Tarea Titanic

Usando el datasets: https://www.kaggle.com/c/titanic

Implemente el mejor clasificador que usted considere conveniente de los vistos en clase. (LR, KNN, SVM) (iterar hiperparámetros)

Sustentar por qué es el mejor (MCC, AUC-ROC, "ACC :(este NO ")

```
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn import svm
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import DistanceMetric
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import matthews_corrcoef
from sklearn.metrics import recall_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
from sklearn import metrics
from matplotlib.colors import ListedColormap
import matplotlib.patches as mpatches
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sb

%matplotlib inline
plt.rcParams['figure.figsize'] = (16, 9)
plt.style.use('ggplot')
```

Primero observamos el contenido de nuestro data set, el de entrenamiento y el de testeo.

```
train = pd.read_csv(r"train.csv")
test = pd.read_csv(r"test.csv")
test_ids = test["PassengerId"]
train.head(-5)
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S
...	...	...	...	...	...	...	...	...	...	...	...	...
881	882	0	3	Markun, Mr. Johann	male	33.0	0	0	349257	7.8958	NaN	S
882	883	0	3	Dahlberg, Miss. Gerda Ulrika	female	22.0	0	0	7552	10.5167	NaN	S
883	884	0	2	Banfield, Mr. Frederick James	male	28.0	0	0	C.A./SOTON 34068	10.5000	NaN	S
884	885	0	3	Sutehall, Mr. Henry Jr	male	25.0	0	0	SOTON/OQ 392076	7.0500	NaN	S
885	886	0	3	Rice, Mrs. William (Margaret Norton)	female	39.0	0	5	382652	29.1250	NaN	Q

886 rows × 12 columns

Luego empezamos con todo el adecuamiento del data set, eliminando valores NaN, Null, etc o reemplazandolos por la media, tambien pasando características como el género de palabras a números.

```
print("Valores nulos en train: \n", train.isna().sum(),"\n")
```

```
Valores nulos en train: 
 PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

Se eliminan las columnas que no aportan al dataset

```
train.drop(['PassengerId','Name', 'Ticket', 'Cabin'], axis = 1, inplace = True) #Las columnas inutiles se eliminan
print(train.head(), "\n")
train.isna().sum()
#Se rellenan los ceros de "Fare" con la media
train['Fare'] = train['Fare'].replace(0, train['Fare'].mean())
#Se rellenan los nulos con su media
train['Age'].fillna(train['Age'].mean(), inplace = True)
train['Embarked'].fillna(train['Embarked'].mode()[0], inplace = True)
#Revisando los vacios
print(train.isna().sum())
train.head()
```

```
   Survived  Pclass     Sex   Age  SibSp  Parch     Fare Embarked
0         0       3    male  22.0      1      0   7.2500        S
1         1       1  female  38.0      1      0  71.2833        C
2         1       3  female  26.0      0      0   7.9250        S
3         1       1  female  35.0      1      0  53.1000        S
4         0       3    male  35.0      0      0   8.0500        S

Survived    0
Pclass      0
Sex         0
Age         0
SibSp       0
Parch       0
Fare        0
Embarked    0
dtype: int64
```

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	male	22.0	1	0	7.2500	S
1	1	1	female	38.0	1	0	71.2833	C
2	1	3	female	26.0	0	0	7.9250	S
3	1	1	female	35.0	1	0	53.1000	S
4	0	3	male	35.0	0	0	8.0500	S

```
train['Sex'] = train['Sex'].apply(lambda val: 1 if val == 'male' else 0) #1 para hombre, 0 para mujer
train['Embarked'] = train['Embarked'].map({'S' : 0, 'C': 1, 'Q': 2}) #Abordaje
print(train.head(), "\n")
train.describe()
```

```
   Survived  Pclass  Sex   Age  SibSp  Parch     Fare  Embarked
0         0       3    1  22.0      1      0   7.2500         0
1         1       1    0  38.0      1      0  71.2833         1
2         1       3    0  26.0      0      0   7.9250         0
3         1       1    0  35.0      1      0  53.1000         0
4         0       3    1  35.0      0      0   8.0500         0
```

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
count	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000
mean	0.383838	2.308642	0.647587	29.699118	0.523008	0.381594	32.746366	0.361392
std	0.486592	0.836071	0.477990	13.002015	1.102743	0.806057	49.514272	0.635673
min	0.000000	1.000000	0.000000	0.420000	0.000000	0.000000	4.012500	0.000000
25%	0.000000	2.000000	0.000000	22.000000	0.000000	0.000000	7.925000	0.000000
50%	0.000000	3.000000	1.000000	29.699118	0.000000	0.000000	15.100000	0.000000
75%	1.000000	3.000000	1.000000	35.000000	1.000000	0.000000	32.204208	1.000000
max	1.000000	3.000000	1.000000	80.000000	8.000000	6.000000	512.329200	2.000000

Realizamos el mismo procedimiento para los datos del Test

```
test.drop(['PassengerId','Name', 'Ticket', 'Cabin'], axis = 1, inplace = True) #Las columnas inutiles se eliminan
print(test.head(), "\n")
test.isna().sum()
```

