```
import numpy as np # A useful package for dealing with mathematical processes, we will be using it this week for vectors and matrices
import pandas as pd # A common package for viewing tabular data
import tensorflow as tf # Tensor flow is a key package for performing automatic differntiation (the gradient descent we use for optimisation)
import sklearn.linear_model, sklearn.datasets # We want to be able to access the sklearn datasets again, also we are using some model evaluation
from sklearn.preprocessing import StandardScaler, MinMaxScaler # We will be using the imbuilt sclaing functions sklearn provides
import matplotlib.pyplot as plt # We will be using Matplotlib for our graphs
from sklearn.preprocessing import LabelEncoder, OneHotEncoder # We will be using these to encode categorical features
from sklearn.preprocessing import PolynomialFeatures
from google.colab import files
import scipy
from sklearn.model_selection import train_test_split # A library that can automatically perform data splitting for us
from sklearn.linear_model import Ridge, Lasso # Ridge & Lasso regression are types of linear model that use regularisation
from sklearn.metrics import mean_squared_error
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, accuracy_score, precision_score, recall_score, f1_score, classification_report, balanced_accuracy_score # Various classification me
from sklearn.ensemble import RandomForestRegressor # getting the random forest model

# Below are a wide selection of tensorflow libraries we will need to construct our Neural networks.
from tensorflow.keras.activations import sigmoid, linear, relu # Activation functions we will use
from tensorflow.keras.models import Model, Sequential # Different mays of constructing models, we will primarily be covering the 'functional api' which uses `Model`
from tensorflow.keras.optimizers import SGD, Adam# We will be using the SGD optimiser today, though there are other options you may want to explore (such as Adam)
from tensorflow.keras.losses import MeanSquaredError, BinaryCrossentropy  # We will be using TFs MSE loss function for regression and BinaryCross Entropy for classification.
from tensorflow.keras.layers import Input, Dense, Dropout # The layers we will be using to construct our network.
from tensorflow.keras.regularizers import L1, L2 # Regularisation being used in model layers
from tensorflow.keras.metrics import BinaryAccuracy # Accuracy Metric for classification
from tensorflow.keras.callbacks import EarlyStopping # Allows Early Stopping regularisation method.
```

```
from sklearn.datasets import make_blobs
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression
import seaborn as sns
import sklearn.svm

from sklearn.metrics import silhouette_score
from yellowbrick.cluster import KElbowVisualizer
```

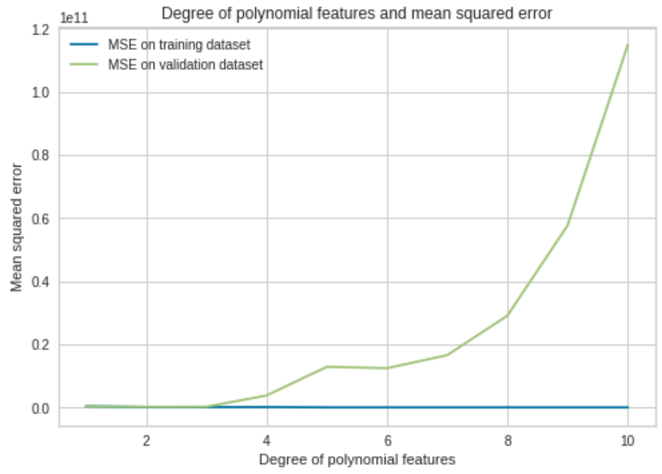
```
uploaded = files.upload()
#customerData = pd.read_csv("D:/raheel/Data Science/GRE Data Science/Machine Learning/Comp1801CourseworkData.csv")
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.
Saving Comp1801CourseworkData.csv to Comp1801CourseworkData.csv

Part 3 – Regression (Linear Regression)

```
# reading the csv file
raw_df = pd.read_csv('Comp1801CourseworkData.csv')
# displaying the top 5 rows
raw_df.head()
# Shuffle dataset
rng = np.random.default_rng(0)
df = raw_df.iloc[rng.permutation(len(raw_df))].reset_index(drop=True)

# using label encoding for categorical data
lblEncoder_X = LabelEncoder()
df['Region'] = lblEncoder_X.fit_transform(df['Region'])
df['Education'] = lblEncoder_X.fit_transform(df['Education'])
df['WorkType'] = lblEncoder_X.fit_transform(df['WorkType'])
df['Sex'] = lblEncoder_X.fit_transform(df['Sex'])

# displaying the top 5 rows after preprocessing
df.head()

#setting the target variables
tar='Salary'
#'Age','SiteSpending','SiteTime','RecommendImpression','Education','Sex','WorkType','Region'
col=['Age','SiteSpending','SiteTime','RecommendImpression','Education','Sex','WorkType','Region']

# prepare NumPy ndarrays
X_raw = np.array(df[col])
y = np.array(df[tar])

# splitting data into train and test data sets in 60:20:20 split
X_non_test_raw, X_test_raw, y_non_test, y_test = train_test_split(X_raw, y, test_size=0.20, shuffle=True, random_state=0)
X_train_raw, X_valid_raw, y_train, y_valid = train_test_split(X_non_test_raw, y_non_test, test_size=0.25, shuffle=True, random_state=0)

#setting the target variables
tar='Salary'
#'Age','SiteSpending','SiteTime','RecommendImpression','Education','Sex','WorkType','Region'
col=['Age','SiteSpending','SiteTime','RecommendImpression','Education','Sex','WorkType','Region']

# prepare NumPy ndarrays
X_raw = np.array(df[col])
y = np.array(df[tar])

# splitting data into train and test data sets in 60:20:20 split
X_non_test_raw, X_test_raw, y_non_test, y_test = train_test_split(X_raw, y, test_size=0.20, shuffle=True, random_state=0)
X_train_raw, X_valid_raw, y_train, y_valid = train_test_split(X_non_test_raw, y_non_test, test_size=0.25, shuffle=True, random_state=0)

max_degree = 10 #Define the max degree to test
# Initialise the MSE arrays, filling them with NaN's
mse_train_array = np.full([max_degree + 1], np.nan)
mse_valid_array = np.full([max_degree + 1], np.nan)
degrees = range(1, max_degree+1) # create list of degree values being iterated through

for degree in degrees:

  # Initialise
  model = sklearn.linear_model.LinearRegression()
  poly = PolynomialFeatures(degree=degree)
  scaler = StandardScaler()
  # Train
  poly.fit(X_train_raw)
  X_train_poly = poly.transform(X_train_raw)
  scaler.fit(X_train_poly)
  X_train = scaler.transform(X_train_poly)
  model.fit(X_train, y_train)
  y_pred_train = model.predict(X_train)
  mse_train = mean_squared_error(y_train, y_pred_train)

  # Validate
  X_valid_poly = poly.transform(X_valid_raw)
```

```
    X_valid = scaler.transform(X_valid_poly)
    y_pred_valid = model.predict(X_valid)
    mse_valid = mean_squared_error(y_valid, y_pred_valid)

    # Store MSE for this degree value
    mse_train_array[degree] = mse_train
    mse_valid_array[degree] = mse_valid


plt.plot(degrees, mse_train_array[1:], label='MSE on training dataset')
plt.plot(degrees, mse_valid_array[1:], label='MSE on validation dataset')
plt.xlabel('Degree of polynomial features')
plt.ylabel('Mean squared error')
plt.title('Degree of polynomial features and mean squared error')
plt.legend()
plt.show()

best_degree = np.nanargmin(mse_valid_array) # Finds the smallest VALIDATION MSE in the array (ignoring any NaN values).
print('The best degree of polynomials:', best_degree)
```

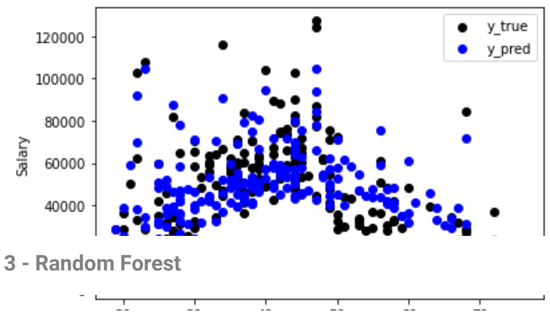



