\text{unbiased}}^2] = \sigma^2$$

Biased version has lower MSE: Bias-Variance tradeoff

Point estimate vs Interval estimate

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- **Point estimate:** a sample statistic calculated using the sample data to estimate the most likely value of the corresponding unknown population parameter.
- **Interval estimate:** a range of values constructed from sample data so that the population parameter will likely occur within the range at a specified probability.

Confidence Intervals

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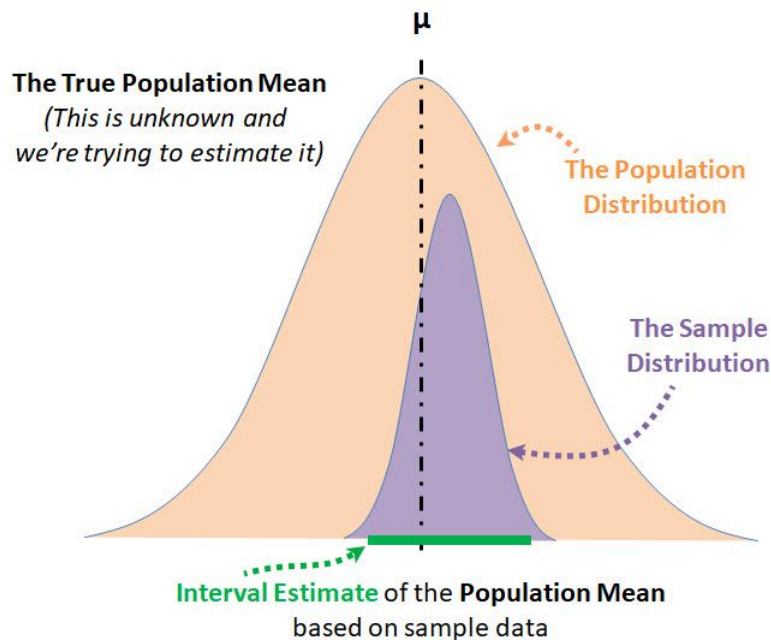
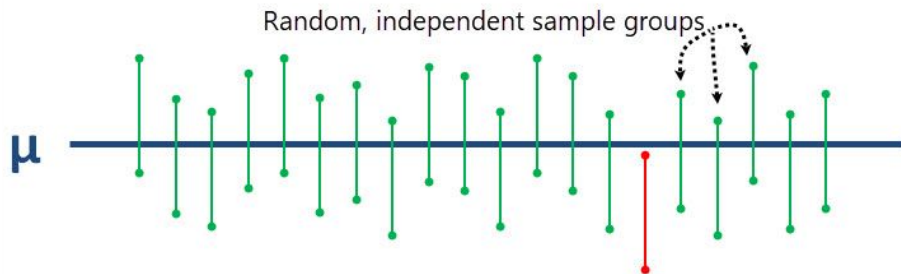
Informally, find an interval such that we are *pretty sure* it encompasses the true parameter value.

failure rate

Given data X_1, \dots, X_n and ~~confidence~~ $\alpha \in (0, 1)$ find interval (a, b) such that,

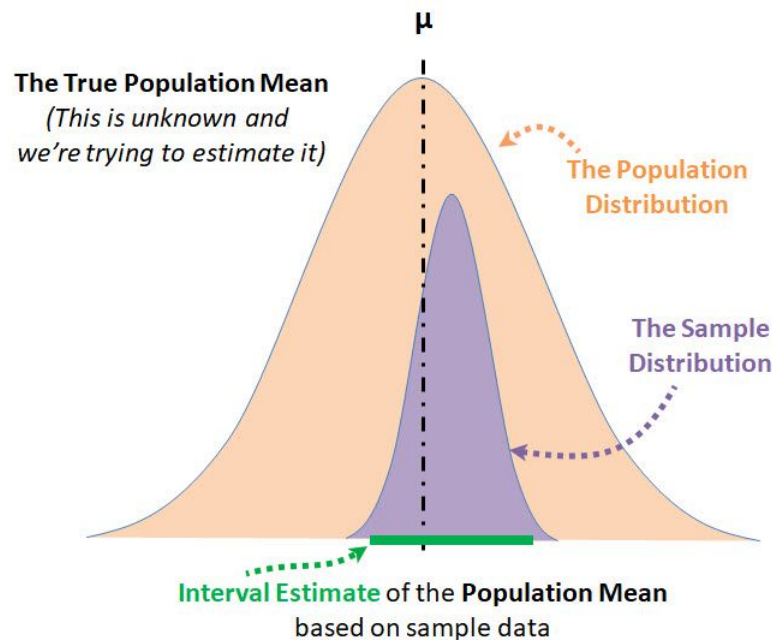
$$P(\theta \in (a, b)) \geq 1 - \alpha$$