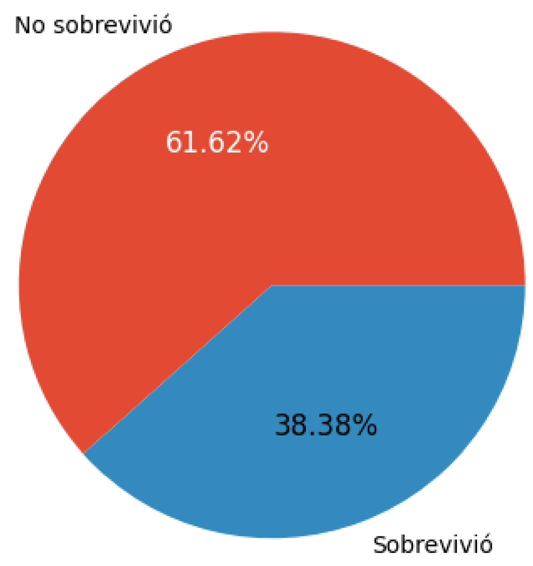
```
test.isna().sum()
#Se rellenan los ceros de "Fare" con la media
test['Fare'] = test['Fare'].replace(0, test['Fare'].mean())
test['Fare'].fillna(test['Fare'].mean(), inplace = True)
#Se rellenan los nulos con su media
test['Age'].fillna(test['Age'].mean(), inplace = True)
test['Embarked'].fillna(test['Embarked'].mode()[0], inplace = True)
#Revisando los vacios
print(test.isna().sum())
test.head()

test['Sex'] = test['Sex'].apply(lambda val: 1 if val == 'male' else 0) #1 para hombre, 0 para mujer
test['Embarked'] = test['Embarked'].map({'S' : 0, 'C': 1, 'Q': 2}) #Abordaje
print(test.head(), "\n")
test.describe()
```

```
   Pclass     Sex   Age  SibSp  Parch     Fare Embarked
0       3    male  34.5      0      0   7.8292        Q
1       3  female  47.0      1      0   7.0000        S
2       2    male  62.0      0      0   9.6875        Q
3       3    male  27.0      0      0   8.6625        S
4       3  female  22.0      1      1  12.2875        S

Pclass      0
Sex         0
Age         0
SibSp       0
Parch       0
Fare        0
Embarked    0
dtype: int64
   Pclass  Sex   Age  SibSp  Parch     Fare  Embarked
0       3    1  34.5      0      0   7.8292         2
1       3    0  47.0      1      0   7.0000         0
2       2    1  62.0      0      0   9.6875         2
3       3    1  27.0      0      0   8.6625         0
4       3    0  22.0      1      1  12.2875         0
```

	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
count	418.000000	418.000000	418.000000	418.000000	418.000000	418.000000	418.000000
mean	2.265550	0.636364	30.272590	0.447368	0.392344	35.798062	0.464115
std	0.841838	0.481622	12.634534	0.896760	0.981429	55.785702	0.685516
min	1.000000	0.000000	0.170000	0.000000	0.000000	3.170800	0.000000
25%	1.000000	0.000000	23.000000	0.000000	0.000000	7.895800	0.000000
50%	3.000000	1.000000	30.272590	0.000000	0.000000	14.479150	0.000000
75%	3.000000	1.000000	35.750000	1.000000	0.000000	31.634400	1.000000
max	3.000000	1.000000	76.000000	8.000000	9.000000	512.329200	2.000000

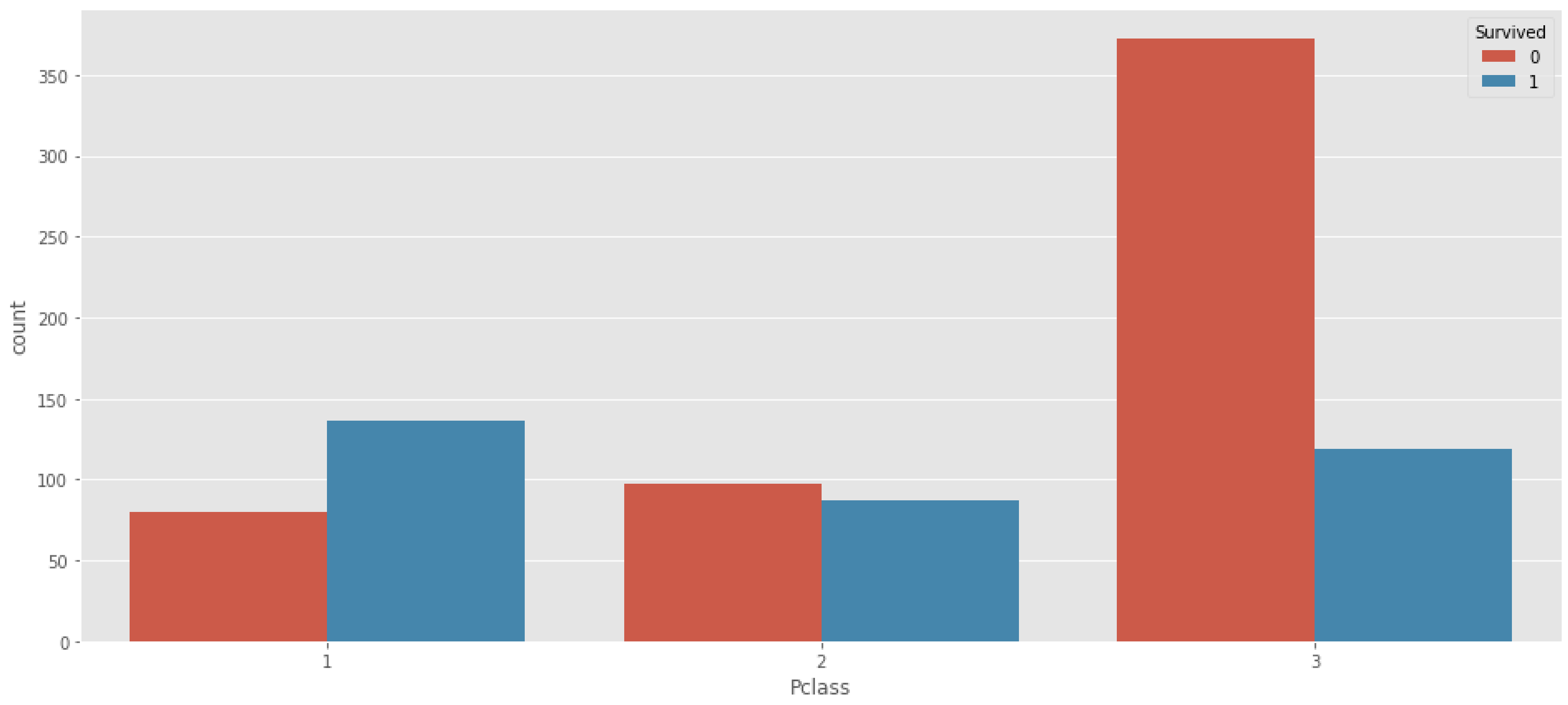
Y por último antes de empezar el entrenamiento de nuestro algortimo revisamos algunas estadísticas del dataset

```
values = train['Survived'].value_counts()
labels = ['No sobrevivió', 'Sobrevivió']
fig, ax = plt.subplots(figsize = (5, 5), dpi = 100)
explode = (0, 0.06)
patches, texts, autotexts = ax.pie(values, labels = labels, autopct = '%1.2f%%')
plt.setp(texts, color = 'black')
plt.setp(autotexts, size = 12, color = 'white')
autotexts[1].set_color('black')
plt.show()
```

