

General:

- $E(b)$ means expected value of b
- **Mean:** $\mu = E(x)$ (mu)
sample mean: \bar{x}
- **Variance:** σ^2 (sigma squared)
 $\sigma^2 = E((x - \mu)^2) = E(x^2) - E(x)^2$
sample variance: $s^2 = \frac{\sum((x - \bar{x})^2)}{n-1}$
- **Standard Deviation:** σ (sigma)
sample standard deviation: s
- **Random Process** can't be predicted
- **Complement** of A is A^c or A'
- $P(A \cap B)$ = probability of A and B
- $P(A \cup B)$ = probability of A or B
 $P(A \cup B) = (P(A \cap B))/P(B)$
- $P(A|B)$ = probability of A given B is true
- A, B independent if $P(A|B) = P(A)P(B)$
therefore $P(A|B) = P(A)$
- **Reliability:** probability that it works
- **Discrete:** finite number of possible values
Continuous: any value between a and b (e.g. any real number)
- Probability Mass Function (PMF) for discrete, Probability Density Function (PDF) for continuous
- Bernoulli random variable: has only 2 states: success or failure

5 Number Summary:

- 5 numbers:
min
Q₁ 25%
Q₂ 50%
Q₃ 75%
Max
- Q_x is a number (called a quartile) such that (25%, 50%, or 75%) of the data falls below that number
- Q_2 is also the median
- IQR: Inner Quartile Range = $Q_3 - Q_1$

Bayes Rule:

- When you've got a grid of the possible outcomes of two different events
- These edges are called marginals; they sum to 1
- if the two events are independent, each cell is the product of the corresponding marginals
 $P(A \cup B) = P(A)P(B)$
example: fair dice roll is independent
- Two events in a grid are only independent if the property holds for every cell in the grid
- **Conditional Probability:** $P(A|B)$ = prob-

ability of A given that B is true $P(A|B) = \frac{P(A \cap B)}{P(B)}$

- if A and B are independent, then $P(A|B) = P(A)$ because B doesn't affect A

Mutual Exclusion:

- A and B are mutually exclusive if $P(A \cap B) = 0$
- can be one or the other, or none, but can't be both
- mutually exclusive events can't be independent, because once you know one is true, you know the other is false

Combinations Formula:

- $\binom{n}{x} = \frac{n!}{x!(n-x)!} = \frac{(n)(n-1)\dots(n-x+1)}{(x)(x-1)\dots(1)}$

Binomial Distribution:

- Discrete. Driven by p and n
 p : probability of success
 n : number of trials
- $\mu = np$
 $\sigma^2 = np(1 - p)$
- PMF: $\binom{n}{x} p^x (1 - p)^{n-x}$

Continuous Distributions:

- PDF: Probability Density Function
 $f(x) = \frac{d}{dx}(F(x))$
 $\int_{-\infty}^{\infty} f(x)dx = 1$
 $f(x) \geq 0$ for all x
- CDF: Cumulative Density Function
 $F(x) = \int_{-\infty}^x f(t)dt$
 $F(x) = P(X \leq x)$
- $P(a \leq X \leq b) = \int_a^b f(x)dx$
 $P(a \leq X \leq b) = F(b) - F(a)$
 $P(X = a) = 0$
- $\mu = E(x) = \int_a^b x f(x)dx$ ((a, b) = domain of $f(x)$)
 $\sigma^2 = E((X - \mu)^2) = E(x^2) - E(x)^2$
 $E(h(x)) = \int_a^b h(x)f(x)dx$ expected value of $h(x)$

Uniform Continuous Distribution:

- All outcomes have the same probability
- $\mu = \frac{B+A}{2}$
- $E(X^2) = (B^2 + AB + A^2)/3$
- $\sigma^2 = (B - A)^2/12$
- PDF: $f(x) = \frac{1}{B-A}$ for $A \leq x \leq B$
- CDF:
 $F(x) = 0$ for $x < A$
 $F(x) = \int_A^x \frac{1}{B-A}dx = \frac{x-A}{B-A}$ for $A \leq x \leq B$
 $F(x) = 1$ for $x > B$

Poisson distribution:

- Discrete. Driven by λ (lambda)
Interval size is fixed, number of occurrences is varied
 λ : number of events occurring per interval
- $\mu = \sigma^2 = \lambda$
 $\sigma = \sqrt{\lambda}$
- PDF: $P(X = x) = \frac{e^{-\lambda} \lambda^x}{x!}$

Gamma Distribution:

- Continuous equivalent of Poisson
- Driven by α and β
Number of occurrences is fixed, interval length is varied
 α : number of events we're interested in
 β : rate at which events happen: " β time until the next event"
- $\lambda = 1/\beta$: shape parameter
 $\mu = \alpha\beta$
 $\sigma^2 = \alpha(\beta^2)$

Normal Distribution:

- Continuous. Defined in terms of μ and σ
- Empirical Rule: (probably don't use)
 $P(x = \mu \pm 1\sigma) : 68\%$
 $P(x = \mu \pm 2\sigma) : 95\%$
 $P(x = \mu \pm 3\sigma) : 99\%$
- **Important Z Values:**

Z	area to the right
1.6450	5.0%
1.9600	2.5%
2.3260	1.0%
2.5758	0.5%

Standard Normal Transformation:

- Z is like x in terms of μ and σ .
- For use with lookup tables
 $Z = \frac{x - \mu}{\sigma}$
- $\Phi(Z) = \text{NormCDF}(\sigma = 1, \mu = 0, x = Z)$
- Prof says this method is prone to error

Joint Distributions:

- $f(x, y)$
- **Independent** if you can split up $f(x, y) = g(x)h(y)$
- Mean and Variance are additive
- Standard Deviation is not additive

Distribution of Sample Totals:

- original distribution: μ_0, σ_0
- sample size: n
- mean: $\mu = n\mu_0$
- variance: $\sigma^2 = n\sigma_0^2$
- (not as easy for standard deviation (σ))

Distribution of Sample Mean:

- original distribution: μ_0, σ_0
- mean: $\mu = \mu_0$

- variance: $\sigma^2 = \frac{\sigma_0^2}{n}$

Confidence Interval - Mean:

- Only works for $n \geq 30$
- Mean: $\bar{x} \pm Z_{\frac{\alpha}{2}} \left(\frac{s}{\sqrt{n}} \right)$
 - s = sample standard deviation
 - $\frac{s}{\sqrt{n}}$ = standard error = standard deviation of distribution of sample means
 - Only works for $n \geq 30$
- sample size in terms of confidence and interval width: $n = \left(2Z_{\frac{\alpha}{2}} \left(\frac{\sigma}{L} \right) \right)^2$
 - L = width of interval
 σ = standard deviation of **population**

Confidence Interval - Mean - $n < 30$:

- Only works when parent distribution is normal
- use the t -distribution
- $n - 1$ = degrees of freedom
- mean: $\bar{x} \pm (t_{\alpha/2, n-1}) \left(\frac{s}{\sqrt{n}} \right)$

Confidence Interval - Variance:

- You can only do this for $n < 30$ if the data is from a normal distribution
- distribution is a (right-skewed) χ^2 (chi-squared) distribution
- $n - 1$ = degrees of freedom
- confidence interval for σ^2 : $\left(\frac{s^2(n-1)}{\chi_{\alpha/2, n-1}^2}, \frac{s^2(n-1)}{\chi_{1-(\alpha/2), n-1}^2} \right)$
 - $\chi_{x,y}^2$ is the chi-squared distribution with $P(X) \leq x$ and y degrees of freedom

Confidence Interval - Proportion:

- proportion of successes in sample of trials
- based on Bernoulli trials
 - each x is either 0 (fail) or 1 (success)
- \hat{p} = sample proportion
 p = population proportion
 \hat{q}, q same, but for failure
 $q = 1 - p, \hat{q} = 1 - \hat{p}$
- you can only assume it's normal when $\hat{p} > 5$ and $1 - \hat{p} > 5$
- $\hat{p} = \frac{\sum x}{n}$
- Central Limit Theorem only applies for $\hat{p}n \geq 5$ and $\hat{q}n \geq 5$ and n much smaller than the population
- Confidence Interval: $\hat{p} \pm Z_{\alpha/2} \sqrt{\frac{\hat{p}\hat{q}}{n}}$
- Sample size: $n = 4Z_{\alpha/2}^2 \hat{p}\hat{q} \frac{1}{L^2}$
 - If you don't have any idea about \hat{p} , use 0.5 to be maximally conservative

Prediction Interval:

- predict the next value that will occur
- $\bar{x} \pm Z_{\alpha/2} \sigma \sqrt{1 + \frac{1}{n}}$

- use s if you don't have the population standard deviation
- if $n < 30$ you can only use this if the parent population is normal
- the standard error is different (wider) than a confidence interval because we're comparing two different distributions:
 - variance of x : σ^2
 - variance of the sampling distribution of means: $\frac{\sigma^2}{n}$
- this follows from the fact that we had to use our sample mean to predict the next value, not the actual mean

Hypothesis Testing:

- Objective is always to reject the null hypothesis
- null hypothesis: H_0
 - usually $H_0 : \mu = \mu_0$
- alternative hypothesis: H_A
 - 1 tail right: $H_A : \mu > \mu_0$
 - 1 tail left: $H_A : \mu < \mu_0$
 - 2 tail: $H_A : \mu \neq \mu_0$
- test statistic: $Z_t = \frac{\bar{x} - \mu_0}{s/\sqrt{n}}$ where $\bar{x} = \frac{\sum x}{n}$
- critical value: Z_C (determined by α level)
 - for a 1 tailed test, it's Z_α
 - for a 2 tailed test, it's $Z_{\alpha/2}$
- p-value: area more extreme than test statistic
 - remember it's two-sided if it's a 2-tail test

Proportion Hypothesis:

- $Z_t = \frac{\hat{p} - p_0}{\sqrt{p_0(1-p_0)/n}}$
- equivalent of $\frac{\bar{x} - \mu}{s/\sqrt{n}}$ is $\frac{\hat{p} - p_0}{\sqrt{p_0(1-p_0)/n}}$

Type 1 Error:

- false positive
- rejecting H_0 when it is true
- probability is equal to our alpha level (α)

Type 2 Error:

- false negative
- probability that we fail to reject when H_0 is false (we should have rejected)
- represents the probability of drawing a sample that just happens to support H_0 (be inside our critical range)
- depends on the actual **population** values μ and σ
- $P(\text{type 2 error}) = \frac{\bar{x}_c - \mu}{\sigma_{\bar{x}}}$
 - $\sigma_{\bar{x}} = \frac{\sigma}{\sqrt{n}}$ standard error of sample from population
 - μ = real mean of population (not the one from H_0)
 - \bar{x}_c critical value for sample mean (deter-

mined by H_0 and α)

- Example: if the real mean is exactly \bar{x}_c , then $P(T_2) = 0.5$
- Technically, the minimum and maximum are 0 and 1 respectively, since it depends on the population values, and that could be anything.

Final stuff:

You calculate $Var(\bar{X} - \bar{y})$ differently depending on if the variances of the two distributions are equal or not

Difference of Means:

- actual variance of difference: $\frac{\sigma_x^2}{m} + \frac{\sigma_y^2}{n}$
 - does not matter if the two variances are (roughly) equal or not
 - don't usually get to use this because we don't have the population values
 - therefore must use s^2 instead of σ^2
 - (this is not the same thing as pooled variance)

Two Distributions, equal variance:

- Δ_0 is the expected difference between the means
- \bar{x} is usually that $\bar{x} = \frac{\sum x}{n}$
- variance considered equal if $\frac{1}{3} \leq \frac{s_x^2}{s_y^2} \leq 3$
- pooled variance $s_p^2 = \frac{(m-1)s_x^2 + (n-1)s_y^2}{n+m-2}$
 - weighted average of the sample variances
- test stat: $T = \frac{\bar{X} - \bar{Y} - \Delta_0}{s_p \sqrt{1/m + 1/n}}$

Two Distributions, unequal variance:

- always use t distribution
- test stat: $T = \frac{\bar{X} - \bar{Y} - \Delta_0}{\sqrt{s_x^2/m + s_y^2/n}}$

Paired Difference Test:

- $D_i = X_i - Y_i$ mean difference is \bar{D}
- test stat: $T = \frac{\bar{D} - \Delta_0}{s_D/\sqrt{n}}$
 - n is the number of paired differences, not the number of total observations

Proportion comparison:

- uses Z distribution
- common \hat{p} is total successes divided by total observations
- test stat: $Z = \frac{\hat{p}_X - \hat{p}_Y}{\sqrt{\hat{p}(1-\hat{p})(1/m + 1/n)}}$
 - \hat{p} is success proportion of the overall study

- C.I: $(\hat{p}_X - \hat{p}_Y) \pm Z_{\alpha/2} \sqrt{\frac{\hat{p}_X(1-\hat{p}_X)}{m} + \frac{\hat{p}_Y(1-\hat{p}_Y)}{n}}$
- We use the common \hat{p} for hypothesis tests but not C.I. because hypothesis tests assume that $\hat{p}_X = \hat{p}_Y$

ANOVA:

- ANalysis Of VAriance
- $H_0 : \mu_1 = \mu_2 = \dots = \mu_i$
 H_A : at least two means (μ 's) are different
- trt = treatment
- err = error
- tot = total
- Assume normal population distribution with equal variance
- $X_{i,j}$ = j th sample from the i th treatment group
 - I = number of treatment groups, n_i = number of samples in treatment group i
- \bar{X}_{GM} or just \bar{X} = Grand Mean
- SS = Sum of Squares
 - $SS_{tot} = SS_{trt} + SS_{err}$
 - $SS_{tot} = \sum_{i=1}^I \sum_{j=0}^{n_i} (X_{i,j} - \bar{X})^2$
 - $SS_{err} = \sum_{i=1}^I \sum_{j=0}^{n_i} (X_{i,j} - \bar{X}_i)^2$
 - $SS_{trt} = \sum_{i=1}^I (\bar{X}_i - \bar{X})^2$
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- MS = Means Squared
 - $MS_{thing} = \frac{SS_{thing}}{DF_{thing}}$
- test statistic: $F_{test} = \frac{MS_{trt}}{MS_{err}}$
 - Describes how much error is due to treatment as opposed to (normally distributed) random errors
- critical value: $F_{\alpha, DF_{trt}, DF_{err}}$
- You can't use pair-wise ANOVA tests to determine which one of the distributions is actually different, because the uncertainty (introduced by the α level) propagates.
 - instead you have to use Tukey's method (not this class)

