SAMPLES:

Sample mean: $\overline{x} = \frac{\sum x}{n}$ Sample variance:

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

Sample standard deviation:

$$s = \sqrt{s^2}$$

Chebyshev's Rule: For all samples

- At least $\frac{3}{4}$ of the data lie between $\overline{x} 2s$ and $\overline{x} + 2s$;
- At least $\frac{8}{9}$ of the data lie between $\overline{x} 3s$ and $\overline{x} + 3s$;
- In general, at least $1 \frac{1}{n^2}$ of the data lie between $\overline{x} ns$ and $\overline{x} + ns$.

Empirical Rule: For roughly normal data sets

- Approximately 68% of the data lie between $\overline{x} s$ and $\overline{x} + s$;
- Approximately 95% of the data lie between $\overline{x} 2s$ and $\overline{x} + 2s$;
- Approximately 99.7% of the data lie between $\overline{x} 3s$ and $\overline{x} + 3s$.

Sample z-score: $z = \frac{x - \overline{x}}{s}$

Population z-score: $z = \frac{x-\mu}{\sigma}$

PROBABILITY:

For any event $S, 0 \leq P(S) \leq 1$

Complement Rule: $P(A^C) = 1 - P(A)$

Addition Rule: $P(A \cup B) = P(A) + P(B) - P(A \cap B)$; if A and B are disjoint, $P(A \cup B) = P(A) + P(B)$.

Multiplication Rule: $P(A \cap B) = P(A) \cdot P(B|A)$; if A and B are independent, $P(A \cap B) = P(A) \cdot P(B)$

Conditional Probability:

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

Independence: A and B are independent if P(A) = P(A|B) or P(B) = P(B|A)

COUNTING:

Multiplicative Rule: If you draw one element from each of sets with size $n_1, n_2, \ldots n_k$, there are $n_1 n_2 n_3 \cdots n_k$ different results possible.

Combinations/Partitions: If you draw n elements from a set of N elements without regard for order, the number of different results is

$$\left(\begin{array}{c} N\\n\end{array}\right) =_N C_n = \frac{N!}{n! \cdot (N-n)!}$$

More generally, if you partition a set of N elements into k groups, with n_1 elements in the first group, n_2 elements in the second group, etc., the number of different results is

$$\frac{N!}{n_1! \cdot n_2! \cdots n_k!}$$

Permutations: If you draw n elements from a set of N elements and arrange the elements into a distinct order, the number of different results is

$${}_{N}P_{n} = \frac{N!}{(N-n)!}$$

DISCRETE VARIABLES:

Mean (or expected value): $\mu = E(X) = \sum x \cdot p(x)$ Variance: $\sigma^2 = E(X - \mu)^2 = \sum (x - \mu)^2 \cdot p(x)$ or $\sigma^2 = E(X^2) - \mu^2 = (\sum x^2 \cdot p(x)) - \mu^2$

Standard deviation: $\sigma = \sqrt{\sigma^2}$

Binomials: If X is binomial with parameters n and p then $\mu = np$, $\sigma^2 = npq$, and $p(x) = \binom{n}{x} p^x q^{n-x}$

Poisson: If X is a Poisson variable with parameter λ then $\mu = \lambda$, $\sigma^2 = \lambda$, and $p(x) = \frac{\lambda^x e^{-\lambda}}{x!}$

Hypergeometrics: If X is hypergeometric, where n elements are drawn from a population of size N that has r successes initially, then $\mu = \frac{nr}{N}$, $\sigma^2 = \frac{r(N-r)n(N-n)}{N^2(N-1)}$, and

$$p(x) = \frac{\binom{r}{x}\binom{N-r}{n-x}}{\binom{N}{n}}$$

CONTINUOUS VARIABLES:

Uniform: If X has a uniform distribution over the interval [a, b], then $\mu = \frac{a+b}{2}$, $\sigma = \frac{b-a}{\sqrt{12}}$, and $f(x) = \frac{1}{b-a}$

Exponential: If X has an exponential distribution with parameter θ then $\mu = \theta$, $\sigma = \theta$, and $f(x) = \frac{1}{\theta}e^{-\frac{x}{\theta}}$ Also, $P(X \ge a) = e^{-\frac{x}{a}}$

Normal: If X is normal then $z = \frac{x-\mu}{\sigma}$

Centiles: For normal variable X, the centile is $x_{\alpha} = \mu + z_{\alpha}\sigma$

SAMPLING DISTRIBUTIONS:

Central Limit Theorem: For a random sample from a (large) population the sampling distribution of \overline{x} is approximately normal.

