Handy Transformations -

$$\boxed{\begin{aligned} \mathbb{E}[a+bX] &= a + b\mathbb{E}[X] \\ \mathbb{E}\left[X^2\right] &= \text{Var}(X) + (\mathbb{E}[X])^2 \\ \textit{(ditto but flipped) } \text{Var}(X) &= \mathbb{E}\left[X^2\right] - (\mathbb{E}[X])^2 \\ \text{Var}(a+bX) &= b^2\text{Var}(X) \\ \text{SD}(a+bX) &= |b|\text{SD}(X) \\ \text{Cov}(a+bX, c+dY) &= b\cdot d\cdot \text{Cov}(X,Y) \\ \text{Corr}(a+bX, c+dY) &= \text{Corr}(X,Y) \end{aligned}}$$

Uniform distribution facts from HW -

1. If $U \sim \text{Unif}[0,1]$, then for any fixed $a > 0$ and $b \in \mathbb{R}$, we have that $aU + b \sim \text{Unif}[b, a+b]$.
2. If $U \sim \text{Unif}[0,1]$, then $\mathbb{E}[U] = \frac{1}{2}$ and $\text{Var}(U) = \frac{1}{12}$.

When I am not protected from me being me

Set Algebra:

- **Union -** A or B; $A \cup B$.
- **Intersection -** A and B; $A \cap B$.
- **Complement -** not A; A^C.
- **Difference -** A but not B; $A \backslash B$
- **Disjoint Events aka. mutually exclusive -** events A and B are disjoint if they don't share any outcomes in common (i.e., A and $B = \varnothing$).
- **Subset -** $A \subseteq B$

Trial - a repetition of a random experiment/process. Trials're independent: none gives information about the others; are stable: reusults could have appeared in any order.

Outcome - a possible result of a trial.

Sample space - the set of all possible outcomes. Often denoted as S.

Event - a set of outcomes of an experiment (i.e., a subset of the sample space).

Probability - is a long run proportion of an outcome in repeated trials.

- Probabilities act as "targets" of estimation
- Proportions based on data "estimate" probabilities. Would approach probabilities if observe infinite trials.

Formally, $\boxed{A \mapsto \mathbb{P}(A), \mathbb{P}(A) \in [0,1]}$ A probability $\mathbb{P}(\cdot)$ on a sample space S is a function that assigns a snumber between 0 and 1 to all events, A in the sample space (i.e., any possible subset of the sample space) and subject to three requirements (axioms):

1. $\mathbb{P}(S) = 1$: probability of *something* in the sample space happening is 1
2. $\mathbb{P}(A) \geq 0, \forall A$
3. A and $B = \varnothing$ (A, B disjoint) $\Rightarrow \mathbb{P}(A \cup B) = \mathbb{P}(A) + \mathbb{P}(B)$

More takeaways

- $A \subseteq B \Rightarrow \mathbb{P}(A) \leq \mathbb{P}(B)$
- A, B, C are pairwise disjoint $\Rightarrow \mathbb{P}(A \cup B \cup C) = \mathbb{P}(A) + \mathbb{P}(B) + \mathbb{P}(C)$
- $\mathbb{P}(A \cup B) = \mathbb{P}(A) + \mathbb{P}(B) - \mathbb{P}(A \text{ and } B)$

Joint Probability - $\mathbb{P}(A \text{ and } B)$ is the joint probability that events A and B occur.

Conditional Probability - $\mathbb{P}(A|B) = \frac{\mathbb{P}(A \text{ and } B)}{\mathbb{P}(B)}, \mathbb{P}(B) > 0$ the probability of observing event A if (given that) one has observed B. Bear in mind: $\mathbb{P}(A|B) \neq \mathbb{P}(B|A)$

Product Rule - $\mathbb{P}(A \text{ and } B) = \mathbb{P}(B) \cdot \mathbb{P}(A|B)$.

Independent Events - A and B are independent if $\mathbb{P}(A \text{ and } B) = \mathbb{P}(A) \cdot \mathbb{P}(B)$; one event happening doesn't affect the probability of the other event happening. Can easily deduce that $\mathbb{P}(A|B) = \mathbb{P}(A)$ and $\mathbb{P}(B|A) = \mathbb{P}(B)$.

Independence and Disjointness are **NOT** synonyms.

- Independent $\Rightarrow \mathbb{P}(A \text{ and } B) = \mathbb{P}(A) \cdot \mathbb{P}(B)$
- Disjoint $\Rightarrow \mathbb{P}(A \text{ and } B) = 0$. Disjoint events are extremely dependent: If one event occurs, the other cannot.

