	Population statistics	Sample statistics
Total Number	N	n
Mean	μ (given)	$\overline{\mathbf{x}} = \frac{\Sigma  \mathbf{x}}{N}$
Median	-	x̃ (middle)
Standard deviation	$\sigma = \sqrt{\frac{\Sigma(x-\mu)^2}{N}} \text{ or given}$	$s = \sqrt{\frac{\Sigma(x - \bar{x})^2}{n - 1}}$
Pearson Coefficient of <u>linear</u> correlation	$\rho: \sigma^2_{x \pm y} = \sigma^2_x + \sigma^2_y \pm 2\rho\sigma_x\sigma_y$	$r = \frac{1}{n-1} \Sigma(\frac{x-\bar{x}}{s_x})(\frac{y-\bar{y}}{s_x})$
Proportion	p (given)	$\hat{\mathbf{p}} = \frac{X}{n}$
Calculated test statistic	-	$z, t, \hat{p}, Binomial$

Rules	Formula Remark		
68-95-99.7 rule	$\mu \pm 1,2,3 \sigma$	Can be used to find extreme data	
Interquartile Range	IQR = Q3 - Q1	Can be used to test spread	
Central location	Median	Compare between two datasets	
5 Numbers Box Plot	Min Q1 Median Q3 Max	Spread & Outliers	
Outliers	>Q3 + 1.5IQR	If outliers' are present, distribution is less	
	<q1 -="" 1.5iqr<="" td=""><td>likely to be normal</td></q1>	likely to be normal	
Influential Point	Recalculation of r value	Is an outlier and removing it affect the best fit	
		line	
Simpson's Paradox		for all of several groups can reverse direction	
		gle group. Due to the difference in weightage	
Restricted Range	Association changes when data range cha	inges	
Average data	Correlation based on average data most li	kely resulting in higher association	
Central Limit Theorem	For sample with large sample size, the	Note it is the <u>sample mean</u> , not the sample	
	sampling distribution of the sample		
	mean is approximately a normal		
	distribution		
Law of Large Numbers	With a large number of experiments, the average will tends towards the expected value		
Binomial probability	$P(x) = \frac{n!}{x!(n-x)!} p^{x} 1 - p^{n-x}$	$p^x 1 - p^{n-x} \qquad \left  \frac{n!}{x!(n-x)!} = nCx \right $	
Normality Test	Anderson Darling Normality	P≥0.05 when normal	
Normanty Test	Normality probability plot		
E1			
Examine graph	Overall pattern (Form/ Direction/ Strength)		
	Deviations (Outliers)		
Confidence Interval	$\alpha\%$ of the confidence intervals constructed in this way would contain the true value for		
	the population parameter of $H_0/H_1$ .		
	We estimate with $lpha\%$ confidence that between CI of $H_0/H_1$		
Conclusion statement	There is sufficient/insufficient evidence to support $H_0/H_1$		

Studies	Method	Remarks
Observational Studies	Observe samples without modification	Contrast to experimental studies Placebo/Control Group/Blinding
Simple Random Sampling	Every sample has equal probability	Essential for N, Z, T tests
Stratified Random Sampling	Divide sample into representative groups before SRS	Useful if the sample contains different groups
Cluster Random Sampling	Divide sample into groups then randomly select a few groups	Low cost and no need sampling frame Large sample size required to reduce margin of error
Voluntary response Sampling	Require sample to voluntarily response	Subject to response/ non-response bias
Multistage Sampling	Conduct the sampling in different stages	Easily mistaken with stratified sampling

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CI (α/2) sample mean	90%	95%	99%
$CI = \pm Z^* \times \frac{\sigma}{\sqrt{n}}$	1.645	1.960	2.576

Biasness		Problem		
Response Bias	Misleading questions, incorre	Misleading questions, incorrect response		
Non-Response Bias	Subjects cannot be reached or	Subjects cannot be reached or refused to participate		
Sampling Bias	Under coverage/ Non-random	Under coverage/ Non-random sample		
Anecdotal data	Anecdotal evidence is based of	Anecdotal evidence is based on haphazardly selected individual cases		
Bias	Affects Mean	Affects Mean Variability Affects Spread		

Linear Transformation	Center, x	Spread, $s$ or $\sigma$
Addition (a)	a $\overline{x}$	no change
Multiplication (b)	$b \overline{x}$	$b^2s^2$

	Assumption	Implication
Z, T test	Normality	All formulas require the sample to be
		normally distributed
Z, T test	Simple Random Sample (Independence)	Result can only apply to selected samples and
		not the population

