

# Stat 101 Formulas

## Sample Statistics

Sample mean

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$$

Sample variance

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

Sample standard deviation

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

5-Number summary

$$\begin{aligned} Q_0 &= \text{minimum} \\ Q_1 &= 1st \text{ quartile} \\ Q_2 &= \text{median} \\ Q_3 &= 3rd \text{ quartile} \\ Q_4 &= \text{maximum} \end{aligned}$$

Range

$$\begin{aligned} \text{Range} &= \text{maximum} - \text{minimum} \\ &= Q_4 - Q_0 \end{aligned}$$

Inter-Quartile Range

$$IQR = Q_3 - Q_1$$

Fences for Outliers

$$Q_1 - 1.5 * IQR, Q_3 + 1.5 * IQR$$

## Simple Linear Regression

Sample Covariance

$$Cov(x, y) = \frac{\sum x_i y_i - n\bar{x}\bar{y}}{(n-1)}$$

Sample Correlation

$$r = \frac{Cov(x, y)}{s_x s_y} = \frac{\sum x_i y_i - n\bar{x}\bar{y}}{(n-1)s_x s_y}$$

Regression Model

$$\hat{y} = a + bx$$

Slope

$$b = r \frac{s_y}{s_x}$$

Intercept

$$a = \bar{y} - b\bar{x}$$

Residual

$$resid_i = y_i - \hat{y}_i = y_i - (a + bx_i)$$

## Normal Distribution

Standardize

$$z = \frac{x - \mu}{\sigma}$$

Un-Standardize

$$x = \mu + z\sigma$$

68/95/99.7 Rule

$$P(-1 < Z < 1) \approx .68$$

$$P(-2 < Z < 2) \approx .95$$

$$P(-3 < Z < 3) \approx .997$$

kth Percentile

$$x \text{ such that } P(X < x) = k\%$$

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## Probability

Complement Rule

$$P(A^C) = 1 - P(A)$$

General Addition Rule

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

Multiplication Rule for Independent Events

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

General Multiplication Rule

$$P(A \cap B) = P(A) * P(B|A) = P(B) * (P(A|B))$$

Conditional Probability

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

A and B are Independent if:

- 1)  $P(A \cap B) = P(A) * P(B)$
- 2)  $P(A) = P(A|B)$
- 3)  $P(B) = P(B|A)$

## Random Variables

Expected Value

$$\mu = E(X) = \sum_{i=1}^k x_i * P(X = x_i) = \sum_{i=1}^k x_i * p_i$$

Variance

$$\sigma^2 = Var(X) = E((X - \mu)^2) = E(X^2) - \mu^2 = \sum_{i=1}^k (x - \mu)^2 * p_i$$

Linearity of Expected Value

$$\begin{aligned}E(aX) &= aE(X) \\E(X + b) &= E(X) + b \\E(X + Y) &= E(X) + E(Y)\end{aligned}$$

Variance of a Linear Combination

$$\begin{aligned}Var(aX) &= a^2 Var(X) \\Var(X + b) &= Var(X) \\Var(aX + bY) &= a^2 Var(X) + b^2 Var(Y) + 2abCov(X, Y)\end{aligned}$$

Variance of Linear Combination of Independent X, Y

$$\begin{aligned}Var(aX + bY) &= a^2 Var(X) + b^2 Var(Y) \\SD(X_1 + X_2 + \dots + X_n) &= \sqrt{n} SD(X)\end{aligned}$$

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## Special Distributions

Bernoulli(p)

$$\begin{aligned} P(X = 1) &= p \\ P(X = 0) &= q = 1 - p \\ E(X) &= p \\ Var(X) &= pq \end{aligned}$$

Binomial(n,p)

Sum of n independent Bernoullis

$$\begin{aligned} P(X = r) &= \binom{n}{r} p^r q^{n-r} = \text{binompdf}(n, p, r) \\ P(X \leq r) &= \sum_{k=0}^r \binom{n}{k} p^k q^{n-k} = \text{binomcdf}(n, p, r) \end{aligned}$$

$$\begin{aligned} E(X) &= np \\ Var(X) &= npq \end{aligned}$$

## Central Limit Theorem

If  $x_1, \dots, x_n$  independent, come from a distribution with mean  $\mu$  and standard deviation  $\sigma$   
 $\bar{x}$  approximately follows a Normal distribution with mean  $\mu$  and standard deviation  $\frac{\sigma}{\sqrt{n}}$ .

