

**SWAMINARAYAN COLLEGE OF ENNG. & TECH.  
(DEGREE)**

**MACHINE LEARNING  
(3170724)**



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**SUBMITTED TO:-  
COMPUTER DEPARTMENT  
SCET, SAIJ, KALOL**

## **SWAMINARAYAN COLLEGE OF ENNG. & TECH. (DEGREE)**



### **CERTIFICATE**

This Certificate is awarded to Mr. Porwal Harsh from **SWAMINARAYAN COLLEGE OF ENNG. & TECH. (DEGREE)** having enrollment no:- 201150107005 has completed practical work of “MACHINE LEARNING” during the 7<sup>th</sup> semester on term 2023-24.

**INTERNAL GUIDE**

**Prof. Nimesh Vaidya**

**DATE OF SUBMISSION**

**H.O.D**

**Prof. Nimesh Vaidya**

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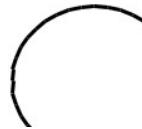
**Subject:** Machine Learning  
**Subject Code:** 3170724

**Branch:** Computer Engineering  
**Semester:** 7<sup>th</sup>

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**FACULTY:** Smit Nayak

**H.O.D:** Prof.Nimesh Vaidya



# Practical – 1

## Machine Learning Tools and Libraries

**Aim:** Introduction to Machine Learning, tools, and libraries.

**Exercise:**

1. Explore Google Collaboratory and other IDE tools.

**Answer**

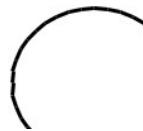
The screenshot shows the Google Colaboratory interface. On the left, there's a sidebar with a 'Table of contents' section containing links to 'Getting started', 'Data science', 'Machine learning', 'More Resources', 'Featured examples', and 'Section'. The main content area has a heading 'Welcome to Colab!' with a sub-section about interactive tables and command palettes. It features a video thumbnail titled '3 Cool Google Colab Features' with a play button. Below this, there's a section titled 'What is Colab?' with a bulleted list: 'Zero configuration required', 'Access to GPUs free of charge', and 'Easy sharing'. A note at the bottom says 'Whether you're a student, a data scientist or an AI researcher, Colab can make your work easier. Watch [Introduction to Colab](#) to learn more, or just get started below!'

*Google Collaboratory*

The screenshot shows a Jupyter notebook titled 'NeMo voice swap app'. The sidebar contains a 'Table of contents' with sections like 'Getting Started: Voice swap application', 'Installation', 'Using the models', 'Results', and 'Next steps'. The main content area has a section titled 'Getting Started: Voice swap application' which describes how to use NVIDIA NeMo to swap voices. It includes a list of tasks: 'Automatic speech recognition of what is said in the file. E.g. converting audio to text', 'Adding punctuation and capitalization to the text', 'Generating spectrogram from resulting text', and 'Generating waveform audio from the spectrogram'. Below this is another section titled 'Installation' with a note that NeMo can be installed via pip. It shows two code snippets in a code cell:

```
[ ] BRANCH = 'r1.20.0'
!python -m pip install git+https://github.com/NVIDIA/NeMo.git@$BRANCH#egg=nemo_toolkit[all]
```

```
[ ] # Ignore pre-production warnings
import warnings
warnings.filterwarnings('ignore')
import nemo
# Import Speech Recognition collection
```



2. Explore the Documentation of various libraries of machine learning.

## Answer

The screenshot shows the scikit-learn User Guide for version 1.3.1. The left sidebar includes links for 'User Guide' (1. Supervised learning, 2. Unsupervised learning, etc.) and 'Sci-Kit Learn Library'. The main content area is titled 'User Guide' and lists 14 categories under '1. Supervised learning': Linear Models, Linear and Quadratic Discriminant Analysis, Kernel ridge regression, Support Vector Machines, Stochastic Gradient Descent, Nearest Neighbors, Gaussian Processes, Cross decomposition, Naive Bayes, Decision Trees, Ensembles, Multiclass and multioutput algorithms, Feature selection, and Semi-supervised Learning.

The screenshot shows the TensorFlow Core documentation homepage. It features a large orange graphic on the left. The main text reads: 'TensorFlow is an end-to-end open source platform for machine learning'. Below this, it says: 'TensorFlow makes it easy for beginners and experts to create machine learning models. See the sections below to get started.' It has two buttons: 'See tutorials' and 'See the guide'. To the right, there's a diagram illustrating a neural network architecture with multiple layers and connections. At the bottom, there are sections for 'For beginners' and 'For experts'.



## Practical – 2

### Data Preprocessing

**Aim:** Introduction to Data Preprocessing.

**Exercise:**

1. On the given dataset perform following data preprocessing techniques:
  - i. Handle missing values.
  - ii. Encoding of Categorical variables.
  - iii. Converting Data of different range to same range iv.

Splitting dataset into training set and test set.

