

Probability

Sampling

with replacement: n^k

without replacement, ordered: $\frac{n!}{(n-k)!} = nPk$

without replacement, unordered: $\frac{n!}{k!(n-k)!} = \binom{n}{k}$

Inclusion-Exclusion Principle

Given two events A and B,

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

Three events:

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

Conditional Probability

$$P(A | B) = \frac{P(A \cap B)}{P(B)} \text{ where } P(B) > 0$$

Statistical Independence

Two events A and B are independent iff

$$P(A \cap B) = P(A) \cdot P(B)$$

Three events A, B, C are independent if

- 1) $P(A \cap B \cap C) = P(A) \cdot P(B) \cdot P(C)$
- 2) Each set of pairwise events are indep.

Mutually Exclusive Events

Two events A and B are mutually exclusive iff

$$P(A \cap B) = 0$$

Law of Total Probability

Let $S = \sum_{k=1}^n B_k$ where $B_i \cap B_j = \emptyset$ if $i \neq j$ then

$$P(A) = \sum_{R=1}^n P(A | B_R) \cdot P(B_R)$$

Bayes' Theorem

Let B_1, \dots, B_n be a partition of S and for event A,

$$P(B_i | A) = \frac{P(A | B_i) \cdot P(B_i)}{P(A)} = \frac{P(A | B_i) \cdot P(B_i)}{\sum_{R=1}^n P(A | B_R) \cdot P(B_R)}$$

Discrete RVs

pmf

$$f(x) = P(X = x)$$

$$f(x) \geq 0 \text{ for all } x$$

$$\sum_{x \in X} f(x) = 1$$

cdf

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

$$F(x) \geq 0, \text{ non-decreasing}$$

$$\lim_{x \rightarrow -\infty} F(x) = 0, \lim_{x \rightarrow \infty} F(x) = 1$$

pmf \leftrightarrow cdf

$$\sum_{y \leq x} f(y) = F(x)$$

$$f(x) = F(x) - F(x-1)$$

Expectation

$$\mu = E(X) = \sum_{x \in X} x \cdot f(x)$$

$$E(g(X)) = \sum_{x \in X} g(x) \cdot f(x)$$

$$E(aX + bY) = aE(X) + bE(Y)$$

where X and Y don't have to be independent

$$E(k) = k \text{ for constant } k$$

$$E(X - \mu) = 0 \text{ for any r.v. } X$$

$$E(XY) = E(X) \cdot E(Y)$$

where X and Y are independent

Memorylessness

X is memoryless if $\forall m, n \in \mathbb{Z}$,
 $P(X > m + n | X > m) = P(X > n)$

Memoryless distributions:

- Geometric
- Exponential

Standard Deviation

$$\sigma = \sqrt{\text{Var}(X)}$$

Independence

X and Y are independent if $\forall x, y$,

$$P(X = x, Y = y) = P(X = x) \cdot P(Y = y)$$

or

$$P(X \leq x, Y \leq y) = P(X \leq x) \cdot P(Y \leq y)$$

Continuous RVs

pdf

$$P(a < X < b) = \int_a^b f(x) dx$$

cdf

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

(same properties as discrete cdf)

pdf \leftrightarrow cdf

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

$$\frac{dF}{dx} = f(x)$$

Expectation

$$E(X) = \int_{-\infty}^{\infty} x \cdot f(x) dx$$

$$E(g(X)) = \int_{-\infty}^{\infty} g(x) \cdot f(x) dx$$

Variance

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

$$- \left[\int_{-\infty}^{\infty} x f(x) dx \right]^2$$

Variance

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

$$= E((X - \mu)^2)$$

$$= E(X^2) - \mu^2$$

$$\text{Var}(k) = 0 \text{ for constant } k$$

$$\text{Var}(aX + b) = a^2 \text{Var}(X)$$

$$\text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y)$$

where X and Y are independent

(for sample variance,

see **Data Analysis** section)