```
The best degree of polynomials: 2
```

Implementing linear regression with ploynomial feature of degree 2 that we got from the above implementation

```
customerData = pd.read_csv('Comp1801CourseworkData.csv')
raw_df = pd.DataFrame(data = customerData)
# Shuffle dataset
rng = np.random.default_rng(0)
df = raw_df.iloc[rng.permutation(len(raw_df))].reset_index(drop=True)

lblEncoder_X = LabelEncoder()
df['Region'] = lblEncoder_X.fit_transform(df['Region'])
df['Education'] = lblEncoder_X.fit_transform(df['Education'])
df['WorkType'] = lblEncoder_X.fit_transform(df['WorkType'])
df['Sex'] = lblEncoder_X.fit_transform(df['Sex'])

#display(df)

tar='Salary'
#'Age','SiteSpending','SiteTime','RecommendImpression','Education','Sex','WorkType','Region'
col_fin=['Age','SiteSpending','SiteTime','RecommendImpression','Education','Sex','WorkType','Region']

X_raw = np.array(df[col_fin])
y = np.array(df[tar])


X_non_test_raw, X_test_raw, y_non_test, y_test = train_test_split(X_raw, y, test_size=0.20, shuffle=True, random_state=0)
X_train_raw, X_valid_raw, y_train, y_valid = train_test_split(X_non_test_raw, y_non_test, test_size=0.25, shuffle=True, random_state=0)


#Using Polynomial freature
degree = 2
poly = PolynomialFeatures(degree) # Create the polynomial features object
X_train_poly = poly.fit_transform(X_train_raw) # Fit the poly object to the training data to make a new feature matrix

scaler = StandardScaler()
scaler.fit(X_train_poly)
X_train_poly_stded = scaler.transform(X_train_poly)

reg = sklearn.linear_model.LinearRegression()
reg.fit(X_train_poly_stded, y_train)

y_pred_train = reg.predict(X_train_poly_stded) # Use our fitted linear regression model to make a prediction
mse_train = mean_squared_error(y_train, y_pred_train) # Calculate the Mean Squared Error for our training data predictions
print('MSE on training data:', mse_train)

#validation
X_valid_poly = poly.transform(X_valid_raw) # Add polynomial features to the validation data
X_valid = scaler.transform(X_valid_poly)

y_pred_valid = reg.predict(X_valid) # Use our fitted linear regression model to make a prediction based on teh validation dataset
mse_valid = mean_squared_error(y_valid, y_pred_valid)  # Calculate the Mean Squared Error for our validation data predictions
print('MSE on validation data:', mse_valid)


#Testing
X_test_poly = poly.transform(X_test_raw)
X_test = scaler.transform(X_test_poly)

y_pred_test = reg.predict(X_test)


print('Mean squared error loss: {:.4f}'.format(sklearn.metrics.mean_squared_error(y_test, y_pred_test)))
# The R2 score: 1 is perfect prediction
print('R2 score: {:.4f}'.format(sklearn.metrics.r2_score(y_test, y_pred_test)))

X_new_disp =X_test_raw[:,0] # for plotting purpose
plt.scatter(X_new_disp, y_test,  color='black', label='y_true') # Observed y values
plt.scatter(X_new_disp, y_pred_test, color='blue', label='y_pred') # predicted y values
plt.xlabel('Age')
plt.ylabel('Salary')
plt.legend()
plt.show()
```

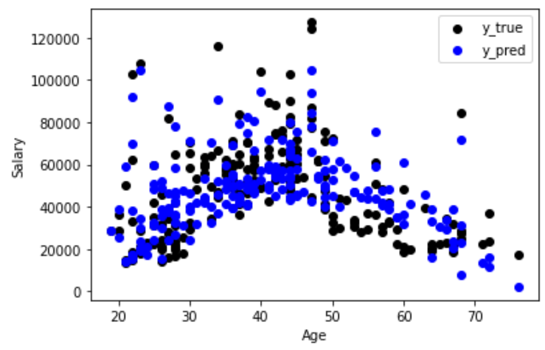
```
MSE on training data: 145472680.09557775
MSE on validation data: 171248860.6741924
Mean squared error loss: 142684141.3982
R2 score: 0.7272
```



Part 3 - Random Forest

```
customerData = pd.read_csv('Comp1801CourseworkData.csv')
raw_df = pd.DataFrame(data = customerData)
# Shuffle dataset
rng = np.random.default_rng(0)
df = raw_df.iloc[rng.permutation(len(raw_df))].reset_index(drop=True)

lblEncoder_X = LabelEncoder()
df['Region'] = lblEncoder_X.fit_transform(df['Region'])
df['Education'] = lblEncoder_X.fit_transform(df['Education'])
df['WorkType'] = lblEncoder_X.fit_transform(df['WorkType'])
df['Sex'] = lblEncoder_X.fit_transform(df['Sex'])

#display(df)

tar='Salary'
#'Age','SiteSpending','SiteTime','RecommendImpression','Education','Sex','WorkType','Region'
col_fin=['Age','SiteSpending','SiteTime','RecommendImpression','Education','Sex','WorkType','Region']

X_raw = np.array(df[col_fin])
y = np.array(df[tar])


X_non_test_raw, X_test_raw, y_non_test, y_test = train_test_split(X_raw, y, test_size=0.20, shuffle=True, random_state=0)
X_train_raw, X_valid_raw, y_train, y_valid = train_test_split(X_non_test_raw, y_non_test, test_size=0.25, shuffle=True, random_state=0)


#Using Polynomial freature
degree = 2
poly = PolynomialFeatures(degree) # Create the polynomial features object
X_train_poly = poly.fit_transform(X_train_raw) # Fit the poly object to the training data to make a new feature matrix

scaler = StandardScaler()
scaler.fit(X_train_poly)
X_train_poly_stded = scaler.transform(X_train_poly)

# create regressor object
regressor = RandomForestRegressor(n_estimators = 200)

# fit the regressor with x and y data
regressor.fit(X_train_poly_stded,y_train)

#MSE for trainig data
y_pred_train = regressor.predict(X_train_poly_stded)
mse_train = mean_squared_error(y_train, y_pred_train)
print('MSE on training data:', mse_train)

#MSE for Validation data
X_valid_poly = poly.transform(X_valid_raw) # Add polynomial features to the validation data
X_valid = scaler.transform(X_valid_poly)

y_pred_valid = regressor.predict(X_valid) # Use our fitted linear regression model to make a prediction based on teh validation dataset
mse_valid = mean_squared_error(y_valid, y_pred_valid)  # Calculate the Mean Squared Error for our validation data predictions
print('MSE on validation data:', mse_valid)

X_test_poly = poly.transform(X_test_raw)
X_test = scaler.transform(X_test_poly)
Y_pred = regressor.predict(X_test)

print('Mean squared error loss: {:.4f}'.format(sklearn.metrics.mean_squared_error(y_test,Y_pred)))
print('R2 score: {:.4f}'.format(sklearn.metrics.r2_score(y_test, Y_pred)))

X_new_disp =X_test_raw[:,0] # for plotting purpose
plt.scatter(X_new_disp, y_test,  color='black', label='y_true') # Observed y values
plt.scatter(X_new_disp, y_pred_test, color='blue', label='y_pred') # predicted y values
plt.xlabel('Age')
plt.ylabel('Salary')
plt.legend()
plt.show()
```

```
MSE on training data: 9835629.985750565
MSE on validation data: 92239509.41753529
Mean squared error loss: 78032950.4912
R2 score: 0.8508
```



Part 3 Ridge regression

