```
#Opeyemi Oloruntola 01128399
import requests
import io
import scipy
import statsmodels.api as sm
from sklearn.feature_selection import f_regression
import numpy as np # A useful package for dealing with mathematical processes, w
import pandas as pd # A common package for viewing tabular data
import time # We will be using this to time the efficiency of vectorisation
import sklearn.linear_model # We want to be able to access the sklearn datasets
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeClassifier
from sklearn.utils import resample
from sklearn import kernel_ridge
from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler, MinMaxScaler # We will be usin
import matplotlib.pyplot as plt # We will be using Matplotlib for our graphs
from mpl_toolkits import mplot3d # Used to make a 3D plot used to demonstrate mu
from sklearn.preprocessing import PolynomialFeatures # A preprocessing function
from google.colab import files # We will be importing a csv file I have provided
from sklearn.preprocessing import LabelEncoder, OneHotEncoder # We will be using
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split # We will be using this to
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, accuracy_s
import seaborn as sns; sns.set()
from scipy.cluster.hierarchy import dendrogram
from sklearn.cluster import AgglomerativeClustering
from sklearn.cluster import KMeans

# Below are a wide selection of tensorflow libraries we will need to construct o
from tensorflow.keras.activations import sigmoid, linear, relu # Activation func
from tensorflow.keras.models import Model, Sequential # Different mays of constr
from tensorflow.keras.optimizers import SGD # We will be using the SGD optimiser
from tensorflow.keras.losses import MeanSquaredError, BinaryCrossentropy  # We w
from tensorflow.keras.layers import Input, Dense, Dropout # The layers we will b
from tensorflow.keras.regularizers import L1, L2 # Regularisation being used in
from tensorflow.keras.metrics import BinaryAccuracy # Accuracy Metric for classi
from tensorflow.keras.callbacks import EarlyStopping # Allows Early Stopping reg
```

Load the Data

The data was downloaded from moodle and uploaded to my github for easy access.

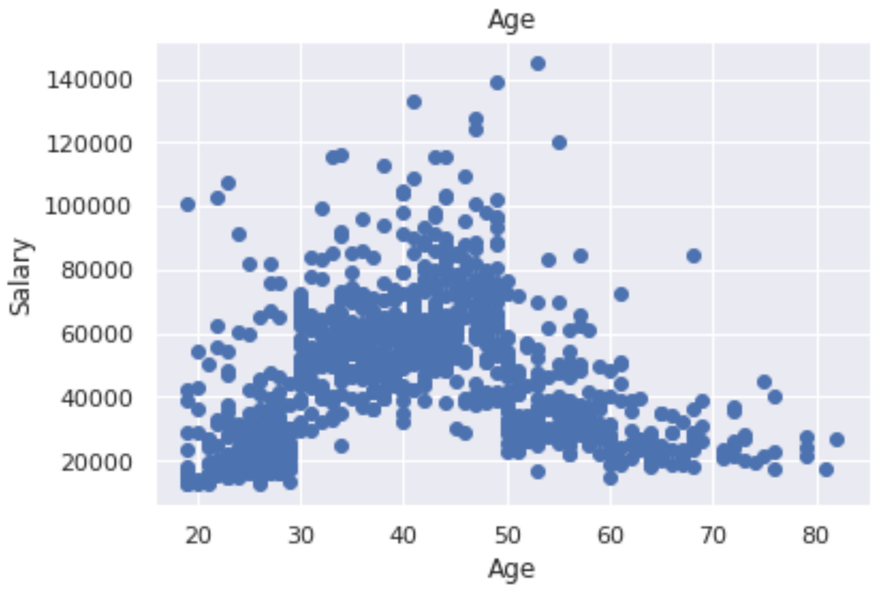
```
url = "https://raw.githubusercontent.com/0xsas/courseworkDatasets/main/datasets/
download = requests.get(url).content # save the raw dataset to the variable down
df = pd.read_csv(io.StringIO(download.decode('utf-8'))) # use the ioString libra
df.head()
```

	Age	SiteSpending	SiteTime	RecommendImpression	Education	WorkType	
0	32	314.06	30.14	0	Degree	Private sector	M
1	20	3758.36	149.36	4	GCSE	Private sector	Fer
2	36	601.72	21.87	0	Masters	Private sector	M
						Private	

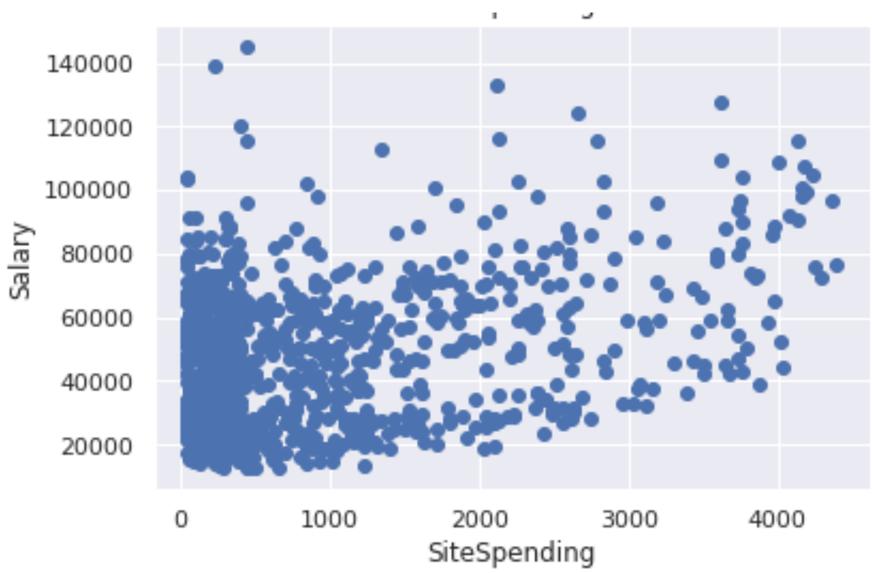
PART 1: REGRESSION

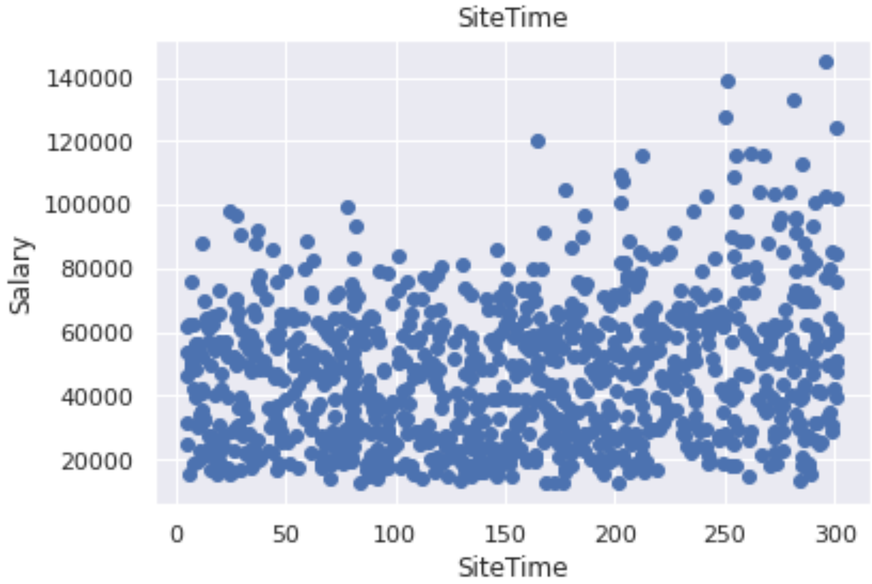
Performing EDA and feature selection

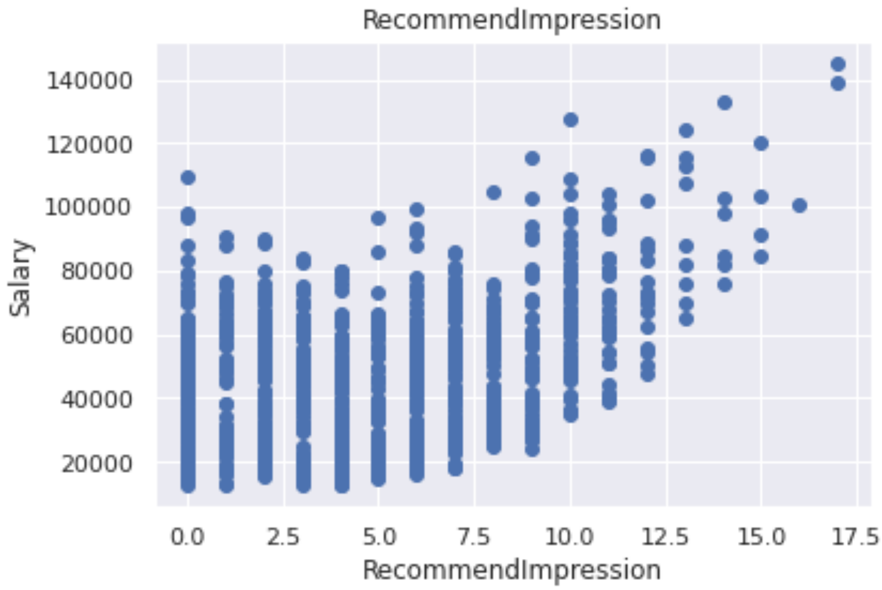
```
# Plot to the various columns to check for obvious correlelations
for label in df[1:]:
  plt.scatter(df[label], df['Salary'])
  plt.title(label)
  plt.ylabel('Salary')
  plt.xlabel(label)
  plt.show()
```