Random variable - a numerical function on a sample space with probabilities. (Think as a scoring mechanism.)

- Input: an outcome in the sample space
- Output: a number

Discrete RVs - only countably many values are possible

Continous RVs - can take on uncountably infinitely many values

Probability Distribution Function (PDF) - $\boxed{\mathbf{p}_X(x) = \mathbb{P}(X = x)}$ is the probability that the random variable X takes on the value x. I really hate $\mathbf{p}_X(x)$ this styling, so only $\mathbb{P}(X = x)$ moving forward.

Properties of PDFs - any function that satisfies the following conditions is a probability distribution function of a Discrete random variable:

1. $\mathbb{P}(X = x) \geq 0, \forall x \in \mathbb{R}$ (for any real number)
2. $\mathbb{P}(X = x) > 0$ for values that the random variable X can actually take on
3. $\mathbb{P}(X = x) = 0$ for values that aren't possible for the random variable X
4. $\sum_x \mathbb{P}(X = x) = 1$

Expected Value - $\boxed{\mathbb{E}[X] = \sum_x x \cdot \mathbb{P}(X = x)}$

Variance - a probability weighted mean of the possible squared deviations.

$$\boxed{\begin{aligned} \text{Var}(X) &= \mathbb{E}\left[(X - \mathbb{E}[X])^2\right] \\ &= \sum_x (x - \mathbb{E}[X])^2 \cdot \mathbb{P}(X = x) \\ &= \mathbb{E}\left[X^2\right] - (\mathbb{E}[X])^2 \end{aligned}}$$

Standard Deviation - $\boxed{\text{SD}(X) = \sqrt{\text{Var}(X)}}$

Given $Y = g(X)$ and X's PDF -

$$\boxed{\begin{aligned} \mathbb{E}[Y] &= \sum_x g(x) \cdot \mathbb{P}(X = x) \\ \text{Var}(Y) &= \sum_x (g(x) - \mathbb{E}[g(X)])^2 \cdot \mathbb{P}(X = x) \end{aligned}}$$

RVs with only 2 outcomes - (not necessarily Bernoullis yet) Suppose RV X's PDF is:

$$\begin{cases} \mathbb{P}(X = a) & = p \\ \mathbb{P}(X = b) & = 1 - p \text{, then:} \\ \mathbb{P}(X = \text{all other values}) & = 0 \end{cases}$$

$$\boxed{\begin{aligned} \mathbb{E}[X] &= ap + b(1-p) \\ \text{Var}(X) &= (a-b)^2 p(1-p) \\ \text{SD}(X) &= |a-b|\sqrt{p(1-p)} \end{aligned}}$$

Bernoulli Random Variable - aforementioned when $\begin{cases} a & = 1 \\ b & = 0 \end{cases}$. If $\boxed{X \sim \text{Bern}(p)}$, then:

$$\boxed{\begin{aligned} \mathbb{E}[X] &= p \\ \text{Var}(X) &= p(1-p) \\ \text{SD}(X) &= \sqrt{p(1-p)} \end{aligned}}$$

- Variance maximized when $p = 0.5$
- Variance minimized when $p = 0$ or 1

Useful for tracking how many successes happen in n independent trials.

Binomial Random Variable - If $\boxed{X \sim \text{Binom}(n,p)}$, then:

$$\boxed{\begin{aligned} \mathbb{E}[X] &= n \cdot p \\ \text{Var}(X) &= n \cdot p(1-p) \\ \text{SD}(X) &= \sqrt{n \cdot p(1-p)} \end{aligned}}$$

Binomial Problems - following must hold:

1. Constant success probability p and failure probability $(1-p)$.
2. Fixed total number of trials: n
3. trials are **independent**
4. Only two outcomes of interest (success or failure) on each trial
5. Want to find the probability of observing k successes among the total number of n trials. (Order doesn't matter.)

$$\boxed{\mathbb{P}(k \text{ successes in } n \text{ trials}) = \binom{n}{k} p^k (1-p)^{n-k}}$$

Combination - how many ways to choose k out of n: $\boxed{\binom{n}{k} = \frac{n!}{k!(n-k!)}}$.

Binomial Distribution - $\boxed{X \sim \text{Binom}(n,p)}$ where X is an RV tracking the number of successes in n independent trials with success probability p. X's PDF: $\boxed{\forall k \in \{0, \ldots, n\}, \mathbb{P}(X = k) = \binom{n}{k} p^k (1-p)^{n-k}}$.

Attn: X here is not for one single trial!.

- A **Bernoulli RV**: useful for one trial's success/failure.
- A **Binomial RV**: useful for total number of successes.