```
#Ridge regression
customerData = pd.read_csv('Comp1801CourseworkData.csv')
raw_df = pd.DataFrame(data = customerData)
# Shuffle dataset
rng = np.random.default_rng(0)
df = raw_df.iloc[rng.permutation(len(raw_df))].reset_index(drop=True)

lblEncoder_X = LabelEncoder()
df['Region'] = lblEncoder_X.fit_transform(df['Region'])
df['Education'] = lblEncoder_X.fit_transform(df['Education'])
df['WorkType'] = lblEncoder_X.fit_transform(df['WorkType'])
```

```
df['Sex'] = lblEncoder_X.fit_transform(df['Sex'])

#display(df)

tar='Salary'
#'Age','SiteSpending','SiteTime','RecommendImpression','Education','Sex','WorkType','Region'
col_fin=['Age','SiteSpending','SiteTime','RecommendImpression','Education','Sex','WorkType','Region']

X_raw = np.array(df[col_fin])
y = np.array(df[tar])


X_non_test_raw, X_test_raw, y_non_test, y_test = train_test_split(X_raw, y, test_size=0.20, shuffle=True, random_state=0)
X_train_raw, X_valid_raw, y_train, y_valid = train_test_split(X_non_test_raw, y_non_test, test_size=0.25, shuffle=True, random_state=0)


#Using Polynomial freature
degree = 2
poly = PolynomialFeatures(degree) # Create the polynomial features object
X_train_poly = poly.fit_transform(X_train_raw) # Fit the poly object to the training data to make a new feature matrix

scaler = StandardScaler()
scaler.fit(X_train_poly)
X_train_poly_stded = scaler.transform(X_train_poly)

rr = Ridge(alpha=0.01)
rr.fit(X_train_poly_stded, y_train)
y_pred_train = rr.predict(X_train_poly_stded)

#validation
X_valid_poly = poly.transform(X_valid_raw) # Add polynomial features to the validation data
X_valid = scaler.transform(X_valid_poly)
y_pred_valid = rr.predict(X_valid)


#testing
X_test_poly = poly.transform(X_test_raw)
X_test = scaler.transform(X_test_poly)
pred_train_rr= rr.predict(X_test)

# The mean squared error loss
print('Mean squared error loss for training data: {:.4f}'.format(sklearn.metrics.mean_squared_error(y_train,y_pred_train)))
print('Mean squared error loss for validation data: {:.4f}'.format(sklearn.metrics.mean_squared_error(y_valid,y_pred_valid)))
print('Mean squared error loss for test data: {:.4f}'.format(sklearn.metrics.mean_squared_error(y_test,pred_train_rr)))
# # The R2 score: 1 is perfect prediction
print('R2 score: {:.4f}'.format(sklearn.metrics.r2_score(y_test, pred_train_rr)))
```

```
Mean squared error loss for training data: 145472930.0386
Mean squared error loss for validation data: 171175765.6515
Mean squared error loss for test data: 142725476.2823
R2 score: 0.7271
```

Part 3 -Lasso Regression

```
# Lasso Regression
customerData = pd.read_csv('Comp1801CourseworkData.csv')
raw_df = pd.DataFrame(data = customerData)
# Shuffle dataset
rng = np.random.default_rng(0)
df = raw_df.iloc[rng.permutation(len(raw_df))].reset_index(drop=True)

lblEncoder_X = LabelEncoder()
df['Region'] = lblEncoder_X.fit_transform(df['Region'])
df['Education'] = lblEncoder_X.fit_transform(df['Education'])
df['WorkType'] = lblEncoder_X.fit_transform(df['WorkType'])
df['Sex'] = lblEncoder_X.fit_transform(df['Sex'])

#display(df)

tar='Salary'
#'Age','SiteSpending','SiteTime','RecommendImpression','Education','Sex','WorkType','Region'
col_fin=['Age','SiteSpending','SiteTime','RecommendImpression','Education','Sex','WorkType','Region']

X_raw = np.array(df[col_fin])
y = np.array(df[tar])


X_non_test_raw, X_test_raw, y_non_test, y_test = train_test_split(X_raw, y, test_size=0.20, shuffle=True, random_state=0)
X_train_raw, X_valid_raw, y_train, y_valid = train_test_split(X_non_test_raw, y_non_test, test_size=0.25, shuffle=True, random_state=0)


#Using Polynomial freature
degree = 2
poly = PolynomialFeatures(degree) # Create the polynomial features object
X_train_poly = poly.fit_transform(X_train_raw) # Fit the poly object to the training data to make a new feature matrix

scaler = StandardScaler()
scaler.fit(X_train_poly)
X_train_poly_stded = scaler.transform(X_train_poly)

alphas = alpha_indices = np.arange(20)
model_lasso = Lasso(alpha=0.01)
model_lasso.fit(X_train_poly_stded, y_train)

y_pred_train = model_lasso.predict(X_train_poly_stded)

#validation
X_valid_poly = poly.transform(X_valid_raw) # Add polynomial features to the validation data
X_valid = scaler.transform(X_valid_poly)
y_pred_valid = model_lasso.predict(X_valid)


#testing
X_test_poly = poly.transform(X_test_raw)
X_test = scaler.transform(X_test_poly)

pred_train_lasso= model_lasso.predict(X_test)

# The mean squared error loss
print('Mean squared error loss for training data: {:.4f}'.format(sklearn.metrics.mean_squared_error(y_train,y_pred_train)))
print('Mean squared error loss for validation data: {:.4f}'.format(sklearn.metrics.mean_squared_error(y_valid,y_pred_valid)))
print('Mean squared error loss: {:.4f}'.format(sklearn.metrics.mean_squared_error(y_test,pred_train_lasso)))
# The R2 score: 1 is perfect prediction
print('R2 score: {:.4f}'.format(sklearn.metrics.r2_score(y_test, pred_train_lasso)))
```

```
Mean squared error loss for training data: 145472680.1939
Mean squared error loss for validation data: 171247279.3170
Mean squared error loss: 142684570.6271
R2 score: 0.7272
/usr/local/lib/python3.8/dist-packages/sklearn/linear_model/_coordinate_descent.py:647: ConvergenceWarning: Objective did not converge. You might want to increase the number of iterations, check
  model = cd_fast.enet_coordinate_descent(
```

Part 4 -Binary classification using Logistic regression

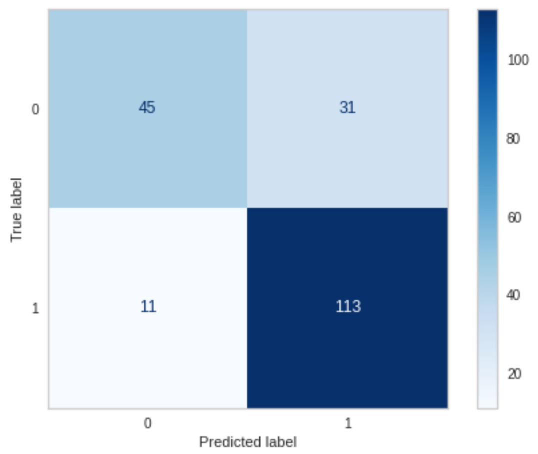
```
rng = np.random.default_rng(0)  # setting a default BitGenerator and seed
df = raw_df.iloc[rng.permutation(len(raw_df))].reset_index(drop=True) # Shuffle the dataset

# Working_data = df.copy() #making copies of the dataset to work on.
# display(Working_data)

oneHotEncoder = OneHotEncoder() #initializing the OneHot Encoder
lblEncoder_X = LabelEncoder()   #initializing the Label Encoder

#implementing label encoding
df['Sex'] = lblEncoder_X.fit_transform(df['Sex']) #implementing label encoding for the column 'Sex' using the fit_transform method.
#implementing one hot encoding
onehot_enc = oneHotEncoder.fit(df[['Region','Education','WorkType']]) #implementing OneHotEncoder for columns Region,Education and WorkType

OHT = onehot_enc.transform(df[['Region','Education','WorkType']]).toarray() #transformming the columns using the onehot_enc.transform method
Region_encoded=onehot_enc.categories_[0] #creating an array for the region
Education_encoded = onehot_enc.categories_[1] #creating an array for the education
WorkType_encoded = onehot_enc.categories_[2] #creating an array for the worktype

Con_encoded= np.concatenate((Region_encoded,Education_encoded,WorkType_encoded)) #creating a nd array by combining all the array
OHT_df = pd.DataFrame(OHT,columns=Con_encoded) #converting the nd array to a dataframe
df_tr = df.join(OHT_df) #merging the one-hot encoded columns back with original DataFrame.