**Answer:**

**Step 1:**

---

### Importing the libraries

```
In [13]: import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

### Importing the dataset

```
In [14]: dataset = pd.read_csv('Data.csv')
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values
```

```
In [15]: print(X)
```

```
[[ 'France' 44.0 72000.0]
 [ 'Spain' 27.0 48000.0]
 [ 'Germany' 30.0 54000.0]
 [ 'Spain' 38.0 61000.0]
 [ 'Germany' 40.0 nan]
 [ 'France' 35.0 58000.0]
 [ 'Spain' nan 52000.0]
 [ 'France' 48.0 79000.0]
 [ 'Germany' 50.0 83000.0]
 [ 'France' 37.0 70000.0]]
```

Importing the Libraries and Dataset



## Step 2:

## Taking care of missing data

```
In [17]: from sklearn.impute import SimpleImputer
imputer = SimpleImputer(missing_values=np.nan, strategy='mean')
imputer.fit(X[:, 1:3])
X[:, 1:3] = imputer.transform(X[:, 1:3])
```

```
In [18]: print(X)
```

```
[['France' 44.0 72000.0]
 ['Spain' 27.0 48000.0]
 ['Germany' 30.0 54000.0]
 ['Spain' 38.0 61000.0]
 ['Germany' 40.0 63777.77777777778]
 ['France' 35.0 58000.0]]
```

*Handling Missing Values*

## Step 3:

## Encoding categorical data

### Encoding the Independent Variable

```
In [19]: from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder(), [0])], remainder='passthrough')
X = np.array(ct.fit_transform(X))
```

```
In [20]: print(X)
```

```
[[1.0 0.0 0.0 44.0 72000.0]
 [0.0 0.0 1.0 27.0 48000.0]
 [0.0 1.0 0.0 30.0 54000.0]
 [0.0 0.0 1.0 38.0 61000.0]
 [0.0 1.0 0.0 40.0 63777.77777777778]
 [1.0 0.0 0.0 35.0 58000.0]
 [0.0 0.0 1.0 38.77777777777778 52000.0]
 [1.0 0.0 0.0 48.0 79000.0]
 [0.0 1.0 0.0 50.0 83000.0]
 [1.0 0.0 0.0 37.0 67000.0]]
```

### Encoding the Dependent Variable

```
In [21]: from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

*Encoding of Categorical Variables*

Step 4:

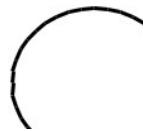
## Feature Scaling

```
In [28]: from sklearn.preprocessing import StandardScaler  
sc = StandardScaler()  
X_train = sc.fit_transform(X_train)  
X_test = sc.transform(X_test)
```

```
In [29]: print(X_train)
```

```
[[ -0.77459667 -0.57735027  1.29099445 -0.19159184 -1.07812594]  
[ -0.77459667  1.73205081 -0.77459667 -0.01411729 -0.07013168]  
[ 1.29099445 -0.57735027 -0.77459667  0.56670851  0.63356243]  
[ -0.77459667 -0.57735027  1.29099445 -0.30453019 -0.30786617]  
[ -0.77459667 -0.57735027  1.29099445 -1.90180114 -1.42046362]  
[ 1.29099445 -0.57735027 -0.77459667  1.14753431  1.23265336]  
[ -0.77459667  1.73205081 -0.77459667  1.43794721  1.57499104]  
[ 1.29099445 -0.57735027 -0.77459667 -0.74014954 -0.56461943]]
```

```
In [30]: print(X_test) Converting Data of different range into same range
```

**Step 5:**

```
In [23]: from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, rand

In [24]: print(X_train)

[[0.0 0.0 1.0 38.77777777777778 52000.0]
 [0.0 1.0 0.0 40.0 63777.7777777778]
 [1.0 0.0 0.0 44.0 72000.0]
 [0.0 0.0 1.0 38.0 61000.0]
 [0.0 0.0 1.0 27.0 48000.0]
 [1.0 0.0 0.0 48.0 79000.0]
 [0.0 1.0 0.0 50.0 83000.0]
 [1.0 0.0 0.0 35.0 58000.0]]

In [25]: print(X_test)

[[0.0 1.0 0.0 30.0 54000.0]
 [1.0 0.0 0.0 37.0 67000.0]]

In [26]: print(y_train)
[0 1 0 0 1 1 0 1]Splitting Dataset into training set and test set
```



## Practical – 3

### Simple Linear Regression Aim:

To Study Simple Linear Regression

**Exercise:**

1. Implement Simple Linear Regression on the given dataset.

**Answer:**

**Step 1:**

### Simple Linear Regression

#### Importing the libraries

```
In [1]: import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

#### Importing the dataset

```
In [2]: dataset = pd.read_csv('Salary_Data.csv')
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values
```

#### Splitting the dataset into the Training set and Test set