Quadratic Formula

Given $ax^2 + bx + c = 0$,

$$x = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

Useful Antiderivatives

$$\int x^n dx = \frac{1}{n+1} x^{n+1} + C \quad \int \frac{1}{x} dx = \ln |x| + C$$

$$\int e^x dx = e^x + C$$

Log Properties

$$\ln(a^b) = b \ln(a)$$

$$\ln(ab) = \ln(a) + \ln(b)$$

$$\ln\left(\frac{a}{b}\right) = \ln(a) - \ln(b)$$

Discrete Distributions

Distribution	Probability Function $f(x)$	Expectation $E(x)$	Variance $Var(x)$
<u>Bernoulli</u> $X \sim Ber(p)$ where X takes values $\{0, 1\}$ with $P(X = 1) = p$ $\{0, 1\}$	$\begin{cases} 1-p & x=0 \\ p & x=1 \end{cases}$	p	$p(1-p)$
<u>Binomial</u> $X \sim Bin(n, p)$ where X is the number of successes in n (Ber.) trials with a p chance of success each trial $\{0, 1, 2, \dots, n\}$	$\binom{n}{x} p^x (1-p)^{n-x}$	np	$np(1-p)$
<u>Geometric</u> $X \sim Geo(p)$ where X is the number of (Ber.) trials required to observe the first success $\{1, 2, 3, \dots\}$	$(1-p)^{x-1} p$	$\frac{1}{p}$	$\frac{1-p}{p^2}$
<u>Negative Binomial</u> $X \sim NB(r, p)$ where X is the number of (Ber.) trials required to observe the r^{th} success $\{r, r+1, r+2, \dots\}$	$\binom{x-1}{r-1} p^r (1-p)^{x-r}$	$\frac{r}{p}$	$\frac{r(1-p)}{p^2}$
<u>Hypergeometric</u> $X \sim HGeo(N, r, n)$ where X is the number of successes when drawing n objects from N total objects containing r successes without replacement $\{\max(0, n+r-N), \dots, \min(r, n)\}$	$\frac{\binom{r}{x} \binom{N-r}{n-x}}{\binom{N}{n}}$	$\frac{nr}{N}$	$\frac{nr}{N} \left(1 - \frac{r}{N}\right) \frac{N-n}{N-1}$
<u>Poisson</u> $X \sim Poi(\lambda)$ where X is the number of events to occur in a space given an average rate of λ events in the space $\{0, 1, 2, \dots\}$	$\frac{e^{-\lambda} \lambda^x}{x!}$	λ	λ

Properties

<u>Poisson Process</u> An experiment is a Poisson process if it has the following: <ul style="list-style-type: none"> - independence: # of occurrences in non-overlapping spaces is independent - individuality: probability that 2 or more events occurring in a short interval is close to zero - homogeneity/uniformity: probability of one event in a short interval is approximately λ <u>Addition of Binomial Distributions</u> If $X \sim Bin(n_1, p)$, $Y \sim Bin(n_2, p)$ and X and Y are indep., then $X + Y \sim Bin(n_1 + n_2, p)$	<u>Poisson vs Binomial</u> If $n \rightarrow \infty, p \rightarrow 0$ and $np = \lambda$ then $Bin(n, p) \rightarrow Poi(\lambda)$ <u>Bernoulli vs Binomial</u> If X_1, \dots, X_n are independent $Ber(p)$ and $X = X_1 + \dots + X_n$, then $X \sim Bin(n, p)$ <u>Geometric vs Negative Binomial</u> If X_1, \dots, X_r are independent $Geo(p)$ and $X = X_1 + \dots + X_r$, then $X \sim NB(r, p)$ <u>Hypergeometric vs Binomial</u> If N is large and n is small, $HGeo(N, r, n) \sim Bin(n, r/N)$
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Continuous Distributions

