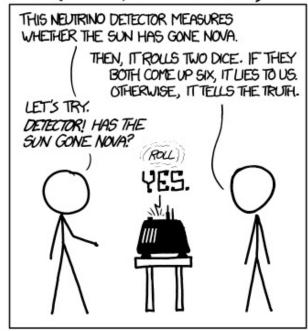
Classical statistical inference

Part 2

Associated notebook:

04-Basic statistical inference frequentists 2/Frequentist inference 01.ipynb

DID THE SUN JUST EXPLODE? (IT'S NIGHT, SO WE'RE NOT SURE.)



What is inference?

Derive **INFORMATION** based on **DATA** Examples:

- Exoplanet transit \Rightarrow M, d \Rightarrow P(M | d)
- Supernovae distances \Rightarrow Expansion rate H_0

Inference generally implies an underlying *statistical* model: PDF or regression laws with parameters θ

FREQUENTIST STATISTICIAN:



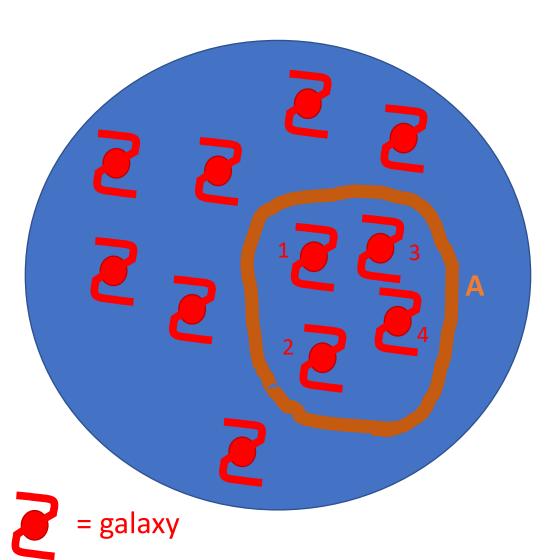
BAYESIAN STATISTICIAN:



Three types of inference:

- Point estimation: "best" θ
- Confidence interval: Confidence around θ
- Hypothesis testing: data OK w. model?

https://xkcd.com/1132/



Example:

 θ = mean mag. of a population of galaxies

A: Your data set = subsample of measurements: $A = \{X_{1}, X_{2}, X_{3}, X_{4}\}$ where X = mag. (this is a RV)

$$\hat{\theta} = \frac{X_1 + X_2 + X_3 + X_4}{4} \equiv \text{Point estimate of } \theta$$

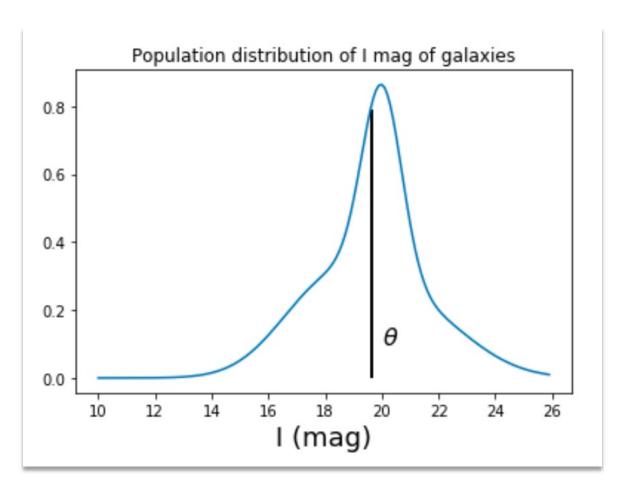
If you do the experiment with another sample $(\Rightarrow \text{ different } realisation)$ you will get another $\hat{\theta}$