```
In [3]: from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 1/3, random_state = 0)
```

#### Training the Simple Linear Regression model on the Training

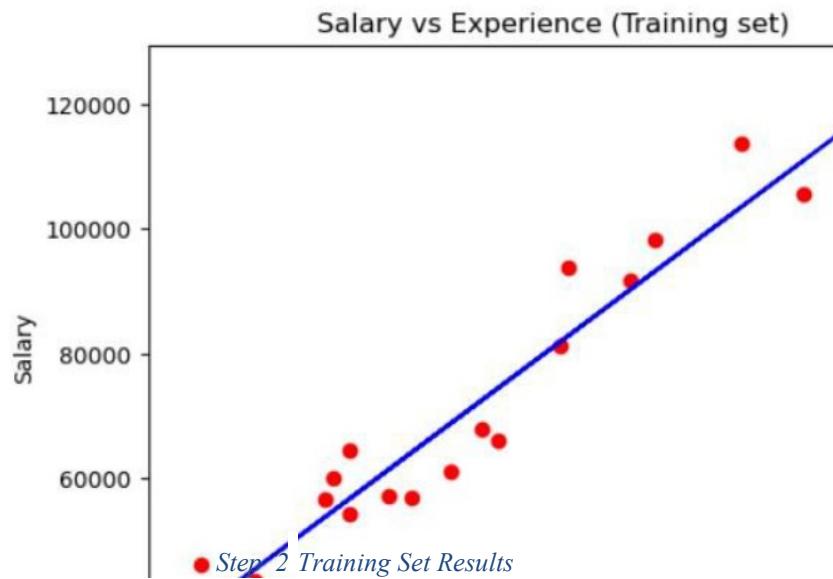
```
In [4]: from sklearn.linear_model import LinearRegression
Step 1 Splitting Data Set into Test and Train and Fitting it into Linear Regression Function
```

**Step 2:**



### Visualising the Training set results

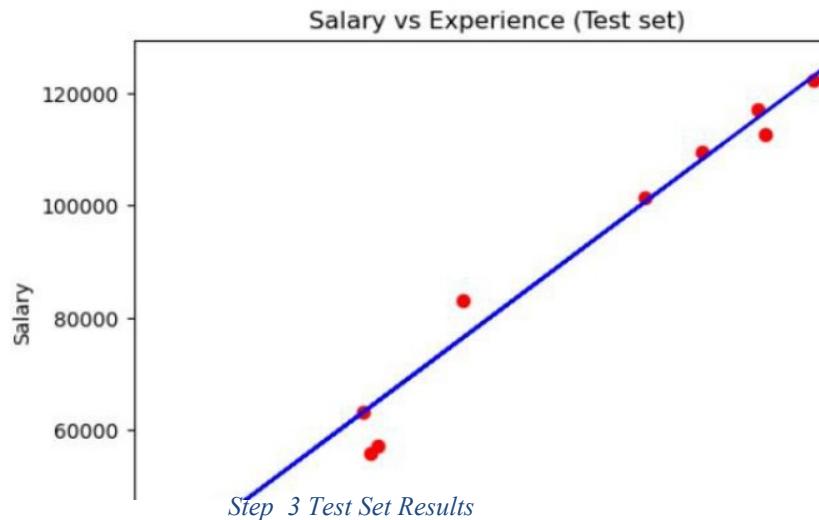
```
In [6]: plt.scatter(X_train, y_train, color = 'red')
plt.plot(X_train, regressor.predict(X_train), color = 'blue')
plt.title('Salary vs Experience (Training set)')
plt.xlabel('Years of Experience')
plt.ylabel('Salary')
plt.show()
```



### Step 3:

### Visualising the Test set results

```
In [7]: plt.scatter(X_test, y_test, color = 'red')
plt.plot(X_train, regressor.predict(X_train), color = 'blue')
plt.title('Salary vs Experience (Test set)')
plt.xlabel('Years of Experience')
plt.ylabel('Salary')
plt.show()
```





## Practical – 4

### Support Vector Machine (SVM)

**Aim:** To study Support Vector Machine.

**Exercise:**

1. Implement Support Vector Machine on given dataset.

**Answer:**

**Step 1:**

### Support Vector Machine (SVM)

#### Importing the libraries

```
In [1]: import numpy as np  
import matplotlib.pyplot as plt  
import pandas as pd
```

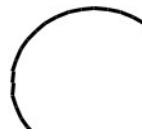
#### Importing the dataset

```
In [2]: dataset = pd.read_csv('Social_Network_Ads.csv')  
X = dataset.iloc[:, :-1].values  
y = dataset.iloc[:, -1].values
```

#### Splitting the dataset into the Training set and Test set

*Importing the Data set and Splitting into test and train*

**Step 2:**



### Training the SVM model on the Training set

```
In [11]: from sklearn.svm import SVC
classifier = SVC(kernel = 'linear', random_state = 0)
classifier.fit(X_train, y_train)

Out[11]: SVC(kernel='linear', random_state=0)
```

### Predicting a new result

```
In [12]: print(classifier.predict(sc.transform([[30,87000]])))
[0]
```

### Predicting the Test set results

```
In [13]: y_pred = classifier.predict(X_test)
print(np.concatenate((y_pred.reshape(len(y_pred),1), y_test.reshape(len(y_test),1)),1))

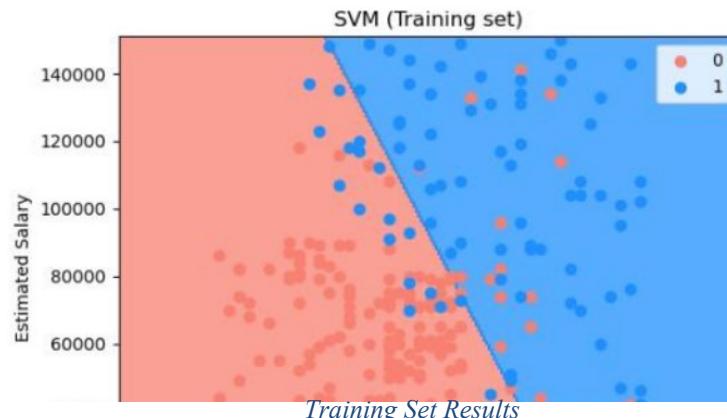
[[0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [1 1]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]]
```

*Training SVM Model on Dataset and Predicting test results.*

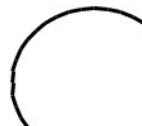
### Step 3:

#### Visualising the Training set results

