OTDM UNIT III

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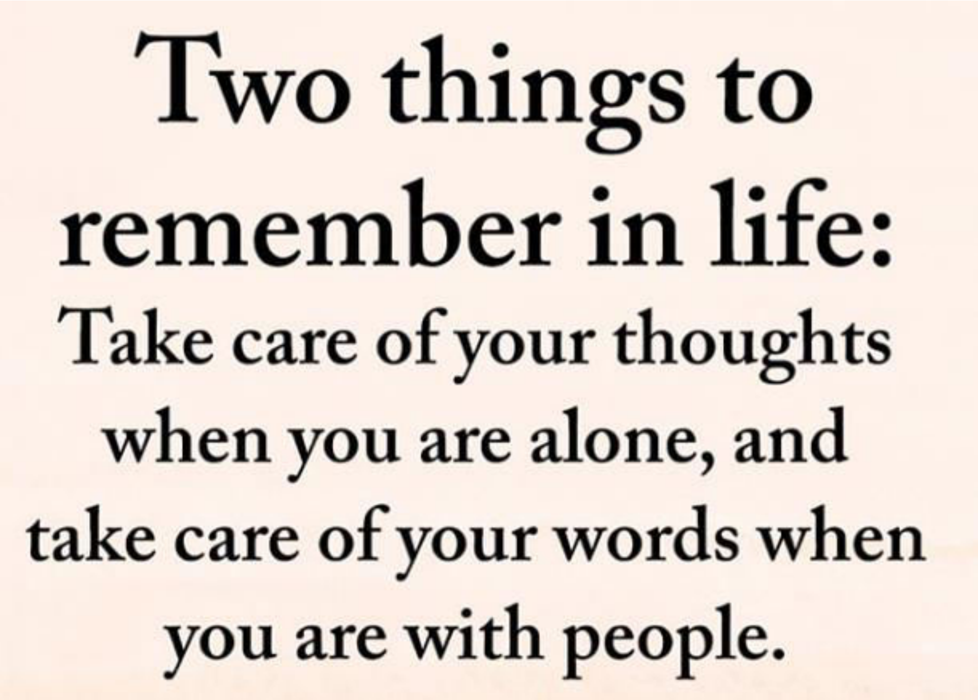
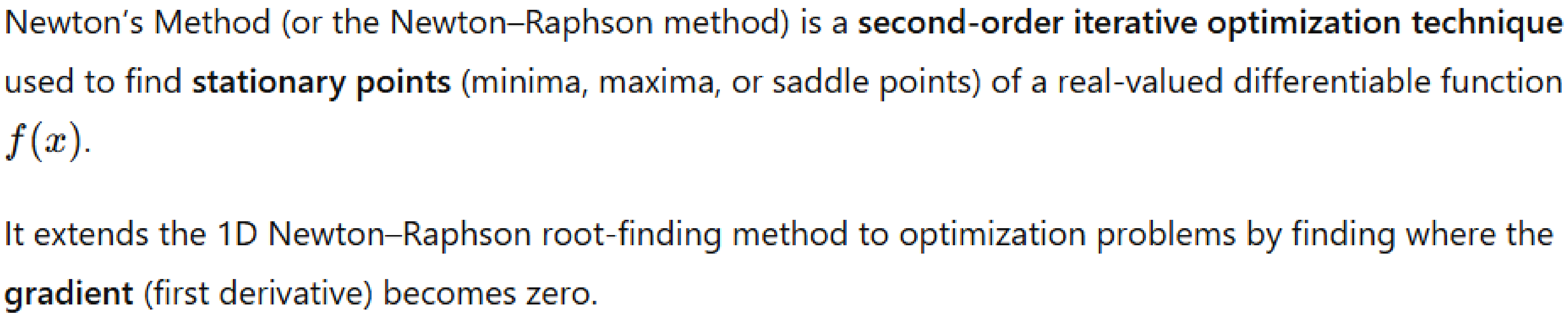


Two things to remember in life:

Take care of your thoughts when you are alone, and take care of your words when you are with people.

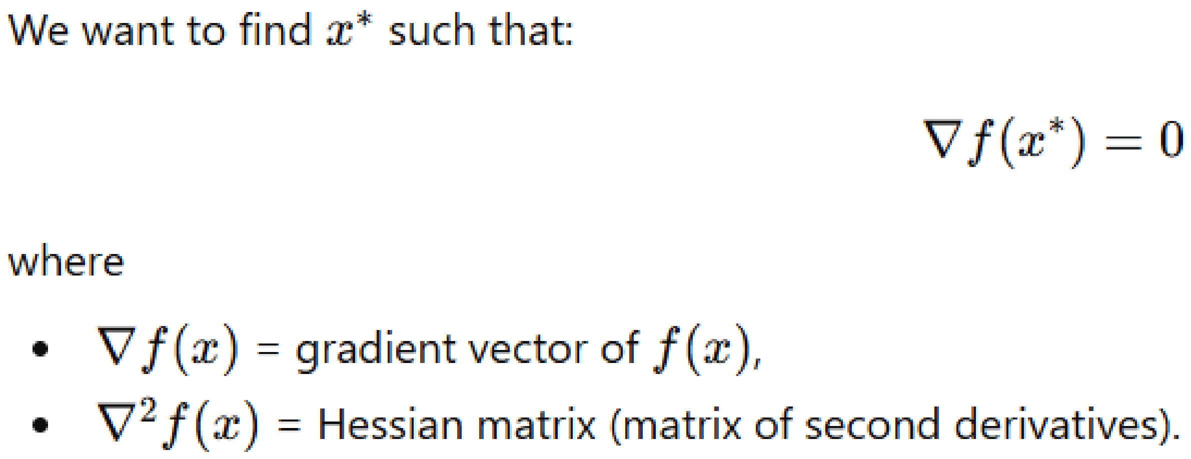
Newton's Method in Optimization



Newton's Method (or the Newton–Raphson method) is a **second-order iterative optimization technique** used to find **stationary points** (minima, maxima, or saddle points) of a real-valued differentiable function $f(x)$.

It extends the 1D Newton–Raphson root-finding method to optimization problems by finding where the **gradient** (first derivative) becomes zero.

Objective



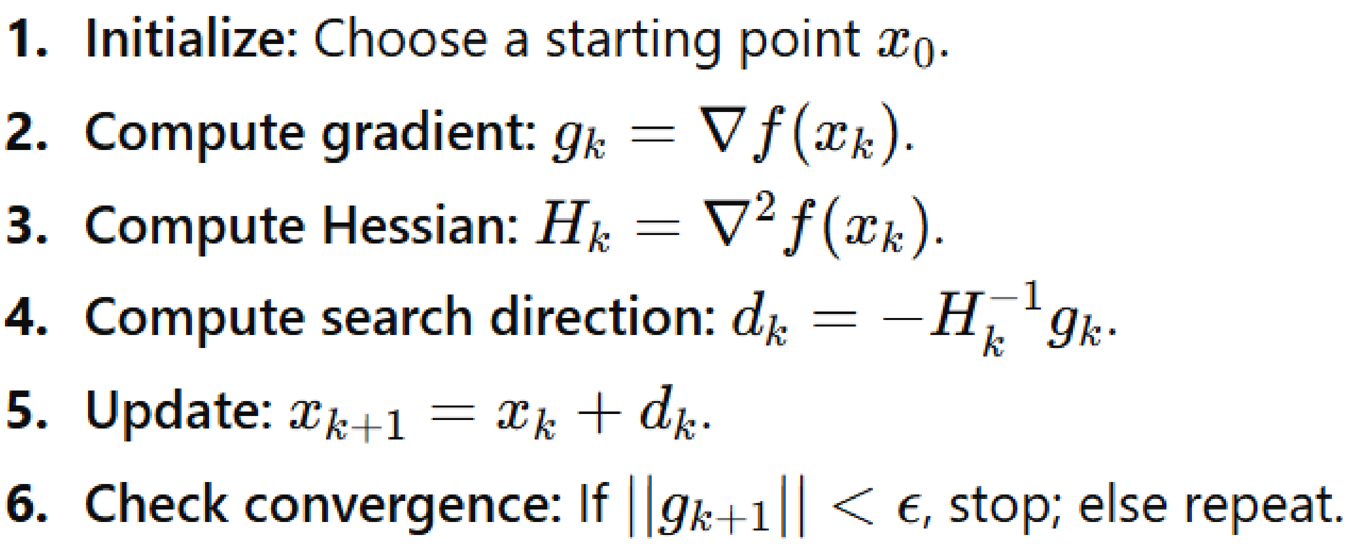
We want to find x^* such that:

$$\nabla f(x^*) = 0$$

where

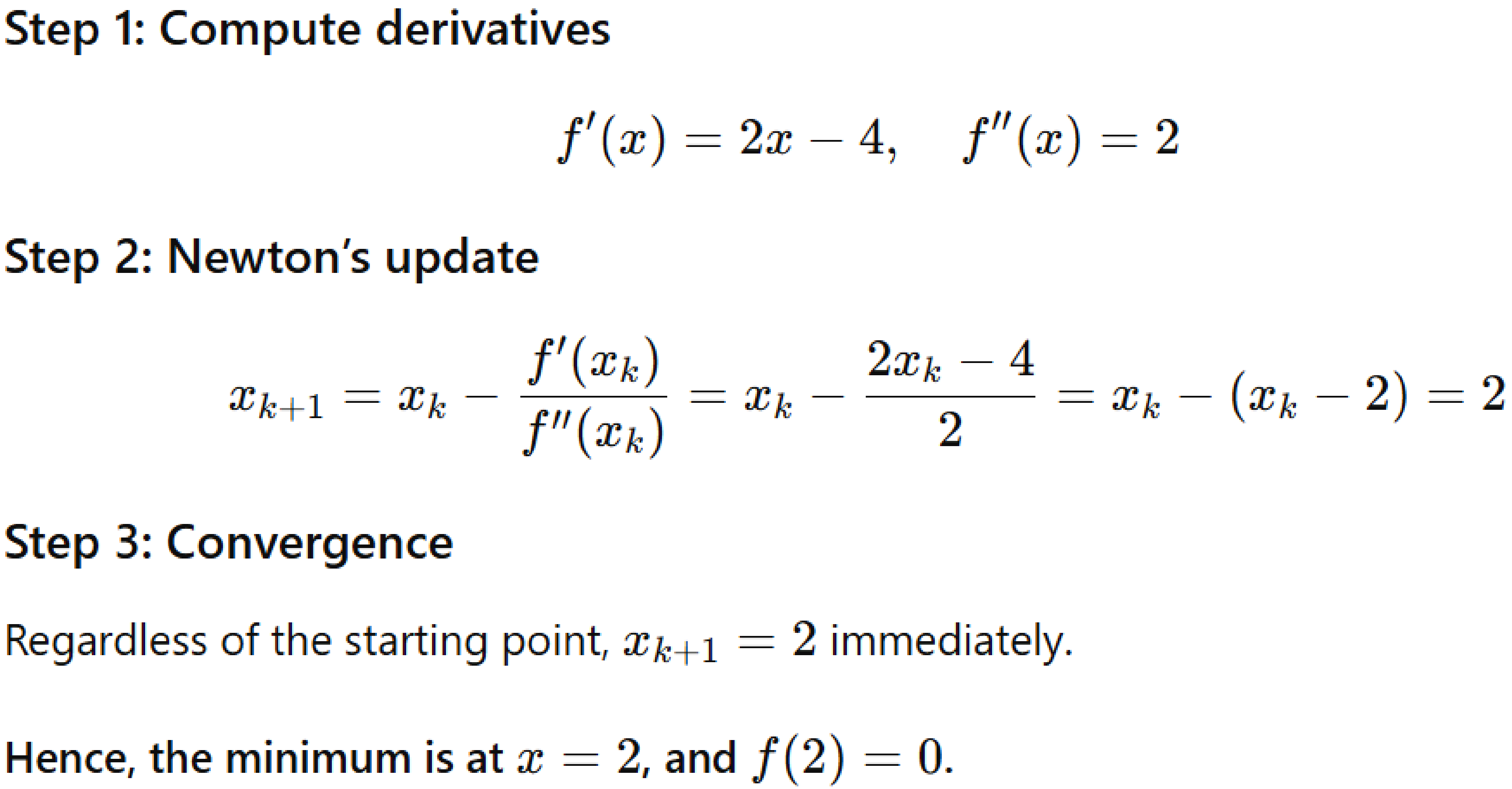
- $\nabla f(x)$ = gradient vector of $f(x)$,
- $\nabla^2 f(x)$ = Hessian matrix (matrix of second derivatives).

Newton’s Method Algorithm (Unconstrained Optimization)



1. **Initialize:** Choose a starting point x_0.
2. **Compute gradient:** $g_k = \nabla f(x_k)$.
3. **Compute Hessian:** $H_k = \nabla^2 f(x_k)$.
4. **Compute search direction:** $d_k = -H_k^{-1} g_k$.
5. **Update:** $x_{k+1} = x_k + d_k$.
6. **Check convergence:** If $||g_{k+1}|| < \epsilon$, stop; else repeat.

Example 1 on Newton's Method – Minimize f(x) = x^2 - 4x +4



Step 1: Compute derivatives

$$f'(x) = 2x - 4, \quad f''(x) = 2$$

Step 2: Newton's update

$$x_{k+1} = x_k - \frac{f'(x_k)}{f''(x_k)} = x_k - \frac{2x_k - 4}{2} = x_k - (x_k - 2) = 2$$

Step 3: Convergence

Regardless of the starting point, $x_{k+1} = 2$ immediately.

Hence, the minimum is at $x = 2$, and $f(2) = 0$.

Disadvantages of Newton’s Method

Disadvantage	**Explanation**
1. Requires Hessian computation	The Hessian ((n \times n) matrix) must be computed and inverted — expensive for large (n).
2. May not converge	If the Hessian is not positive definite (saddle point or maximum), the step can move away from minimum.
3. Sensitive to initial guess	Poor starting point can lead to divergence or convergence to the wrong stationary point.
4. High computational cost	Computing and inverting the Hessian costs (O(n^3)).
5. Not suitable for non-smooth functions	Requires continuous second derivatives.
6. Step may overshoot	If the step size is too large, the quadratic approximation fails — often a line search or damping factor is added.

Newton method

Question: Minimize $f(x_1,x_2) = x_1 - x_2 + 2x_1^2 + 2x_1x_2 + x_2^2$ by taking the starting Point as $X_1 = \begin{Bmatrix} 0 \\ 0 \end{Bmatrix}$

Sol. To find X_2.

$$[J_1] = \begin{bmatrix} \frac{d^2f}{dx_1^2} \checkmark & \frac{d^2f}{dx_1 dx_2} \checkmark \\ \frac{d^2f}{dx_2 dx_1} & \frac{d^2f}{dx_2^2} \checkmark \end{bmatrix}$$

$$[J_1] = \begin{bmatrix} 4 & 2 \\ 2 & 2 \end{bmatrix}$$

$$[J_1]^{-1} = \frac{1}{4\times2-2\times2}\begin{bmatrix} 2 & -2 \\ -2 & 4 \end{bmatrix}$$

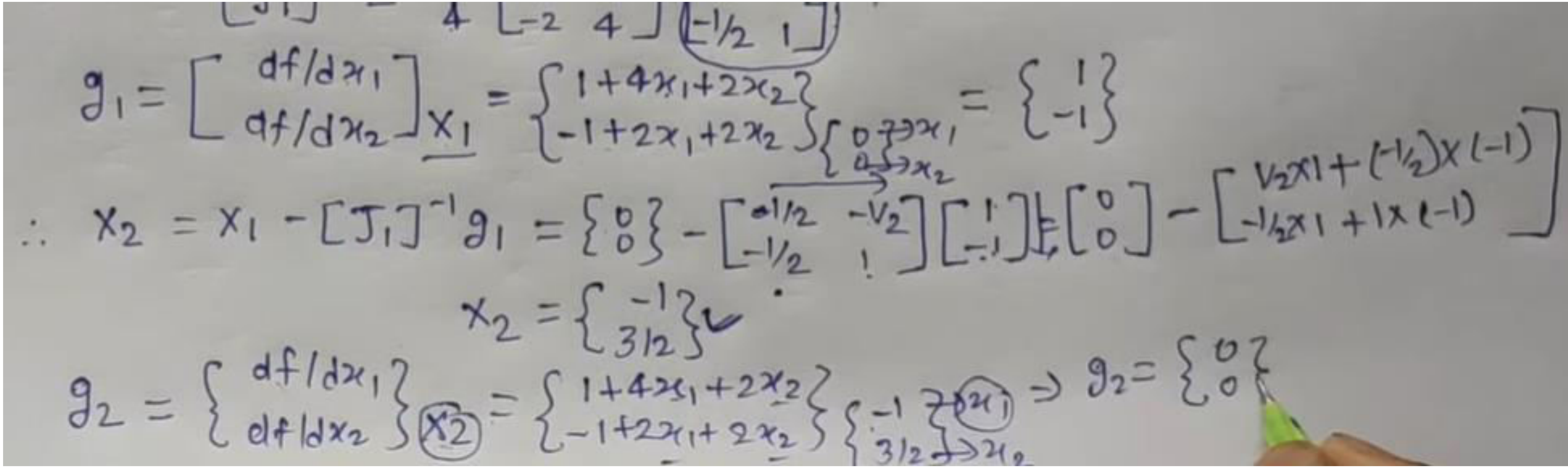
$$[J_1]^{-1} = \frac{1}{4}\begin{bmatrix} 2 & -2 \\ -2 & 4 \end{bmatrix} = \begin{bmatrix} 1/2 & -1/2 \\ -1/2 & 1 \end{bmatrix}$$

$$\frac{df}{dx_1} = 1 + 4x_1 + 2x_2, \quad \boxed{\frac{d^2f}{dx_1 dx_2} = 2}$$

$$\boxed{\frac{d^2f}{dx_1^2} = 4}$$

$$\frac{df}{dx_2} = -1 + 2x_1 + 2x_2, \quad \boxed{\frac{d^2f}{dx_2 dx_1} = 2}$$

$$\boxed{\frac{d^2f}{dx_2^2} = 2}$$



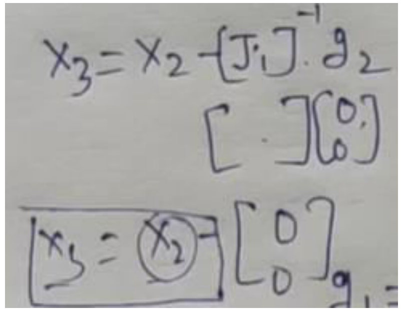
$$4 \begin{bmatrix} -2 & 4 \end{bmatrix} \begin{bmatrix} -1/2 & 1 \end{bmatrix}$$

$$g_1 = \begin{bmatrix} df/dx_1 \\ df/dx_2 \end{bmatrix}_{\underline{X_1}} = \begin{Bmatrix} 1+4x_1+2x_2 \\ -1+2x_1+2x_2 \end{Bmatrix} \begin{Bmatrix} 0 \to x_1 \\ 0 \to x_2 \end{Bmatrix} = \begin{Bmatrix} 1 \\ -1 \end{Bmatrix}$$

$$\therefore X_2 = X_1 - [J_1]^{-1} g_1 = \begin{Bmatrix} 0 \\ 0 \end{Bmatrix} - \begin{bmatrix} 1/2 & -1/2 \\ -1/2 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} - \begin{bmatrix} 1/2 \times 1 + (-1/2) \times (-1) \\ -1/2 \times 1 + 1 \times (-1) \end{bmatrix}$$

$$X_2 = \begin{Bmatrix} -1 \\ 3/2 \end{Bmatrix} ✓$$

$$g_2 = \begin{Bmatrix} df/dx_1 \\ df/dx_2 \end{Bmatrix}_{\textcircled{X_2}} = \begin{Bmatrix} 1+4x_1+2x_2 \\ -1+2x_1+2x_2 \end{Bmatrix} \begin{Bmatrix} -1 \to x_1 \\ 3/2 \to x_2 \end{Bmatrix} \Rightarrow g_2 = \begin{Bmatrix} 0 \\ 0 \end{Bmatrix}$$



$$X_3 = X_2 - [J_1]^{-1} . g_2$$

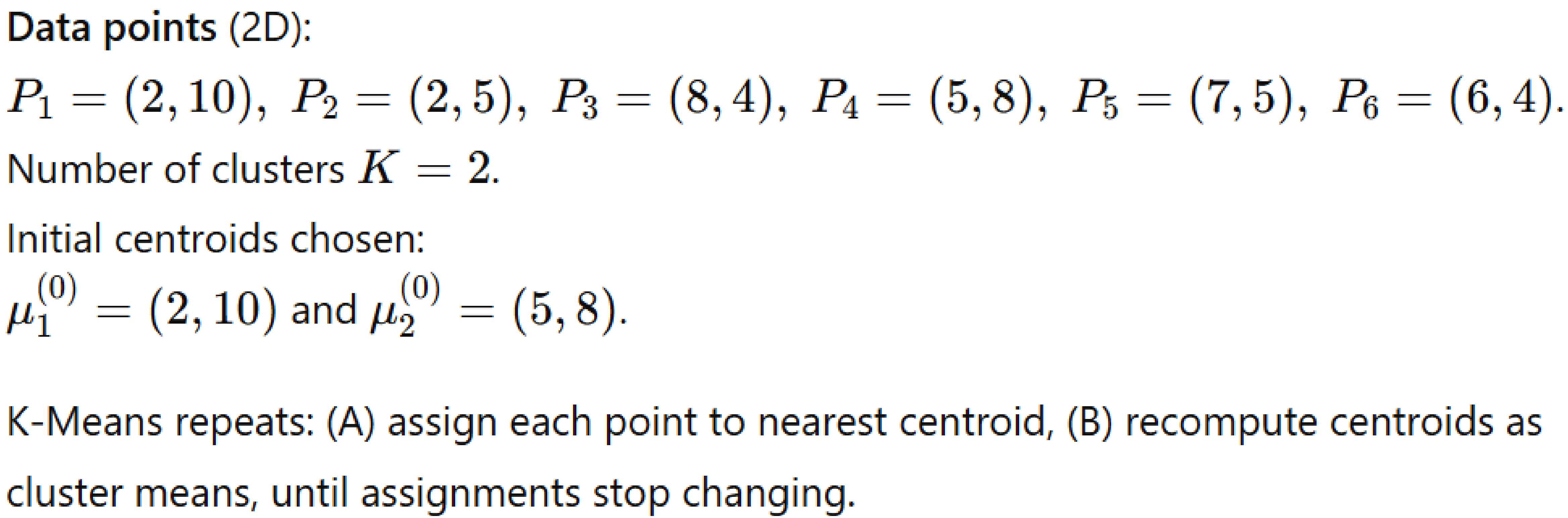
$$[\ \ ] \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\boxed{X_3 = X_2} - \begin{bmatrix} 0 \\ 0 \end{bmatrix} g_1 =$$

Example: K-Means (Solved Problem)

Data points: (2,10), (2,5), (8,4), (5,8), (7,5), (6,4)

Let K=2 , initial centroids = (2,10) and (5,8)



Data points (2D):

$$P_1 = (2, 10),\ P_2 = (2, 5),\ P_3 = (8, 4),\ P_4 = (5, 8),\ P_5 = (7, 5),\ P_6 = (6, 4).$$

Number of clusters $K = 2$.

Initial centroids chosen:

$\mu_1^{(0)} = (2, 10)$ and $\mu_2^{(0)} = (5, 8)$.

K-Means repeats: (A) assign each point to nearest centroid, (B) recompute centroids as cluster means, until assignments stop changing.

Iteration 1 — Assignment step (distances to initial centroids)

We use **Euclidean distance** $d(a,b) = \sqrt{(x_a - x_b)^2 + (y_a - y_b)^2}$. (Only relative comparisons matter; I show squared distances to avoid unnecessary square roots.)

Distances to $\mu_1^{(0)} = (2,10)$

- $P_1 = (2,10)$: $d^2 = (2-2)^2 + (10-10)^2 = 0$
- $P_2 = (2,5)$: $d^2 = (2-2)^2 + (5-10)^2 = 25$
- $P_3 = (8,4)$: $d^2 = (8-2)^2 + (4-10)^2 = 36 + 36 = 72$
- $P_4 = (5,8)$: $d^2 = (5-2)^2 + (8-10)^2 = 9 + 4 = 13$
- $P_5 = (7,5)$: $d^2 = (7-2)^2 + (5-10)^2 = 25 + 25 = 50$
- $P_6 = (6,4)$: $d^2 = (6-2)^2 + (4-10)^2 = 16 + 36 = 52$

Distances to $\mu_2^{(0)} = (5,8)$

- P_1: $d^2 = (2-5)^2 + (10-8)^2 = 9 + 4 = 13$
- P_2: $d^2 = (2-5)^2 + (5-8)^2 = 9 + 9 = 18$
- P_3: $d^2 = (8-5)^2 + (4-8)^2 = 9 + 16 = 25$
- P_4: $d^2 = (5-5)^2 + (8-8)^2 = 0$
- P_5: $d^2 = (7-5)^2 + (5-8)^2 = 4 + 9 = 13$
- P_6: $d^2 = (6-5)^2 + (4-8)^2 = 1 + 16 = 17$

Assign each point to the closer centroid (compare squared distances)

- P_1: to μ_1 (0 vs 13) → **Cluster 1**
- P_2: to μ_1 (25 vs 18) → **Cluster 2** (18 smaller)
- P_3: to μ_2 (72 vs 25) → **Cluster 2**
- P_4: to μ_2 (13 vs 0) → **Cluster 2**
- P_5: to μ_2 (50 vs 13) → **Cluster 2**
- P_6: to μ_2 (52 vs 17) → **Cluster 2**

Resulting clusters after Iteration 1:

- Cluster 1: $\{P_1\} = \{(2, 10)\}$
- Cluster 2: $\{P_2, P_3, P_4, P_5, P_6\} = \{(2, 5), (8, 4), (5, 8), (7, 5), (6, 4)\}$

Regression Analysis

- In machine learning, regression analysis is a statistical technique that predicts continuous numeric values based on the relationship between independent and dependent variables. The main goal of regression analysis is to plot a line or curve that best fit the data and to estimate how one variable affects another.
- Regression analysis is a fundamental concept in machine learning and it is used in many applications such as forecasting, predictive analytics, etc.
- In machine learning, **regression is a type of supervised learning**. The key objective of regression-based tasks is to predict output labels or responses, which are continuous numeric values, for the given input data. The output will be based on what the model has learned in the training phase.
- **Regression models** use the input data features (independent variables) and their corresponding continuous numeric output values (dependent or outcome variables) to learn specific associations between inputs and corresponding outputs.

Terms used in Regression Analysis

- **Independent Variables** – These variables are used to predict the value of the dependent variable. These are also called predictors. In dataset, these are represented as **features**.
- **Dependent Variables** – These are the variables whose values we want to predict. These are the main factors in regression analysis. In dataset, these are represented as **target variables**
- **Regression line** – It is a straight line or curve that a regressor plots to fit the data points best (Y = a + bX)
- **Overfitting and underfitting** – Overfitting is when the regression model works well with the training dataset but not with the testing dataset. It's also referred to as the problem of high variance. Underfitting is when the model doesn't work well with training datasets. It's also referred to as the problem of high bias.
- **Outliers** – These are data points that don't fit the pattern of the rest of the data. They are the extremely high or extremely low values in the data set.
- **Multicollinearity** – Multicollinearity occurs when independent variables (features) have dependency among them.

Types of Regression in ML

- Generally, the classification of **regression methods** is done based on the three metrics – the number of independent variables, type of dependent variables, and shape of the regression line.
- There are numerous regression techniques used in ML –
    1. Simple Linear Regression
    2. Multiple Linear Regression
    3. Logistic Regression
    4. Polynomial Regression
    5. Lasso Regression
    6. Ridge Regression
    7. Decision Tree Regression
    8. Random Forest Regression
    9. Support Vector Regression

Types of Regression(2)

- **Simple Linear Regression** - is one of the simplest and most widely used statistical models. This assumes that there is a linear relationship between the independent and dependent variables. This means that the change in the dependent variable is proportional to the change in the independent variables. For example predicting the price of a house based on its size.
- **Multiple Linear Regression-** extends simple linear regression by using multiple independent variables to predict target variable. For example predicting the price of a house based on multiple features such as size, location, number of rooms, etc.
- **Polynomial Regression-** is used to model with non-linear relationships between the dependent variable and the independent variables. It adds polynomial terms to the linear regression model to capture more complex relationships. Relationship is modelled as an n^{th} degree polynomial. For example when we want to predict a non-linear trend like population growth over time we use polynomial regression.
- **Logistic Regression** is a supervised machine learning algorithm used for classification problems. Unlike linear regression which predicts continuous values it predicts the probability that an input belongs to a specific class. It is used for binary classification where the output can be one of two possible categories such as Yes/No, True/False or 0/1. It uses sigmoid function to convert inputs into a probability value between 0 and 1.

Types of Regression(2)

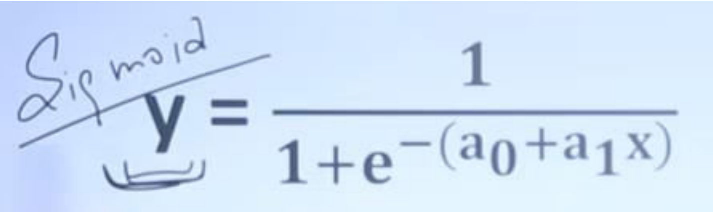
- **Lasso Regression** – is is a regression method based on Least Absolute Shrinkage and Selection Operator and is used in regression analysis for variable selection and regularization. Also known as L1 regularization technique. It helps remove irrelevant data features and prevents overfitting. This allows features with weak influence to be clearly identified as the coefficients of less important variables are shrunk toward zero.
- **Ridge Regression,** also known as L2 regularization, is a technique used in linear regression to address the **problem of multicollinearity among predictor variables. Multicollinearity** occurs when independent variables in a regression model are highly correlated, which can lead to unreliable and unstable estimates of regression coefficients.
- **Decision Tree Regression** Uses a tree-like structure to make decisions where each branch of tree represents a decision and leaves represent outcomes. For example predicting customer behavior based on features like age, income, etc there we use decision tree regression.
- **Random Forest Regression** is is a ensemble method that builds multiple decision trees and each tree is trained on a different subset of the training data. The final prediction is made by averaging the predictions of all of the trees. For example customer churn or sales data using this.
- **Support Vector Regression (SVR)** is a type of regression algorithm that is based on the Support Vector Machine (SVM) algorithm. SVM is a type of algorithm that is used for classification tasks but it can also be used for regression tasks. SVR works by finding a hyperplane that minimizes the sum of the squared residuals between the predicted and actual values.

Applications of Regression

- **Forecasting or Predictive analysis** − One of the important uses of regression is forecasting or predictive analysis. For example, we can forecast GDP, oil prices, or, in simple words, the quantitative data that changes with the passage of time.
- **Optimization** − We can optimize business processes with the help of regression. For example, a store manager can create a statistical model to understand the peak time of coming customers.
- **Error correction** − In business, making correct decisions is equally important as optimizing the business process. Regression can help us to make correct decision as well as correct the already implemented decision.
- **Economics** − It is the most used tool in economics. We can use regression to predict supply, demand, consumption, inventory investment, etc.
- **Fintech Companies** − A FINTECH company is always interested in minimizing the risk portfolio and wants to know the factors that affect the customers. All these can be predicted with the help of a regression model.

