

**Descriptive Statistics:**

Term	Meaning	Population Formula	Sample Formula	Example {1,16,1,3,9}
<b>Mean</b>	Average	$\mu = \frac{\sum_{i=1}^N X_i}{N}$	$\bar{X} = \frac{X_1 + X_2 + \dots + X_n}{n} = \frac{\sum_{i=1}^n X_i}{n}$	6
<b>Median</b>	The middle value – half are below and half are above			3
<b>Mode</b>	The value with the most appearances			1
<b>Spread</b>		$1/n (\sum x - \mu)$		
<b>MAD</b>	Mean Absolute Deviation	$1/n (\sum  x - \mu )$		
<b>Variance</b>	The average of the squared deviations between the values and the mean	$\sigma^2 = \frac{1}{N} \sum_{i=1}^N (X_i - \mu)^2$	$s^2 = \frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n - 1}$	$(1-6)^2 + (1-6)^2 + (3-6)^2 + (9-6)^2 + (16-6)^2$ divided by 5 values = $168/5 = 33.6$
<b>Standard Deviation</b>	The square root of Variance, thought of as the “average” deviation from the mean.	$\sigma = \sqrt{\sigma^2}$	$s = \sqrt{s^2} = \sqrt{\frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n - 1}}$	Square root of 33.6 = 5.7966
<b>Coefficient of Variation</b>	The variation relative to the value of the mean		$CV = \frac{s}{\bar{X}}$	5.7966 divided by 6 = 0.9661
<b>Range</b>	Maximum minus Minimum			$16 - 1 = 15$
<b>IQR</b>	Interquartile Range	3rd quartile – 1st quartile (Dataset has 4 quartiles)	Outliers = $Q1 - 1.5 \cdot IQR$ and $Q3 + 1.5 \cdot IQR$	

**Linear Transformation:**

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

$$\text{Average}(a + bX) = a + b[\text{Average}(X)]$$

**Z-Score(Normalize data - Useful when two datasets with different metrics eg: GRE v/s GMAT):**

$$Z = (X - \mu) / \sigma$$

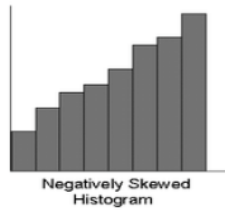
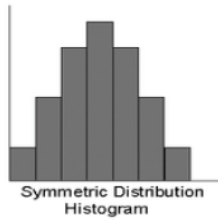
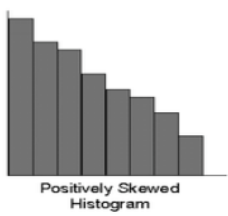
By “z scoring” a data set, the new data set will have **mean 0 and variance 1**.

Different exams but Jason’s Z-Score = -1, Mary’s Z score = +2 → Jason is 1SD below mean, Mary is 2 SD above

**Outlier Detection:** Z-score  $\geq 2$

**Dataset Distribution:**

Empirical Rule - Mound Shaped/ Symmetric Data	Chebyshev’s Rule - Any set of data
$X \mp \sigma \rightarrow 68\%$ of Data	At least $1 - \frac{1}{K^2}$ data is in <b>K</b> SD
$X \mp 2\sigma \rightarrow 95\%$ of Data	$1 - 1/4$ i.e. 75% in 2 SD



Negative Skewed - Skewed Left - Long tail to Left  
Positive Skewed - Skewed Right - Long tail to right

### Covariance, Correlation and not Causation:

Both measure existence of a **linear relationship**. Does not imply anything about another relationship.

Correlation does not imply causation.

Covariance	Correlation
$S_{xy} = \frac{1}{n-1} \sum (x - \mu_x)(y - \mu_y)$	Correlation coeff $r_{xy} = \sigma_{xy} / (\sigma_x * \sigma_y)$
possible: +ve, -ve, 0   not possible: weak, strong, slightly Covariance gives you direction, not strength	Possible values: -1 → 1 Direction of relationship: +ve or -ve Strength of relationship: absolute value(-0.6 stronger than 0.4)
$Cov(X, X) = Var(X)$	$r_{xx} = r_{yy} = 1$
$Cov(X, Y) \neq Cov(Y, X)$	$r_{xy} = r_{yx}$

### Regression:

One variable is considered the **explanatory variable(x-axis)** and the other the **dependent variable(y-axis)**.