```
In [16]: from matplotlib.colors import ListedColormap
X_set, y_set = sc.inverse_transform(X_train), y_train
X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 10, stop = X_set[:, 0].max() + 10,
                               step = 1),
                     np.arange(start = X_set[:, 1].min() - 1000, stop = X_set[:, 1].max() + 1000,
                               step = 1))
plt.contourf(X1, X2, classifier.predict(sc.transform(np.array([X1.ravel(), X2.ravel()]).T)).reshape(1000, 1000),
              alpha = 0.75, cmap = ListedColormap(('salmon', 'dodgerblue')))
plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())
for i, j in enumerate(np.unique(y_set)):
    plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('salmon', 'dodgeblue'))(i))
plt.title('SVM (Training set)')
plt.xlabel('Age')
plt.ylabel('Estimated Salary')
plt.legend()
plt.show()
```



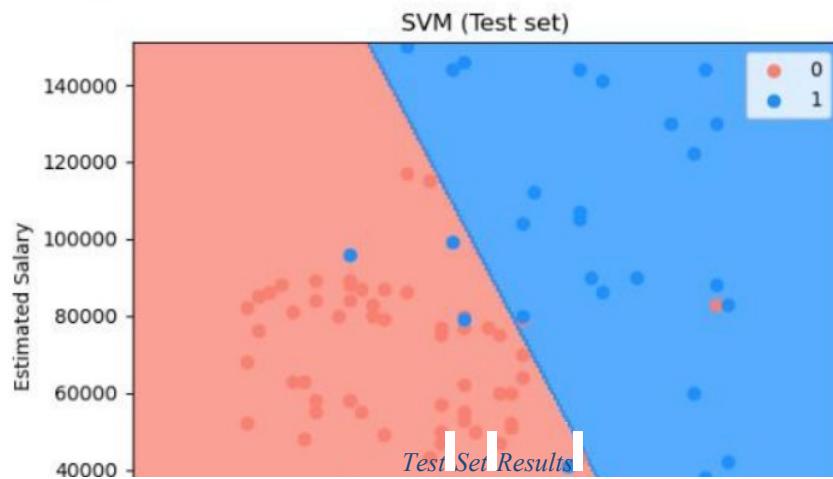
*Training Set Results*



## Step 4:

## Visualising the Test set results

```
In [17]: from matplotlib.colors import ListedColormap
X_set, y_set = sc.inverse_transform(X_test), y_test
X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 10, stop = X_set[:, 0].max() + 10, step = 0.5),
                     np.arange(start = X_set[:, 1].min() - 1000, stop = X_set[:, 1].max() + 1000, step = 1))
plt.contourf(X1, X2, classifier.predict(sc.transform(np.array([X1.ravel(), X2.ravel()]).T)).reshape(X1.shape[0], X1.shape[1]),
             alpha = 0.75, cmap = ListedColormap(('salmon', 'dodgerblue')))
plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())
for i, j in enumerate(np.unique(y_set)):
    plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('salmon', 'dodgerblue'))[i])
plt.title('SVM (Test set)')
plt.xlabel('Age')
plt.ylabel('Estimated Salary')
plt.legend()
plt.show()
```



## 5

**K- Means Algorithm Aim:**

To study how to implement K-means Algorithm

**Exercise:**

1. Implement K-means algorithm on the given dataset.

**Answer:****Step 1:****Importing the libraries**

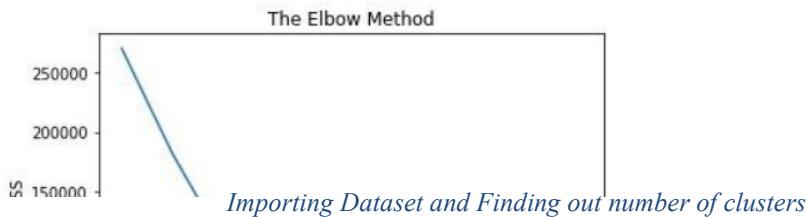
```
In [0]: import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

**Importing the dataset**

```
In [0]: dataset = pd.read_csv('Mall_Customers.csv')
X = dataset.iloc[:, [3, 4]].values
```

**Using the elbow method to find the optimal number of clusters**

```
In [3]: from sklearn.cluster import KMeans
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state = 42)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)
plt.plot(range(1, 11), wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```

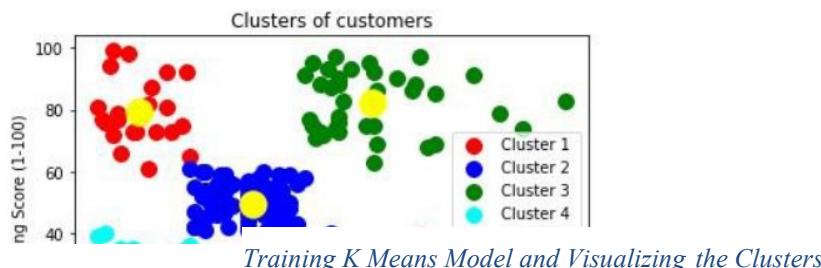
**Step 2:**

## Training the K-Means model on the dataset