Logistic Regression

- SUPERVISED LEARNING used in CLASSIFICATION MODEL
- Predict the classes e.g. Predict email is Spam(Y=1) or Not Spam(Y=0)
- **Dependent variable data which is to be precited is categorial and binary (o or 1) in nature.**
- Exam Result to be predicted (Pass Y=1) or Fail (Y = 0) based on the number of study hours.
- There can be one or more independent variables to predict the dependent var. (0 or 1).
- **Logistic Regression** is a **supervised learning** algorithm used for **classification**, not regression and it predicts **categorical outcomes**, usually **binary** (Yes/No, 0/1, Pass/Fail, Spam/Not Spam, etc.).
- Even though the name has "regression," it is actually a **classification algorithm** based on the **logistic (sigmoid) function**.
- Sigmoid function will give values in the range 0 to 1.



Sigmoid

$$\underbrace{y} = \frac{1}{1+e^{-(a_0+a_1x)}}$$

Independent variable

Dependent variable

Study Hours	Exam Result
2	0 (Fail)
3	0
4	1 (Pass)
5	1
6	1
7	1
8	1

Logistic Regression

The **sigmoid** function maps any real number to a value between 0 and 1:

$$\sigma(z) = \frac{1}{1+e^{-z}}$$

where

$$z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$$

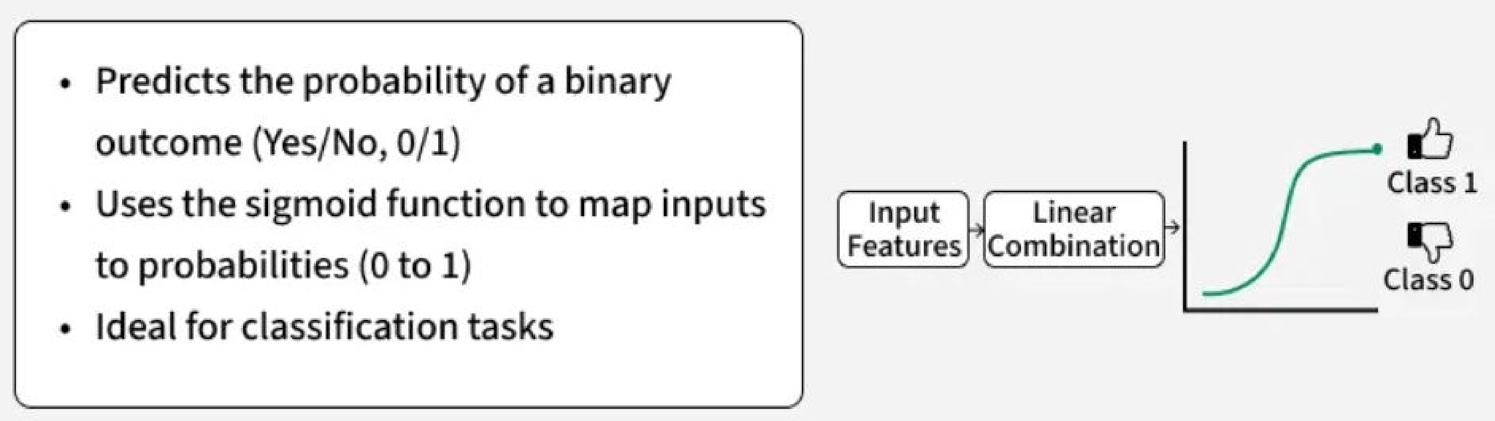
Interpretation:

$$P(Y=1|X) = \frac{1}{1+e^{-(\beta_0+\beta_1 X)}}$$

- $P(Y=1|X)$ is the **probability** that the outcome is 1 (for example, success, yes, etc.).
- The **decision boundary** is usually set at **0.5**:
  - If $P(Y=1|X) \geq 0.5 \Rightarrow \text{predict } 1$
  - Else $\text{predict } 0$

Logistic Regression

- SUPERVISED LEARNING used in CLASSIFICATION MODEL
- Algorithm used for **classification**, not regression and it predicts **categorical outcomes of the dependent variable Y**, usually **binary** (Yes/No, 0/1, Pass/Fail, Spam/Not Spam, etc.). Predict the classes e.g. Predict email is Spam(Y=1) or Not Spam(Y=0)
- Exam Result to be predicted (Pass Y=1) or Fail (Y = 0) based on the number of study hours. There can be one or more independent variables to predict the dependent var. (0 or 1).
- Even though the name has “regression,” it is actually a **classification algorithm** based on the **logistic (sigmoid) function**. Sigmoid function will give values in the range 0 to 1. here a0 and a1 are based on the MLE (Maximum Likelihood Estimation) method.

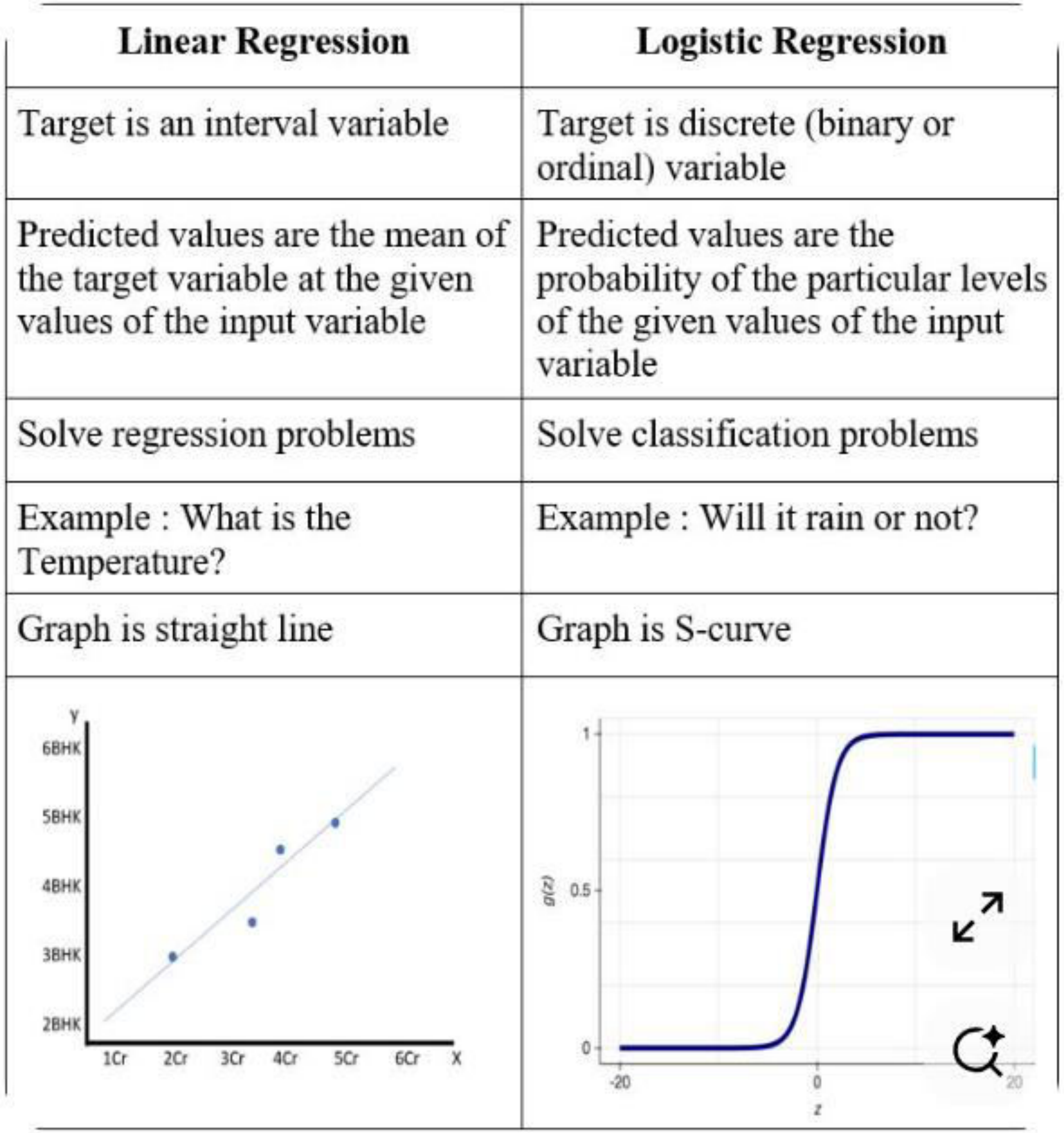


- Predicts the probability of a binary outcome (Yes/No, 0/1)
- Uses the sigmoid function to map inputs to probabilities (0 to 1)
- Ideal for classification tasks

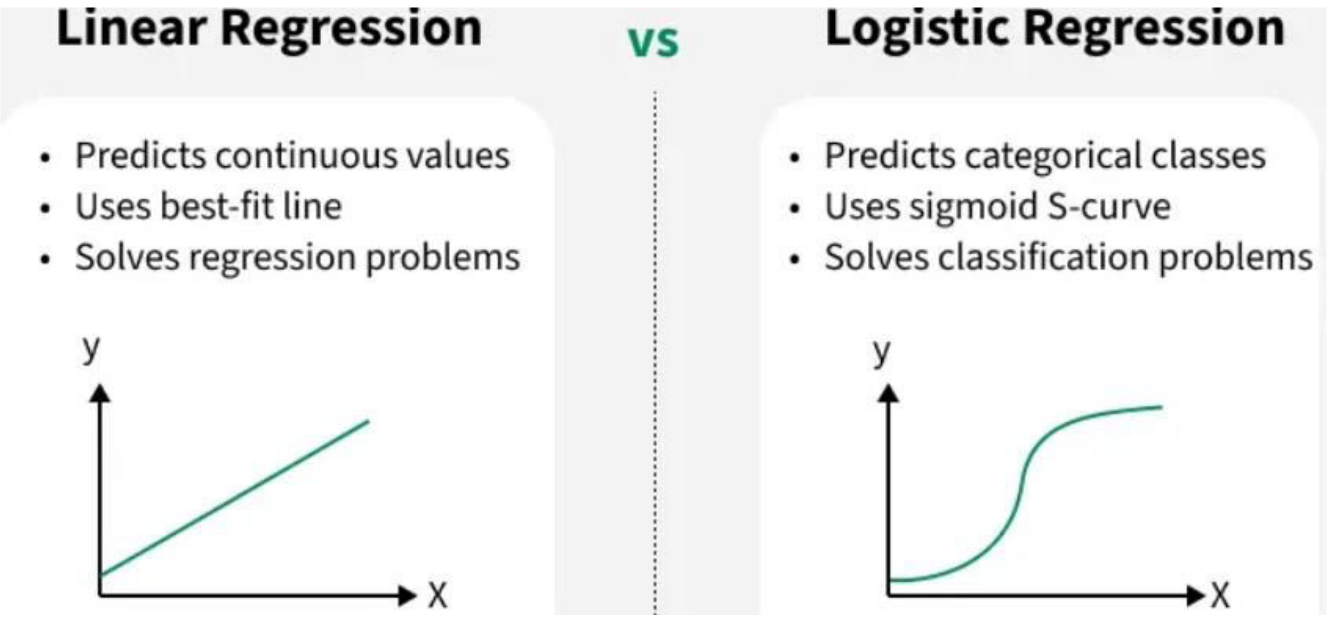
Independent variable	Dependent variable
Study Hours	**Exam Result**
2	0 (Fail)
3	0
4	1 (Pass)
5	1
6	1
7	1
8	1

Sigmoid

$$\underbrace{y}_{} = \frac{1}{1+e^{-(a_0+a_1x)}}$$



Linear Regression	Logistic Regression
Target is an interval variable	Target is discrete (binary or ordinal) variable
Predicted values are the mean of the target variable at the given values of the input variable	Predicted values are the probability of the particular levels of the given values of the input variable
Solve regression problems	Solve classification problems
Example : What is the Temperature?	Example : Will it rain or not?
Graph is straight line	Graph is S-curve



Linear Regression vs **Logistic Regression**

- Predicts continuous values
- Uses best-fit line
- Solves regression problems

- Predicts categorical classes
- Uses sigmoid S-curve
- Solves classification problems

Formula for Logistic Regression Model is :

$$P(Y=1|X)=\frac{1}{1+e^{-(\beta_0+\beta_1 X)}}$$

- $P(Y=1|X)$ is the **probability** that the outcome is 1 (for example, success, yes, etc.).
- The **decision boundary** is usually set at **0.5**:
  - If $P(Y=1|X)\geq 0.5 \Rightarrow \text{predict } 1$
  - Else $\text{predict } 0$

Log-Odds (Logit) formula for Logistic Regression

We can rewrite the logistic model in terms of **log-odds** (or **logit**):

$$\text{logit}(p)=\ln\left(\frac{p}{1-p}\right)=\beta_0+\beta_1 X$$

This shows that logistic regression models a **linear relationship between the independent variable(s) and the log-odds of the outcome**.

Problem 1

Suppose the logistic regression model is:

$$p = \frac{1}{1 + e^{-(-4+0.8x)}}$$

where x represents **hours studied**, and p is the **probability of passing an exam.**

Find: a) The probability that a student who studied 5 hours passes the exam.

b) The decision (Pass or Fail) if the threshold = 0.5.

SOLUTION : First write the model and in next step substitute x = 5 in the model

$$p = \frac{1}{1 + e^{-(-4+0.8x)}}$$

$$z = -4 + 0.8(5) = -4 + 4 = 0$$

$$p = \frac{1}{1 + e^{-0}} = \frac{1}{1+1} = 0.5$$

Interpretation (Step 3) : The probability of passing when studying 5 hours is **0.5.**

Since the threshold = 0.5, we predict “Pass” if we take p ≥ 0.5

Step 4 : Check another case (for another value of *x*)

If $x = 7$:

$$z = -4 + 0.8(7) = -4 + 5.6 = 1.6$$

$$p = \frac{1}{1 + e^{-1.6}} \approx \frac{1}{1 + 0.201} = 0.832$$

So, the probability of passing when studying 7 hours is **0.83** → **Predict Pass.**

If $x = 2$:

$$z = -4 + 0.8(2) = -4 + 1.6 = -2.4$$

$$p = \frac{1}{1 + e^{2.4}} \approx \frac{1}{1 + 11.02} = 0.083$$

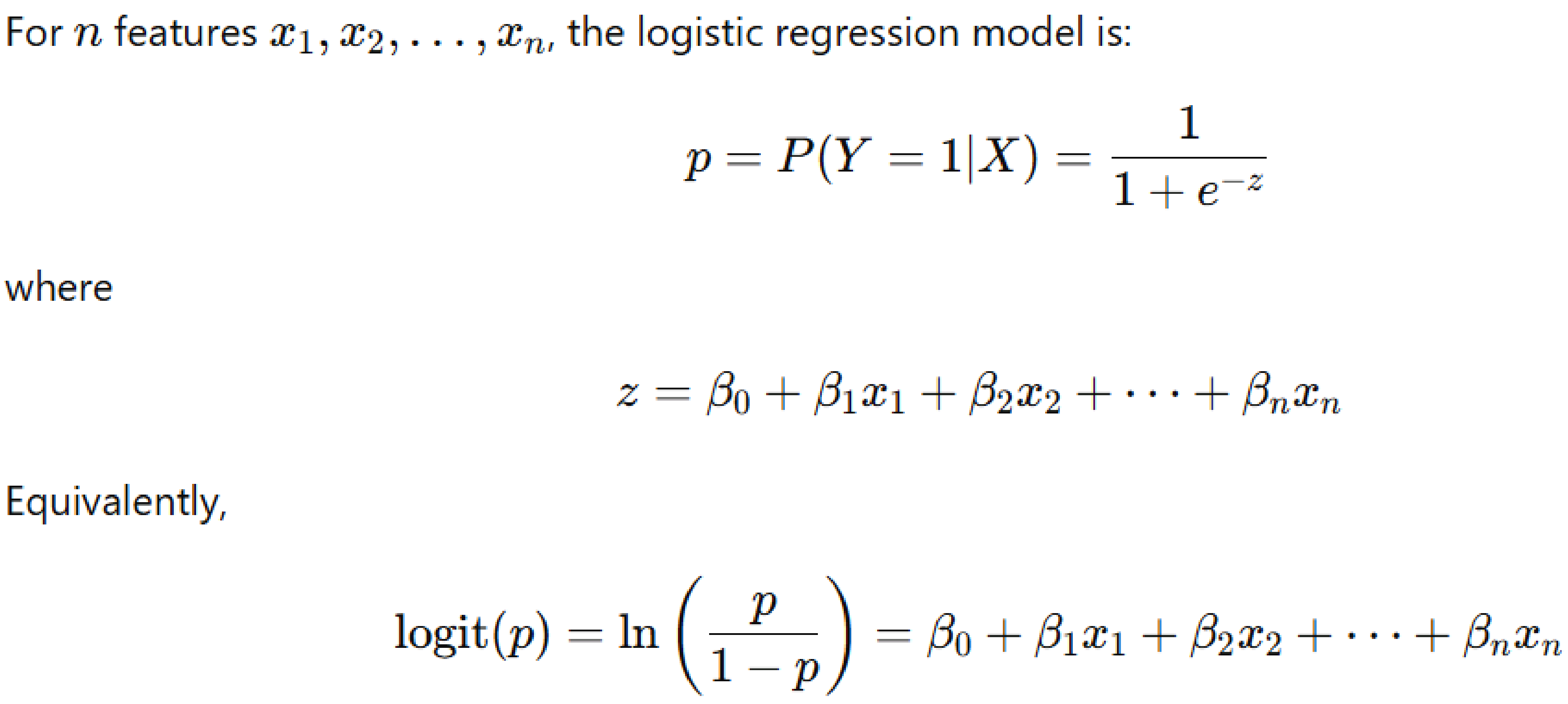
Probability of passing is **0.08** → **Predict Fail.**

Hours Studied (x)	z	p (Probability of Pass)	Prediction
2	-2.4	0.083	Fail
5	0	0.5	Pass (boundary)
7	1.6	0.832	Pass

Concept	Description
Output	Probability between 0 and 1
Decision rule	Usually threshold = 0.5
Link function	Logit = ln(p / (1 - p))
Estimation	Coefficients (β) are found using **Maximum Likelihood Estimation (MLE)**
Use cases	Binary classification: spam detection, disease prediction, churn prediction, etc.

Multivariate Logistic Regression

When we have **more than one independent variable**, logistic regression generalizes easily. Model Definition in this case is as follows:



For n features $x_1, x_2, \ldots, x_n$, the logistic regression model is:

$$p = P(Y = 1|X) = \frac{1}{1 + e^{-z}}$$

where

$$z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$$

Equivalently,

$$\text{logit}(p) = \ln\left(\frac{p}{1 - p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$$

Example - A company wants to predict whether a customer will buy a product (**Y = 1**) or not (**Y = 0**) based on:

Variable	Description
x_1	Age (in years)
x_2	Monthly Income (in ₹ thousands)

The fitted logistic regression model is:

$$p = \frac{1}{1 + e^{-(-6+0.04x_1+0.3x_2)}}$$

Calculate: a) The probability of purchase for a 30-year-old earning ₹25,000/month.

b) The decision (Buy / Not Buy) at a 0.5 threshold.

Step 1: Compute the value of z

$$z = -6 + 0.04(30) + 0.3(25)$$

$$z = -6 + 1.2 + 7.5 = 2.7$$

4. Step 2: Compute Probability

$$p = \frac{1}{1 + e^{-2.7}} = \frac{1}{1 + 0.067} = 0.937$$

So, **probability = 0.937 (93.7%)** that the customer will buy the product.

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5. Step 3: Decision

Since $p = 0.937 > 0.5$,

Prediction: Customer will buy the product (Y = 1).

6. Step 4: Try another case

Customer B: $x_1 = 22$ years, $x_2 = 10$ (₹10,000/month)

$$z = -6 + 0.04(22) + 0.3(10) = -6 + 0.88 + 3 = -2.12$$

$$p = \frac{1}{1 + e^{2.12}} = \frac{1}{1 + 8.33} = 0.107$$

So, $p = 0.107$ → **Prediction: Will not buy (Y = 0).**

7. Step 5: Interpret Coefficients

Coefficient	Meaning
$\beta_0 = -6$	Base log-odds when all predictors = 0.
$\beta_1 = 0.04$	For each **extra year of age**, log-odds of buying increase by 0.04.
$\beta_2 = 0.3$	For each **₹1000 increase in monthly income**, log-odds of buying increase by 0.3.

Thus, **income** has a stronger effect on purchase probability than **age**.

8. Step 6: Decision Boundary

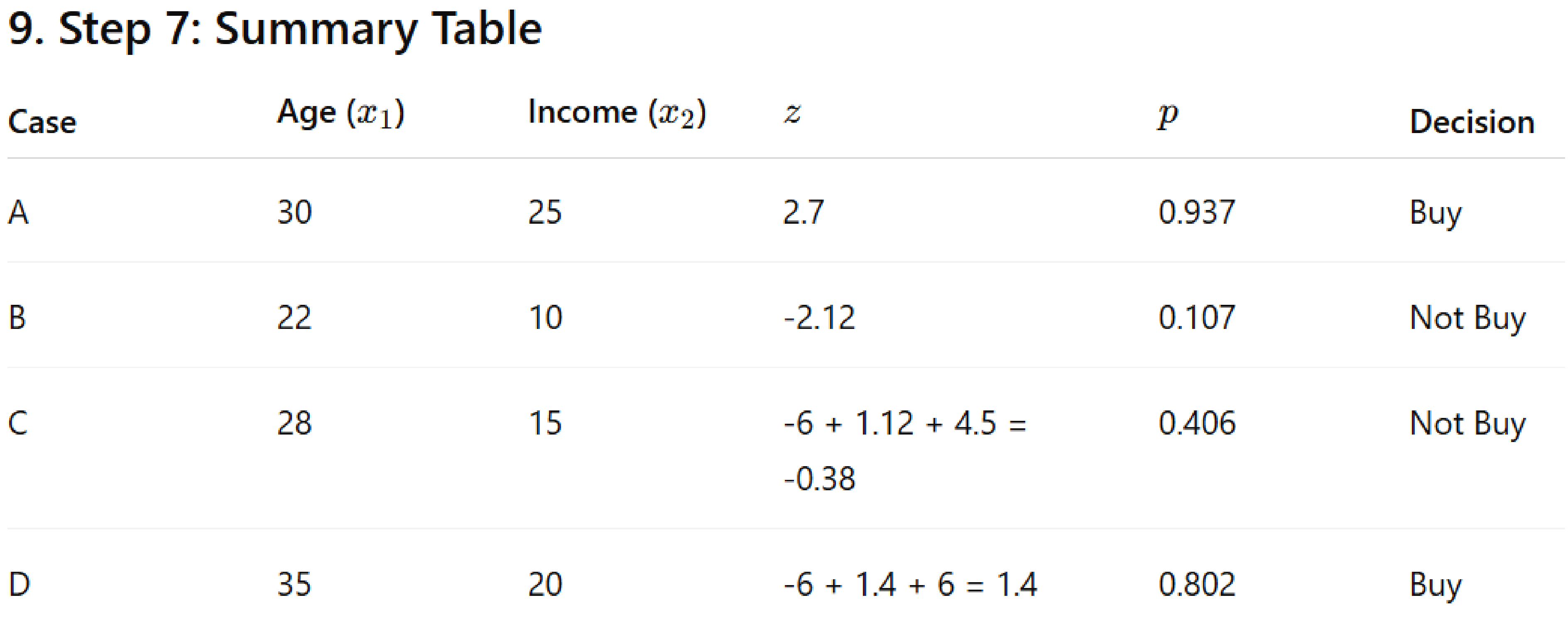
The decision boundary is found when $p = 0.5$, i.e., $z = 0$:

$$-6 + 0.04x_1 + 0.3x_2 = 0$$

$$0.3x_2 = 6 - 0.04x_1$$

$$x_2 = 20 - 0.133x_1$$

So the decision boundary is a **straight line** in the (x_1, x_2) plane dividing “Buy” and “Not Buy” regions.



9. Step 7: Summary Table

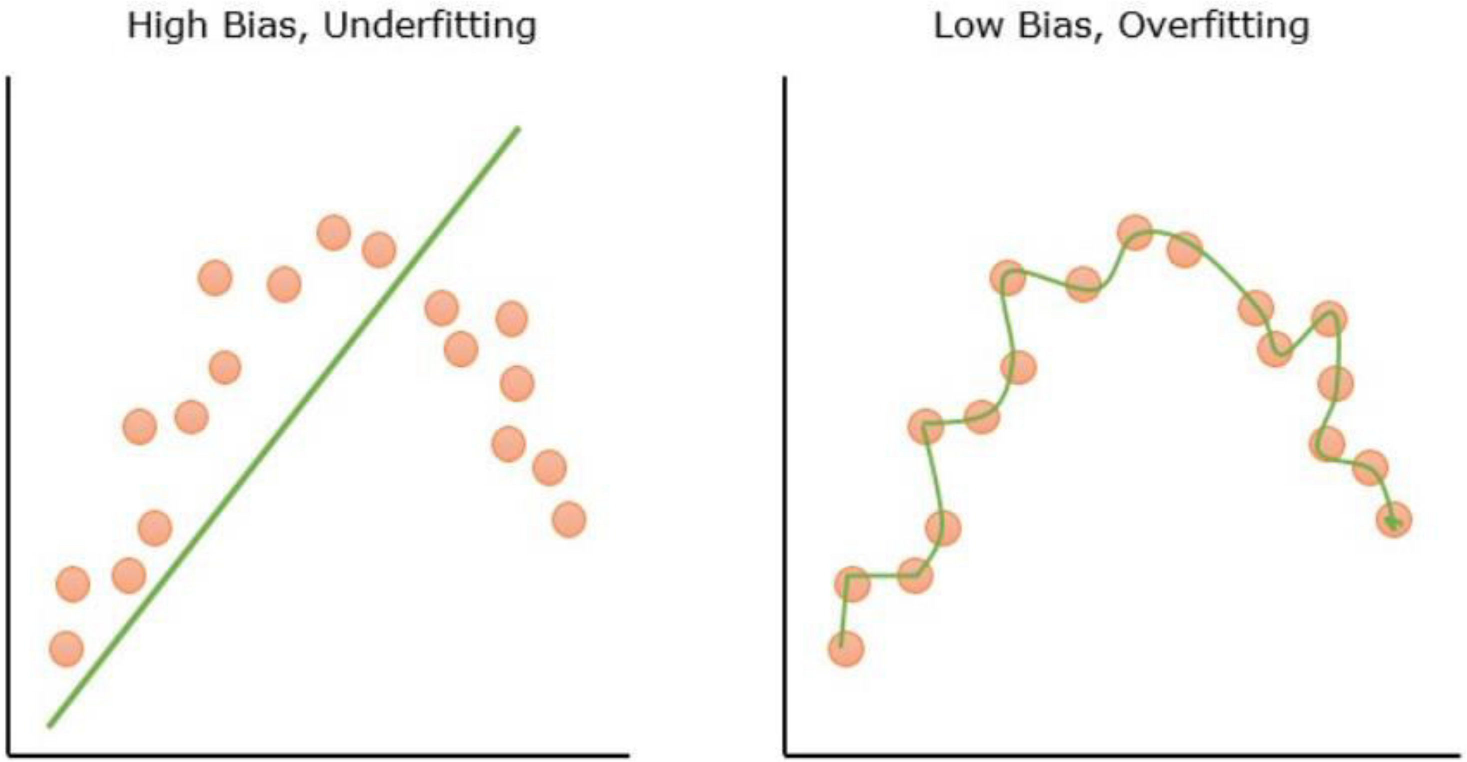
Case	Age (x_1)	Income (x_2)	z	p	Decision
A	30	25	2.7	0.937	Buy
B	22	10	-2.12	0.107	Not Buy
C	28	15	-6 + 1.12 + 4.5 = -0.38	0.406	Not Buy
D	35	20	-6 + 1.4 + 6 = 1.4	0.802	Buy

Key Interpretations

- Logistic regression models the **probability** that $Y = 1$as a function of predictors.
- The coefficients affect the **log-odds**, not directly the probability.
- The model creates a **linear decision boundary** between classes.

Bias Variance Dichotomy Model (Trade-off Model)

- **Bias** refers to the error that results from oversimplifying the underlying relationship between the input features and the output variable. At the same time, **variance** refers to the error that results from being too sensitive to fluctuations in the training data.
- In Optimization, we strive to **minimize both bias and variance** in order to build a model that can accurately predict on unseen data. A high-bias model may be too simplistic and underfit the training data. In contrast, a model with high variance may overfit the training data and fail to generalize to new data.
- Bias is calculated as the difference between average prediction and actual value. Bias (systematic error) occurs when a model makes incorrect assumptions about data. A model with high bias does not match well training data as well as test data. It leads to high errors in training and test data. While the model with low bias matches the training data well (high training accuracy or less error in training). It leads to low error in training data
- **High Bias** – High bias occurs due to erroneous assumptions in the machine learning model. Models with high bias cannot capture the hidden pattern in the training data. This leads to **underfitting**. Features of high bias are a highly simplified model, underfitting, and high error in training and test data.
- **Low Bias** – Models with low bias can capture the hidden pattern in the training data. Low bias leads to high variance and, eventually, **overfitting**. Low bias generally occurs due to the ML model being overly complex.



