```
from sklearn.datasets import make_classification
from matplotlib import pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
import pandas as pd
import numpy as np
import seaborn as sns
from sklearn.metrics import r2_score, explained_variance_score, confusion_matrix, accuracy_score, classification_report, log_loss
from math import sqrt
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import Lasso
```

```
df = pd.read_csv("CellDNA.csv", header= None)
```

```
df.columns =['x0', 'x1', 'x2', 'x3', 'x4', 'x5', 'x6', 'x7','x8','x9','x10','x11','x12','x13']
```

```
df.loc[:, 'x13'] = np.where(df.x13>0, 1, 0)
```

```
df
```

	x0	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11	x12	x13
0	222	31.189189	40.342342	35.579087	8.883917	0.968325	-80.113673	222	1	16.812471	0.816176	0.578125	78.591	0
1	73	29.493151	271.397260	15.517202	6.407490	0.910764	76.042946	73	1	9.640876	0.858824	0.608333	39.217	0
2	256	58.816406	289.941406	37.226013	9.863895	0.964256	85.324742	256	1	18.054067	0.752941	0.562637	89.111	0
3	126	71.023810	477.412698	13.112980	12.790672	0.220351	63.523477	126	1	12.666025	0.881119	0.646154	43.832	0
4	225	90.808889	541.946667	44.463110	7.858879	0.984256	-52.874983	225	1	16.925688	0.728155	0.252525	90.072	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1212	216	738.527778	216.449074	38.229761	9.556174	0.968254	12.847813	216	1	16.583719	0.640950	0.397059	98.589	0
1213	328	748.896341	47.664634	63.138991	9.101974	0.989555	57.919494	328	1	20.435816	0.607407	0.205257	131.431	1
1214	97	761.690722	207.288660	22.751513	8.230351	0.932275	-24.674618	97	1	11.113246	0.591463	0.384921	67.427	0
1215	223	770.654708	235.502242	53.491654	8.643053	0.986860	73.244715	223	1	16.850294	0.557500	0.252834	112.656	0
1216	87	764.954023	265.655172	13.459738	8.521929	0.774035	18.595633	87	1	10.524820	0.956044	0.743590	32.295	0

1217 rows × 14 columns

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
df[['x0', 'x1', 'x2', 'x3', 'x4', 'x5', 'x6', 'x7','x8','x9','x10','x11','x12']] = scaler.fit_transform(df[['x0', 'x1', 'x2', 'x3', 'x4', 'x5
```

```
numeric_cols = ['x0', 'x1', 'x2', 'x3', 'x4', 'x5', 'x6', 'x7','x8','x9','x10','x11','x12']
scaler = StandardScaler()
scaler.fit(df[numeric_cols])
scaled_inputs = scaler.transform(df[numeric_cols])
scaled_inputs
```

```
array([[ 0.15952762, -1.80200559, -1.20813407, ...,  0.34511514,
         0.65289142, -0.00691284],
       [-0.93921222, -1.80987674,  0.42436331, ...,  0.7072868 ,
         0.84374979, -0.81411281],
       [ 0.41024678, -1.67379037,  0.55538528, ..., -0.19189804,
         0.55503945,  0.20875597],
       ...,
       [-0.76223399,  1.58818067, -0.02859014, ..., -1.56321582,
        -0.56778731, -0.23578419],
       [ 0.16690172,  1.62978166,  0.17075035, ..., -1.85164337,
        -1.40231699,  0.69144818],
       [-0.83597492,  1.60332534,  0.38379311, ...,  1.53291195,
         1.69830929, -0.95601961]])
```

```
df
```

	x0	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11	x12	x13
0	0.159528	-1.802006	-1.208134	0.114420	-0.135689	0.538311	-1.587426	0.135833	0.233292	0.329626	0.345115	0.652891	-0.006913	0
1	-0.939212	-1.809877	0.424363	-0.933511	-0.817247	0.019258	1.500586	-0.909580	0.233292	-1.221986	0.707287	0.843750	-0.814113	0
2	0.410247	-1.673790	0.555385	0.200447	0.134019	0.501621	1.684134	0.374384	0.233292	0.598252	-0.191898	0.555039	0.208756	0
3	-0.548385	-1.617137	1.879947	-1.059096	0.939523	-6.206504	1.253012	-0.537722	0.233292	-0.567479	0.896626	1.082702	-0.719501	0
4	0.181650	-1.525316	2.335905	0.578476	-0.417798	0.681969	-1.048779	0.156881	0.233292	0.354121	-0.402387	-1.404271	0.228457	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1212	0.115283	1.480684	0.036132	0.252878	0.049329	0.537678	0.250896	0.093736	0.233292	0.280134	-1.142965	-0.491097	0.403063	0
1213	0.941181	1.528803	-1.156399	1.554010	-0.075675	0.729753	1.142193	0.879550	0.233292	1.113556	-1.427815	-1.702917	1.076351	1
1214	-0.762234	1.588181	-0.028590	-0.555628	-0.315562	0.213238	-0.491114	-0.741192	0.233292	-0.903431	-1.563216	-0.567787	-0.235784	0
1215	0.166902	1.629782	0.170750	1.050082	-0.201979	0.705453	1.445251	0.142849	0.233292	0.337809	-1.851643	-1.402317	0.691448	0
1216	-0.835975	1.603325	0.383793	-1.040983	-0.235315	-1.213681	0.364560	-0.811354	0.233292	-1.030740	1.532912	1.698309	-0.956020	0

1217 rows × 14 columns

```
x = df.drop('x13', axis = 1).values
y = df['x13']
y = y.astype(int)

print(x.shape)
print(y.shape)
```

```
(1217, 13)
(1217,)
```

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.25, random_state=10)
```

```
reg = Lasso(alpha=0.5)
reg.fit(x_train, y_train)
```

```
Lasso(alpha=0.5, copy_X=True, fit_intercept=True, max_iter=1000,
      normalize=False, positive=False, precompute=False, random_state=None,
      selection='cyclic', tol=0.0001, warm_start=False)
```

```
print('Lasso Regression: R^2 score on training set', reg.score(x_train, y_train)*100)
print('Lasso Regression: R^2 score on test set', reg.score(x_test, y_test)*100)
```

```
Lasso Regression: R^2 score on training set 0.0
Lasso Regression: R^2 score on test set -0.39948214876439625
```

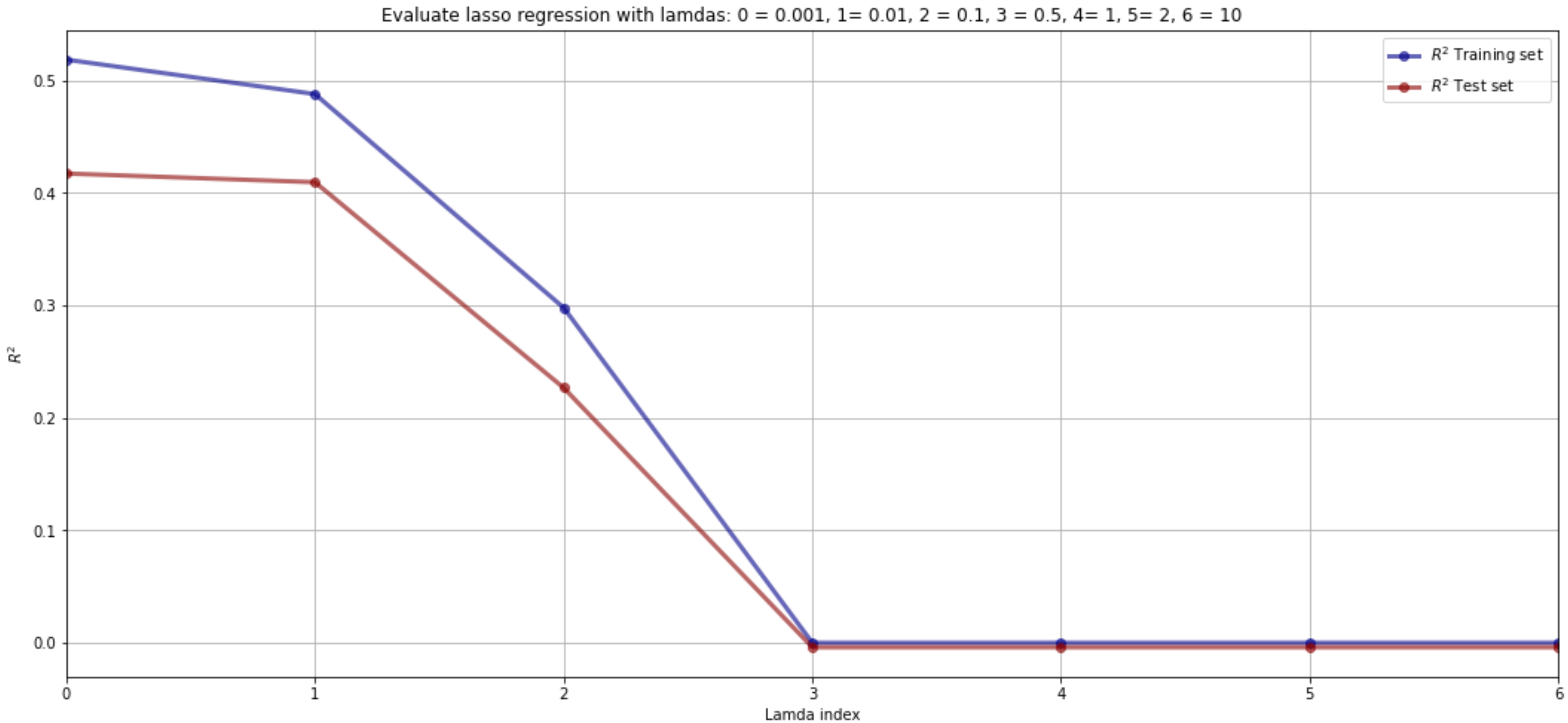
```
lambdas = (0.001, 0.01, 0.1, 0.5, 1, 2, 10)
l_num = 7
pred_num = x.shape[1]

# prepare data for enumerate
coeff_a = np.zeros((l_num, pred_num))
train_r_squared = np.zeros(l_num)
test_r_squared = np.zeros(l_num)


for ind, i in enumerate(lambdas):
    reg = Lasso(alpha = i)
    reg.fit(x_train, y_train)

    coeff_a[ind,:] = reg.coef_
    train_r_squared[ind] = reg.score(x_train, y_train)
    test_r_squared[ind] = reg.score(x_test, y_test)


plt.figure(figsize=(18, 8))
plt.plot(train_r_squared, 'bo-', label=r'$R^2$ Training set', color="darkblue", alpha=0.6, linewidth=3)
plt.plot(test_r_squared, 'bo-', label=r'$R^2$ Test set', color="darkred", alpha=0.6, linewidth=3)
plt.xlabel('Lamda index'); plt.ylabel(r'$R^2$')
plt.xlim(0, 6)
plt.title(r'Evaluate lasso regression with lamdas: 0 = 0.001, 1= 0.01, 2 = 0.1, 3 = 0.5, 4= 1, 5= 2, 6 = 10')
plt.legend(loc='best')
plt.grid()
```


Evaluate lasso regression with lamdas: 0 = 0.001, 1= 0.01, 2 = 0.1, 3 = 0.5, 4= 1, 5= 2, 6 = 10
R^2 Training set
R^2 Test set
R^2
0.0
0.1
0.2
0.3
0.4
0.5
0
1
2
3
4
5
6
Lamda index

```
df_lam = pd.DataFrame(test_r_squared*100, columns=['R_squared'])
df_lam['lambda'] = (lambdas)
# returns the index of the row where column has maximum value.
df_lam.loc[df_lam['R_squared'].idxmax()]
```

```
R_squared    41.741223
lambda        0.001000
Name: 0, dtype: float64
```

```
reg_best = Lasso(alpha = 0.1)
reg_best.fit(x_train, y_train)
```

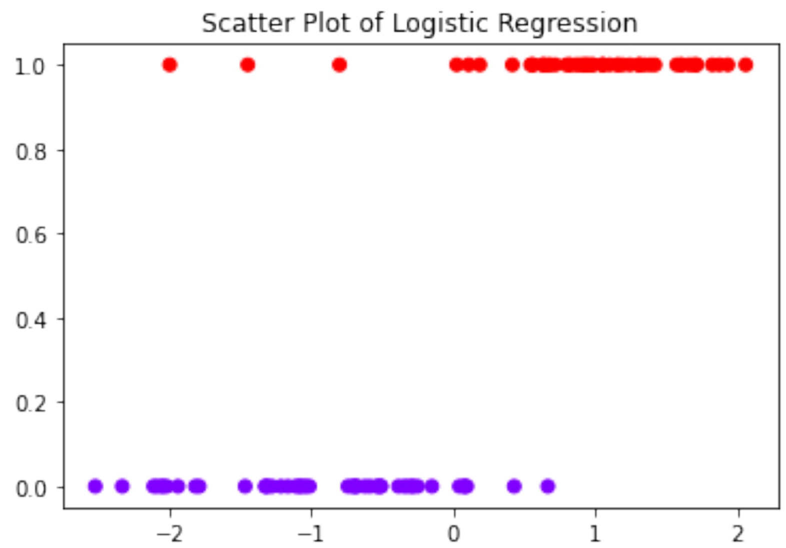
```
Lasso(alpha=0.1, copy_X=True, fit_intercept=True, max_iter=1000,
      normalize=False, positive=False, precompute=False, random_state=None,
      selection='cyclic', tol=0.0001, warm_start=False)
```

```
from sklearn.metrics import mean_squared_error
mean_squared_error(y_test, reg_best.predict(x_test))
l_min = 0.05
l_max = 0.2
l_num = 20
lambdas = np.linspace(l_min,l_max, l_num)
train_r_squared = np.zeros(l_num)
test_r_squared = np.zeros(l_num)
pred_num = x.shape[1]
coeff_a = np.zeros((l_num, pred_num))
```

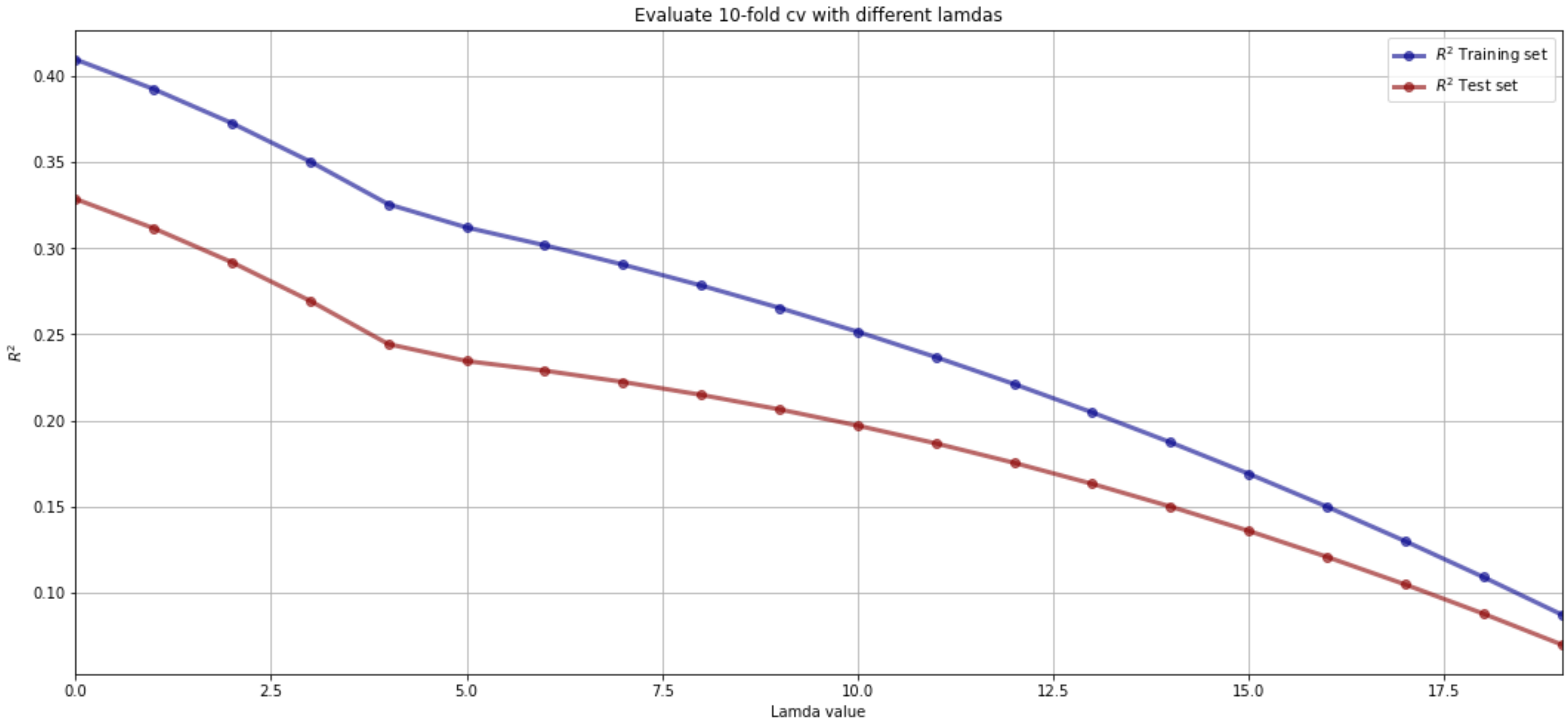
```
for ind, i in enumerate(lambdas):
  reg = Lasso(alpha = i)
  reg.fit(x_train, y_train)
  results = cross_val_score(reg, x, y, cv=10, scoring="r2")
  train_r_squared[ind] = reg.score(x_train, y_train)
  test_r_squared[ind] = reg.score(x_test, y_test)


# Generate and dataset for Logistic Regression
x, y = make_classification(
    n_samples=100,
    n_features=1,
    n_classes=2,
    n_clusters_per_class=1,
    flip_y=0.03,
    n_informative=1,
    n_redundant=0,
    n_repeated=0
)
```

```
# Create a scatter plot
plt.scatter(x, y, c=y, cmap='rainbow')
plt.title('Scatter Plot of Logistic Regression')
plt.show()
```




```
# Plotting
plt.figure(figsize=(18, 8))
plt.plot(train_r_squared, 'bo-', label=r'$R^2$ Training set', color="darkblue", alpha=0.6, linewidth=3)
plt.plot(test_r_squared, 'bo-', label=r'$R^2$ Test set', color="darkred", alpha=0.6, linewidth=3)
plt.xlabel('Lamda value'); plt.ylabel(r'$R^2$')
plt.xlim(0, 19)
plt.title(r'Evaluate 10-fold cv with different lamdas')
plt.legend(loc='best')
plt.grid()
```




```
# Split the dataset into training and test dataset
x_train, x_test, y_train, y_test = train_test_split(x, y, random_state=1)
```

```
# Create a Logistic Regression Object, perform Logistic Regression
log_reg = LogisticRegression()
log_reg.fit(x_train, y_train)
```

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

```
# Perform prediction using the test dataset
y_pred = log_reg.predict(x_test)
```

```
# Show to Coeficient and Intercept
print(log_reg.coef_)
print(log_reg.intercept_)
```

```
[[-0.28788025  0.06454795 -0.10178408  2.24973594 -3.07328242  1.61082795
  -0.22587435 -0.31696034  0.57513313  1.05870398  0.10624406  0.02116713
   0.49229669]]
[-4.56225241]
```

```
# Show the Confusion Matrix
confusion_matrix(y_test, y_pred)
```

```
array([[245,  15],
       [  9,  36]])
```

```
# True positive: 245 (upper-left) - Number of positives we predicted correctly
# True negative: 36(lower-right) - Number of negatives we predicted correctly
# False positive: 15 (top-right) - Number of positives we predicted wrongly
# False negative:  9(lower-left) - Number of negatives we predicted wrongly
```

5. Data Preprocessing

- 5.1 Exploratory Data Analysis

```
# Training my model

log_reg = LogisticRegression(random_state=10, solver = 'lbfgs')

log_reg.fit(x_train, y_train)
```

```
    LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                       intercept_scaling=1, l1_ratio=None, max_iter=100,
                       multi_class='auto', n_jobs=None, penalty='l2',
                       random_state=10, solver='lbfgs', tol=0.0001, verbose=0,
                       warm_start=False)
```

```
# Methods we can use in Logistic

# predict - Predict class labels for samples in X
log_reg.predict(x_train)
y_pred = log_reg.predict(x_train)

# predict_proba - Probability estimates
pred_proba = log_reg.predict_proba(x_train)

# coef_ - Coefficient of the features in the decision function
log_reg.coef_

# score- Returns the mean accuracy on the given test data and labels - below
```

```
array([[-0.28788025,  0.06454795, -0.10178408,  2.24973594, -3.07328242,
         1.61082795, -0.22587435, -0.31696034,  0.57513313,  1.05870398,
         0.10624406,  0.02116713,  0.49229669]])
```

```
# Accuracy on Train
print("The Training Accuracy is: ", log_reg.score(x_train, y_train))

# Accuracy on Test
print("The Testing Accuracy is: ", log_reg.score(x_test, y_test))


# Classification Report
print(classification_report(y_train, y_pred))
```

```
The Training Accuracy is:  0.9177631578947368
The Testing Accuracy is:  0.921311475409836
              precision    recall  f1-score   support

           0       0.94      0.96      0.95       757
           1       0.80      0.69      0.74       155

    accuracy                           0.92       912
   macro avg       0.87      0.83      0.85       912
weighted avg       0.91      0.92      0.92       912
```

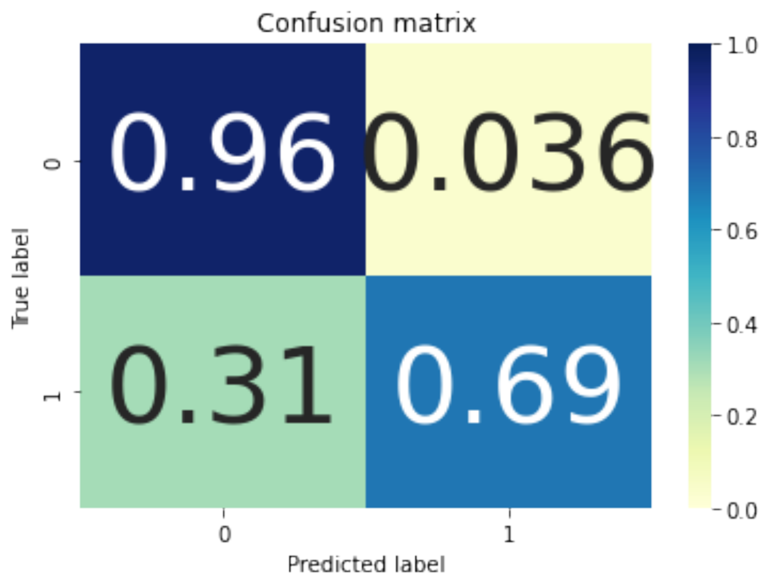
```
# Confusion Matrix function

def plot_confusion_matrix(cm, classes=None, title='Confusion matrix'):
    """Plots a confusion matrix."""
    if classes is not None:
        sns.heatmap(cm, cmap="YlGnBu", xticklabels=classes, yticklabels=classes, vmin=0., vmax=1., annot=True, annot_kws={'size':50})
    else:
        sns.heatmap(cm, vmin=0., vmax=1.)
    plt.title(title)
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