```
In [0]: kmeans = KMeans(n_clusters = 5, init = 'k-means++', random_state = 42)
y_kmeans = kmeans.fit_predict(X)
```

## Visualising the clusters

```
In [5]: plt.scatter(X[y_kmeans == 0, 0], X[y_kmeans == 0, 1], s = 100, c = 'red', label = 'Cluster 1')
plt.scatter(X[y_kmeans == 1, 0], X[y_kmeans == 1, 1], s = 100, c = 'blue', label = 'Cluster 2')
plt.scatter(X[y_kmeans == 2, 0], X[y_kmeans == 2, 1], s = 100, c = 'green', label = 'Cluster 3')
plt.scatter(X[y_kmeans == 3, 0], X[y_kmeans == 3, 1], s = 100, c = 'cyan', label = 'Cluster 4')
plt.scatter(X[y_kmeans == 4, 0], X[y_kmeans == 4, 1], s = 100, c = 'magenta', label = 'Cluster 5')
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s = 300, c = 'yellow', label = 'Centroids')
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```



*Training K Means Model and Visualizing the Clusters*



## K-fold Cross Validation

**Aim:** To study how to do implementation of K-fold cross validation.

**Exercise:**

1. Implement K-fold cross validation on the given dataset.

**Answer:**

**Step 1:**

```
In [1]: from sklearn.datasets import load_breast_cancer
import pandas as pd
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import KFold
from sklearn.metrics import accuracy_score

In [2]: data = load_breast_cancer(as_frame = True)
df = data.frame

In [3]: X = df.iloc[:, :-1]
Y = df.iloc[:, -1]

In [4]: #Implementing k-fold cross-validation
k = 5
k_fold = KFold(n_splits = k, random_state = None)
Lr = LogisticRegression(solver = 'liblinear')

In [5]: acc_scores = []

In [6]: # Looping over each split to get the accuracy score of each split
for training_index, testing_index in k_fold.split(X):
    X_train, X_test = X.iloc[training_index, :], X.iloc[testing_index]
    Y_train, Y_test = Y.iloc[training_index], Y.iloc[testing_index]
```

Implementing K-Fold Cross Validation using Logistic Regression Model

**Step 2:**



```
In [10]: # Predicting values for the testing dataset  
Y_pred = Lr.predict(X_test)  
  
In [11]: # Calculatinf accuracy score using in-built sklearn accuracy_score  
acc = accuracy_score(Y_pred , Y_test)  
acc_scores.append(acc)  
  
In [12]: # Calculating mean accuracy score  
mean_acc_score = sum(acc_scores) / k  
  
In [13]: print("Accuracy score of each fold: ", acc_scores)  
print("Mean accuracy score: ", mean acc score)  
Predicting Values and Calculating Accuracy
```

## Dimensionality Reduction Aim:

To study Introduction to dimensionality reduction.

**Exercise:**

1. Implement PCA algorithm on the given dataset.

**Answer:**

**Step 1:**

### Importing the libraries

```
In [1]: import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
```

### Importing the dataset

```
In [2]: dataset = pd.read_csv('Wine.csv')
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values
```

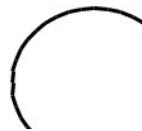
### Splitting the dataset into the Training set and Test set

```
In [3]: from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 1)
```

### Feature Scaling

```
In [4]: from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

*Importing Dataset and Applying PCA*

**Step 2:****Training the Logistic Regression model on the Training set**

```
In [6]: from sklearn.linear_model import LogisticRegression  
classifier = LogisticRegression(random_state = 0)  
classifier.fit(X_train, y_train)
```

```
Out[6]: LogisticRegression  
LogisticRegression(random_state=0)
```

**Making the Confusion Matrix**

```
In [7]: from sklearn.metrics import confusion_matrix, accuracy_score  
y_pred = classifier.predict(X_test)  
cm = confusion_matrix(y_test, y_pred)  
print(cm)  
accuracy_score(y_test, y_pred)
```

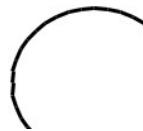
```
[[14  0  0]  
 [ 1 15  0]] Training Logistic Regression Model
```

**Step 3:**

## Visualising the Training set results