Regression allows one to do predictions which cannot be done with correlation.

$$b_1 = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sum_{i=1}^n (X_i - \bar{X})^2} = \frac{s_y}{s_x}$$

$$b_0 = \bar{Y} - b_1 \bar{X}$$

Fitted line:  $\hat{Y} = b_0 + b_1 X$  ( $\hat{Y}$  → predicted value)

Fitting error:  $Y - \hat{Y}$

Stock return:  $\alpha + \beta(\text{Index Return})$

### Basic Probability:

$$P(\text{Event Occurs}) = \frac{\text{no. of successful events}}{\text{no. of possible outcomes}}$$

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

$$\text{i.e. } P(A \text{ or } B) = P(A) + P(B) - P(A \text{ and } B)$$

$$(\text{Joint Probability}) P(A \cap B) = P(A|B) * P(B) = P(B|A) * P(A)$$

$$\text{If } A, B \text{ independent} \rightarrow P(A \cap B) = P(A) * P(B)$$

$$\rightarrow P(A|B) = P(A)$$

$$\text{If } A, B \text{ mutually exclusive } P(A \cap B) = 0$$

$$P(A|B) > P(A) \rightarrow \text{Positively related}$$

$$P(A|B) < P(A) \rightarrow \text{Negatively related}$$

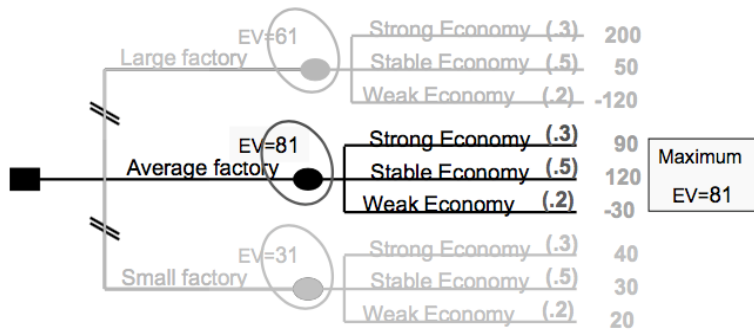
$$P(A|B) = \frac{P(A \text{ and } B)}{P(B)}$$

	B	$\bar{B}$
A	$P(A \text{ and } B)$ $= P(B)P(A B)$	$P(A \text{ and } \bar{B})$ $= P(\bar{B})P(A \bar{B})$
$\bar{A}$	$P(\bar{A} \text{ and } B)$ $= P(\bar{A})P(B \bar{A})$	$P(\bar{A} \text{ and } \bar{B})$ $= P(\bar{A})P(\bar{B} \bar{A})$

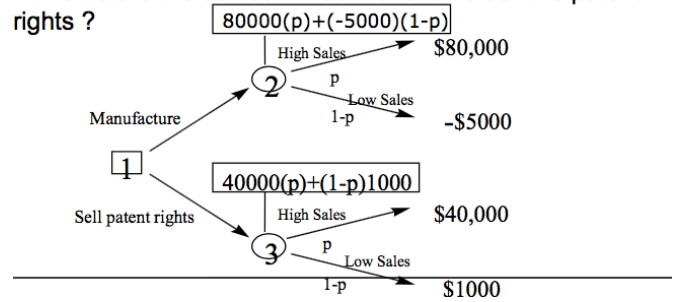
### Decision Analysis:

Maximax solution	Maximin Solution	Expected Value Solution
Best possible scenario. Optimistic and aggressive. Highest payoff.	Worst case scenario. Pessimistic and conservative decision making. Guaranteed minimum payoff.	Probability estimate can be incorporated in search for optimal decision. Weighted average payoff. Never really the outcome
For each option, find the maximum payoff. Choose the option with greatest maximum payoff.	For each option, find the minimum payoff. Choose the option with the greatest maximum payoff.	EV of option $= \sum (\text{Prob. Of Outcome} * \text{Value of Outcome})$

## Decision Tree Analysis:



What is the value of the probability of high sales at which it makes no difference whether the engineer should manufacture the device himself or should sell the patent rights?



The inventor should manufacture the device himself if

$$\begin{aligned}
 80000(p) - 5000(1-p) &> 40000(p) + (1-p)1000 \\
 \Rightarrow 40000(p) &> 6000(1-p) \\
 \Rightarrow \frac{p}{(1-p)} &> 0.15 \\
 \Rightarrow p &> 0.15(1-p) \\
 \Rightarrow p &> 0.13
 \end{aligned}$$

Conclusion: if  $p > .13$  then he should manufacture the device himself.

## Discrete Random Variables:

Probability mass function: For most, output will be zero. For specific inputs, some value between 0 and 1.