```
# Visualizing cm

cm = confusion_matrix(y_train, y_pred)
cm_norm = cm / cm.sum(axis=1).reshape(-1,1)

plot_confusion_matrix(cm_norm, classes = log_reg.classes_, title='Confusion matrix')
```




```
df_lam = pd.DataFrame(test_r_squared*100, columns=['R_squared'])
df_lam['lambda'] = (lambdas)
# returns the index of the row where column has maximum value.
df_lam.loc[df_lam['R_squared'].idxmax()]
```

```
R_squared    32.864342
lambda        0.050000
Name: 0, dtype: float64
```

```
from sklearn.metrics import mean_squared_error

mean_squared_error(y_test, reg_best.predict(x_test))
```

```
0.08896359365167045
```

```
reg_best.coef_
```

```
array([0.29733003])
```

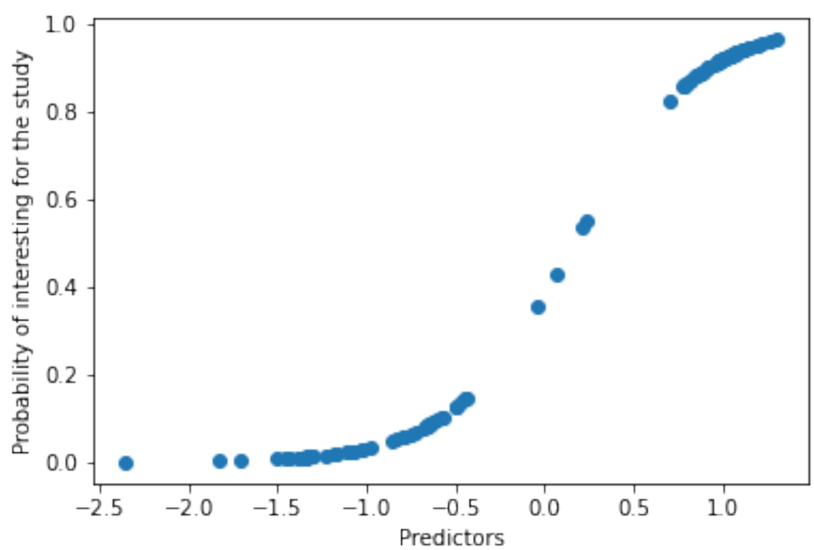
```
reg_best = Lasso(alpha = 0.1)
reg_best.fit(x_train, y_train)
reg_best.coef_
```

```
array([0.34056139])
```

```
LogR = LogisticRegression()
LogR.fit(x,np.ravel(y.astype(int)))

#matplotlib scatter funcion w/ logistic regression
plt.scatter(x,LogR.predict_proba(x)[:,1])
plt.xlabel("Predictors")
plt.ylabel("Probability of interesting for the study")
```

```
Text(0, 0.5, 'Probability of interesting for the study')
```



```
# Best Model
reg_best = Lasso(alpha = 0.144737)
reg_best.fit(x_train, y_train)
```

```
Lasso(alpha=0.144737, copy_X=True, fit_intercept=True, max_iter=1000,
      normalize=False, positive=False, precompute=False, random_state=None,
      selection='cyclic', tol=0.0001, warm_start=False)
```

```
from sklearn.metrics import mean_squared_error

mean_squared_error(y_test, reg_best.predict(x_test))
```

```
0.10370895326859364
```

```
reg_best.coef_
```

```
array([ 0.        ,  0.        , -0.        ,  0.08348593, -0.        ,
        0.        , -0.        ,  0.        ,  0.        ,  0.        ,
       -0.        , -0.        ,  0.        ])
```

```
reg_best = Lasso(alpha = 0.1)
reg_best.fit(x_train, y_train)
reg_best.coef_
```

```
array([ 0.        ,  0.        , -0.        ,  0.12782836, -0.        ,
        0.        , -0.        ,  0.        ,  0.        ,  0.        ,
       -0.        , -0.        ,  0.        ])
```

```
clf_l1_LR = LogisticRegression(C = 1, penalty = 'l2')
clf_l1_LR.fit(x, y)
```

```
LogisticRegression(C=1, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```