Binomial as the Sum of Bernoullis - n independent Bernoulli RVs each with the same success probability p: $\forall i \in 1, \ldots, n, X_i \sim \text{Bern}(p)$.

Define $\boxed{S_n = \sum_{i=1}^n X_i}$, then denote $\boxed{S_n \sim \text{Binom}(n,p)}$. $\text{Binom}(1,p) = \text{Bern}(p)$

Joint Distribution of 2 RVs - the probability that 2 RVs simultaneously take on 2 values. $\forall x \in X, \forall y \in Y$ $\boxed{\mathbb{P}(X = x, Y = y)}$.

Marginal probability distribution - can be found given with the joint PDF: $\boxed{\mathbb{P}(X = x) = \sum_y \mathbb{P}(X = x, Y = y)}$

Z-Score of a Random Variable X - $\boxed{Z(X) = \frac{X - \mathbb{E}[X]}{SD(X)}}$

$\mathbb{E}[Z(X)] = 0$ and $SD(Z(X)) = 1$

Correlation and Covariance

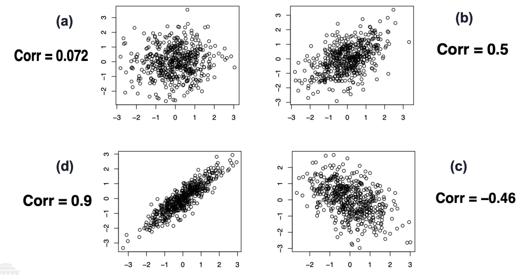
Correlation Between RVs X and Y - "average of the product of z-scores"

$$\boxed{\begin{aligned} \text{Corr}(X,Y) &= \mathbb{E}[Z(X) \cdot Z(Y)] \\ &= \frac{\text{Cov(X, Y)}}{SD(X) \cdot SD(Y)} \end{aligned}}$$

- $\text{Corr}(X,Y)$ is unit-free.
- $\text{Corr}(X,Y)$ doesn't exist if either $SD(X) = 0$ or $SD(Y) = 0$ (can't divide by 0!).
- Correlation is guaranteed to lie between +1 (perfect positive correlation) and −1 (perfect negative correlation). Hence Corr is more commonly used than Covariance.

$\text{Corr}(X,Y)$ here quantifies the strength and direction of the **linear relationship** between two variables. Therefore, if two variables have a strong but non-linear relationship, $\text{Corr}(X,Y) \approx 0$, indicating no linear correlation, even though a strong non-linear relationship exists.

Correlation Examples



Covariance Between RVs X and Y - "average of the product of the centered variables". Necessary for assessing variability of sums of RVs (e.g. portfolios).

$$\boxed{\begin{aligned} \text{Cov}(X,Y) &= \mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])] \\ &= \text{Corr}(X,Y) \cdot SD(X) \cdot SD(Y) \end{aligned}}$$

- $\text{Cov}(X,Y)$ has funny units: product of the X and Y units.
- $\text{Cov}(X,Y)$ always exists. If SDs are 0, $\text{Cov}(X,Y) = 0$
- $\text{Cov}(X,X) = V(X)$
- If $SD(X) > 0$ and $SD(Y) > 0$, then $\text{Corr}(X,Y)$ and $\text{Cov}(X,Y)$ have the same sign.

Expected Value of RVs summed - is regardless of RVs' joint distribution:

$$\boxed{\begin{aligned}&\mathbb{E}[X+Y]=\mathbb{E}[X]+\mathbb{E}[Y]\\&\mathbb{E}[X+Y+W]=\mathbb{E}[X]+\mathbb{E}[Y]+\mathbb{E}[W]\\&\mathbb{E}\left[\sum_{i=1}^{n}X_i\right]=\sum_{i=1}^{n}\mathbb{E}[X_i]=\mathbb{E}[X_i]+\cdots+\mathbb{E}[X_n]\end{aligned}}$$

Variance of RVs summed -

$$\boxed{\begin{aligned}&\mathrm{Var}(X+Y)=\mathrm{Var}(X)+\mathrm{Var}(Y)+2\mathrm{Cov}(X,Y)\\&\mathrm{Var}(X+Y+W)=\mathrm{Var}(X)+\mathrm{Var}(Y)+\mathrm{Var}(W)\\&\quad+2\mathrm{Cov}(X,Y)+2\mathrm{Cov}(X,W)+2\mathrm{Cov}(Y,W)\\&\mathrm{Var}\left(\sum_{i=1}^{n}X_i\right)=\sum_{i=1}^{n}\mathrm{Var}(X_i)+2\sum_{i<j}\mathrm{Cov}(X_i,X_j)\end{aligned}}$$

Have to consider the covariance of all possible pairs: X_i and X_j.