Distribution	Probability Density Function $f(x)$	Cumulative Distribution Function $F(x)$	Mean $E(x)$	Variance $Var(x)$
<u>Uniform Continuous</u> $X \sim Uniform(a, b)$ where X is a real number in the interval $[a, b]$	$\begin{cases} \frac{1}{b-a} & a \leq x \leq b \\ 0 & otherwise \end{cases}$	$\begin{cases} 0 & x < a \\ \frac{x-a}{b-a} & a \leq x \leq b \\ 1 & x > b \end{cases}$	$\frac{a+b}{2}$	$\frac{(b-a)^2}{12}$
<u>Exponential</u> $X \sim Exp(\lambda)$ where X is the “waiting time” between events given an average rate of λ events (Poisson)	$\begin{cases} \lambda e^{-\lambda x} & x \geq 0 \\ 0 & x < 0 \end{cases}$	$\begin{cases} 1 - e^{-\lambda x} & x \geq 0 \\ 0 & x < 0 \end{cases}$	$\frac{1}{\lambda}$	$\frac{1}{\lambda^2}$
<u>Normal</u> $X \sim N(\mu, \sigma^2)$ $(-\infty, \infty)$	$\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$	$\int_{-\infty}^x \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2} dy$	μ	σ^2
<u>Chi-Squared</u> $W \sim \chi^2(n)$ where $W = Z_1^2 + Z_2^2 + \dots + Z_n^2$ such that $Z_i \sim N(0, 1)$ and indep. n: degrees of freedom (d.f.) $(0, \infty)$	$\frac{1}{2^{\frac{n}{2}}\Gamma\left(\frac{n}{2}\right)} w^{\frac{n}{2}-1} e^{-\frac{w}{2}}$ $\Gamma(a) = \int_0^{\infty} x^{a-1} e^{-x} dx$	$\int_{-\infty}^x \frac{1}{2^{\frac{n}{2}}\Gamma\left(\frac{n}{2}\right)} w^{\frac{n}{2}-1} e^{-\frac{w}{2}} dw$	n	$2n$
<u>Student's t</u> $T \sim T(n)$ where $T = \frac{Z}{\sqrt{\frac{W}{n}}}$ where $Z \sim N(0, 1)$ and $W \sim \chi^2(n)$ and independent n: degrees of freedom (d.f.) $(-\infty, \infty)$	$\frac{\Gamma\left(\frac{n+1}{2}\right)}{\sqrt{n\pi}\Gamma\left(\frac{n}{2}\right)} \left(1 + \frac{t^2}{n}\right)^{-\frac{n+1}{2}}$	$\int_{-\infty}^x \frac{\Gamma\left(\frac{n+1}{2}\right)}{\sqrt{n\pi}\Gamma\left(\frac{n}{2}\right)} \left(1 + \frac{t^2}{n}\right)^{-\frac{n+1}{2}} dt$	0	N/A

Properties

Universality of the Uniform Distribution

Let X be a continuous R.V. with an invertible cdf F , then

$$F(X) \sim U(0, 1)$$

To generate a random variable for a given distribution, uniformly generate values and put them into the inverted cdf to get R.V. values.

Exponential vs Geometric

Exponential is to Poisson as Geometric is to Bernoulli

Bernoulli: seq. of 0 or 1 \rightarrow “waiting time” for 1st success \sim Geo

Poisson: cont. vers. of Ber. \rightarrow “waiting time” for 1st success \sim Exp

Special Cases of Chi-Squared Distribution

For $n = 1$: $W = Z^2$

e.g. $P(W \geq a) = P(Z^2 \geq a)$

For $n = 2$: $W \sim Exp(\lambda = \frac{1}{2})$

For intermediate n ($2 < n < 30$): use χ^2 chart

For large n ($n \geq 30$): $W \sim N(n, 2n)$ by CLT

Student's t vs Normal

As $n \rightarrow \infty$, $T \rightarrow Z \sim N(0, 1)$

Normal and Standard Normal

Standard Normal

$$Z \sim N(0, 1)$$

$$\text{where the pdf } \phi \text{ is } \phi(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}}$$

Normal ↔ Standard Normal

$$\text{If } X \sim N(\mu, \sigma^2) \text{ and } Z = \frac{X - \mu}{\sigma}, \text{ then } Z \sim N(0, 1)$$

68-95-99 Rule

$$\text{If } X \sim N(\mu, \sigma^2),$$

- ~68% are between $\mu \pm \sigma$
- ~95% are between $\mu \pm 2\sigma$
- ~99% are between $\mu \pm 3\sigma$

Central Limit Theorem

The Sampling Distribution of the Sample Mean

Let X_1, X_2, \dots, X_n be i.i.d. $N(\mu, \sigma^2)$, then

$$1. S_n \sim N(n\mu, n\sigma^2)$$

$$2. \bar{X}_n \sim N\left(\mu, \frac{\sigma^2}{n}\right)$$

$$\text{where } S_n = \sum X_i \text{ and } \bar{X}_n = \frac{1}{n} \sum X_i$$

Standard Error of the Mean: $\frac{\sigma}{\sqrt{n}}$ (std. dev. of the mean)

Law of Large Numbers

Consider a sequence of n i.i.d random variables; X_1, X_2, \dots, X_n , where $E(X_i) = \mu$ and $Var(X_i) = \sigma^2$ for all i ,

$$\text{Let } \bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i, \text{ then } \bar{X}_n \rightarrow \mu \text{ as } n \rightarrow \infty$$

for any distribution with a finite mean and finite variance

Central Limit Theorem

Let $\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$ for some sequence of n i.i.d rvs X_1, X_2, \dots, X_n with $E(X_i) = \mu$ and $Var(X_i) = \sigma^2$.