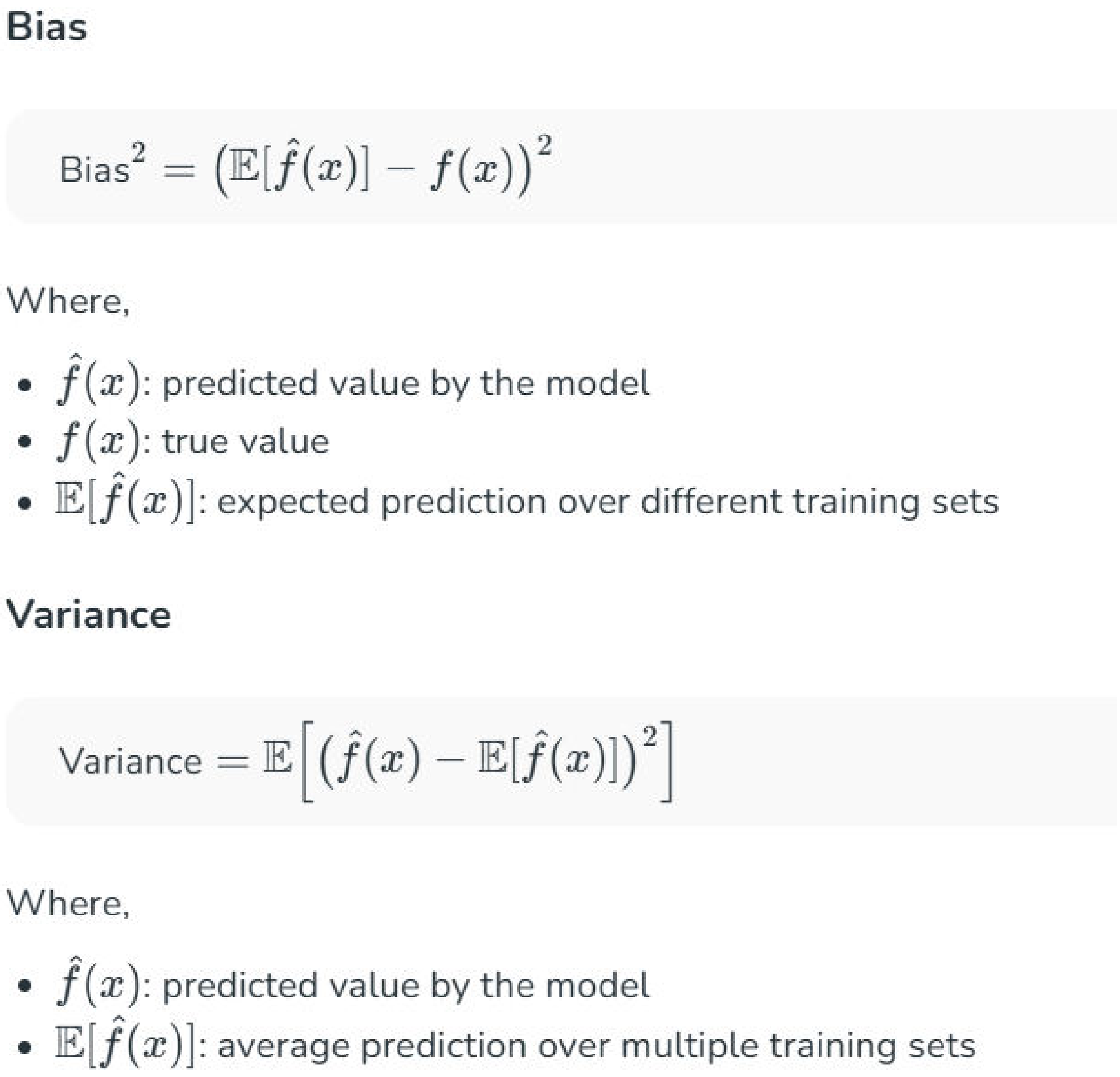
High Bias, Underfitting

Low Bias, Overfitting

Variance Concept in Bias Variance Dichotomy Model

- **Variance** is a measure of the spread or dispersion of numbers in a given set of observations with respect to the mean.
- In Optimization, Variance is how much a model's predictions change when it's trained on different data.
- It shows how much model prediction varies when there is a slight variation in data. If model accuracies on training and test data vary greatly, the model has high variance.
- A model with high variance can even fit noises on training data but lacks generalization to new, unseen data.
    - **High variance:** The model is too sensitive to small changes and may overfit.
    - **Low variance:** The model is more stable but might miss some patterns

Mathematical Formula for Bias and Variance



Bias

$$\text{Bias}^2 = \left(\mathbb{E}[\hat{f}(x)] - f(x)\right)^2$$

Where,

- $\hat{f}(x)$: predicted value by the model
- $f(x)$: true value
- $\mathbb{E}[\hat{f}(x)]$: expected prediction over different training sets

Variance

$$\text{Variance} = \mathbb{E}\left[\left(\hat{f}(x) - \mathbb{E}[\hat{f}(x)]\right)^2\right]$$

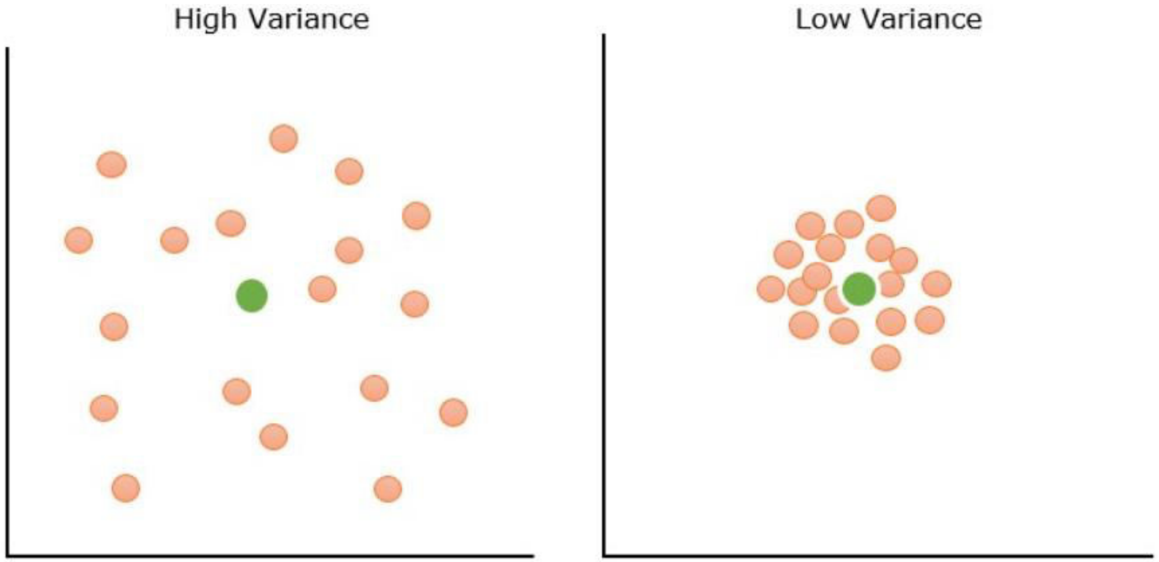
Where,

- $\hat{f}(x)$: predicted value by the model
- $\mathbb{E}[\hat{f}(x)]$: average prediction over multiple training sets

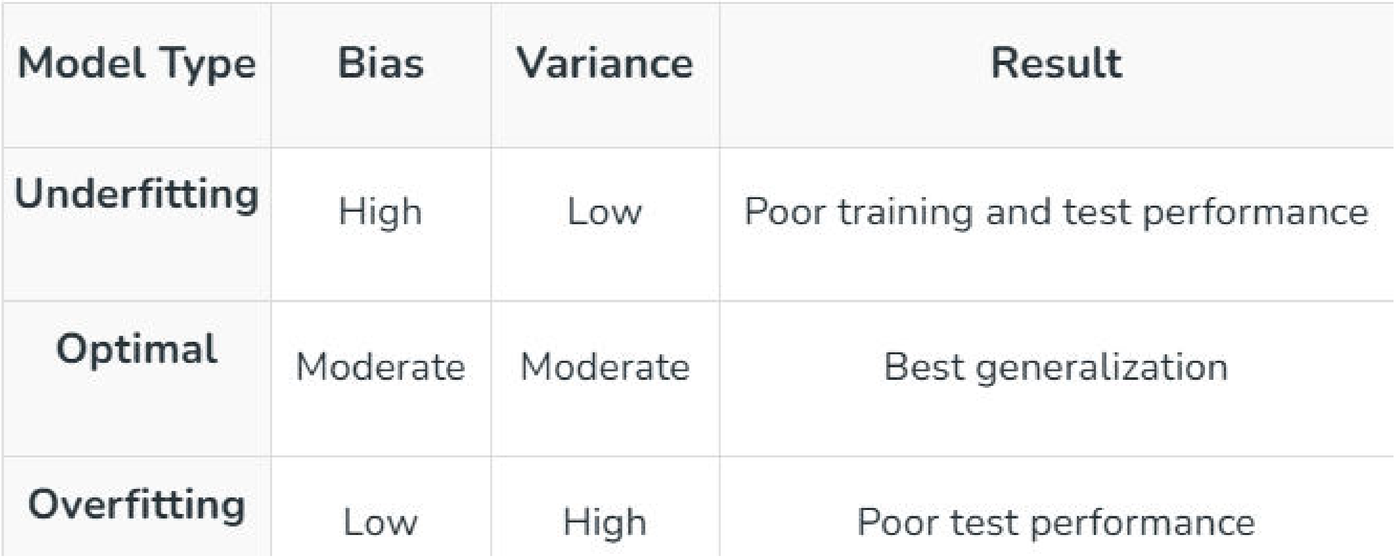
Types of Variance

High Variance – High variance models capture noise along with hidden pattern. It leads to **overfitting**. High variance models show high training accuracy but low test accuracy. Some features of a high variance model are an overly complex model, overfitting, low error on training data, and high error or test data.

Low Variance – A model with low variance is unable to capture the hidden pattern in the data. Low variance may occur when we have a very small amount of data or use a very simplified model. Low variance leads to **underfitting**.



Bias-Variance Tradeoff



Model Type	Bias	Variance	Result
Underfitting	High	Low	Poor training and test performance
Optimal	Moderate	Moderate	Best generalization
Overfitting	Low	High	Poor test performance

$$\text{Total Error} = \text{Bias}^2 + \text{Variance} + \text{Irreducible Error}$$

This decomposition helps us understand why models sometimes **underfit** or **overfit**.

Irreducible Error - This is the noise inherent in data that **no model** can explain.

$$\text{Irreducible Error} = Var(\varepsilon)$$

where ε is the random noise.

Total Expected Prediction Error Formula

The expected mean squared error (MSE) at a point x can be decomposed as:

$$E[(Y - \hat{f}(x))^2] = [\text{Bias}(\hat{f}(x))]^2 + \text{Variance}(\hat{f}(x)) + \sigma^2$$

Where:

- $Y = f(x) + \varepsilon$,
- σ^2 is the variance of noise (irreducible error).

This decomposition is known as the **Bias–Variance Trade-off**.

(a) Irreducible Error

- Comes from the random noise ε.
- Even a perfect model can't predict noise.
- Formally: $\mathrm{Var}(\varepsilon) = \sigma^2$

You **cannot reduce** this part — it's inherent in the data.

(b) Bias

- Bias measures the **systematic error** in your model's assumptions.
- It is the **difference between the true function** $f(x)$ and the **expected prediction** $E[\hat{f}(x)]$ of your model.

$$\mathrm{Bias}(x) = E[\hat{f}(x)] - f(x)$$

and

$$\mathrm{Bias}^2 = [E[\hat{f}(x)] - f(x)]^2$$

High Bias → Model makes strong assumptions, oversimplifies relationships.

Example: Linear regression used for a nonlinear relationship.

(c) Variance

- Variance measures how much $\hat{f}(x)$ would vary if we trained it on different datasets.
- High variance means the model is **too sensitive to training data** — small changes in data cause big changes in prediction.

Formally:

$$\text{Variance}(x) = E[(\hat{f}(x) - E[\hat{f}(x)])^2]$$

High Variance → Model memorizes training data instead of generalizing.

Example: Deep decision trees or k-NN with $k = 1$.

3. Total Error Decomposition

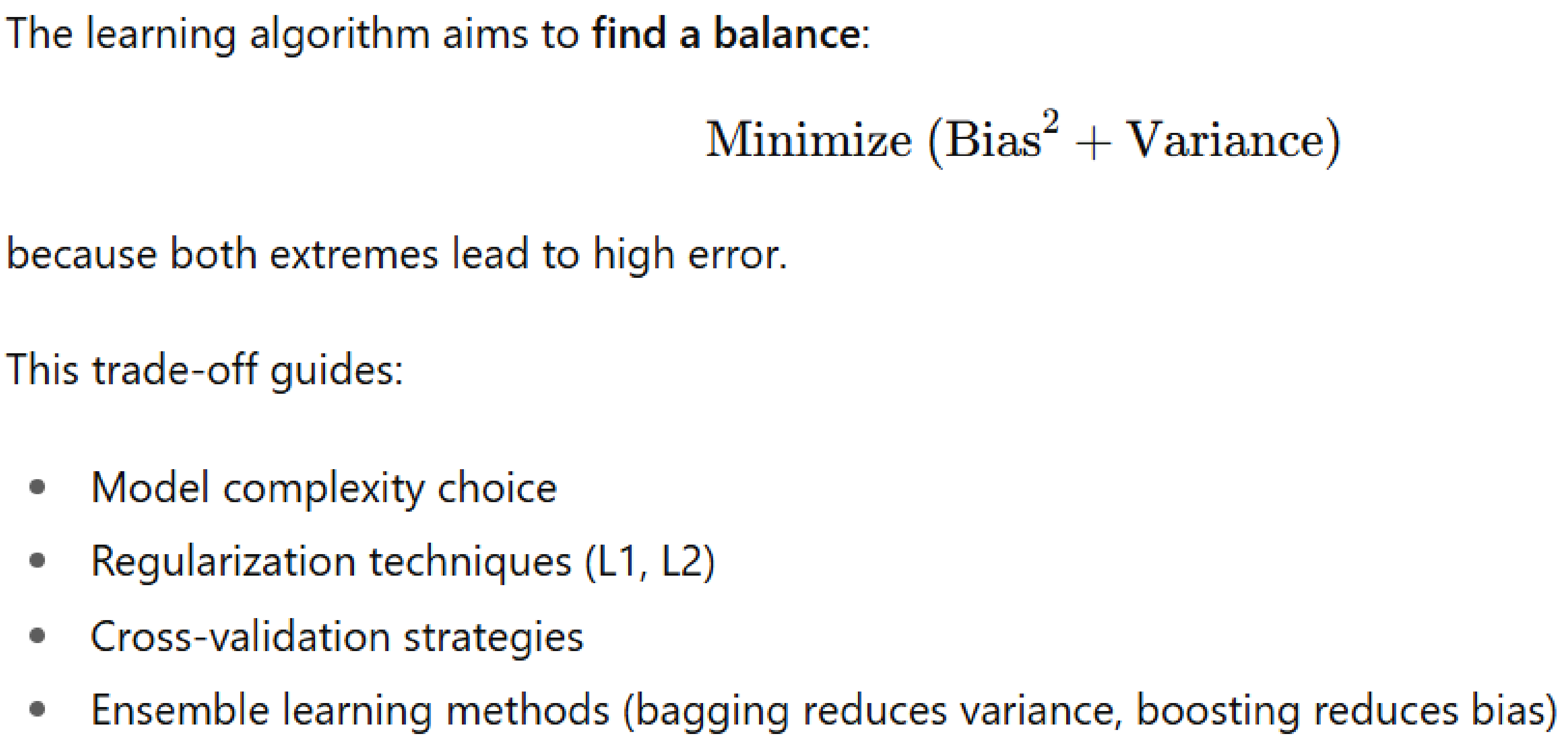
Putting it together:

$$E[(y - \hat{f}(x))^2] = \underbrace{[\text{Bias}(x)]^2}_{\text{Systematic error}} + \underbrace{\text{Variance}(x)}_{\text{Model sensitivity}} + \underbrace{\sigma^2}_{\text{Irreducible noise}}$$

Interpretation

Model Complexity	Bias	Variance	Total Error
Very Simple (Underfit)	High	Low	High
Optimal (Balanced)	Medium	Medium	**Lowest**
Very Complex (Overfit)	Low	High	High

Goal of Model



The learning algorithm aims to **find a balance**:

$$\text{Minimize } (\text{Bias}^2 + \text{Variance})$$

because both extremes lead to high error.

This trade-off guides:

- Model complexity choice
- Regularization techniques (L1, L2)
- Cross-validation strategies
- Ensemble learning methods (bagging reduces variance, boosting reduces bias)

Practical Insight

Situation	Cause	Remedy
High Bias	Model too simple, underfitting	Use more features, increase model capacity
High Variance	Model too complex, overfitting	Regularize, collect more data, use cross-validation

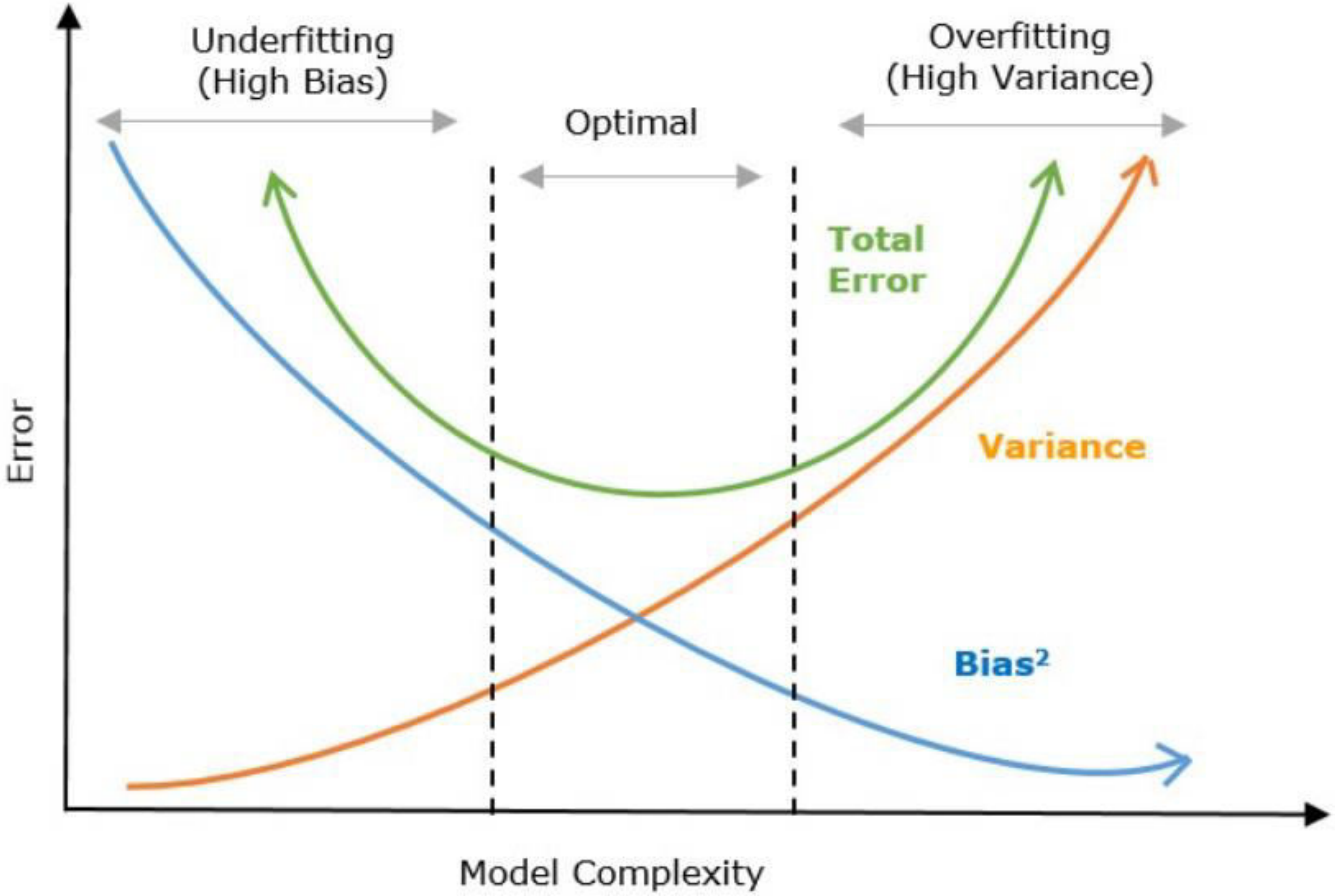
Summary

Concept	Description
Bias	Error from wrong assumptions
Variance	Error from sensitivity to training data
Irreducible Error	Random noise not explainable by model
Goal	Find sweet spot minimizing both Bias^2 and Variance
Techniques to Control Bias/Variance	Regularization (Lasso/Ridge), Cross-validation, Pruning, Bagging/Boosting

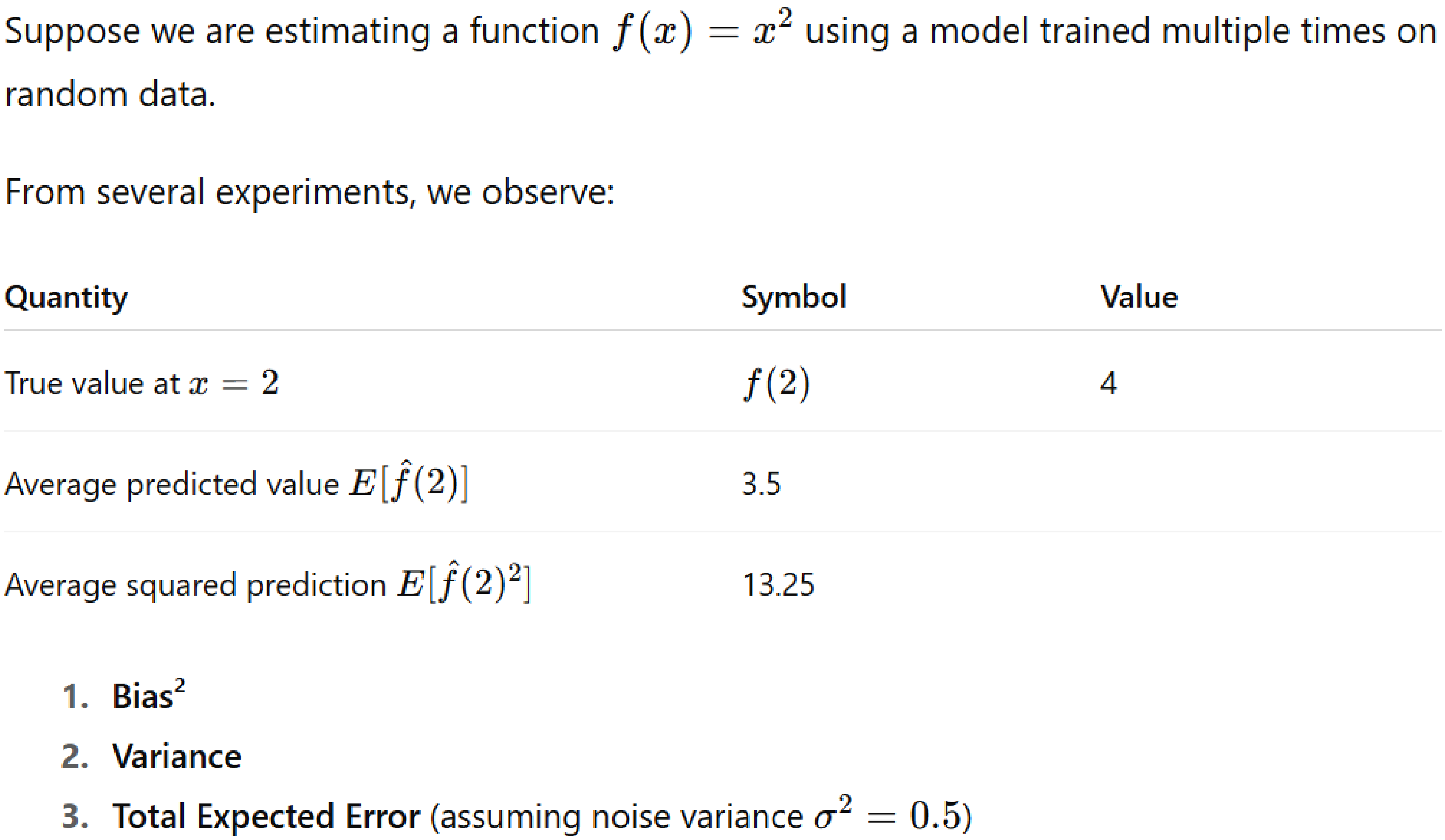
The Tradeoff

Model Type	Bias	Variance	Behavior
Simple Model (Linear)	High	Low	Underfits
Complex Model (High-degree polynomial)	Low	High	Overfits

The **goal** is to find an optimal model complexity where the **sum of bias² + variance** is minimized.



Example

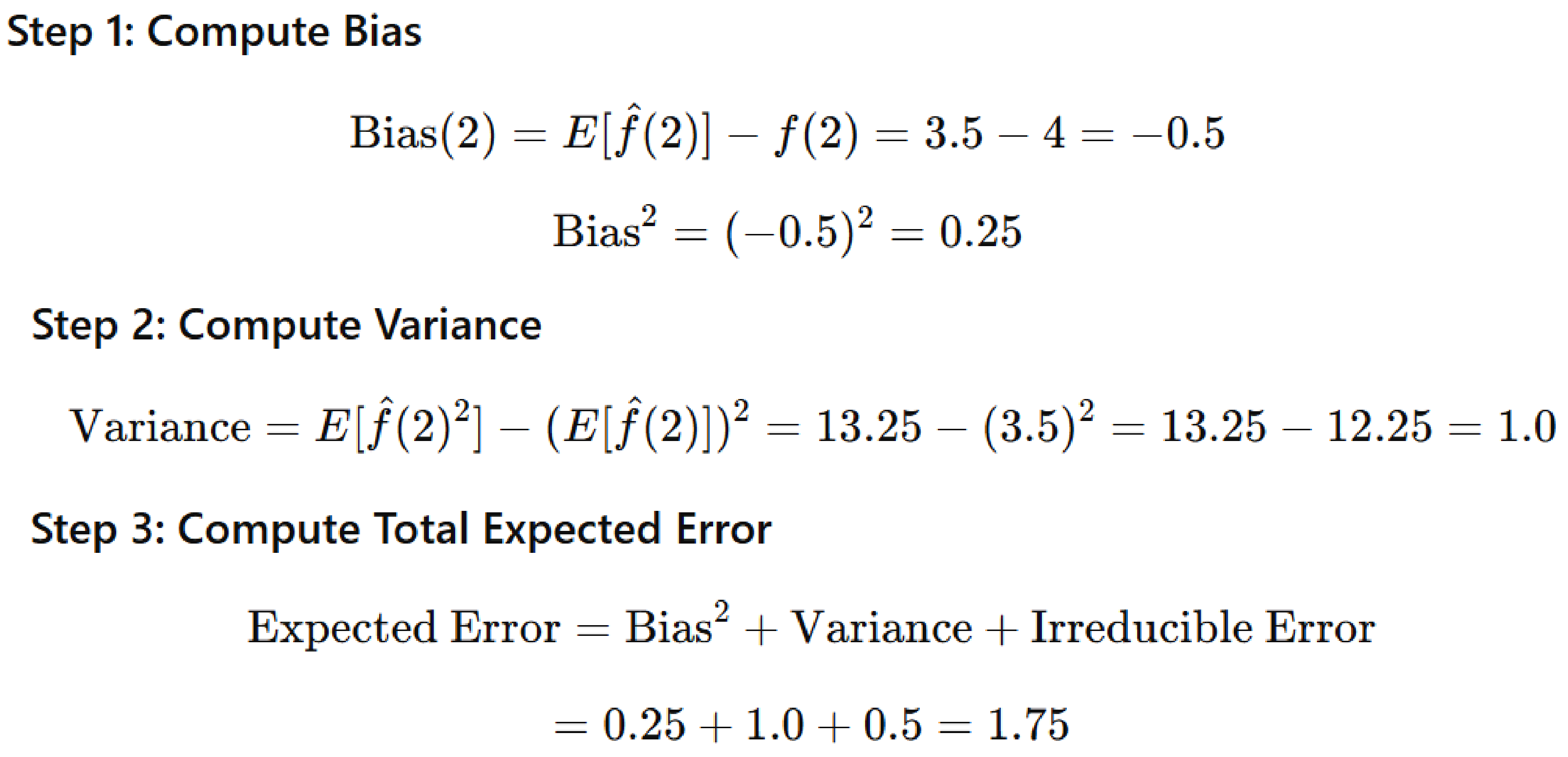


Suppose we are estimating a function $f(x) = x^2$ using a model trained multiple times on random data.

From several experiments, we observe:

Quantity	Symbol	Value
True value at $x = 2$	$f(2)$	4
Average predicted value $E[\hat{f}(2)]$	3.5	
Average squared prediction $E[\hat{f}(2)^2]$	13.25	

1. **Bias^2**
2. **Variance**
3. **Total Expected Error** (assuming noise variance $\sigma^2 = 0.5$)



Step 1: Compute Bias

$$\text{Bias}(2) = E[\hat{f}(2)] - f(2) = 3.5 - 4 = -0.5$$

$$\text{Bias}^2 = (-0.5)^2 = 0.25$$

Step 2: Compute Variance

$$\text{Variance} = E[\hat{f}(2)^2] - (E[\hat{f}(2)])^2 = 13.25 - (3.5)^2 = 13.25 - 12.25 = 1.0$$

Step 3: Compute Total Expected Error

$$\text{Expected Error} = \text{Bias}^2 + \text{Variance} + \text{Irreducible Error}$$

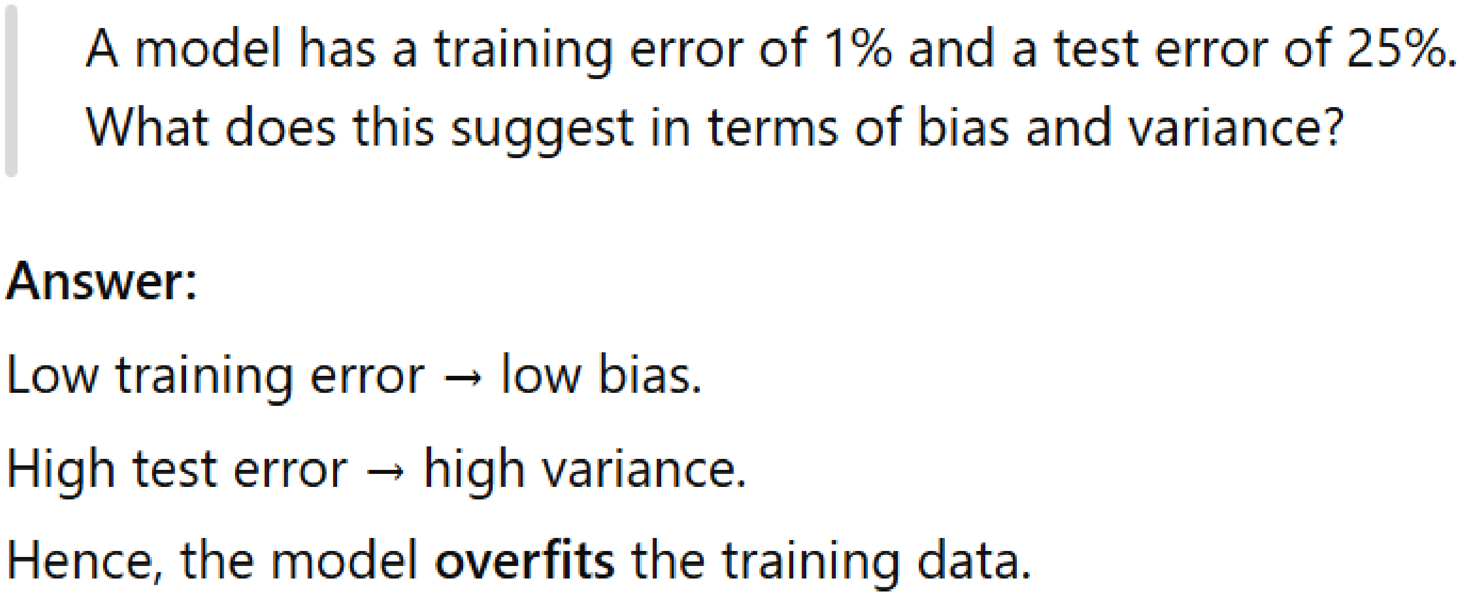
$$= 0.25 + 1.0 + 0.5 = 1.75$$

Interpretation

- **Bias^2 (0.25)** is small → model's predictions are close to the true function.
- **Variance (1.0)** is significant → model predictions vary across datasets.
- **Total error (1.75)** indicates that reducing variance (via regularization or ensemble) could improve model stability.

Summary

Term	Meaning	Desirable?
Bias	Systematic error	Low
Variance	Sensitivity to training data	Low
Irreducible Error	Noise	Unavoidable
Tradeoff	Balance between bias² and variance	Optimal complexity minimizes total error



> A model has a training error of 1% and a test error of 25%.
> What does this suggest in terms of bias and variance?

Answer:

Low training error → low bias.

High test error → high variance.