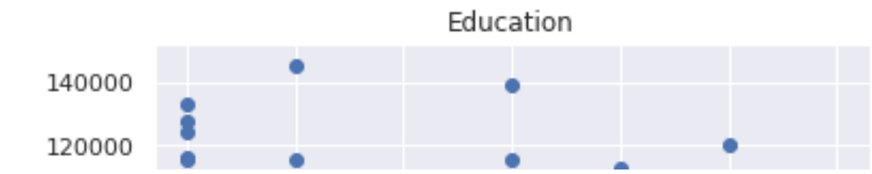


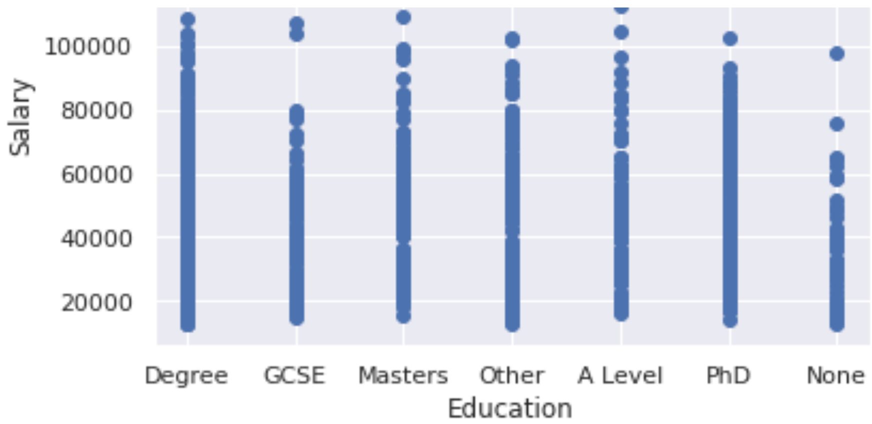
SiteSpending

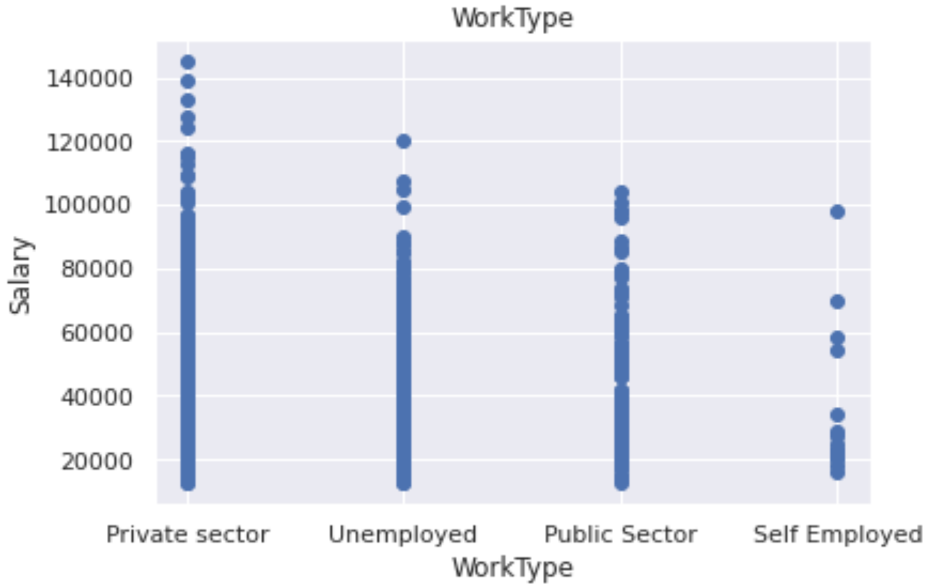

140000
120000
100000
80000
60000
40000
20000
Salary
0
1000
2000
3000
4000
SiteSpending

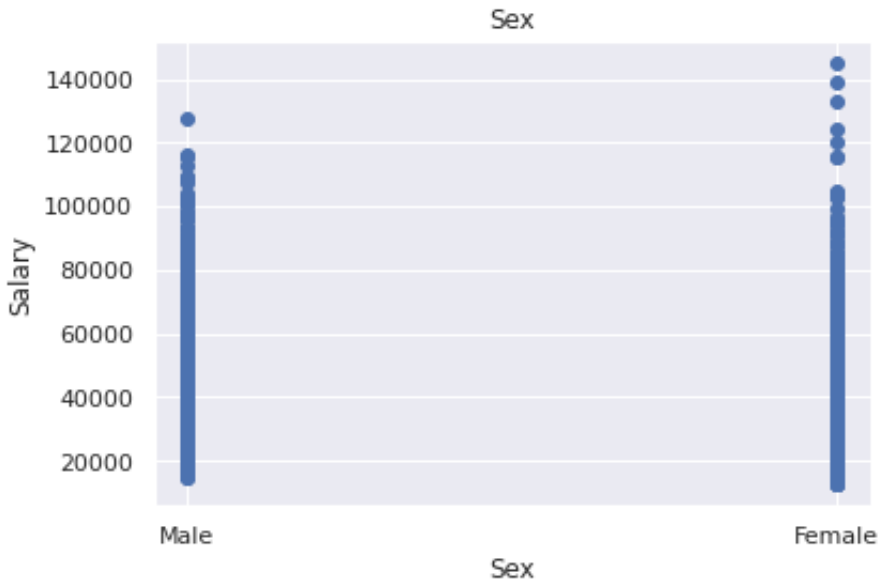

SiteTime
140000
120000
100000
80000
60000
40000
20000
Salary
0
50
100
150
200
250
300
SiteTime

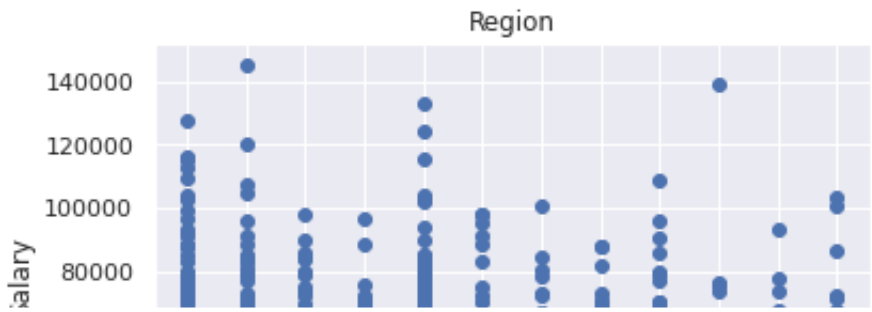

RecommendImpression
140000
120000
100000
80000
60000
40000
20000
Salary
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
RecommendImpression

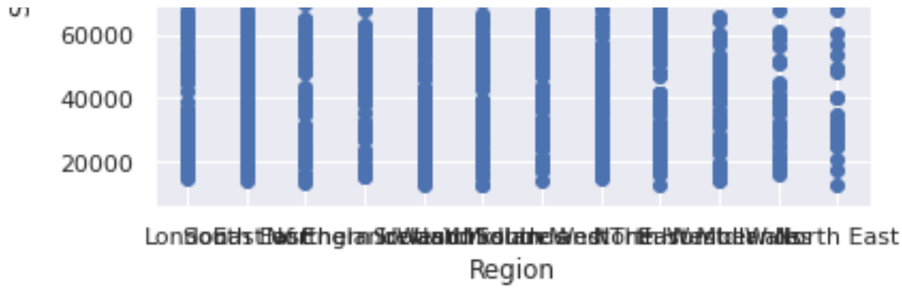

Education
140000
120000


Salary
100000
80000
60000
40000
20000
Degree
GCSE
Masters
Other
A Level
PhD
None
Education


WorkType
Salary
140000
120000
100000
80000
60000
40000
20000
Private sector
Unemployed
Public Sector
Self Employed
WorkType


Sex
Salary
140000
120000
100000
80000
60000
40000
20000
Male
Female
Sex


Region
140000
120000
100000
80000




```
#Shuffle the dataset
rng = np.random.default_rng(0) # This sets the random seed, meaning that we will
df = df.iloc[rng.permutation(len(df))].reset_index(drop=True) # Shuffle data
```

```
# Encoding the categorical Features of our dataset
lblEncoder_X = LabelEncoder()
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['Region'] = lblEncoder_X.fit_transform(df['Region'])

#df = pd.get_dummies(df, drop_first=True)
df.columns
```

```
Index(['Age', 'SiteSpending', 'SiteTime', 'RecommendImpression',
'Education',
       'WorkType', 'Sex', 'Region', 'Salary'],
      dtype='object')
```

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
variables = df[['Age', 'SiteSpending', 'SiteTime', 'RecommendImpression', 'Educa
       'WorkType', 'Sex', 'Region', 'Salary']]
vif = pd.DataFrame()
vif['VIF'] = [variance_inflation_factor(variables.values,i) for i in range(varia
vif['Features'] = variables.columns
vif
```

	VIF	Features
0	6.658374	Age
1	2.113952	SiteSpending
2	7.364734	SiteTime
3	6.055080	RecommendImpression
4	2.540188	Education
5	1.460958	WorkType
6	1.834322	Sex
7	3.426002	Region
8	7.079411	Salary

From the above, we can see there exist no multicolinearity in our data. However, in our scatter plot, site time does not seem to have any obvious correlation with Salary and the VIF is very high. So we can proceed to either drop it or use it and see how much it contributes to our model.