As $n \rightarrow \infty$,

$$\bar{X}_n \sim N\left(\mu, \frac{\sigma^2}{n}\right) \text{ or } Z = \frac{\bar{X}_n - \mu}{\frac{\sigma}{\sqrt{n}}} \sim N(0, 1)$$

If X_i are normal distr., then \bar{X}_n is normal

If X_i are not normal distr., then \bar{X}_n approaches normal

CLT and Binomial

$$\text{If } X \sim \text{Bin}(n, p), \text{ then } X \sim N(np, np(1-p))$$

CLT and Poisson

$$\text{If } X_1, X_2, \dots, X_n \sim \text{Poi}(\lambda), \text{ then } \bar{X}_n \sim N\left(\lambda, \frac{\lambda}{n}\right)$$

Data Analysis

Datatypes

Categorical

- Ordinal (implied order)

Numerical

- Continuous
- Discrete

Quantiles/Quartiles

$$Q_1 \text{ (1st quartile)} = P_{25}$$

$$Q_2 \text{ (2nd quartile)} = \text{median} = P_{50}$$

$$Q_3 \text{ (3rd quartile)} = P_{75}$$

5-number summary:

(min, Q_1 , median, Q_3 , max)

Population Symbols vs Sample Symbols

Symbol	Population	Sample
Mean	μ	\bar{x}
Variance	σ^2	s^2
Std. deviation	σ	s
Std. error	$\sigma_{\bar{x}} = \frac{\sigma}{\sqrt{n}}$	$s_{\bar{x}} = \frac{s}{\sqrt{n}}$

Measures of dispersion and symmetry

$$\text{Range} = \text{max} - \text{min}$$

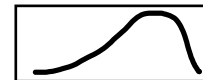
$$\text{IQR} = Q_3 - Q_1$$

Sample variance:

$$s^2 = \frac{1}{n-1} \sum (x_i - \bar{x})^2$$

$$= \frac{1}{n-1} \left[\sum y_i^2 - \frac{(\sum y_i)^2}{n} \right]$$

Skewness:



Left skew



Right skew

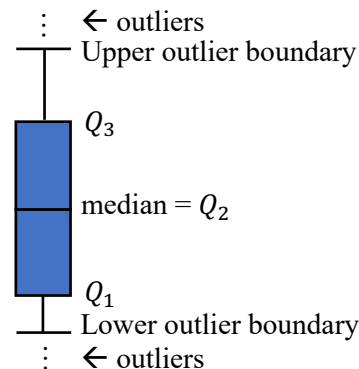
Density Histogram

Graph of relative frequencies of groups where
rel. freq. = freq / total

Empirical CDF

$$\hat{F}(y) = \sum_{Y \leq y} \text{rel. freq. of } Y$$

Box Plots



upper outlier boundary: $Q_3 + 1.5\text{IQR}$

lower outlier boundary: $Q_1 - 1.5\text{IQR}$

Maximum Likelihood Estimates

Likelihood Function

If $Y_i \sim f(y_i, \theta)$, $i = 1, 2, \dots, n$, where Y_i are i.i.d. RVs with observations $\{y_1, y_2, \dots, y_n\}$, then

$$L(\theta; y_1, y_2, \dots, y_n) = P(Y_1 = y_1, Y_2 = y_2, \dots, Y_n = y_n) = \prod_{i=1}^n f(y_i, \theta)$$

L is a function equal to the likelihood of observing outcomes $\{y_1, y_2, \dots, y_n\}$ given θ as a parameter

For discrete distributions,

- $f(y_i, \theta)$ is the pmf of the distribution
- The likelihood function L is the probability of observing our data given θ

For continuous distributions,

- $f(y_i, \theta)$ is the pdf of the distribution
- The likelihood function L is NOT a probability

The Maximum Likelihood Estimate (MLE)

$\hat{\theta}$ is the MLE if $\hat{\theta}$ maximizes $L(\theta; y_1, y_2, \dots, y_n)$

To find the MLE, set the derivative of the likelihood function L (or derivative of the log likelihood function $\ell = \ln L$) w.r.t the parameter equal to 0. Solve for θ .