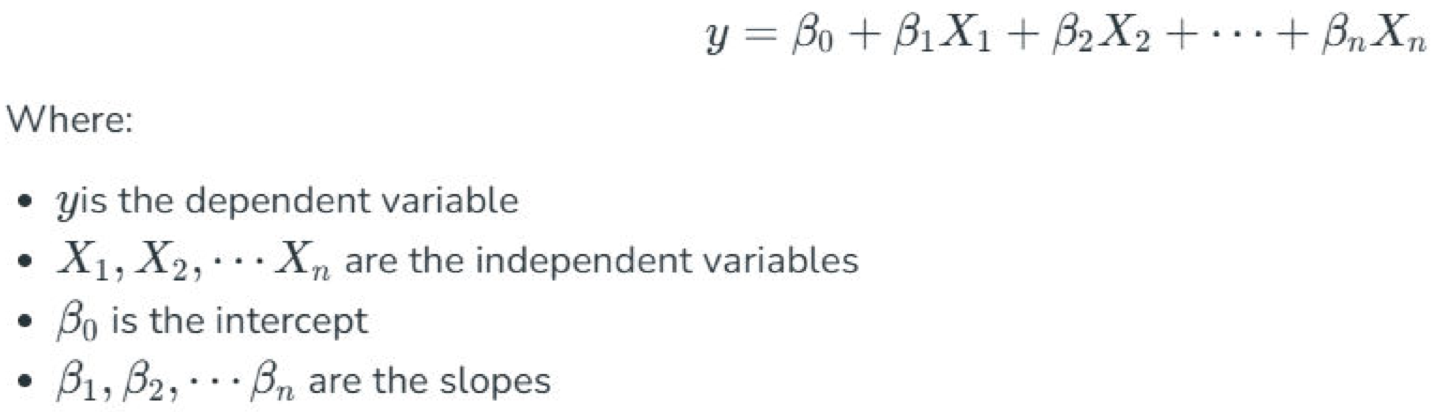
Hence, the model **overfits** the training data.

1. Linear Regression

- It is the most commonly used regression model in machine learning. It may be defined as the statistical model that analyzes the linear relationship between a dependent variable with a given set of independent variables.
- A linear relationship between variables means that when the value of one or more independent variables changes (increase or decrease), the value of the dependent variable will also change accordingly (increase or decrease).
- Linear regression is further divided into two subcategories: simple linear regression and multiple linear regression (also known as multivariate linear regression).
- In simple linear regression, a single independent variable (or predictor) is used to predict the dependent variable. Mathematically, the simple linear regression can be represented as follows- $Y = a + bX$ where,
  - Y is the dependent variable we are trying to predict.
  - X is the independent variable we are using to make predictions
  - *b* is the slope of the regression line, which represents the effect X has on Y.
  - *a* is a constant known as the Y-intercept. If $X = 0$, Y would be equal to a.
- In multi-linear regression, multiple independent variables are used to predict the dependent variables.

Multiple Linear Regression Model

- Multiple Linear Regression extends this concept by modelling the relationship between a dependent variable and two or more independent variables. This technique allows us to understand how multiple features collectively affect the outcomes.
- Steps to perform this are similar to that of simple linear Regression but difference comes in the evaluation process. We can use it to find out which factor has the highest influence on the predicted output and how different variables are related to each other. Assumptions of this Model are:
  1. **Linearity**: Relationship between dependent and independent variables should be linear.
  2. **Homoscedasticity**: Variance of errors should remain constant across all levels of independent variables.
  3. **Multivariate Normality**: Residuals should follow a normal distribution.
  4. **No Multicollinearity**: Independent variables should not be highly correlated
- Equation for multiple linear regression is:



$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$$

Where:

- $y$is the dependent variable
- $X_1, X_2, \cdots X_n$ are the independent variables
- β_0 is the intercept
- $\beta_1, \beta_2, \cdots \beta_n$ are the slopes

Multicollinearity in Regression Analysis

- Multicollinearity occurs when two or more independent variables in a regression model are highly correlated with each other. So, **multicollinearity e**xists when there are linear relationships among the independent variables, this causes issues in regression analysis because it does not follow the assumption of independence among predictors.
- **Causes of Multicollinearity in Regression Analysis**

  1. **Correlation Among Predictor Variables**: Multicollinearity often occurs when predictor variables in a regression model exhibit a **high correlation** with one another. This situation arises when one predictor variable can be accurately predicted from the others, complicating the estimation of individual predictor effects within the model.
  2. **Overparameterization of the Model**: Introducing too many predictor variables closer to the number of observations can also lead to multicollinearity. More predictors can cause redundancy and increase the variance of the coefficient estimates.
  3. **Data Collection Issues**: Problems in the data collection process can also introduce multicollinearity. For instance, if certain variables are measured with exceptional precision or are inherently interconnected, it can lead to multicollinearity in the regression model.

- **To detect multicollinearity we can use:**

  1. **Correlation Matrix:** A correlation matrix helps to find relationships between independent variables. High correlations (close to 1 or -1) suggest multicollinearity.
  2. **VIF (Variance Inflation Factor):** VIF quantifies how much the variance of a regression coefficient increases if predictors are correlated. A high VIF typically above 10 indicates multicollinearity.

This Concludes Today’s Presentation

Thank you for your attention

OTDM UNIT III

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ANALYTICS

What is Analytics?

Analytics is the use of:

data,

information technology,

statistical analysis,

quantitative methods, and

mathematical or computer-based models

to help decision-making executives gain improved insight about their business operations and make better, fact-based decisions.

Analytics is the discovery and communication of meaningful patterns in data. Especially valuable in areas rich with recorded information, Analytics relies on the simultaneous application of Statistics, computer Programming and Optimization Techniques models to quantify performance. Analytics often favors data visualization to communicate insight.

Analytics refers to the process of working with data to find out valuable insights (by applying some statistical models or methods) which can lead to extremely useful solutions for the entire business.

There are various kind of Analytics depending on the kind of problems the company is facing – such as Digital Marketing Analytics, Financial Analytics, Healthcare Analytics etc.

Past Data
Insights
Business planning

The goal of Data Analytics is to get actionable insights resulting in smarter decisions and better business outcomes.

Analytics Scenarios (Examples)

Example 1: Let’s say some company which is trying to launch a new product into the market, and is looking for funding – they might be looking into the sales forecast and trying to get probable investors, and trying to find out what should be the basic price point of the product that they are going to put into the market. So, if you are launching a new product, you have to do a lot of research and find out different insights as to what price point may work, doing what kind of marketing, what kind of branding would work. That is also a part of **ANALYTICS**.

Example 2 : There is a company, which is a good company but they don’t understand why so many employees are leaving them. If they cannot find out, they may be doing **ANALYTICS** to find out what triggers the employee attrition rate, and how they can find ways to fix it.

Data Analytics

- Data Analytics is the process of collecting, organizing and studying data to find useful information understand what’s happening and make better decisions.
- In simple words it helps people and organizations learn from data like what worked in the past, what is happening now and what might happen in the future
- Data analytics converts raw data into actionable insights. It includes a range of tools, technologies, and processes used to find trends and solve problems using data.
- Data analytics can shape business processes, improve decision-making, and foster business growth. It helps businesses grow by turning raw data into useful insights.
- It supports smarter decisions, better planning and improve customer service across many industries not just finance. From retail to government data analytics plays a key role in today’s world by helping organizations find patterns, solve problems and plan for the future.

Importance and Scope of Analytics

- *People often mix up data analytics and data analysis but they're not exactly the same.*
- *Data analysis is just one part of data analytics it focuses on finding meaning in data. On the other hand data analytics includes more than just analysis. It also involves things like coming up with ideas and predictions from data and building the tools and systems needed to handle large amounts of data.*
- Data analytics is used in many fields like banking, farming, shopping, government and more. It helps in many ways:

   1. **Helps in Decision Making**: It gives clear facts and patterns from data which help people make smarter choices.
   2. **Helps in Problem Solving**: It points out what's going wrong and why making it easier to fix problems.
   3. **Helps Identify Opportunities**: It shows trends and new chances for growth that might not be obvious.
   4. **Improved Efficiency**: It helps reduce waste, saves time and makes work smoother by finding better ways to do things.

Methods of Analytics

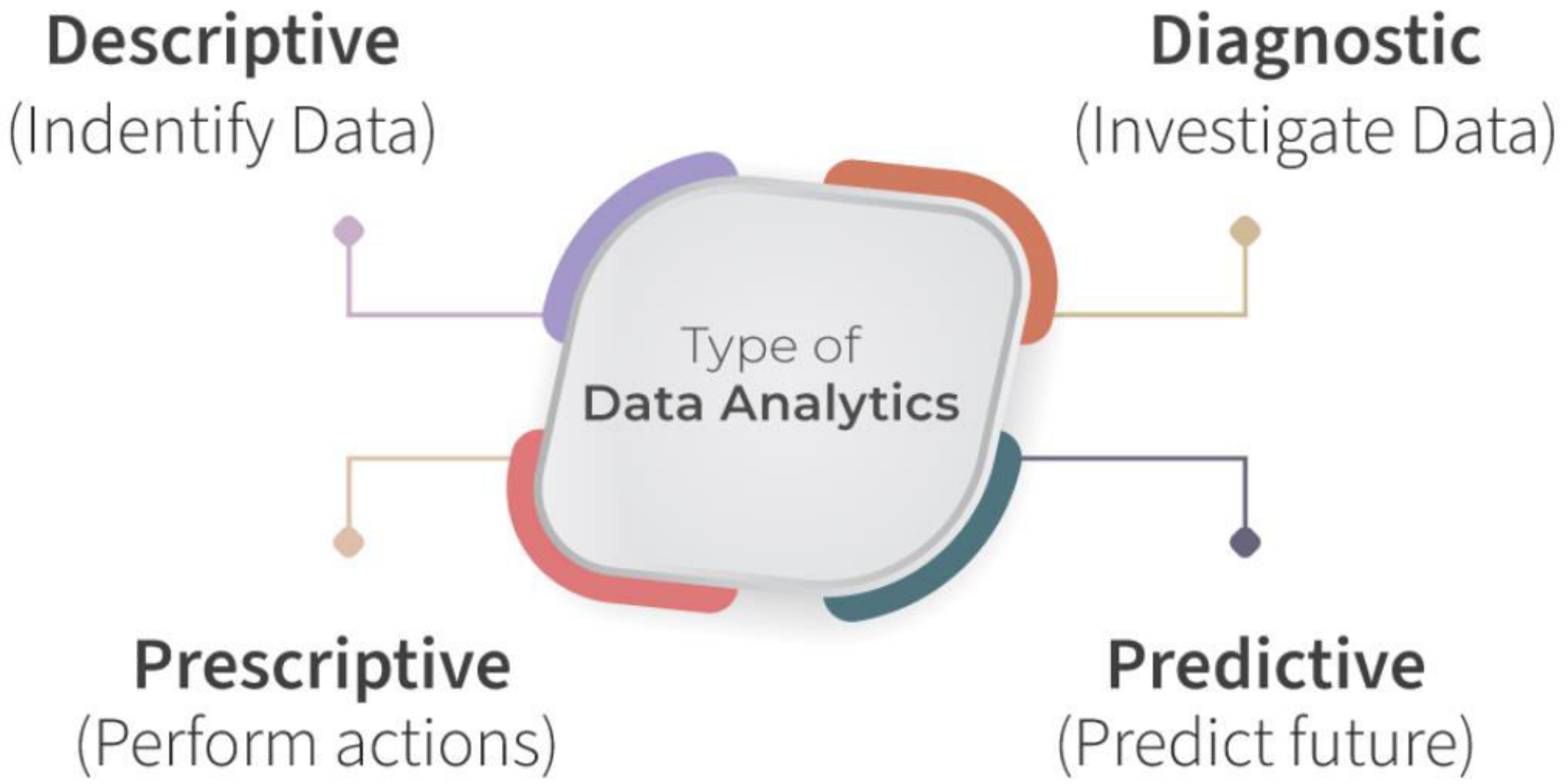
1. **Qualitative Data Analytics-** Qualitative data analysis doesn’t use statistics and derives data from the words, pictures and symbols. Some common qualitative methods are:

   - Narrative Analytics is used for working with data acquired from diaries, interviews and so on.
   - Content Analytics is used for Analytics of verbal data and behaviour.
   - Grounded theory is used to explain some given event by studying.

2. **Quantitative Data Analytics -** is used to collect data and then process it into the numerical data. Some of the quantitative methods are mentioned below:

   - Hypothesis testing assesses the given hypothesis of the data set.
   - Sample size determination is the method of taking a small sample from a large group of people and then analysing it.
   - Average or mean of a subject is dividing the sum total numbers in the list by the number of items present in that list.

Types Of Analytics

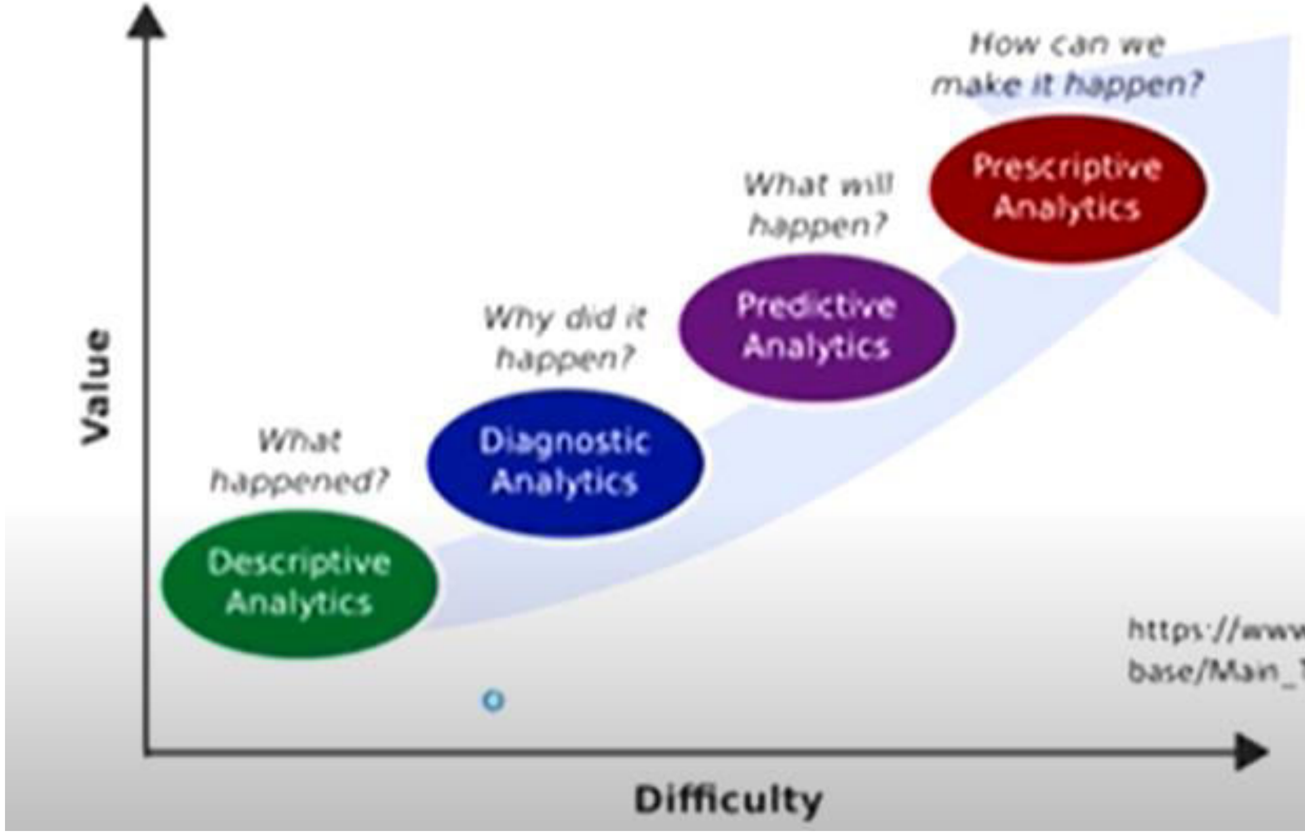


Types Of Analytics

- **Descriptive Data Analytics :** Descriptive data analytics helps to summarize and understand past data. It shows what has happened by using tables, charts and averages. Companies use it to compare results, find strengths and weaknesses and spot any unusual patterns.
- **Diagnostic Data Analytics:** Diagnostic data analytics looks at why something happened in the past. It uses tools like correlation, regression or comparison to find the cause of a problem. This helps companies understand the reason behind a drop in sales or a sudden change in performance.
- **Predictive Data Analytics:** Predictive data analytics is used to guess what might happen in the future. It looks at current and past data to find patterns and make forecasts. Businesses use it to predict things like customer behavior, future sales or possible risks.
- **Prescriptive Data Analytics:** Prescriptive data analytics helps to choose the best action or solution. It looks at different options and suggests what should be done next. Companies use it for things like loan approval, pricing decisions and managing machines or schedules.

- Analytics solutions offer a convenient way to leverage business data.
- But the number of solutions on the market can be daunting—and many may seem to cover a different category of analytics.
- How can organizations make sense of it all?
- Start by understanding the different types of analytics, including descriptive, diagnostic, predictive, and prescriptive analytics.
- In short, they are all forms of data analytics, but each use the data to answer different questions.
- At a high level:
  - **Descriptive Analytics** tells you what happened in the past.
  - **Diagnostic Analytics** helps you understand why something happened in the past.
  - **Predictive Analytics** predicts what is most likely to happen in the future.
  - **Prescriptive Analytics** recommends actions you can take to affect those outcomes.

Classification of Data analytics



What happened?

Descriptive Analytics

Why did it happen?

Diagnostic Analytics

What will happen?

Predictive Analytics

How can we make it happen?

Prescriptive Analytics

https://www.governanceanalytics.org/knowledge-base/Main_Tools/Data_classification_and_analysis

Descriptive Analytics
(business intelligence and data mining)

- **Descriptive analytics** looks at data statistically to tell you what happened in the past. Descriptive analytics helps a business understand how it is performing by providing context to help stakeholders interpret information. This can be in the form of data visualizations like graphs, charts, reports, and dashboards.
- ***How can descriptive analytics help in the real world?***
  - In a healthcare setting, for instance, say that an unusually high number of people are admitted to the emergency room in a short period of time. **Descriptive analytics** tells you that this is happening and provides real-time data with all the corresponding statistics (date of occurrence, volume, patient details, etc.).
  - Descriptive models can be used, for example, to categorize customers by their product preferences and life stage.
  - These models can de utilized to develop further models that can simulate large number of individualized agents and make predictions. For example, descriptive analytics examines historical electricity usage data to help plan power needs and allow electric companies to set optimal prices.

Diagnostic Analytics

- **Diagnostic analytics** takes descriptive data a step further and provides deeper analysis to answer the question: Why did this happen? Often, diagnostic analysis is referred to as root cause analysis. This includes using processes such as data discovery, data mining, and drill down and drill through.
- In the healthcare example mentioned earlier, diagnostic analytics would explore the data and make correlations. For instance, it may help you determine that all of the patients' symptoms—high fever, dry cough, and fatigue—point to the same infectious agent. You now have an explanation for the sudden spike in volume at the ER.

Predictive Analytics (forecasting)

- **Predictive analytics** takes historical data and feeds it into a machine learning model that considers key trends and patterns. The model is then applied to current data to predict what will happen next.
- The 3 basic cornerstones of Predictive Analytics are:
  - Predictive modelling
  - Decision Analysis and Optimization
  - Prescriptive (optimization and simulation)
- Back in our hospital example, predictive analytics may forecast a surge in patients admitted to the ER in the next several weeks. Based on patterns in the data, the illness is spreading at a rapid rate.
- Example 2 - optimizing CRM(customer relationship management) systems. They can help enable an org to analyse all customer data therefore exposing patterns that predict customer behaviour
- Example 3 – For an organization that offers multiple products, predictive analytics can help analyze customers’ spending, usage, and other behaviour, leading to efficient cross sales, or selling additional products to current customers.

Prescriptive Analytics (optimization and simulation)

- **Prescriptive analytics** automatically synthesizes big data, mathematical sciences, business rules, and machine learning to make predictions and then suggests decision options to take advantage of the predictions.
- **Prescriptive analytics** takes predictive data to the next level. Now that you have an idea of what will likely happen in the future, what should you do? It suggests various courses of action and outlines what the potential implications would be for each.
- Back to our hospital example: now that you know the illness is spreading, the prescriptive analytics tool may suggest that you increase the number of staff on hand to adequately treat the influx of patients.
- Another example is energy and utilities. Natural gas prices fluctuate dramatically depending upon supply, demand, econometrics, geo-politics, and weather conditions. Prescriptive analytics can accurately predict prices by modelling internal and external variables simultaneously and also provide decision options and show the impact of each option.

Regression Analysis

- In machine learning, regression analysis is a statistical technique that predicts continuous numeric values based on the relationship between independent and dependent variables. The main goal of regression analysis is to plot a line or curve that best fit the data and to estimate how one variable affects another.

- Regression analysis is a fundamental concept in machine learning and it is used in many applications such as forecasting, predictive analytics, etc.

- In machine learning, **regression is a type of supervised learning**. The key objective of regression-based tasks is to predict output labels or responses, which are continuous numeric values, for the given input data. The output will be based on what the model has learned in the training phase.

- **Regression models** use the input data features (independent variables) and their corresponding continuous numeric output values (dependent or outcome variables) to learn specific associations between inputs and corresponding outputs.

Terms used in Regression Analysis

- **Independent Variables** – These variables are used to predict the value of the dependent variable. These are also called predictors. In dataset, these are represented as **features**.
- **Dependent Variables** – These are the variables whose values we want to predict. These are the main factors in regression analysis. In dataset, these are represented as **target variables**
- **Regression line** – It is a straight line or curve that a regressor plots to fit the data points best (Y = a + bX)
- **Overfitting and underfitting** – Overfitting is when the regression model works well with the training dataset but not with the testing dataset. It's also referred to as the problem of high variance. Underfitting is when the model doesn't work well with training datasets. It's also referred to as the problem of high bias.
- **Outliers** – These are data points that don't fit the pattern of the rest of the data. They are the extremely high or extremely low values in the data set.
- **Multicollinearity** – Multicollinearity occurs when independent variables (features) have dependency among them.

Types of Regression in ML

- Generally, the classification of **regression methods** is done based on the three metrics – the number of independent variables, type of dependent variables, and shape of the regression line.
- There are numerous regression techniques used in ML –
  1. Simple Linear Regression
  2. Multiple Linear Regression
  3. Logistic Regression
  4. Polynomial Regression
  5. Lasso Regression
  6. Ridge Regression
  7. Decision Tree Regression
  8. Random Forest Regression
  9. Support Vector Regression

Types of Regression(2)

- **Simple Linear Regression** - is one of the simplest and most widely used statistical models. This assumes that there is a linear relationship between the independent and dependent variables. This means that the change in the dependent variable is proportional to the change in the independent variables. For example predicting the price of a house based on its size.
- **Multiple Linear Regression-** extends simple linear regression by using multiple independent variables to predict target variable. For example predicting the price of a house based on multiple features such as size, location, number of rooms, etc.
- **Polynomial Regression-** is used to model with non-linear relationships between the dependent variable and the independent variables. It adds polynomial terms to the linear regression model to capture more complex relationships. Relationship is modelled as an n^{th} degree polynomial. For example when we want to predict a non-linear trend like population growth over time we use polynomial regression.
- **Logistic Regression** is a supervised machine learning algorithm used for classification problems. Unlike linear regression which predicts continuous values it predicts the probability that an input belongs to a specific class. It is used for binary classification where the output can be one of two possible categories such as Yes/No, True/False or 0/1. It uses sigmoid function to convert inputs into a probability value between 0 and 1.

Types of Regression(2)

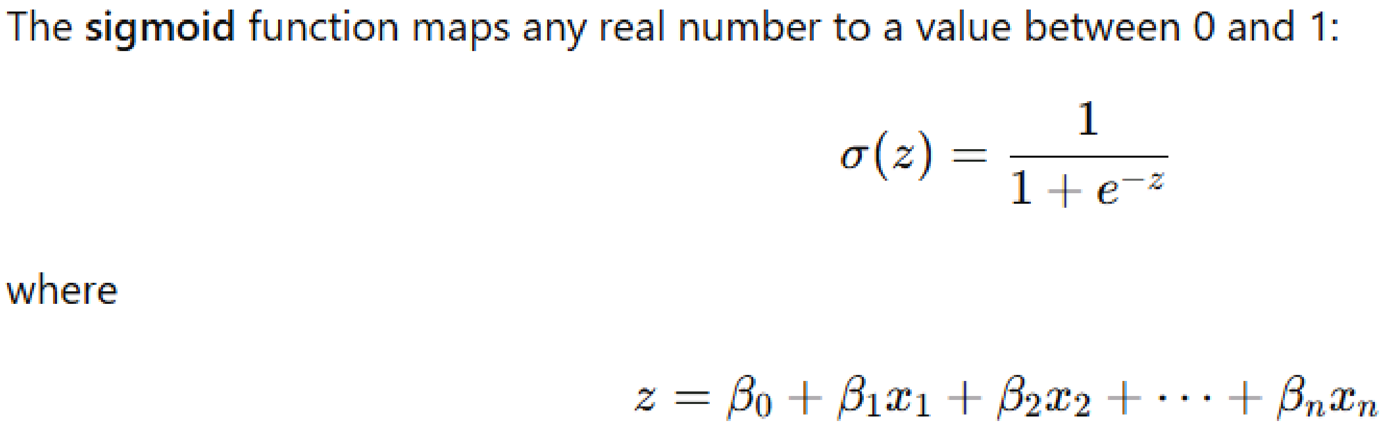
- **Lasso Regression** – is is a regression method based on Least Absolute Shrinkage and Selection Operator and is used in regression analysis for variable selection and regularization. Also known as L1 regularization technique. It helps remove irrelevant data features and prevents overfitting. This allows features with weak influence to be clearly identified as the coefficients of less important variables are shrunk toward zero.
- **Ridge Regression,** also known as L2 regularization, is a technique used in linear regression to address the **problem of multicollinearity among predictor variables. Multicollinearity** occurs when independent variables in a regression model are highly correlated, which can lead to unreliable and unstable estimates of regression coefficients.
- **Decision Tree Regression** Uses a tree-like structure to make decisions where each branch of tree represents a decision and leaves represent outcomes. For example predicting customer behavior based on features like age, income, etc there we use decision tree regression.
- **Random Forest Regression** is is a ensemble method that builds multiple decision trees and each tree is trained on a different subset of the training data. The final prediction is made by averaging the predictions of all of the trees. For example customer churn or sales data using this.
- **Support Vector Regression (SVR)** is a type of regression algorithm that is based on the Support Vector Machine (SVM) algorithm. SVM is a type of algorithm that is used for classification tasks but it can also be used for regression tasks. SVR works by finding a hyperplane that minimizes the sum of the squared residuals between the predicted and actual values.

Applications of Regression

- **Forecasting or Predictive analysis** – One of the important uses of regression is forecasting or predictive analysis. For example, we can forecast GDP, oil prices, or, in simple words, the quantitative data that changes with the passage of time.
- **Optimization** – We can optimize business processes with the help of regression. For example, a store manager can create a statistical model to understand the peak time of coming customers.
- **Error correction** – In business, making correct decisions is equally important as optimizing the business process. Regression can help us to make correct decision as well as correct the already implemented decision.
- **Economics** – It is the most used tool in economics. We can use regression to predict supply, demand, consumption, inventory investment, etc.
- **Fintech Companies** – A FINTECH company is always interested in minimizing the risk portfolio and wants to know the factors that affect the customers. All these can be predicted with the help of a regression model.

Logistic Regression

- **Logistic Regression** is a **supervised learning** algorithm used for **classification**, not regression.
- It predicts **categorical outcomes**, usually **binary** (Yes/No, 0/1, Pass/Fail, Spam/Not Spam, etc.).
- Even though the name has “regression,” it is actually a **classification algorithm** based on the **logistic (sigmoid) function**.



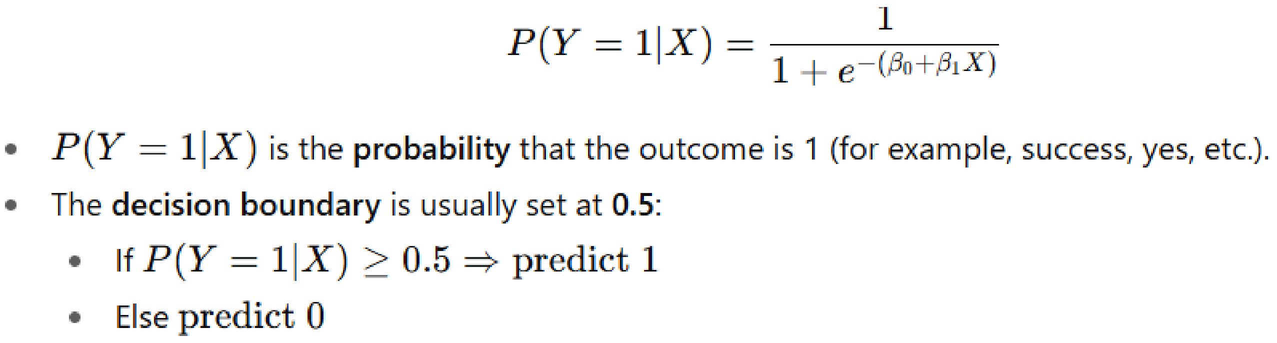
The **sigmoid** function maps any real number to a value between 0 and 1:

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

where

$$z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$$

Interpretation:



$$P(Y = 1|X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X)}}$$

- $P(Y = 1|X)$ is the **probability** that the outcome is 1 (for example, success, yes, etc.).
- The **decision boundary** is usually set at **0.5**:
  - If $P(Y = 1|X) \geq 0.5 \Rightarrow \text{predict } 1$
  - Else $\text{predict } 0$

Formula for Logistic Regression Model is :

$$P(Y=1|X)=\frac{1}{1+e^{-(\beta_0+\beta_1 X)}}$$

- $P(Y=1|X)$ is the **probability** that the outcome is 1 (for example, success, yes, etc.).
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  - If $P(Y=1|X)\geq 0.5 \Rightarrow \text{predict } 1$
  - Else $\text{predict } 0$

Log-Odds (Logit) formula for Logistic Regression

We can rewrite the logistic model in terms of **log-odds** (or **logit**):

$$\text{logit}(p)=\ln\left(\frac{p}{1-p}\right)=\beta_0+\beta_1 X$$

This shows that logistic regression models a **linear relationship between the independent variable(s) and the log-odds of the outcome**.

Problem 1

Suppose the logistic regression model is:

$$p = \frac{1}{1 + e^{-(-4+0.8x)}}$$

where x represents **hours studied**, and p is the **probability of passing an exam**.

Find: a) The probability that a student who studied 5 hours passes the exam.

b) The decision (Pass or Fail) if the threshold = 0.5.

