



Welcome to this session: Task Walkthrough - Tasks 17 - 21

The session will start shortly...

Questions? Drop them in the chat.
We'll have dedicated moderators
answering questions.



Safeguarding & Welfare

We are committed to all our students and staff feeling safe and happy; we want to make sure there is always someone you can turn to if you are worried about anything.

If you are feeling upset or unsafe, are worried about a friend, student or family member, or you feel like something isn't right, speak to our safeguarding team:



Ian Wyles
Designated Safeguarding
Lead



Simone Botes



Nurhaan Snyman



Rafiq Manan



Ronald Munodawafa



Tevin Pitts

Scan to report a
safeguarding concern



or email the Designated
Safeguarding Lead:
Ian Wyles

safeguarding@hyperiondev.com

Skills Bootcamp Data Science

- The use of disrespectful language is prohibited in the questions, this is a supportive, learning environment for all - please engage accordingly. **(Fundamental British Values: Mutual Respect and Tolerance)**
- No question is daft or silly - **ask them!**
- There are **Q&A sessions** midway and at the end of the session, should you wish to ask any follow-up questions. Moderators are going to be answering questions as the session progresses as well.
- If you have any questions outside of this lecture, or that are not answered during this lecture, please do submit these for upcoming Academic Sessions. You can submit these questions here: [Questions](#)

Skills Bootcamp Data Science

- For all **non-academic questions**, please submit a query:
www.hyperiondev.com/support
- **Report a safeguarding incident:** **www.hyperiondev.com/safeguardreporting**
- We would love your feedback on lectures: **[Feedback on Lectures](#)**
- If you are hearing impaired, please kindly use your computer's function through Google chrome to enable captions.

Learning Outcomes

- ❖ **Explain the differences** between Linear Regression, Logistic Regression, and Decision Trees.
- ❖ **Implement Linear Regression** to predict continuous outcomes.
- ❖ **Implement Logistic Regression** to classify categorical outcomes.
- ❖ **Apply Decision Trees** for classification and regression problems.
- ❖ **Compare and evaluate** the strengths, weaknesses, and use cases of each model.

Lecture Overview

- Presentation of the Task
- Machine Learning
- Linear Regression
- Logistic Regression
- Decision Trees
- Task Walkthrough



Task Walkthrough

Imagine you are a data scientist in a healthcare organization. Your team is developing a model to predict diabetes risk and glucose levels based on patient information. Your tasks include:

- ❖ Linear Regression model: to predict Glucose Levels using BMI, Age, and BP.
- ❖ Logistic Regression model: to classify Diabetes Risk (Yes/No).
- ❖ Decision Tree model: to classify patients into risk categories based on their features.
- ❖ Compare model performance and decide which one is best for this problem.



What type of variable does Linear Regression predict?

- A. Categorical
- B. Numerical
- C. Boolean
- D. Ordinal



When is Logistic Regression used instead of Linear Regression?

- A. When predicting numerical values
- B. When classifying categorical outcomes
- C. When performing clustering analysis
- D. When visualizing data



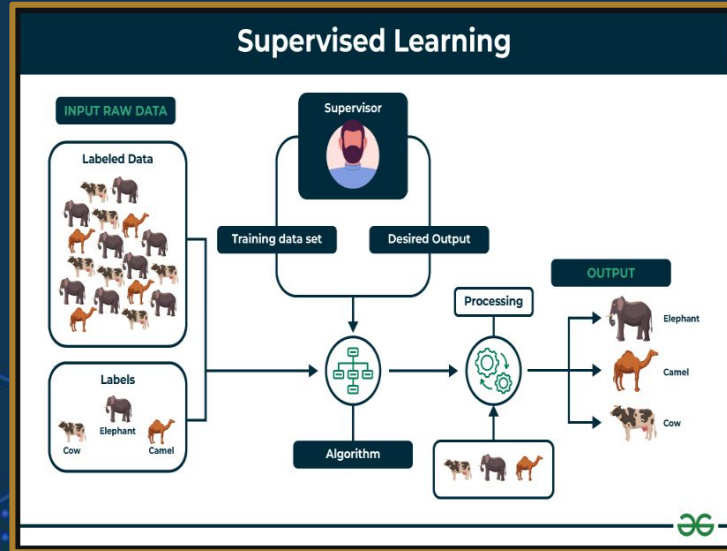
Introduction to Machine Learning



- ❖ Machine learning is a way of teaching computers to learn and improve from experience without being explicitly programmed.
- ❖ It allows computers to automatically learn and adapt based on data.