Properties:

- Consistency: As $n \rightarrow \infty$, $\hat{\theta} \rightarrow \theta$
“As the size of our data increases, the MLE will be more accurate”
- Efficiency: Variance is minimized when finding the MLE
- Invariance: If $\hat{\theta}$ is the MLE of θ , then $g(\hat{\theta})$ is the MLE of $g(\theta)$

Distributions and their MLEs

Binomial	Poisson	Exponential	Normal
$\hat{\theta} = \frac{y}{n}$	$\hat{\lambda} = \bar{y}$	$\hat{\lambda} = \frac{1}{\bar{y}}$	$\hat{\mu} = \bar{y}$ $\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (y_i - \bar{y})^2$

The Relative Likelihood Function

$$R(\theta) = \frac{L(\theta)}{L(\hat{\theta})}$$

where L is the likelihood function and $\hat{\theta}$ is the MLE of θ

$0 \leq R(\theta) \leq 1$ for all θ , $R(\theta) = 1$ when $\theta = \hat{\theta}$

Interpretation:

$R(x) = k$ means:

“Given the observed data, a parameter value of x is k times as likely compared to the MLE value $\hat{\theta}$ ”

Likelihood Intervals

A $100p\%$ Likelihood Interval is $\{\theta: R(\theta) \geq p\}$
e.g. a 50% Likelihood Interval is $\{\theta: R(\theta) \geq 0.5\}$

Plausibility

- If $R(\theta) \geq 0.5$, it is **very plausible**
- If $R(\theta) \geq 0.1$, it is **plausible**
- If $R(\theta) < 0.1$, it is **implausible**
- If $R(\theta) < 0.01$, it is **very implausible**

Estimators

The estimator $\tilde{\theta}$ is a RV that has $\hat{\theta}$ as an outcome

Unbiased estimator: The expected value of the estimator is equal to the true population value
e.g. $E(S^2) = \sigma^2$

Biased estimator: The expected value of the estimator is **not** equal to the true population value
e.g. $E(\hat{\sigma}^2) \neq \sigma^2$

Confidence Intervals

Confidence Intervals

A $100p\%$ Confidence Interval for θ is an estimate of the interval $[L, U]$ for RVs, $L(Y_1, \dots, Y_n)$ and $U(Y_1, \dots, Y_n)$, such that

$$P(L(Y_1, \dots, Y_n) < \theta < U(Y_1, \dots, Y_n)) = p$$

Interpretation:

WRONG: “There is a $100p\%$ chance the interval contains θ ”

RIGHT: “ $100p\%$ of constructed confidence intervals contain θ ”

RIGHT: “We are $100p\%$ **confident** that θ is contained in the interval”

Choosing a sample size for a Binomial CI

To find a sample size n such that

$$z^* \sqrt{\frac{\hat{\theta}(1 - \hat{\theta})}{n}} < \text{error}$$

use $\hat{\theta} = 0.5$ and solve for n .

(see next page for CI formulas)

Hypothesis Testing

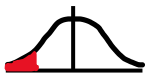

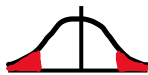
Hypothesis: some claim about a population (i.e. parameter)

Null Hypothesis (H_0): the “current belief”; status quo

Alternative Hypothesis (H_A): a challenge to H_0

p-value: the probability of observing our evidence given H_0

Types of Tests

One-tailed (left)	One-tailed (right)	Two-tailed
$H_0: \theta \geq k$ $H_A: \theta < k$	$H_0: \theta \leq k$ $H_A: \theta > k$	$H_0: \theta = k$ $H_A: \theta \neq k$
		

Type I and Type II errors

Type I error: Rejecting H_0 when H_0 is actually true

$$P(\text{Rejecting } H_0 \text{ when } H_0 \text{ is actually true}) = \alpha$$

where α is the significance level

Type II error: Failing to reject H_0 when H_0 is actually false

$$P(\text{Failing to reject } H_0 \text{ when } H_0 \text{ is actually false}) = 1 - \beta$$

where β is the power

Relationship between p , α , Z_{test} , Z_{crit}

p -val vs α	Z_{test} vs Z_{crit}	Conclusion
$p < \alpha$	$Z_{test} \notin [-Z_{crit}, Z_{crit}]$	Can reject $<H_0>$
$p > \alpha$	$Z_{test} \in [-Z_{crit}, Z_{crit}]$	Can't reject $<H_0>$

Guidelines for t-tests and t-based CIs

Given that σ^2 is unknown and normality is not specified,

If $n > 40$: they perform well in most practical situations

If $15 < n < 40$: they perform reasonably well, but outliers or strong skewness can cause problems

If $n < 15$: we need to be confident the population is approximately normal before proceeding.