SOLUTION : First write the model and in next step substitute x = 5 in the model

$$p = \frac{1}{1 + e^{-(-4+0.8x)}}$$

$$z = -4 + 0.8(5) = -4 + 4 = 0$$

$$p = \frac{1}{1 + e^{-0}} = \frac{1}{1+1} = 0.5$$

Interpretation (Step 3) : The probability of passing when studying 5 hours is **0.5.**

Since the threshold = 0.5, we predict “Pass” if we take p ≥ 0.5

Step 4 : Check another case (for another value of *x*)

If $x = 7$:

$$z = -4 + 0.8(7) = -4 + 5.6 = 1.6$$

$$p = \frac{1}{1 + e^{-1.6}} \approx \frac{1}{1 + 0.201} = 0.832$$

So, the probability of passing when studying 7 hours is **0.83 → Predict Pass.**

If $x = 2$:

$$z = -4 + 0.8(2) = -4 + 1.6 = -2.4$$

$$p = \frac{1}{1 + e^{2.4}} \approx \frac{1}{1 + 11.02} = 0.083$$

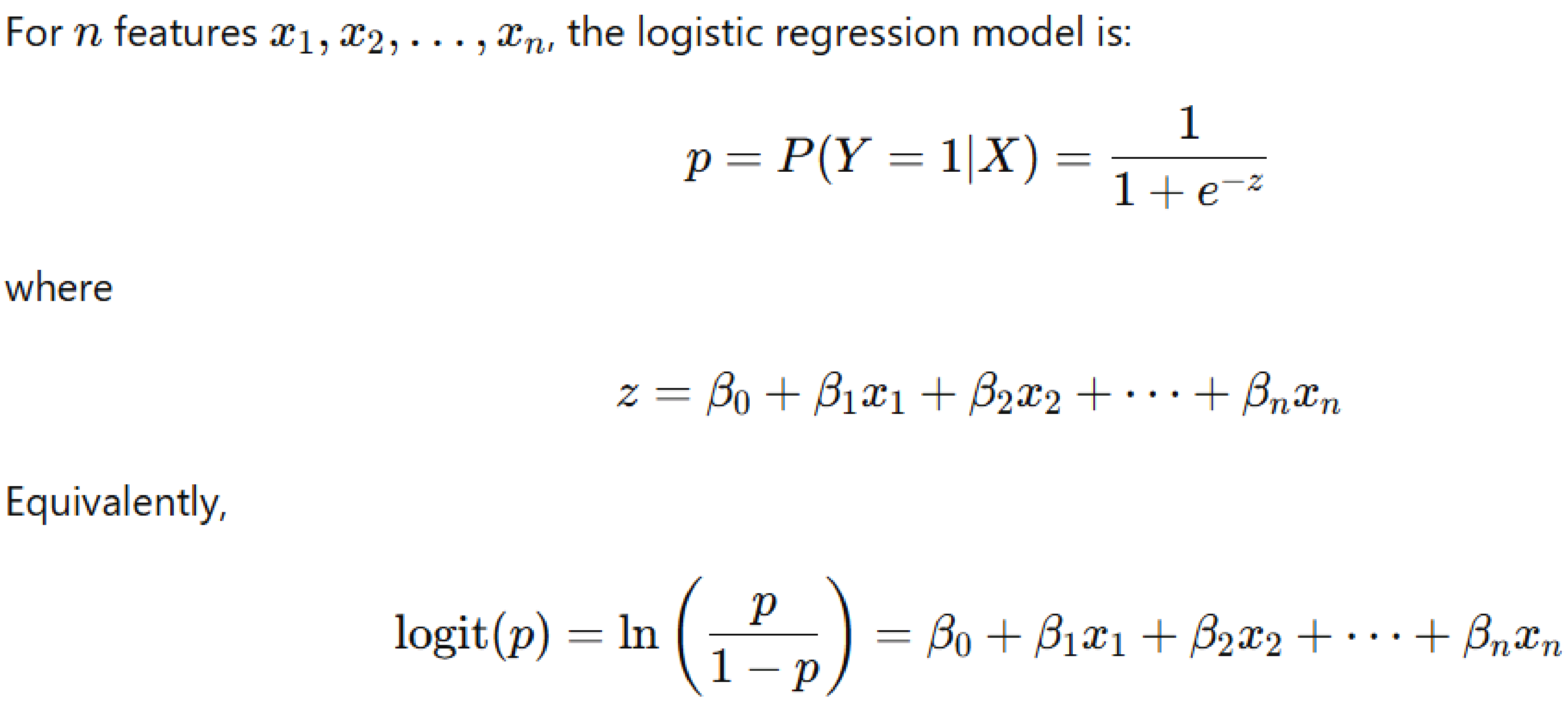
Probability of passing is **0.08 → Predict Fail.**

Hours Studied (x)	**z**	**p (Probability of Pass)**	**Prediction**
2	-2.4	0.083	Fail
5	0	0.5	Pass (boundary)
7	1.6	0.832	Pass

Concept	Description
Output	Probability between 0 and 1
Decision rule	Usually threshold = 0.5
Link function	Logit = ln(p / (1 - p))
Estimation	Coefficients (β) are found using **Maximum Likelihood Estimation (MLE)**
Use cases	Binary classification: spam detection, disease prediction, churn prediction, etc.

Multivariate Logistic Regression

When we have **more than one independent variable**, logistic regression generalizes easily.
Model Definition in this case is as follows:



For n features $x_1, x_2, \dots, x_n$, the logistic regression model is:

$$p = P(Y = 1|X) = \frac{1}{1 + e^{-z}}$$

where

$$z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$$

Equivalently,

$$\text{logit}(p) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$$

Example - A company wants to predict whether a customer will buy a product (**Y = 1**) or not (**Y = 0**) based on:

Variable	Description
x_1	Age (in years)
x_2	Monthly Income (in ₹ thousands)

The fitted logistic regression model is:

$$p = \frac{1}{1 + e^{-(-6+0.04x_1+0.3x_2)}}$$

Calculate: a) The probability of purchase for a 30-year-old earning ₹25,000/month.

b) The decision (Buy / Not Buy) at a 0.5 threshold.

Step 1: Compute the value of z

$$z = -6 + 0.04(30) + 0.3(25)$$

$$z = -6 + 1.2 + 7.5 = 2.7$$

4. Step 2: Compute Probability

$$p = \frac{1}{1+e^{-2.7}} = \frac{1}{1+0.067} = 0.937$$

So, **probability = 0.937 (93.7%)** that the customer will buy the product.

5. Step 3: Decision

Since $p = 0.937 > 0.5$,

Prediction: Customer will buy the product (Y = 1).

6. Step 4: Try another case

Customer B: $x_1 = 22$ years, $x_2 = 10$ (₹10,000/month)

$$z = -6 + 0.04(22) + 0.3(10) = -6 + 0.88 + 3 = -2.12$$

$$p = \frac{1}{1+e^{2.12}} = \frac{1}{1+8.33} = 0.107$$

So, $p = 0.107$ → **Prediction: Will not buy (Y = 0).**

7. Step 5: Interpret Coefficients

Coefficient	Meaning
$\beta_0 = -6$	Base log-odds when all predictors = 0.
$\beta_1 = 0.04$	For each **extra year of age**, log-odds of buying increase by 0.04.
$\beta_2 = 0.3$	For each **₹1000 increase in monthly income**, log-odds of buying increase by 0.3.

Thus, **income** has a stronger effect on purchase probability than **age**.

8. Step 6: Decision Boundary

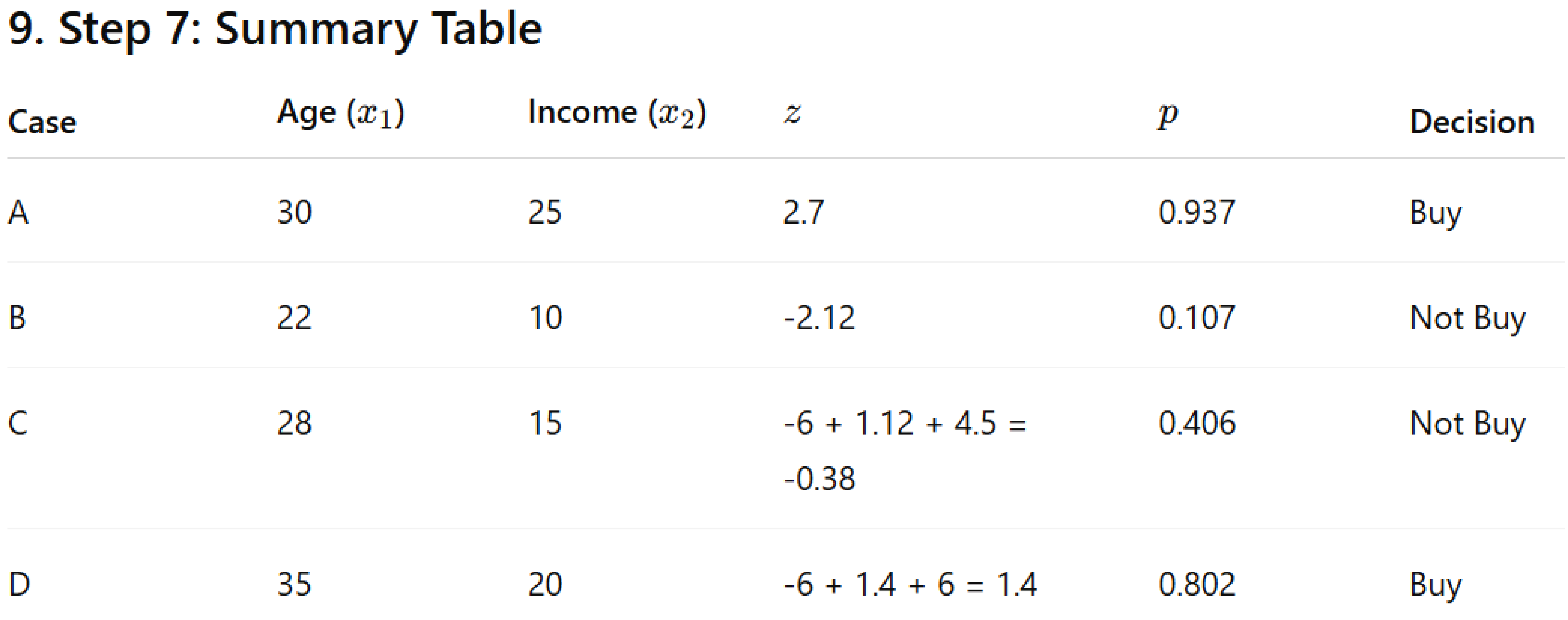
The decision boundary is found when $p = 0.5$, i.e., $z = 0$:

$$-6 + 0.04x_1 + 0.3x_2 = 0$$

$$0.3x_2 = 6 - 0.04x_1$$

$$x_2 = 20 - 0.133x_1$$

So the decision boundary is a **straight line** in the (x_1, x_2) plane dividing “Buy” and “Not Buy” regions.



9. Step 7: Summary Table

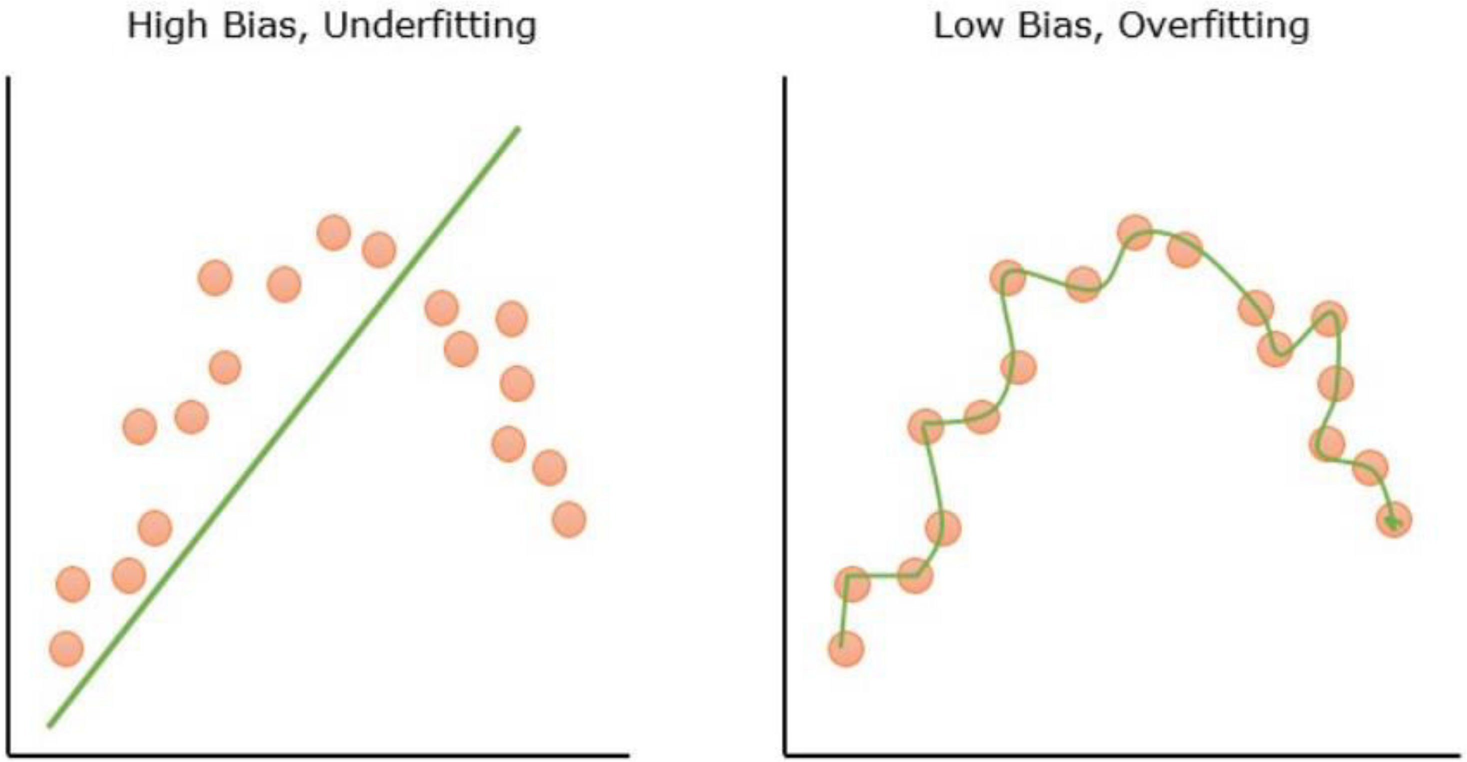
Case	Age (x_1)	Income (x_2)	z	p	Decision
A	30	25	2.7	0.937	Buy
B	22	10	-2.12	0.107	Not Buy
C	28	15	-6 + 1.12 + 4.5 = -0.38	0.406	Not Buy
D	35	20	-6 + 1.4 + 6 = 1.4	0.802	Buy

Key Interpretations

- Logistic regression models the **probability** that $Y = 1$as a function of predictors.
- The coefficients affect the **log-odds**, not directly the probability.
- The model creates a **linear decision boundary** between classes.

Bias Variance Dichotomy Model (Trade-off Model)

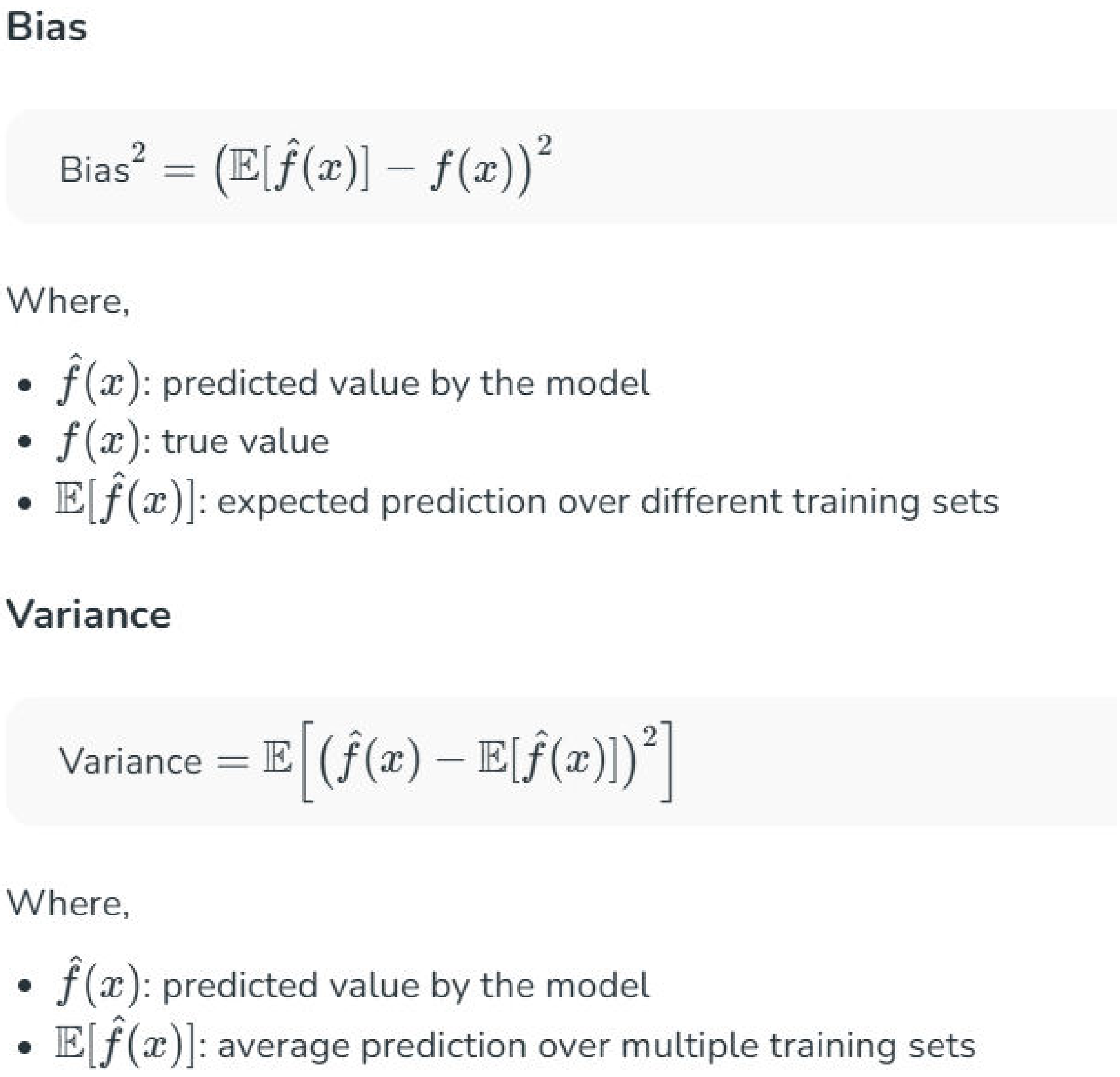
- **Bias** refers to the error that results from oversimplifying the underlying relationship between the input features and the output variable. At the same time, **variance** refers to the error that results from being too sensitive to fluctuations in the training data.
- In Optimization, we strive to **minimize both bias and variance** in order to build a model that can accurately predict on unseen data. A high-bias model may be too simplistic and underfit the training data. In contrast, a model with high variance may overfit the training data and fail to generalize to new data.
- Bias is calculated as the difference between average prediction and actual value. Bias (systematic error) occurs when a model makes incorrect assumptions about data. A model with high bias does not match well training data as well as test data. It leads to high errors in training and test data. While the model with low bias matches the training data well (high training accuracy or less error in training). It leads to low error in training data
- **High Bias** – High bias occurs due to erroneous assumptions in the machine learning model. Models with high bias cannot capture the hidden pattern in the training data. This leads to **underfitting**. Features of high bias are a highly simplified model, underfitting, and high error in training and test data.
- **Low Bias** – Models with low bias can capture the hidden pattern in the training data. Low bias leads to high variance and, eventually, **overfitting**. Low bias generally occurs due to the ML model being overly complex.


High Bias, Underfitting
Low Bias, Overfitting

Variance Concept in Bias Variance Dichotomy Model

- **Variance** is a measure of the spread or dispersion of numbers in a given set of observations with respect to the mean.
- In Optimization, Variance is how much a model's predictions change when it's trained on different data.
- It shows how much model prediction varies when there is a slight variation in data. If model accuracies on training and test data vary greatly, the model has high variance.
- A model with high variance can even fit noises on training data but lacks generalization to new, unseen data.
  - **High variance:** The model is too sensitive to small changes and may overfit.
  - **Low variance:** The model is more stable but might miss some patterns

Mathematical Formula for Bias and Variance



Bias

$$\text{Bias}^2 = \left(\mathbb{E}[\hat{f}(x)] - f(x)\right)^2$$

Where,

- $\hat{f}(x)$: predicted value by the model
- $f(x)$: true value
- $\mathbb{E}[\hat{f}(x)]$: expected prediction over different training sets

Variance

$$\text{Variance} = \mathbb{E}\left[\left(\hat{f}(x) - \mathbb{E}[\hat{f}(x)]\right)^2\right]$$

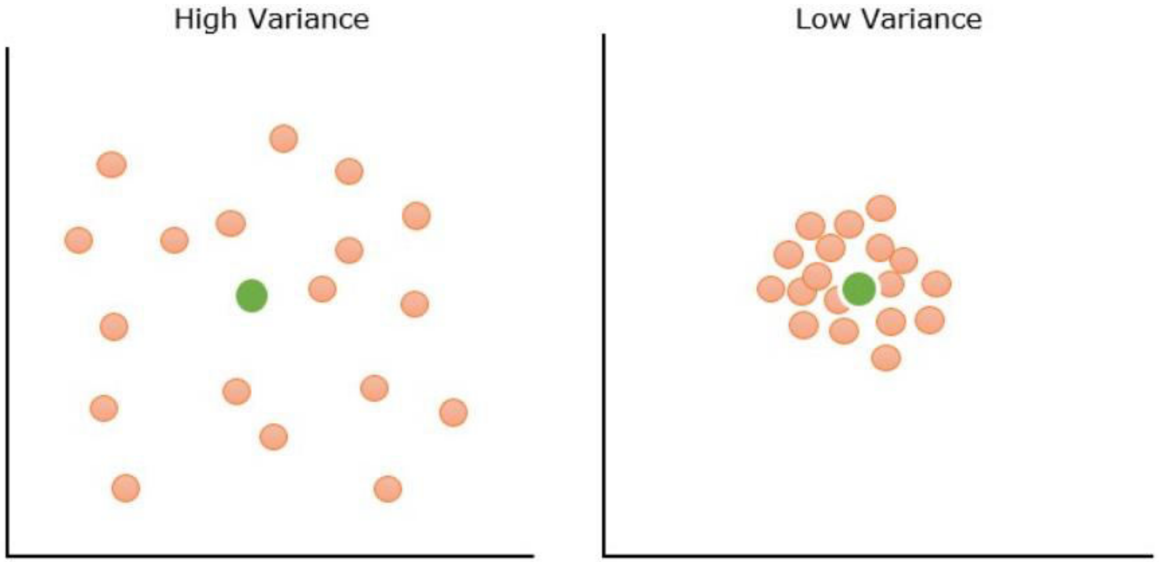
Where,

- $\hat{f}(x)$: predicted value by the model
- $\mathbb{E}[\hat{f}(x)]$: average prediction over multiple training sets

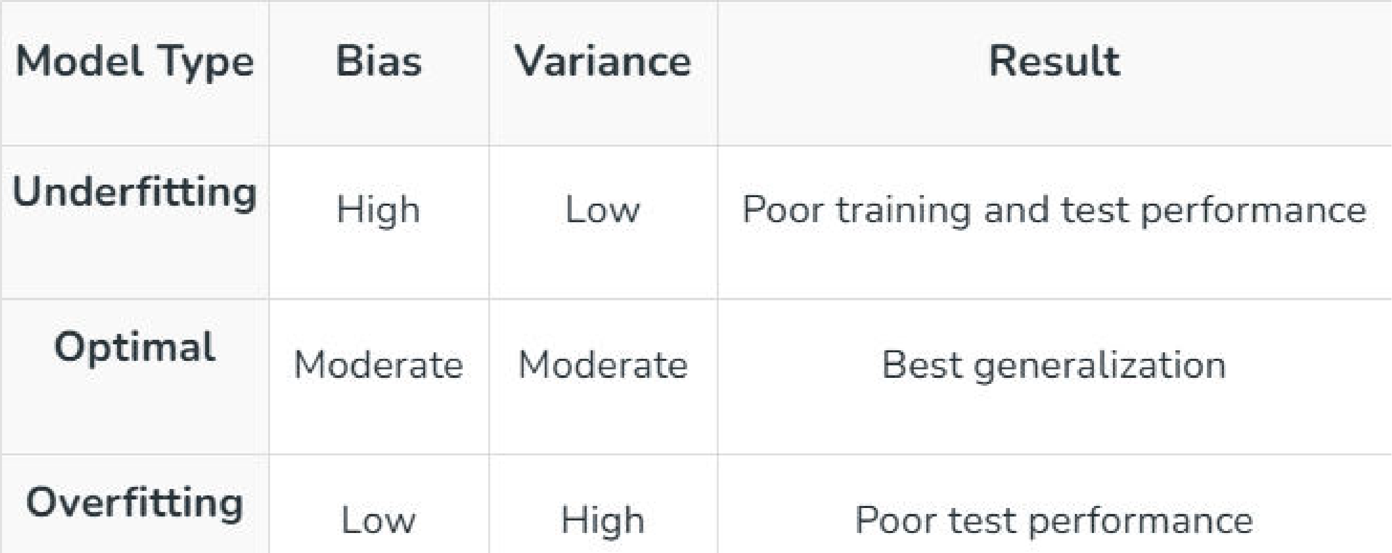
Types of Variance

High Variance – High variance models capture noise along with hidden pattern. It leads to **overfitting**. High variance models show high training accuracy but low test accuracy. Some features of a high variance model are an overly complex model, overfitting, low error on training data, and high error or test data.

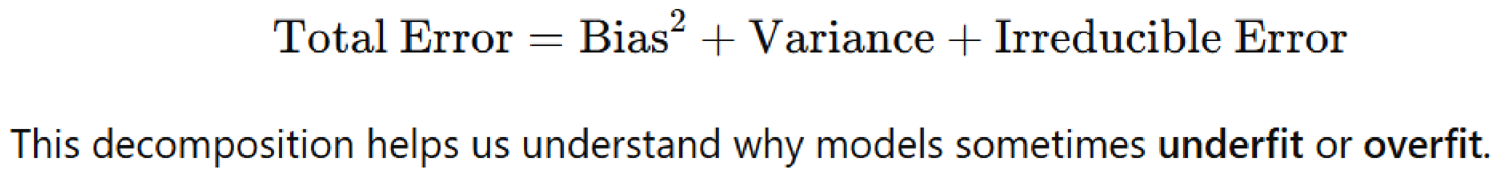
Low Variance – A model with low variance is unable to capture the hidden pattern in the data. Low variance may occur when we have a very small amount of data or use a very simplified model. Low variance leads to **underfitting**.



Bias-Variance Tradeoff



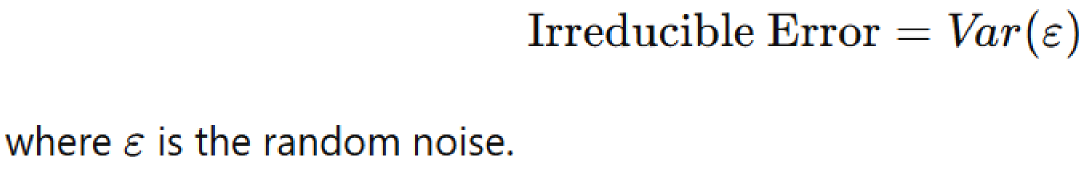
Model Type	Bias	Variance	Result
Underfitting	High	Low	Poor training and test performance
Optimal	Moderate	Moderate	Best generalization
Overfitting	Low	High	Poor test performance



$$\text{Total Error} = \text{Bias}^2 + \text{Variance} + \text{Irreducible Error}$$

This decomposition helps us understand why models sometimes **underfit** or **overfit**.

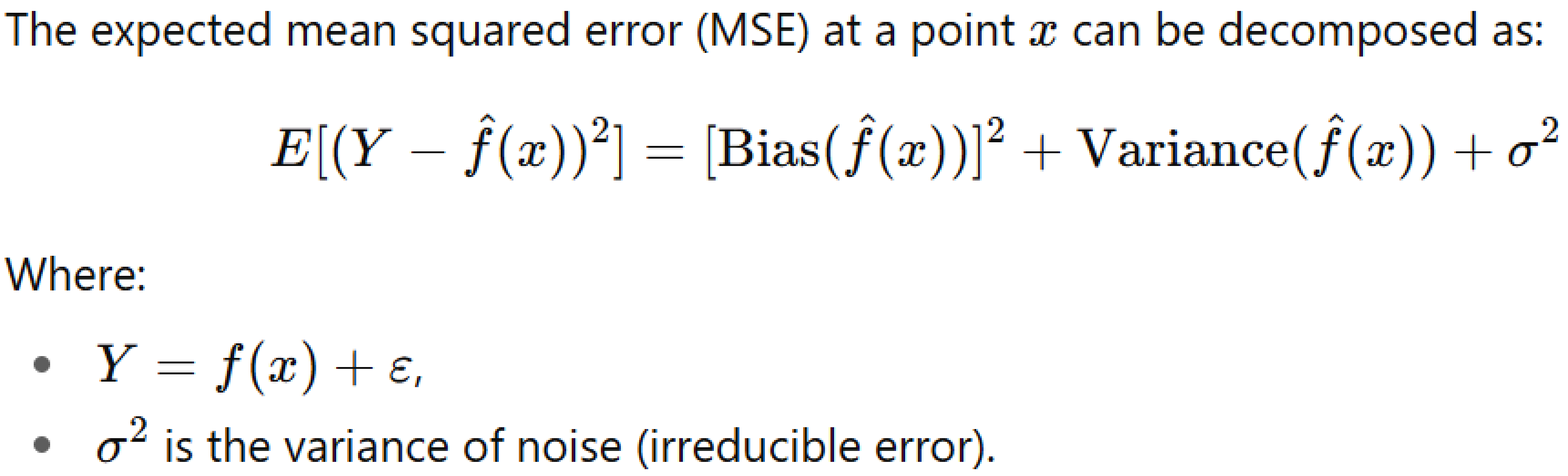
Irreducible Error - This is the noise inherent in data that **no model** can explain.



$$\text{Irreducible Error} = Var(\varepsilon)$$

where ε is the random noise.

Total Expected Prediction Error Formula



The expected mean squared error (MSE) at a point x can be decomposed as:

$$E[(Y - \hat{f}(x))^2] = [\text{Bias}(\hat{f}(x))]^2 + \text{Variance}(\hat{f}(x)) + \sigma^2$$

Where:

- $Y = f(x) + \varepsilon$,
- σ^2 is the variance of noise (irreducible error).

This decomposition is known as the **Bias–Variance Trade-off**.

(a) Irreducible Error

- Comes from the random noise ε.
- Even a perfect model can't predict noise.
- Formally: $\mathrm{Var}(\varepsilon) = \sigma^2$

You **cannot reduce** this part — it's inherent in the data.

(b) Bias

- Bias measures the **systematic error** in your model's assumptions.
- It is the **difference between the true function** $f(x)$ and the **expected prediction** $E[\hat{f}(x)]$ of your model.

$$\mathrm{Bias}(x) = E[\hat{f}(x)] - f(x)$$

and

$$\mathrm{Bias}^2 = [E[\hat{f}(x)] - f(x)]^2$$

High Bias → Model makes strong assumptions, oversimplifies relationships.

Example: Linear regression used for a nonlinear relationship.

(c) Variance

- Variance measures how much $\hat{f}(x)$ would vary if we trained it on different datasets.
- High variance means the model is **too sensitive to training data** — small changes in data cause big changes in prediction.

Formally:

$$\text{Variance}(x) = E[(\hat{f}(x) - E[\hat{f}(x)])^2]$$

High Variance → Model memorizes training data instead of generalizing.

Example: Deep decision trees or k-NN with $k = 1$.