- If $\mathrm{Corr}(X,Y)$ increases, then $\mathrm{Var}(X+Y)$ increases.
- If $V(X)=V(Y)$, then $\mathrm{Var}(X+Y)$ is maximized when $\mathrm{Cov}(X,Y)$ is maximized.

Uncorrelated RVs - if $\mathrm{Corr}(X,Y)=0$. Equivalently, they are uncorrelated if $\mathrm{Cov}(X,Y)=0, SD(X)>0, SD(Y)>0$

Variance of of Uncorrelated or Independent RVs summed -

$$\boxed{\begin{aligned}&\mathrm{Var}(X+Y)=\mathrm{Var}(X)+\mathrm{Var}(Y)\\&\mathrm{Var}\left(\sum_{i=1}^{n}X_i\right)=\sum_{i=1}^{n}\mathrm{Var}(X_i)\end{aligned}}$$

No change in expected value's formula.

Independent RVs -

$$\boxed{\forall x,y,\mathbb{P}(X=x,Y=y)=\mathbb{P}(X=x)\mathbb{P}(Y=y)}$$

Independence implies uncorrelatedness: if two RVs X and Y are independent, then they are uncorrelated.

$$\boxed{\text{Independence}\Rightarrow\mathrm{Corr}(X,Y)=0=\mathrm{Cov}(X,Y)}$$

But uncorrelated RVs can be dependent!

***(iid)* Independent and Identically Distributed RVs -** for a collection of *iid* RVs $\{X_1,\ldots,X_n\}$: $\forall i\in\{1,\ldots,n\}$

$$\boxed{\begin{aligned}\mathbb{E}[X_i]&=\mu\\\mathrm{Var}(X_i)&=\sigma^2\\\mathrm{SD}(X_i)&=\sigma\end{aligned}}$$

Sum of *iid* RVs - $S_n=X_1+\cdots+X_n$:

$$\boxed{\begin{aligned}\mathbb{E}[S_n]&=n\cdot\mu\\\mathrm{Var}(S_n)&=n\cdot\sigma^2\\\mathrm{SD}(X_i)&=\sqrt{n}\cdot\sigma\end{aligned}}$$

Central Limit Theorem (CLT)

If $\{X_1,\ldots,X_n\}$ are *iid* with expected value $\mathbb{E}[X_i]=\mu$ and variance $\mathrm{Var}(X_i)=\sigma^2<\infty$, then as $n\to\infty$:

- $S_n\sim\mathcal{N}(n\cdot\mu,\sqrt{n}\cdot\sigma)$
- $\mathrm{Mean}_n\sim\mathcal{N}(\mu,\frac{\sigma}{\sqrt{n}})$

If n is large enough (heuristic: $n>30$), we can calculate probabilities for the sum and mean of RVs by using the normal distribution.

Emperical Rules under CLT -

- 50% of the time,
  - S_n will fall within $n\mu\pm\frac{2}{3}\sqrt{n}\sigma$
  - M_n will fall within $\mu\pm\frac{2}{3}\frac{\sigma}{\sqrt{n}}$
- 68% of the time,
  - S_n will fall within $n\mu\pm\sqrt{n}\sigma$
  - M_n will fall within $\mu\pm\frac{\sigma}{\sqrt{n}}$
- 95% of the time,
  - S_n will fall within $n\mu\pm2\sqrt{n}\sigma$
  - M_n will fall within $\mu\pm2\frac{\sigma}{\sqrt{n}}$
- 99.7% of the time,
  - S_n will fall within $n\mu\pm3\sqrt{n}\sigma$
  - M_n will fall within $\mu\pm3\frac{\sigma}{\sqrt{n}}$

Sampling and Confidence Intervals

Confidence Interval - contains an unknown (population) quantity at some specified sampling frequency.

- Confidence intervals do not depend on population size, but only on sample size.
- For a given sample size, can be very precise with low confidence or very imprecise with high confidence.
- 2x the precision requires 4x sample size; 3x the precision requires 9x sample size.

Wording matters...