Interpret Association	Quantitative	Categorical variable
	Scatter diagram	Two-Way Table

	Left-Skewed	Symmetric Q1 Q2 Q3	Right-Skewed
	<b>├</b>	<b>——</b>	H
Outliers	Left	No	Right
	Mean < Median	Mean = Median	Mean > Median

Type I Error	Type II Error
P(Reject $H_0 \mid H_0$ is true) = significant level ( $\alpha$ )	P(Accept $H_0 \mid H_a$ is true) = $\beta$
α times there will be an error	Power = 1 - $\beta$ = P(Reject $H_0 \mid H_a$ is true),
	Higher power = better
A Type I error occurs when the researcher rejects a null	A Type II error occurs when the researcher accepts
hypothesis when it is true	a null hypothesis that is false
Null Hypothesis H <sub>0</sub> Type II error   Type I error	Both errors are calculated using <b>Z</b> test  Despite their initial distributions  The probability of <i>not</i> committing a Type II error is called the Power of the test. Power helps to determine if sample size is large enough. If your sample size is too small, your results may be inconclusive when they may have been conclusive with a large enough sample.  It's better to commit Type II error than Type I error

Regression	Implication	Remark	
R-Squared	Fraction of the variation in the values of y that is explained	Fraction of the variation in the values of y that is explained by the least-squares regressions of	
	y on x	y on x	
Least-squares	Least square is when the minimum sum of residual <sup>2</sup>	Least square is when the minimum sum of residual^2	
Correlation, r	Strength and direction of the <u>linear</u> association between two quantitative variables Non linear r/s: Circular r/s, Curve r/s	Independent of response/explanatory variable Not resistant to outliers (e.g. influential observation)	
Residual	Sum of residual = 0, above 0 = overestimated, under 0 = underestimated		

	6		
	Residual = $y - \hat{y}$ , vertical distance between actual and predicted response variable Regression Line should contains both positive and negative residuals (uniform residual plot)		
Regression Equation	$\hat{y} = b_0 + b_1 x$		
	$b_0 = \bar{y} - b_1 \bar{x}$ , regression line always pass through $\bar{y}, \bar{x}$		
	$b_1 = r \frac{s_y}{s_x}$		
Lurking Variable	An unobserved variable that influences the association	Confounding effect	
	between variable of primary interest		
Common response	Similar to confounding, difference in x and y has no relationships		

Probability rules						
False Negative: P(NEG P)	False Positive: P(POS A)					
Sensitivity: P (POS P)	Specificity: P (NEG A)					
P(Outcome occurring as first n even	ents) = P(outcome as last n events)					
Conditional Probability						
Addition rule for disjoint events	General Addition rule					
P(A  or  B) = P(A) + P(B)	P(A  or  B) = P(A) + P(B) - P(A  and  B)					
If events are disjoint, then events are <u>dependent</u> (if dice is	$P(A \cup B) = P(A) + P(B) - P(A \cap B)$					
odd, the chance of dice is even can never happen)						
Multiplication Rule for independent events	Complement					
P(A  and  B) = P(A) P(B)	$P(A^c) = 1 - P(A)$					
Conditional probabilities	Intersection					
P(A B) = P(A  and  B)	P(A  and  B  and  C) = P(A)P(B A)P(C A  and  B)					
$P(A B) = \frac{P(A \text{ and } B)}{P(A)}$						
Independence						
P(B A) = P(B)						

Calculator function	Implication		
Normal Calculation	$P(-x \le X \le x)$		
Binomial Calculation	$P(X = x), P(X \le x)$		

Standard Normal	$\frac{x-\mu}{\sigma} \sim N(0, 1)$	1. Unimodal 2. Bell shaped 3. Symmetric		
Normal Proximation	Binomial distribution	$np \ge 10$		
	Sample Proportion	$n(1-p) \ge 10$		
Continuity Correction Required for Binomial approximation to		$P(X \ge x) \to -0.5, P(X > x) \to +0.5$		
(cc)	normal distribution	$P(X \le x) \to -0.5, P(X < x) \to +0.5$		