The interval (a, b) contains the true parameter value θ with probability **at least** $1 - \alpha$

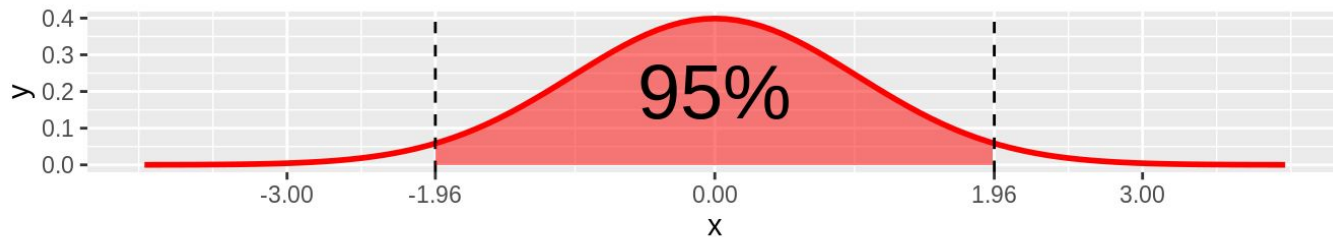


The interval (a, b) contains the true parameter value θ with probability **at least** $1 - \alpha$

- Intervals must be computed from data:
i.e., $a(X_1, \dots, X_n)$ and $b(X_1, \dots, X_n)$
- Interval (a, b) is **random**
- parameter θ is **not random** (it is fixed)
- Usually, you compute an estimator $\hat{\theta}$ and then set $a = \hat{\theta} - \epsilon_a$ and $b = \hat{\theta} + \epsilon_b$ for a carefully chosen $\epsilon_a, \epsilon_b > 0$



Finding Confidence Interval



- Suppose X follows a distribution, given: $P(X \in [-1.96, 1.96]) = 0.95$
 - We are 95% sure that X will fall into the interval $[-1.96, 1.96]$
- If we find the distribution of $\hat{\mu} - \mu$, we can get the interval that has the probability as 95% (or 99%, can choose confidence level)
- Use $\hat{\mu}$ and the interval to calculate a range for μ , so that we are 95% sure μ fall into the range

Q: how to find the distribution of $\hat{\mu} - \mu$?

Suppose $X_1, \dots, X_n \sim \mathcal{N}(\mu, \sigma^2)$ with unknown μ & known σ^2 . Let $\hat{\mu} := \frac{1}{n} \sum_i X_i$.

(Fact 1) $\hat{\mu} \sim \mathcal{N}\left(\mu, \frac{\sigma^2}{n}\right)$

quiz candidate

$$\sqrt{n} \frac{\hat{\mu} - \mu}{\sigma} \sim N(0, 1)$$

Recall:

- Closed under additivity:

$$X \sim \mathcal{N}(\mu_x, \sigma_x^2) \quad Y \sim \mathcal{N}(\mu_y, \sigma_y^2)$$

$$X + Y \sim \mathcal{N}(\mu_x + \mu_y, \sigma_x^2 + \sigma_y^2)$$


- Closed under affine transformation (a and b constant):

$$aX + b \sim \mathcal{N}(a\mu_x + b, a^2\sigma_x^2)$$

(proof)

$$\sum_{i=1}^n X_i \sim \mathcal{N}(n\mu, n\sigma^2)$$

Use this with $X = \sum_{i=1}^n X_i$, $a = \frac{1}{n}$, $b = 0$.



