

Probability

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- Probability calculus helps understand rules
- Very complicated though, simplify it via **density** and **mass** functions
- Random Variables- numerical outcome of experiment
 - Discrete
 - Continuous
- Probability Mass Function:
 - Discrete
 - Function that associates every outcome with a probability
 - Must always be ≥ 0
 - Sum of possible vars must always = 1
- Prevalent example:

$$(p)^x (1-p)^{1-x} = p(x)$$

p = prob. of event

x = ~~prob.~~ prob. of trials

- Probability Density Function:
 - Continuous
 - Must be larger than 0 everywhere
 - Total area under it must be 1
 - Areas under PDFs correspond to prob for that random var



Is this a valid?

Area = 1

Always ≥ 0

Cumulative Distribution Function

Probability var $\leq x$

$$F(x) = P(X \leq x)$$

Survival Function:

Opposite of CDF

$$S(x) = P(X > x)$$

Quantile:

The α^{th} quantile

$$CDF \rightarrow F(x) = \alpha \quad \nearrow \text{percentile}$$

Conditional Probability

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$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

Bayes' Rule:

$P(B|A)$ if you know $P(A|B)$

Diagnostic Tests:

+ and - events result of diagnostic test

D and D^c event that subject has or does not have disease

retrievable

$P(+|D) = \text{sensitivity}$

$P(-|D^c) = \text{specificity}$

What people care about

$P(D|+)$

convert

$P(D^c|-)$

~~Bayes~~ Bayes' Formula

$$P(A|B) P(B)$$

$$P(B|A) = \frac{P(A|B)P(B)}{P(A|B)P(B) + P(A|B^c)P(B^c)}$$

Likelihood Ratios:

$$\frac{P(A|C)}{P(B|C)} = \frac{P(C|A)}{P(C|B)}$$

Independence

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- A is independent of B if:
 - $P(A|B) = P(A)$ where $P(B) > 0$
 - $P(A \cap B) = P(A)P(B)$
- Independent
 - Statistically independent of another event
- Identical Distribution
 - Drawn from the same population distribution

Expected Values

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- Making conclusions based on noisy data
- Sample expected values will predict population expected values

- Mean

- $E[X] = \sum_x xp(x)$

- Variance

- Population mean is center of mass of population
- Sample mean is center of mass of sample population
- Sample mean is estimate of population mean
- More data in sample mean, closer to actual mean it is

Variability

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- Variance
 - Variance of random var is measure of spread
 - $\text{Var}(X) = E[(X-u)]^2$
 - Square root of variance is std deviation
 - Sample Variance:

$$s^2 = \frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n - 1}$$

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- Sample Variance
 - Distribution of sample variance centered at what's being estimated
 - Gets more concentrated and thus closer to population variance with more samples
 - Variance of sample mean is population variance divided by n

Binomial Distribution

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- Bernoulli Distribution
 - Binomial is a series of Bernoullis
- $(x + a)^n = \sum_{k=0}^n \binom{n}{k} x^k a^{n-k}$

Normal Distribution

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- Centered on mean
- Standard deviations have equal number of values
- 1 std dev away- 68% of data
- 2 std devs- 95%
- 3 std devs- 99%

Poisson Distribution

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- Used to model counts

$$P(X = x; \lambda) = \frac{\lambda^x e^{-\lambda}}{x!}$$

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- Mean and variance are lambda
- Uses:
 - Count data (especially unbounded)
 - Unknown bounds
 - Contingency tables (qualitative values basically quantified)
 - Approximating binomials if n is too large and p is too small
- Poisson random vars represent rates
 - $X \sim \text{Poisson}(\lambda t)$
 - $\lambda = E \left[\frac{X}{t} \right]$ is the expected count per unit time
 - t is total monitoring time

Asymptotics and LLN

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- Asymptotics
 - Behavior of estimators as sample size approaches infinity
 - Frequency interpretation of probabilities
- Law of Large Numbers
 - Average limits what its estimating, the population mean
 - As number of samples goes up, converge to true value
- Estimator is **consistent** if converges to what you want to estimate
- Good estimators must be consistent, with consistent variance and mean