```
In [8]: from matplotlib.colors import ListedColormap
X_set, y_set = X_train, y_train
X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 1, stop = X_set[:, 0].max() + 1,
                               np.arange(start = X_set[:, 1].min() - 1, stop = X_set[:, 1].max() + 1,
                                         plt.contourf(X1, X2, classifier.predict(np.array([X1.ravel(), X2.ravel()]).T).reshape(X1.shape),
                                         alpha = 0.75, cmap = ListedColormap(('red', 'green', 'blue'))))
plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())
for i, j in enumerate(np.unique(y_set)):
    plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1],
                c = ListedColormap(('red', 'green', 'blue'))(i), label = j)
plt.title('Logistic Regression (Training set)')
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.legend()
plt.show()
```

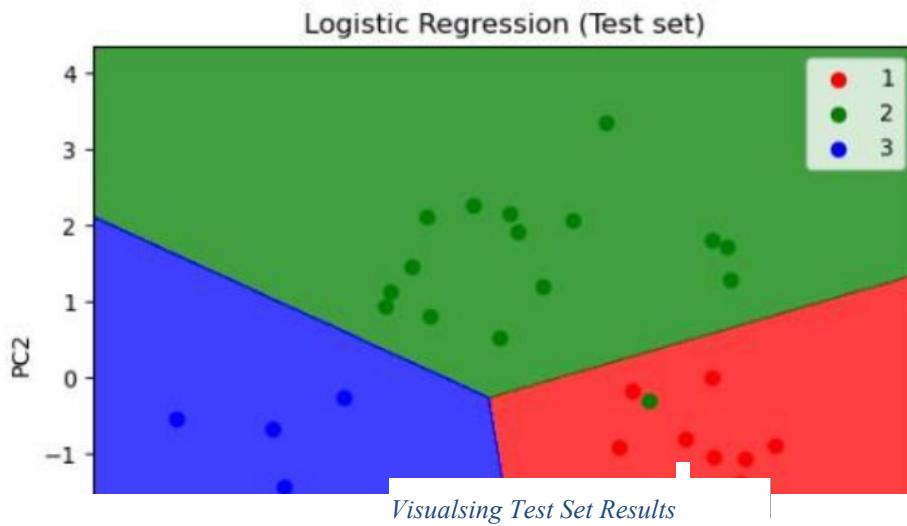




## Step 4:

## Visualising the Test set results

```
In [9]: from matplotlib.colors import ListedColormap
X_set, y_set = X_test, y_test
X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 1, stop = X_set[:, 0].max() + 1, step = 0.01),
                     np.arange(start = X_set[:, 1].min() - 1, stop = X_set[:, 1].max() + 1, step = 0.01))
plt.contourf(X1, X2, classifier.predict(np.array([X1.ravel(), X2.ravel()]).T).reshape(X1.shape),
             alpha = 0.75, cmap = ListedColormap(('red', 'green', 'blue')))
plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())
for i, j in enumerate(np.unique(y_set)):
    plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1],
                c = ListedColormap(('red', 'green', 'blue'))(i), label = j)
plt.title('Logistic Regression (Test set)')
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.legend()
plt.show()
```



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## Practical – 8

### Association Rule Learning Aim:

To study introduction to Association Rule Learning.

**Exercise:**

1. Implement Apriori algorithm on the given dataset.

**Answer:**

**Step 1:**

## Apriori

### Importing the libraries

```
In [1]: !pip install apyori
Collecting apyori
  Downloading apyori-1.1.2.tar.gz (8.6 kB)
  Preparing metadata (setup.py): started
  Preparing metadata (setup.py): finished with status 'done'
Building wheels for collected packages: apyori
  Building wheel for apyori (setup.py): started
  Building wheel for apyori (setup.py): finished with status 'done'
  Created wheel for apyori: filename=apyori-1.1.2-py3-none-any.whl size=5975 sha256=33b1730bb5b7519779
ac0e131b53cfc1025945a
  Stored in directory: c:\users\dharm\appdata\local\pip\cache\wheels\84\45\aa\8ade6576f75410d8162c6da1
3
Successfully built apyori
Installing collected packages: apyori
Successfully installed apyori-1.1.2
```

```
In [2]: import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

### Data Preprocessing

```
In [3]: dataset = pd.read_csv('Market_Basket_Optimisation.csv', header = None)
transactions = []
for i in range(0, 7501):
    transactions.append([str(dataset.values[i, j]) for j in range(0, 20)])

```

*Importing Libraries and Training Apriori Model*

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## Step 2:

### Visualising the results

Displaying the first results coming directly from the output of the apriori function

```
In [5]: results = list(rules)
```

```
In [6]: results
```

```
Out[6]: [RelationRecord(items=frozenset({'chicken', 'light cream'}), support=0.004532728969470737, ordered_statistics=[{'items_base': frozenset({'light cream'}), 'items_add': frozenset({'chicken'}), 'confidence': 0.2905982905982905}], RelationRecord(items=frozenset({'mushroom cream sauce', 'escalope'}), support=0.005732568990801226, ordered_statistics=[{'items_base': frozenset({'mushroom cream sauce'}), 'items_add': frozenset({'escalope'}), 'confidence': 3.790832696715049}], RelationRecord(items=frozenset({'pasta', 'escalope'}), support=0.005865884548726837, ordered_statistics=[{'items_base': frozenset({'pasta'}), 'items_add': frozenset({'escalope'}), 'confidence': 0.3728813559322034, 'lift': 4}], RelationRecord(items=frozenset({'honey', 'fromage blanc'}), support=0.003332888948140248, ordered_statistics=[{'items_base': frozenset({'fromage blanc'}), 'items_add': frozenset({'honey'}), 'confidence': 0.2450980392156869}], RelationRecord(items=frozenset({'herb & pepper', 'ground beef'}), support=0.015997866951073192, ordered_statistics=[{'items_base': frozenset({'herb & pepper'}), 'items_add': frozenset({'ground beef'}), 'confidence': 0.3239938411349285}], RelationRecord(items=frozenset({'tomato sauce', 'ground beef'}), support=0.005332622317024397, ordered_statistics=[{'items_base': frozenset({'tomato sauce'}), 'items_add': frozenset({'ground beef'}), 'confidence': 0.3773519481324083}], RelationRecord(items=frozenset({'light cream', 'olive oil'}), support=0.003199573390214638, ordered_statistics=[{'items_base': frozenset({'light cream'}), 'items_add': frozenset({'olive oil'}), 'confidence': 0.20512820512519573}], RelationRecord(items=frozenset({'whole wheat pasta', 'olive oil'}), support=0.007998933475536596, ordered_statistics=[{'items_base': frozenset({'whole wheat pasta'}), 'items_add': frozenset({'olive oil'}), 'confidence': 4.122410097642296}], RelationRecord(items=frozenset({'pasta', 'shrimp'}), support=0.005065991201173177, ordered_statistics=[{'items_base': frozenset({'pasta'}), 'items_add': frozenset({'shrimp'}), 'confidence': 0.3220338983050847, 'lift': 4.5066}]]
```