Cumulative Distribution Function:  $F(x) = P(X \leq x)$

$$\mu_x = \sum x_i \cdot P(x_i)$$

$$(\sigma_x)^2 = \text{Var}(X) = E[(x - \mu_x)^2] = \sum (x - \mu)^2 \cdot P(X=x_i)$$

$$(\sigma_x)^2 = \text{Var}(X) = E[X^2] - (\mu_x)^2 \rightarrow E[X^2] = \sum x_i^2 \cdot P(x_i)$$

	Chebyshev's Rule	Empirical Rule
	Applies to any probability Distribution	Applies to probability Distributions that are mound Shaped and symmetric
$P(\mu - \sigma < x < \mu + \sigma)$	$\geq 0$	$\approx 68\%$
$P(\mu - 2\sigma < x < \mu + 2\sigma)$	$\geq 75\%$	$\approx 95\%$
$P(\mu - 3\sigma < x < \mu + 3\sigma)$	$\geq 89\%$	$\approx 100\%$

## Binomial Distribution:

Criteria:

Each instance of a trial has only two outcomes, "success" or "failure".

The trials of the experiment are independent of each other.

The probability of a success,  $p$ , remains constant from trial to trial

We are interested in the total number of successes (out of  $n$  trials)

Not:

The college administration surveys students until they find one not on financial aid. Let the random variable  $X$  denote the number of students surveyed.

Learnings:

Probability of  $x$  successes in  $n$  trials =

where  $p = P(X=x)$  i.e.  $P(\text{success})$

All successes =  $p^n$

All failures =  $(1-p)^n$

$1-p^n$  = negating all successes = at least one failure

$1-(1-p)^n$  = negating all failures = at least one success

Mean:  $n \cdot p$

Var:  $n \cdot p \cdot q$

Shape depends on  $p$ :  $p = 0.5 \rightarrow$  symmetric

$p = 0.1 \rightarrow$  Skewed(tail) to the right

## Continuous Random Variables:

$P(X=x) = 0$  for any  $x$ . There are just too many values out there.

CDF: Probability of being less than that value. Used to calculate probability of any interval.

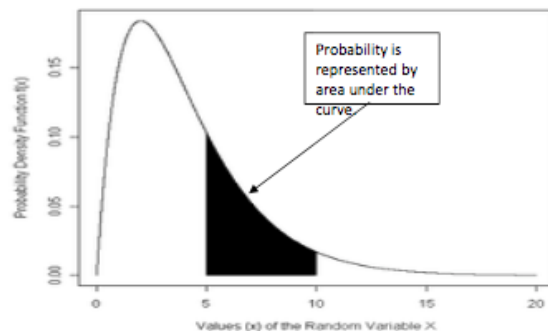
$$F_X(X \leq x) = P(X \leq x) = \int_{-\infty}^x f(x) dx \quad P(a \leq X \leq b) = F_X(b) - F_X(a)$$

$$P(x) = \frac{n!}{x!(n-x)!} p^x (1-p)^{n-x}$$

Number of ways to have  $x$  successes in  $n$  trials

Probability of  $x$  successes

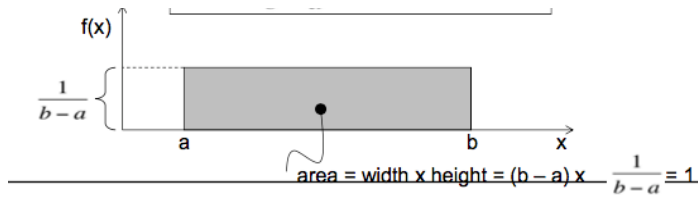
Probability of  $n-x$  failures



The density curve  $f(x)$  is such that  $f(x) \geq 0$  for all  $x$  and the area under the curve = 1

$$\mu = E(X) = \int_{-\infty}^{\infty} xf(x)dx \quad \sigma^2 = Var(X) = \int_{-\infty}^{\infty} (x - \mu)^2 f(x)dx$$

### Uniform Distribution(Example of Continuous RV):



$$f(x) = \begin{cases} \frac{1}{(b-a)} & \text{for } x \text{ values between } a \text{ and } b \\ 0 & \text{everywhere else} \end{cases}$$

$$\text{Mean} = E(X) = \frac{(a+b)}{2} \quad \text{Variance} = Var(X) = \frac{(b-a)^2}{12}$$

### Normal Distribution(Example of Continuous RV):

$\sigma$  governs height and width. Area has to be 1 so as you get higher, you must get skinnier.

For area under the curve, Z-score  $\rightarrow Z = \frac{(X - \text{mean})}{SD}$

Once it is normalized, we can use the Z-score table that has cumulative probabilities for Z-values

$$P(a < X < b) = P\left(\frac{a - \mu}{\sigma} < Z < \frac{b - \mu}{\sigma}\right) \quad P(110 \leq X \leq 175) = P\left(\frac{110 - 160}{25} \leq \frac{X - 160}{25} \leq \frac{175 - 160}{25}\right) = P(-2 \leq Z \leq 0.6)$$

Normal distribution is mound shaped: Empirical rules from Discrete RV apply

Reverse look up: Need to find top 10% of population? Find Z where the z-score is 0.9 i.e.  $z = 1.28 \rightarrow$  find x