## Sampling Distributions (assuming CLT applies)

If  $x_1, \dots, x_n \sim \text{Bernoulli}(p)$

$$\begin{aligned} \sum x_i \sim \text{Binom}(n, p) &\approx N(np, \sqrt{npq}) \\ \hat{p} = \frac{\sum x_i}{n} &\sim N\left(p, \sqrt{\frac{pq}{n}}\right) \end{aligned}$$

If  $x_1, \dots, x_n \sim$  have mean  $\mu$  and standard deviation  $\sigma$

$$\begin{aligned} \sum x_i &\sim N(n\mu, \sqrt{n}\sigma) \\ \bar{x} = \frac{\sum x_i}{n} &\sim N\left(\mu, \frac{\sigma}{\sqrt{n}}\right) \end{aligned}$$

## Confidence Intervals

(1- $\alpha$ )100% Confidence Interval

Estimate  $\pm$  Margin of Error

Margin of Error = (# of Standard errors)\*(Size of Standard Error)

Population proportion $p$ (n large)	$\hat{p} \pm z_{\alpha/2} * \sqrt{\frac{\hat{p}\hat{q}}{n}}$
Population difference $p_1 - p_2$ ( $n_1, n_2$ large)	$\hat{p}_1 - \hat{p}_2 \pm z_{\alpha/2} * \sqrt{\frac{\hat{p}_1\hat{q}_1}{n_1} + \frac{\hat{p}_2\hat{q}_2}{n_2}}$
Population mean $\mu$ ( $n \geq 30$ , $\sigma$ known)	$\bar{x} \pm z_{\alpha/2} * \frac{\sigma}{\sqrt{n}}$

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Population mean $\mu$ ( $n < 30$ , $\sigma$ known)	$\bar{x} \pm t_{\alpha/2} * \frac{\sigma}{\sqrt{n}}$ , $t \sim T(n - 1 \text{ d.f.})$
Population mean $\mu$ ( $\sigma$ unknown)	$\bar{x} \pm t_{\alpha/2} * \frac{s}{\sqrt{n}}$ , $t \sim T(n - 1 \text{ d.f.})$

## Hypothesis Testing

$$\alpha = P(\text{Type I Error}) = P(\text{Reject } H_0 \mid H_0 \text{ is true})$$

$$\beta = P(\text{Type II Error}) = P(\text{Don't reject } H_0 \mid H_0 \text{ is false})$$

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

## Calculate the Test Statistic

Population proportion $p$ ( $n$ large)	$z = \frac{\hat{p} - p_0}{\sqrt{p_0 q_0 / n}}$
Population difference $p_1 - p_2$ ( $n_1, n_2$ large) $H_0: p_1 - p_2 = 0$	$z = \frac{\hat{p}_1 - \hat{p}_2}{\sqrt{\hat{p}_{\text{pooled}} \hat{q}_{\text{pooled}} \left( \frac{1}{n_1} + \frac{1}{n_2} \right)}}$ And $\hat{p}_{\text{pooled}} = \frac{x_1 + x_2}{n_1 + n_2} = \frac{n_1 p_1 + n_2 p_2}{n_1 + n_2}$
Population mean $\mu$ ( $n \geq 30$ , $\sigma$ known)	$z = \frac{\bar{x} - \mu_0}{\sigma / \sqrt{n}}$
Population mean $\mu$ ( $n < 30$ , $\sigma$ known)	$t = \frac{\bar{x} - \mu_0}{\sigma / \sqrt{n}}$
Population mean $\mu$ ( $\sigma$ unknown)	$t = \frac{\bar{x} - \mu_0}{s / \sqrt{n}}$

## Conclusion

Test Type	p-value formula	calculator
Upper-Tail	$P(Z > z)$	<code>normalcdf(z, 10)</code>
Lower-Tail	$P(Z < z)$	<code>normalcdf(-10, z)</code>
Two-Tailed	$2 * P(Z >  z )$	<code>2*normalcdf( z , 10)</code>

Reject  $H_0$  if  $p\text{-value} < \alpha$