CDF of Normal Distribution

(Fact 2) If $Z \sim \mathcal{N}(0,1)$,

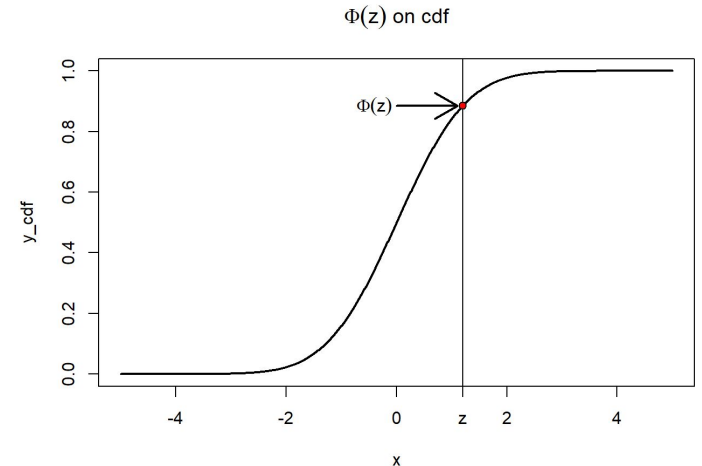
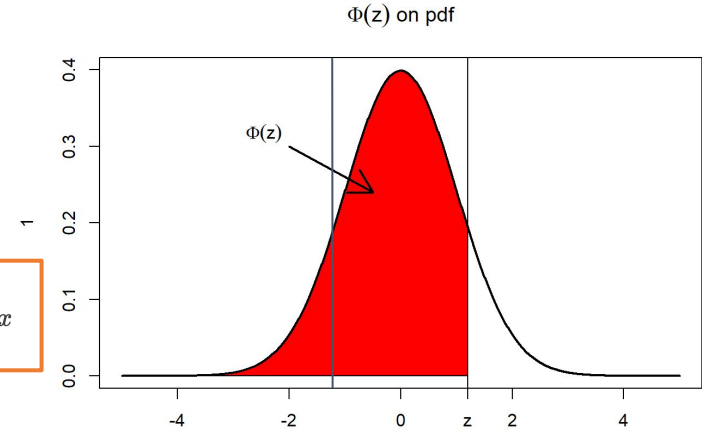
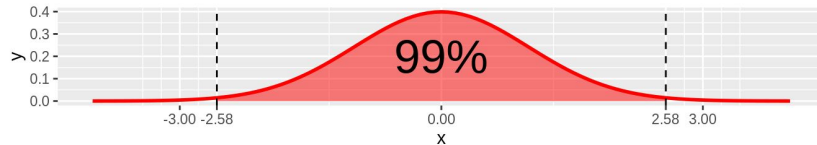
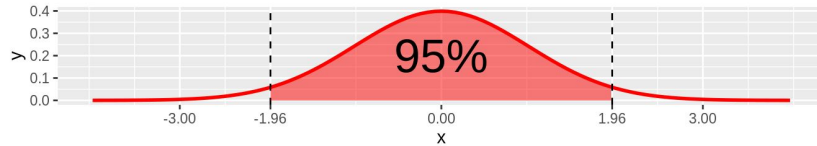
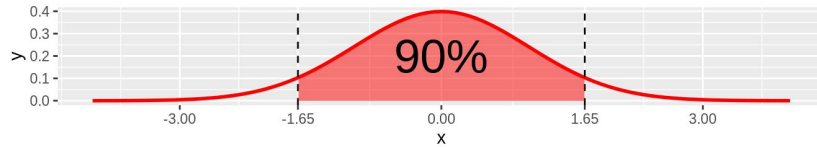
$$P(Z \in [-z, z]) = 1 - 2(1 - \Phi(z))$$

where $\Phi(z) := P(Z \leq z)$ is the CDF of Z .

$z = 1.96$: RHS $\approx .95$, 95% confident

$z = 2.58$: RHS $\approx .99$,

$$\Phi(z) = \int_{-\infty}^z \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$$



(Fact 2) If $Z \sim \mathcal{N}(0,1)$,

$$P(Z \in [-z, z]) = 1 - 2(1 - \Phi(z))$$

where $\Phi(z) := P(Z \leq z)$ is the CDF of Z .

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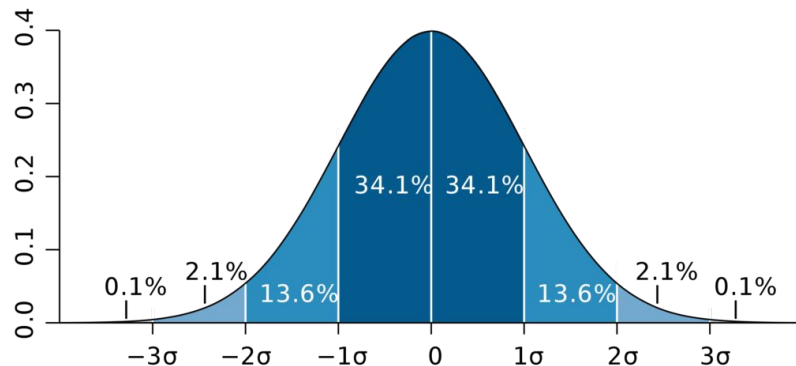
(Corollary)