Types of machine learning

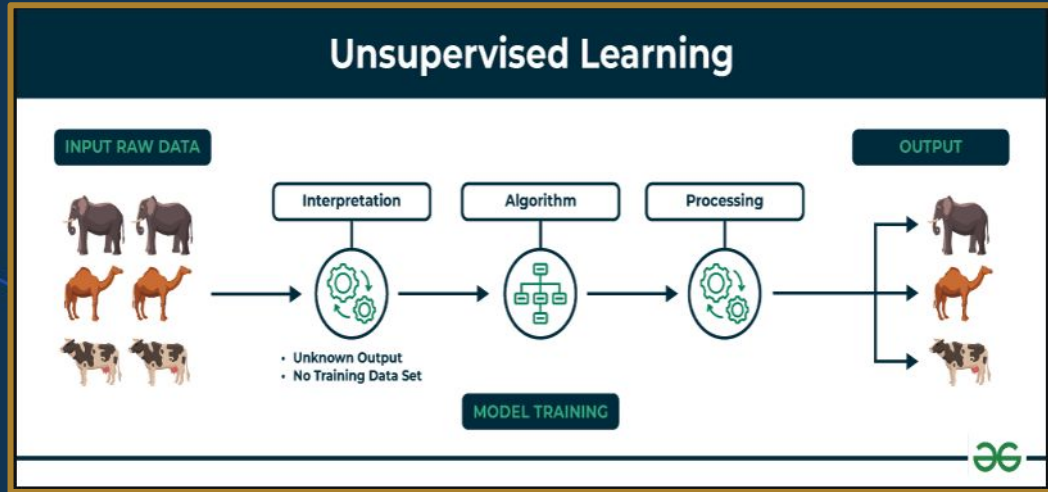
- ❖ **Supervised learning:** The computer learns from labelled data, where both input and output data are provided.



Source: [geeksforgeeks](https://www.geeksforgeeks.org/)

Types of machine learning

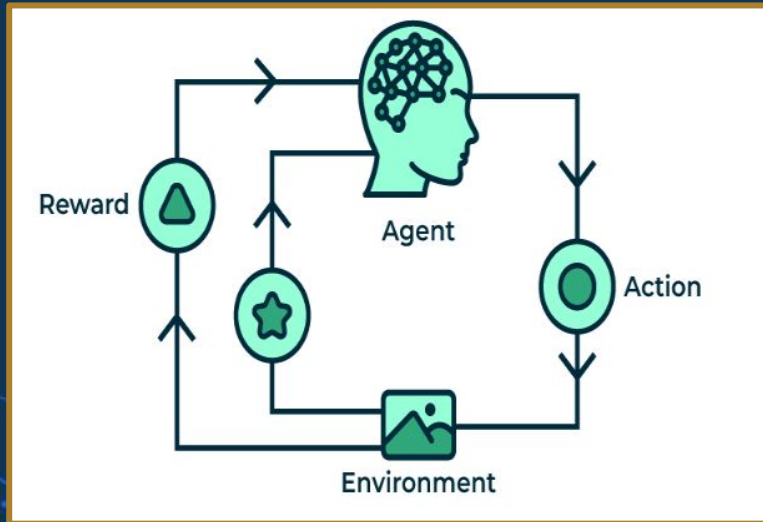
- ❖ **Unsupervised learning:** The computer learns from unlabeled data, discovering hidden patterns or structures on its own.



Source: [geeksforgeeks](https://www.geeksforgeeks.org/)

Types of machine learning

- ❖ **Reinforcement learning:** The computer learns through interaction with an environment, receiving rewards or penalties for its actions.



Source: [geeksforgeeks](https://www.geeksforgeeks.com/reinforcement-learning/)




Types of Supervised Learning

- ❖ **Regression:** Predicting continuous numerical values, such as house prices or stock prices.
- ❖ **Classification:** Predicting discrete categories or classes, such as whether an email is spam or not.



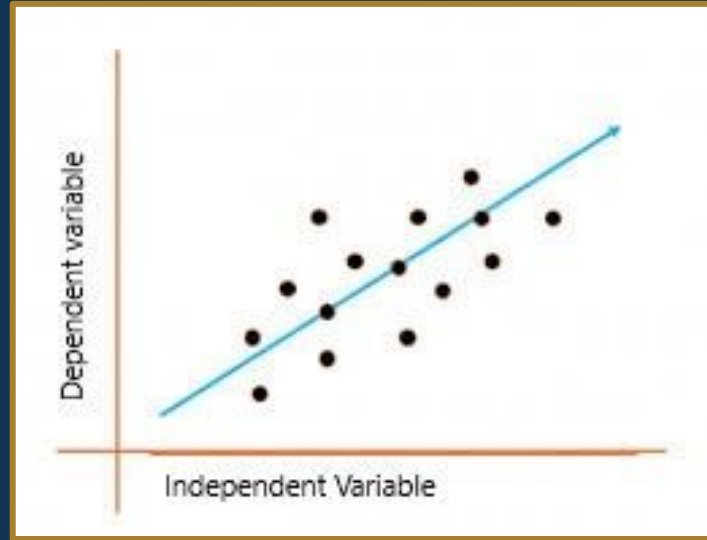


Supervised Learning Algorithms

- ❖ **Linear regression:** Fitting a straight line to data points to make predictions.
 - ❖ **Logistic regression:** Predicting binary outcomes, such as yes/no or true/false.
 - ❖ **Decision trees:** Making decisions based on a series of questions or conditions.
 - ❖ **Support vector machines (SVM):** Finding the best boundary to separate different classes.
 - ❖ **Neural networks:** Mimicking the structure and function of the human brain to learn complex patterns.
- 