Sample mean: For a random sample of *n* elements from a population with mean μ and standard deviation σ , the sampling distribution has $\mu_{\overline{x}} = \mu$ and $\sigma_{\overline{x}} = \frac{\sigma}{\sqrt{n}}$

Normal approximation to binomial: If X is binomial with parameters n and p, and $np \pm 3\sqrt{npq}$ is in the interval [0, n], (same as $9q \le np$ and $9p \le nq$), then $P(a \le X \le b) = P(a - 1 < X < b + 1)$ is approximately $P(a - \frac{1}{2} < Y < b + \frac{1}{2})$ where Y is normal with $\mu = np$ and $\sigma = \sqrt{npq}$

CONFIDENCE INTERVALS:

For μ with known σ or large random sample: $\overline{x} \pm z_{\frac{\alpha}{2}}(\frac{\sigma}{\sqrt{n}})$

Sample size (margin of error b) for μ :

$$n \ge \left(\frac{z_{\frac{\alpha}{2}} \cdot \sigma}{b}\right)^2$$

For μ with unknown σ and small sample from a normal population: $\overline{x} \pm t_{\frac{\alpha}{2}}(\frac{s}{\sqrt{n}})$ for t with n-1 degrees of freedom

For proportion p: If $\hat{p} \pm 3\sqrt{\frac{\hat{p}\hat{q}}{n}}$ is within the interval (0,1), (same as $9\hat{q} < n\hat{p}$ and $9\hat{p} < n\hat{q}),$ then $\hat{p} \pm z_{\frac{\alpha}{2}} \cdot \sqrt{\frac{\hat{p}\hat{q}}{n}}$

Sample size (margin of error b) for p:

$$n \ge \left(\frac{z_{\frac{\alpha}{2}}}{b}\right)^2 pq$$

ONE-POPULATION TESTS:

One-sample z-**test** for μ with known σ or large random sample: The test statistic is $z = \frac{\overline{x} - \mu_0}{(\frac{\sigma}{\sigma})}$

One-sample t-**test** for μ with unknown σ and small random sample from a normal population: The test statistic is $t = \frac{\overline{x} - \mu_0}{\left(\frac{s}{\sqrt{n}}\right)}$ and we use t with n - 1 degrees of freedom

H_1	Reject H_0 if	p-value
$\mu eq \mu_0$	$ t > t_{\frac{\alpha}{2}}$	2P(T > t)
$\mu > \mu_0$	$t > t_{\alpha}$	P(T > t)
$\mu < \mu_0$	$t < -t_{\alpha}$	P(T < t)

One-sample test for p : If $\hat{p} \pm 3\sigma_{\hat{p}}$ is within the interval (0,1) then the test statistic is $z = \frac{\hat{p} - p_0}{\sigma_{\hat{p}}}$ where $\sigma_{\hat{p}} = \sqrt{\frac{p_0 q_0}{n}}$

H_1	Reject H_0 if	p-value
$p \neq p_0$	$ z > z_{\frac{\alpha}{2}}$	2P(Z > z)
$p > p_0$	$z > z_{\alpha}$	P(Z > z)
$p < p_0$	$z < -z_{\alpha}$	P(Z < z)

TWO-POPULATION TESTS

Two-sample z-**test** for means with known $\sigma's$ or large random samples: The test statistic is $z = \frac{(\overline{x_1} - \overline{x_2}) - D_0}{\sigma}$ where $\sigma = \sqrt{\frac{(\sigma_1)^2}{n_1} + \frac{(\sigma_2)^2}{n_2}}$

H_1	Reject H_0 if	p-value
$\mu_1 - \mu_2 \neq D_0$	$ z > z_{\frac{\alpha}{2}}$	2P(Z > z)
$\mu_1 - \mu_2 > D_0$	$z > z_{\alpha}$	P(Z > z)
$\mu_1 - \mu_2 < D_0$	$z < -z_{\alpha}$	P(Z < z)

Two-sample t-**test** for means with unknown $\sigma's$ and small random samples, where variances are equal: The test statistic is $t = \frac{(\overline{x_1} - \overline{x_2}) - D_0}{s}$ for $s = s_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}$ and $s_p = \sqrt{\frac{(n_1-1)(s_1)^2 + (n_2-1)(s_2)^2}{n_1+n_2-2}}$ and we use t with $n_1 + n_2 - 2$ degrees of freedom

H_1	Reject H_0 if	p-value
$\mu_1 - \mu_2 \neq D_0$	$ t > t_{\frac{\alpha}{2}}$	2P(T > t) $P(T > t)$
$\mu_1 - \mu_2 > D_0$	$t > t_{\alpha}$	P(T > t)
$\mu_1 - \mu_2 < D_0$	$t < -t_{\alpha}$	P(T < t)

Paired sample *t*-**test:** The test statistic is $t = \frac{\overline{x_D} - D_0}{\sigma}$ where $\sigma = \frac{\sigma_D}{\sqrt{n}}$ and use *t* with n - 1 degrees of freedom

H_1	Reject H_0 if	p-value
$\mu_D \neq D_0$	$ t > t_{\frac{\alpha}{2}}$	2P(T > t)
$\mu_D > D_0$	$t > t_{\alpha}$	P(T > t)
$\mu_D < D_0$	$t < -t_{\alpha}$	P(T < t)

Two-sample z-**test for proportions:** The test statistic is $\hat{m}_1 - \hat{m}_2$

$$z = \frac{p_1 - p_2}{\sqrt{\hat{p}\hat{q}(\frac{1}{n_1} + \frac{1}{n_2})}}$$

where
$$\hat{p} = \frac{x_1 + x_2}{n_1 + n_2}$$

H_1	Reject H_0 if	p-value
$p_1 - p_2 \neq 0$	$ z > z_{\frac{\alpha}{2}}$	2P(Z > z)
$p_1 - p_2 > 0$	$z > z_{\alpha}$	P(Z > z)
$p_1 - p_2 < 0$	$z < -z_{\alpha}$	P(Z < z)

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