#dropping the columns that were
df_tr=df_tr.drop(columns='WorkType')
df_tr=df_tr.drop(columns='Region')
df_tr=df_tr.drop(columns='Education')

print('data frame after pre-processing')
#diaplay the processed data frame
display(df_tr)

#selecting our feature for our model
Features=['Age', 'SiteSpending', 'SiteTime', 'RecommendImpression','Private sector', 'Public Sector', 'Unemployed', 'Self Employed',
         'Sex','East Midlands', 'East of England','London', 'North East', 'North West', 'Northern Ireland',
          'Scotland','South East', 'South West', 'Wales', 'West Midlands','Yorkshire and The Humber','A Level', 'Degree', 'GCSE', 'Masters','None', 'Other', 'PhD']

X = np.array(df_tr[Features]) #creating an nd array  of the features
#test = pd.DataFrame(data=X,columns=[Features]) #creating a dataframe


# df_tr['Salary'].loc[df_tr['Salary'] < 35000 ] = 0
# df_tr['Salary'].loc[df_tr['Salary'] >= 35000 ] = 1
#creating a columns on 1's and 0's
df_tr['Salary'] = np.where(df_tr['Salary'] > 35000.00,1,0)

display(df_tr['Salary'])
y = np.array(df_tr['Salary']) #convert the Tragetvariable dataframe to nd array and store in y

#test2 = pd.DataFrame(data=y,columns=['Salary'])
#display(test2)


# Split the data
X_non_test_raw, X_test_raw, y_non_test, y_test = train_test_split(X, y, train_size=0.80, shuffle=True, random_state=2)
X_train_raw, X_valid_raw, y_train, y_valid = train_test_split(X_non_test_raw, y_non_test, test_size=0.25, shuffle=True, random_state=2)

degree = 2
poly = PolynomialFeatures(degree=degree) #initializing the PolynomialFeatures object
scaler = StandardScaler() #initializing the StandardScaler object.

poly.fit(X_train_raw) #fitting the polynomialfeature object to the training data
X_train_poly = poly.transform(X_train_raw) #transforming the training data using  poly.transform

scaler.fit(X_train_poly) #fitting the StandardScaler object to the training data.
X_train = scaler.transform(X_train_poly) #transform the training data using scaler.transform method.

X_valid_poly = poly.transform(X_valid_raw) #transform the validation data using  poly.transform method with degree from the range.
X_valid = scaler.transform(X_valid_poly)   #transform the validation data using scaler.transform method.

model = LogisticRegression(random_state=0, C=1.0,solver='liblinear',penalty ='l1')
model.fit(X_train, y_train)

#using validation data
y_pred_valid = model.predict(X_valid)
print(classification_report(y_valid, y_pred_valid))
disp = ConfusionMatrixDisplay(confusion_matrix(y_valid, y_pred_valid))
disp.plot(cmap=plt.cm.Blues)
plt.grid(False)
plt.show()

#using test data
X_test_poly = poly.transform(X_test_raw)
X_test = scaler.transform(X_test_poly)
y_pred_test = model.predict(X_test)
print(classification_report(y_test, y_pred_test))
disp = ConfusionMatrixDisplay(confusion_matrix(y_test, y_pred_test))
disp.plot(cmap=plt.cm.Blues)
plt.grid(False)
plt.show()
```

data frame after pre-processing

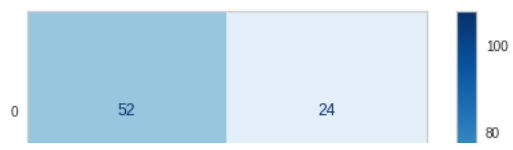
	Age	SiteSpending	SiteTime	RecommendImpression	Sex	Salary	East Midlands	East of England	Lond
0	43	1877.77	50.30	2	0	64891.98	0.0	0.0	(
1	38	265.03	71.00	0	1	57963.67	0.0	0.0	(
2	24	624.06	87.70	3	0	14969.50	0.0	0.0	(
3	34	3185.07	194.51	7	0	71403.80	0.0	0.0	(
4	52	141.47	290.55	5	1	26001.26	0.0	0.0	(
...	...	...	...	...	...	...	...	...	
995	59	124.65	163.45	9	1	38391.92	0.0	0.0	(
996	37	1061.61	97.25	3	0	36076.76	0.0	1.0	(
997	38	1859.63	160.02	0	0	58524.18	0.0	0.0	(
998	50	40.43	271.73	9	0	39573.28	0.0	0.0	(
999	20	234.55	267.19	10	0	36503.27	0.0	0.0	1

1000 rows × 29 columns

```
0      1
1      1
2      0
3      1
4      0
      ..
995    1
996    1
997    1
998    1
999    1
Name: Salary, Length: 1000, dtype: int64
              precision    recall  f1-score   support

           0       0.80      0.59      0.68        76
           1       0.78      0.91      0.84       124

    accuracy                           0.79       200
   macro avg       0.79      0.75      0.76       200
weighted avg       0.79      0.79      0.78       200
```




```
              precision    recall  f1-score   support

           0       0.76      0.68      0.72        76
           1       0.82      0.87      0.84       124

    accuracy                           0.80       200
   macro avg       0.79      0.78      0.78       200
weighted avg       0.80      0.80      0.80       200
```



Part 4 - SVM (Support Vector Machine)

implementing grid search for svm

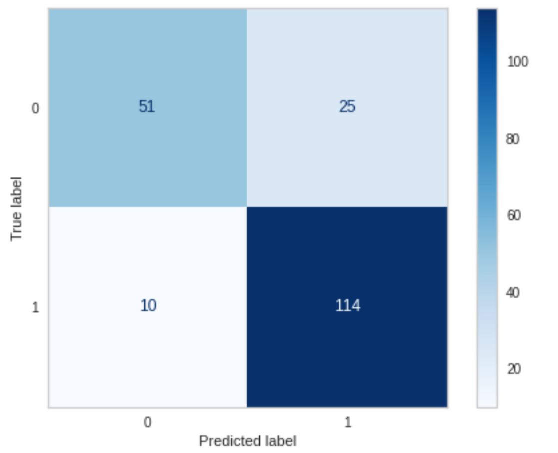
```
#implementing grid search for SVM
from sklearn.model_selection import GridSearchCV
import sklearn.svm
# Create support vector classifier object
rng = np.random.default_rng(0)  # Construct a new Generator with the default BitGenerator and seed
df = raw_df.iloc[rng.permutation(len(raw_df))].reset_index(drop=True) #Randomize the data set.

lblEncoder_X = LabelEncoder()   #initialize the Label Encoder
oneHotEncoder = OneHotEncoder() #initialize the OneHot Encoder

#performing label Encoding and One hot encoding

df['Sex'] = lblEncoder_X.fit_transform(df['Sex'])  #Label Encoding our categorical variable (columns - 'Sex') using the fit_transform method.
df['WorkType'] = lblEncoder_X.fit_transform(df['WorkType']) #Label Encoding our categorical variable (columns - 'WorkType') using the fit_transform method.
df['Region'] = lblEncoder_X.fit_transform(df['Region'])
df['Education'] = lblEncoder_X.fit_transform(df['Education'])

Sal_data_df = df


#Select feature names for fitiing the model.
Features=['Age', 'SiteSpending', 'SiteTime', 'RecommendImpression','WorkType',
         'Sex','Region','Education']
X = np.array(Sal_data_df[Features]) #convert the feature dataframe into nd array and store in X
Sal_data_df['Salary'].loc[Sal_data_df['Salary'] < 35000 ] = 0
Sal_data_df['Salary'].loc[Sal_data_df['Salary'] >= 35000 ] = 1
display(Sal_data_df['Salary'])
y = np.array(Sal_data_df['Salary'])

X_non_test_raw, X_test_raw, y_non_test, y_test = train_test_split(X, y, train_size=0.80, shuffle=True, random_state=2)
X_train_raw, X_valid_raw, y_train, y_valid = train_test_split(X_non_test_raw, y_non_test, test_size=0.25, shuffle=True, random_state=2)

degree = 2
poly = PolynomialFeatures(degree=degree) #initializing the PolynomialFeatures object
scaler = StandardScaler() #initializing the StandardScaler object.

poly.fit(X_train_raw) #fitting the polynomialfeature object to the training data
X_train_poly = poly.transform(X_train_raw) #transforming the training data using  poly.transform
```

```
scaler.fit(X_train_poly) #fitting the StandardScaler object to the training data.
X_train = scaler.transform(X_train_poly)

X_valid_poly = poly.transform(X_valid_raw) #transform the validation data using  poly.transform method with degree from the range.
X_valid = scaler.transform(X_valid_poly)

# defining parameter range
param_grid = {'C': [0.1, 1, 10, 100, 1000],
              'gamma': [1, 0.1, 0.01, 0.001, 0.0001],
              'kernel': ['rbf']}

grid = GridSearchCV(sklearn.svm.SVC(), param_grid, refit = True, verbose = 3)

# fitting the model for grid search
grid.fit(X_train, y_train)

# print best parameter after tuning
print(grid.best_params_)

# print how our model looks after hyper-parameter tuning
print(grid.best_estimator_)

y_pred = grid.predict(X_valid)
```

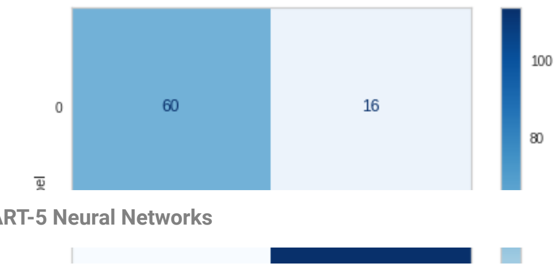
implementing svm based on the values got for the hyper parameters from the above grid search

```
import sklearn.svm
# Create support vector classifier object
rng = np.random.default_rng(0)  # Construct a new Generator with the default BitGenerator and seed
df = raw_df.iloc[rng.permutation(len(raw_df))].reset_index(drop=True) #Randomize the data set.

lblEncoder_X = LabelEncoder()   #initialize the Label Encoder
oneHotEncoder = OneHotEncoder() #initialize the OneHot Encoder

#performing label Encoding and One hot encoding

df['Sex'] = lblEncoder_X.fit_transform(df['Sex'])  #Label Encoding our categorical variable (columns - 'Sex') using the fit_transform method.
df['WorkType'] = lblEncoder_X.fit_transform(df['WorkType']) #Label Encoding our categorical variable (columns - 'WorkType') using the fit_transform method.
df['Region'] = lblEncoder_X.fit_transform(df['Region'])
df['Education'] = lblEncoder_X.fit_transform(df['Education'])

Sal_data_df = df


#Select feature names for fitiing the model.
Features=['Age', 'SiteSpending', 'SiteTime', 'RecommendImpression','WorkType',
         'Sex','Region','Education']
X = np.array(Sal_data_df[Features]) #convert the feature dataframe into nd array and store in X
Sal_data_df['Salary'].loc[Sal_data_df['Salary'] < 35000 ] = 0
Sal_data_df['Salary'].loc[Sal_data_df['Salary'] >= 35000 ] = 1
display(Sal_data_df['Salary'])
y = np.array(Sal_data_df['Salary'])##convert the Tragetvariable dataframe to nd array and store in y


# Split the data
X_non_test_raw, X_test_raw, y_non_test, y_test = train_test_split(X, y, train_size=0.80, shuffle=True, random_state=2)
X_train_raw, X_valid_raw, y_train, y_valid = train_test_split(X_non_test_raw, y_non_test, test_size=0.25, shuffle=True, random_state=2)

degree = 2
poly = PolynomialFeatures(degree=degree) #initializing the PolynomialFeatures object
scaler = StandardScaler() #initializing the StandardScaler object.

poly.fit(X_train_raw) #fitting the polynomialfeature object to the training data
X_train_poly = poly.transform(X_train_raw) #transforming the training data using  poly.transform

scaler.fit(X_train_poly) #fitting the StandardScaler object to the training data.
X_train = scaler.transform(X_train_poly) #transform the training data using scaler.transform method.

X_valid_poly = poly.transform(X_valid_raw) #transform the validation data using  poly.transform method with degree from the range.
X_valid = scaler.transform(X_valid_poly)   #transform the validation data using scaler.transform method.

model = sklearn.svm.SVC(C=1000,gamma=0.001,kernel='rbf',random_state=40)
#model = sklearn.svm.SVC(C=50,gamma='scale',kernel='poly')
model.fit(X_train, y_train)

#using validation data
y_pred_valid = model.predict(X_valid)
print(classification_report(y_valid, y_pred_valid))
disp = ConfusionMatrixDisplay(confusion_matrix(y_valid, y_pred_valid))
disp.plot(cmap=plt.cm.Blues)
plt.grid(False)
plt.show()

#using test data
X_test_poly = poly.transform(X_test_raw)
X_test = scaler.transform(X_test_poly)
y_pred_test = model.predict(X_test)
print(classification_report(y_test, y_pred_test))
disp = ConfusionMatrixDisplay(confusion_matrix(y_test, y_pred_test))
disp.plot(cmap=plt.cm.Blues)
plt.grid(False)
plt.show()

# obj = sklearn.svm.SVC(C=1000,gamma=0.01,kernel='rbf',random_state=40)

# # Train the model using the training sets
# obj.fit(X_train, y_train)

# # Make predictions using the testing set
# y_pred = obj.predict(X_new)
```

```
/usr/local/lib/python3.8/dist-packages/pandas/core/indexing.py:1732: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guid
  self._setitem_single_block(indexer, value, name)
0      1.0
1      1.0
2      0.0
3      1.0
4      0.0
      ...
995    1.0
996    1.0
997    1.0
998    1.0
999    1.0
Name: Salary, Length: 1000, dtype: float64
              precision    recall  f1-score   support

         0.0       0.84      0.67      0.74        76
         1.0       0.82      0.92      0.87       124

    accuracy                           0.82       200
   macro avg       0.83      0.80      0.81       200
weighted avg       0.83      0.82      0.82       200
```




```
              precision    recall  f1-score   support

         0.0       0.86      0.79      0.82        76
         1.0       0.88      0.92      0.90       124

    accuracy                           0.87       200
   macro avg       0.87      0.85      0.86       200
weighted avg       0.87      0.87      0.87       200
```



PART-5 Neural Networks

```
raw_df = pd.read_csv('Comp1801CourseworkData.csv')
# displaying the top 5 rows
raw_df.head()
# Shuffle dataset
rng = np.random.default_rng(0)
df = raw_df.iloc[rng.permutation(len(raw_df))].reset_index(drop=True)

lblEncoder_X = LabelEncoder()
df['Region'] = lblEncoder_X.fit_transform(df['Region'])
df['Education'] = lblEncoder_X.fit_transform(df['Education'])
df['WorkType'] = lblEncoder_X.fit_transform(df['WorkType'])
df['Sex'] = lblEncoder_X.fit_transform(df['Sex'])

df_copy = df.copy() # making a copy for the data frame
df_copy['GreaterThan35K'] = np.where(df['Salary'] > 35000.00,1,0)
#display(df_copy)
df_copy['GreaterThan35K'].value_counts()
tar='GreaterThan35K'
#'Age','SiteSpending','SiteTime','RecommendImpression','Education','Sex','WorkType','Region','Salary'
col_fin=['Age','SiteSpending','SiteTime','RecommendImpression','Education','Sex','WorkType','Region']

X_pd = pd.DataFrame(df_copy[col_fin])
#y_pd = pd.DataFrame(df_copy[tar])
Y_pd = df_copy[tar].to_frame()

# Display the dataset
XY_pd = pd.concat([X_pd, Y_pd], axis=1)
display(XY_pd)

# prepare NumPy ndarrays
X_raw = X_pd.to_numpy()
Y = Y_pd.to_numpy()

# Split the data into training/test data
# `shuffle=True` for non-time series case. You should set `shuffle=False` to avoid future data being contaminated in the training data.
X_nontest_raw, X_test_raw, Y_nontest, Y_test = train_test_split(X_raw, Y, test_size=0.20, shuffle=True, random_state=0)
X_train_raw, X_valid_raw, Y_train, Y_valid = train_test_split(X_nontest_raw, Y_nontest, test_size=0.25, shuffle=True, random_state=0)

scaler = StandardScaler()
scaler.fit(X_train_raw)
X_train = scaler.transform(X_train_raw)
X_valid = scaler.transform(X_valid_raw)
X_test = scaler.transform(X_test_raw)

#checking the shape of our datasets
print('The shape of `X_train`:', X_train.shape)
print('The shape of `X_valid`:', X_valid.shape)
print('The shape of `X_test`:', X_test.shape)

# Define the regularizer.
alpha = 0.01
kernel_regularizer = L2(l2=alpha)

# Define the `Dense` layer.
# The output dimension is 1, so we specify `units=1`.
# The as we are performing binary classification, we specify `activation=sigmoid`.
# We apply l2 regularization on the kernel parameters by specifying a `kernel_regularizer` argument.
```

```
dense_layer_1 = Dense(units=10, activation=relu, kernel_regularizer=kernel_regularizer)
output_layer = Dense(units=1, activation=sigmoid, kernel_regularizer=kernel_regularizer)

# Define the "virtual" input
input = Input(shape=X_train.shape[1:])

# Define the "virtual" output
output = dense_layer_1(input)
output = output_layer(output)

# Define the neural network model.
model = Model(inputs=[input], outputs=[output], name='logistic_regression')

# Output the summary of the model.
model.summary()

#initalizing varaibles for evalution
adam = Adam(learning_rate=0.1)
ce = BinaryCrossentropy()
acc = BinaryAccuracy()
model.compile(optimizer=adam, loss=ce, metrics=[acc])

# Train the model.
# `epochs` determines the number of epochs.
# `batch_size` determines the batch_size.

history = model.fit(X_train, Y_train, batch_size=100, epochs=50, validation_data=(X_valid, Y_valid))


# Plot validation MSE, alwys nice to have plots to help us visualise things!
plt.plot(history.history['binary_accuracy'], label='accuracy')
plt.plot(history.history['val_binary_accuracy'], label = 'val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')

ce_test, acc_test = model.evaluate(X_test, Y_test)
print('The cross entropy loss on the test data:', ce_test)
print('The accuracy on the test data:', acc_test)

#testing
Y_test_logit = model.predict(X_test)

Y_test_pred = (Y_test_logit > 0.5).astype(int)
disp = ConfusionMatrixDisplay(confusion_matrix(Y_test, Y_test_pred),display_labels=['<35k', '>=35k'])
disp.plot(cmap=plt.cm.Blues)
plt.grid(False)

acc_test = accuracy_score(Y_test, Y_test_pred)
f1_test = f1_score(Y_test, Y_test_pred, pos_label=1)
print('The accuracy on the test data with the selected hyperparameter:', acc_test)
print('The F1 score on the test data with the selected hyperparameter:', f1_test)
pre_test = precision_score(Y_test, Y_test_pred, pos_label=1)
print('Precision on validation data:', pre_test)
reca_test = precision_score(Y_test, Y_test_pred, pos_label=1)
print('Recall on validation data:', reca_test)
```

	Age	SiteSpending	SiteTime	RecommendImpression	Education	Sex	WorkType	Region	Grea
0	43	1877.77	50.30	2	1	0	0	6	
1	38	265.03	71.00	0	1	1	0	7	
2	24	624.06	87.70	3	4	0	0	6	
3	34	3185.07	194.51	7	6	0	0	11	
4	52	141.47	290.55	5	2	1	0	6	
...	...	...	...	...	...	...	...	...	
995	59	124.65	163.45	9	2	1	3	5	
996	37	1061.61	97.25	3	4	0	0	1	
997	38	1859.63	160.02	0	2	0	2	7	
998	50	40.43	271.73	9	0	0	0	10	
999	20	234.55	267.19	10	5	0	0	2	

1000 rows × 9 columns

```
The shape of `X_train`: (600, 8)
The shape of `X_valid`: (200, 8)
The shape of `X_test`: (200, 8)
Model: "logistic_regression"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_7 (InputLayer)        [(None, 8)]               0

 dense_12 (Dense)            (None, 10)                90

 dense_13 (Dense)            (None, 1)                 11

=================================================================
Total params: 101
Trainable params: 101
Non-trainable params: 0
_________________________________________________________________
Epoch 1/50
6/6 [==============================] - 1s 31ms/step - loss: 0.7302 - binary_accuracy: 0.5900
Epoch 2/50
6/6 [==============================] - 0s 7ms/step - loss: 0.6206 - binary_accuracy: 0.7150
Epoch 3/50
6/6 [==============================] - 0s 6ms/step - loss: 0.5707 - binary_accuracy: 0.8200
Epoch 4/50
6/6 [==============================] - 0s 7ms/step - loss: 0.5230 - binary_accuracy: 0.8633
Epoch 5/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4817 - binary_accuracy: 0.8817
Epoch 6/50
6/6 [==============================] - 0s 7ms/step - loss: 0.4733 - binary_accuracy: 0.8867
Epoch 7/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4656 - binary_accuracy: 0.8783
Epoch 8/50
6/6 [==============================] - 0s 10ms/step - loss: 0.4639 - binary_accuracy: 0.8950
Epoch 9/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4660 - binary_accuracy: 0.8883
Epoch 10/50
6/6 [==============================] - 0s 7ms/step - loss: 0.4498 - binary_accuracy: 0.8983
Epoch 11/50
6/6 [==============================] - 0s 9ms/step - loss: 0.4540 - binary_accuracy: 0.8850
Epoch 12/50
6/6 [==============================] - 0s 11ms/step - loss: 0.4534 - binary_accuracy: 0.8800
Epoch 13/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4552 - binary_accuracy: 0.8767
Epoch 14/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4545 - binary_accuracy: 0.8767
Epoch 15/50
6/6 [==============================] - 0s 7ms/step - loss: 0.4550 - binary_accuracy: 0.8917
Epoch 16/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4572 - binary_accuracy: 0.8700
Epoch 17/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4505 - binary_accuracy: 0.8867
Epoch 18/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4496 - binary_accuracy: 0.9000
Epoch 19/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4542 - binary_accuracy: 0.8683
Epoch 20/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4541 - binary_accuracy: 0.8950
Epoch 21/50
6/6 [==============================] - 0s 10ms/step - loss: 0.4541 - binary_accuracy: 0.8850
Epoch 22/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4510 - binary_accuracy: 0.8900
Epoch 23/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4581 - binary_accuracy: 0.8733
Epoch 24/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4503 - binary_accuracy: 0.8850
Epoch 25/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4530 - binary_accuracy: 0.8733
Epoch 26/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4524 - binary_accuracy: 0.8950
Epoch 27/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4477 - binary_accuracy: 0.8883
Epoch 28/50
6/6 [==============================] - 0s 10ms/step - loss: 0.4487 - binary_accuracy: 0.8733
Epoch 29/50
6/6 [==============================] - 0s 10ms/step - loss: 0.4444 - binary_accuracy: 0.8983
Epoch 30/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4495 - binary_accuracy: 0.8867
Epoch 31/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4502 - binary_accuracy: 0.8833
Epoch 32/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4517 - binary_accuracy: 0.8817
Epoch 33/50
6/6 [==============================] - 0s 8ms/step - loss: 0.4482 - binary_accuracy: 0.8800
Epoch 34/50
6/6 [==============================] - 0s 7ms/step - loss: 0.4484 - binary_accuracy: 0.8783
Epoch 35/50
6/6 [==============================] - 0s 8ms/step - loss: 0.4520 - binary_accuracy: 0.8950
Epoch 36/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4485 - binary_accuracy: 0.8750
Epoch 37/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4499 - binary_accuracy: 0.8900
Epoch 38/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4500 - binary_accuracy: 0.8883
Epoch 39/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4469 - binary_accuracy: 0.8833
Epoch 40/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4455 - binary_accuracy: 0.8967
Epoch 41/50
6/6 [==============================] - 0s 8ms/step - loss: 0.4483 - binary_accuracy: 0.8950
Epoch 42/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4495 - binary_accuracy: 0.8883
Epoch 43/50
6/6 [==============================] - 0s 7ms/step - loss: 0.4522 - binary_accuracy: 0.9000
Epoch 44/50
```

Checking for class imbalance

```
6/6 [==============================] - 0s 6ms/step - loss: 0.4474 - binary_accuracy: 0.8933
```

```
raw_df = pd.read_csv('Comp1801CourseworkData.csv')
# displaying the top 5 rows
raw_df.head()
# Shuffle dataset
rng = np.random.default_rng(0)
df = raw_df.iloc[rng.permutation(len(raw_df))].reset_index(drop=True)

lblEncoder_X = LabelEncoder()
df['Region'] = lblEncoder_X.fit_transform(df['Region'])
df['Education'] = lblEncoder_X.fit_transform(df['Education'])
df['WorkType'] = lblEncoder_X.fit_transform(df['WorkType'])
df['Sex'] = lblEncoder_X.fit_transform(df['Sex'])

df_copy = df.copy() # making a copy for the data frame
df_copy['GreaterThan35K'] = np.where(df['Salary'] > 35000.00,1,0)
#display(df_copy)
df_copy['GreaterThan35K'].value_counts()
tar='GreaterThan35K'
#'Age','SiteSpending','SiteTime','RecommendImpression','Education','Sex','WorkType','Region','Salary'
col_fin=['Age','SiteSpending','SiteTime','RecommendImpression','Education','Sex','WorkType','Region']

X_pd = pd.DataFrame(df_copy[col_fin])
#y_pd = pd.DataFrame(df_copy[tar])
Y_pd = df_copy[tar].to_frame()

# Display the dataset
XY_pd = pd.concat([X_pd, Y_pd], axis=1)
display(XY_pd)

# prepare NumPy ndarrays
X_raw = X_pd.to_numpy()
Y = Y_pd.to_numpy()

# Split the data into training/test data
# `shuffle=True` for non-time series case. You should set `shuffle=False` to avoid future data being contaminated in the training data.
X_nontest_raw, X_test_raw, Y_nontest, Y_test = train_test_split(X_raw, Y, test_size=0.20, shuffle=True, random_state=0)
X_train_raw, X_valid_raw, Y_train, Y_valid = train_test_split(X_nontest_raw, Y_nontest, test_size=0.25, shuffle=True, random_state=0)

scaler = StandardScaler()
scaler.fit(X_train_raw)
X_train = scaler.transform(X_train_raw)
X_valid = scaler.transform(X_valid_raw)
X_test = scaler.transform(X_test_raw)

# Define the regularizer.
alpha = 0.01
kernel_regularizer = L2(l2=alpha)

# Define the `Dense` layer.
# The output dimension is 1, so we specify `units=1`.
# The as we are performing binary classification, we specify `activation=sigmoid`.
# We apply l2 regularization on the kernel parameters by specifying a `kernel_regularizer` argument.
dense_layer_1 = Dense(units=10, activation=relu, kernel_regularizer=kernel_regularizer)
output_layer = Dense(units=1, activation=sigmoid, kernel_regularizer=kernel_regularizer)

# Define the "virtual" input
input = Input(shape=X_train.shape[1:])

# Define the "virtual" output
output = dense_layer_1(input)
output = output_layer(output)

# Define the neural network model.
model = Model(inputs=[input], outputs=[output], name='logistic_regression')

# Output the summary of the model.
model.summary()

adam = Adam(learning_rate=0.1)
ce = BinaryCrossentropy()
acc = BinaryAccuracy()
model.compile(optimizer=adam, loss=ce, metrics=[acc])

# Train the model.
# `epochs` determines the number of epochs.
# `batch_size` determines the batch_size.

m = {}
m[0] = np.sum((Y_train == 0).astype(int)) # Count how many times `0` appears in the target matrix.
m[1] = np.sum((Y_train == 1).astype(int)) # Count how many times `1` appears in the target matrix.
m_total = m[0] + m[1]
class_weight = {0: m_total / (2.0 * m[0]), 1: m_total / (2.0 * m[1])}

history = model.fit(X_train, Y_train, batch_size=100, epochs=50, validation_data=(X_valid, Y_valid), class_weight=class_weight)

# Plot validation MSE, alwys nice to have plots to help us visualise things!
plt.plot(history.history['binary_accuracy'], label='accuracy')
plt.plot(history.history['val_binary_accuracy'], label = 'val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')

Y_test_logit = model.predict(X_test)
Y_test_pred = (Y_test_logit > 0.5).astype(int)
bacc = balanced_accuracy_score(Y_test, Y_test_pred)
print('The balanced accuracy score on the test data:', bacc)

disp = ConfusionMatrixDisplay(confusion_matrix(Y_test, Y_test_pred),display_labels=['<35k', '>=35k'])
disp.plot(cmap=plt.cm.Blues)
plt.grid(False)

acc_test = accuracy_score(Y_test, Y_test_pred)
f1_test = f1_score(Y_test, Y_test_pred, pos_label=1)
print('The accuracy on the test data with the selected hyperparameter:', acc_test)
print('The F1 score on the test data with the selected hyperparameter:', f1_test)
pre_test = precision_score(Y_test, Y_test_pred, pos_label=1)
print('Precision on test data:', pre_test)
reca_test = precision_score(Y_test, Y_test_pred, pos_label=1)
print('Recall on test data:', reca_test)
```

	Age	SiteSpending	SiteTime	RecommendImpression	Education	Sex	WorkType	Region	Grea
0	43	1877.77	50.30	2	1	0	0	6	
1	38	265.03	71.00	0	1	1	0	7	
2	24	624.06	87.70	3	4	0	0	6	
3	34	3185.07	194.51	7	6	0	0	11	
4	52	141.47	290.55	5	2	1	0	6	
...	...	...	...	...	...	...	...	...	
995	59	124.65	163.45	9	2	1	3	5	
996	37	1061.61	97.25	3	4	0	0	1	
997	38	1859.63	160.02	0	2	0	2	7	
998	50	40.43	271.73	9	0	0	0	10	
999	20	234.55	267.19	10	5	0	0	2	

1000 rows × 9 columns

```
Model: "logistic_regression"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_4 (InputLayer)        [(None, 8)]               0

 dense_6 (Dense)             (None, 10)                90

 dense_7 (Dense)             (None, 1)                 11

=================================================================
Total params: 101
Trainable params: 101
Non-trainable params: 0
_________________________________________________________________
Epoch 1/50
6/6 [==============================] - 1s 33ms/step - loss: 0.7237 - binary_accuracy: 0.5767
Epoch 2/50
6/6 [==============================] - 0s 7ms/step - loss: 0.6247 - binary_accuracy: 0.6550
Epoch 3/50
6/6 [==============================] - 0s 7ms/step - loss: 0.5499 - binary_accuracy: 0.7883
Epoch 4/50
6/6 [==============================] - 0s 6ms/step - loss: 0.5130 - binary_accuracy: 0.8367
Epoch 5/50
6/6 [==============================] - 0s 7ms/step - loss: 0.4889 - binary_accuracy: 0.8817
Epoch 6/50
6/6 [==============================] - 0s 8ms/step - loss: 0.4769 - binary_accuracy: 0.9050
Epoch 7/50
6/6 [==============================] - 0s 7ms/step - loss: 0.4801 - binary_accuracy: 0.8783
Epoch 8/50
6/6 [==============================] - 0s 10ms/step - loss: 0.4740 - binary_accuracy: 0.8800
Epoch 9/50
6/6 [==============================] - 0s 12ms/step - loss: 0.4664 - binary_accuracy: 0.8917
Epoch 10/50
6/6 [==============================] - 0s 7ms/step - loss: 0.4681 - binary_accuracy: 0.8850
Epoch 11/50
6/6 [==============================] - 0s 7ms/step - loss: 0.4680 - binary_accuracy: 0.8750
Epoch 12/50
6/6 [==============================] - 0s 7ms/step - loss: 0.4678 - binary_accuracy: 0.8883
Epoch 13/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4656 - binary_accuracy: 0.8700
Epoch 14/50
6/6 [==============================] - 0s 8ms/step - loss: 0.4657 - binary_accuracy: 0.8783
Epoch 15/50
6/6 [==============================] - 0s 8ms/step - loss: 0.4614 - binary_accuracy: 0.8867
Epoch 16/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4706 - binary_accuracy: 0.8800
Epoch 17/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4675 - binary_accuracy: 0.8967
Epoch 18/50
6/6 [==============================] - 0s 9ms/step - loss: 0.4705 - binary_accuracy: 0.8850
Epoch 19/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4752 - binary_accuracy: 0.8633
Epoch 20/50
6/6 [==============================] - 0s 8ms/step - loss: 0.4683 - binary_accuracy: 0.8933
Epoch 21/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4695 - binary_accuracy: 0.8883
Epoch 22/50
6/6 [==============================] - 0s 7ms/step - loss: 0.4679 - binary_accuracy: 0.8867
Epoch 23/50
6/6 [==============================] - 0s 7ms/step - loss: 0.4661 - binary_accuracy: 0.8900
Epoch 24/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4622 - binary_accuracy: 0.8867
Epoch 25/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4639 - binary_accuracy: 0.8783
Epoch 26/50
6/6 [==============================] - 0s 11ms/step - loss: 0.4592 - binary_accuracy: 0.9000
Epoch 27/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4628 - binary_accuracy: 0.8917
Epoch 28/50
6/6 [==============================] - 0s 7ms/step - loss: 0.4641 - binary_accuracy: 0.8767
Epoch 29/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4603 - binary_accuracy: 0.9017
Epoch 30/50
6/6 [==============================] - 0s 8ms/step - loss: 0.4688 - binary_accuracy: 0.8750
Epoch 31/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4664 - binary_accuracy: 0.8917
Epoch 32/50
6/6 [==============================] - 0s 7ms/step - loss: 0.4636 - binary_accuracy: 0.8867
Epoch 33/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4571 - binary_accuracy: 0.8917
Epoch 34/50
6/6 [==============================] - 0s 7ms/step - loss: 0.4660 - binary_accuracy: 0.8833
Epoch 35/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4603 - binary_accuracy: 0.8850
Epoch 36/50
6/6 [==============================] - 0s 8ms/step - loss: 0.4611 - binary_accuracy: 0.8967
Epoch 37/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4646 - binary_accuracy: 0.8900
Epoch 38/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4644 - binary_accuracy: 0.8833
Epoch 39/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4661 - binary_accuracy: 0.8933
Epoch 40/50
6/6 [==============================] - 0s 7ms/step - loss: 0.4642 - binary_accuracy: 0.8800
Epoch 41/50
6/6 [==============================] - 0s 7ms/step - loss: 0.4727 - binary_accuracy: 0.8817
Epoch 42/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4685 - binary_accuracy: 0.8833
Epoch 43/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4641 - binary_accuracy: 0.8900
Epoch 44/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4697 - binary_accuracy: 0.8867
Epoch 45/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4628 - binary_accuracy: 0.8783
Epoch 46/50
6/6 [==============================] - 0s 6ms/step - loss: 0.4628 - binary_accuracy: 0.8950
```

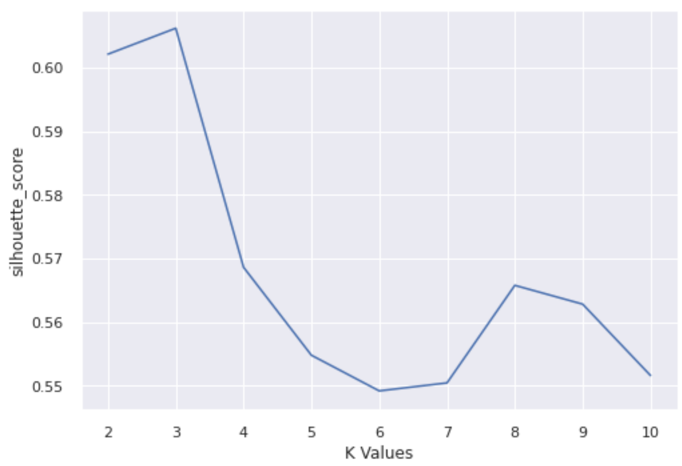
Part-6 Kmeans clustering

```
6/6 [==============================] - 0s 8ms/step - loss: 0.4601 - binary_accuracy: 0.8917
```

Computing the idea cluster number k

```
Epoch 50/50
```

```
import sklearn.svm
import matplotlib.pyplot as plt # A library to draw a scatter plot
import seaborn as sns
from sklearn.cluster import KMeans

customerData = pd.read_csv('Comp1801CourseworkData.csv')
raw_df = pd.DataFrame(data = customerData)

rng = np.random.default_rng(0)  # Construct a new Generator with the default BitGenerator and seed
df = raw_df.iloc[rng.permutation(len(raw_df))].reset_index(drop=True) #Randomize the data set.


col = ['Age','Salary']
X = np.array(df[col])

# visualizer = KElbowVisualizer(model,k = (2,10), metric = 'silhouette')#, metric = 'silhouette'
# visualizer.fit(X)
# visualizer.show()
# plt.show()
sil = []
kvalues = [2,3,4,5,6,7,8,9,10]

for k in kvalues:
  kmeans = KMeans(n_clusters = k).fit(X)
  labels = kmeans.labels_
  sil.append(silhouette_score(X, labels, metric = 'euclidean'))

plt.plot(kvalues,sil)
plt.xlabel("K Values")
plt.ylabel("silhouette_score")
plt.show()
```




```
model = KMeans(n_clusters=3)
cluster_labels = model.fit_predict(X)
sns.set() # For a more sophisticated plot style.


plt.scatter(X[:, 0], X[:, 1], c=cluster_labels, s=50, cmap='viridis')
plt.scatter(model.cluster_centers_[:, 0], model.cluster_centers_[:, 1], c='black', s=200);
plt.xlabel('Age')
plt.ylabel('Salary')
plt.title('Clustering results')
```

```
Text(0.5, 1.0, 'Clustering results')
```