$$P\left(\hat{\mu} \in \left[\mu - \frac{z\sigma}{\sqrt{n}}, \mu + \frac{z\sigma}{\sqrt{n}}\right]\right) = 1 - 2(1 - \Phi(z))$$

hints: use the fact $\sqrt{n} \frac{\hat{\mu} - \mu}{\sigma} \sim N(0,1)$. Set $Z :=$

$\sqrt{n} \frac{\hat{\mu} - \mu}{\sigma}$ and use Fact 2.

Terminology:
"standard" normal
distribution $:= \mathcal{N}(0,1)$



Gaussians almost do not have tails!

Suppose $X_1, \dots, X_n \sim \mathcal{N}(\mu, \sigma^2)$ with unknown μ & known σ^2 . Let $\hat{\mu} := \frac{1}{n} \sum_i X_i$.

Fact 1

$$\sqrt{n} \frac{\hat{\mu} - \mu}{\sigma} \sim N(0, 1)$$


Fact 2

$$Z \sim N(0, 1)$$
$$P(Z \in [-z, z]) = 1 - 2(1 - \phi(z))$$

$$Z \longrightarrow \sqrt{n} \frac{\hat{\mu} - \mu}{\sigma}$$

$z = 1.96$: RHS $\approx .95$, 95% confident
 $z = 2.58$: RHS $\approx .99$,

$$P\left(\sqrt{n} \frac{\hat{\mu} - \mu}{\sigma} \in [-z, z]\right) = 1 - 2(1 - \phi(z))$$

$$P\left(\sqrt{n} \frac{\hat{\mu} - \mu}{\sigma} \in [-z, z]\right) = P\left(\hat{\mu} \in \left[\mu - \frac{z\sigma}{\sqrt{n}}, \mu + \frac{z\sigma}{\sqrt{n}}\right]\right)$$


Finally, by our corollary,

$$P\left(\hat{\mu} \in \left[\mu - \frac{1.96\sigma}{\sqrt{n}}, \mu + \frac{1.96\sigma}{\sqrt{n}}\right]\right) \geq 0.95$$

$$P\left(\hat{\mu} \in \left[\mu - \frac{2.58\sigma}{\sqrt{n}}, \mu + \frac{2.58\sigma}{\sqrt{n}}\right]\right) \geq 0.99$$

note we can switch $\hat{\mu}$ and μ

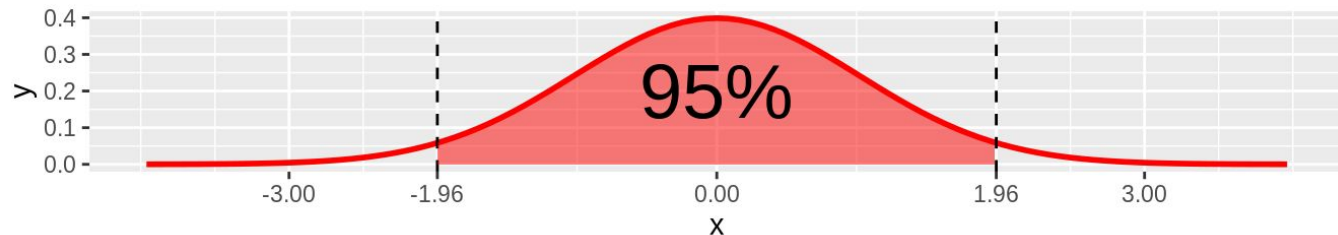
$$P\left(\mu \in \left[\hat{\mu} - \frac{1.96\sigma}{\sqrt{n}}, \hat{\mu} + \frac{1.96\sigma}{\sqrt{n}}\right]\right) \geq 0.95$$

$$\hat{\mu} \in [\mu - 3, \mu + 3]$$

$$\begin{aligned} \mu - 3 &\leq \hat{\mu} \leq \mu + 3 \\ \hat{\mu} - 3 &\leq \mu \leq \hat{\mu} + 3 \end{aligned}$$

This is a confidence bound for the mean μ !!