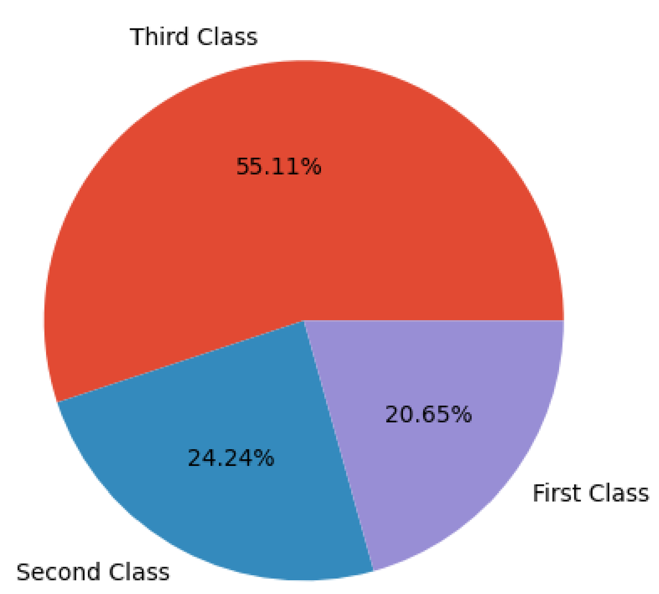



```
print(train.groupby(['Pclass', 'Survived'])['Survived'].count(), "\n")
plt.figure(figsize = (16, 7))
sb.countplot('Pclass', hue = 'Survived', data = train)
plt.show()
```

```
Pclass  Survived
1       0            80
        1           136
2       0            97
        1            87
3       0           372
        1           119
Name: Survived, dtype: int64

/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `dat
  FutureWarning
```




```
values = train['Pclass'].value_counts()
labels = ['Third Class', 'Second Class', 'First Class']
explode = (0, 0, 0.08)
fig, ax = plt.subplots(figsize = (5, 6), dpi = 100)
patches, texts, autotexts = ax.pie(values, labels = labels, autopct = '%1.2f%%')
```

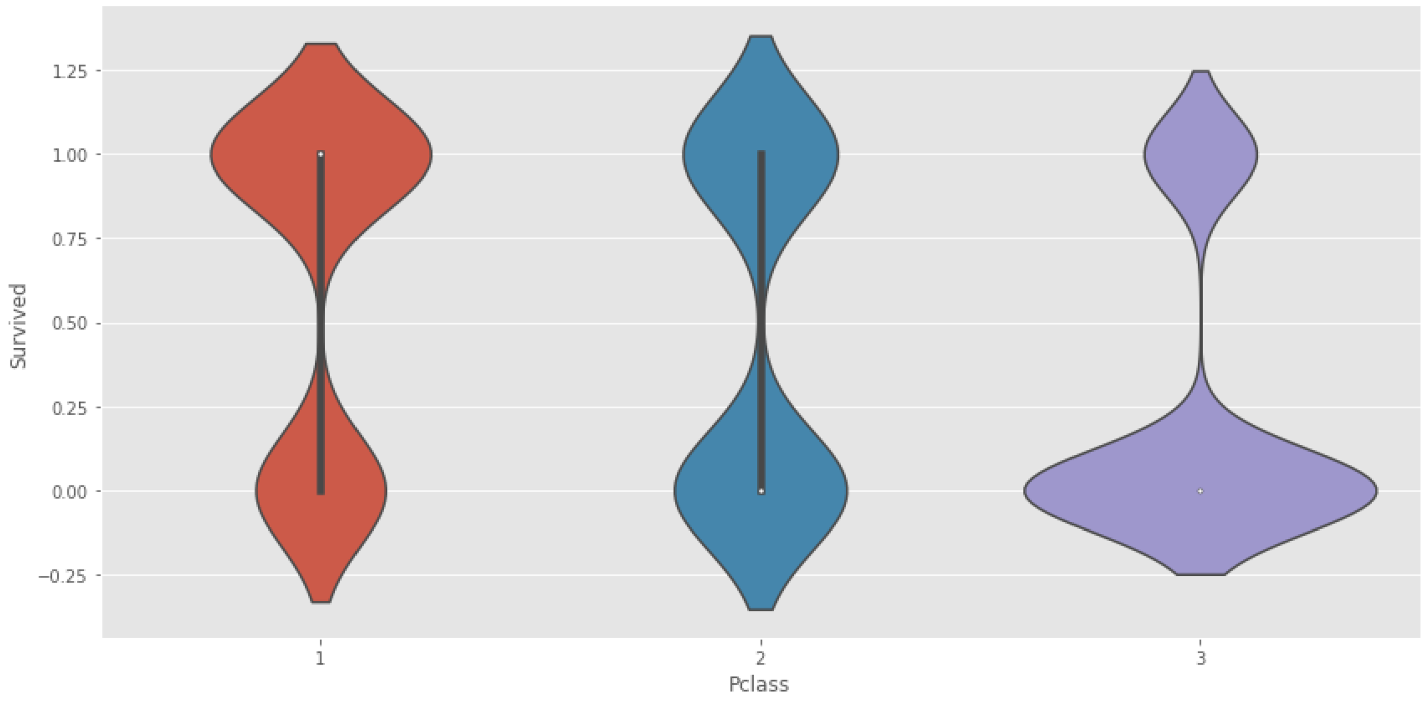


Relación entre posibilidad de sobrevivir y clase

```
plt.setp(texts, color = 'black')
plt.setp(autotexts, size = 13, color = 'white')
autotexts[2].set_color('black')
plt.show()
```

```
sb.catplot('Pclass', 'Survived', kind = 'violin', data = train,height = 6, aspect = 2)
plt.show()
```

