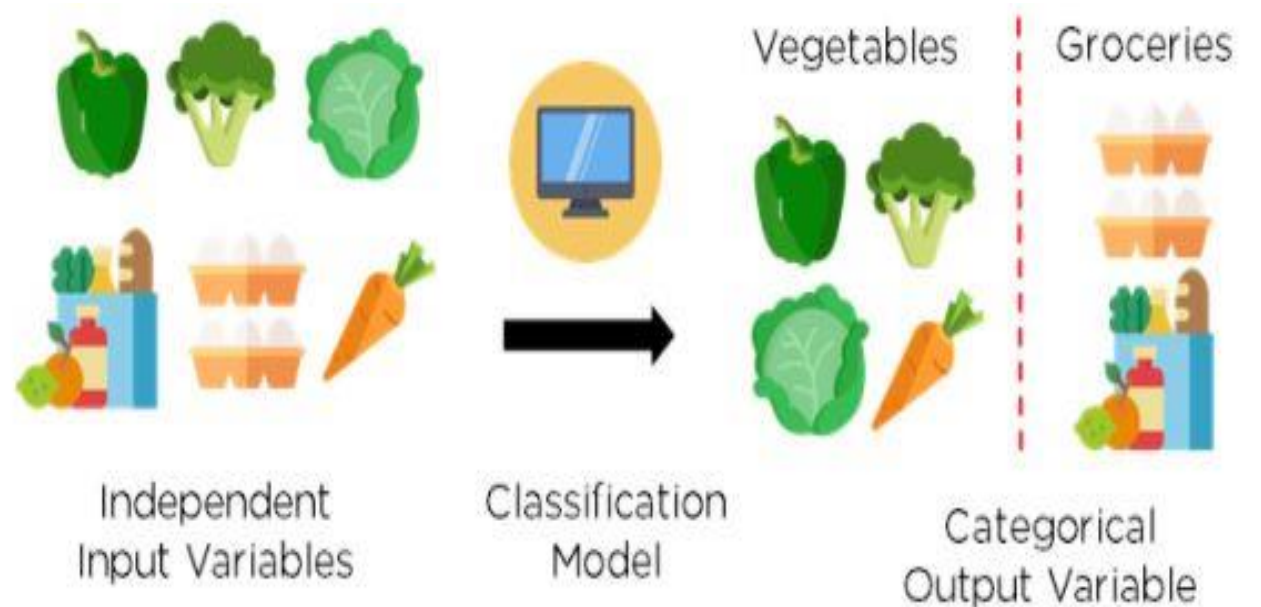


# Classification

# What is Classification?

- Classification is defined as the process of recognition, understanding, and grouping of objects and ideas into preset categories a.k.a “sub-populations.”



# Classification Terminologies

- **Classifier**
- **Classification Model**
- **Feature**
- **Binary Classification**
- **Multi-Class Classification**
- **Multi-label Classification**
- **Initialize**
- **Train the Classifier**
- **Predict the Target**
- **Evaluate**

# Types Of Learners In Classification

- **Lazy Learners**

1. Just store Data set **without** learning from it
2. Start classifying data when it receive **Test data**
3. So it takes less time learning and more time classifying data

- **Eager Learners**

1. When it receive data set it starts classifying (learning)
2. Then it does not wait for test data to learn
3. So it takes long time learning and less time classifying data

# Binary Classification

- Email spam detection (spam or not).
- Churn prediction (churn or not).
- Conversion prediction (buy or not).

# What is hypothesis testing

- Hypothesis testing is a statistical method that is used in making statistical decisions using experimental data.
- Hypothesis Testing is basically an assumption that we make about the population parameter.
- Ex : you say avg student in class is 40 or a boy is taller than girls.

# Need of hypothesis

- **Hypothesis testing** is an essential procedure in statistics.
- A **hypothesis test** evaluates two mutually exclusive statements about a population to determine which statement is best supported by the sample data.
- When **we** say that a finding is statistically significant means a **hypothesis test**.