=> Compute $\left[\hat{\mu} - \frac{1.96\sigma}{\sqrt{n}}, \hat{\mu} + \frac{1.96\sigma}{\sqrt{n}}\right]$. Done!



Question How should we interpret a confidence interval (e.g. 95%)?

$$P(\theta \in (a(X), b(X))) \geq 0.95$$

Hint Think about what is random and what is not...

This is NOT about the randomness of θ

Wrong If someone reveals θ when we have exactly the same data, then θ will be in the interval with probability at least 95%

the moment you compute the interval with the data, whether or not θ is in the interval is determined.. you just don't know it!

This is commonly misinterpreted

Interpreting CI (think of parallel universe...)

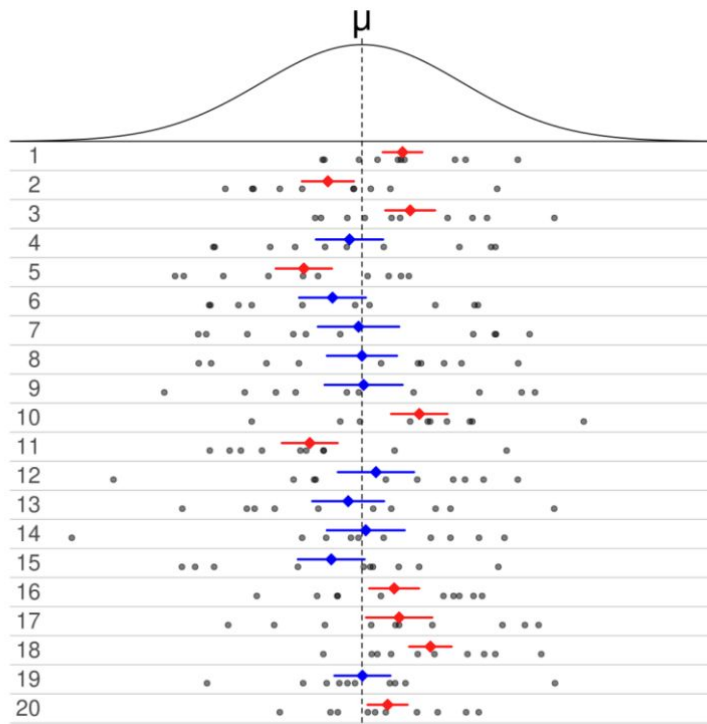


Multiple different universes...

Caveat: interpreting confidence intervals

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Recommended point of view:



universe 1: get confidence interval 1

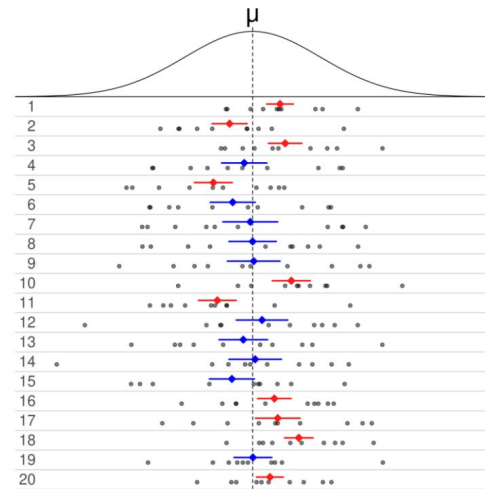
universe 2: get confidence interval 2

.....

universe m: get confidence interval m

Recommended point of view:

- Assume: Heights of UA students follow a normal distribution $\mathcal{N}(\mu, 1)$ with unknown μ
- Fork **m parallel universes**. For each universe $u \in \{1, 2, \dots, m\}$,
 - Subsample n UA students randomly, take the sample mean $\hat{\mu}^{(u)}$.
 - Compute the confidence bound $\left[\hat{\mu}^{(u)} - \frac{1.96\sigma}{\sqrt{n}}, \hat{\mu}^{(u)} + \frac{1.96\sigma}{\sqrt{n}} \right]$
- The fraction of parallel universes where the random interval includes μ is *approximately* at least 0.95 if m is large enough.
- As m goes to infinity, the fraction will become arbitrarily close to a value that is at least 0.95.



Recall: *If X_1, \dots, X_n from an **arbitrary** distribution, can we still use the same method used for Gaussian?*

Short answer: YES, if n is large enough.