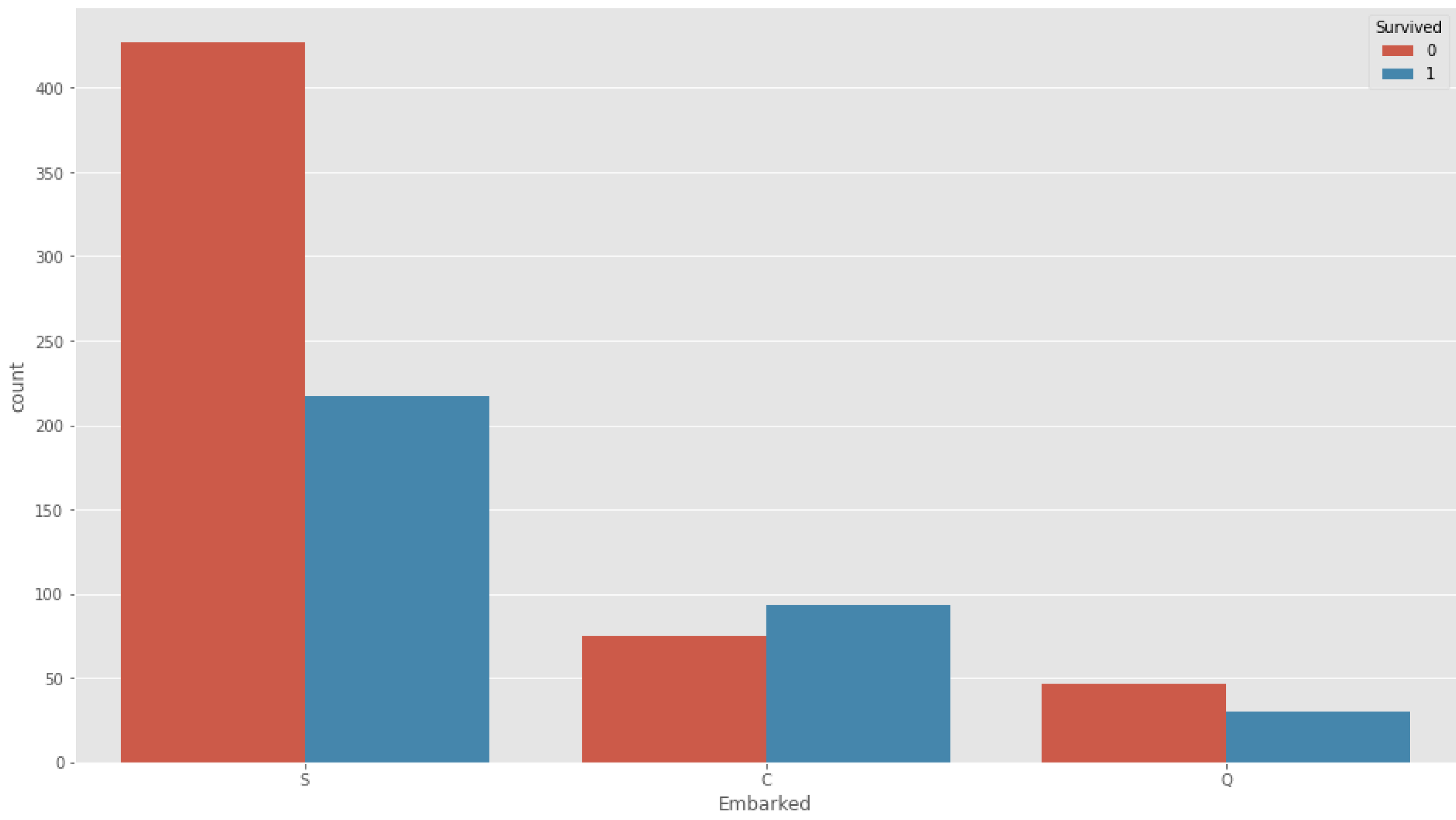
```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `
  FutureWarning
```



Relación entre lugar de abordaje y supervivencia

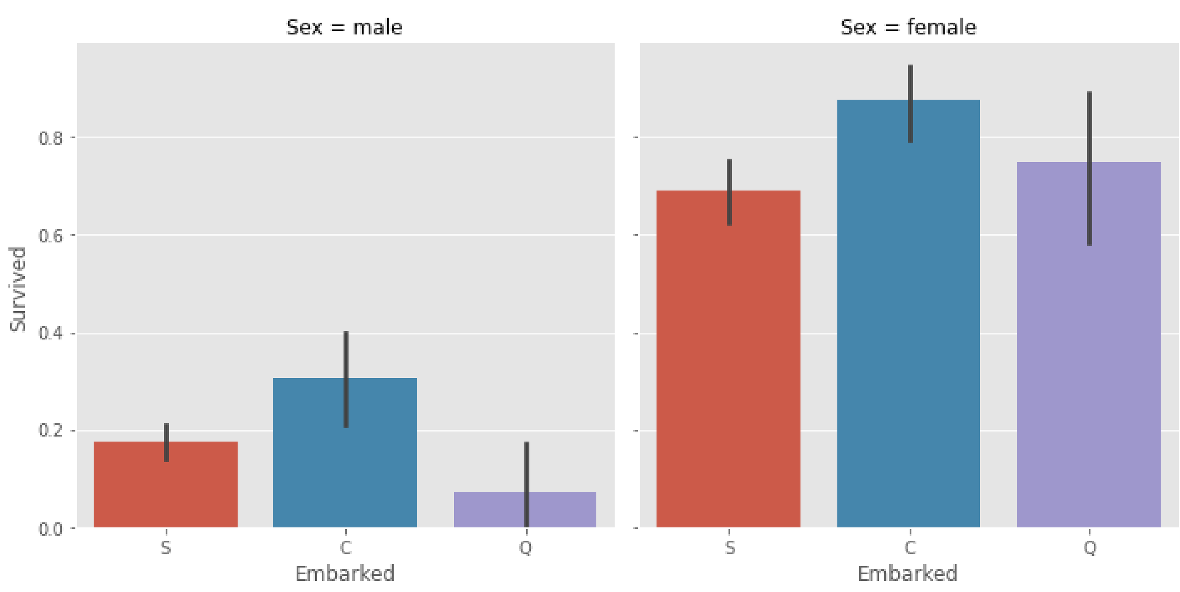
```
sb.countplot('Embarked', hue = 'Survived', data = train)
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `dat
  FutureWarning
```