3. Total Error Decomposition

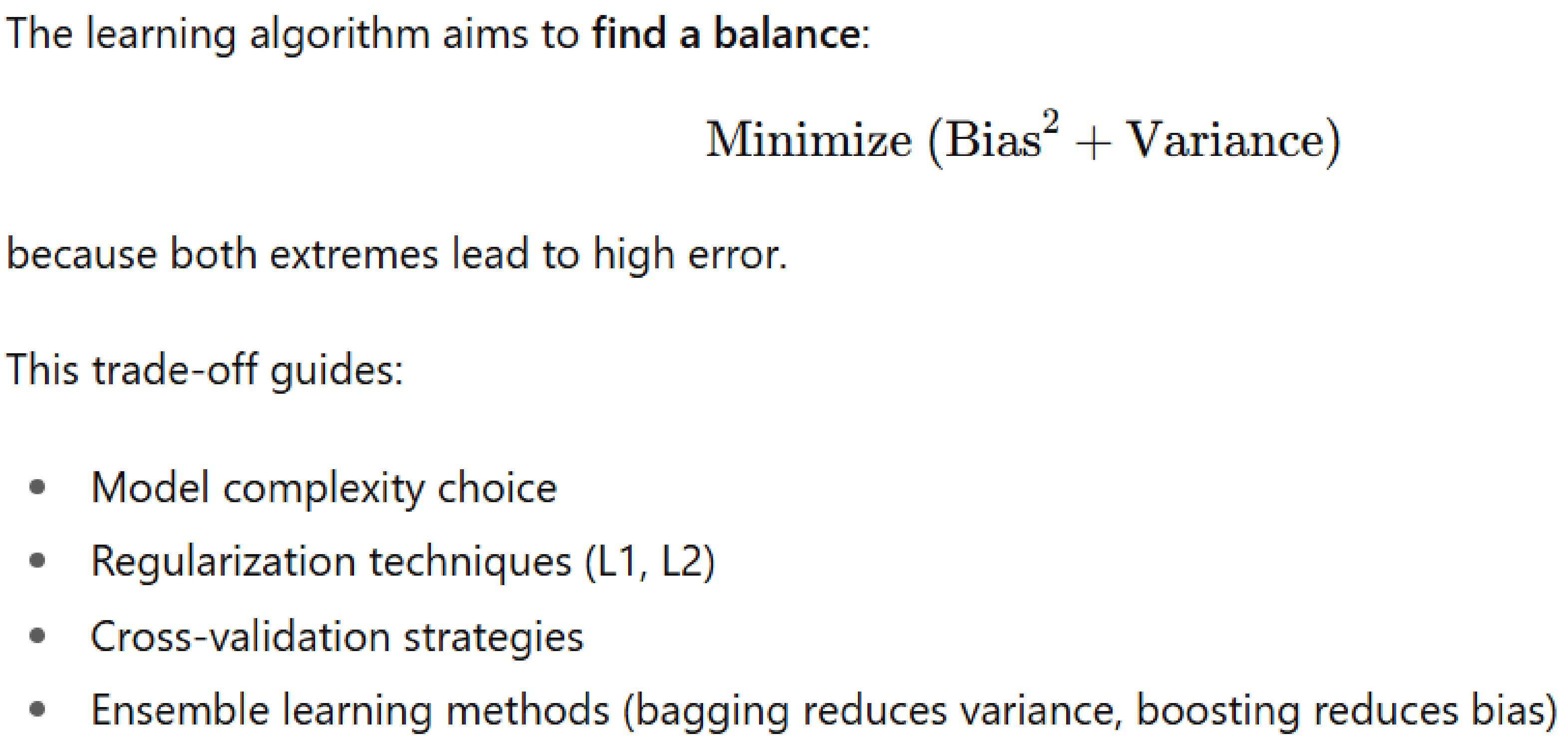
Putting it together:

$$E[(y - \hat{f}(x))^2] = \underbrace{[\text{Bias}(x)]^2}_{\text{Systematic error}} + \underbrace{\text{Variance}(x)}_{\text{Model sensitivity}} + \underbrace{\sigma^2}_{\text{Irreducible noise}}$$

Interpretation

Model Complexity	**Bias**	**Variance**	**Total Error**
Very Simple (Underfit)	High	Low	High
Optimal (Balanced)	Medium	Medium	**Lowest**
Very Complex (Overfit)	Low	High	High

Goal of Model



The learning algorithm aims to **find a balance**:

$$\text{Minimize } (\text{Bias}^2 + \text{Variance})$$

because both extremes lead to high error.

This trade-off guides:

- Model complexity choice
- Regularization techniques (L1, L2)
- Cross-validation strategies
- Ensemble learning methods (bagging reduces variance, boosting reduces bias)

Practical Insight

Situation	Cause	Remedy
High Bias	Model too simple, underfitting	Use more features, increase model capacity
High Variance	Model too complex, overfitting	Regularize, collect more data, use cross-validation

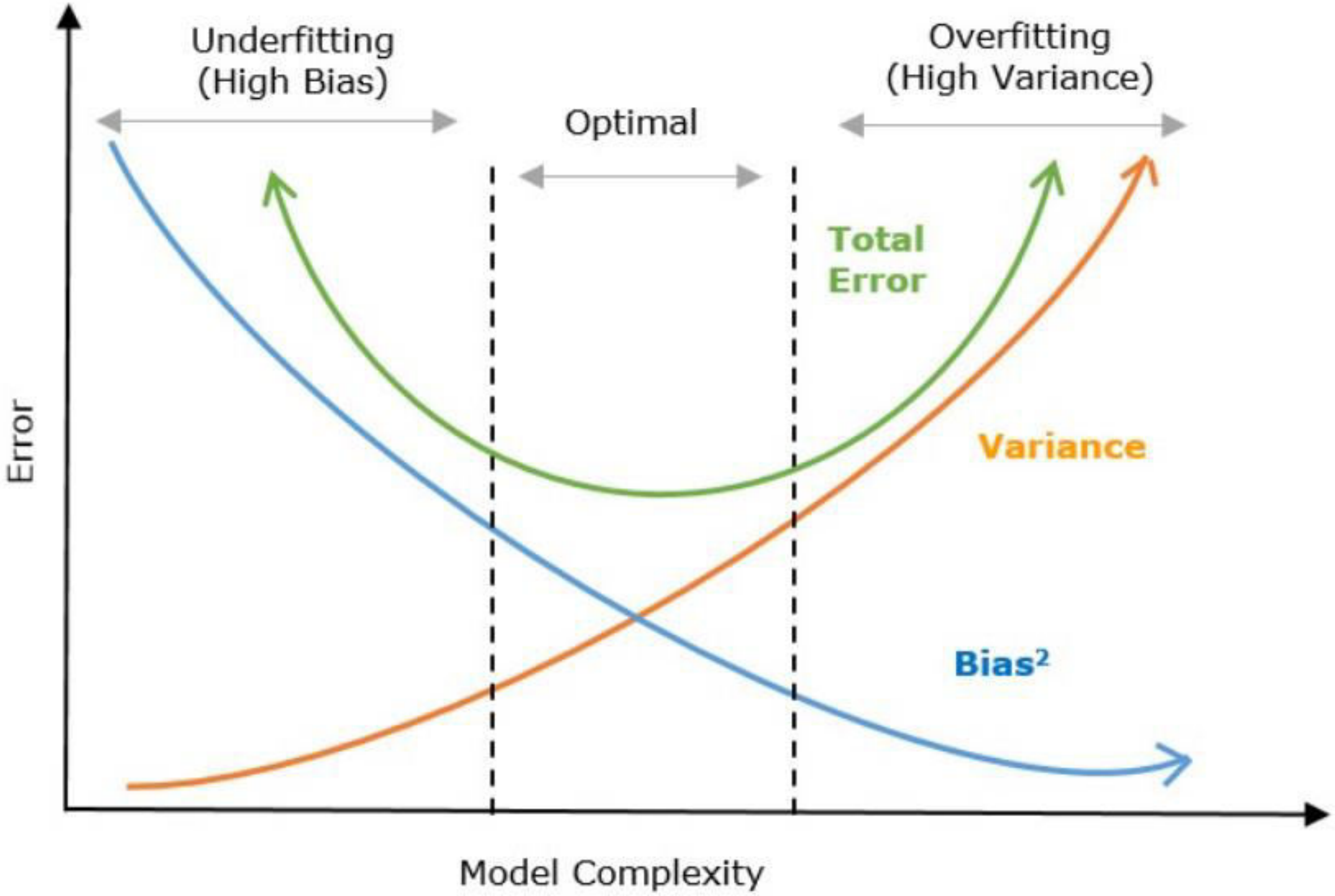
Summary

Concept	Description
Bias	Error from wrong assumptions
Variance	Error from sensitivity to training data
Irreducible Error	Random noise not explainable by model
Goal	Find sweet spot minimizing both Bias^2 and Variance
Techniques to Control Bias/Variance	Regularization (Lasso/Ridge), Cross-validation, Pruning, Bagging/Boosting

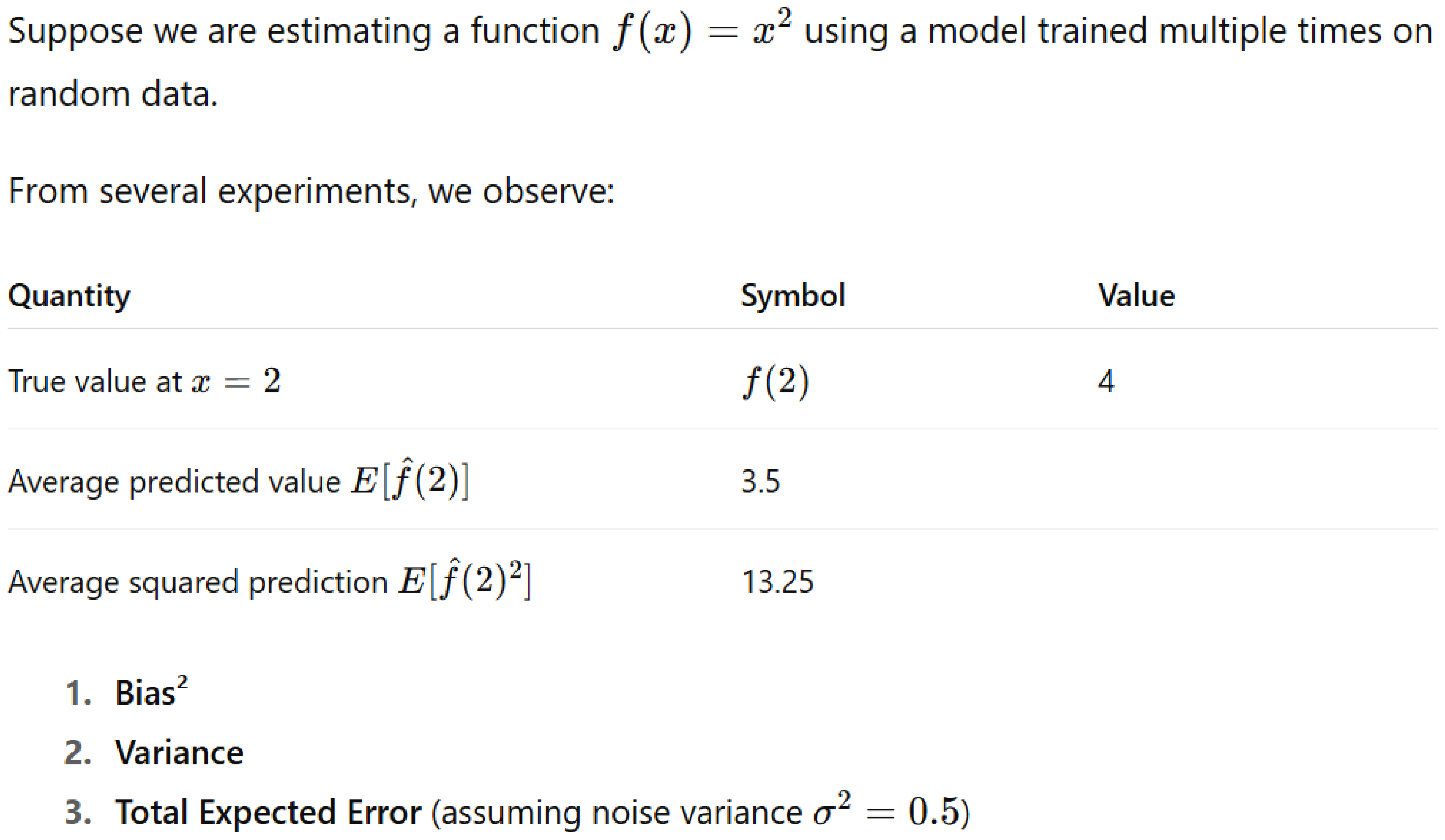
The Tradeoff

Model Type	Bias	Variance	Behavior
Simple Model (Linear)	High	Low	Underfits
Complex Model (High-degree polynomial)	Low	High	Overfits

The **goal** is to find an optimal model complexity where the **sum of bias² + variance** is minimized.



Example

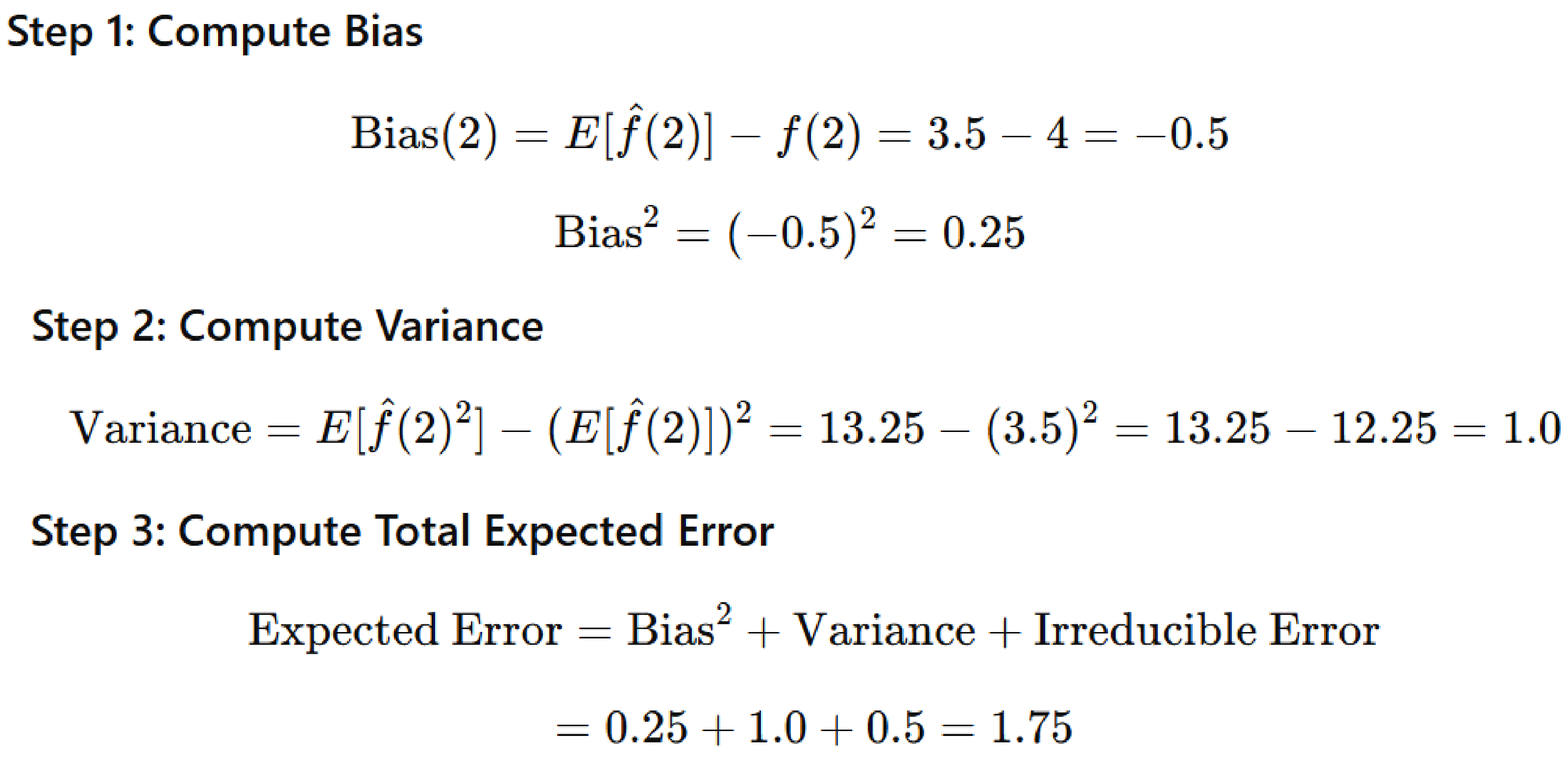


Suppose we are estimating a function $f(x) = x^2$ using a model trained multiple times on random data.

From several experiments, we observe:

Quantity	**Symbol**	**Value**
True value at $x = 2$	$f(2)$	4
Average predicted value $E[\hat{f}(2)]$	3.5	
Average squared prediction $E[\hat{f}(2)^2]$	13.25	

1. **Bias^2**
2. **Variance**
3. **Total Expected Error** (assuming noise variance $\sigma^2 = 0.5$)



Step 1: Compute Bias

$$\text{Bias}(2) = E[\hat{f}(2)] - f(2) = 3.5 - 4 = -0.5$$

$$\text{Bias}^2 = (-0.5)^2 = 0.25$$

Step 2: Compute Variance

$$\text{Variance} = E[\hat{f}(2)^2] - (E[\hat{f}(2)])^2 = 13.25 - (3.5)^2 = 13.25 - 12.25 = 1.0$$

Step 3: Compute Total Expected Error

$$\text{Expected Error} = \text{Bias}^2 + \text{Variance} + \text{Irreducible Error}$$

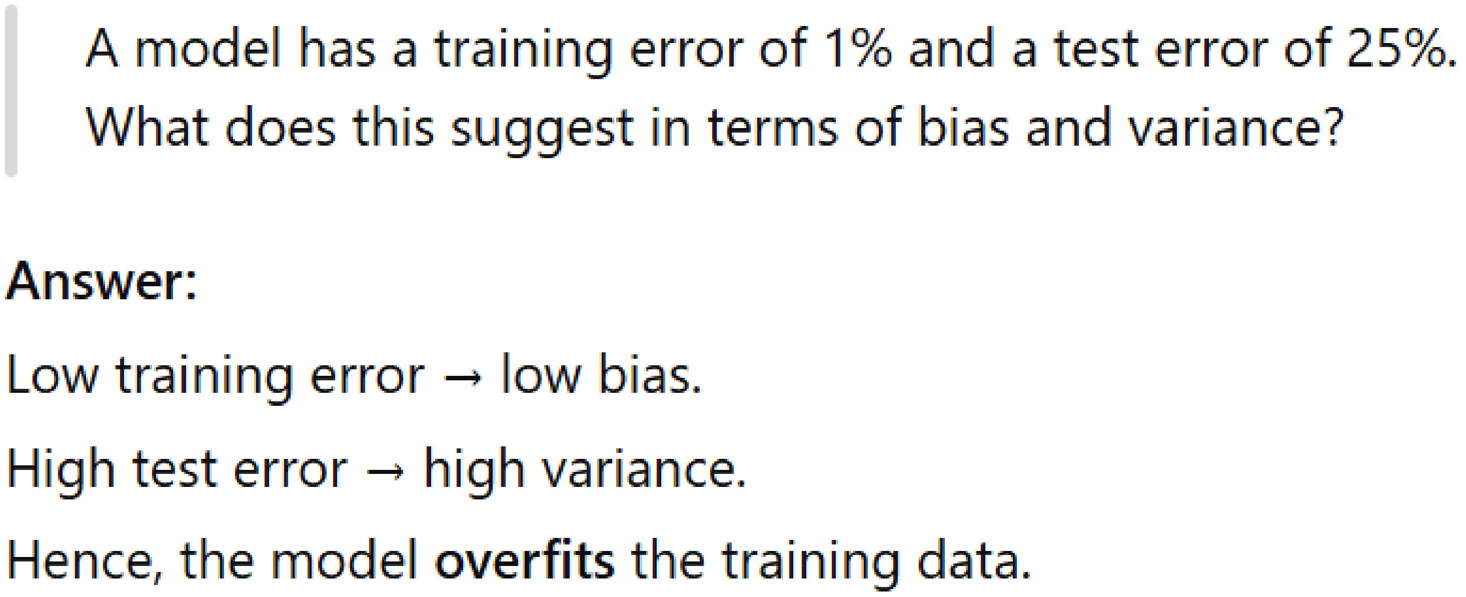
$$= 0.25 + 1.0 + 0.5 = 1.75$$

Interpretation

- **Bias^2 (0.25)** is small → model's predictions are close to the true function.
- **Variance (1.0)** is significant → model predictions vary across datasets.
- **Total error (1.75)** indicates that reducing variance (via regularization or ensemble) could improve model stability.

Summary

Term	Meaning	Desirable?
Bias	Systematic error	Low
Variance	Sensitivity to training data	Low
Irreducible Error	Noise	Unavoidable
Tradeoff	Balance between bias² and variance	Optimal complexity minimizes total error



> A model has a training error of 1% and a test error of 25%. What does this suggest in terms of bias and variance?

Answer:

Low training error → low bias.

High test error → high variance.

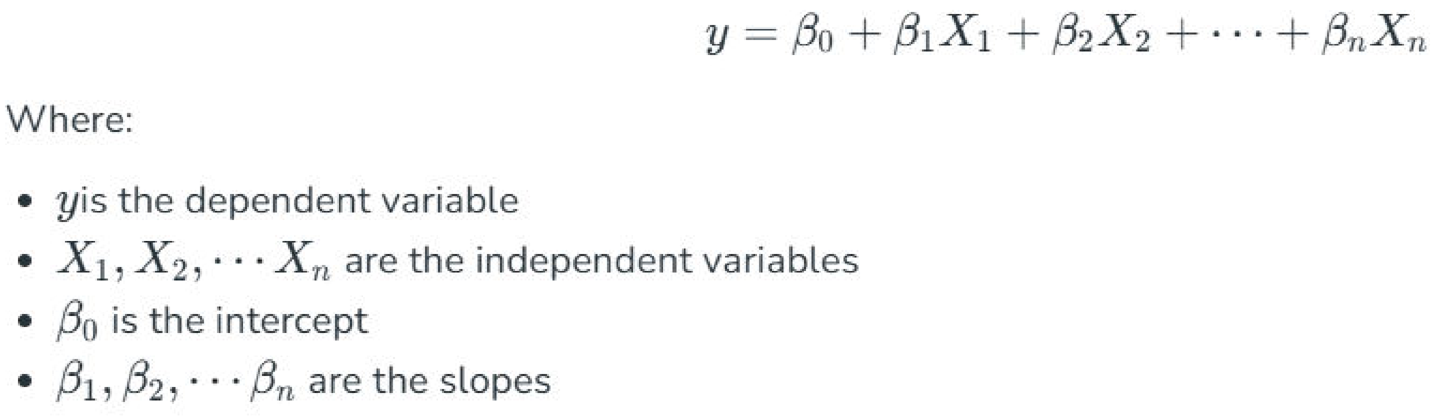
Hence, the model **overfits** the training data.

1. Linear Regression

- It is the most commonly used regression model in machine learning. It may be defined as the statistical model that analyzes the linear relationship between a dependent variable with a given set of independent variables.
- A linear relationship between variables means that when the value of one or more independent variables changes (increase or decrease), the value of the dependent variable will also change accordingly (increase or decrease).
- Linear regression is further divided into two subcategories: simple linear regression and multiple linear regression (also known as multivariate linear regression).
- In simple linear regression, a single independent variable (or predictor) is used to predict the dependent variable. Mathematically, the simple linear regression can be represented as follows- Y = a + bX where,
  - Y is the dependent variable we are trying to predict.
  - X is the independent variable we are using to make predictions
  - *b* is the slope of the regression line, which represents the effect X has on Y.
  - *a* is a constant known as the Y-intercept. If X = 0, Y would be equal to a.
- In multi-linear regression, multiple independent variables are used to predict the dependent variables.

Multiple Linear Regression Model

- Multiple Linear Regression extends this concept by modelling the relationship between a dependent variable and two or more independent variables. This technique allows us to understand how multiple features collectively affect the outcomes.
- Steps to perform this are similar to that of simple linear Regression but difference comes in the evaluation process. We can use it to find out which factor has the highest influence on the predicted output and how different variables are related to each other. Assumptions of this Model are:
  1. **Linearity**: Relationship between dependent and independent variables should be linear.
  2. **Homoscedasticity**: Variance of errors should remain constant across all levels of independent variables.
  3. **Multivariate Normality**: Residuals should follow a normal distribution.
  4. **No Multicollinearity**: Independent variables should not be highly correlated
- Equation for multiple linear regression is:



$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$$

Where:

- $y$is the dependent variable
- $X_1, X_2, \cdots X_n$ are the independent variables
- β_0 is the intercept
- $\beta_1, \beta_2, \cdots \beta_n$ are the slopes

Multicollinearity in Regression Analysis

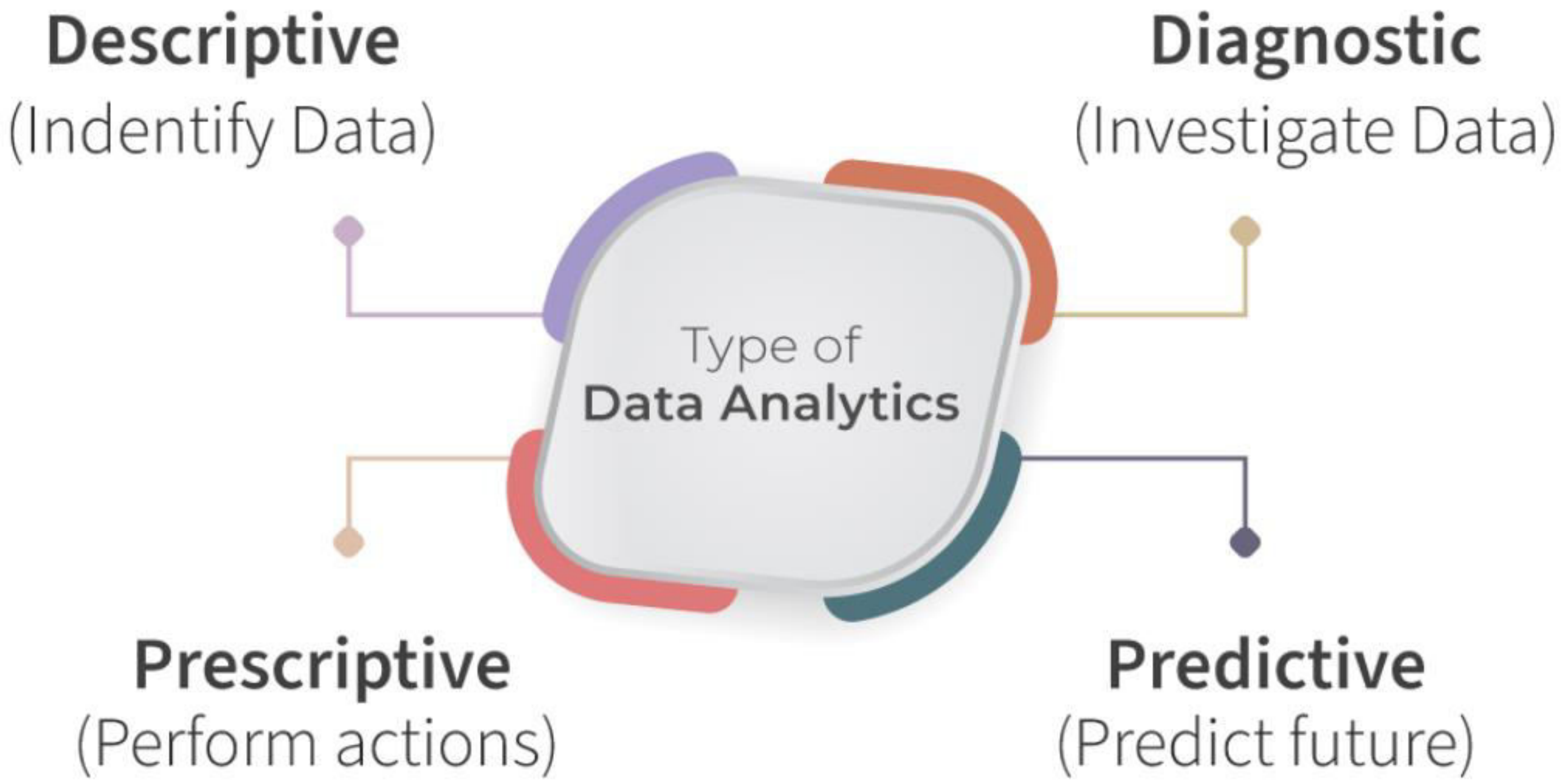
- Multicollinearity occurs when two or more independent variables in a regression model are highly correlated with each other. So, **multicollinearity e**xists when there are linear relationships among the independent variables, this causes issues in regression analysis because it does not follow the assumption of independence among predictors.
- **Causes of Multicollinearity in Regression Analysis**

  1. **Correlation Among Predictor Variables**: Multicollinearity often occurs when predictor variables in a regression model exhibit a **high correlation** with one another. This situation arises when one predictor variable can be accurately predicted from the others, complicating the estimation of individual predictor effects within the model.
  2. **Overparameterization of the Model**: Introducing too many predictor variables closer to the number of observations can also lead to multicollinearity. More predictors can cause redundancy and increase the variance of the coefficient estimates.
  3. **Data Collection Issues**: Problems in the data collection process can also introduce multicollinearity. For instance, if certain variables are measured with exceptional precision or are inherently interconnected, it can lead to multicollinearity in the regression model.

- **To detect multicollinearity we can use:**

  1. **Correlation Matrix:** A correlation matrix helps to find relationships between independent variables. High correlations (close to 1 or -1) suggest multicollinearity.
  2. **VIF (Variance Inflation Factor):** VIF quantifies how much the variance of a regression coefficient increases if predictors are correlated. A high VIF typically above 10 indicates multicollinearity.