```
# I assume education is ordinal, so lets order this feature and map it to our da
#enc_dict = {'None': 0, 'Other':1,'GCSE':2, 'A Level':3, 'Degree':4, 'Masters':5
#df['Education'] = df['Education'].map(enc_dict):
# This wasn't the case, model performed badly.

# Select Columns
#cols = df[[ 'Age', 'SiteSpending', 'RecommendImpression', 'Education', 'Sex']]
cols = df[['Age', 'SiteSpending', 'RecommendImpression', 'Education',
       'WorkType', 'Sex', 'Region']]
```

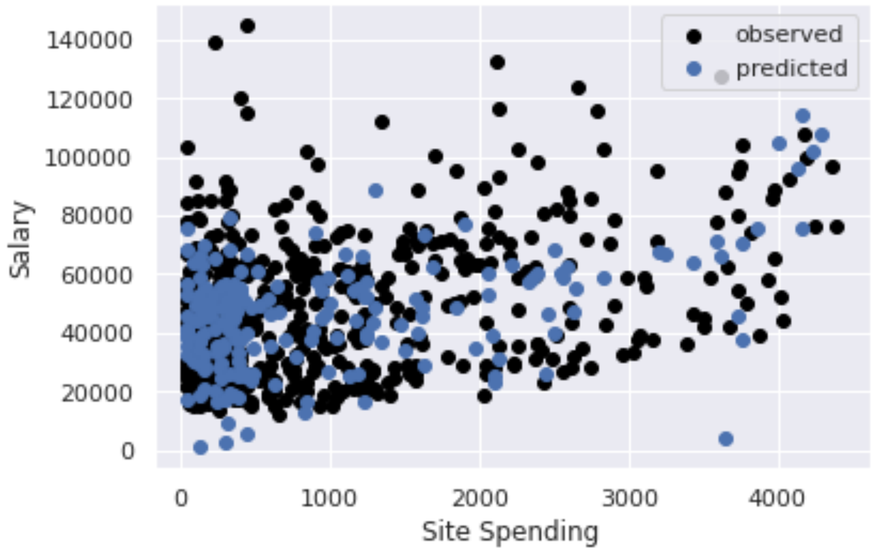
Declare the dependent and independent Variable

```
# Select your features and Target variables
X = np.array(df[cols.columns])
y = np.array(df['Salary'])

# Split Dataset
X_, X_test, y_, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
X_train, X_val, y_train, y_val = train_test_split(X_, y_, test_size=0.25, random

# Poly Transform
degree = 2 # Define the maximum power of polynomial features you want to include
poly = PolynomialFeatures(degree) # Create the polynomial features object
X_train_poly = poly.fit_transform(X_train) # Fit the poly object to the training
X_test_poly = poly.fit_transform(X_test)
X_val_poly = poly.fit_transform(X_val)

# Standardize your Data
scaler = StandardScaler()
scaler.fit(X_train_poly)
X_train_poly_stded = scaler.transform(X_train_poly)
X_test_poly_stded = scaler.transform(X_test_poly)
X_val_poly_stded = scaler.transform(X_val_poly)
```

SKLEARN LINEAR REGRESSION

```
# Create, Train the model and predict on validation and Test Data
obj = sklearn.linear_model.LinearRegression(fit_intercept=True)
obj.fit(X_train_poly_stded, y_train)

y_val_pred = obj.predict(X_val_poly_stded)
y_pred = obj.predict(X_test_poly_stded)

#print(obj.intercept_)
#print(obj.coef_)

plt.scatter(X_train[:,1], y_train, label='observed', color='black')
plt.scatter(X_test[:,1], y_pred, label='predicted')
#plt.plot(np.r_[0:12:0.1], obj.predict(np.r_[0:12:0.1][:, np.newaxis]), color='r
plt.xlabel('Site Spending')
plt.ylabel('Salary')
plt.legend()
plt.show()

print('Training Score: ', round(obj.score(X_train_poly_stded, y_train),3))
```

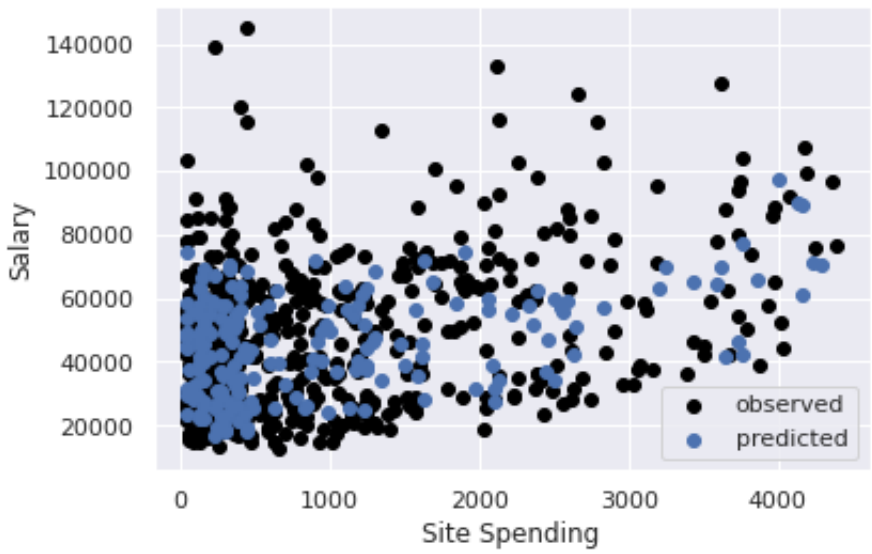
```
print('Validation Score: ', round(sklearn.metrics.r2_score(y_val, y_val_pred),3)

print('R2 Score: ', round(sklearn.metrics.r2_score(y_test, y_pred),3))
print('MSE: ', round(sklearn.metrics.mean_squared_error(y_test, y_pred),3))
print('MAE: ', round(sklearn.metrics.mean_absolute_error(y_test, y_pred),3))
print('Max error: ', round(sklearn.metrics.max_error(y_test, y_pred),3))

# one hot encoding all the categorical features and taking site time out
# we got a training score of 83% and a negative testing score.
# excluding the region, we get 74% training and 65% testing.
```




```
Training Score:  0.732
Validation Score:  0.629
R2 Score:  0.66
MSE:  163153530.831
MAE:  10322.927
Max error:  43033.349
```

KERNEL RIDGE LAPLACIAN

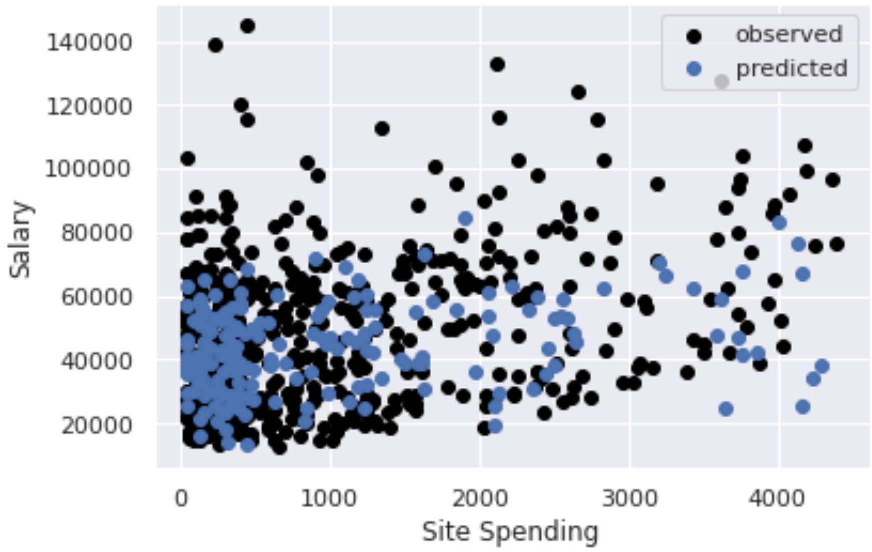
```
obj = kernel_ridge.KernelRidge(kernel='laplacian')
# 79% with Site time,  83% without site time however it doesnt explain the outli
obj.fit(X_train_poly_stded, y_train)
y_val_pred = obj.predict(X_val_poly_stded)
y_pred = obj.predict(X_test_poly_stded)