Simple Linear Regression

- ❖ Simple linear regression is a method to study the relationship between two variables: an independent variable (x) and a dependent variable (y).
- ❖ It helps us understand how changes in the independent variable affect the dependent variable.

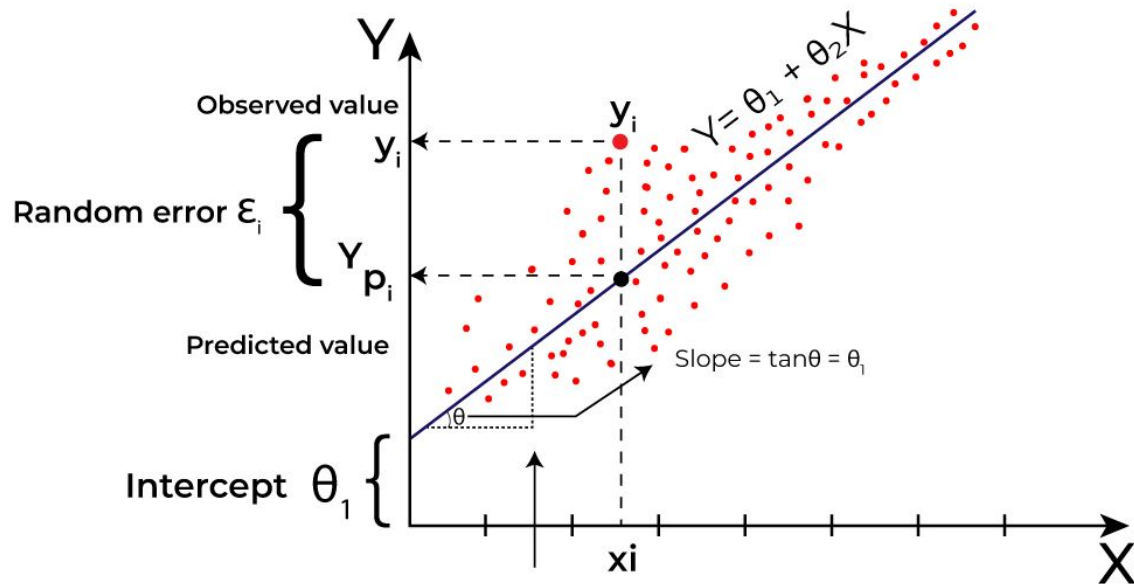


Source: [Analytics Vidhya](#)



Math behind Simple Linear Regression

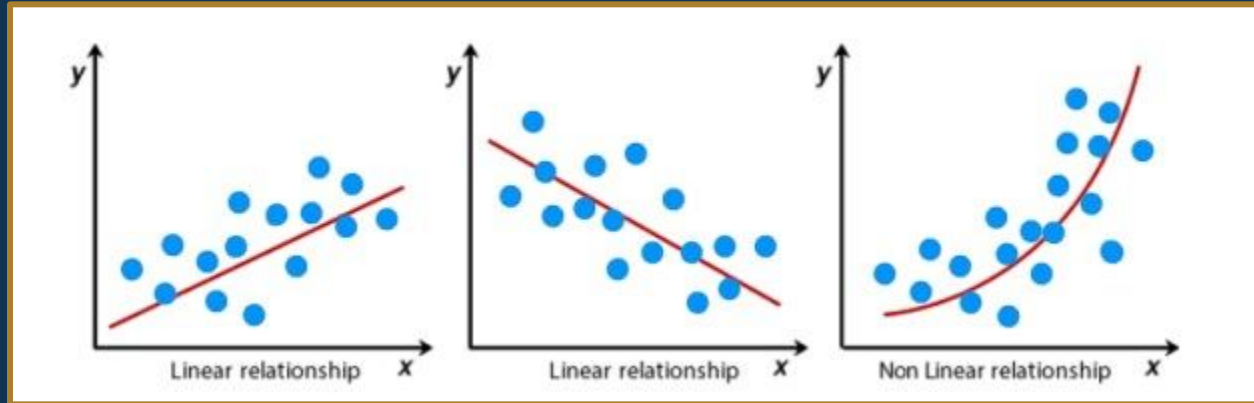
- ❖ The equation is written as: $y = \beta_0 + \beta_1 x + \varepsilon$
 - β_0 is the intercept, representing the value of y when x is zero.
 - β_1 is the slope, indicating how much y changes for a one-unit increase in x .
 - ε is the error term, accounting for the variability in y that cannot be explained by x .