Central Limit Theorem

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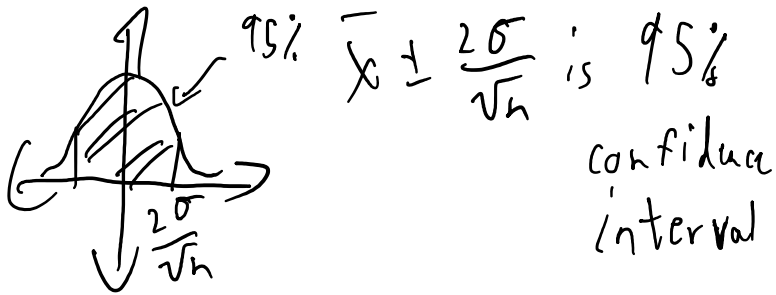
- Central Limit Theorem
 - Distribution of averages of iid (Independent Identically Distributed) (properly normalized) approaches standard normal as sample size increases

Confidence Intervals

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\bar{X} is \approx normal w/ mean μ and
sd $\frac{\sigma}{\sqrt{n}}$



For examples look at Mikes
notes

T Confidence Intervals

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T distribution: centered around 0

w/ degrees of freedom as only parameter — not reliant on mean or variance

$$\frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \rightarrow \frac{\bar{X} - \mu}{S/\sqrt{n}}$$

T interval is similar to Z-interval,
and w/ more data approaches it.

t interval

- assumes data are iid normal
- dist. of data symmetric round shape
- Paired observations
- DON'T use skewed
or discrete data, as
loses

Hypothesis Testing

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Null hypothesis: H_0 - "status quo"

↳ Attempt to refute

Truth	Decide	Result
H_0	H_0	Correctly accept null
H_0	H_a	Type I Error
H_a	H_0	Correctly reject null
H_a	H_a	Type II Error

Executing a test:

Reject null if $\bar{X} >$ than a constant C

C is chosen to set prob. Type I Error to low, but not too low.

↓
 α

P-values

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- Biggest measure of stat. significance
- Idea: how unusual is it to see current estimate

Approach:

1. Define hyp. distribution
2. Calculate summary/statistic w/ data we have
3. Compare calculation w/ hypothesis, bigger difference = bigger p-value.

Power

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Prob. of rejecting null hypothesis
(when it's false)

β = prob. of type 2 error
(choosing H_a incorrectly)

$$\text{Power} = 1 - \beta$$

Calculating Power

Under $H_0: \bar{X} \sim N(\mu_0, \sigma^2/n)$

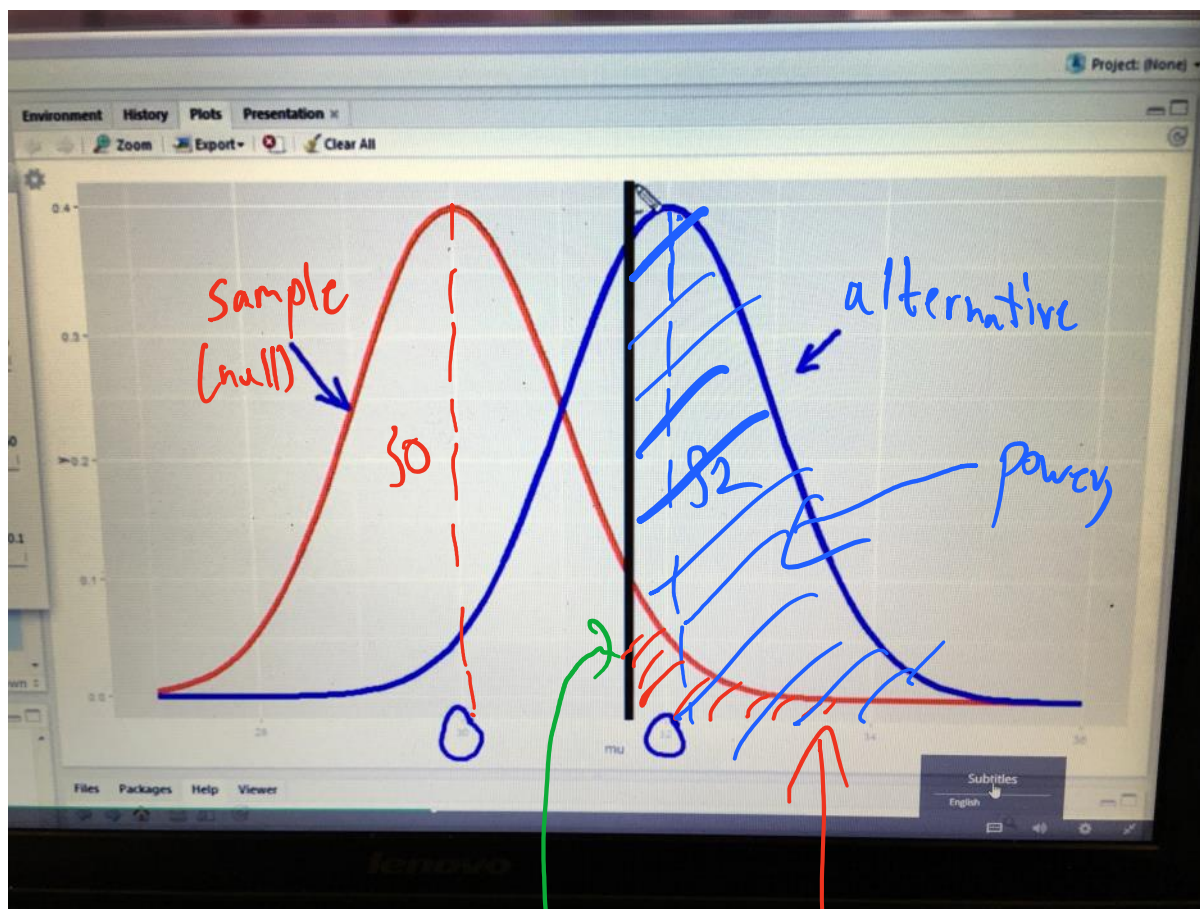
Under $H_a: \bar{X} \sim N(\mu_a, \sigma^2/n)$