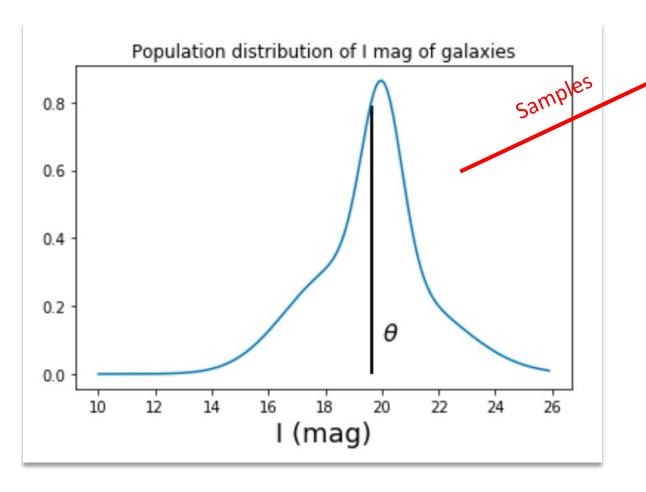
Generalisation:

$$\hat{\theta} = g(X_1, X_2, X_3, \dots X_n)$$

- Point estimate of a param. is a *function* of RV X₁, ...
- It is as well a Random Variable (RV)
- It can be biased, is characterized by a variance but should ideally be consistent (converges towards θ)
- Distribution of $\hat{\theta}$ is called sampling distribution

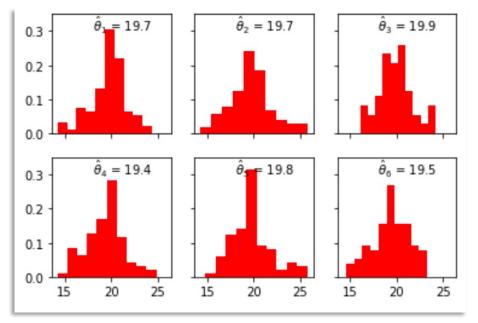


Population mean: $\theta = 19.66$



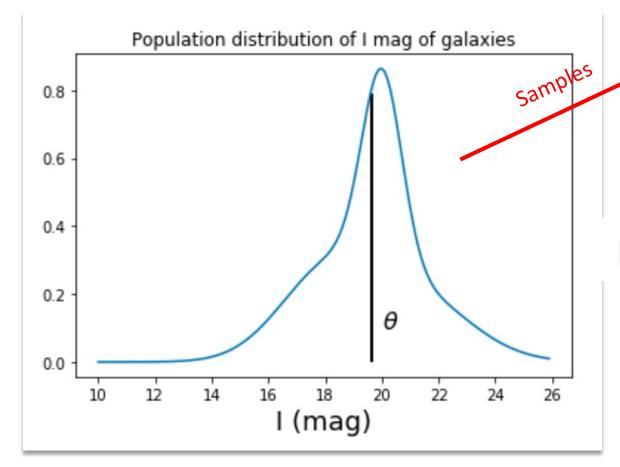
Population mean: $\theta = 19.66$

Six different *samples* drawn from the true population



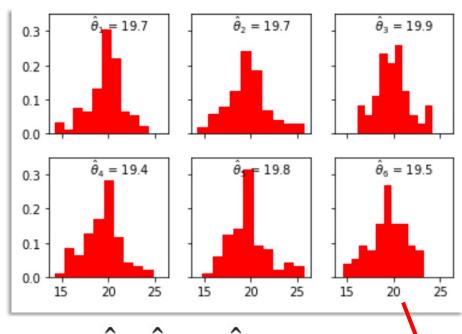
Six different samples drawn from the true population