# parameter of hypothesis testing

- Null Hypothesis
- Alternate Hypothesis



# Terms...

- **Level of significance**
- **Type I error**
- **Type II error**

# T test

*It helps us understand if the difference between two sample means is actually real or simply due to chance.*

compares the means (averages) of two populations to determine how different they are from each other.

```
from scipy.stats import ttest_ind
import numpy as np
import pandas as pd
df=pd.read_csv('F:/amol_college/DeepLearning/week1.csv')
print("week 1 data ",df)

df1=pd.read_csv('F:/amol_college/DeepLearning/week2.csv')
print("week 2 data ",df1)

week1_mean = np.mean(df)
week2_mean = np.mean(df1)

print("mean of week 1 " , week1_mean)
print("mean of week 2 " , week2_mean)

week1_std = np.std(df)
week2_std = np.std(df1)
print("week1 std value:",week1_std)
print("week2 std value:",week2_std)
```

```
ttest,pval = ttest_ind(df,df1)
print("p-value",pval)
if pval <0.05:
    print("we reject null hypothesis")
else:
    print("we accept null hypothesis")
```

is there any association between week1 and week2

# 5 Common Machine Learning Errors

- Lack of understanding the mathematical aspect of machine learning algorithms
- Data Preparation and Sampling
  - Data Cleansing**
  - Feature Engineering**
  - Sampling**
- Implementing machine learning algorithms without a strategy
- Implementing everything from scratch
- Ignoring outliers

# Probability and P Values

Probability provides a common way to interpret the statistical strength of a model. Called the **p value**, it can range from **0 to 1** and represents how likely it is to get a result if the **null hypothesis (H1) is true**. This means the lower the value the better indication that the alternative hypothesis (H1) is actually true.

# What is a Confusion Matrix

- **The confusion matrix shows the ways in which your classification model is confused when it makes predictions.**
- A Confusion matrix is an  $N \times N$  matrix used for evaluating the performance of a classification model, where  $N$  is the number of target classes.
- The matrix compares the actual target values with those predicted by the machine learning model.
- This gives us a holistic view of how well our classification model is performing and what kinds of errors it is making.

# How to Calculate a Confusion Matrix

1. You need a test dataset or a validation dataset with expected outcome values.
2. Make a prediction for each row in your test dataset.
3. From the expected outcomes and predictions count:
  - The number of correct predictions for each class.
  - The number of incorrect predictions for each class, organized by the class that was predicted.
4. These numbers are then organized into a table, or a matrix as follows:
  - **Expected down the side:** Each row of the matrix corresponds to a predicted class.
  - **Predicted across the top:** Each column of the matrix corresponds to an actual class.

Expected,	Predicted
man,	woman
man,	man
woman,	woman
man,	man
woman,	man
woman,	woman
woman,	woman
man,	man
man,	woman
woman,	woman

men classified as men: 3  
 women classified as women: 4

men classified as women: 2  
 woman classified as men: 1

	men	women
men	3	1
women	2	4

- The total actual men in the dataset is the sum of the values on the men column (3 + 2)
- The total actual women in the dataset is the sum of values in the women column (1 +4).
- The correct values are organized in a diagonal line from top left to bottom-right of the matrix (3 + 4).
- More errors were made by predicting men as women than predicting women as men



# Confusion matrix

		ACTUAL VALUES	
		POSITIVE	NEGATIVE
PREDICTED VALUES	POSITIVE	TP	FP
	NEGATIVE	FN	TN

## True Positive (TP)

- The predicted value matches the actual value
- The actual value was positive and the model predicted a positive value

## True Negative (TN)





- The predicted value matches the actual value
- The actual value was negative and the model predicted a negative value

## False Positive (FP)

- The predicted value was falsely predicted
- The actual value was negative but the model predicted a positive value

## False Negative (FN)

- The predicted value was falsely predicted
- The actual value was positive but the model predicted a negative value

		Actual Values	
		1	0
Predicted Values	1	<b>TRUE POSITIVE</b> 	<b>FALSE POSITIVE</b>  <b>TYPE 1 ERROR</b>
	0	<b>FALSE NEGATIVE</b>  <b>TYPE 2 ERROR</b>	<b>TRUE NEGATIVE</b> 

### **True Positive:**

Interpretation: You predicted positive and it's true.  
You predicted that a woman is pregnant and she actually is.

### **True Negative:**

Interpretation: You predicted negative and it's true.  
You predicted that a man is not pregnant and he actually is not

### **False Positive:**

Interpretation: You predicted positive and it's false.  
You predicted that a man is pregnant but he actually is not.

### **False Negative:**

Interpretation: You predicted negative and it's false.  
You predicted that a woman is not pregnant but she actually is.

# Type 1 and Type 2 Error

- **Scenario 1:** We don't have a kitten among the group. Yet, ML algo predicts **it is there**. If we accept the ML algo prediction then it is **Type 1 error** also known as 'False Positive'
- **Scenario 2:** We have a kitten among the group. Yet, ML algo predicts it is **not there**. If we accept the ML algo prediction then it is **Type 2 error** also known as 'False Negative'.

# Use cases of Type 1 and Type 2

**Scenario/Problem Statement 1:** Providing access to an asset post a biometric scan.

Type I error: Possibility of rejection even with an authorized match.

Type II error: Possibility of acceptance even with a unauthorized match.

**Scenario/Problem Statement 2:** Construction Model of a bridge is correct

**Type I error:** Predicting that the model is correct when it is not.

**Type II error:** Predicting that a model is not correct when it is correct.

**Scenario/Problem Statement 3:** Medical trials for a drug which is a cure for Cancer

**Type I error:** Predicting that a cure is found when it is not the case.

**Type II error:** Predicting that a cure is not found when in fact it is the case.

# Need for Confusion Matrix in Machine learning

- It evaluates the performance of the classification models, when they make predictions on test data, and tells how good our classification model is.
- It not only tells the error made by the classifiers but also the type of errors such as it is either type-I or type-II error.
- With the help of the confusion matrix, we can calculate the different parameters for the model, such as accuracy, precision, etc.

We can perform various calculations for the model, such as the model's accuracy, using this matrix. These calculations are given below:

- **Classification Accuracy:** It is one of the important parameters to determine the accuracy of the classification problems. It defines how often the model predicts the correct output. It can be calculated as the ratio of the number of correct predictions made by the classifier to all number of predictions made by the classifiers. The formula is given below:

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

- **Misclassification rate:** It is also termed as Error rate, and it defines how often the model gives the wrong predictions. The value of error rate can be calculated as the number of incorrect predictions to all number of the predictions made by the classifier. The formula is given below:

$$\text{Error rate} = \frac{FP+FN}{TP+FP+FN+TN}$$

- **Precision:** It can be defined as the number of correct outputs provided by the model or out of all positive classes that have predicted correctly by the model, how many of them were actually true. It can be calculated using the below formula:

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

- **Recall:** It is defined as the out of total positive classes, how our model predicted correctly. The recall must be as high as possible.

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

- **F-measure:** If two models have low precision and high recall or vice versa, it is difficult to compare these models. So, for this purpose, we can use F-score. This score helps us to evaluate the recall and precision at the same time. The F-score is maximum if the recall is equal to the precision. It can be calculated using the below formula:

$$\text{F-measure} = \frac{2 * \text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}}$$

*Precision tells us how many of the correctly predicted cases actually turned out to be positive.*

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

*Recall tells us how many of the actual positive cases we were able to predict correctly with our model.*

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

# Write a note on evaluation of machine learning algorithm wrt following points

- Classification Accuracy
- Logarithmic Loss
- Confusion Matrix
- Area under Curve
- F1 Score
- Mean Absolute Error
- Mean Squared Error