Confidence Intervals and Two-tailed Hypothesis Tests

A $100p\%$ CI consists of all values of θ_0 for which

$H_0: \theta = \theta_0$ would not be rejected for a significance level $\alpha = 1 - p$

e.g. If our mean lies within the 95% CI, we would not reject H_0 with a significance level of 0.05

Issues with Hypothesis Testing

1. Testing Unknowns
(We “know” that $\theta = \dots$ is false)
2. Existence vs Effect Size
(CIs est. effect size rather than stating an effect exists)
3. Prior Information
4. Publication Bias

Distribution	Parameter	Pivotal Quantity & Distr.	Confidence Interval	Test Statistic
Normal (σ^2 is known)	μ	$\frac{\bar{Y} - \mu}{\sigma/\sqrt{n}} \sim N(0, 1)$	$\bar{y} \pm z^* \frac{\sigma}{\sqrt{n}}$	$z_{test} = \frac{\bar{X} - \mu_0}{\sigma/\sqrt{n}}$
Normal (σ^2 is unknown)	μ	$\frac{\bar{Y} - \mu}{s/\sqrt{n}} \sim T(n-1)$	$\bar{y} \pm t^* \frac{s}{\sqrt{n}}$	$t_{test} = \frac{\bar{X} - \mu_0}{s/\sqrt{n}}$
Normal (σ^2 is unknown)	σ^2	$\frac{(n-1)s^2}{\sigma^2} \sim \chi^2(n-1)$	$\left[\frac{(n-1)s^2}{a}, \frac{(n-1)s^2}{b} \right]$	$w_{test} = \frac{(n-1)S^2}{\sigma_0^2}$
Binomial	θ	$\frac{Y - n\theta}{\sqrt{n\theta(1-\theta)}} \sim N(0, 1)$	$\hat{\theta} \pm z^* \sqrt{\frac{\hat{\theta}(1-\hat{\theta})}{n}}$	$\frac{\hat{\theta} - \theta_0}{\sqrt{\frac{\theta_0(1-\theta_0)}{n}}}$
Poisson	θ	$\frac{\bar{Y} - \theta}{\sqrt{\frac{\bar{Y}}{n}}} \sim N(0, 1)$	$\bar{y} \pm z^* \sqrt{\frac{\bar{y}}{n}}$	$\frac{\bar{y} - \mu_0}{\sqrt{\frac{\mu_0}{n}}}$

*For CIs using χ^2 , a and b are chosen so that the tails are equal size

**For CIs, z^* is a value of z such that $[-z^*, z^*]$ encloses an area p under the curve (likewise for t^*)

Test Statistics for the difference of two means ($\mu_1 - \mu_2 = d_0$)

μ 's indep., σ^2 known	μ 's indep., σ^2 unknown equal variance	μ 's indep., σ^2 unknown, unequal variance	μ 's not indep., σ^2 unknown
$Z = \frac{(\bar{X}_1 - \bar{X}_2) - d_0}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}$	$t = \frac{(\bar{X}_1 - \bar{X}_2) - d_0}{s_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}$ $s_p^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}$ d.f. = $n_1 + n_2 - 2$	$t = \frac{(\bar{X}_1 - \bar{X}_2) - d_0}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$ d.f. = $\frac{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^2}{\frac{1}{n_1 - 1} \left(\frac{s_1^2}{n_1}\right)^2 + \frac{1}{n_2 - 1} \left(\frac{s_2^2}{n_2}\right)^2}$ (round d.f. down)	$t = \frac{\bar{X}_d - \mu_d}{\frac{s_d}{\sqrt{n}}}$ d.f. = $n - 1$ \bar{X}_d : mean sample diff μ_d : mean pop. diff. s_d : std dev. sample diff n : number of pairs