Point estimate $\hat{\theta}$

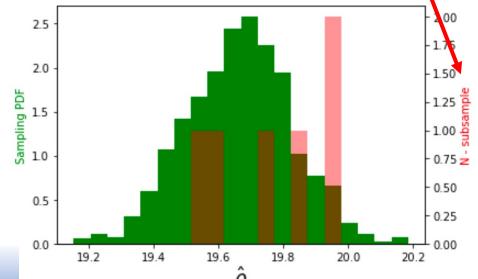


Population mean: $\theta = 19.66$

Go to: Sect. II.1 of the notebook

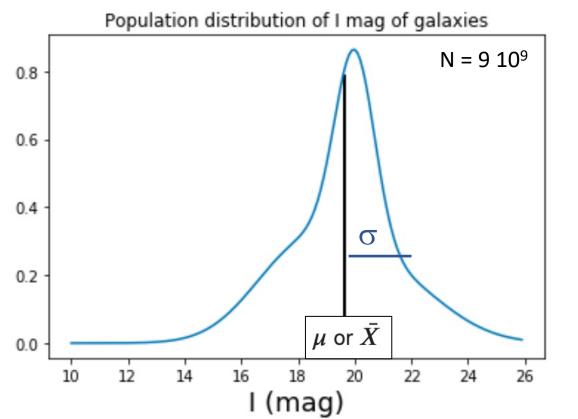


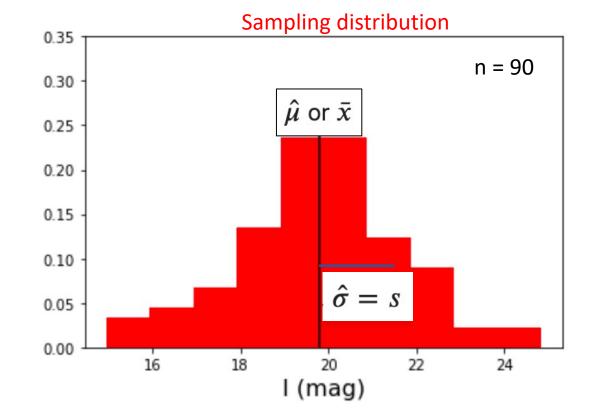
Distribution of $\{\hat{\theta}_1, \hat{\theta}_2, ..., \hat{\theta}_k\} = \text{sample distribution}$



Summary statistics

Name	Population Statistics	Sample Statistics
size	N	n
mean	$\mu = \bar{X} = \frac{\sum_{i} X_{i}}{N}$	$\hat{\mu} = \bar{x} = \frac{\sum_{i} x_{i}}{n}$
Variance	$\sigma^2 = \frac{\sum_i (X_i - \bar{X})^2}{N}$	$s^2 = \frac{\sum_i (x_i - \bar{x})^2}{n - 1}$
Standard deviation	$\sigma = \sqrt{\sigma^2}$	$\hat{\sigma} = s = \sqrt{s^2}$





Summary (sample) statistics: standard error

Standard error (stde) ≠ Standard deviation (std)

Name	Formula
Standard error on the mean	$stde(\bar{x}) = \frac{s}{\sqrt{n}}$
Standard error on the sample stdev	$stde(s) = s/\sqrt{2(n-1)}$
Standard error on proportions	$stde(\hat{p}) = \frac{\sqrt{p(1-p)}}{\sqrt{n}}$

Central limit theorem

When independent random variables are added, their sum tends towards a normal distribution (if n >>)

- This is true even if the original RV are not normally distributed
- Sampling dist. of mean tends (for large *n*) towards a Normal distribution
- Sampling dist. of variance (for large n) does NOT tend towards a Normal distribution

Go to: Sect. II.1.1. of the notebook

Distribution of sample quantities

If RV $\{X_i\}$ whose population is distributed as $N(\mu, \sigma)$

- Sample distribution of $\hat{\mu} \sim N(\mu, \sigma/\sqrt{n}) \iff Z = \frac{\mu \hat{\mu}}{(\sigma/\sqrt{n})} \sim N(0, 1)$
- Sample distribution of $t = \frac{\mu \mu}{(s/\sqrt{n})} \sim t(n-1)$ s is derived from the sample dist.
- Sample distribution of