- Central limit theorem


$$\lim_{N \rightarrow \infty} \frac{\sqrt{N}}{\sigma} (\bar{X}_N - \mu) \rightarrow \mathcal{N}(0, 1)$$

Q: what if σ^2 is unknown and sample size is small (< 30)?

Method 1: Gaussian (Corrected)

Suppose $X_1, \dots, X_n \sim \mathcal{N}(\mu, \sigma^2)$ with unknown μ & known σ^2 .

(Fact 1) $\hat{\mu} \sim \mathcal{N}\left(\mu, \frac{\sigma^2}{n}\right)$ $\sqrt{n} \frac{\hat{\mu} - \mu}{\sigma} \sim N(0,1)$  T-dist

(Fact 2) If $Z \sim \mathcal{N}(0,1)$, 

$$P(Z \in [-z, z]) = 1 - 2(1 - \Phi(z))$$

where $\Phi(z) := P(Z \leq z)$ is the CDF of Z .

$z = 1.96$: RHS $\approx .95$, 95% confident

$z = 2.58$: RHS $\approx .99$,

Let: $Z \longrightarrow \sqrt{n} \frac{\hat{\mu} - \mu}{\sigma}$

$$P\left(\hat{\mu} \in \left[\mu - \frac{1.96\sigma}{\sqrt{n}}, \mu + \frac{1.96\sigma}{\sqrt{n}}\right]\right) \geq 0.95$$

$$P\left(\hat{\mu} \in \left[\mu - \frac{2.58\sigma}{\sqrt{n}}, \mu + \frac{2.58\sigma}{\sqrt{n}}\right]\right) \geq 0.99$$

Q: what if σ^2 is unknown and sample size is small (< 30)?

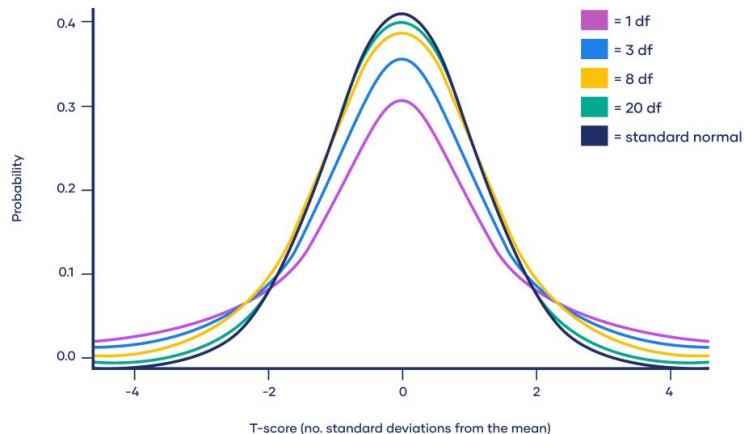
\Rightarrow Compute $\left[\hat{\mu} - \frac{1.96\sigma}{\sqrt{n}}, \hat{\mu} + \frac{1.96\sigma}{\sqrt{n}}\right]$. Done!

Recall: Gaussian confidence interval with $\sqrt{n} \frac{\hat{\mu}_n - \mu}{\sigma} \sim \mathcal{N}(0,1)$.

What if we use $\hat{\sigma}^2$ instead of σ ?

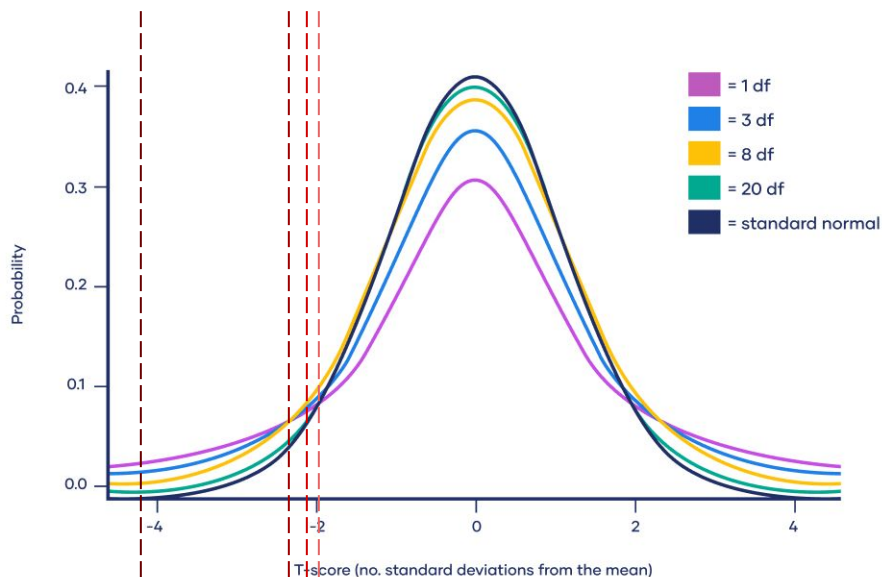
(Theorem) X_1, \dots, X_n with unknown μ, σ^2 .