Source: [geeksforgeeks](https://www.geeksforgeeks.org/)

Assumptions and Limitations of Simple Linear Regression

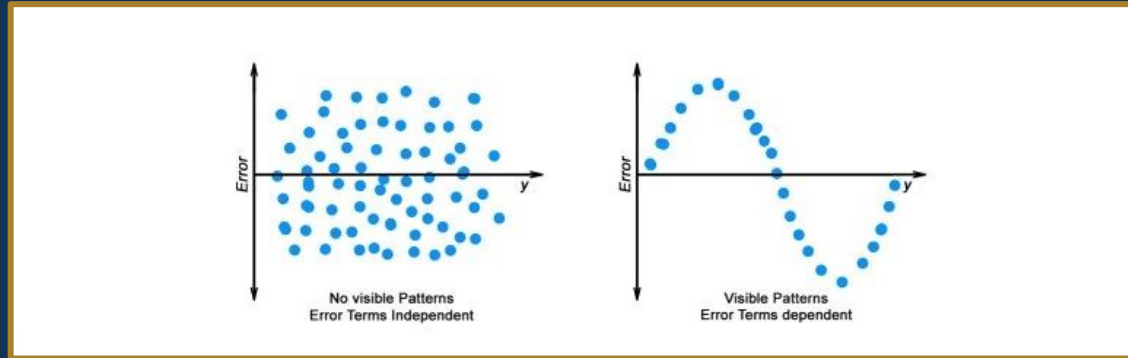
- ❖ **Linearity:** The relationship between x and y should be linear.



Source: [Analytics Vidhya](#)

Assumptions and Limitations of Simple Linear Regression

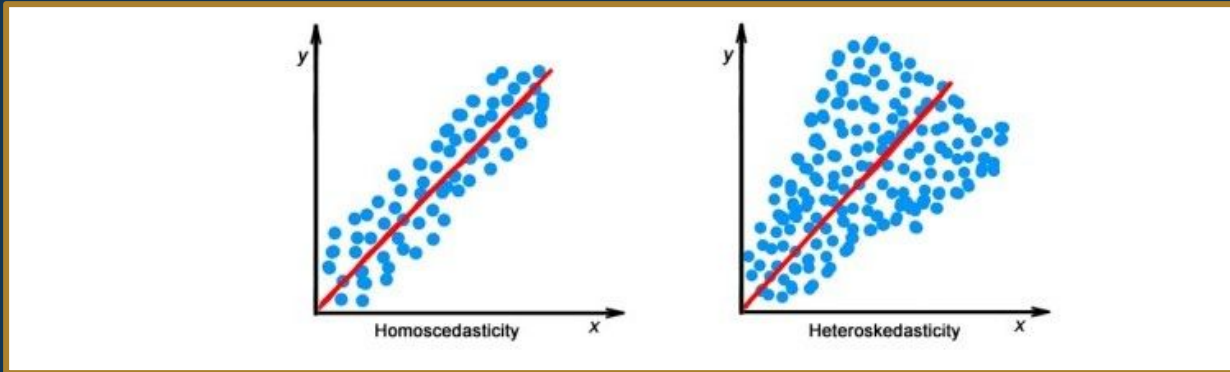
- ❖ **Independence:** The observations should be independent of each other.



Source: [Analytics Vidhya](#)

Assumptions and Limitations of Simple Linear Regression

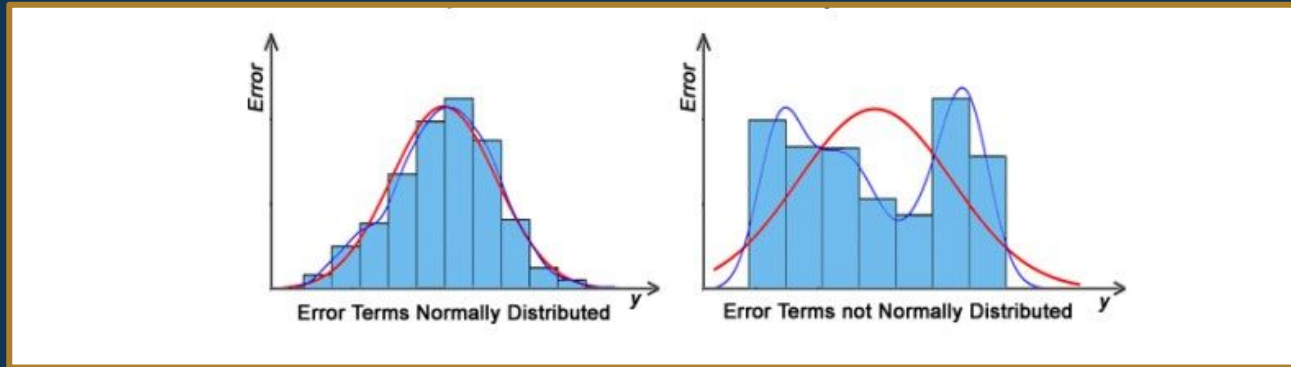
- ❖ **Homoscedasticity:** The variability of y should be constant across all values of x .