$$S = \frac{(n-1)s^2}{\sigma^2} \sim \chi^2(n-1).$$
Chi square distribution

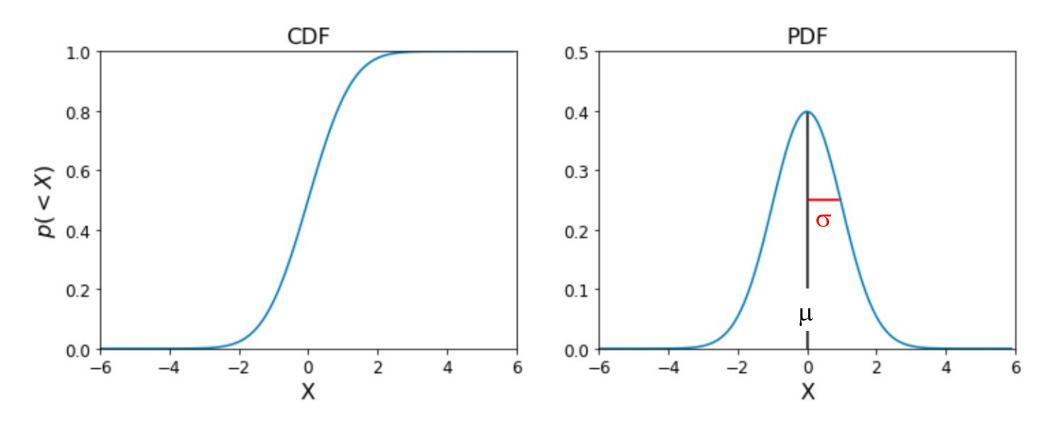
Student distribution

Classical statistical inference: confidence interval

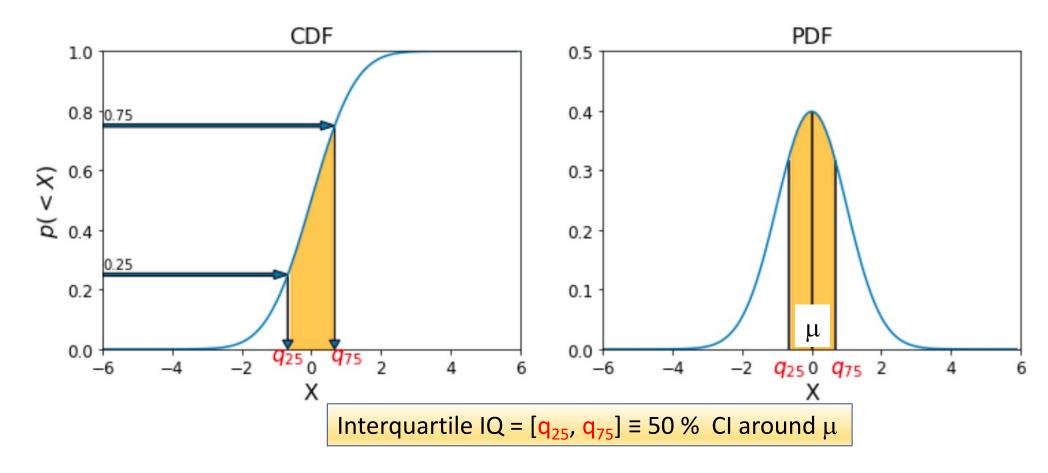
Part 3

Associated notebook:

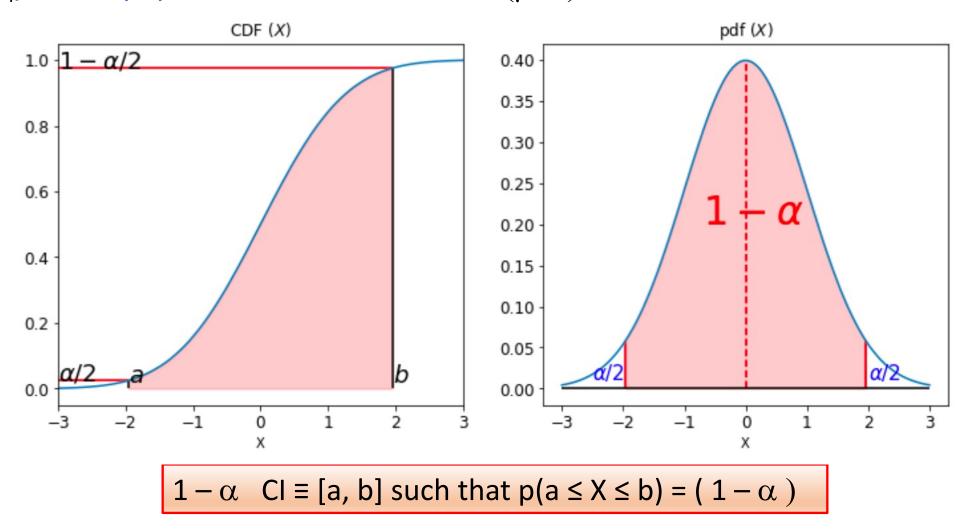
04-Basic statistical inference frequentists 2/Frequentist inference 02.ipynb

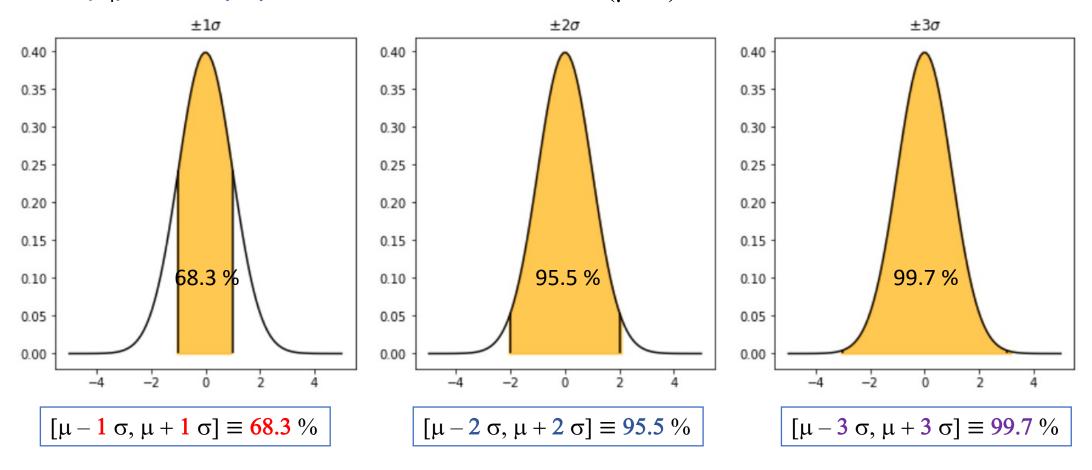


If RV $\{X_i\}$ whose population is distributed as $N(\mu, \sigma)$

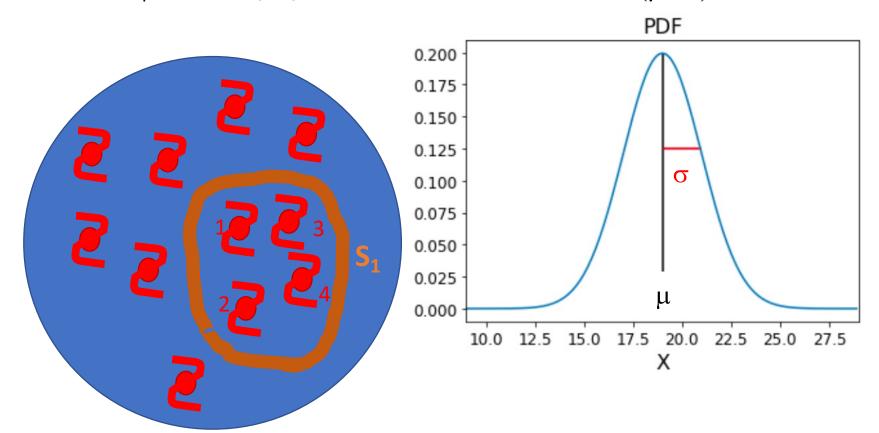


 $1-\alpha$ CI = [a, b] such that p(a \leq X \leq b) = (1- α)



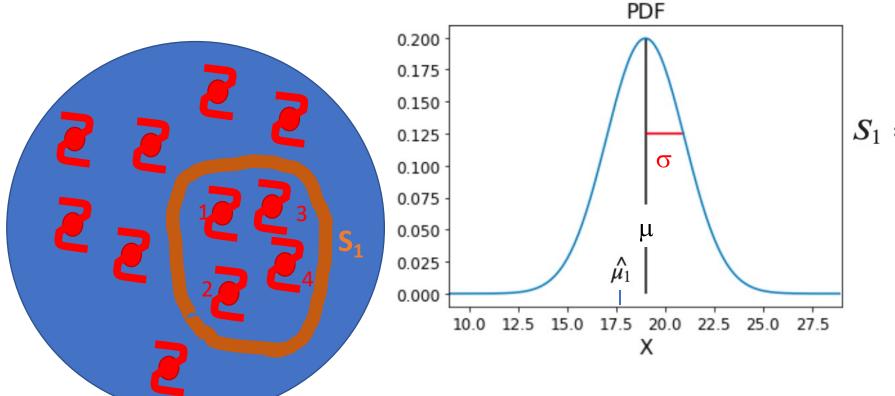


Confidence interval from an estimator



$$S_1 = \{x_1, x_2, x_3, x_4\}$$

Confidence interval from an estimator



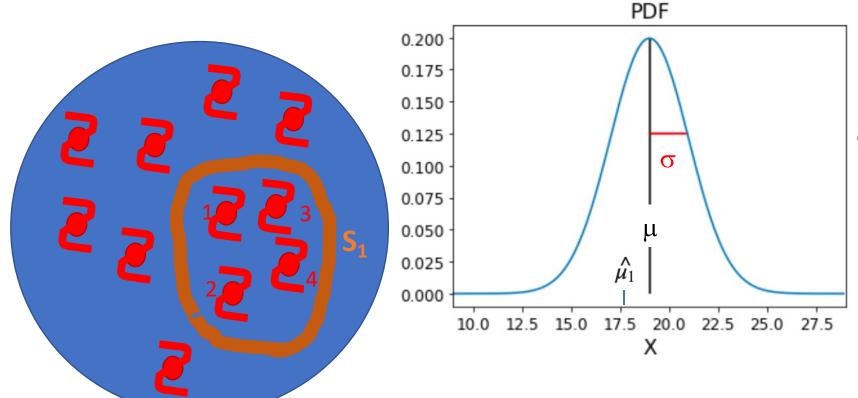
$$S_1 = \{x_1, x_2, x_3, x_4\}$$

$$S_1 = \{19.45, 16.20, 16.43, 19.10\}$$

$$\hat{\mu}_1 = 17.8$$

Confidence interval from an estimator

If RV $\{X_i\}$ whose population is distributed as $N(\mu, \sigma)$



$$S_1 = \{x_1, x_2, x_3, x_4\}$$

$$S_1 = \{19.45, 16.20, 16.43, 19.10\}$$

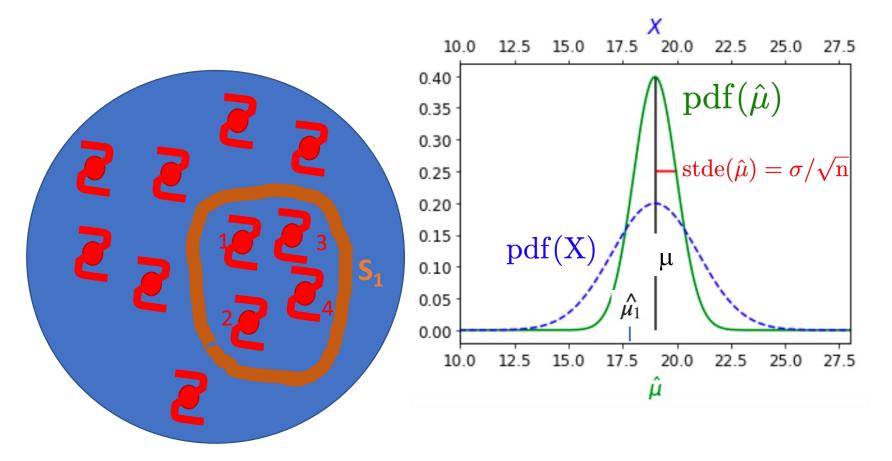
$$\hat{\mu}_1 = 17.8$$

95.5 % CI on sample mean?

We need to look at the distribution of the sample mean

95.5 % Cl on $\hat{\mu}$?

If RV $\{X_i\}$ whose population is distributed as $N(\mu, \sigma)$



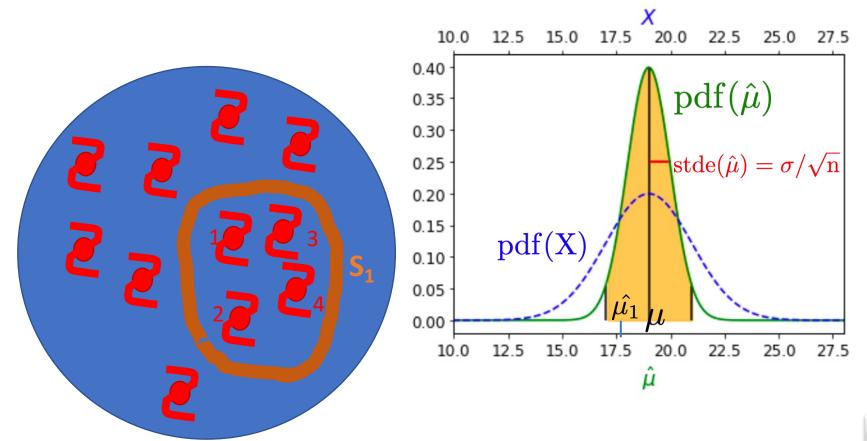
Case 1: σ is known

$$\hat{\mu} \sim N(\mu, \sigma/\sqrt{n})$$

$$stde(\hat{\mu}) = \sigma/\sqrt{n}$$

95.5 % Cl on $\hat{\mu}$?

If RV $\{X_i\}$ whose population is distributed as $N(\mu, \sigma)$



Case 1: σ is known

$$\hat{\mu} \sim N(\mu, \sigma/\sqrt{n})$$

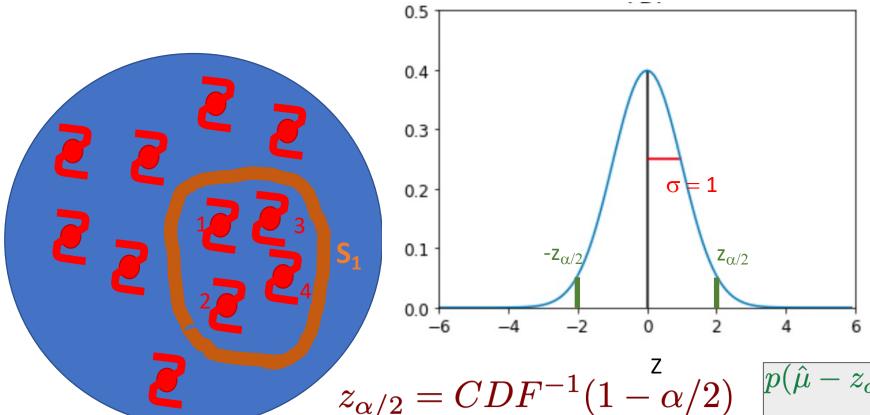
$$stde(\hat{\mu}) = \sigma/\sqrt{n}$$

$$p(\hat{\mu}_1 \in [\mu \pm 2 \, \text{stde}]) = 0.955$$



Confidence interval on the mean

If RV $\{X_i\}$ whose population is distributed as $N(\mu, \sigma)$



Case 1: σ is known

$$stde(\hat{\mu}) = \sigma/\sqrt{n}$$

$$Z = rac{\mu - \hat{\mu}}{\sigma / \sqrt{\mathrm{n}}} \sim N(0, 1)$$

$$p(-z_{\alpha/2} < Z < z_{\alpha/2}) = \alpha * 100 \%$$

p (-
$$z_{\alpha/2}$$
 * stde < $\mu - \hat{\mu}$ < $z_{\alpha/2}$ *stde)

$$= \alpha * 100 \%$$

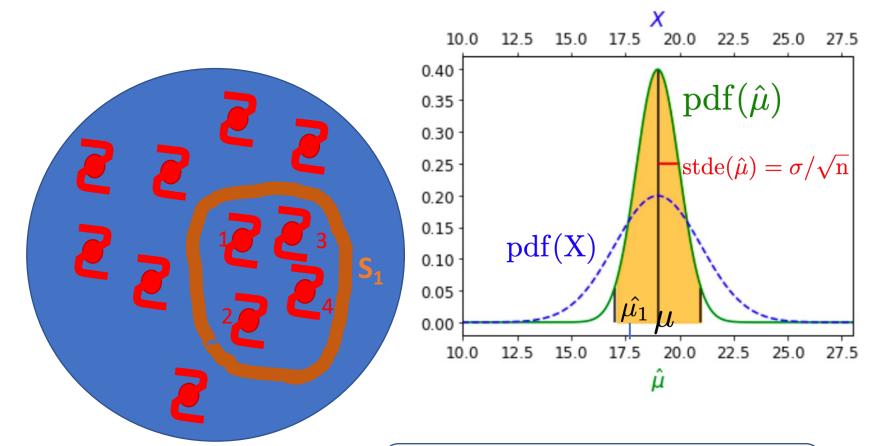
$$p(\hat{\mu} - z_{\alpha/2} \text{ stde} < \mu < \hat{\mu} + z_{\alpha/2} \text{ stde})$$
$$= \alpha \times 100\%$$

$$CI \equiv [\hat{\mu} \pm m \times stde]$$

For 95.5 % CI,
$$z_{\alpha/2} = m = 2$$

Confidence interval on the mean

If RV $\{X_i\}$ whose population is distributed as $N(\mu, \sigma)$



Case 1: σ is known

$$stde(\hat{\mu}) = \sigma/\sqrt{n}$$

$$Z = rac{\mu - \hat{\mu}}{\sigma / \sqrt{\mathrm{n}}} \sim N(0, 1)$$

Case 2: σ is **un**known

$$stde(\hat{\mu}) = s/\sqrt{n}$$

$$t = \frac{\mu - \hat{\mu}}{s/\sqrt{n}} \sim t(n-1)$$

$$CI \equiv [\hat{\mu} \pm m \times stde]$$

Go to: Student_vs_Gauss.ipynb

Confidence interval

"Generic" strategy:

- Look at the PDF of a normalised/scaled estimator of known distribution.
- Define region around your (normalised) estimator (of know the distribution) that encloses (1 α) X 100 % of the area under the PDF.
- For CI around the mean:

$$CI_{\alpha} = [\mu - q_{\alpha/2} \text{ stde}, \mu + q_{\alpha/2} \text{ stde}]$$

$$q_{\alpha/2} = CDF^{-1}(1 - \alpha/2)$$

For CI on other statistics (e.g. variance, difference between 2 means, proportions): see Frequentist_inference_03.ipynb is supplementary material)

Go to: Sect. II.2. of the notebooks