Let $\widehat{UVar}_n := \frac{1}{n-1} \sum_{i=1}^n (X_i - \hat{\mu}_n)^2$ (unbiased version of sample variance). Then,
 $\sqrt{n} \frac{\hat{\mu}_n - \mu}{\sqrt{\widehat{UVar}_n}} \sim \text{student-t}(\text{mean } 0, \text{ scale } 1, \text{ degrees of freedom } = n - 1)$



As df approaches infinity, T distribution becomes gaussian

T scores for different df



much larger number
compensates for the
inaccuracy of $\hat{\sigma}^2$

(recall: 1.96 for gaussian)

```
import scipy.stats as st  
alpha = 0.05  
st.t.ppf(1-alpha/2,df=2)  
=> 4.302652729911275
```

```
st.t.ppf(1-alpha/2,df=5)  
=> 2.5705818366147395
```

```
st.t.ppf(1-alpha/2,df=10)  
=> 2.2281388519649385
```

```
st.t.ppf(1-alpha/2,df=30)  
=> 2.0422724563012373
```

```
st.t.ppf(1-alpha/2,df=100)  
=> 1.9839715184496334
```

T Table

Degrees of freedom	Significance level					
	20% (0.20)	10% (0.10)	5% (0.05)	2% (0.02)	1% (0.01)	0.1% (0.001)
1	3.078	6.314	12.706	31.821	63.657	636.619
2	1.886	2.920	4.303	6.965	9.925	31.598
3	1.638	2.353	3.182	4.541	5.841	12.941
4	1.533	2.132	2.776	3.747	4.604	8.610
5	1.476	2.015	2.571	3.365	4.032	6.859
6	1.440	1.943	2.447	3.143	3.707	5.959
7	1.415	1.895	2.365	2.998	3.499	5.405
8	1.397	1.860	2.306	2.896	3.355	5.041
9	1.383	1.833	2.262	2.821	3.250	4.781
10	1.372	1.812	2.228	2.764	3.169	4.587
.....						
40	1.303	1.684	2.021	2.423	2.704	3.551
60	1.296	1.671	2.000	2.390	2.660	3.460
120	1.289	1.658	1.980	2.158	2.617	3.373
∞	1.282	1.645	1.960	2.326	2.576	3.291

With a similar derivation we have done before,

With at least 95% confidence:

$$\left[\hat{\mu} - t_{\alpha/2, n-1} \frac{\hat{\sigma}}{\sqrt{n}}, \hat{\mu} + t_{\alpha/2, n-1} \frac{\hat{\sigma}}{\sqrt{n}} \right]$$

Where $t_{\alpha/2, n-1}$ can be computed numerically.

Key take away: more conservative!
=> more likely to be correct.

Common practice: Apply this method even if we do not know whether true distribution is Gaussian.

(recall: 1.96 for gaussian)

much larger number
compensates for the
inaccuracy of $\hat{\sigma}^2$

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Method 2: Bootstrap

Suppose $X_1, \dots, X_n \sim \mathcal{N}(\mu, \sigma^2)$ with unknown μ & known σ^2 .

(Fact 1) $\hat{\mu} \sim \mathcal{N}\left(\mu, \frac{\sigma^2}{n}\right)$ $\sqrt{n} \frac{\hat{\mu} - \mu}{\sigma} \sim \mathcal{N}(0, 1)$

(Fact 2) If $Z \sim \mathcal{N}(0, 1)$,

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$$P\left(\hat{\mu} \in \left[\mu - \frac{2.58\sigma}{\sqrt{n}}, \mu + \frac{2.58\sigma}{\sqrt{n}}\right]\right) \geq 0.99$$

\Rightarrow Compute $\left[\hat{\mu} - \frac{1.96\sigma}{\sqrt{n}}, \hat{\mu} + \frac{1.96\sigma}{\sqrt{n}}\right]$. Done!

Directly approximate distributions of $\hat{\mu} - \mu$