Types Of Analytics



Type of Data Analytics

Descriptive
(Indentify Data)

Diagnostic
(Investigate Data)

Prescriptive
(Perform actions)

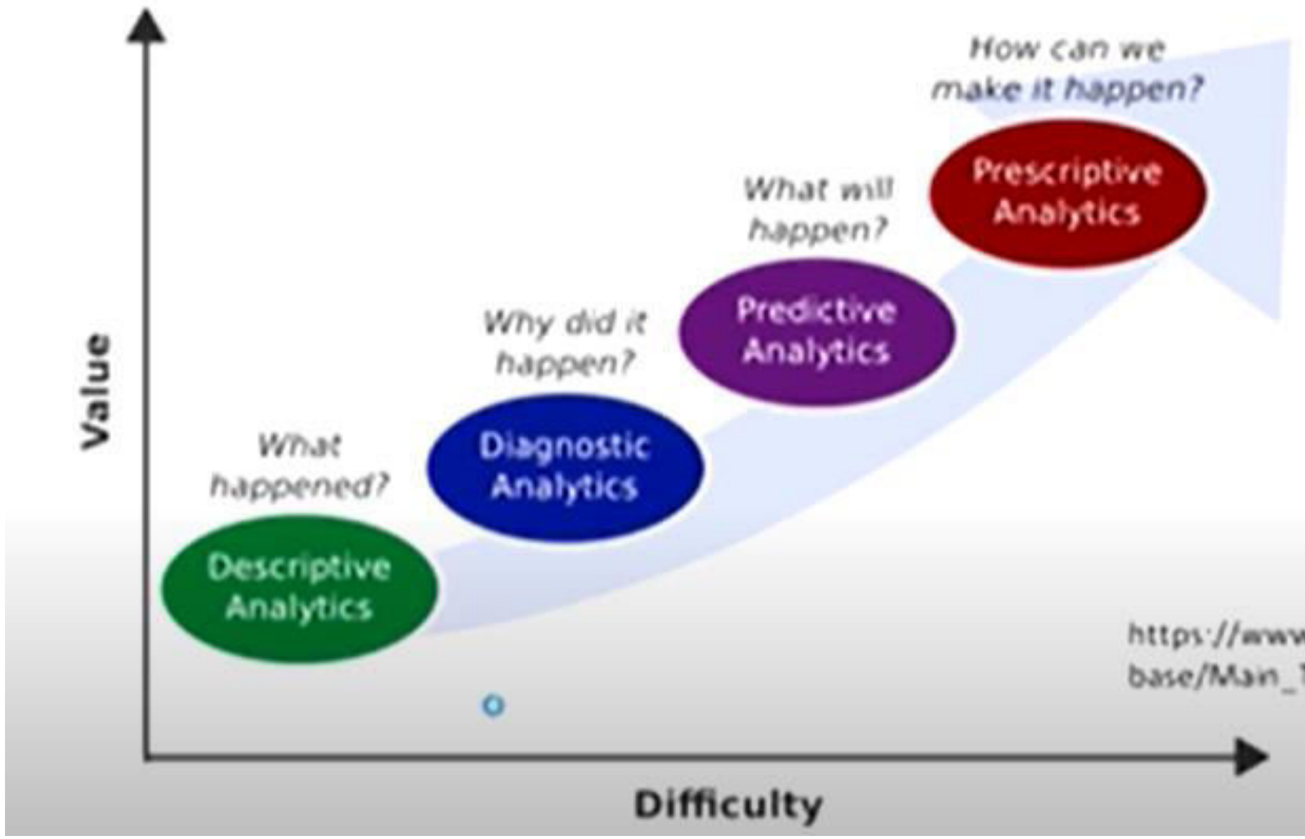
Predictive
(Predict future)

Types Of Analytics

- **Descriptive Data Analytics :** Descriptive data analytics helps to summarize and understand past data. It shows what has happened by using tables, charts and averages. Companies use it to compare results, find strengths and weaknesses and spot any unusual patterns.
- **Diagnostic Data Analytics:** Diagnostic data analytics looks at why something happened in the past. It uses tools like correlation, regression or comparison to find the cause of a problem. This helps companies understand the reason behind a drop in sales or a sudden change in performance.
- **Predictive Data Analytics:** Predictive data analytics is used to guess what might happen in the future. It looks at current and past data to find patterns and make forecasts. Businesses use it to predict things like customer behavior, future sales or possible risks.
- **Prescriptive Data Analytics:** Prescriptive data analytics helps to choose the best action or solution. It looks at different options and suggests what should be done next. Companies use it for things like loan approval, pricing decisions and managing machines or schedules.

- Analytics solutions offer a convenient way to leverage business data.
- But the number of solutions on the market can be daunting—and many may seem to cover a different category of analytics.
- How can organizations make sense of it all?
- Start by understanding the different types of analytics, including descriptive, diagnostic, predictive, and prescriptive analytics.
- In short, they are all forms of data analytics, but each use the data to answer different questions.
- At a high level:
  - **Descriptive Analytics** tells you what happened in the past.
  - **Diagnostic Analytics** helps you understand why something happened in the past.
  - **Predictive Analytics** predicts what is most likely to happen in the future.
  - **Prescriptive Analytics** recommends actions you can take to affect those outcomes.

Classification of Data analytics



What happened?

Descriptive Analytics

Why did it happen?

Diagnostic Analytics

What will happen?

Predictive Analytics

How can we make it happen?

Prescriptive Analytics

https://www.governanceanalytics.org/knowledge-base/Main_Tools/Data_classification_and_analysis

BIG DATA

BIG DATA – SCOPE IN AI

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Learning Objectives

At the end of this session, you will be able to:

- Understand the importance and Scope of Big Data
- The types of data and Characteristics of Big Data

What is Big Data

- Big data is a term for data sets that are so large and complex that it becomes difficult to process using on-hand database management tools or traditional data processing applications.
- **According to Gartner, the definition of Big Data – “Big data is high-volume, velocity, and variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making.”**

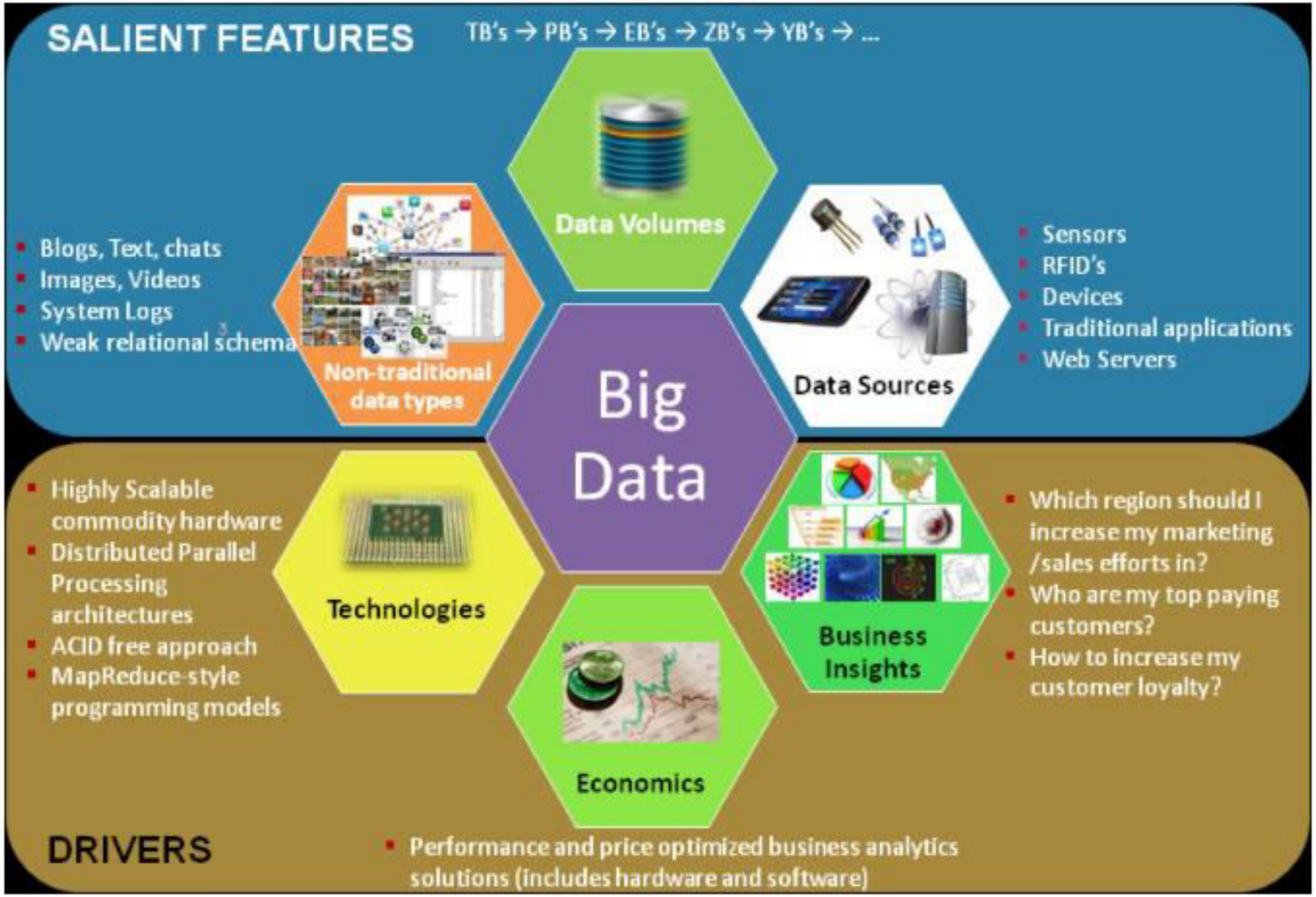
- The trend to larger data sets is due to the additional information derivable from analysis of a single set of large related data, as compared to smaller data sets with the same total amount of data, allowing correlations to be found to “spot business trends, determine quality of research, prevent diseases, link legal citations, combat crime and determine real-time road way traffic conditions”.

What is Big Data (2)

- 2.5 quintillion bytes of data are generated every day by users. Predictions by Statista suggest that by the end of 2021, 74 Zettabytes(74 trillion GBs) of data would be generated by the internet. Managing such a vacuous and perennial outsourcing of data is increasingly difficult. So, to manage such huge complex data, Big data was introduced, it is related to the extraction of large and complex data into meaningful data which can’t be extracted or analyzed by traditional methods.

- All data cannot be stored in the same way. The methods for data storage can be accurately evaluated after the type of data has been identified. A Cloud Service, like Microsoft Azure, is a one-stop destination for storing all kinds of data; blobs, queues, files, tables, disks, and applications data. However, even within the Cloud, there are special services to deal with specific sub-categories of data.
- *For example*, Azure Cloud Services like Azure SQL and Azure Cosmos DB help in handling and managing sparsely varied kinds of data.

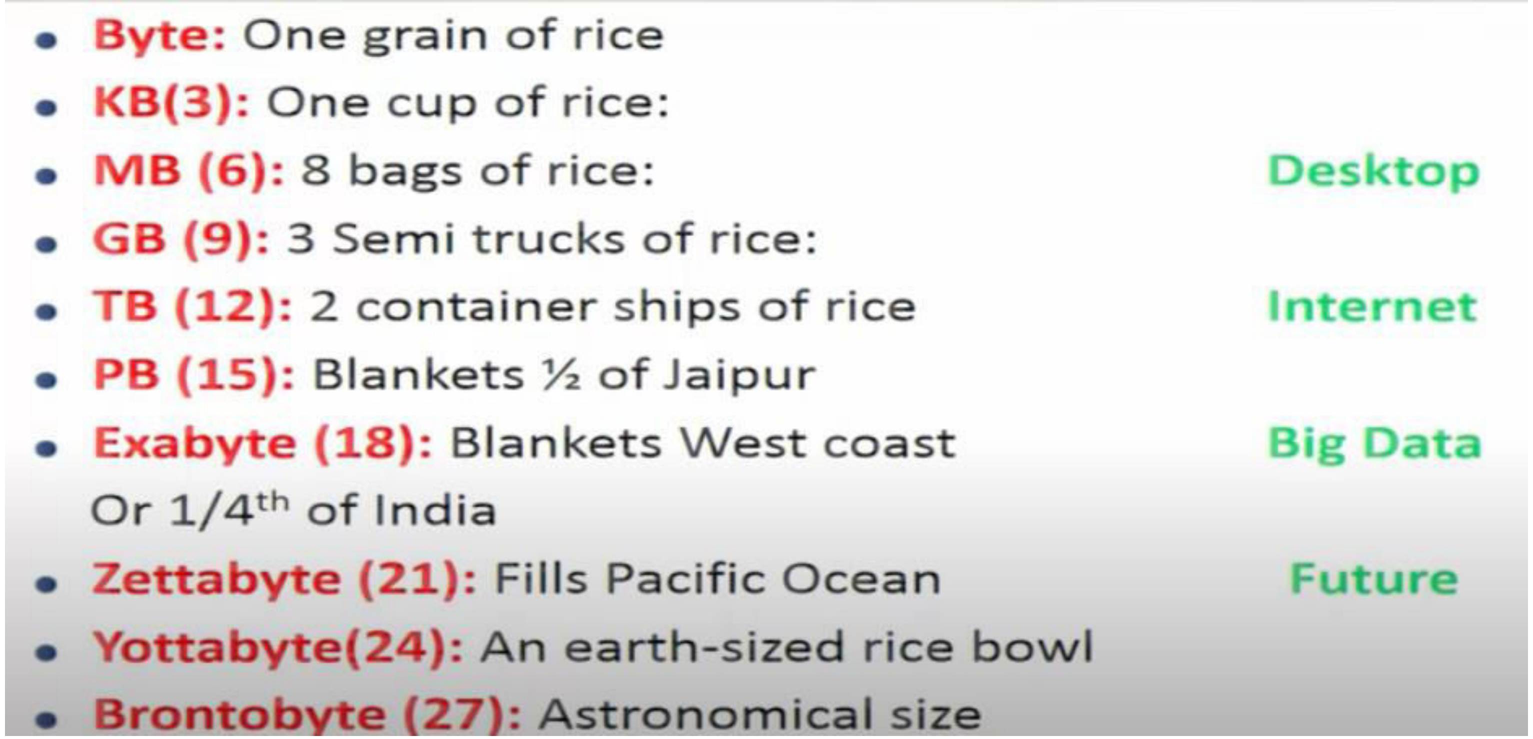
Salient features of Big Data


SALIENT FEATURES
TB's → PB's → EB's → ZB's → YB's → ...
Data Volumes
Non-traditional data types
Blogs, Text, chats
Images, Videos
System Logs
Weak relational schema
Data Sources
Sensors
RFID's
Devices
Traditional applications
Web Servers
Big Data
Technologies
Highly Scalable commodity hardware
Distributed Parallel Processing architectures
ACID free approach
MapReduce-style programming models
Business Insights
Which region should I increase my marketing /sales efforts in?
Who are my top paying customers?
How to increase my customer loyalty?
Economics
DRIVERS
Performance and price optimized business analytics solutions (includes hardware and software)

Facts and Figures

- **Walmart** handles 1 million customer transactions/hour.
- **Facebook** handles 40 billion photos from its user base!
- **Facebook** inserts 500 Terabytes of new data everyday.
- **Facebook** stores, accesses, analyzes, 30-plus petabytes of user-generated data, every day.
- **A flight generates** 240 terabytes of flight data in 6 to 8 hours of flight to make the customer safe, flight and also to basically ensure the, the comforts, during the flight journey.
- **More than 5 billion people**, are calling, texting, tweeting, browsing, on their mobile phones, worldwide. So here the people are involved in generating the bog data.
- **Decoding the human genome** originally took 10 years to process; now it can be achieved in one week
- **The largest AT&T databases**, boasts titles including the largest volumes of data, in one database(312 terabytes) and the second largest number of rows in a unique database (1.9 trillion), which comprises AT&T's extensive calling records.

An insight into Big Data



- Byte: One grain of rice
- KB(3): One cup of rice:
- MB (6): 8 bags of rice: Desktop
- GB (9): 3 Semi trucks of rice:
- TB (12): 2 container ships of rice Internet
- PB (15): Blankets ½ of Jaipur
- Exabyte (18): Blankets West coast Big Data
  Or 1/4th of India
- Zettabyte (21): Fills Pacific Ocean Future
- Yottabyte(24): An earth-sized rice bowl
- Brontobyte (27): Astronomical size

- So, we are going and moving towards this kind of huge volume of data, which is of astronomical size
- **How to handle this kind of data is called a big data computation.**

What’s making so much data (Big data Sources)?

Now, what's make so much of data? Now, here we consider **there are three different sources**, which make or which contributes to this so much of data?

1. **People-** carrying their mobile phone, all the time they are generating the data either in the form of a text in a Facebook, or a GPS when mobile is being carried.

2. **Sensors**- which generates a huge volume of data is using sensors.

3. **Organizations-** normally do the transactions of other services, and its customers

Sources of Data Generation in Big Data

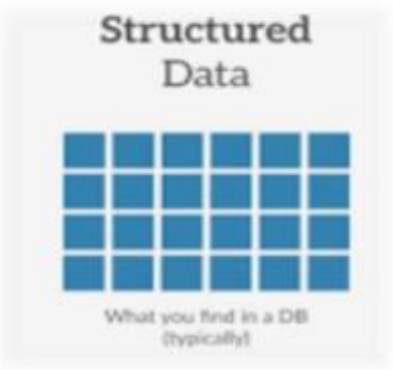
Social Media Sensors Cell Phones GPS Purchase

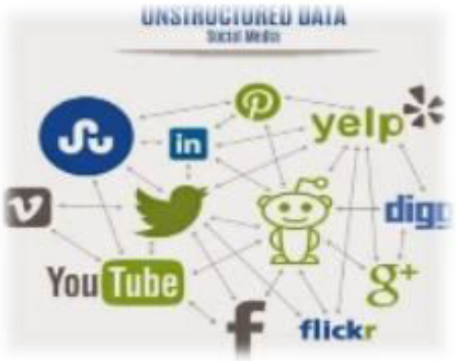
WWW E-mails Media streaming Healthcare IOT

30 billion RFID tags today (1.3B in 2005)
4.6 billion camera phones world wide
100s of millions of GPS enabled devices sold annually
2+ billion people on the Web by end 2011
76 million smart meters in 2009... 200M by 2014
http://www.
Google
talk
YouTube

Data Types in Big Data

- Structured Data
- Unstructured Data
- Semi-Structured Data





information with a degree of organization that is readily searchable and quickly consolidate into facts.

Examples: RDMBS, spreadsheet

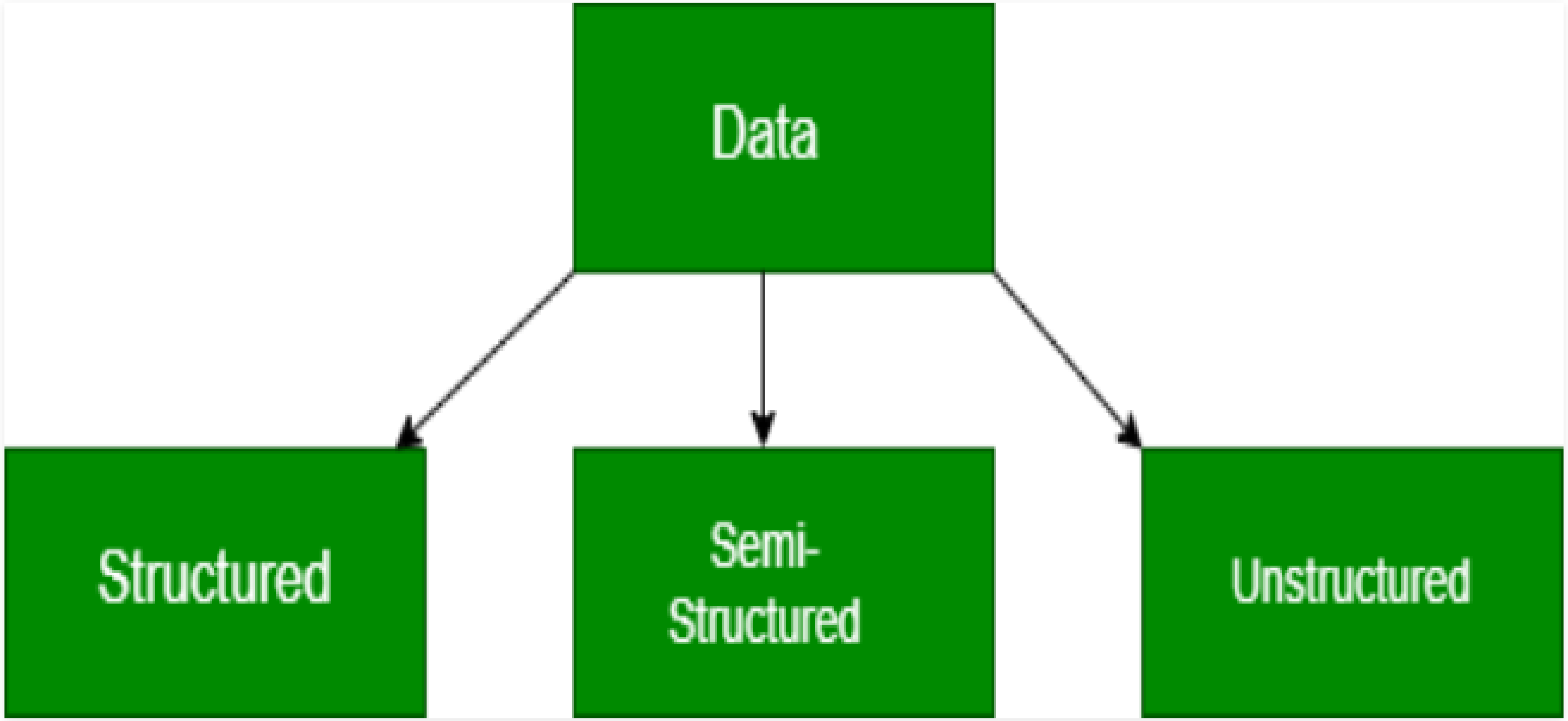
information with a lack of structure that is time and energy consuming to search and find and consolidate into facts

Exemples: email, documents, images, reports

Semi Structured data : XML data

Types of Data in Big Data

Types of Big Data



- **STRUCTURED DATA**
  - Structured data can be crudely defined as the data that resides in a fixed field within a record. It is bound by a certain schema, so all the data has the same set of properties. Structured data is also called relational data. It is split into multiple tables to enhance the integrity of the data by creating a single record to depict an entity. Relationships are enforced by the application of table constraints. A *Structured Query Language (SQL)* is needed to bring the data together. Structured data is easy to enter, query, and analyze the data.
  - *Examples* of structured data include numbers, dates, strings, etc. The business data of an e-commerce website can be considered to be structured data.

Types of Data in Big Data (2)

- **SEMI-STRUCTURED DATA**
  - Semi-structured data is not bound by any rigid schema for data storage and handling. The data is not in the relational format and is not neatly organized into rows and columns like that in a spreadsheet. However, there are some features like key-value pairs that help in discerning the different entities from each other.

SEMI-STRUCTURED DATA

- **Since semi-structured data doesn't need a structured query language, it is commonly called *NoSQL data*.** A data serialization language is used to exchange semi-structured data across systems that may even have varied underlying infrastructure.
- *Examples* of structured data include numbers, dates, strings, etc. The business data of an e-commerce website can be considered to be structured data.
- **XML (Extensible markup language), JSON (JavaScript Object Notation), YAML make use of unstructured data**
- A product catalog organized by tags is an example of semi-structured data.

Types of Data in Big Data (3)

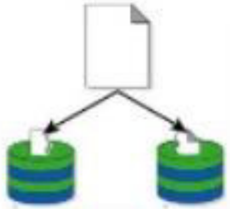
- **UNSTRUCTURED DATA**
  - Unstructured data doesn’t have any structure (or specified format) at all.
  - Unstructured data is the kind of data that doesn’t adhere to any definite schema or set of rules. Its arrangement is unplanned and haphazard.
  - Books, journals, documents, metadata, health records, audio, video, analog data, text documents, body of an email, Web page, word-processor document, and log files etc. can be generally considered unstructured data.
  - Even though the metadata accompanying an image or a video may be semi-structured, the actual data being dealt with is unstructured.
  - 80% of data available to enterprises is unstructured, and is really most of the data that you will encounter.

Challenges of Unstructured Data

How do you store
Billions of Files?

How long does it take to
migrate 100's of TB's or
data every 3-5 years

Data has no
structure



Data Redundancy

Data Backup

Resources Limitation

Why is Big Data important?

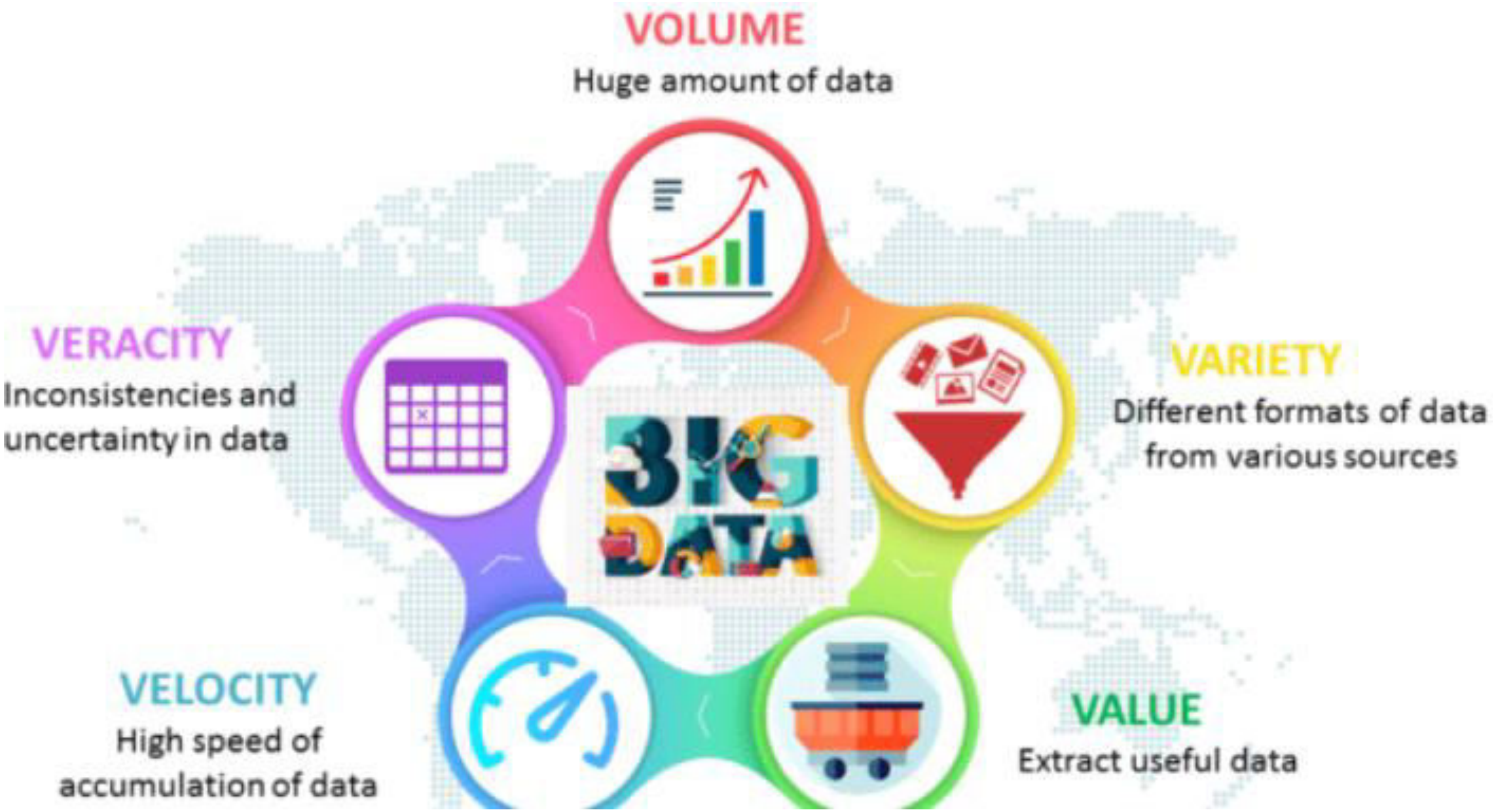
The importance of big data does not revolve around how much data a company has but how a company utilizes the collected data. Big Data enables:

1. Cost Savings
2. Time Reductions
3. Understand the market conditions
4. Sentiment analysis
5. Boost Customer Acquisition and Retention
6. Solve Advertisers Problem and Offer Marketing Insights
7. Innovations and Product Development

The five V’s of Big Data

- Volume
- Variety
- Velocity
- Veracity
- Value

The five V's of Big Data defined



VOLUME
Huge amount of data

VERACITY
Inconsistencies and uncertainty in data

VARIETY
Different formats of data from various sources

VELOCITY
High speed of accumulation of data

VALUE
Extract useful data

Advantages of Big Data

- Big Data has enabled predictive analysis which can save organizations from operational risks
- Predictive analysis has helped organizations grow business by analyzing customer needs
- Big Data has enabled many multimedia platforms to share data Ex: YouTube, Instagram
- Medical and Healthcare sectors can keep patients under constant observations
- Big Data changed the face of customer-based companies and worldwide market

Applications of Big Data

Big Data is considered the most valuable and powerful **fuel** that can run the massive IT industries of the 21st Century. Big Data is being the most wide-spread technology that is being used in almost every business sector.

- Travel and Tourism
- Banking & Financial Services Institutions (BFSI)
- Telecommunications and Multimedia
- Government and Military

Challenges with Big Data

- **Sharing and Accessing Data**
- **Privacy and Security**
- **Analytical Challenges**
- **Technical challenges**
- **Fault tolerance**
- **Scalability**

Challenges with Big Data

- Sharing and Accessing Data
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Industry Examples of Big Data

1. Fraud Detection
2. IT Log Analytics
3. Call Center Analytics
4. Social Media Analytics (SMA) / Mobile Analytics
5. Improving Healthcare and Public Health
6. The Role of Big Data in Medicine (Pharmacy)
7. Science and Technology

- **Some other fields that come under the umbrella of Big Data are :**
  - Stock Exchange Data
  - Power Grid Data
  - Metrological and Transport data
  - Search Engine Data and Social Web data
  - Social, Census and Meta-morphical data
  - Financial Services
  - Advertising and marketing agencies track social media to understand responsiveness to campaigns, promotions, and other advertising mediums.
  - Hospitals are analysing medical data and patient records to predict those patients that are likely to seek readmission within a few months of discharge

What is Analytics?

Analytics is the use of:

data,
information technology,
statistical analysis,
quantitative methods, and
mathematical or computer-based models

to help managers gain improved insight about their business operations and make better, fact-based decisions.

ANALYTICS is the discovery and communication of meaningful patterns in data. Especially valuable in areas rich with recorded information, Analytics relies on the simultaneous application of statistics, computer programming and Operations Research to quantify performance. Analytics often favors data visualization to communicate insight.

Analytics refers to the process of working with data to find out valuable insights (by applying some statistical models or methods) which can lead to extremely useful solutions for the entire business. There are various kind of Business Analytics depending on the kind of problems the company is facing – such as Marketing Analytics, Financial Analytics, Healthcare Analytics etc.

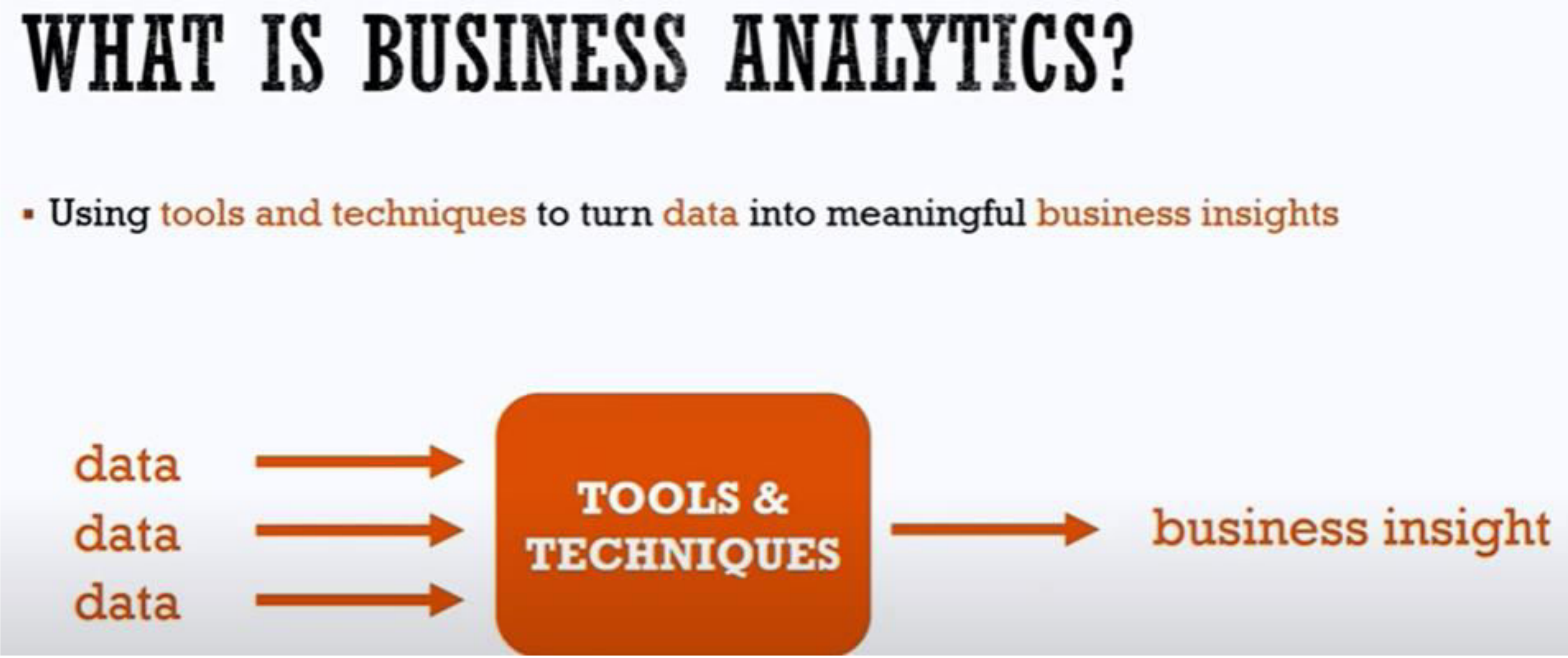
Past Data
Insights
Business planning

The GOAL of Data Analytics is to get actionable insights resulting in smarter decisions and better business outcomes.

