```
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, classificat
from math import sqrt
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import Lasso
from sklearn import svm
```

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

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[['
```

```
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	x1
0	0.159528	-1.802006	-1.208134	0.114420	-0.135689	0.538311	-1.587426	0.135833	0.233292	0.329626	0.34511
1	-0.939212	-1.809877	0.424363	-0.933511	-0.817247	0.019258	1.500586	-0.909580	0.233292	-1.221986	0.70728
2	0.410247	-1.673790	0.555385	0.200447	0.134019	0.501621	1.684134	0.374384	0.233292	0.598252	-0.19189
3	-0.548385	-1.617137	1.879947	-1.059096	0.939523	-6.206504	1.253012	-0.537722	0.233292	-0.567479	0.89662
4	0.181650	-1.525316	2.335905	0.578476	-0.417798	0.681969	-1.048779	0.156881	0.233292	0.354121	-0.40238
...	...	...	...	...	...	...	...	...	...	...	.
1212	0.115283	1.480684	0.036132	0.252878	0.049329	0.537678	0.250896	0.093736	0.233292	0.280134	-1.14296
1213	0.941181	1.528803	-1.156399	1.554010	-0.075675	0.729753	1.142193	0.879550	0.233292	1.113556	-1.42781
1214	-0.762234	1.588181	-0.028590	-0.555628	-0.315562	0.213238	-0.491114	-0.741192	0.233292	-0.903431	-1.56321
1215	0.166902	1.629782	0.170750	1.050082	-0.201979	0.705453	1.445251	0.142849	0.233292	0.337809	-1.85164
1216	-0.835975	1.603325	0.383793	-1.040983	-0.235315	-1.213681	0.364560	-0.811354	0.233292	-1.030740	1.53291

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,)
```

check distribution of target_class column

```
df['x13'].value_counts()
```

```
0    1017
1     200
Name: x13, dtype: int64
```

```
df['x13'].value_counts()/np.float(len(df))
```

```
0    0.835661
1    0.164339
Name: x13, dtype: float64
```

```
round(df.describe(),2)
```

	x0	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11	x1
count	1217.00	1217.00	1217.00	1217.00	1217.00	1217.00	1217.00	1217.00	1217.00	1217.00	1217.00	1217.00	1217.(
mean	0.00	0.00	-0.00	0.00	-0.00	0.00	0.00	0.00	-0.00	0.00	-0.00	0.00	-0.(
std	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.(
min	-0.96	-1.82	-1.30	-1.21	-1.73	-6.23	-1.77	-0.93	-12.80	-1.27	-4.37	-2.28	-1.(
25%	-0.69	-0.82	-0.81	-0.76	-0.51	-0.21	-0.82	-0.66	0.23	-0.78	-0.62	-0.77	-0.6
50%	-0.30	-0.02	-0.19	-0.29	-0.25	0.37	-0.01	-0.29	0.23	-0.22	0.12	-0.00	-0.2
75%	0.38	0.89	0.58	0.58	0.12	0.63	0.81	0.35	0.23	0.57	0.77	0.74	0.3
max	6.55	1.64	2.57	6.37	9.39	0.81	1.77	6.71	0.23	4.75	1.91	2.72	8.5

```
clf = svm.SVC(probability=True)
clf.fit(x, y)
results = clf.predict_proba(x)[0]
```

```
clf.support_vectors_
```

```
array([[-0.5483853 , -1.61713701,  1.87994654, ...,  0.89662564,
         1.08270245, -0.71950145],
       [ 0.64621776, -1.43758979, -0.16636889, ...,  0.56531025,
         1.66590892,  0.16941486],
       [ 1.64909439, -1.39855593,  0.13882352, ..., -1.97568425,
        -0.32889369,  2.48576347],
       ...,
       [ 0.55772864, -0.13732092, -0.58518741, ..., -0.71172753,
        -0.8172806 ,  0.59786186],
       [ 0.98542603,  0.3343214 ,  1.61671055, ..., -0.35219228,
        -1.12730684,  0.88169595],
       [ 0.94118147,  1.52880321, -1.15639909, ..., -1.42781464,
        -1.70291747,  1.0763514 ]])
```

```
clf.n_support_
```

```
array([169, 143], dtype=int32)
```

```
print(clf.score(x, y), '\n')
```

```
0.9276910435497124
```

```
clf.predict(x)
```

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

```
print(clf.decision_function(x), '\n')
```

```
[-1.08084927 -1.25233452 -1.33365989 ... -1.76057738 -0.20813551
 -1.41115986]
```

```
clf= svm.SVC(kernel = 'linear')
```

```
# import SVC classifier
from sklearn.svm import SVC


# import metrics to compute accuracy
from sklearn.metrics import accuracy_score


# instantiate classifier with default hyperparameters
svc=SVC()


# fit classifier to predictors & target set
svc.fit(x,y)


# make predictions on predictors set
y_pred=svc.predict(x)


# compute and print accuracy score
print('Model accuracy score with default hyperparameters: {0:0.4f}'. format(accuracy_score(y, y_pred)))
```

```
Model accuracy score with default hyperparameters: 0.9277
```

```
# instantiate classifier with rbf kernel and C=1000
clf= svm.SVC(kernel = 'linear', C = 1000)
# fit classifier to predictors & target set
clf.fit(x,y)
# of support vectors in EACH class
print(clf.n_support_)
# indices of support vectors
```

```
print(clf.support_)
# coefficients in "primary" form
print(clf.coef_)
# coefficients in "dual" form
print(clf.dual_coef_)
# make predictions on predictors set
y_pred=clf.predict(x)
# compute and print accuracy score
print('Model accuracy score with rbf kernel and C=1000 : {0:0.4f}'. format(accuracy_score(y, y_pred)))
```

```
  -0.1925175   1.9395231   0.44159776  0.50224639  0.05799626  0.11239126
   0.17183158]]
[[-1000.         -1000.           -75.78627518 -1000.
  -1000.          -435.36631657 -1000.         -1000.
  -1000.         -1000.         -1000.         -1000.
  -1000.         -1000.         -1000.         -1000.
  -1000.         -1000.         -1000.         -1000.
  -1000.         -1000.         -1000.         -1000.
   -121.39315922 -1000.         -1000.         -1000.
    -22.51789822 -1000.         -1000.         -1000.
  -1000.         -1000.         -1000.           -10.29747767
  -1000.         -1000.         -1000.         -1000.
   -435.4082784  -1000.         -1000.          -468.59191986
  -1000.         -1000.         -1000.         -1000.
  -1000.         -1000.          -682.0842007  -1000.
  -1000.         -1000.         -1000.         -1000.
  -1000.         -1000.         -1000.         -1000.
  -1000.         -1000.         -1000.         -1000.
  -1000.         -1000.         -1000.         -1000.
  -1000.         -1000.         -1000.         -1000.
   -193.81243475 -1000.         -1000.         -1000.
  -1000.         -1000.         -1000.         -1000.
  -1000.         -1000.         -1000.         -1000.
  -1000.         -1000.         -1000.         -1000.
  -1000.         -1000.         -1000.         -1000.
  -1000.         -1000.         -1000.         -1000.
```

```
 -1000.        -1000.        -1000.        -1000.
 -1000.        -1000.        -1000.        -1000.
 -1000.        -1000.        -1000.        -1000.
 -1000.        -1000.        -1000.         -832.50547975
 -1000.         1000.         1000.         1000.
  1000.         1000.         1000.         1000.
  1000.         1000.         1000.         1000.
  1000.         1000.         1000.         1000.
  1000.         1000.         1000.         1000.
    90.30512186  1000.        1000.         1000.
  1000.         1000.         1000.         1000.
   183.180635   1000.         1000.           10.69531106
  1000.         1000.         1000.         1000.
  1000.         1000.         1000.         1000.
  1000.         1000.         1000.         1000.
  1000.         1000.         1000.         1000.
  1000.         1000.         1000.         1000.
  1000.         1000.         1000.          251.92106332
  1000.         1000.         1000.         1000.
  1000.         1000.         1000.         1000.
  1000.         1000.         1000.         1000.
  1000.         1000.         1000.         1000.
  1000.         1000.         1000.         1000.
  1000.         1000.         1000.         1000.
  1000.         1000.         1000.         1000.
  1000.         1000.         1000.         1000.
  1000.         1000.         1000.         1000.
  1000.         1000.         1000.         1000.
  1000.         1000.         1000.         1000.
  1000.         1000.         1000.         1000.
   741.66130908  1000.        1000.         1000.
  1000.         1000.         1000.       ]]
Model accuracy score with rbf kernel and C=1000 : 0.9244
```

```
print(clf.predict(x), '\n')
```

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

```
print(clf.score(x, y), '\n')
```

```
0.9178307313064914
```

```
print(clf.decision_function(x), '\n')
```

```
[-1.44783076 -2.73494909 -2.69961638 ... -2.9482961   0.06799006
 -3.11732434]
```

```
# Support vectors content values
print(clf.support_vectors_)
```

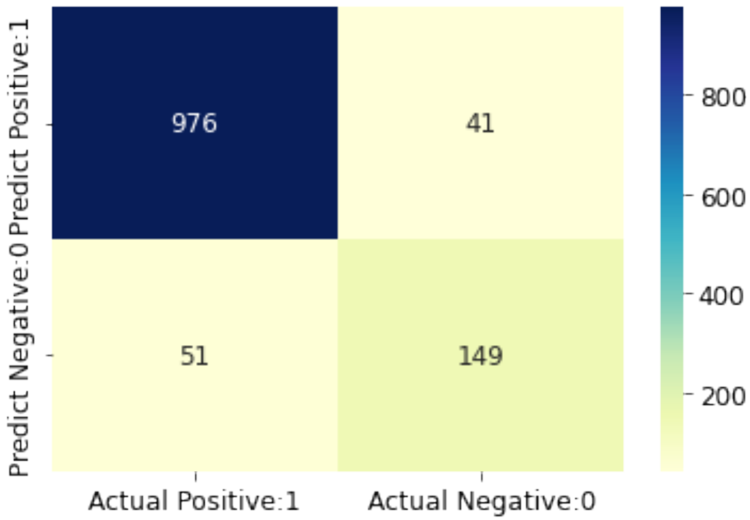
```
[[-0.04694698 -1.31338801  2.50887484 ...  0.11107933 -1.22335795
   0.03939855]
 [ 0.04891623 -1.05894919  1.70865549 ...  0.99108125  2.27380761
  -0.19629958]
 [ 2.75520833 -0.87846275 -0.41747922 ... -1.52948211 -0.646354
   2.90504659]
 ...
 [ 0.41024678  1.24591731 -0.16948148 ... -0.01803752 -0.64883306
   0.34523004]
 [ 0.24801674  1.56018396 -0.75703818 ... -0.37610604 -0.92911486
   0.39525208]
 [ 0.98542603  0.3343214   1.61671055 ... -0.35219228 -1.12730684
   0.88169595]]
```

```
# Print the Confusion Matrix and slice it into four pieces

from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y, y_pred)

print('Confusion matrix\n\n', cm)

print('\nTrue Positives(TP) = ', cm[0,0])

print('\nTrue Negatives(TN) = ', cm[1,1])

print('\nFalse Positives(FP) = ', cm[0,1])

print('\nFalse Negatives(FN) = ', cm[1,0])
```

```
Confusion matrix

 [[976  41]
 [ 51 149]]

True Positives(TP) =  976

True Negatives(TN) =  149

False Positives(FP) =  41

False Negatives(FN) =  51
```

```
# visualize confusion matrix with seaborn heatmap

cm_matrix = pd.DataFrame(data=cm, columns=['Actual Positive:1', 'Actual Negative:0'],
                                 index=['Predict Positive:1', 'Predict Negative:0'])

sns.heatmap(cm_matrix, annot=True, fmt='d', cmap='YlGnBu')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7dafef49d0>
```



```
from sklearn.metrics import classification_report

print(classification_report(y, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.95      0.96      0.95      1017
           1       0.78      0.74      0.76       200

    accuracy                           0.92      1217
   macro avg       0.87      0.85      0.86      1217
weighted avg       0.92      0.92      0.92      1217
```