Distributio n	Usage	Mean	Standard deviation	Hypothesis Testing	Standard Error/ Sample Size	Confidence Interval  Point estimate ± margin of  error(m)	Remarks	
Population Only if given population parameters								
Normal $X \sim N(\mu, \sigma)$	Known population s.d.	μ	σ	$Z = \frac{x - \mu_0}{\sigma}$	Known true parameters	Known true parameters	Must be Normal	
Binomial $X \sim B(n, p)$	Known pop. probability Two outcomes	$\mu = np$	$\sigma = \sqrt{np(1-p)}$	$Z = \frac{\mu - \mu_0}{\sqrt{np(1-p)}}$ [extreme cases] $P(X \ge x) \text{ or } P(x \le X)$	Known true parameters	Known true parameters	Approx. Normal w. condition	
	1	ı	Sample	Must be Normal, or large sar	nple through CLT		1	
Sample proportion $\hat{p}$	<u>Unknown</u> pop. probability	$\hat{p} = \frac{X}{n}$	$\sigma = \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$	$Z = \frac{\hat{p} - p_0}{\sqrt{\frac{p_0(1 - p_0)}{n}}}$	$n = \frac{z^{*2}}{m} p^* (1 - p^*)$	$\hat{p} \pm z^* \cdot \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$	Approx. Normal w. condition	
Sample Mean $\bar{x} \sim N \ (\mu, \ \frac{\sigma}{\sqrt{n}})$	Normal distribution or CLT	μ	$\frac{\sigma}{\sqrt{n}}$	$Z = \frac{\bar{x} - \mu_0}{\sigma / \sqrt{n}}$	$n = \frac{z^* \sigma^2}{m}$	$\bar{x} \pm z^* \frac{\sigma}{\sqrt{n}}$		
Student's T	Unknown     population s.d.     Small sample     size	μ	$\frac{s}{\sqrt{n}}$	$t_{n-1} = \frac{\bar{x} - \mu_0}{s / \sqrt{n}}$	$n = \frac{t^*s^2}{m}$	$ar{x}\pm t^*rac{s}{\sqrt{n}}$	$df = (n-1)$ Degree of freedom: $\lim_{(n-1)\to\infty} t = N$	
			Two samples	Must be Normal, or large san	<u>iple through CLT</u>			
Matched Paired	Before & After $\mu_{before} - \mu_{after}$	$\mu_d$	$\frac{s_d}{\sqrt{n}}$	$t_{n-1} = \frac{\bar{d} - 0}{s_d / \sqrt{n}}$	$n = \frac{t^* s_d^2}{m}$	$\bar{x} \pm t^* \frac{s_d}{\sqrt{n}}$	df = (n-1)	
2 Samples Mean $\mu_1 - \mu_2$	Z test, Compare Differences	$\mu_1 - \mu_2$	$s = \sqrt{\frac{{\sigma_1}^2}{n_1} + \frac{{\sigma_2}^2}{n_2}}$	$z = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{\sigma_1^2 + \sigma_2^2}{n_1 + \frac{\sigma_2^2}{n_2}}}}$	$\sqrt{\frac{{\sigma_1}^2}{n_1} + \frac{{\sigma_2}^2}{n_2}}$	$(\bar{x}_1 - \bar{x}_2) \pm z^* \sqrt{\frac{{\sigma_1}^2}{n_1} + \frac{{\sigma_2}^2}{n_2}}$		
2 Samples Mean $\mu_1 - \mu_2$	t test, Compare Differences	$\mu_1 - \mu_2$	$s = \sqrt{\frac{{s_1}^2}{n_1} + \frac{{s_2}^2}{n_2}}$	$t_{df} = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$	$\sqrt{\frac{{s_1}^2}{n_1} + \frac{{s_2}^2}{n_2}}$	$(\bar{x}_1 - \bar{x}_2) \pm t^* \cdot \sqrt{\frac{{s_1}^2}{n_1} + \frac{{s_2}^2}{n_2}}$	Must be between two independent samples df: $\min(n_1, n_2) - 1$	
Pooled Test $\mu_1 - \mu_2$	$\frac{{\sigma_x}^2}{{\sigma_y}^2} < 3$	$\mu_1 - \mu_2$	$s = \sqrt{\frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}}$	$t_{df} = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{s\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}$	$s_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}$	$(\bar{x}_1 - \bar{x}_2) \pm t^* \cdot s_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}$	$df = n_1 + n_2 - 2$	
Two sample proportions $\hat{p}_1 - \hat{p}_2$	p̂, Compare Differences	$\hat{p}_1 - \hat{p}_2$	$\sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{n_1} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2}}$	$z = \frac{(\hat{p}_1 - \hat{p}_2) - (p_1 - p_2)}{\sqrt{\hat{p}(1 - \hat{p})(\frac{1}{n_1} + \frac{1}{n_2})}}$	$\sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{n_1} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2}}$	$(\hat{p}_1 - \hat{p}_2) \pm z^* \cdot SE$	$\hat{p} = \frac{X_1 + X_2}{n_1 + n_2}$	