Source: [Analytics Vidhya](#)

Assumptions and Limitations of Simple Linear Regression

- ❖ **Normality:** The errors should be normally distributed.



Source: [Analytics Vidhya](#)

Scikit-learn

- ❖ Scikit-learn is a popular Python library for machine learning.
- ❖ It provides simple and efficient tools for data analysis and modelling.

```
from sklearn.datasets import load_diabetes
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```


Evaluation Metrics

- ❖ Mean Squared Error (MSE):
 - MSE measures the average squared difference between the predicted and actual values.
 - A lower MSE indicates better model performance.
- ❖ R-squared (R^2) score:
 - R^2 represents the proportion of variance in the target variable that can be explained by the model.
 - An R^2 value closer to 1 indicates a better fit of the model to the data.

Evaluation Metrics

- ❖ **Accuracy** is another commonly used metric for evaluating the performance of a machine learning model, particularly in classification problems.
 - **Accuracy = (Number of correct predictions) / (Total number of predictions) * 100%**
- ❖ While accuracy is more suitable for classification tasks, metrics like Mean Squared Error (MSE) and R-squared (R^2) are used for regression problems.

Logistic Regression

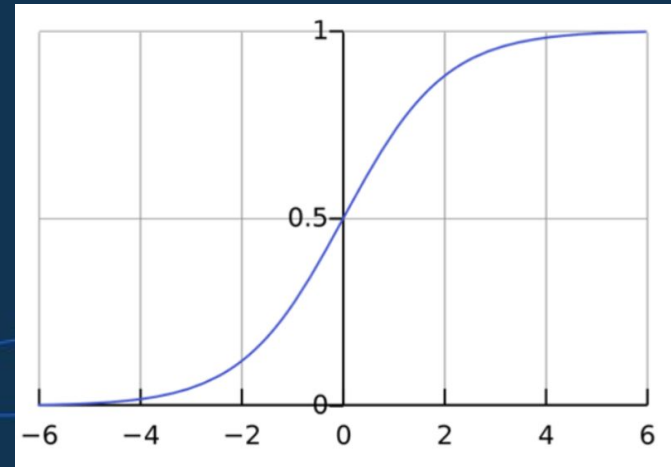
- ❖ **Linear regression** models make **predictions** for the datasets for which dependent variables have **continuous numerical values**.
- ❖ **Logistic Regression**
 - **supervised learning** algorithm
 - **classification** algorithm
 - dependent variables are **distinct, non-continuous, categorical**
- ❖ **Classification** - predicting **probability** of **categorical variables** for a given observation and assigning the observation to the category with the highest probability.

Logistic function

- ❖ Logistic regression: statistical model that uses the **logistic (logit) function**, as the equation between x and y (also called **sigmoid function** or **S-shaped curve**).
- ❖ Returns only values between 0 and 1 for the dependent variable, irrespective of the values of the independent variable.
- ❖ Also model equations between **multiple independent variables** and **one dependent variable**.

Sigmoid function

$$p = \frac{1}{(1 + e^{-y})}$$



Assumptions of Logistic Regression

- ❖ The **independent variables** should **not be correlated** with each other i.e. the model should have little or **no multicollinearity**.
- ❖ The **dependent variable** must be **categorical** in nature.
- ❖ The relationship between the **independent variables** and the **log odds** of the dependent variable should be **linear**.
- ❖ There should be **no outliers** in the dataset.
- ❖ The data sample size should be **sufficiently large**.

Data splitting

```
# Splitting the dataset into features and target
```

```
x = data.drop('smoker', axis=1)
```

```
y = data['smoker']
```

```
# Splitting the data into training and testing sets
```

```
from sklearn.model_selection import train_test_split
```

```
from sklearn.preprocessing import StandardScaler
```

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)
```

```
# Normalize the features
```

```
scaler = StandardScaler()
```

```
x_train_scaled = scaler.fit_transform(x_train)
```

```
x_test_scaled = scaler.transform(x_test)
```


Model fitting and prediction

```
# Fit the logistic regression model  
from sklearn.linear_model import LogisticRegression  
  
log_reg = LogisticRegression()  
log_reg.fit(X_train_scaled, y_train)
```

```
# Predict the model  
y_pred = log_reg.predict(X_test_scaled)
```

Accuracy

Accuracy of classifier: Total number of correct predictions by the classifier divided by the total number of predictions.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

For virus example, **Accuracy = 96%**

According to the **Accuracy** value, the model “can predict sick people 96% of the time”. However, it is **predicting the people who will not get sick with 96% accuracy while the sick are spreading the virus.**

Better to measure how many **positive cases we can predict correctly** to arrest spread of the contagious virus or **out of the correct predictions**, how many **are positive cases** to check the reliability of the model.