Analytics Scenarios (Examples)

Example 1: Let’s say some company which is trying to launch a new product into the market, and is looking for funding – they might be looking into the sales forecast and trying to get probable investors, and trying to find out what should be the basic price point of the product that they are going to put into the market. So, if you are launching a new product, you have to do a lot of research and find out different insights as to what price point may work, doing what kind of marketing, what kind of branding would work. That is also a part of ANALYTICS.

Example 2 : There is a company, which is a good company but they don’t understand why so many employees are leaving them. If they cannot find out, they may be doing ANALYTICS to find out what triggers the employee attrition rate, and how they can find ways to fix it.



WHAT IS BUSINESS ANALYTICS?

- Using tools and techniques to turn data into meaningful business insights

data

data

data

TOOLS & TECHNIQUES

business insight

Business Analytics – An Overview

❑ Business Analytics is the process by which businesses use statistical methods and technologies for analyzing historical data in order to *gain new insight and improve strategic decision-making.*

❑ It refers to the use of methodologies such as data mining, predictive analytics, and statistical analysis in order to analyze and transform data into useful information, identify and anticipate trends and outcomes, and ultimately *make smarter, data-driven business decisions.*

Introduction to Business Analytics

- **The primary purpose of business analytics is to assist and aid in and drive in decision making activities of a busines or organisation.**

- **What is Business Analytics?**

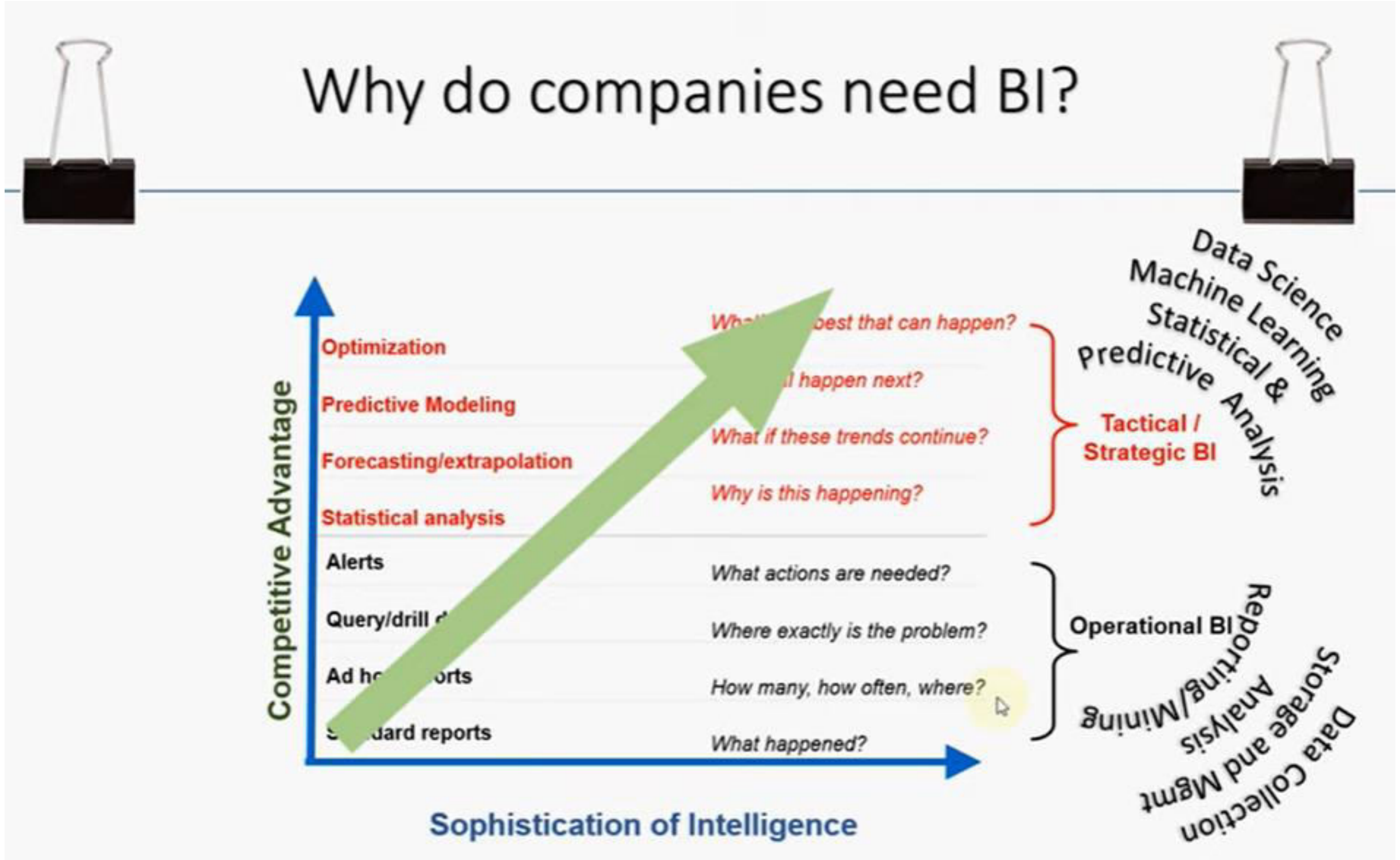
  - “**Business analytics** is comprised of solutions used to build analysis models and simulations to create scenarios, understand realities and predict future states. “ – Gartner IT Glossary

  - Includes Data Mining, predictive analytics, applied analytics and statistics, and is delivered as an application suitable for a business user.

  - These analytics solutions often come with prebuilt industry content that is targeted at an industry business process (for example, claims, underwriting or a specific regulatory requirement).”

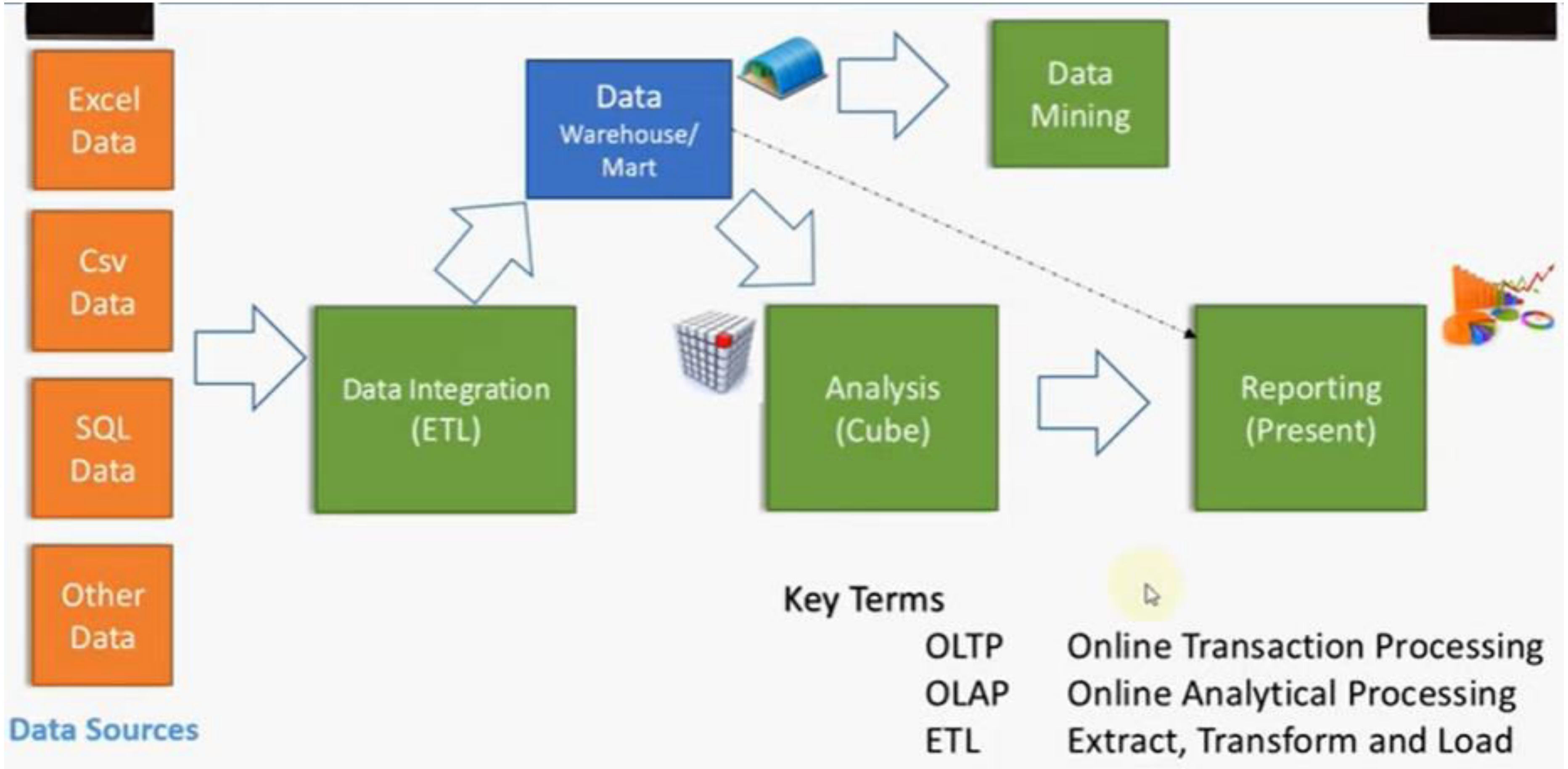
BIG DATA AND BUSINESS INTELLIGENCE

- BI is a system that collects, integrates , analyses and presents business information to support **better** decision making. Decisions can be at the strategic, tactical or operational level of management .
- The **right information**, at the **right time**, and in **the right format** has to be provided for enhanced decision making in business.
- Competitive Advantage vs. Sophistication of Intelligence



Why do companies need BI?

BUSINESS INTELLIGENCE COMPONENTS



Key Terms

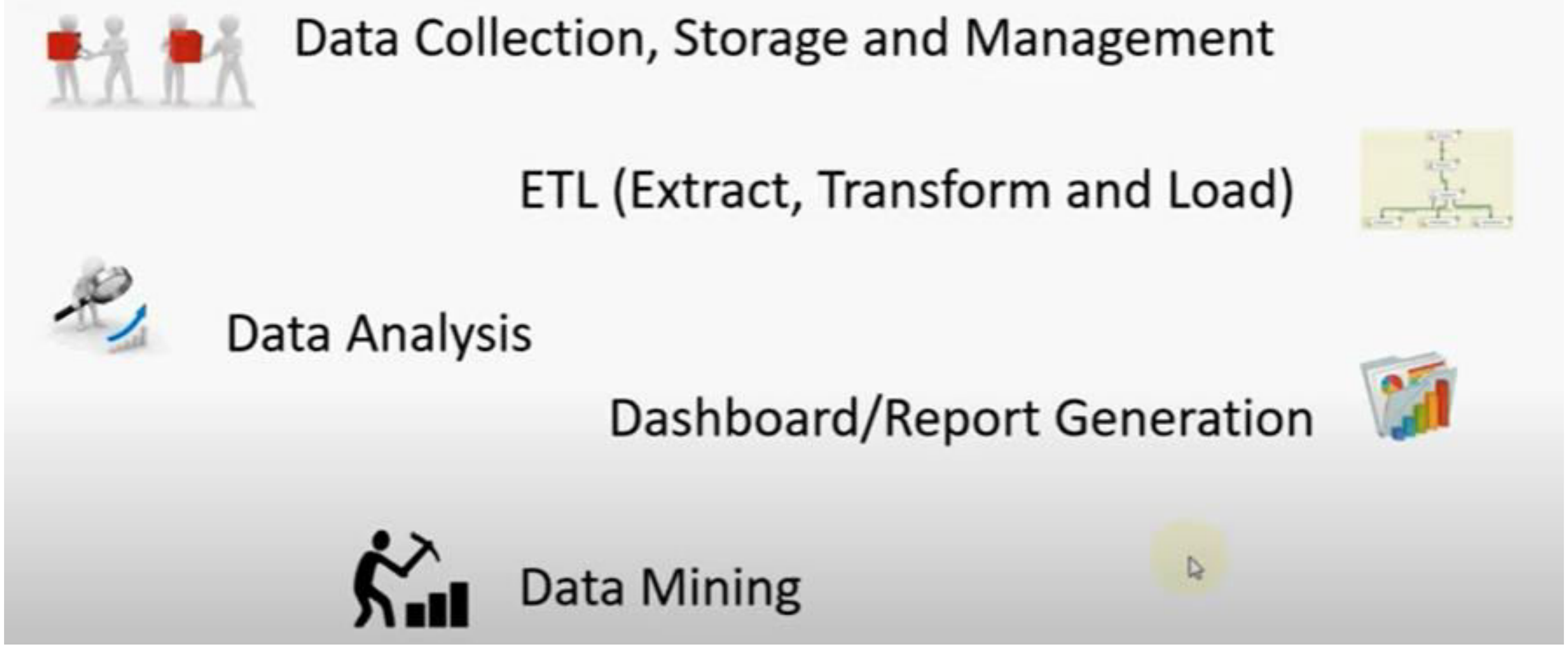
OLTP	Online Transaction Processing
OLAP	Online Analytical Processing
ETL	Extract, Transform and Load

BIG DATA AND DATA RISK

- According to Bernard Marr “As with any business initiative, a big data project involves an element of risk. Any project can fail for any number of reasons: bad management, under-budgeting, or a lack of relevant skills. However, big data projects bring their own specific risks.”
- Care must be taken at every step of a big data project to ensure you don’t stumble into pitfalls which could lead to wasted time and money, or even legal trouble.

1. DATA SECURITY
2. DATA PRIVACY
3. COSTS OF DATA COLLECTION, ANALYSIS AND REPORTING
4. BAD ANALYTICS (Misinterpreting the Patterns shown by your data)
5. BAD DATA (Data projects that start off on the wrong foot by collecting irrelevant, out of date, or erroneous data gets impounded heavily).
6. RULES AND REGULATIONS

BI Capabilities



Data Collection, Storage and Management

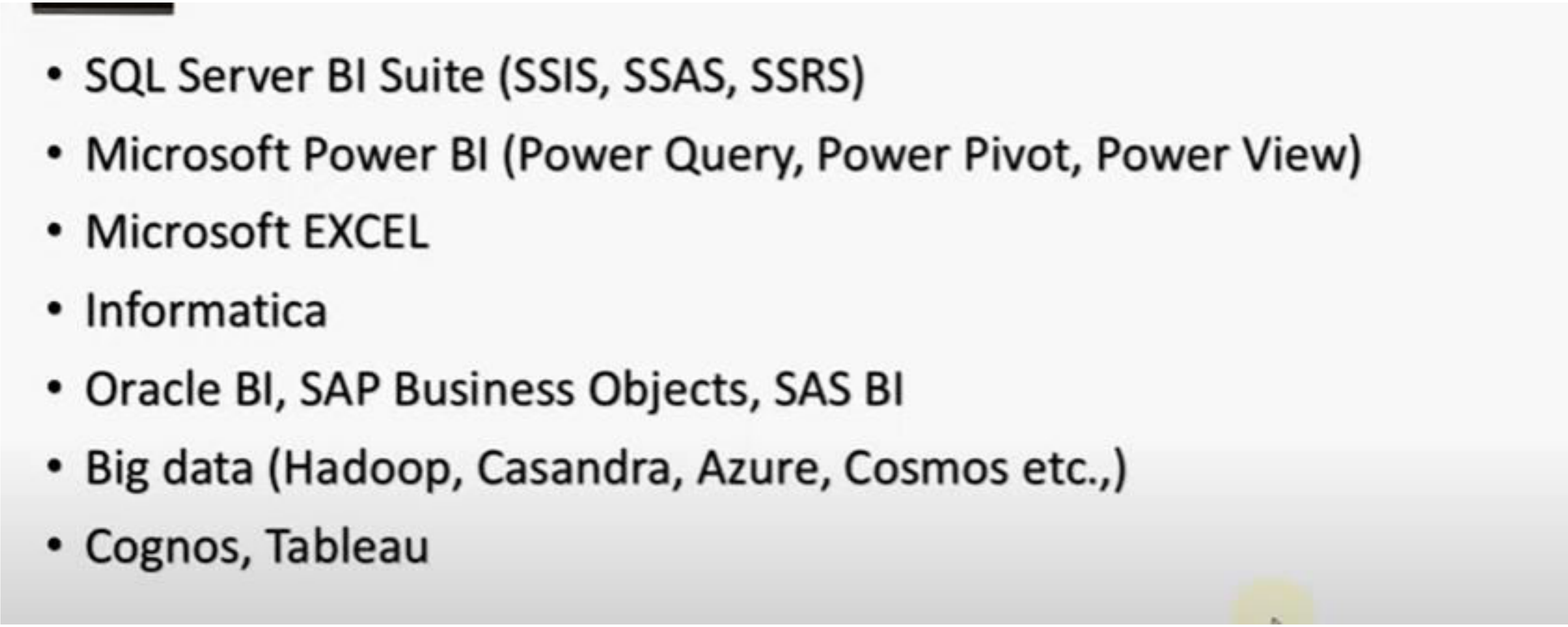
ETL (Extract, Transform and Load)

Data Analysis

Dashboard/Report Generation

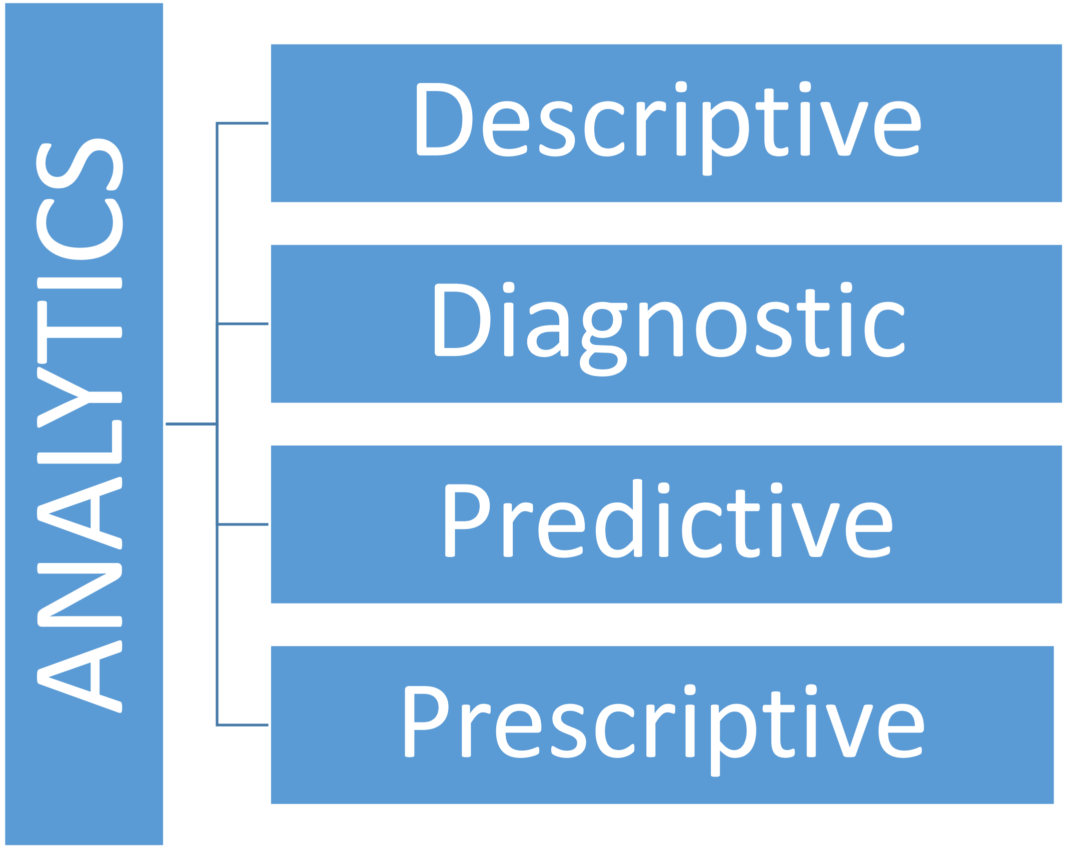
Data Mining

BI / Analytics Tools



- SQL Server BI Suite (SSIS, SSAS, SSRS)
- Microsoft Power BI (Power Query, Power Pivot, Power View)
- Microsoft EXCEL
- Informatica
- Oracle BI, SAP Business Objects, SAS BI
- Big data (Hadoop, Casandra, Azure, Cosmos etc.,)
- Cognos, Tableau

TYPES OF ANALYTICS



ANALYTICS

Descriptive

Diagnostic

Predictive

Prescriptive

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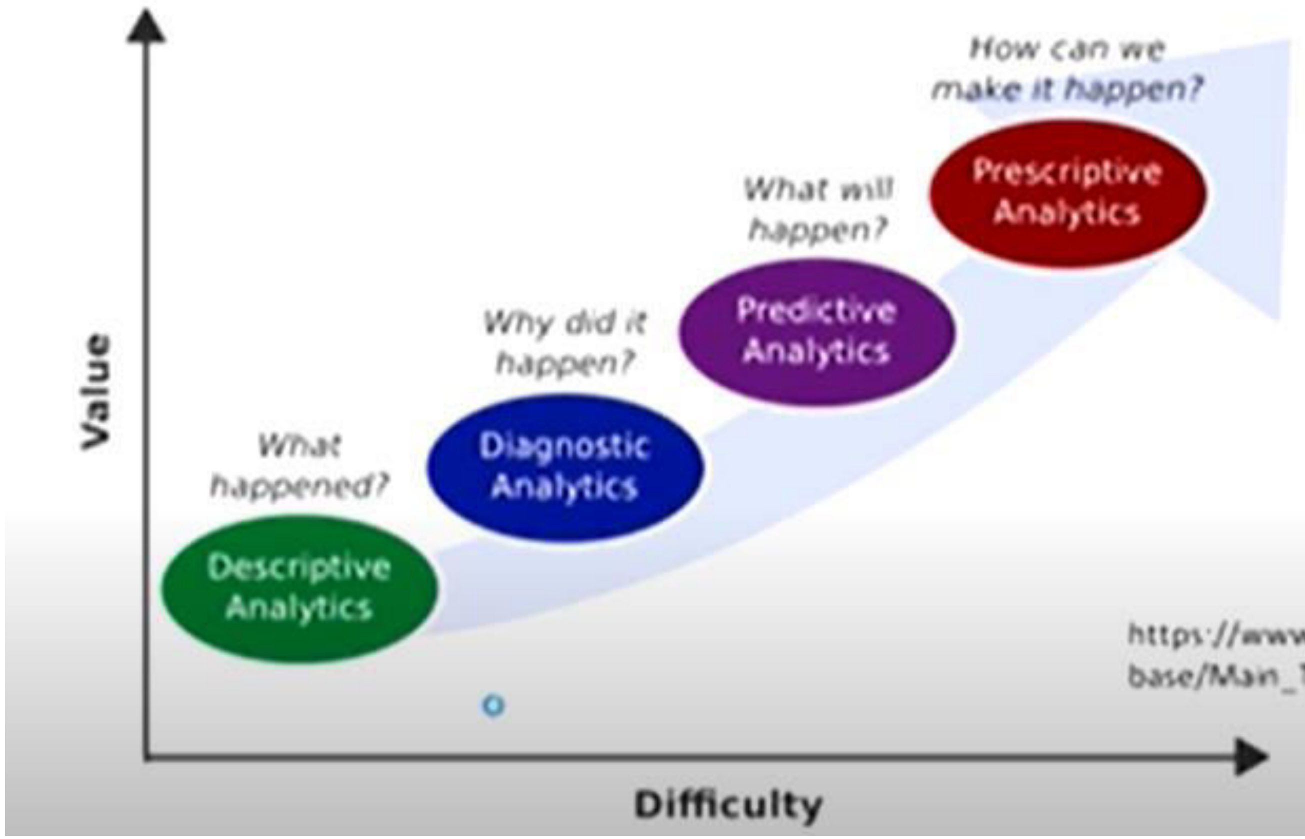
Classification of Data analytics



https://www.governanceanalytics.org/knowledge-base/Main_Tools/Data_classification_and_analysis

Descriptive Analytics
(business intelligence and data mining)

- **Descriptive analytics** looks at data statistically to tell you what happened in the past. Descriptive analytics helps a business understand how it is performing by providing context to help stakeholders interpret information. This can be in the form of data visualizations like graphs, charts, reports, and dashboards.
- ***How can descriptive analytics help in the real world?***
- In a healthcare setting, for instance, say that an unusually high number of people are admitted to the emergency room in a short period of time. Descriptive analytics tells you that this is happening and provides real-time data with all the corresponding statistics (date of occurrence, volume, patient details, etc.).
- Descriptive models can be used, for example, to categorize customers by their product preferences and life stage.
- These models can de utilized to develop further models that can simulate large number of individualized agents and make predictions. For example, descriptive analytics examines historical electricity usage data to help plan power needs and allow electric companies to set optimal prices

Diagnostic Analytics

- **Diagnostic analytics** takes descriptive data a step further and provides deeper analysis to answer the question: Why did this happen? Often, diagnostic analysis is referred to as root cause analysis. This includes using processes such as data discovery, data mining, and drill down and drill through.
- In the healthcare example mentioned earlier, diagnostic analytics would explore the data and make correlations. For instance, it may help you determine that all of the patients’ symptoms—high fever, dry cough, and fatigue—point to the same infectious agent. You now have an explanation for the sudden spike in volume at the ER.

Predictive Analytics (forecasting)

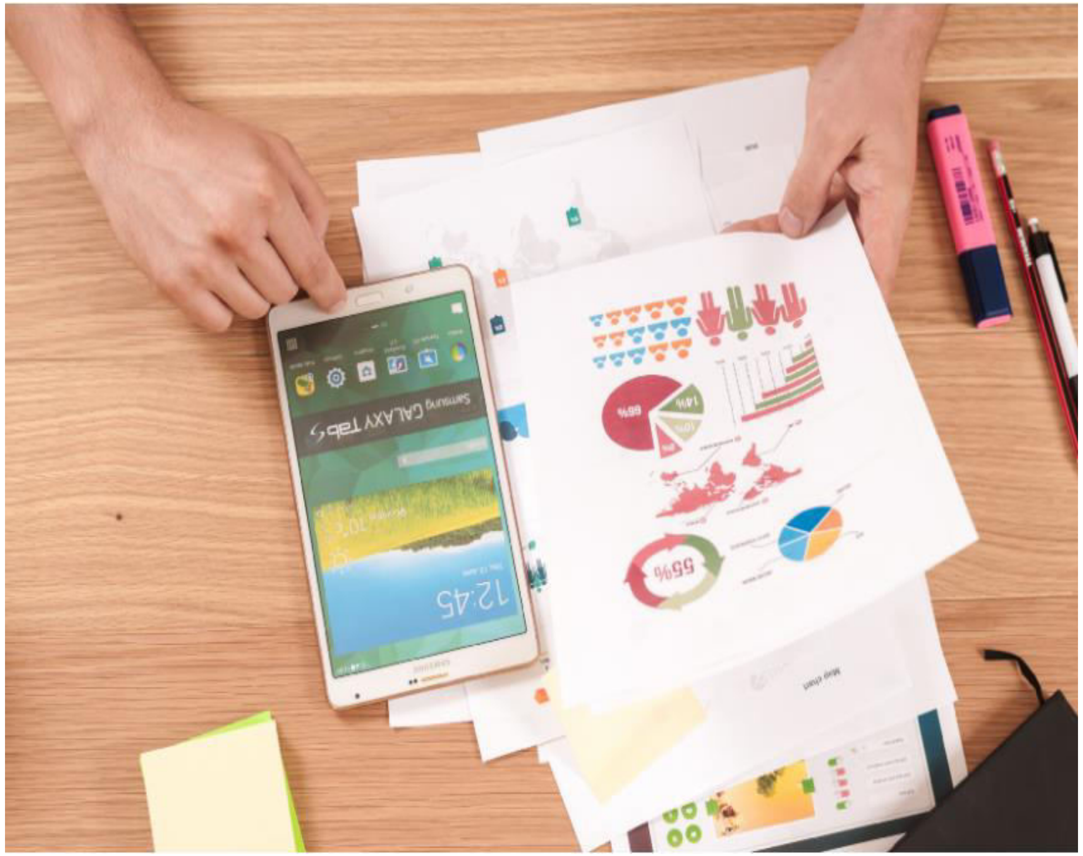
- **Predictive analytics** takes historical data and feeds it into a machine learning model that considers key trends and patterns. The model is then applied to current data to predict what will happen next.
- The 3 basic cornerstones of Predicitive Analytics are:
  - Predictive modelling
  - Decision Analysis and Optimization
  - Prescriptive (optimization and simulation)
- Back in our hospital example, predictive analytics may forecast a surge in patients admitted to the ER in the next several weeks. Based on patterns in the data, the illness is spreading at a rapid rate.
- Example 2 - optimizing CRM(customer relationship management) systems. They can help enable an org to analyse all customer data therefore exposing patterns that predict customer behaviour
- Example 3 – For an organization that offers multiple products, predictive analytics can help analyze customers' spending, usage, and other behaviour, leading to efficient cross sales, or selling additional products to current customers.

Prescriptive Analytics (optimization and simulation)

- **Prescriptive analytics** automatically synthesizes big data, mathematical sciences, business rules, and machine learning to make predictions and then suggests decision options to take advantage of the predictions.
- **Prescriptive analytics** takes predictive data to the next level. Now that you have an idea of what will likely happen in the future, what should you do? It suggests various courses of action and outlines what the potential implications would be for each.
- Back to our hospital example: now that you know the illness is spreading, the prescriptive analytics tool may suggest that you increase the number of staff on hand to adequately treat the influx of patients.
- Another example is energy and utilities. Natural gas prices fluctuate dramatically depending upon supply, demand, econometrics, geo-politics, and weather conditions. Prescriptive analytics can accurately predict prices by modelling internal and external variables simultaneously and also provide decision options and show the impact of each option.

Analytics Applications

- Management of customer relationships
- Financial and marketing activities
- Supply chain management
- Human resource planning
- Pricing decisions
- Sport team game strategies



Importance of Analytics

- There is a strong relationship of ANALYTICS with:
  - profitability of businesses
  - revenue of businesses
  - shareholder return
- ANALYTICS enhances understanding of data
- ANALYTICS is vital for businesses to remain competitive
- ANALYTICS enables creation of informative reports

This Concludes Today’s Presentation

Thank you for your attention