Relación entre lugar de abordaje, supervivencia y sexo

```
sb.catplot(x = 'Embarked', y = 'Survived', kind = 'bar', data = train, col = 'Sex')
plt.show()
```




```
print(train['Age'].value_counts(), "\n")
```

```
29.699118    177
24.000000     30
22.000000     27
18.000000     26
28.000000     25
            ... 
55.500000      1
53.000000      1
20.500000      1
23.500000      1
0.420000       1
Name: Age, Length: 89, dtype: int64
```

Empezando nuestro entrenamiento

```
X = train[['Sex','Age','SibSp','Parch','Pclass','Fare','Embarked']].values
y = train['Survived'].values

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0,test_size=0.3)

scaler = StandardScaler() #Se escalizan los datos
scaler.fit(X_train) #El fit de los datos se hace con el conjunto de entrenamiento!
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
```

REGRESIÓN LOGÍSTICA

```
log = LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=200,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=0, solver='liblinear', tol=0.0001, verbose=0,
                   warm_start=False)

log.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=200,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=0, solver='liblinear', tol=0.0001, verbose=0,
                   warm_start=False)
```

```
pred = log.predict(X_test)
print(classification_report(y_test, pred))
```

```
              precision    recall  f1-score   support

           0       0.83      0.84      0.84       168
           1       0.73      0.72      0.72       100

    accuracy                           0.79       268
   macro avg       0.78      0.78      0.78       268
weighted avg       0.79      0.79      0.79       268
```

```
matthews_corrcoef(y_test,pred)
```

```
0.5604377974938483
```

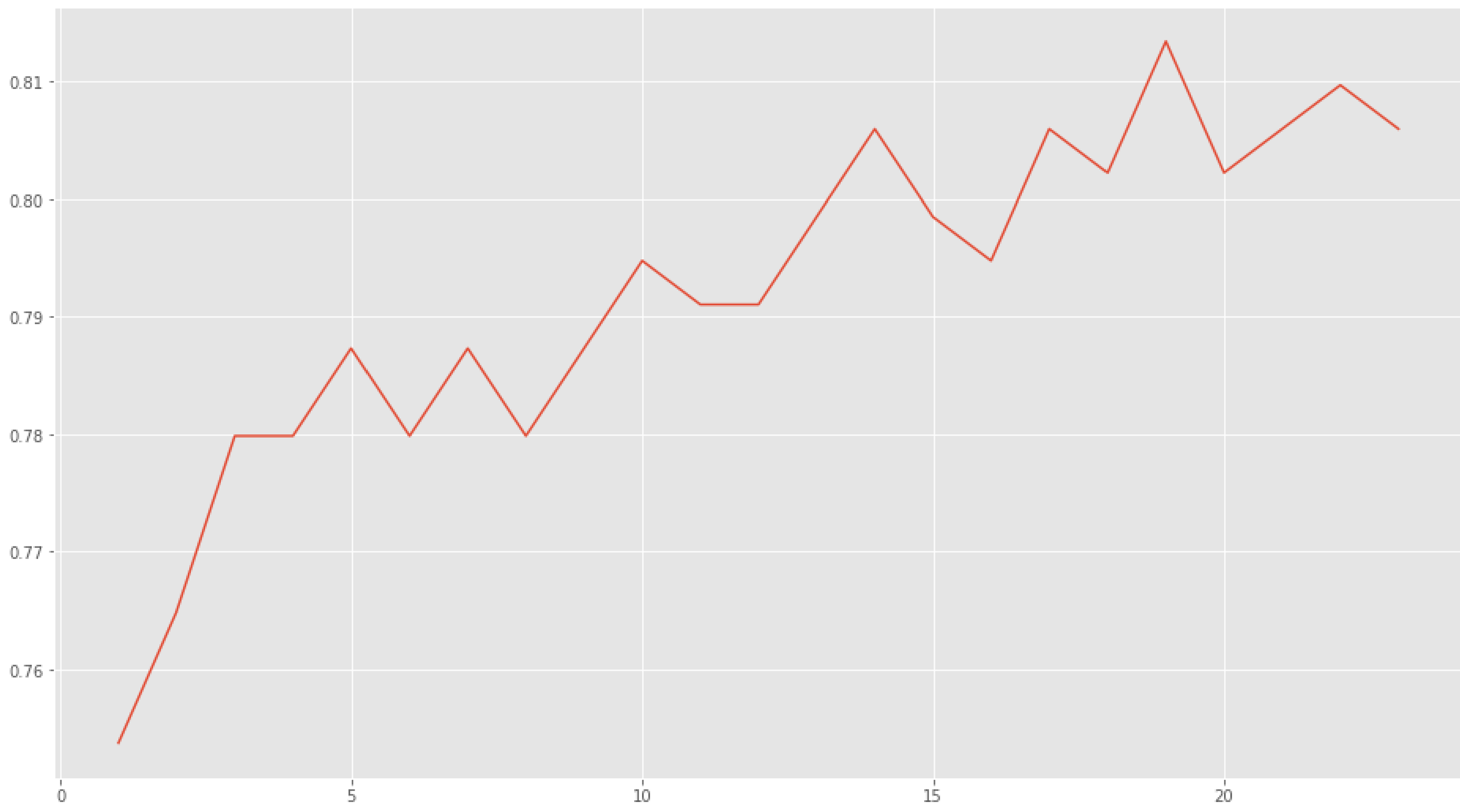
```
score = log.predict_proba(X_test)
roc_auc_score(y_test,score[:, 1])
```

```
0.8494642857142857
```