- OK: "I am 95% confident the interval [a,b] contains the true population proportion"
- OK: "There is a 95% probability the interval [a,b] contains the true population proportion"
- Not OK: "There is a 95% probability the true population proportion lies in the interval [a,b]"

Confidence Level (L) to c -

$\boxed{c=\texttt{qnorm}(p=\frac{(1+L)}{2},\mu=0,\sigma=1)}$ (find the value c such that the area under $\mathcal{N}(\mu,\sigma)$ is p)

confidence level	L	c
90%	0.9	1.65
95%	0.95	1.96
99%	0.99	2.58

For a population mean - Given sample size n, sample average $\bar{x}$, and sample standard deviation s, we are X% confident the true population mean lies in the interval: $\boxed{\bar{x}\pm\left(c\frac{s}{\sqrt{n}}\right)}$ "MOE": $\left(c\frac{s}{\sqrt{n}}\right)$

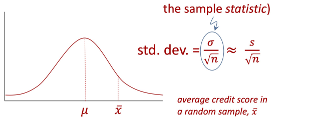
For a population proportion - Given sample size n, sample proportion $\bar{p}$, and standard deviation in the population to be 0.5, we are X% confident the true population mean lies in the interval: $\boxed{\bar{p}\pm\left(c\frac{0.5}{\sqrt{n}}\right)}$ "MOE": $\left(c\frac{0.5}{\sqrt{n}}\right)$

Important assumptions:

- Sample is random
- Sample is large enough ($n>30$) for CLT
- The worst possible standard deviation in the population to be 0.5

Sampling Distribution - is well approximated by $\mathcal{N}(\mu=\text{true population parameter},\sigma=\frac{\text{population SD}}{\sqrt{n}})$, based on CLT.

Using the Sampling Distribution to Construct a Confidence Interval

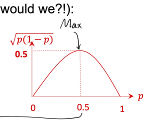


The fact that 95% of the sample means lie within 1.96 standard errors of the true (unknown) population mean ⇒ The confidence intervals constructed using the given formula will 'capture the true mean' 95% of the time!

Take away: assuming a conservative confidence interval based on 0.5 is not the only way! Can estimate standard error using the surveyed proportion too.

Similar Analysis for Proportions

- When outcomes are binary, the standard deviation of observations in the population equals $\sqrt{p(1-p)}$.
- We get the standard error by dividing by $\sqrt{n}$. The exact interval is $\bar{p}\pm1.96\sqrt{\frac{p\,(1-p)}{n}}$. the 'standard error' P (not $\bar{p}$) Theoretical real value
- But since we don't know p (if we did we won't be sampling would we?!):
  - We can take a conservative approach and assume p = 0.5, $\boxed{\bar{p}\pm1.96\frac{0.5}{\sqrt{n}}}$
  - Or, an approximate approach by assuming p = $\bar{p}$ to get the practical alternative, $\boxed{\bar{p}\pm1.96\sqrt{\frac{\bar{p}\,(1-\bar{p})}{n}}}$



Sampling Errors - the sample-to-sample variations due to pure chance. MOE and confidence intervals quantify this uncertainty well.

Non-Sampling Errors - (some examples)

- Selection Bias: happens when each member of the population does not have the same chance of being selected.
- Response/Non-response Bias: happens when some fraction of the individuals surveyed don't respond for reasons related to what's being asked in the survey

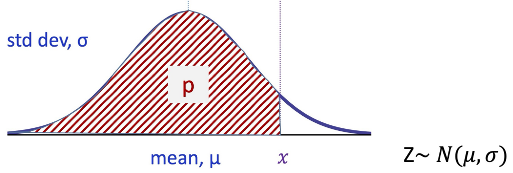
R Distribution Functions

- `p` ("probability"): cumulative distribution function ("what is the probability above or below a cutoff?")
- `q` ("quantile"): inverse CDF ("what value do we find at, say, 80% of the way to the maximal value?")
- `d` ("density"): density function (gives us the "height" or y-value of distribution for a particular z-score - mainly useful in plotting)

`pnorm` **-** returns the integral (a.k.a. "area under the curve") from $-\infty$ to `q` of the pdf of the normal distribution where `q` is a Z-score

```
# Probability of this value or less
pnorm(value, mean, sd)
# Probability of this value or
    greater
pnorm(value, mean, sd, lower.tail=
    FALSE)
```

If `lower.tail` is set equal to `FALSE` then `pnorm` returns the integral from `q` to ∞ of the pdf of the normal distribution. Note that `pnorm(q)` is the same as `1 - pnorm(q, lower.tail = FALSE)`



x = qnorm(p, μ, σ)

`qnorm` **-** simply the inverse of the cdf, which you can also think of as the inverse of pnorm! You can use `qnorm` to determine the answer to the question: What is the Z-score of the p-th quantile of the normal distribution?

```
# Highest value associated with a
    given percentile
qnorm(percentile, mean, sd)
```

Binomial functions - unlikely tested but why not.

```
# Exactly k successes in n trials
    given success probability p
dbinom(k, size=n, p=p)
# k or more successes in n trials
    given success probability p
sum(dbinom(k:n, size=n, p=p))
```