#print(obj.intercept_)
#print(obj.coef_)

plt.scatter(X_train[:,1], y_train, label='observed', color='black')
plt.scatter(X_test[:,1], y_pred, label='predicted')
plt.xlabel('Site Spending')
plt.ylabel('Salary')
plt.legend()
plt.show()

print('Training Score: ', round(obj.score(X_train_poly_stded, y_train),3))
print('Validation Score: ', round(sklearn.metrics.r2_score(y_val, y_val_pred),3)

print('R2 Score: ', round(sklearn.metrics.r2_score(y_test, y_pred),3))
print('MSE: ', round(sklearn.metrics.mean_squared_error(y_test, y_pred),3))
print('MAE: ', round(sklearn.metrics.mean_absolute_error(y_test, y_pred),3))
print('Max error: ', round(sklearn.metrics.max_error(y_test, y_pred),3))

# one hot encoding score is: 72% on training and 67% on testing.
# 80% training and 74% testing
```




```
Training Score:  0.854
Validation Score:  0.786
R2 Score:  0.782
MSE:  104653082.3
MAE:  7881.056
Max error:  39440.493
```

KERNEL RIDGE RBF

```
obj = kernel_ridge.KernelRidge(kernel='rbf')
obj.fit(X_train_poly_stded, y_train)

y_val_pred = obj.predict(X_val_poly_stded)
y_pred = obj.predict(X_test_poly_stded)

#print(obj.intercept_)
#print(obj.coef_)

plt.scatter(X_train[:,1], y_train, label='observed', color='black')
plt.scatter(X_test[:,1], y_pred, label='predicted')
#plt.plot(np.r_[0:12:0.1], obj.predict(np.r_[0:12:0.1][:, np.newaxis]), color='r
plt.xlabel('Site Spending')
plt.ylabel('Salary')
plt.legend()
plt.show()

print('Training Score: ', round(obj.score(X_train_poly_stded, y_train),3))
print('Validation Score: ', round(sklearn.metrics.r2_score(y_val, y_val_pred),3)

print('R2 Score: ', round(sklearn.metrics.r2_score(y_test, y_pred),3))
print('MSE: ', round(sklearn.metrics.mean_squared_error(y_test, y_pred),3))
print('MAE: ', round(sklearn.metrics.mean_absolute_error(y_test, y_pred),3))
print('Max error: ', round(sklearn.metrics.max_error(y_test, y_pred),3))

# Obs: 56% with site time, 64% without site time.
# ohe: 54% training and 7% testing.
```

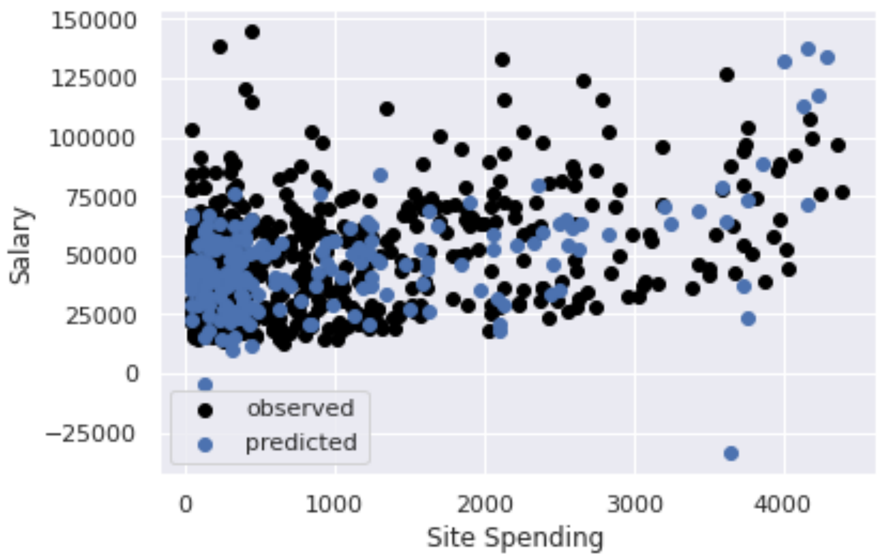



```
Training Score:  0.698
Validation Score:  0.548
R2 Score:  0.443
MSE:  267184812.192
MAE:  12354.677
Max error:  72572.244
```

POLYNOMIAL

```
obj = kernel_ridge.KernelRidge(kernel='polynomial')
obj.fit(X_train_poly_stded, y_train)

y_val_pred = obj.predict(X_val_poly_stded)
y_pred = obj.predict(X_test_poly_stded)

#print(obj.intercept_)
#print(obj.coef_)

plt.scatter(X_train[:,1], y_train, label='observed', color='black')
plt.scatter(X_test[:,1], y_pred, label='predicted')
#plt.plot(np.r_[0:12:0.1], obj.predict(np.r_[0:12:0.1][:, np.newaxis]), color='r
plt.xlabel('Site Spending')
plt.ylabel('Salary')
plt.legend()
plt.show()

print('Training Score: ', round(obj.score(X_train_poly_stded, y_train),3))
print('Validation Score: ', round(sklearn.metrics.r2_score(y_val, y_val_pred),3)

print('R2 Score: ', round(sklearn.metrics.r2_score(y_test, y_pred),3))
print('MSE: ', round(sklearn.metrics.mean_squared_error(y_test, y_pred),3))
print('MAE: ', round(sklearn.metrics.mean_absolute_error(y_test, y_pred),3))
```

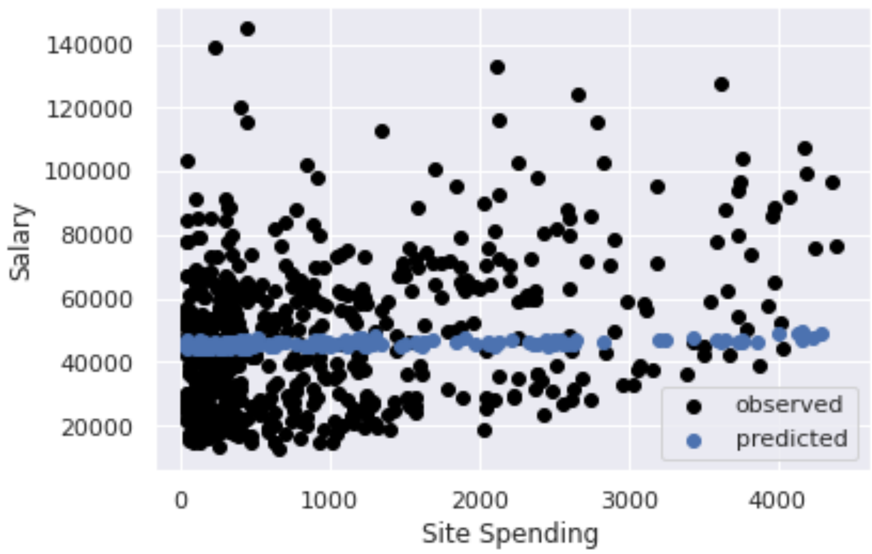
```
print('Max error: ', round(sklearn.metrics.max_error(y_test, y_pred),3))


# obs: 60% with site time,  67% without site time.
r2 = obj.score(X_train_poly_stded, y_train)
n = X.shape[0]
p = X.shape[1]
adj_r2 = 1-(1-r2)*(n-1)/(n-p-1)
adj_r2
print('Adjusted R2 on training :', adj_r2)

r2 = sklearn.metrics.r2_score(y_test, y_pred)
n = X.shape[0]
p = X.shape[1]
adj_r2 = 1-(1-r2)*(n-1)/(n-p-1)
adj_r2
print('Adjusted R2 on testing :', adj_r2)

#ohe: 76% on training and 43% on testing
```




```
Training Score:  0.817
Validation Score:  0.61
R2 Score:  0.549
MSE:  215988056.506
MAE:  10982.152
Max error:  78791.434
Adjusted R2 on training : 0.8155574828635834
Adjusted R2 on testing : 0.546271542719654
```

SVM Linear

```
obj = SVR(kernel='linear')
obj.fit(X_train_poly_stded, y_train)

y_val_pred = obj.predict(X_val_poly_stded)
y_pred = obj.predict(X_test_poly_stded)

#print(obj.intercept_)
#print(obj.coef_)

plt.scatter(X_train[:,1], y_train, label='observed', color='black')
plt.scatter(X_test[:,1], y_pred, label='predicted')
#plt.plot(np.r_[0:12:0.1], obj.predict(np.r_[0:12:0.1][:, np.newaxis]), color='r
plt.xlabel('Site Spending')
plt.ylabel('Salary')
plt.legend()
plt.show()

print('Training Score: ', round(obj.score(X_train_poly_stded, y_train),3))
print('Validation Score: ', round(sklearn.metrics.r2_score(y_val, y_val_pred),3)

print('R2 Score: ', round(sklearn.metrics.r2_score(y_test, y_pred),3))
print('MSE: ', round(sklearn.metrics.mean_squared_error(y_test, y_pred),3))
print('MAE: ', round(sklearn.metrics.mean_absolute_error(y_test, y_pred),3))
print('Max error: ', round(sklearn.metrics.max_error(y_test, y_pred),3))

#obs: 6% with site time, 4.8% without site time
```




```
Training Score:  0.045
Validation Score:  0.041
R2 Score:  0.042
MSE:  459262865.68
MAE:  17542.113
Max error:  66744.114
```

*Adjusted R-squared *

$$R^2_{adj.} = 1 - (1 - R^2) * \frac{n-1}{n-p-1}$$

Notes:

1. Just using the numerical features with label encoded sex, and no poly fit, our linear model does 24% and a mean absolute error of 16186 and a max error of 58570
2. Next we assumed eductation is ordinal, encoded it mapped it to our data. This reduced our mean absolute error to 15828, max error to 56378 and an R2 score of 27% which is much better than 24%.
3. I used label encoding on the education data and this made our model perform badly. with an R2 score of 22.9%, MAE of 16,480 and max error of 58,662.

Based on this observation, I manually map numbers to the education data with PHD=6, and None=0.

4. I label encoded the Worktype feature, but this did not improve the model significantly, as we get 27% R2 score and 55638 max error. However, one hot encoding the Worktype further reduces the max error to 54611. Less error same R2 is a better model to me.

Since we're begining to one hot encode our data, we'll need to implement the polyfit.

5. Our model does significantly well with an R2 score of 65%, a max error of 49966 and mean absolute error of 9890 which is much better than all the other tests we've run.
6. I'm not convinced region contributes to our model, but i'm going to one hot encode it and add it to our feature to see how our model performs. Well, as expected, I got a negative R2 score -2.05, a max error of 9.92e+16. However, label encoding the region improves the model R2 score to 66.7%, we get a max error of 49851 and an MAE of 9793.

Increased the polynomial degree from 2 to 3 up to 10. The higher we went, the worse our model performed.

We've been using SkLearn linear regression to get the tuning right. Let's see if regressions will model our data correctly.

7. Lastly i'll like to just naively label encode all the categorical features and train the model with this.

Doing this our model is currently doing pretty alright with as high as 83% in laplacian, however, it does not explain the outliers in the age feature for example. '''

PART 2: BINARY CLASSIFICATION

```
# We classify our Target into two categories, those with salary above 35000 or n

df['target'] = df['Salary'].apply(lambda x: 1 if x > 35000 else 0)

#Shuffle the data again
# Shuffle the dataset again
rng = np.random.default_rng(0)
df = df.iloc[rng.permutation(len(df))].reset_index(drop=True)

#Lets have a look at the numbers
df.target.value_counts() # we see there are more salary above $35000
```

```
1    631
0    369
Name: target, dtype: int64
```

```
# Even though our model gave usa high accuracy using, i think it's bias towards
# salary above 35k cos it's almost 2ce the size of the salary under 35k
# Next lets resample our target and rerun our model.
df_over = df[(df['target']==1)]
df_under = df[(df['target']==0)]

df_undersampled = resample(df_over, replace=True,n_samples= len(df_under),random
df_undersampled = pd.concat([df_undersampled, df_under])

df_undersampled['target'].value_counts()
```

```
1    369
0    369
Name: target, dtype: int64
```

```
df_undersampled.drop(['Salary'], axis=1)
# Declare your target and feature columns
cols = df_undersampled[[ 'Age', 'SiteSpending','RecommendImpression']]

X = np.array(df_undersampled[cols.columns])
y = np.array(df_undersampled['target'])
```

```
# Split your data into training and testing set
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.2, random_s
```

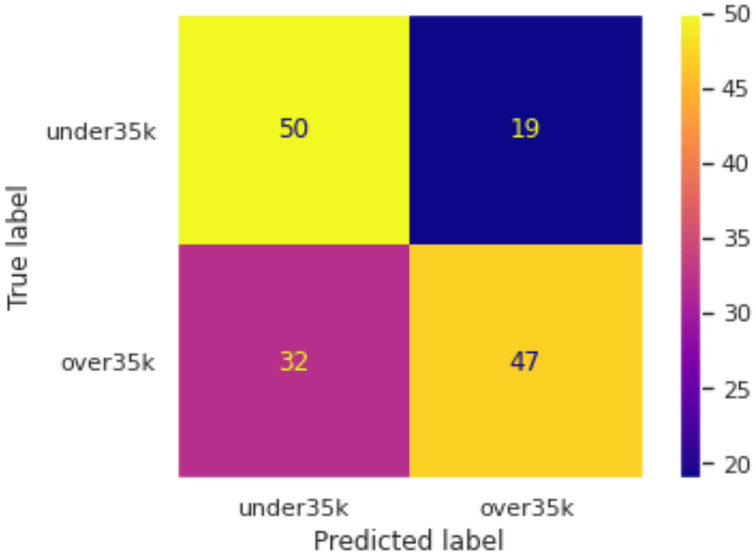
```
#Standardize your dataset
scaler = StandardScaler()
scaler.fit(X_train) # calculate the mean and variance for each feature and store

X_train = scaler.transform(X_train) # standardize X_train
X_test = scaler.transform(X_test)
```

Using Logistic Regression

```
# Create logistic regression object

obj = sklearn.linear_model.LogisticRegression(penalty='l1', C=10, solver='liblin

# Tuning hyperparamters: obj = sklearn.linear_model.LogisticRegression(penalty='

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

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

```
# The accuracy score: 1 for perfect prediction
print("The training score: {:.3f}".format(obj.score(X_train, y_train)))
print('Accuracy: {:.4f}'.format(sklearn.metrics.accuracy_score(y_test, y_pred)))
# Confusion matrix
confusion_mat = sklearn.metrics.confusion_matrix(y_test, y_pred)#, normalize='al
print('Confusion matrix: ', confusion_mat)
# Visualize the confusion matrix
sklearn.metrics.ConfusionMatrixDisplay(confusion_mat, display_labels=['under35k'
plt.grid(False)
# The classification report, which contains accuracy, precision, recall, F1 scor
print(sklearn.metrics.classification_report(y_test, y_pred))
```

```
The training score: 0.664
Accuracy: 0.6554
Confusion matrix:  [[50 19]
 [32 47]]
              precision    recall  f1-score   support

           0       0.61      0.72      0.66        69
           1       0.71      0.59      0.65        79

    accuracy                           0.66       148
   macro avg       0.66      0.66      0.66       148
weighted avg       0.66      0.66      0.65       148
```



```
# Checking p-values and removing p-values that are close to 1 as they do not con
x1 = sm.add_constant(X_train)
reg_log = sm.Logit(y_train, x1)
results_log = reg_log.fit()
results_log.pred_table()
```

```
    Optimization terminated successfully.
             Current function value: 0.613605
             Iterations 5
    array([[207.,  93.],
           [104., 186.]])
```

```
results_log.summary()
```

Logit Regression Results

Dep. Variable:	y	**No. Observations:**	590
Model:	Logit	**Df Residuals:**	586
Method:	MLE	**Df Model:**	3
Date:	Fri, 16 Dec 2022	**Pseudo R-squ.:**	0.1146
Time:	20:06:59	**Log-Likelihood:**	-362.03
converged:	True	**LL-Null:**	-408.87
Covariance Type:	nonrobust	**LLR p-value:**	3.529e-20

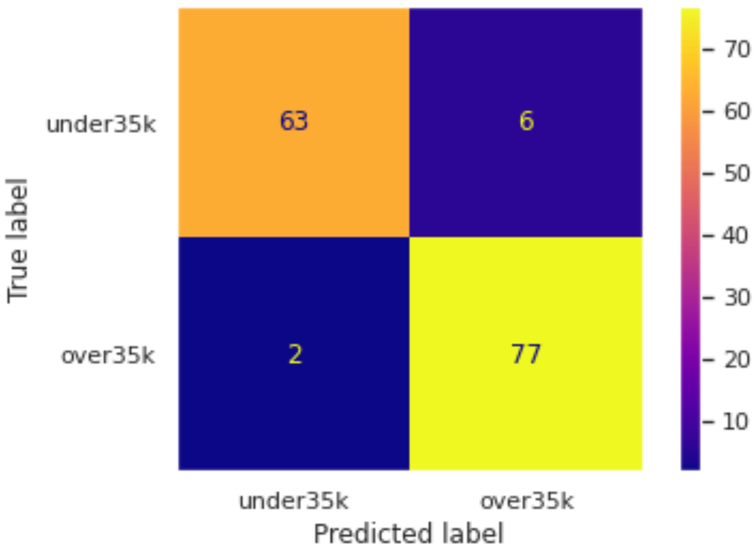
	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-0.0220	0.089	-0.246	0.806	-0.197	0.153
x1	0.1537	0.089	1.724	0.085	-0.021	0.328
x2	0.4913	0.096	5.115	0.000	0.303	0.680
x3	0.7497	0.097	7.719	0.000	0.559	0.940

using SVM

```
# Tuning hyperparamters: penalty='l1', C=10, solver='liblinear'
import sklearn.svm

# Create support vector classifier object
obj = sklearn.svm.SVC(C=10,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_test)

# The higher the better# The accuracy score: 1 for perfect prediction
print("The training score: {:.3f}".format(obj.score(X_train, y_train)))
```

```
print('Accuracy: {:.4f}'.format(sklearn.metrics.accuracy_score(y_test, y_pred)))
# Confusion matrix
confusion_mat = sklearn.metrics.confusion_matrix(y_test, y_pred)#, normalize='al
print('Confusion matrix: ', confusion_mat)
# Visualize the confusion matrix
sklearn.metrics.ConfusionMatrixDisplay(confusion_mat, display_labels=['under35k'
plt.grid(False)
# The classification report, which contains accuracy, precision, recall, F1 scor
print(sklearn.metrics.classification_report(y_test, y_pred))
```

```
The training score: 0.953
Accuracy: 0.9459
Confusion matrix:  [[63  6]
 [ 2 77]]
              precision    recall  f1-score   support

           0       0.97      0.91      0.94        69
           1       0.93      0.97      0.95        79

    accuracy                           0.95       148
   macro avg       0.95      0.94      0.95       148
weighted avg       0.95      0.95      0.95       148
```

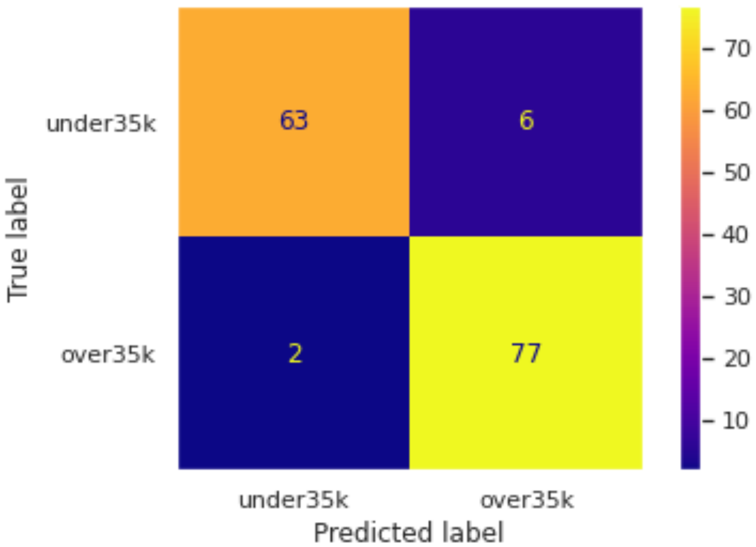


Using Decision Tree

```
# Create Decison Tree object
from sklearn.tree import DecisionTreeClassifier
obj = DecisionTreeClassifier(min_samples_split=2, min_samples_leaf=9,random_stat

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

```
# Make predictions using the testing set
y_new_pred = obj.predict(X_test)

# The higher the better
# The accuracy score: 1 for perfect prediction
print("The training score: {:.3f}".format(obj.score(X_train, y_train)))
print('Accuracy: {:.4f}'.format(sklearn.metrics.accuracy_score(y_test, y_pred)))
# Confusion matrix
confusion_mat = sklearn.metrics.confusion_matrix(y_test, y_pred)#, normalize='al
print('Confusion matrix: ', confusion_mat)
# Visualize the confusion matrix
sklearn.metrics.ConfusionMatrixDisplay(confusion_mat, display_labels=['under35k'
plt.grid(False)
# The classification report, which contains accuracy, precision, recall, F1 scor
print(sklearn.metrics.classification_report(y_test, y_pred))
```

```
The training score: 0.964
Accuracy: 0.9459
Confusion matrix:  [[63  6]
 [ 2 77]]
              precision    recall  f1-score   support

           0       0.97      0.91      0.94        69
           1       0.93      0.97      0.95        79

    accuracy                           0.95       148
   macro avg       0.95      0.94      0.95       148
weighted avg       0.95      0.95      0.95       148
```



PART 3: NEURAL NETWORK

```
df_undersampled.drop(['Salary'], axis=1)
# Declare your target and feature columns
cols = df_undersampled[[ 'Age', 'SiteSpending','RecommendImpression']]

X_nn = np.array(df_undersampled[cols.columns])
y_nn = np.array(df_undersampled['target'])


#Split your data
X_nn_, X_nn_test, y_nn_, y_nn_test = train_test_split(X_nn, y_nn, test_size=0.2,
X_nn_train, X_nn_val, y_nn_train, y_nn_val = train_test_split(X_nn_, y_nn_, test


# Standardize your data
scaler = StandardScaler()
scaler.fit(X_nn_train) # calculate the mean and variance for each feature and st

X_nn_train = scaler.transform(X_nn_train) # standardize X_train
X_nn_test = scaler.transform(X_nn_test)
X_nn_val = scaler.transform(X_nn_val)
```

Random tests

```
import tensorflow as tf
input_size = 8
output_size = 2
hidden_layer_size = 50

acc = BinaryAccuracy()

model = tf.keras.Sequential([tf.keras.layers.Dense(hidden_layer_size, activation
                             tf.keras.layers.Dense(hidden_layer_size, activation
                             tf.keras.layers.Dense(output_size, activation='soft
                             ])
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=

batch_size = 100
max_epochs = 100
early_stopping = tf.keras.callbacks.EarlyStopping(patience=2)

model.fit(X_nn_train,y_nn_train,
          batch_size = batch_size, epochs = max_epochs, validation_data= (X_nn_v
          callbacks = [early_stopping],
          verbose = 2)
```

```
5/5 - 0s - loss: 0.5188 - accuracy: 0.7534 - val_loss: 0.4817 - val_accurac
```

```
Epoch 9/100
5/5 - 0s - loss: 0.5036 - accuracy: 0.7579 - val_loss: 0.4640 - val_accurac
Epoch 10/100
5/5 - 0s - loss: 0.4886 - accuracy: 0.7602 - val_loss: 0.4466 - val_accurac
Epoch 11/100
5/5 - 0s - loss: 0.4744 - accuracy: 0.7647 - val_loss: 0.4301 - val_accurac
Epoch 12/100
5/5 - 0s - loss: 0.4602 - accuracy: 0.7670 - val_loss: 0.4148 - val_accurac
Epoch 13/100
5/5 - 0s - loss: 0.4466 - accuracy: 0.7692 - val_loss: 0.4006 - val_accurac
Epoch 14/100
5/5 - 0s - loss: 0.4337 - accuracy: 0.7738 - val_loss: 0.3861 - val_accurac
Epoch 15/100
5/5 - 0s - loss: 0.4205 - accuracy: 0.7692 - val_loss: 0.3729 - val_accurac
Epoch 16/100
5/5 - 0s - loss: 0.4084 - accuracy: 0.7738 - val_loss: 0.3605 - val_accurac
Epoch 17/100
5/5 - 0s - loss: 0.3966 - accuracy: 0.8032 - val_loss: 0.3480 - val_accurac
Epoch 18/100
5/5 - 0s - loss: 0.3841 - accuracy: 0.8077 - val_loss: 0.3368 - val_accurac
Epoch 19/100
5/5 - 0s - loss: 0.3731 - accuracy: 0.8258 - val_loss: 0.3265 - val_accurac
Epoch 20/100
5/5 - 0s - loss: 0.3630 - accuracy: 0.8394 - val_loss: 0.3151 - val_accurac
Epoch 21/100
5/5 - 0s - loss: 0.3513 - accuracy: 0.8575 - val_loss: 0.3056 - val_accurac
Epoch 22/100
5/5 - 0s - loss: 0.3417 - accuracy: 0.8597 - val_loss: 0.2975 - val_accurac
Epoch 23/100
5/5 - 0s - loss: 0.3328 - accuracy: 0.8552 - val_loss: 0.2900 - val_accurac
Epoch 24/100
5/5 - 0s - loss: 0.3246 - accuracy: 0.8643 - val_loss: 0.2817 - val_accurac
Epoch 25/100
5/5 - 0s - loss: 0.3161 - accuracy: 0.8778 - val_loss: 0.2750 - val_accurac
Epoch 26/100
5/5 - 0s - loss: 0.3089 - accuracy: 0.8733 - val_loss: 0.2695 - val_accurac
Epoch 27/100
5/5 - 0s - loss: 0.3022 - accuracy: 0.8846 - val_loss: 0.2649 - val_accurac
Epoch 28/100
5/5 - 0s - loss: 0.2958 - accuracy: 0.8846 - val_loss: 0.2623 - val_accurac
Epoch 29/100
5/5 - 0s - loss: 0.2893 - accuracy: 0.8869 - val_loss: 0.2600 - val_accurac
Epoch 30/100
5/5 - 0s - loss: 0.2841 - accuracy: 0.8869 - val_loss: 0.2559 - val_accurac
Epoch 31/100
5/5 - 0s - loss: 0.2782 - accuracy: 0.8846 - val_loss: 0.2554 - val_accurac
Epoch 32/100
5/5 - 0s - loss: 0.2739 - accuracy: 0.8801 - val_loss: 0.2519 - val_accurac
Epoch 33/100
5/5 - 0s - loss: 0.2694 - accuracy: 0.8914 - val_loss: 0.2417 - val_accurac
Epoch 34/100
5/5 - 0s - loss: 0.2660 - accuracy: 0.8914 - val_loss: 0.2369 - val_accurac
Epoch 35/100
5/5 - 0s - loss: 0.2617 - accuracy: 0.8937 - val_loss: 0.2356 - val_accurac
Epoch 36/100
```

```
Epoch 36/100
5/5 - 0s - loss: 0.2584 - accuracy: 0.8982 - val_loss: 0.2361 - val_accurac
Epoch 37/100
5/5 - 0s - loss: 0.2551 - accuracy: 0.9005 - val_loss: 0.2349 - val_accurac
Epoch 38/100
```

```
test_loss, test_accuracy = model.evaluate(X_nn_test, y_nn_test)
```

```
5/5 [==============================] - 0s 3ms/step - loss: 0.2323 - accurac
```

```
history = model.fit(X_nn_train,y_nn_train,
          batch_size = batch_size, epochs = max_epochs, validation_data= (X_nn_v
          callbacks = [early_stopping],
          verbose = 2)
```

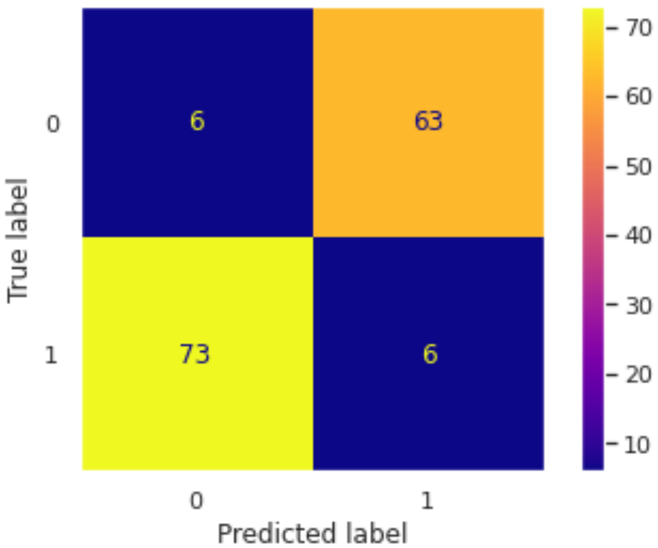
```
Epoch 1/100
5/5 - 0s - loss: 0.2455 - accuracy: 0.8982 - val_loss: 0.2330 - val_accurac
Epoch 2/100
5/5 - 0s - loss: 0.2442 - accuracy: 0.9027 - val_loss: 0.2311 - val_accurac
Epoch 3/100
5/5 - 0s - loss: 0.2423 - accuracy: 0.9072 - val_loss: 0.2305 - val_accurac
Epoch 4/100
5/5 - 0s - loss: 0.2397 - accuracy: 0.9005 - val_loss: 0.2309 - val_accurac
Epoch 5/100
5/5 - 0s - loss: 0.2387 - accuracy: 0.8959 - val_loss: 0.2279 - val_accurac
Epoch 6/100
5/5 - 0s - loss: 0.2367 - accuracy: 0.9005 - val_loss: 0.2261 - val_accurac
Epoch 7/100
5/5 - 0s - loss: 0.2357 - accuracy: 0.9027 - val_loss: 0.2293 - val_accurac
Epoch 8/100
5/5 - 0s - loss: 0.2337 - accuracy: 0.9027 - val_loss: 0.2318 - val_accurac
```

```
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
plt.legend()
plt.show()
```


```
Y_test_logit = model.predict(X_nn_test)
```

```
5/5 [==============================] - 0s 3ms/step
```

```
Y_test_pred = (Y_test_logit > 0.5).astype(int)
# Evaluate the model by plotting the confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix(y_nn_test, Y_test_pred[:,0]))
disp.plot(cmap=plt.cm.plasma)
plt.grid(False)
```



Main NN Model

```
# 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_re
dense_layer_1 = Dense(units=10, activation=relu, kernel_regularizer=kernel_regul
output_layer = Dense(units=1, activation=sigmoid, kernel_regularizer=kernel_regu

# Define the "virtual" input
input = Input(shape=X_nn_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])

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

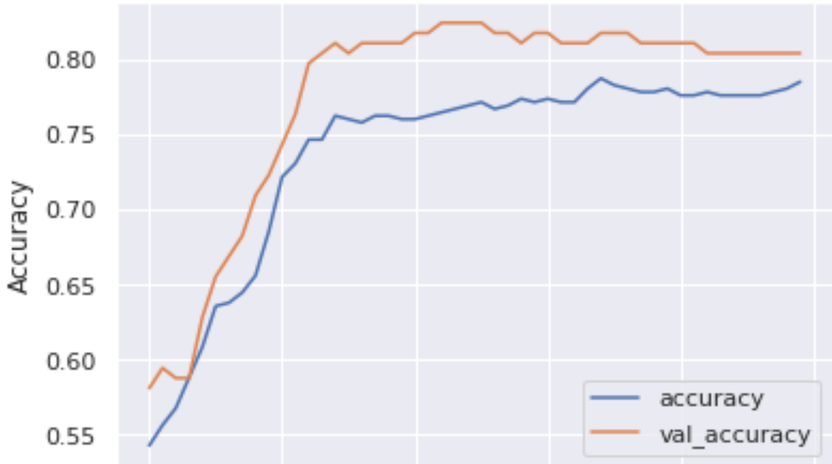
```
Model: "model_7"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_8 (InputLayer)        [(None, 3)]               0

 dense_35 (Dense)            (None, 10)                40

 dense_36 (Dense)            (None, 1)                 11

=================================================================
Total params: 51
Trainable params: 51
Non-trainable params: 0
_________________________________________________________________
```

```
# Compile the model by specifying the optimization algorithm and the loss functi
# Here, we specify the vanilla stochastic gradient descent
# (a `tensorflow.keras.optimizers.SGD` instance) as an optimizer,
# and the binary cross entropy function (a `BinaryCrossentropy` instance)
# as a loss function.

# If we want to observe metrics other than the loss function we specified,
# we can also specify the metrics in the `metrics` parameter
# in the `compile` method.

sgd = SGD(learning_rate=0.04)
ce = BinaryCrossentropy()
acc = BinaryAccuracy()
model.compile(optimizer=sgd, loss=ce, metrics=[acc])


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

history = model.fit(X_nn_train, y_nn_train, batch_size=90, epochs=50, validation


# 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')
```

```
Epoch 1/50
5/5 [==============================] - 1s 59ms/step - loss: 0.7524 - binary
Epoch 2/50
5/5 [==============================] - 0s 12ms/step - loss: 0.7397 - binary
Epoch 3/50
5/5 [==============================] - 0s 10ms/step - loss: 0.7283 - binary
Epoch 4/50
5/5 [==============================] - 0s 11ms/step - loss: 0.7181 - binary
Epoch 5/50
5/5 [==============================] - 0s 11ms/step - loss: 0.7089 - binary
Epoch 6/50
5/5 [==============================] - 0s 10ms/step - loss: 0.7004 - binary
Epoch 7/50
5/5 [==============================] - 0s 15ms/step - loss: 0.6928 - binary
Epoch 8/50
5/5 [==============================] - 0s 11ms/step - loss: 0.6856 - binary
Epoch 9/50
5/5 [==============================] - 0s 11ms/step - loss: 0.6792 - binary
Epoch 10/50
5/5 [==============================] - 0s 9ms/step - loss: 0.6731 - binary_
```

```
Epoch 11/50
5/5 [==============================] - 0s 10ms/step - loss: 0.6677 - binary
Epoch 12/50
5/5 [==============================] - 0s 9ms/step - loss: 0.6626 - binary_
Epoch 13/50
5/5 [==============================] - 0s 10ms/step - loss: 0.6578 - binary
Epoch 14/50
5/5 [==============================] - 0s 14ms/step - loss: 0.6534 - binary
Epoch 15/50
5/5 [==============================] - 0s 9ms/step - loss: 0.6491 - binary_
Epoch 16/50
5/5 [==============================] - 0s 9ms/step - loss: 0.6450 - binary_
Epoch 17/50
5/5 [==============================] - 0s 9ms/step - loss: 0.6410 - binary_
Epoch 18/50
5/5 [==============================] - 0s 10ms/step - loss: 0.6372 - binary
Epoch 19/50
5/5 [==============================] - 0s 9ms/step - loss: 0.6334 - binary_
Epoch 20/50
5/5 [==============================] - 0s 11ms/step - loss: 0.6299 - binary
Epoch 21/50
5/5 [==============================] - 0s 10ms/step - loss: 0.6265 - binary
Epoch 22/50
5/5 [==============================] - 0s 15ms/step - loss: 0.6233 - binary
Epoch 23/50
5/5 [==============================] - 0s 9ms/step - loss: 0.6202 - binary_
Epoch 24/50
5/5 [==============================] - 0s 9ms/step - loss: 0.6173 - binary_
Epoch 25/50
5/5 [==============================] - 0s 9ms/step - loss: 0.6143 - binary_
Epoch 26/50
5/5 [==============================] - 0s 12ms/step - loss: 0.6116 - binary
Epoch 27/50
5/5 [==============================] - 0s 10ms/step - loss: 0.6089 - binary
Epoch 28/50
5/5 [==============================] - 0s 9ms/step - loss: 0.6065 - binary_
Epoch 29/50
5/5 [==============================] - 0s 9ms/step - loss: 0.6043 - binary_
Epoch 30/50
5/5 [==============================] - 0s 11ms/step - loss: 0.6019 - binary
Epoch 31/50
5/5 [==============================] - 0s 13ms/step - loss: 0.5995 - binary
Epoch 32/50
5/5 [==============================] - 0s 10ms/step - loss: 0.5973 - binary
Epoch 33/50
5/5 [==============================] - 0s 12ms/step - loss: 0.5951 - binary
Epoch 34/50
5/5 [==============================] - 0s 9ms/step - loss: 0.5929 - binary_
Epoch 35/50
5/5 [==============================] - 0s 11ms/step - loss: 0.5908 - binary
Epoch 36/50
5/5 [==============================] - 0s 14ms/step - loss: 0.5887 - binary
Epoch 37/50
5/5 [==============================] - 0s 10ms/step - loss: 0.5867 - binary
```

```
Epoch 38/50
5/5 [==============================] - 0s 9ms/step - loss: 0.5848 - binary_
Epoch 39/50
5/5 [==============================] - 0s 9ms/step - loss: 0.5829 - binary_
Epoch 40/50
5/5 [==============================] - 0s 9ms/step - loss: 0.5811 - binary_
Epoch 41/50
5/5 [==============================] - 0s 16ms/step - loss: 0.5794 - binary
Epoch 42/50
5/5 [==============================] - 0s 11ms/step - loss: 0.5776 - binary
Epoch 43/50
5/5 [==============================] - 0s 9ms/step - loss: 0.5761 - binary_
Epoch 44/50
5/5 [==============================] - 0s 9ms/step - loss: 0.5743 - binary_
Epoch 45/50
5/5 [==============================] - 0s 10ms/step - loss: 0.5731 - binary
Epoch 46/50
5/5 [==============================] - 0s 8ms/step - loss: 0.5715 - binary_
Epoch 47/50
5/5 [==============================] - 0s 10ms/step - loss: 0.5702 - binary
Epoch 48/50
5/5 [==============================] - 0s 9ms/step - loss: 0.5685 - binary_
Epoch 49/50
5/5 [==============================] - 0s 8ms/step - loss: 0.5672 - binary_
Epoch 50/50
5/5 [==============================] - 0s 8ms/step - loss: 0.5658 - binary_
<matplotlib.legend.Legend at 0x7fed2bec4fa0>
```




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

```
5/5 [==============================] - 0s 2ms/step - loss: 0.5353 - binary_
The cross entropy loss on the test data: 0.5353154540061951
The accuracy on the test data: 0.7972972989082336
```

```
Y_test_logit = model.predict(X_nn_test)
print(Y_test_logit[:10]) # just show you the first 10 to not spam you
```

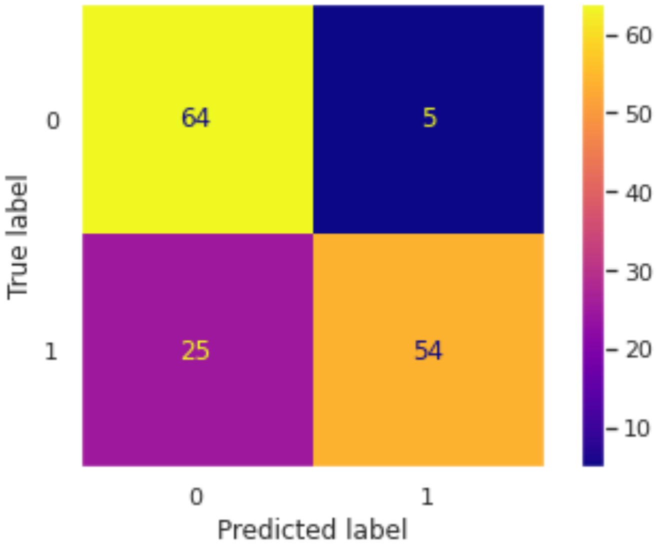
```
5/5 [==============================] - 0s 3ms/step
[[0.91027135]
 [0.5324582 ]
 [0.6529702 ]
 [0.23224595]
 [0.7312142 ]
 [0.6944584 ]
 [0.29540297]
 [0.43163633]
 [0.34733844]
 [0.29564974]]
```

```
Y_test_pred = (Y_test_logit > 0.5).astype(int)
print(Y_test_pred[:10])
```

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

```
disp = ConfusionMatrixDisplay(confusion_matrix(y_nn_test, Y_test_pred))
disp.plot(cmap=plt.cm.plasma)
plt.grid(False)

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

```
The accuracy on the test data with the selected hyperparameter: 0.797297297
The F1 score on the test data with the selected hyperparameter: 0.782608695
Precision on validation data: 0.9152542372881356
Recall on validation data: 0.9152542372881356
```

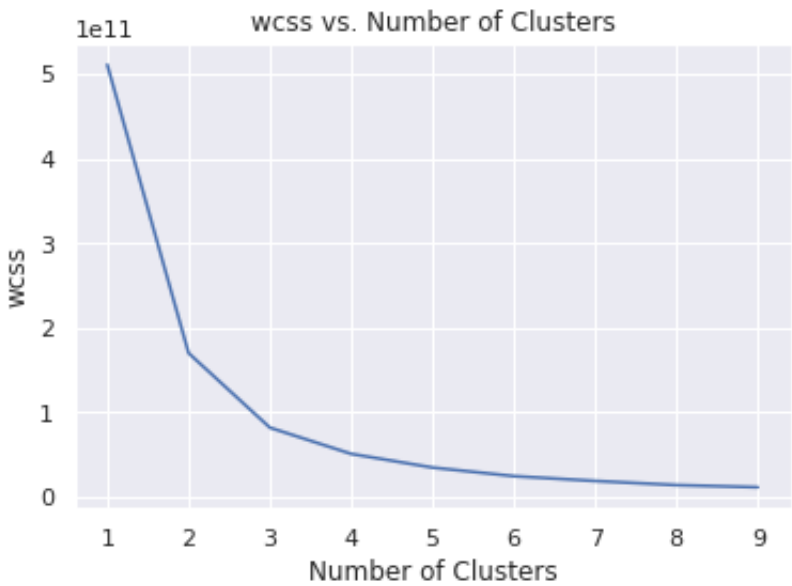


PART 3: CLUSTERING

```
X = df.copy()
```

K-Means Clustering

```
# Trying to find the best number of clusters
# Initialize a list to store the inertia values
wcss = []

# Loop over a range of number of clusters
for i in range(1, 10):
  # Initialize the model with the current number of clusters
  model = KMeans(n_clusters=i, random_state=0)

  # Fit the model to the data
  model.fit(X)

  # Get the inertia for the model
  inertia = model.inertia_

  # Append the inertia to the list
  wcss.append(inertia)

# Plot the inertia values
plt.plot(range(1, 10), wcss)

# Add a title and labels to the plot
plt.title('wcss vs. Number of Clusters')
plt.xlabel('Number of Clusters')
plt.ylabel('wcss')

# Show the plot
plt.show()
```



```
# Initialize the model with gotten k
model = KMeans(n_clusters=4, random_state=0)

# Fit the model to the data
model.fit(X)

# Predict the clusters for each data point
predictions = model.predict(X)
```

```
# Select the columns to use for the x and y axes
x_column = 'SiteSpending'
y_column = 'Salary'

# Extract the values for the x and y axes
x = df[x_column]
y = df[y_column]

# Get the cluster labels for each data point
labels = model.predict(X)

# Create a scatter plot of the data
plt.scatter(x, y, c=labels, cmap='viridis', s=50)

# Add the cluster centers to the plot
centers = model.cluster_centers_
plt.scatter(centers[:, 0], centers[:, 1], c='black', s=200);

# Add the x and y labels and a title
plt.xlabel(x_column)
plt.ylabel(y_column)
plt.title('K-Means Clustering')
plt.show()
```

```
x_scaled = preprocessing.scale(X)
model = KMeans(n_clusters=4, random_state=0)

# Fit the model to the data
model.fit(x_scaled)

# Predict the clusters for each data point
predictions = model.predict(x_scaled)
```

```
# Select the columns to use for the x and y axes
x_column = 'SiteSpending'
y_column = 'Salary'

# Extract the values for the x and y axes
x = df[x_column]
y = df[y_column]

# Get the cluster labels for each data point
labels = model.predict(x_scaled)

# Create a scatter plot of the data
plt.scatter(x, y, c=labels, cmap='viridis')

# Add the cluster centers to the plot
centers = model.cluster_centers_
plt.scatter(centers[:, 0], centers[:, 1], c='black', s=200, alpha=0.5)

# Add the x and y labels and a title
plt.xlabel(x_column)
plt.ylabel(y_column)
plt.title('K-Means Clustering')

# Show the plot
plt.show()
```


```
from sklearn.metrics import silhouette_score
print(silhouette_score(x_scaled, labels))
```

```
0.17117942704579303
```