Regression:

- we assume different measurements are independent of each other
- model: $Y_i = \beta_0 + \beta_1 X_i + \epsilon_i$
 - β_0 : intercept
 - β_1 : slope
 - ϵ_i : (random) error term
 - * assumed to have a normal distribution with $\mu = 0$
 - X_i : independent variable; predictor
 - Y_i : dependent variable; response
- $Q = \sum_{i=1}^I (Y_i - \beta_0 - X_i \beta_1)$
 - sum of squared vertical deviations
 - sum-of-squares minimizes this
- $S_{xx} = \sum (x_i - \bar{x})^2$
- $S_{xy} = \sum (y_i - \bar{y})(x_i - \bar{x})$
- $\hat{\beta}_1 = \frac{S_{xy}}{S_{xx}}$ ratio of joint variability of X and Y to variability of just X

- $\hat{(\)}$ means estimate
- $\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$
- $\epsilon_i = y_i - \hat{y}_i$, error term, residual
 - actual - estimated
- total sum of squares $SST = \sum (y_i - \bar{y})^2 = \sum y_i^2 - \frac{1}{n} (\sum y_i)^2$
- error sum of squares $SSE = \sum (e_i^2) = \sum (y_i - \bar{y})^2 = \sum y_i^2 - \hat{\beta}_0 \sum y_i - \hat{\beta}_1 \sum x_i y_i$
- regression sum of squares $SSR = \sum (\hat{y}_i - \bar{y})^2 = SST - SSE$
- **measure of fit:** $r^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST}$
 - r^2 = proportion of variation in y explained by the linear relationship model with x
 - $0 \leq r^2 \leq 1$
 - $r^2 = 1$: all data perfectly on straight line
 - r^2 near zero: no linear relationship (may be other type of relationship)
- sample correlation: r
- you can do an ANOVA test for regression
 - $DF_{total} = n - 2$ (because two estimates β_0, β_1)
 - $DF_{regression} = 1$
- hypothesis test: $T = \frac{\hat{\beta}_1 - \beta_1}{s_{\hat{\beta}_1}}$
 - $s_{\hat{\beta}_1} = \frac{s_{\epsilon}}{\sqrt{\sum (x_i - \bar{x})^2}}$
- $H_0: \beta_1 = \Delta_0$
- s_{ϵ} = estimate of standard deviation of error term
- Δ_0 : expected slope (usually 0)
- confidence interval: $\hat{\beta}_1 \pm t_{\alpha/2, n-2} s_{\hat{\beta}_1}$
- confidence interval for mean response
 - mean y value at given value x^*
 - means that you're $(1 - \alpha)100\%$ sure that the mean response will be inside this interval
 - variance = $\sigma_{\epsilon}^2 \left(\frac{1}{n} + \frac{(x^* - \bar{x})^2}{\sum (x_i - \bar{x})^2} \right)$
 - C.I. $\hat{\beta}_0 + \hat{\beta}_1 x^* \pm t_{\alpha/2, n-2} s_{\epsilon} \sqrt{\frac{1}{n} + \frac{(x^* - \bar{x})^2}{\sum (x_i - \bar{x})^2}}$
- prediction interval
 - means you're $(1 - \alpha)100\%$ sure that a new value will lie inside this interval
 - C.I. $\hat{\beta}_0 + \hat{\beta}_1 x^* \pm t_{\alpha/2, n-2} s_{\epsilon} \sqrt{1 + \frac{1}{n} + \frac{(x^* - \bar{x})^2}{\sum (x_i - \bar{x})^2}}$

Law of Total Probability:

- If a probability is made up of sub-probabilities, the total probability is equal to the weighted average
- Example:
 - Lightbulb makers X and Y , probabilities of failure are $\Pr B_X$ and $\Pr B_Y$ respectively

- our lightbulb population is $\frac{6}{10}X$ and $\frac{4}{10}Y$
- A is total probability that any bulb will fail
- $\Pr(A) = \Pr(A|B_X)\Pr(B_X) + \Pr(A|B_Y)\Pr(B_Y)$
 $= \frac{99}{100} \cdot \frac{6}{10} + \frac{95}{100} \cdot \frac{4}{10} = \frac{594+380}{1000} = \frac{974}{1000}$

Long Range Frequency:

- as sample size increases, the relative frequencies of outcomes will approach their theoretical values.
- Example: A fair dice will give each number approximately $\frac{1}{2}$ of the time