? ? This lecture is
hard to understand

\uparrow Sample size, \uparrow power

\uparrow difference μ_a/μ_0 , \uparrow power

$\uparrow \alpha, \uparrow \text{power}$



Solving Equations in Power

$$1 - \beta = P(\bar{X} \geq \mu_0 + z_{1-\alpha} \frac{\sigma}{\sqrt{n}}; \mu = \mu_a)$$

$$\bar{X} \sim N(\mu_a, \sigma^2/n)$$

Unknown

Vars: μ_a, σ, n, β

Vars: μ_a, σ, n, β

Known: μ_0, α

Specify β var, find y^{th} as known

T-test Power

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power. t. test — the actual
R function ~~eq~~ application
of power, previous
page more to explain
concept

$$P\left(\frac{\bar{X} - \mu_0}{S/\sqrt{n}} > t_{1-\alpha, n-1}, \mu = \mu_a\right)$$

Multiple Testing

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- Hypothesis testing/significance analysis often overused
- Correcting for multiple testing avoids false positives or discoveries
- 2 components
 - Error measure
 - Correction
- Use large numbers of analyses and data today, small errors pile up
- 2 Types of Errors
 - Type 1- False positives (say there's a correlation, but there's not)
 - Type 2- False negatives (say there's no correlation, but there is)

Controlling False Positives

- Bonferroni correction is oldest multiple testing correction
- Approach
 - Var: m = # of tests
 - P-values normally
 - Set $\alpha(\text{fwer}) = \alpha/m$
 - Call all P-values below $\alpha(\text{fwer})$ accurate

Controlling False Discovery Rate (false negatives)

- Var: m tests

Controlling false discovery rate (FDR)

This is the most popular correction when performing lots of tests say in genomics, imaging, astronomy, or other signal-processing disciplines

Basic idea:

- Suppose you do m tests
- You want to control FDR at level α so $E\left[\frac{V}{n}\right]$
- Calculate P-values normally
- Order the P-values from smallest to largest $P_{(1)}, \dots, P_{(m)}$ *smallest largest*
- Call any $P_{(i)} \leq \alpha \times \frac{i}{m}$ significant ✓

Pros: Still pretty easy to calculate, less conservative (maybe much less)

Cons: Allows for more false positives, may behave strangely under dependence

lot of signal and you allow for just a few false positives

Alternative approaches

Adjusted P-values

- One approach is to adjust the threshold α
- A different approach is to calculate "adjusted p-values"
- They are not p-values anymore !!!
- But they can be used directly without adjusting α

Example:

- Suppose P-values are P_1, \dots, P_n
- You could adjust them by taking $P_i^{fwer} = \max(m \times P_i, 1)$ for each P-value.
- Then if you call all $P_i^{fwer} < \alpha$ significant you will control the FWER.

- ^ Use in conjunction with the other methods

Bootstrapping

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- Bootstrap: useful tool for constructing confidence intervals and calculating standard errors for difficult statistics
- Bootstrap in practice
 - Non-parametric
 - Better percentile bootstrap confidence intervals correct for bias
 - Easily done via R, just feed in data

Permutation Tests

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- Group comparisons
- Null hypothesis that distribution of observations from each group is the same
- Group labels are irrelevant
- Randomly permute labels (and all their data)
- See if permuting the data receives a different result
- Recalculate statistic
 - Mean difference in counts
 - Geometric means
 - T statistic
- Calculate percentage of simulations where the simulated statistic was more extreme