Precision and Recall

- ❖ **Precision:** tells us how many of the correctly predicted cases actually turned out to be positive, determine whether the model is reliable or not.
- ❖ **Recall:** how many of the actual positive cases we were able to predict correctly with our model.

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

For virus example, Precision = 50%, Recall = 75%

For virus example, 50% percent of the correctly predicted cases turned out to be positive cases. Whereas 75% of the positives were successfully predicted by the model.

Precision and Recall

- ❖ **Precision**: useful in cases where **False Positive** is a greater concern.
- ❖ *Music or video recommendation systems, e-commerce websites.*
- ❖ *Wrong results could lead to customer churn and be harmful to the business.*
- ❖ **Recall**: useful in cases where **False Negative** trumps.
- ❖ *Medical cases where it does not matter whether a false alarm flag is raised, but the actual positive cases should not go undetected.*

For **contagious virus example**, the **Confusion Matrix** is more insightful measure in such critical scenarios.

Recall, assessing the ability to capture all actual positives, emerges as a **better metric**. **Accuracy** proves **inadequate** as a metric for the model's evaluation.

Avoid mistakenly releasing an infected person into the healthy population, potentially spreading the virus.

F1-score

- ❖ Cases where there is no clear distinction between whether Precision is more important or Recall.
- ❖ **F1-score**: harmonic mean of **Precision** and **Recall**, gives a combined idea about these two metrics, appropriate metric for imbalanced dataset.
- ❖ **Maximum** when **Precision** is **equal** to **Recall**.
- ❖ Use in combination with other evaluation metrics.

$$F_1 = 2 * \frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}}$$

Metrics using scikit-learn

```
#Evaluate the model
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

print("Accuracy Score:", accuracy_score(y_pred, y_test))
print("Confusion Matrix: \n", confusion_matrix(y_pred, y_test))
print("Classification Report: \n " , classification_report(y_pred, y_test))
```

Classification report: Precision, Recall, and F1-score for each target class.

Macro average = average of Precision / Recall / F1-score.

Weighted average of Precision / Recall / F1-score.

Accuracy Score: 0.9589552238805971

Confusion Matrix:

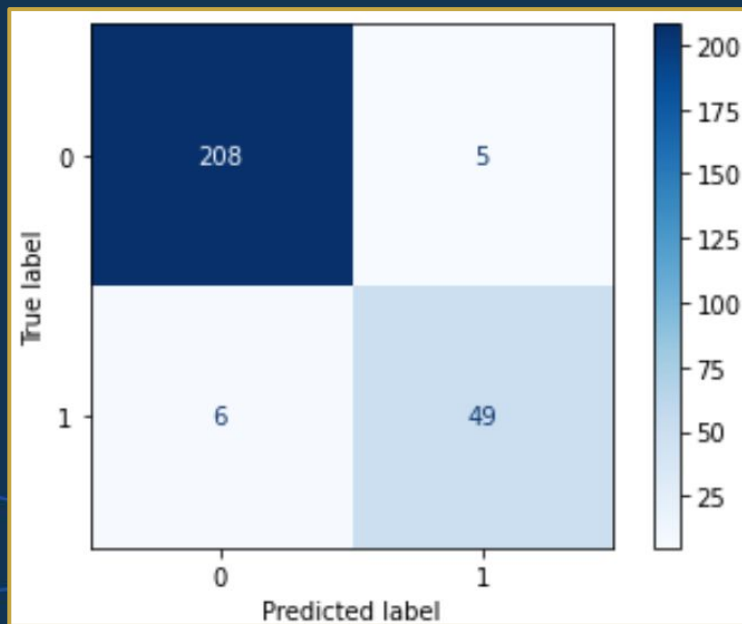
```
[[208  5]
 [ 6 49]]
```

Classification Report:

	precision	recall	f1-score	support
0	0.97	0.98	0.97	213
1	0.91	0.89	0.90	55
accuracy			0.96	268
macro avg	0.94	0.93	0.94	268
weighted avg	0.96	0.96	0.96	268

Metrics using scikit-learn

```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
cm = confusion_matrix(y_pred, y_test, labels=log_reg.classes_)
# sns.heatmap can also be used to get the confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=log_reg.classes_)
disp.plot(cmap='Blues')
```



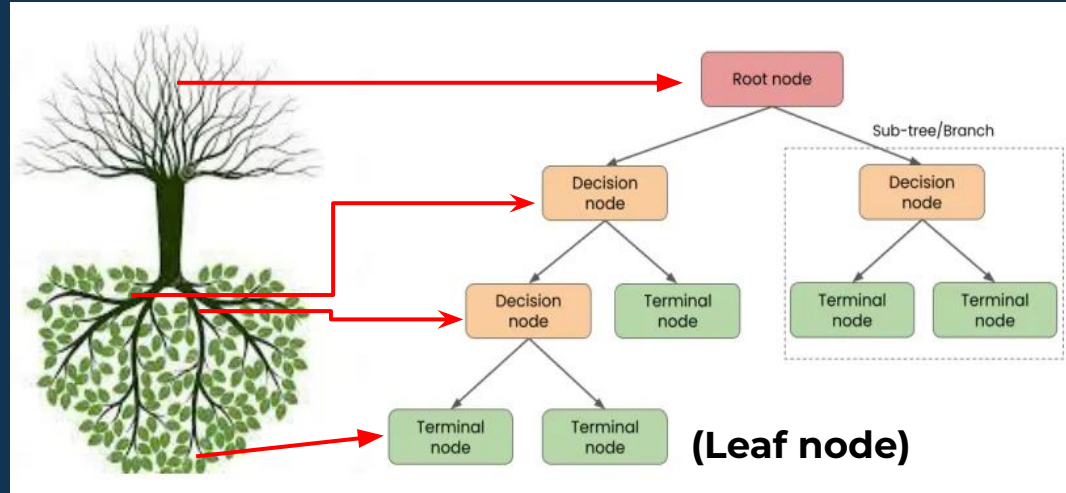
Decision Trees

- ❖ Represent data by **partitioning** it into different **smaller subsets** based on questions asked of predictive variable in the data.
- ❖ **Hierarchical**: model is defined by a **sequential questions** that lead to a class label or a value when applied to any observation; model acts like a protocol in a series of “if this occurs then this occurs” conditions that produce a specific result from input data.
- ❖ **Non-parametric**: model is constructed based on the observed data; there are no underlying assumptions about the distribution of the errors or the data.



Components of Decision Trees

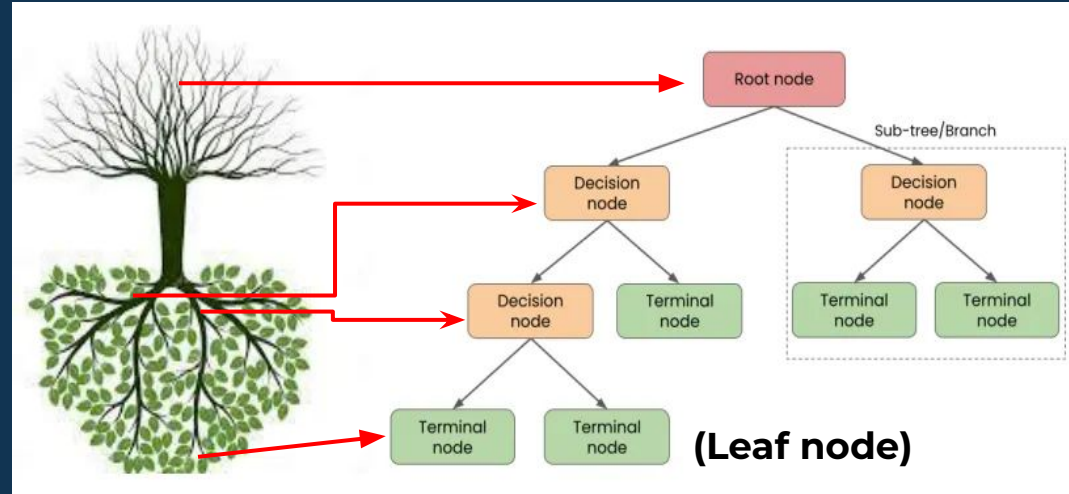
- ❖ **Root Node:** initial node at the beginning of a decision tree, where the entire population or dataset starts dividing based on various features or conditions.
- ❖ **Decision Nodes:** nodes resulting from the splitting of root nodes; represent intermediate decisions or conditions within the tree.



- ❖ **Leaf (Terminal) Nodes:** nodes where further splitting is not possible, often indicating the final classification or outcome.

Components of Decision Trees

- ❖ **Branch / Sub-Tree:**
subsection of entire decision tree; represents specific path of decisions and outcomes within the tree.
- ❖ **Parent and Child Node:**
Parent node is divided into sub-nodes or **child nodes**. Parent represents a decision or condition. Child nodes represent outcomes or further decisions.