KNN

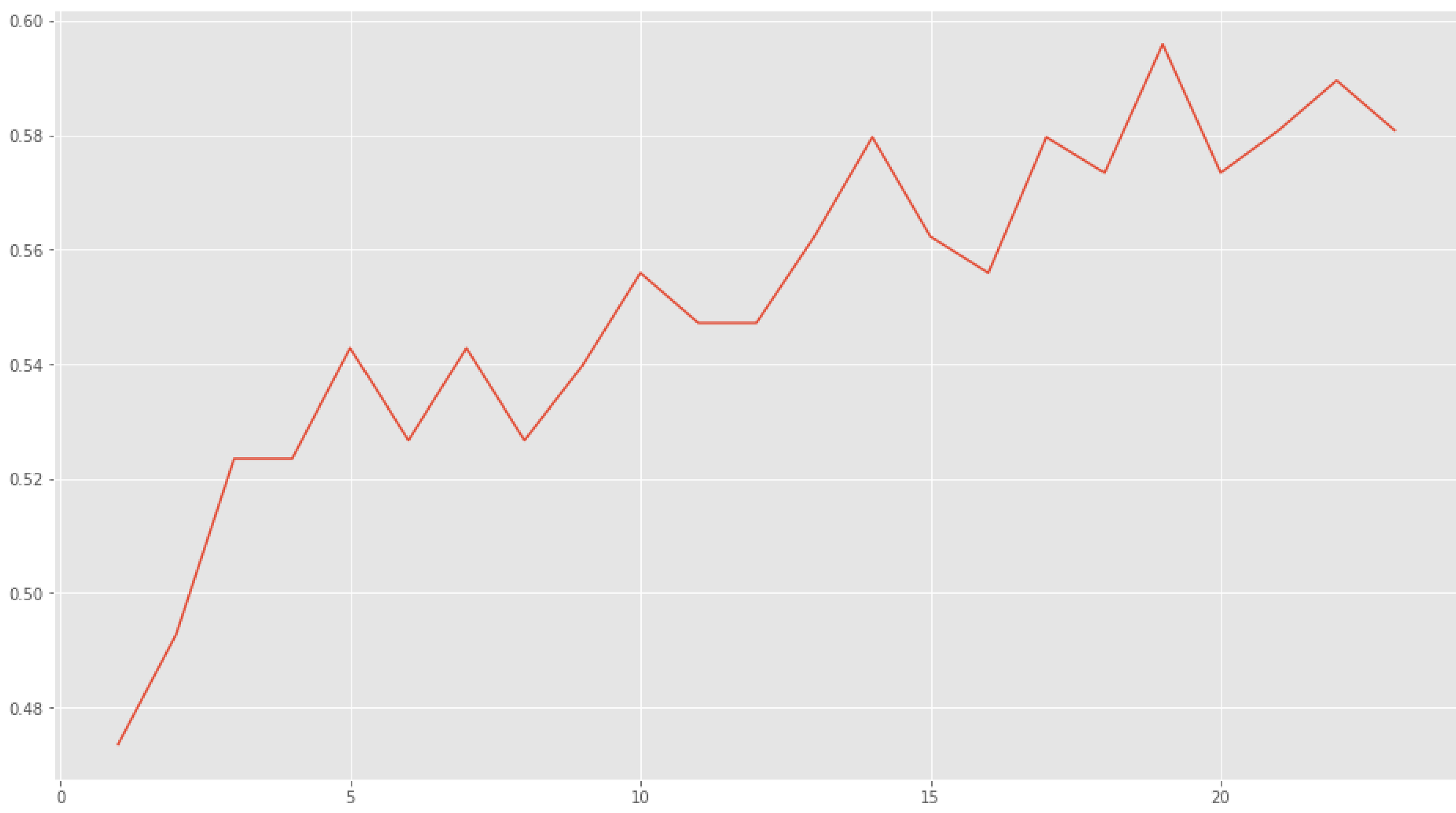
```
k_range = range(1, int(np.sqrt(len(y_train))))
print(k_range)
#por ejemplo euclidean. manhattan. chebyshev. minkowski. wminkowski. seuclidean. mahalanobis. hamming
#import sklearn
#sorted(sklearn.neighbors.VALID_METRICS['brute'])
distance='minkowski'#podemos hacer un for que recorra las distancias que queremos probar en un enfoque grid-search.

ACC=[]
MCC=[]
TPR=[]
FPR=[]
AUC=[]

for k in k_range:#por ahora variemos K,
    knn = KNeighborsClassifier(n_neighbors = k,weights='distance',metric=distance, metric_params=None,algorithm='brute')
    #knn = KNeighborsClassifier(n_neighbors = k)
    knn.fit(X_train, y_train)
    y_predicted=knn.predict(X_test)

    y_score=knn.predict_proba(X_test)
    #Les toca hacer:
    #Hallar: Accuracy
    ACC.append(knn.score(X_test, y_test))
    #MCC
    MCC.append(matthews_corrcoef(y_test,y_predicted))
    #https://scikit-learn.org/stable/modules/generated/sklearn.metrics.matthews_corrcoef.html
    #TPR
    #Ustedes buscan
    TPR.append(recall_score(y_test,y_predicted))
    #FPR esuno menos TNR no TPR
    #Ustedes buscan
    tn, fp, fn, tp = confusion_matrix(y_test,y_predicted).ravel()
    #FPR= FP/N =FP/(FP+TN)
    FPR.append(fp/(fp+tn))
    # AUC de la ROC
    #AUC.append(y_score[:, 1])
    AUC.append(roc_auc_score(y_test,y_score[:, 1]))

    fpr, tpr, thresholds = metrics.roc_curve(y_test, y_score[:, 1], pos_label=1)
    plt.figure()
    lw = 2
    plt.plot(fpr, tpr, color='darkorange',lw=lw, label='ROC curve (area = %0.5f)' % roc_auc_score(y_test,y_score[:, 1]))
    plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic. ROC')
    plt.legend(loc="lower right")
    plt.show()


print(ACC)
plt.figure()
plt.plot(k_range,ACC)
plt.show()
```

```
[0.753731343283582, 0.7649253731343284, 0.7798507462686567, 0.7798507462686567, 0.7873134328358209, 0.7798507462686567, 0.7873134328358209, 0.7798507462686567, 0.7873134328358209, 0.79477611940298
```



