

# Stats 3Y03 Summary

---

Note: R might be on the final :\$

## Chapter 1

**Categorical variable:** qualitative variable, such as funny; limited number of options

- e.g. Blood type, Political party
- It can still be a number if the number doesn't describe a quantity
- **Ordinal:** Values that can be ordered, such as academic grade
- **Nominal:** Values that cannot be ordered, such as brand name

## Types of variables

**Numerical variable:** quantitative variable, such as position

- **Continuous:** decimals
- **Discrete:** integer

**Univariate Data:** single variable

**Bivariate Data:** 2 variables (not required in this course)

**Multivariate Data:** more than 2 variables

**Probability:** average of population is from average of sample

**Inferential statistics:** average of sample is from average of population

**Sampling Frame:** list of things in a list that can be sampled

- telemarketers' sample frame is the people with a phone number in the phone book/phone archive of the company
- when doing a culture study of farms, the sample frame could even be a map

**Enumerative study:**

- identifiable goal
- well-defined, unchanging sample frame
- enumerate (explain, evaluate, describe) a condition that exists with the existing population

**Analytic study:**

- focused on improvement of the process which created the results and which will continue creating results in the future
- no well-defined sampling frame

## Target population

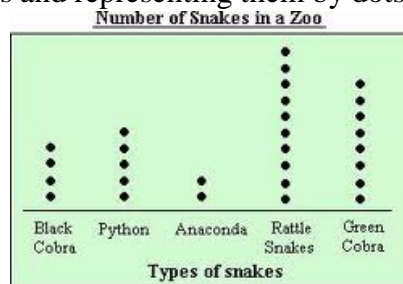
- population you want to be collecting data from
- **sample population** is the population you are collecting data from
- sample population is usually subset of target population
- sample population is useful when the target population is too large
- sometimes it is not the same as the sample population
  - e.g., when informing factory workers that their productivity is being observed, they'll act differently

**Simple random sample:** from entire population

**Stratified random sample:** from a sub-population (1 from each row)

**Convenience sample:** not entirely random; what is easy to obtain (first row)

**Dot plot:** quantifying increments and representing them by dots



**Mean:** average

**Median:** middle value; if length of set is even, average of  $(n+1)/2$  and  $n/2$ ; if length of set is odd,  $(n+1)/2$

**Mode:** common number

**Unimodal:** 1 peak

**Bimodal:** 2 peaks

**Multimodal:** more than 2 peaks

Graphs can also be **symmetric** or **asymmetric**, which is when the top half of the boxplot looks similar to the bottom half.

**Left skew:** mostly on right side

**Right skew:** mostly on left side

Graphs can also be **unskewed**.

**Outliers:**

- values that must be mistakes or abstract exceptions
- $> 1.5 \times$  forth spread (see below) beyond closest quartile
- **extreme outlier** is  $> 3 \times$  forth spread

Each data set is split up into 4 **quartiles**.

Q1: median of bottom half (includes middle number if odd length)

Q2:

Q3: median of top half (includes middle number if odd length)

### **The Five-Number Summary:**

1. Minimum
2. Q1
3. Q2
4. Q3
5. Maximum

The range, minimum, and maximum can include outliers

**range:**  $\text{max} - \text{min}$

### **Variance**

**Variance:** distribution of range

$N$  is [target population](#) size

$x_i$  are the values

$n$  is [sample population](#) size

**Trimmed mean:** mean calculated by trimming away a given percentage of elements (relative to number of elements) from the top and bottom. If the percentage gives a non-discrete number of elements, you have to calculate multiple trimmed means and find the mean of the 2 trimmed means

**Population mean:** expected outcome of mean of [target population](#), i.e. average given a theoretically infinite amount of measurements; a.k.a. true mean, expected value

$$\mu = \frac{1}{N} \sum_{i=1}^N x_i$$

**Sample mean:** average given finite number of inputs; an estimate of the population mean

$$\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$$

**Sample median:**  $\tilde{x}$

**Sample variance:**  $s^2 = \frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2$

**Population variance:**  $\sigma^2 = \frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2$

**Spread:** interquartile range

## Standard Deviation

s.d.