Putting the results well organised into a Pandas DataFrame

*Visualizing Results and Putting Results into Pandas Data Frame*

201150107005

SWAMINARAYAN COLLEGE OF ENNG. & TECH. 3170724 ML Step 3:

Displaying the results non sorted

In [8]: resultsinDataFrame

Out[8]:

|   | Left Hand Side       | Right Hand Side | Support  | Confidence | Lift     |
|---|----------------------|-----------------|----------|------------|----------|
| 0 | light cream          | chicken         | 0.004533 | 0.290598   | 4.843951 |
| 1 | mushroom cream sauce | escalope        | 0.005733 | 0.300699   | 3.790833 |
| 2 | pasta                | escalope        | 0.005866 | 0.372881   | 4.700812 |
| 3 | fromage blanc        | honey           | 0.003333 | 0.245098   | 5.164271 |
| 4 | herb & pepper        | ground beef     | 0.015998 | 0.323450   | 3.291994 |
| 5 | tomato sauce         | ground beef     | 0.005333 | 0.377358   | 3.840659 |
| 6 | light cream          | olive oil       | 0.003200 | 0.205128   | 3.114710 |
| 7 | whole wheat pasta    | olive oil       | 0.007999 | 0.271493   | 4.122410 |
| 8 | pasta                | shrimp          | 0.005066 | 0.322034   | 4.506672 |

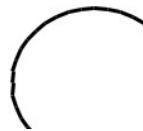
Displaying the results sorted by descending lifts

In [9]: resultsinDataFrame.nlargest(n = 10, columns = 'Lift')

Out[9]:

|   | Left Hand Side | Right Hand Side | Support  | Confidence | Lift     |
|---|----------------|-----------------|----------|------------|----------|
| 3 | fromage blanc  | honey           | 0.003333 | 0.245098   | 5.164271 |
| 0 | light cream    | chicken         | 0.004533 | 0.290598   | 4.843951 |
| 2 | pasta          | escalope        | 0.005866 | 0.372881   | 4.700812 |
| 8 | pasta          | shrimp          | 0.005066 | 0.322034   | 4.506672 |

Displaying Sorted and Non -Sorted Results



## Practical – 9

### Reinforcement Learning

**Aim:** To study the Introduction of Reinforcement Learning

**Exercise:**

1. Implement Thompson Sampling algorithm on the given dataset.

**Answer:**

**Step 1:**

### Thompson Sampling

#### Importing the libraries

```
In [0]: import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

#### Importing the dataset

```
In [0]: dataset = pd.read_csv('Ads_CTR_Optimisation.csv')
```

#### Implementing Thompson Sampling

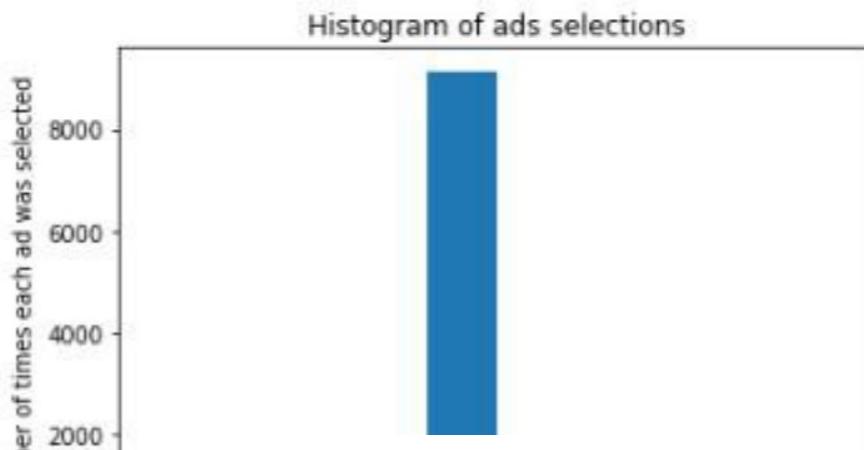
```
In [0]: import random
N = 10000
d = 10
ads_selected = []
numbers_of_rewards_1 = [0] * d
numbers_of_rewards_0 = [0] * d
total_reward = 0
for n in range(0, N):
    ad = 0
    max_random = 0
    for i in range(0, d):
        random_beta = random.betavariate(numbers_of_rewards_1[i] + 1, numbers_of_rewards_0[i] + 1)
        if random_beta > max_random:
```

*Implementing Thompson Sampling*

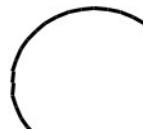
**Step 2:**

## Visualising the results - Histogram