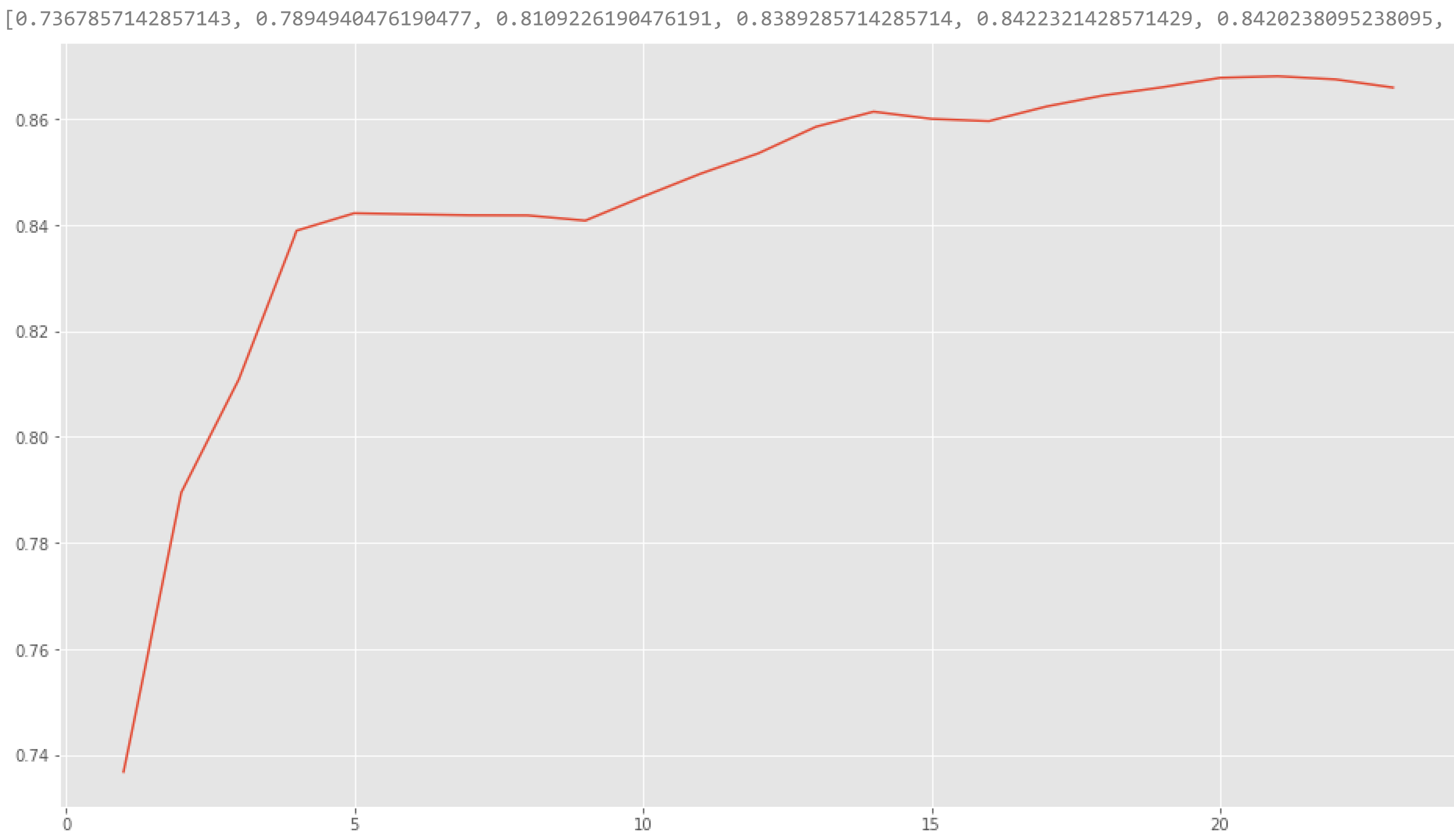

```
print(MCC)
plt.figure()
plt.plot(k_range,MCC)
plt.show()
```

```
[0.4735714285714286, 0.4927632817554276, 0.5234824282445948, 0.5234824282445948, 0.5427372558705581, 0.5266827763370802, 0.5427372558705581, 0.5266827763370802, 0.5396900634998572, 0.5558976987551
```




```
print(AUC)
plt.figure()
plt.plot(k_range,AUC)
plt.show()
```

```
[0.7367857142857143, 0.7894940476190477, 0.8109226190476191, 0.8389285714285714, 0.8422321428571429, 0.8420238095238095, 0.8418452380952381, 0.8418154761904764, 0.8408333333333333, 0.8453571428571
```