- Average distance from the mean
- Larger s.d. means more spread
- i.e. when all values are the same, s.d. = 0
- Square root of variance =  $\sqrt{s^2}$

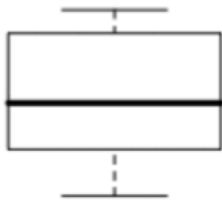
**Degrees of freedom:**  $n - 1$

Another measure of spread is **interquartile range** or **forth spread**. ( $Q_3 - Q_1$ )

**Whiskers:** minimum and maximum points of the range that does not include outliers

**Boxplot:**

- Top and bottom lines are whiskers
- Box surrounds forth spread
- Middle line is median
- Can be vertical or horizontal
- Outliers are still placed on boxplots, using circles (o) or stars (\*)
- (a.k.a. Boxplot-and-whisker plot)



## Chapter 2

This is similar to the logic course [SFWR ENG 2FA3](#).  
Probability is between 0 and 1

**Sample space:** all possible outcomes

The size of the sample space is: outcomes<sup>events</sup>.

N: number of outcomes for an event

N(A): number of outcomes in sample space, A

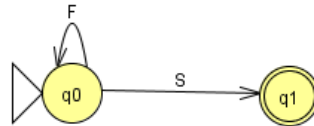
**Relative frequency probability:** events that occur frequently, such as rolling dice or buying lottery tickets

**Relative frequency** of a value =  $\frac{\text{occurrences of value}}{\text{observations in data set}}$

**Personal probability:** events that cannot be repeated or non-random events with unknown quantities that is based on belief of an individual

**Coherent:** personal probability of one event does not contradict personal probability of another

Sometimes you can have an **infinite number of possible outcomes**. For example, if you are testing something until failure, you will repeat testing until success {S, FS, FFS, ...}



If there are a given number of outcomes, such as 1 through 6 for a dice, and a sample space, A, such as containing all odd outcomes, A', the **complement**, contains everything A does not, such as all even outcomes. Therefore,  $P(A) + P(A') = 1$

**Simple Event:** Only one way to get each outcome

**Compound Event:** Multiple ways to get the same outcome

## Replacement

**Without replacement:** e.g. if you are picking names out of a hat and you put the names back after each pick

**With replacement:** when you use each option only once

## Mutually-Exclusive Events

**Mutually exclusive** (a.k.a. disjoint event): 2 outcomes cannot occur simultaneously;  $A \cap B = \emptyset$ ; e.g. rolling a dice can either be 3 or 5—not both, whereas it being 3 or odd is not mutually exclusive

The **probability** is the sum of the probability of each individual event:

$$P(A_1 \cup A_2 \cup \dots \cup A_k) = \sum_{i=1}^{i=k} P(A_i)$$

$$P(A) = \frac{N(A)}{N}$$

For ordered pairs, number of possible arrangements is:  $N!$

**Permutations** are ordered sequences that are made up by  $k$  elements that are a subset of a set of  $n$  elements.

The notation for **number of permutations** is:  $P_{k,n} = \frac{n!}{(n-k)!}$

**Bayes's Theorem:**  $P(A|B) = \frac{P(B|A)P(A)}{P(B)}$

## Non-mutually exclusive events

For non-mutually exclusive events, there can be overlap, so:

$$P(A \cup B) = P(A) + P(B) - P(A \cap B)$$

For ordered pairs, number of possible arrangements for k events is:  $\prod_{i=1}^k N(A_i)$

Unordered permutations are known as **combinations** (n choose k). They are denoted:

$$C_{k,n} = \binom{n}{k} = \frac{n!}{k!(n-k)!}$$

For unordered pairs, number of combinations is:  $\frac{n!}{k!(n-k)!}$ , where n is the number of objects and

k is the size of the group (pick k, 5, players for the team from n, 8 people. number of permutations?)

**Dependent:** you can't put it back

**Independent:** you can put it back

**Conditional probability:** Probability of A given B:  $P(A|B) = \frac{P(A \cap B)}{P(B)}$

## Chapter 3

### Random variables

rv

- function whose domain is the sample space and whose range is the set of real numbers, but is subject to random variations
- denoted by a capital letter, whereas its values have the same letter as the rv, but lower-case
- can either be [continuous or discrete](#)
- x is a particular value of a [random variable](#)

**Bernoulli:** binary output; can only be either a 0 or a 1

**Probability Mass Function (pmf):** a function that gives the probability that a [discrete random variable](#) is exactly equal to some value

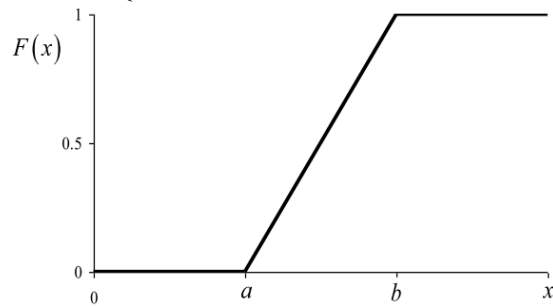
### Cumulative Distribution Function

**CDF:** add up all probabilities within a given range

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

$$= \int_{-\infty}^x f(y) dy$$

$$= \begin{cases} 0, & x < a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ 1, & x > b \end{cases}$$



### Expected Value

- mean using probability of [discrete](#) rv's
- gives same result as population mean
- use if you're not given data, but given probability

$$E(X) = \mu_x$$

- $$= \sum_{x \in D} xp(x)$$
- $$= \int_{-\infty}^{\infty} xf(x) dx$$

- **Variance:** 
$$V(X) = \sum_{x \in D} (x - \mu)^2 p(x) = E[(X - \mu)^2]$$

- **General Expectation formula:** 
$$E(x) = \sum xP(x)$$

### Variance of CDF

$$\text{Var}(X) = E[(X - \mu)^2]$$

$$= \sigma^2$$

$$= \int_{-\infty}^{\infty} (x - \mu)^2 f(x) dx$$

$$= \int x^2 f(x) dx - \mu^2$$

### Binomial experiment

1. fixed trial
2. 2 outcomes—success or failure
3. Trials are independent ([without replacement](#))
4. Probability of each outcome is the same for each trial

- If the sample size is at most 5% of the population size, the experiment can be analyzed as though it were a binomial experiment ([without replacement](#)).
- $n$ : repetitions of trials
- $p = P(\text{success in single trial})$
- $q = P(\text{fail in single trial})$
- $x$ : total number of successes
- $$b(x; n, p) = \begin{cases} \binom{n}{x} p^x (1-p)^{n-x}, & x = 0..n \\ 0, & \text{else} \end{cases}$$

**Hypergeometric (H.D.):** same as [binomial](#), but dependent ([with replacement](#))

- $N$ : number of items in population
- $M$ : number of successes in population
- $n$ : number of items in sample
- $x$ : number of successes in sample
- $$P(X = x) = h(x; n, M, N) = \frac{\binom{M}{x} \binom{N-M}{n-x}}{\binom{N}{n}}$$
- $E(X) = n \cdot \frac{M}{N}$  (same as binomial)
- $$V(X) = \left( \frac{N-n}{N-1} \right) \cdot n \cdot \frac{M}{N} \cdot \left( 1 - \frac{M}{N} \right)$$

**Negative Binomial Distribution:**

- $n$  is fixed in [binomial](#), whereas *here*,  $n$  is random
- trials repeated until success we want
- $r$  is the number of successes you want
- If  $r = 1$ , this is known as a **geometric distribution**

**Poisson distribution:**

- discrete pdf
- number of occurrences of an event in a given interval, given average rate and time (independent), since last event
- $$p(x; \lambda) = \frac{e^{-\lambda} \lambda^x}{x!}$$
- $x$ : probability that  $x$  things will happen
- $\lambda$  (or  $\mu$ ): average occurrences given population (multiply average rate by population)
- mean = variance =  $\lambda$ , so [S.D.](#) =  $\sqrt{\lambda}$
- $\alpha$  – expected number of events during unit interval
- $t$  – time interval length
- $\lambda = \alpha t$



- $P_k(t) = \frac{e^{-\alpha t} \cdot (\alpha t)^k}{k!}$

**Exponential:** time between events, whereas poisson is more the number of events; continuous distribution

Expected value:  $\frac{1}{\lambda} = \mu$

$$p(x) = \lambda e^{-\lambda x} = \frac{1}{\mu} e^{-\frac{x}{\mu}}$$

For ranges,  $p(x) = \int_a^b \frac{1}{\mu} e^{-\frac{x}{\mu}} dx$

## Chapter 4

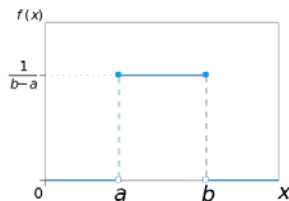
### Probability Density Function

**PDF:** a function that gives the probability that a [continuous](#) random variable is exactly equal to some value, such that:  $P[a \leq X \leq b] = \int_a^b f(x) dx$

Area under whole curve = 1

**Uniform Distribution:** if a [continuous](#) random variable,  $X$ , has a [pdf](#),  $f(x; a, b)$ :

$$f(x) = \begin{cases} \frac{1}{b-a}, & a \leq x \leq b \\ 0, & \text{else} \end{cases}$$



Note:  $a$  and  $b$  do not represent the entire range of the [PDF](#). Just look at the  $f(x)$  formula above!

To get [pdf](#) from [cdf](#), take the derivative of the [cdf](#).

$$F'(x) = f(x)$$

**Percentile:** percentage of data below you; relative to other data in the range

- $p$ : percentile
- $\eta$ : percentile function
- $p = F(\eta(p)) = \int_{-\infty}^{\eta(p)} f(y) dy$

$$\mu_x = E(X)$$

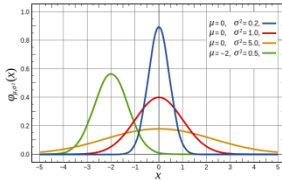
$$E(X) = \alpha\beta$$

## Normal Distribution

A.k.a. population normality

symmetric; mean = median = mode

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}, \quad -\infty < x < \infty$$



**Bell curve (a.k.a. Gaussian curve):** normal curve, normal distribution; **Central Limit Theory** says the sampling distribution of sample means will be bell-shaped; s.d. = population s.d./ $\sqrt{\text{sample size}}$

## Z-Tables

A.K.A. Standard Normal Cumulative Probability Table

**Z-function:** a standardized [cdf](#) that you use to predict data

- $Z = \frac{X - \mu}{\sigma}$
- It's horizontal units are s.d.'s

$z_c$ : critical value

If you're given a probability, you find the value on the z-table and choose the values at the location. If you cannot find the value on the z-table, find the two closest ones and find the weighted average.

$$E = z_c \frac{\sigma}{\sqrt{n}}$$

**Standardized Score:** a.k.a. "z-score"  $\frac{\text{observed value} - \text{mean}}{\text{s.d.}}$

$\alpha$ -level is the area of the graph of a normal distribution curve  $\alpha = P(Z \geq z_\alpha)$

$Z_\alpha$ : for the standard normal distribution

**Empirical rule:** you can identify that your data has normal distribution by using the rule that:

- 68% of data is within 1 s.d. from mean
- 95% of data is within 2 s.d. from mean
- 99.7% is within 3 s.d. from mean
- there are 3 [s.d.](#)'s from the mean

## Chapter 5

p  $\leftarrow$  discrete

f  $\leftarrow$  continuous

$$p_x(x) = \sum_y p(x, y), p_y(y) = \sum_x p(x, y)$$

$$\text{Mean of sum of joint pdf (discrete): } E(x + y) = \sum_{x,y} (x + y) p(x, y)$$

$$\text{Mean of sum of joint pmf (continuous): } E(x + y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h(x, y) \cdot f(x, y) dx dy$$

**Covariance:** variance for multiple variables;  $\text{Cov} = E(XY) - \mu_x \cdot \mu_y$

Independent and Identically Distributed (i.i.d.):

- form a simple, random sample of size  $n$
- $X_i$ 's are independent r.v.'s
- $X_i$ 's all have same probability distribution

**Multinomial distribution:** represented by the pmf,  $f(x_{1..k}; n, p_{1..k}) = \prod_{i=1}^n \frac{i}{x_i!} p_i^{x_i}$

$$\text{Marginal pdf (continuous): } f_x(x) = \int_{-\infty}^{\infty} f(x, y) dy, -\infty < x < \infty$$

$$f_y(y) = \int_{-\infty}^{\infty} f(x, y) dx, -\infty < y < \infty$$

$$\text{Conditional probability of joint pdf: } f(x|y) = \frac{f(x, y)}{f_y(y)}, -\infty < x < \infty$$

$$\text{Correlation coefficient: } \rho_{x,y} = \frac{\text{Cov}(x, y)}{\sigma_x \cdot \sigma_y}$$

## Chapter 6

$\theta$  represents the parameter of interest

$\hat{\theta} = \theta + \text{error of estimation}$

- a function of the sample, i.e. rv

**Point estimate:** mean from multiple estimate(s), using the standard error, where  $\theta$  represents parameter of interest (e.g.  $\mu$  or  $\sigma$ ), where you estimate  $\hat{\theta}$ .

$$\text{Bias of } \hat{\theta}: E(\hat{\theta}) - \theta$$

$$\text{Unbiased: } E(\hat{\theta}) = \theta$$

**Estimator:** the formula

- Should be unbiased (0 avg. error)

$$\sigma^2 = S^2 = \frac{\sum (X_i - \bar{X})^2}{n-1}$$

$$E(S^2) = \sigma^2$$

- Should have minimum variance (i.e. little spread)

- Summary for good estimators: Minimum Variance Unbiased Estimator (MVUE)
  - Unbiased is not always better than minimum variance

**Estimate:** value obtained from the formula after data has been inputted

What is point estimate for each  $\theta$ :

- $\mu : \bar{x}$
- $p : \hat{p} = \frac{x}{n}$

**True value:** mean of the population (instead of sample)

Trimmed means will result in **robust estimator**.

**Robust estimators** are less affected by outliers

Standard error of an estimator,  $\hat{\theta}$  is its standard deviation,  $\sigma_{\hat{\theta}} = \sqrt{V(\hat{\theta})}$

Estimated standard error:  $\hat{\sigma}_{\hat{\theta}}$  or  $s_{\hat{\theta}}$

**Bootstrapping:** Creating multiple samples from one sample with replacement

- Only works for independent, equally-distributed, random samples
  - Not useful if small data set, lots of outliers (remove outliers first), dependence structures (data based on changing time, etc.)
  - $n^*$  depends on computing capacity, type of problem, and complexity
  - Computed bootstrap value is indicative of the accuracy of your sample. If it is higher than sample, sample is probably higher than actual; if lower than sample, sample is probably lower than actual
1. Compute  $x^*$ , which is from  $x$ , sampled with replacement
  2. Compute  $\hat{\theta}^*$  from  $x^*$

$$3. \text{ Estimate standard error, } \text{Se}_B(\hat{\theta}) = \sqrt{\frac{\sum_{i=1}^B (\theta_i^* - \bar{\theta}^*)^2}{B-1}}$$

**Parametric bootstrap:**

**Point estimation:** 2 main methods: a method of getting the population based on a guess by calculating standard error

- [Method of moments](#)
- [Maximum Likelihood estimation](#)

Minimum Variance Unbiased Estimator (MVUE)

## Method of Moments

$k^{\text{th}}$  moment of  $f(x)$  is  $E(X^k) = \frac{1}{n} \sum_{i=1}^n X_i^k$

$$\lambda = \frac{1}{E(X^k)} \xrightarrow{E(X^k) = \bar{X}} = \frac{1}{\bar{X}}$$

Recall:  $E(X) = \mu = \alpha\beta$

## Maximum Likelihood Estimation

(MLE)

Maximum value of the random sample that you have

$\hat{\theta} = \max(P(X_i))$  is the value of X where you have the highest probability

More popular

Equating the derivative of the logarithm of the pmf to 0 gives maximizing value

**Method of Moments Estimator (MME):**

**Joint pdf:**

- Likelihood
- Independent
- $f(x_1, \dots, x_n; \lambda) = (\lambda e^{-\lambda x_1}) \dots (\lambda e^{-\lambda x_n}) = \lambda^n e^{-\lambda \sum x_i}$
- pdf governing occurrences of A & B, not just one (i.e. pdf of occurrences of multiple potential events), like for regular pdf's

$$n \ln(\lambda) - \lambda \sum x_i$$

$\hat{a}$ : variables with a hat means they are an estimate

$$\hat{\lambda} = 1 / \bar{X}$$

**e.g.)**

$$\prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y_i - \mu)^2}{2\sigma^2}} = \left( \frac{1}{\sqrt{2\pi\sigma^2}} \right)^n e^{-\frac{n(y_i - \mu)^2}{2\sigma^2}}$$

$$\lambda = \frac{1}{\sqrt{2\pi\sigma^2}}$$

$$e^{-\lambda \sqrt{2\pi\sigma^2} \frac{n(y_i - \mu)^2}{2\sigma^2}} = e^{-\lambda \sqrt{2\pi\sigma^2} \frac{n\pi(y_i - \mu)^2}{2\pi\sigma^2}}$$

$$= e^{-\lambda \frac{n\pi(y_i - \mu)^2}{\sqrt{2\pi\sigma^2}}}$$

$$= e^{-\lambda \sum_{i=1}^n \frac{\pi(y_i - \mu)^2}{\sqrt{2\pi\sigma^2}}}$$

$$x_i = \frac{\pi(y_i - \mu)^2}{\sqrt{2\pi\sigma^2}}$$

## Chapter 7

Most important chapter!!!

### Confidence interval

**Confidence level:** measures reliability of confidence interval; most popular confidence levels: 90, 95, and 99%; the percent of all samples that will give correct results

**Confidence interval:** interval where certain where data is reliable

- Precision is width of confidence interval
- First determine confidence level
- use the [z tables](#) to find
- In order for this to work:
  - Population distribution is [normal](#)
  - [s.d.](#) given
- Actual mean  $\mu$  does not necessarily have to be in the interval even if the estimated mean *is* in it

Sample mean  $\pm 1.96$  standard errors

$$P(CI) = 100(1 - \alpha)\%$$

$$CI = \left( \bar{x} - z_{\frac{\alpha}{2}} \cdot \frac{\sigma}{\sqrt{n}}, \bar{x} + z_{\frac{\alpha}{2}} \cdot \frac{\sigma}{\sqrt{n}} \right)$$

$$CI = \left( \bar{x} - t_{\frac{\alpha}{2}, \underbrace{n-1}_{\text{DOF}}} \cdot \frac{s}{\sqrt{n}}, \bar{x} + t_{\frac{\alpha}{2}, n-1} \cdot \frac{s}{\sqrt{n}} \right)$$

### Hypothesis:

**Standard error:** conversion of standard deviation (total population) to sample distribution

$$(\text{sample population}) = \frac{\text{s.d.}}{\sqrt{n}}$$

Bound of the error is half the width

$$\text{Sample size: } n = \left( 2z_{\frac{\alpha}{2}} \cdot \frac{\sigma}{w} \right)^2$$

A larger sample size gives a narrower confidence interval.

A smaller sample size gives a wider confidence interval.

### Statistical Inference:

#### Sampling variability:

**T-Table:** Z-Table, but for s, instead of  $\sigma$ , but you can still use z if sample size  $> 40$ ; uses 2 parameters: degrees of freedom and probability level

## Chapter 8

The point of this to see if the error in the sample mean is low enough to make the sample valid/satisfactory.

**Statistical hypothesis:** assumption about a population characteristic; 2 types:

- [Null Hypothesis](#)
- [Alternative Hypothesis](#)
- Choose the hypothesis based on the [level of significance](#)
  - for lower level, choose Type I / Null
  - for higher level, choose Type II / Alternative

### Null Hypothesis

- $H_0: \mu = \mu_0$ 
  - $z = \frac{\bar{x} - \mu_0}{\sigma} \sqrt{n}$
- proof by contradiction
- assume it is the thing you think it isn't and prove that wrong
- think *equality*
- If you reject it, the evidence is **statistically significant**

### Alternative Hypothesis

- $H_A$  OR  $H_a$  OR  $H_1$ 
  - $\mu > \mu_0, z \geq z_\alpha$
  - $\mu < \mu_0, z \leq z_\alpha$
  - $\mu \neq \mu_0, \dots$
- specified *range*
- think  $>$ ,  $<$ , or  $\neq$
- if you only choose one inequality, it is called a **one-sided hypothesis test**
  - **upper:**  $\mu > H_a$
  - **lower:**  $\mu < H_a$

### Errors

- **Type I:** say something is right when it's wrong
  - **Level of significance** ( $\alpha$ ):  $P(\text{Type I error})$
  - Proving [null hypothesis](#) true
  - Since null hypothesis is a value, P has one value
- **Type II:** say something is wrong when it's right
  - $P(\text{Type II error}) = \beta$
  - Proving [alternative hypothesis](#) true
  - Since alternative hypothesis is a range, P is a range

### Case I

$\sigma$  given (not  $s$ ), normal distribution

$$z = \frac{\bar{x} - \mu_0}{\sigma} \sqrt{n}$$

### Case II

For large n (i.e.  $n > 40$ ), s is close to  $\sigma$

$$z = \frac{\bar{x} - \mu_0}{s} \sqrt{n}$$

### Case III

normal dist, s given

$$\text{Test statistic value: } t = \frac{\bar{x} - \mu_0}{s} \sqrt{n}$$

One tail:  $z_{\alpha}$

Two tails:  $z_{\alpha/2}$

If in rejection region, reject the null hypothesis.

### P-Value

**P-Value:** observed level of significance

**Level of significance ( $\alpha$ ):** a percentage or decimal that represents the cut-off value

- If P-value is small enough, reject the null hypothesis and accept the alternative hypothesis
- If p-value is not small enough, don't reject the null hypothesis and there is not enough information to determine whether or not to accept the alternative hypothesis.

## Chapter 9 – Test Statistics

**Degrees of Freedom:** number of samples – 1

For normal populations with known variances, test statistic value:  $z = \frac{\bar{x} - \bar{y} - \Delta_0}{\sqrt{\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}}}$

$\Delta_0$  is usually 0

**Null hypothesis:**  $\mu_1 - \mu_2 = \Delta_0$

**Alternative Hypothesis:** 
$$\begin{cases} \mu - \mu_0 > \Delta_0 \\ \mu - \mu_0 < \Delta_0 \\ \mu - \mu_0 \neq \Delta_0 \end{cases}$$

3 Cases (conditions stay the same as before):

1. [Case I:](#)
2. [Case II:](#)
3. [Case III:](#) t distribution

Round down to the nearest integer

Pooled t happens when  $\sigma_1^2 = \sigma_2^2$



**Margin of Error:**  $E = t_{\frac{\alpha}{2}} \frac{s_d}{\sqrt{n}}$

***f* distribution:**

- pdf distribution is too difficult, so we will work with tables
- Assumptions:
  - 2 populations independent
  - Simple random samples
  - Normally distributed
  - Test statistic for test hypothesis, given two variances is:  $f = \frac{s_1^2}{s_2^2}$
- Demonstrates the difference between the two variances
- Determines whether or not the rejection region is too high or not
- Inputs:
  - Significance level,  $\alpha$
- Null Hypothesis:  $\sigma_1^2 = \sigma_2^2$
- Alternative Hypothesis:  $\sigma_1^2 < \sigma_2^2$

## Chapter 10

Determine a line with the least variance

**Deterministic Relationship:**  $y = \beta_0 + \beta_1 x$  (i.e.  $y = mx + b$ )

**Regression Analysis:**

**Model equation:**  $y = \beta_0 + \beta_1 x + \varepsilon$

$\varepsilon$ : measure of variation; error in data

**Principle of least squares:** gives minimum error

$$s_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{n-1}$$

$$s_x^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n-1}$$

$$b_1 = \frac{s_{xy}}{s_x^2} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2} =$$

$$\boxed{b_0 = \bar{y} - b_1 \bar{x}}$$

**Point Prediction:** plugging in values of  $x$  into the regression equation

**Residual:** error; vertical deviation from estimated line ( $y - y_0$ )

**Extrapolation:** usually doesn't work, though

library (MASS)

summary() gives 5-number summary

**Sum of Squares for Errors (SSE):**  $SSE = \sum (y_i - \hat{y})^2 = \sum y_i^2 - \hat{B}_0 \sum y_i - \hat{B}_1 \sum x_i y_i$

## Chapter 11

(actually chapter 10, but week 11. Go back and rename the sections by chapter and not by week)

**ANOVA:**

**Factor:**

**levels of the factor:**

The number of populations being compared is  $I$ .

$X_{i,j}$  represents the random variable for the  $j^{\text{th}}$  experiment for the  $i^{\text{th}}$  population

## Hypothesis

$$H_0 : \mu_1 = \mu_2 = \dots = \mu_I$$

$H_a$  : at least 2 values of  $\mu_i$

$$E(X_{i,j}) = \mu_i$$

$$V(X_{i,j}) = \sigma$$