```
TP = cm[0,0]
TN = cm[1,1]
FP = cm[0,1]
FN = cm[1,0]


# print classification accuracy

classification_accuracy = (TP + TN) / float(TP + TN + FP + FN)

print('Classification accuracy : {0:0.4f}'.format(classification_accuracy))
```

```
Classification accuracy : 0.9244
```

```
x = df.drop('x13', axis = 1).values[50:, 2:4]
y = df['x13'][50:]
C = 1.0
# SVM regularization parameter
clf = svm.SVC(kernel = 'linear', C = C, probability=True)
clf.fit(x, y)
yhat = clf.predict_proba(x)
y_pred = clf.predict(x)
```

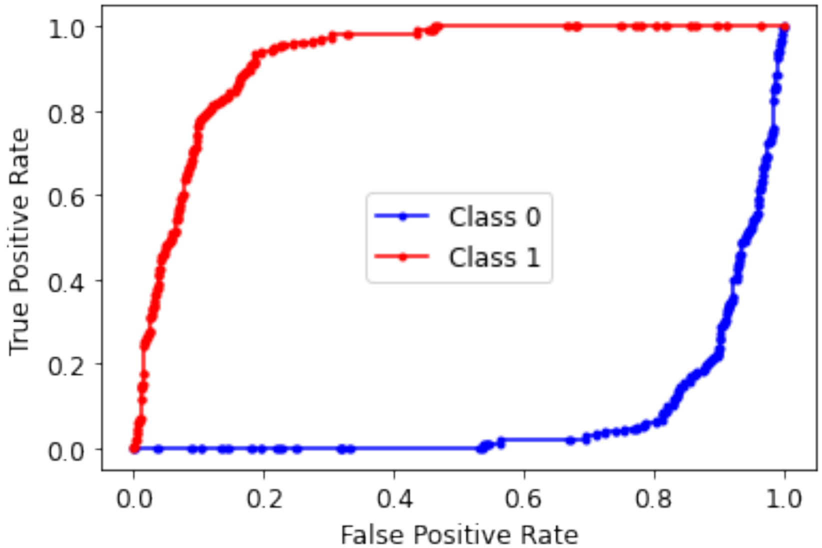
```
print(y.shape, y.size)
print(y_pred)
print(yhat)
```

```
(1167,) 1167
[0 0 0 ... 0 0 0]
[[0.98563836 0.01436164]
 [0.97646447 0.02353553]
 [0.65174412 0.34825588]
 ...
 [0.9650246  0.0349754 ]
 [0.62450023 0.37549977]
 [0.98598946 0.01401054]]
```

```
from sklearn.metrics import roc_curve, roc_auc_score, precision_recall_curve, confusion_matrix, auc, accuracy
fpr_0, tpr_0, _=roc_curve(y, yhat[:,0])
roc_auc_0=roc_auc_score(y, yhat[:,0])
fpr_1, tpr_1, _=roc_curve(y, yhat[:,1])
roc_auc_1=roc_auc_score(y, yhat[:,1])
# plot ROC curves
print('roc_auc_0: ', roc_auc_0)
```

```
print('roc_auc_1: ', roc_auc_1, '\n')
plt.plot(fpr_0, tpr_0, marker='.', label='Class 0', color='b')
plt.plot(fpr_1, tpr_1, marker='.', label='Class 1', color='r')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```

```
roc_auc_0:  0.07844799271039722
roc_auc_1:  0.9215520072896027
```



```
# compute ROC AUC

from sklearn.metrics import roc_auc_score

ROC_AUC = roc_auc_score(y, y_pred)

print('ROC AUC : {:.4f}'.format(ROC_AUC))
```

```
ROC AUC : 0.6722
```

```
# calculate cross-validated ROC AUC

from sklearn.model_selection import cross_val_score
linear_svc=SVC(kernel='linear', C=1.0)

Cross_validated_ROC_AUC = cross_val_score(linear_svc, x, y, cv=10, scoring='roc_auc').mean()

print('Cross validated ROC AUC : {:.4f}'.format(Cross_validated_ROC_AUC))
```

```
Cross validated ROC AUC : 0.9285
```

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