```
In [4]: plt.hist(ads_selected)
plt.title('Histogram of ads selections')
plt.xlabel('Ads')
plt.ylabel('Number of times each ad was selected')
plt.show()
```



*Visualizing the Results Using Histogram*



## Practical – 10

### Deep Learning

**Aim:** To Study the introduction of Deep Learning.

**Exercise:**

1. Design Implement and Train an artificial neural network on the given dataset.

**Answer:**

**Step 1: Data Preprocessing**

### Artificial Neural Network

**Importing the libraries**

```
In [0]: import numpy as np
import pandas as pd
import tensorflow as tf
```

```
In [2]: tf.__version__
Out[2]: '2.2.0'
```

### Part 1 - Data Preprocessing

**Importing the dataset**

```
In [0]: dataset = pd.read_csv('Churn_Modelling.csv')
X = dataset.iloc[:, 3:-1].values
y = dataset.iloc[:, -1].values
```

```
In [4]: print(X)
[[619 'France' 'Female' ... 1 1 101348.88]
 [608 'Spain' 'Female' ... 0 1 112542.58]
 [502 'France' 'Female' ... 1 0 113931.57]
 ...]
```

*Importing Libraries and Dataset*



## Encoding categorical data

Label Encoding the "Gender" column

```
In [0]: from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
X[:, 2] = le.fit_transform(X[:, 2])
```

```
In [7]: print(X)

[[619 'France' 0 ... 1 1 101348.88]
 [608 'Spain' 0 ... 0 1 112542.58]
 [502 'France' 0 ... 1 0 113931.57]
 ...
 [709 'France' 0 ... 0 1 42085.58]
 [772 'Germany' 1 ... 1 0 92888.52]
 [792 'France' 0 ... 1 0 38190.78]]
```

One Hot Encoding the "Geography" column

```
In [0]: from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder(), [1])], remainder='passthrough')
X = np.array(ct.fit_transform(X))
```

```
In [9]: print(X)

[[1.0 0.0 0.0 ... 1 1 101348.88]
 [0.0 0.0 1.0 ... 0 1 112542.58]]
```

## Splitting the dataset into the Training set and Test set

```
In [0]: from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2,
```

## Feature Scaling

```
In [0]: from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
```

*Splitting into Train and Test and Scaling Data*



## Step 2: Building the ANN

### Part 2 - Building the ANN

#### Initializing the ANN

```
In [0]: ann = tf.keras.models.Sequential()
```

#### Adding the input layer and the first hidden layer

```
In [0]: ann.add(tf.keras.layers.Dense(units=6, activation='relu'))
```

#### Adding the second hidden layer

```
In [0]: ann.add(tf.keras.layers.Dense(units=6, activation='relu'))
```

#### Adding the output layer

*Building ANN*



### Step 3: Training the ANN

#### Compiling the ANN

```
In [0]: ann.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['acc'])
```

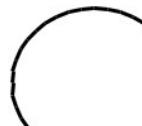
#### Training the ANN on the Training set

```
In [17]: ann.fit(X_train, y_train, batch_size = 32, epochs = 100)
```

Epoch 1/100  
250/250 [=====] - 0s 1ms/step - loss: 0.8037 - accuracy: 0.4123  
Epoch 2/100  
250/250 [=====] - 0s 1ms/step - loss: 0.5291 - accuracy: 0.4478  
Epoch 3/100  
250/250 [=====] - 0s 1ms/step - loss: 0.4888 - accuracy: 0.4302  
Epoch 4/100  
250/250 [=====] - 0s 1ms/step - loss: 0.4668 - accuracy: 0.4123  
Epoch 5/100  
250/250 [=====] - 0s 1ms/step - loss: 0.4478 - accuracy: 0.4123  
Epoch 6/100  
250/250 [=====] - 0s 1ms/step - loss: 0.4302 - accuracy: 0.4123  
Epoch 7/100  
250/250 [=====] - 0s 1ms/step - loss: 0.4123 - accuracy: 0.4123  
Epoch 8/100

*Compiling And Training ANN*

### Step 4: Making Predictions and Evaluating the Model



## Part 4 - Making the predictions and evaluating the model

### Predicting the result of a single observation

Use our ANN model to predict if the customer with the following informations will leave the bank  
 Geography: France  
 Credit Score: 600  
 Gender: Male  
 Age: 40 years old  
 Tenure: 3 years  
 Balance: \\$ 60000  
 Number of Products: 2  
 Does this customer have a credit card ? Yes  
 Is this customer an Active Member: Yes  
 Estimated Salary: \\$ 50000  
 So, should we say goodbye to that customer ?

...  
 Predicting Using Sample Data

### Predicting the Test set results

```
In [19]: y_pred = ann.predict(X_test)
y_pred = (y_pred > 0.5)
print(np.concatenate((y_pred.reshape(len(y_pred),1), y_test.reshape(len(y
[[[0 0]
[0 1]
[0 0]
...
[0 0]
[0 0]
[0 0]]
```

### Making the Confusion Matrix

```
In [20]: from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

*Predicting Test Results and Making Confusion Matrix*