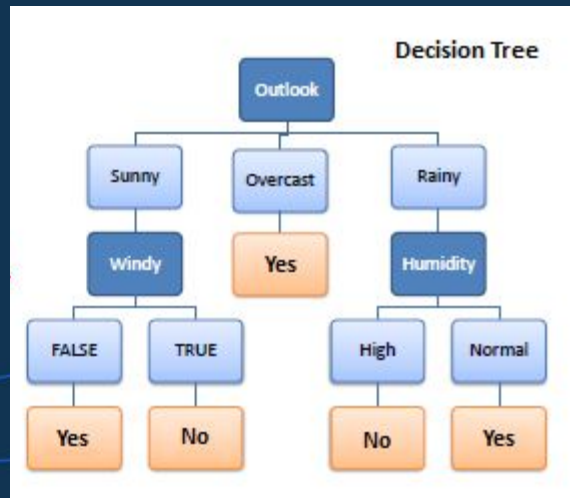


- ❖ **Pruning:** The process of removing or cutting down specific nodes in a decision tree to prevent overfitting and simplify the model.

Classification Trees

Decision tree models where the **target variable** uses a **discrete set of values**, **classification** problems, determine whether an event happened or didn't happen, involving a “yes” or “no” outcome. Each **node**, or **leaf**, represent **class labels** while **branches** represent conjunctions of **features** leading to class labels.

- ❖ The **root node (Outlook)** has two or more **decision nodes (Sunny, Overcast and Rainy)** with other **predictors (Windy, Humidity)**.
- ❖ The **leaf node (Play golf)** is the **target**, and represents a classification of decision.

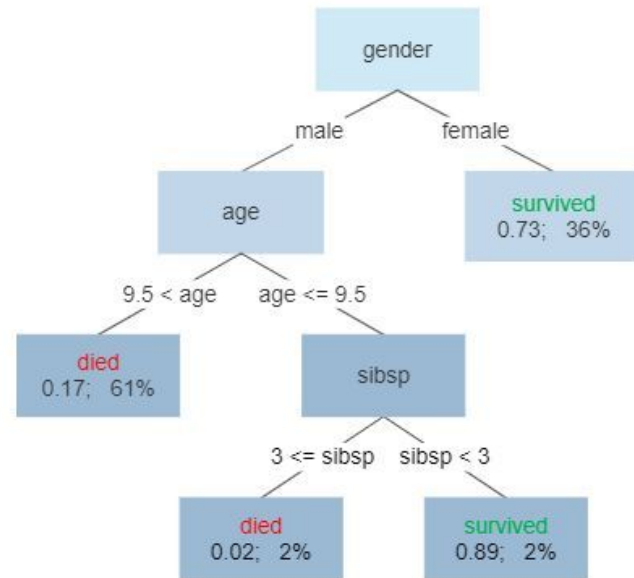


Regression Trees

Decision trees which **predict continuous values** as **targets** based on previous data or information sources. **Predicts** what is likely to happen, given previous behavior/trends.

- ❖ Survival of passengers on the Titanic. Figures under the leaves show the **probability of survival** and the **percentage of observations** in the leaf.
- ❖ "sibsp" is the number of spouses or siblings aboard.

Survival of passengers on the Titanic



CART algorithm

Classification and Regression Trees (CART) algorithm

- ❖ **Tree structure:** CART builds a tree-like structure with nodes and branches.
- ❖ **Nodes:** represent different decision points.
- ❖ **Branches:** represent possible outcomes.
- ❖ **Leaf nodes:** contain a predicted class label or value for the target variable.
- ❖ **Splitting criteria:** CART evaluates all possible splits and selects the one that best reduces the impurity of the resulting subsets.
 - **Gini impurity** (for **classification**, lower means purer subset) and **residual reduction** (for **regression**, lower means better model's fit to the data).
- ❖ **Pruning:** done to prevent overfitting of the data, removes the nodes that contribute little to the model accuracy.

Task Walkthrough

Imagine you are a data scientist in a healthcare organization. Your team is developing a model to predict diabetes risk and glucose levels based on patient information. Your tasks include:

- ❖ Linear Regression model: to predict Glucose Levels using BMI, Age, and BP.
- ❖ Logistic Regression model: to classify Diabetes Risk (Yes/No).
- ❖ Decision Tree model: to classify patients into risk categories based on their features.
- ❖ Compare model performance and decide which one is best for this problem.



What does the Sigmoid function in Logistic Regression do?

- A. Predicts continuous values
- B. Normalizes data between 0 and 1
- C. Converts a linear output into a probability
- D. Increases model accuracy



What makes Decision Trees different from Regression models?

- A. They require fewer features
- B. They work only with categorical data
- C. They split data into branches based on conditions
- D. They cannot be visualized

Summary

- ★ **Linear Regression** predicts continuous values.
- ★ **Logistic Regression** classifies binary outcomes.
- ★ **Decision Trees** handle both classification and regression with clear decision rules.

CoGrammar

Q & A SECTION

**Please use this time to ask
any questions relating to the
topic, should you have any.**

Thank you for attending



CoGrammar



Department
for Education