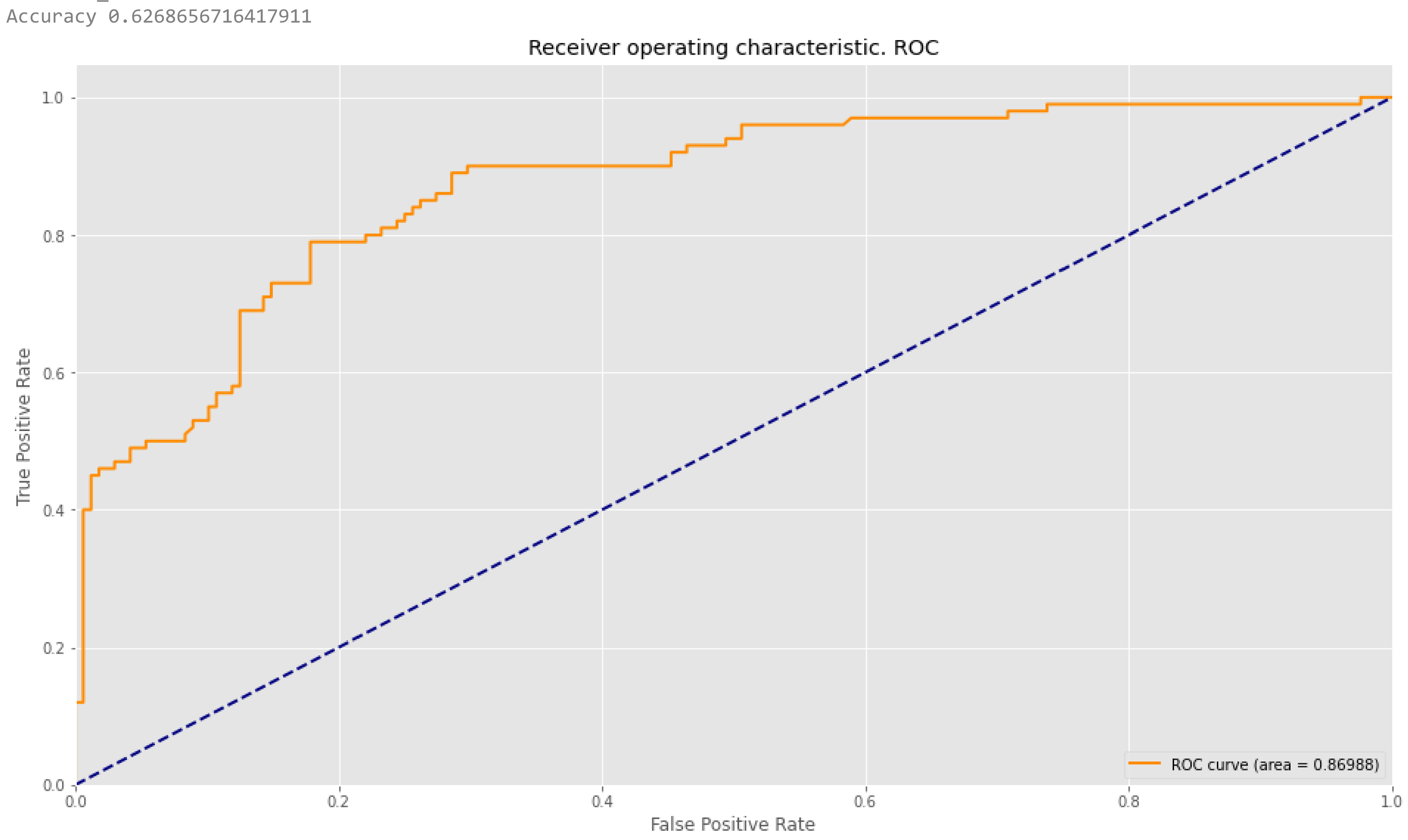


```
kernels=['linear', 'poly', 'rbf', 'sigmoid']
#lineal
#Kernel=0
#msv = svm.SVC(kernel=kernels[Kernel])

#polinomial cuadrático
#Kernel=1
#msv = svm.SVC(kernel=kernels[Kernel],degree=2)

#polinomial cúbico
#Kernel=1
#msv = svm.SVC(kernel=kernels[Kernel],degree=3)
#rbf
Kernel=2
msv = svm.SVC(kernel=kernels[Kernel],C=0.001)
#https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html#sklearn.svm.SVC

msv.fit(X_train, y_train)
```

```
SVC(C=0.001, break_ties=False, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='scale', kernel='rbf',
    max_iter=-1, probability=False, random_state=None, shrinking=True,
    tol=0.001, verbose=False)
```

```
y_test_predicted = msv.predict(X_test)
y_test_scores = msv.decision_function(X_test)
MCC = matthews_corrcoef(y_test, y_test_predicted)
print("matthews_corrcoef", MCC)
ACC = accuracy_score(y_test, y_test_predicted)
print("Accuracy", ACC)

fpr,tpr,thresholds = roc_curve(y_test, y_test_scores)
roc_auc=roc_auc_score(y_test, y_test_scores)
plt.figure()
lw = 2
plt.plot(fpr, tpr, color='darkorange',lw=lw, label='ROC curve (area = %0.5f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic. ROC')
plt.legend(loc="lower right")
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:900: RuntimeWarning: invalid value encountered in double_scalars
  mcc = cov_ytyp / np.sqrt(cov_ytyt * cov_ypyp)
matthews_corrcoef 0.0
Accuracy 0.6268656716417911
```



Modificando la regularización (C) del método obtenemos la mejor evaluación de la ROC para SVM y de todos los métodos de clasificación implementados.

Por ello el método a evaluar en la competición de Kaggle sera el de Máquinas de soporte vectorial.

```
pre = msv.predict(test)
df = pd.DataFrame({"PassengerId": test_ids.values,"Survived": pre})
df.to_csv("submission.csv", index=False)
```

Subiendo el archivo submission a la competición en kaggle se obtuvo el siguiente resultado: