P10

June 6, 2019

1 Reporte de práctica 10: Clasificación de datos con sklearn

Para esta práctica solamente trabajamos con los datos del año 2017 para clasificar la categoría a la que pertenecen los cortos tomando como base la edad y sexo del concursante y el género del corto. Utilizaremos los clasificadores de scikit-learn y la distribución de los datos que vamos a usar serán 60% para entrenar y 40% para validar.

1.1 Objetivos

- Utiliza por lo menos tres distintos métodos de clasificación
- Por lo menos una división de interés en tus datos

1.2 Preparación de los datos

Primero tomamos los archivos originales y los procesamos fuera de la nube, producto de esta limpieza se generó el archivo "clasificacion2017.csv"

Para poder trabajar importaremos la librería necesaria y cargaremos el documento .csv

```
In [7]: import pandas as pd
        from sklearn.decomposition import PCA
        from matplotlib.colors import ListedColormap
        from numpy import isnan, nan
        from sklearn import metrics
        from sklearn.model_selection import train_test_split
        from sklearn.preprocessing import StandardScaler
        from sklearn.datasets import make_moons, make_circles, make_classification
        from sklearn.neural_network import MLPClassifier
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.svm import SVC
        from sklearn.gaussian_process import GaussianProcessClassifier
        from sklearn.gaussian_process.kernels import RBF
        from sklearn.tree import DecisionTreeClassifier
        from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
        from sklearn.naive_bayes import GaussianNB
        from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis

        df = pd.read_csv("https://raw.githubusercontent.com/SamatarouKami/CIENCIA_DE_DATOS/mas
```

```
df = df.dropna()
print(len(df))
```

```
649
```

1.3 Categorización de los campos

Como tenemos campos con cadenas de caracteres utilizaremos la Categorización por defecto de pandas, y generaremos una columna con la etiqueta que utilizaremos para la clasificación.

```
In [8]: gen = pd.Categorical(df.Genero)
        df.Genero = gen.codes

        pai = pd.Categorical(df.Pais)
        df.Pais = pai.codes

        sex = pd.Categorical(df.Sexo)
        df.Sexo = pai.codes

        #cat = pd.Categorical(df.Categoria)
        #df['CategoriaCat'] = cat.codes


        df['etiquetas1'] = [1 if df['Categoria'][i] == 'Aficionado' else 0 for i in df['Catego
        df['etiquetas2'] = [1 if df['Categoria'][i] == 'Juvenil' else 0 for i in df['Categoria
        df['etiquetas3'] = [1 if df['Categoria'][i] == 'Profesional' else 0 for i in df['Categ
        df['etiquetas4'] = [1 if df['Categoria'][i] == 'SmarTIC' else 0 for i in df['Categoria

        #df['etiquetas'] = df.CategoriaCat
        print(df.etiquetas1.value_counts())
        print(df.etiquetas2.value_counts())
        print(df.etiquetas3.value_counts())
        print(df.etiquetas4.value_counts())
```

```
1    362
0    287
Name: etiquetas1, dtype: int64
0    521
1    128
Name: etiquetas2, dtype: int64
0    573
1     76
Name: etiquetas3, dtype: int64
0    566
1     83
Name: etiquetas4, dtype: int64
```

1.4 Procedimiento

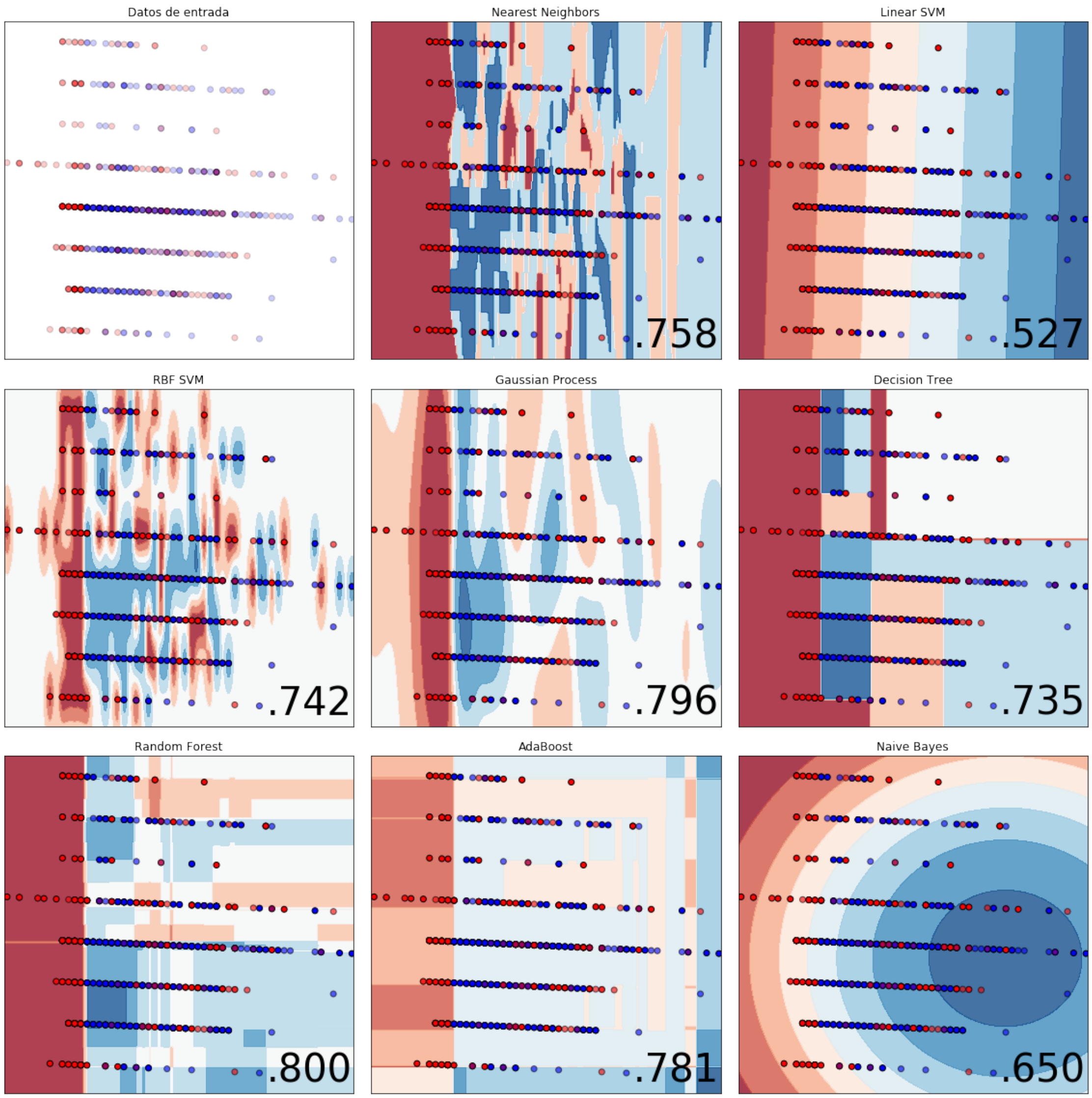
Se preparan las variables que necesitamos para preparar el clasificador y además aplicamos un PCA. Se separan los datos y se pone el 60% para entrenamiento del clasificador y el 40% para pruebas. Se busca clasificar la categoría de participación del filme, donde cada categoría es clasificada individualmente, y no en grupo, para buscar particularidades en los datos.

Después se muestran las tablas de confusión para entender mejor porque les otorgaron esas precisiones a los diferentes métodos de clasificación.

```
In [12]: for indexEtiqueta in range(1,5):
             print("-------------------------Iniciando Proceso con Etiqueta {:d}--------------
             y = df['etiquetas'+str(indexEtiqueta)]

             xVars = ['Edad', 'Sexo', 'Genero']
             x = df.loc[:, xVars].values
             #x = StandardScaler().fit_transform(x)
             pca = PCA(n_components = 2) # pedimos uno bidimensional
             X = pca.fit_transform(x)

             from math import ceil, sqrt
             from numpy import isnan, nan, arange, meshgrid, c_
             import matplotlib.pyplot as plt
             h=0.2
             # código de https://scikit-learn.org/stable/auto_examples/classification/plot_cla
             names = ["Nearest Neighbors", "Linear SVM", "RBF SVM", "Gaussian Process", \
                      "Decision Tree", "Random Forest", "AdaBoost", "Naive Bayes"]
             classifiers = [KNeighborsClassifier(3), SVC(kernel="linear", C=0.025), \
                 SVC(gamma=2, C=1), GaussianProcessClassifier(1.0 * RBF(1.0)), \
                 DecisionTreeClassifier(max_depth=5), RandomForestClassifier(max_depth=5, n_es
                 AdaBoostClassifier(), GaussianNB()]
             k = int(ceil(sqrt(len(classifiers) + 1)))
             X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.4, random_sta
             x_min, x_max = X[:, 0].min() - .5, X[:, 0].max() + .5
             y_min, y_max = X[:, 1].min() - .5, X[:, 1].max() + .5
             xx, yy = meshgrid(arange(x_min, x_max, h), arange(y_min, y_max, 0.02))
             cm = plt.cm.RdBu
             cm_bright = ListedColormap(['#FF0000', '#0000FF'])
             plt.rcParams["figure.figsize"] = [16, 16]
             figure = plt.figure()
             ax = plt.subplot(k, k, 1)
             ax.set_title("Datos de entrada")
             ax.scatter(X_train[:, 0], X_train[:, 1], c=y_train, cmap=cm_bright, alpha=0.2, edg
             ax.scatter(X_test[:, 0], X_test[:, 1], c=y_test, cmap=cm_bright, alpha=0.2, edgec
             ax.set_xlim(xx.min(), xx.max())
             ax.set_ylim(yy.min(), yy.max())
             ax.set_xticks(())
             ax.set_yticks(())
             i = 2
```

```
for name, clf in zip(names, classifiers):
    ax = plt.subplot(k, k, i)
    clf.fit(X_train, y_train)
    score = clf.score(X_test, y_test)
    if hasattr(clf, "decision_function"):
        Z = clf.decision_function(c_[xx.ravel(), yy.ravel()])
    else:
        Z = clf.predict_proba(c_[xx.ravel(), yy.ravel()])[:, 1]
    Z = Z.reshape(xx.shape)
    ax.contourf(xx, yy, Z, cmap=cm, alpha=.8)
    ax.scatter(X_train[:, 0], X_train[:, 1], c=y_train, cmap=cm_bright, edgecolors
    ax.scatter(X_test[:, 0], X_test[:, 1], c=y_test, cmap=cm_bright, edgecolors='
    ax.set_xlim(xx.min(), xx.max())
    ax.set_ylim(yy.min(), yy.max())
    ax.set_xticks(())
    ax.set_yticks(())
    ax.set_title(name)
    ax.text(xx.max() - .3, yy.min() + .3, ('%.3f' % score).lstrip('0'), size=40, 
    i += 1
plt.tight_layout()
plt.show()

print("Ahora calcularemos las matrices de confusión para la etiqueta{:d}.".format

# código de https://scikit-learn.org/stable/auto_examples/classification/plot_cla
names = ["Nearest Neighbors", "Linear SVM", "RBF SVM", "Gaussian Process", \
         "Decision Tree", "Random Forest", "AdaBoost", "Naive Bayes"]
classifiers = [KNeighborsClassifier(3), SVC(kernel="linear", C=0.025), \
    SVC(gamma=2, C=1), GaussianProcessClassifier(1.0 * RBF(1.0)), \
    DecisionTreeClassifier(max_depth=5), RandomForestClassifier(max_depth=5, n_es
    AdaBoostClassifier(), GaussianNB()]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.4, random_st

for name, clf in zip(names, classifiers):
    clf.fit(X_train, y_train)
    print(name, clf.score(X_test, y_test))
    expected, predicted = y_test, clf.predict(X_test)
    print(metrics.classification_report(expected, predicted))
    print(metrics.confusion_matrix(expected, predicted))
    print('-' * 60)
print("%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

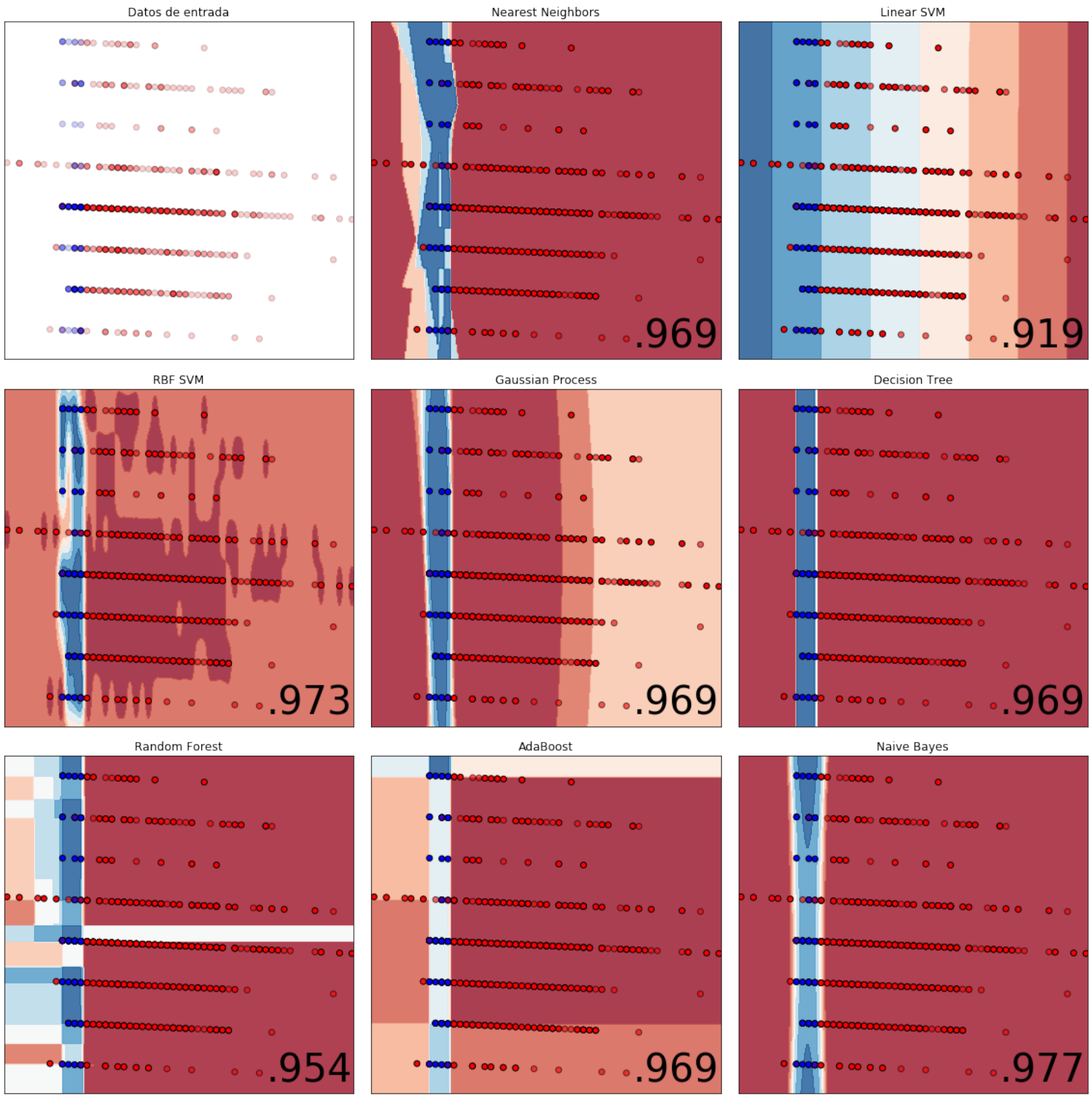
```
-------------------------Iniciando Proceso con Etiqueta 1---------------------
```




```
Ahora calcularemos las matrices de confusión para la etiqueta1.
('Nearest Neighbors', 0.7576923076923077)
             precision    recall  f1-score   support

          0       0.68      0.66      0.67        96
          1       0.80      0.82      0.81       164

avg / total       0.76      0.76      0.76       260

[[ 63  33]
 [ 30 134]]
------------------------------------------------------------
('Linear SVM', 0.5269230769230769)
```

```
             precision    recall  f1-score   support

          0       0.41      0.61      0.49        96
          1       0.68      0.48      0.56       164

avg / total       0.58      0.53      0.53       260

[[59 37]
 [86 78]]
------------------------------------------------------------
('RBF SVM', 0.7423076923076923)
             precision    recall  f1-score   support

          0       0.67      0.60      0.63        96
          1       0.78      0.82      0.80       164

avg / total       0.74      0.74      0.74       260

[[ 58  38]
 [ 29 135]]
------------------------------------------------------------
('Gaussian Process', 0.7961538461538461)
             precision    recall  f1-score   support

          0       0.80      0.59      0.68        96
          1       0.79      0.91      0.85       164

avg / total       0.80      0.80      0.79       260

[[ 57  39]
 [ 14 150]]
------------------------------------------------------------
('Decision Tree', 0.7346153846153847)
             precision    recall  f1-score   support

          0       0.64      0.65      0.64        96
          1       0.79      0.79      0.79       164

avg / total       0.74      0.73      0.73       260

[[ 62  34]
 [ 35 129]]
------------------------------------------------------------
('Random Forest', 0.7807692307692308)
             precision    recall  f1-score   support

          0       0.76      0.59      0.67        96
          1       0.79      0.89      0.84       164
```

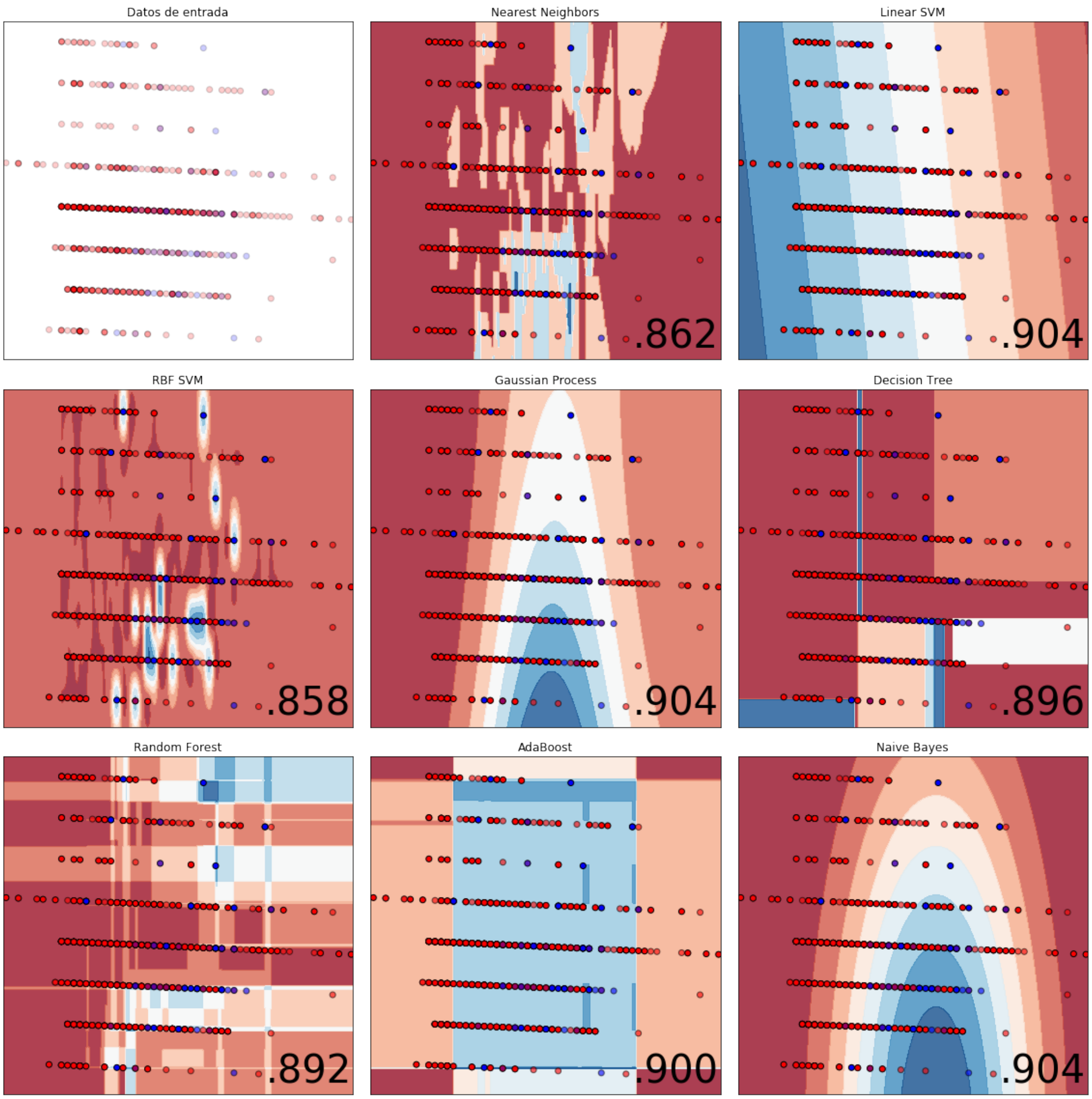
```
avg / total       0.78      0.78      0.77       260

[[ 57  39]
 [ 18 146]]
------------------------------------------------------------
('AdaBoost', 0.7807692307692308)
             precision    recall  f1-score   support

          0       0.75      0.61      0.67        96
          1       0.80      0.88      0.83       164

avg / total       0.78      0.78      0.78       260

[[ 59  37]
 [ 20 144]]
------------------------------------------------------------
('Naive Bayes', 0.65)
             precision    recall  f1-score   support

          0       0.52      0.60      0.56        96
          1       0.74      0.68      0.71       164

avg / total       0.66      0.65      0.65       260

[[ 58  38]
 [ 53 111]]
------------------------------------------------------------
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
-------------------------Iniciando Proceso con Etiqueta 2---------------------
```




```
Ahora calcularemos las matrices de confusión para la etiqueta2.
('Nearest Neighbors', 0.9692307692307692)
             precision    recall  f1-score   support

          0       1.00      0.96      0.98       223
          1       0.82      1.00      0.90        37

avg / total       0.97      0.97      0.97       260

[[215   8]
 [  0  37]]
------------------------------------------------------------
('Linear SVM', 0.9192307692307692)
```

```
             precision    recall  f1-score   support

          0       1.00      0.91      0.95       223
          1       0.64      1.00      0.78        37

avg / total       0.95      0.92      0.93       260

[[202  21]
 [  0  37]]
------------------------------------------------------------
('RBF SVM', 0.9730769230769231)
             precision    recall  f1-score   support

          0       0.99      0.98      0.98       223
          1       0.88      0.95      0.91        37

avg / total       0.97      0.97      0.97       260

[[218   5]
 [  2  35]]
------------------------------------------------------------
('Gaussian Process', 0.9692307692307692)
             precision    recall  f1-score   support

          0       0.99      0.97      0.98       223
          1       0.85      0.95      0.90        37

avg / total       0.97      0.97      0.97       260

[[217   6]
 [  2  35]]
------------------------------------------------------------
('Decision Tree', 0.9692307692307692)
             precision    recall  f1-score   support

          0       0.99      0.97      0.98       223
          1       0.85      0.95      0.90        37

avg / total       0.97      0.97      0.97       260

[[217   6]
 [  2  35]]
------------------------------------------------------------
('Random Forest', 0.9692307692307692)
             precision    recall  f1-score   support

          0       0.99      0.97      0.98       223
          1       0.85      0.95      0.90        37
```

```
avg / total       0.97      0.97      0.97       260

[[217   6]
 [  2  35]]
------------------------------------------------------------
('AdaBoost', 0.9692307692307692)
             precision    recall  f1-score   support

          0       0.99      0.97      0.98       223
          1       0.85      0.95      0.90        37

avg / total       0.97      0.97      0.97       260

[[217   6]
 [  2  35]]
------------------------------------------------------------
('Naive Bayes', 0.9769230769230769)
             precision    recall  f1-score   support

          0       1.00      0.97      0.99       223
          1       0.86      1.00      0.92        37

avg / total       0.98      0.98      0.98       260

[[217   6]
 [  0  37]]
------------------------------------------------------------
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
-------------------------Iniciando Proceso con Etiqueta 3---------------------
```

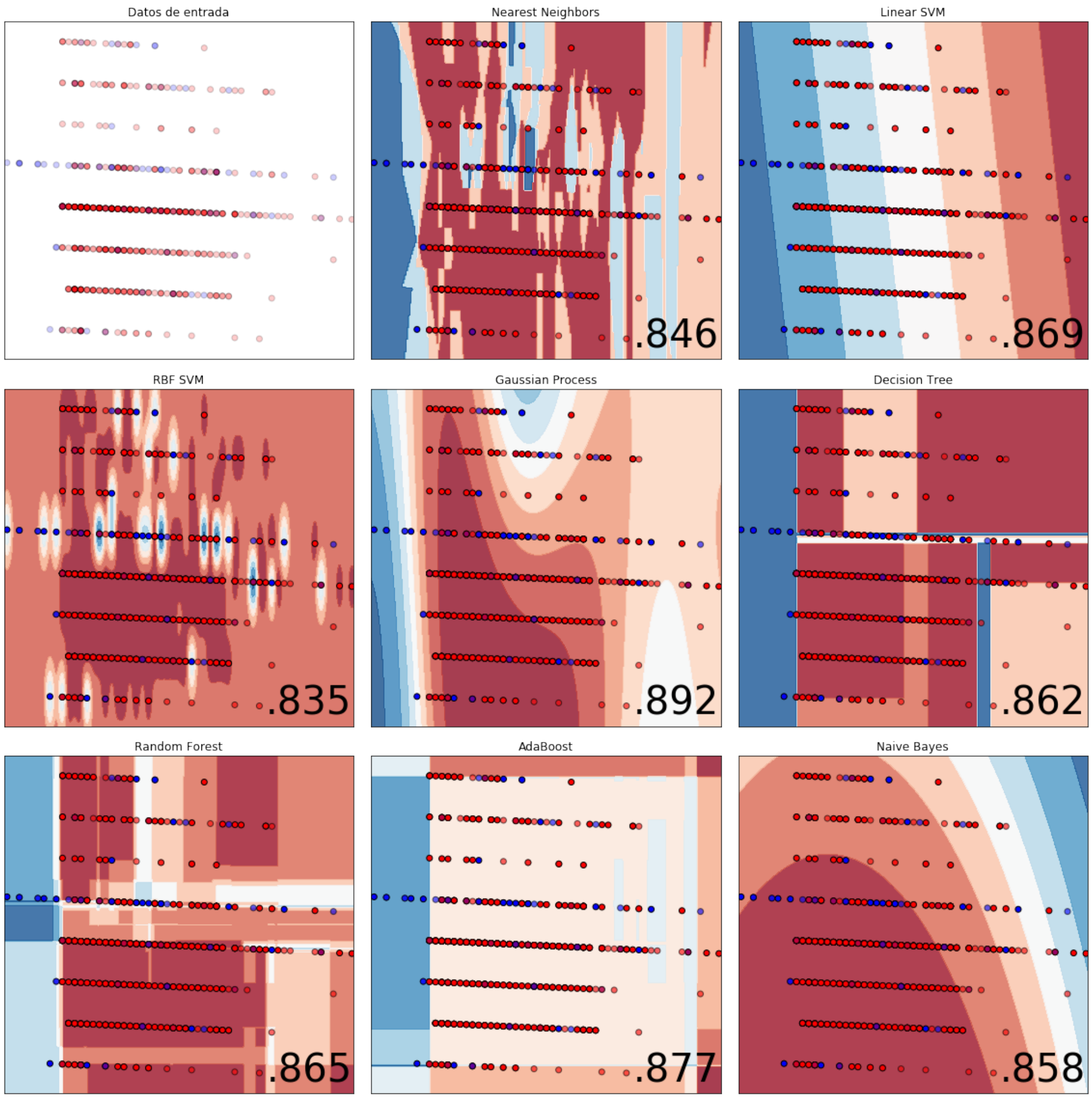


Ahora calcularemos las matrices de confusión para la etiqueta3.

```
('Nearest Neighbors', 0.8615384615384616)
             precision    recall  f1-score   support

          0       0.91      0.94      0.92       235
          1       0.21      0.16      0.18        25

avg / total       0.85      0.86      0.85       260

[[220  15]
 [ 21   4]]
------------------------------------------------------------
('Linear SVM', 0.9038461538461539)
```

```
             precision    recall  f1-score   support

          0       0.90      1.00      0.95       235
          1       0.00      0.00      0.00        25

avg / total       0.82      0.90      0.86       260

[[235   0]
 [ 25   0]]
------------------------------------------------------------
('RBF SVM', 0.8576923076923076)
             precision    recall  f1-score   support

          0       0.90      0.94      0.92       235
          1       0.07      0.04      0.05        25

avg / total       0.82      0.86      0.84       260

[[222  13]
 [ 24   1]]
------------------------------------------------------------
('Gaussian Process', 0.9038461538461539)
             precision    recall  f1-score   support

          0       0.90      1.00      0.95       235
          1       0.00      0.00      0.00        25

avg / total       0.82      0.90      0.86       260

[[235   0]
 [ 25   0]]
------------------------------------------------------------
('Decision Tree', 0.8961538461538462)
             precision    recall  f1-score   support

          0       0.91      0.98      0.94       235
          1       0.33      0.08      0.13        25

avg / total       0.85      0.90      0.87       260

[[231   4]
 [ 23   2]]
------------------------------------------------------------
('Random Forest', 0.8730769230769231)
             precision    recall  f1-score   support

          0       0.91      0.95      0.93       235
          1       0.21      0.12      0.15        25
```

```
avg / total       0.84      0.87      0.86       260

[[224  11]
 [ 22   3]]
------------------------------------------------------------
('AdaBoost', 0.9)
             precision    recall  f1-score   support

          0       0.90      1.00      0.95       235
          1       0.00      0.00      0.00        25

avg / total       0.82      0.90      0.86       260

[[234   1]
 [ 25   0]]
------------------------------------------------------------
('Naive Bayes', 0.9038461538461539)
             precision    recall  f1-score   support

          0       0.90      1.00      0.95       235
          1       0.00      0.00      0.00        25

avg / total       0.82      0.90      0.86       260

[[235   0]
 [ 25   0]]
------------------------------------------------------------
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
-------------------------Iniciando Proceso con Etiqueta 4---------------------
```




```
Ahora calcularemos las matrices de confusión para la etiqueta4.
('Nearest Neighbors', 0.8461538461538461)
             precision    recall  f1-score   support

          0       0.89      0.94      0.91       226
          1       0.36      0.24      0.29        34

avg / total       0.82      0.85      0.83       260

[[212  14]
 [ 26   8]]
------------------------------------------------------------
('Linear SVM', 0.8692307692307693)
```

```
             precision    recall  f1-score   support

          0       0.87      1.00      0.93       226
          1       0.00      0.00      0.00        34

avg / total       0.76      0.87      0.81       260

[[226   0]
 [ 34   0]]
------------------------------------------------------------
('RBF SVM', 0.8346153846153846)
             precision    recall  f1-score   support

          0       0.87      0.95      0.91       226
          1       0.20      0.09      0.12        34

avg / total       0.79      0.83      0.81       260

[[214  12]
 [ 31   3]]
------------------------------------------------------------
('Gaussian Process', 0.8923076923076924)
             precision    recall  f1-score   support

          0       0.89      1.00      0.94       226
          1       1.00      0.18      0.30        34

avg / total       0.90      0.89      0.86       260

[[226   0]
 [ 28   6]]
------------------------------------------------------------
('Decision Tree', 0.8615384615384616)
             precision    recall  f1-score   support

          0       0.90      0.95      0.92       226
          1       0.45      0.29      0.36        34

avg / total       0.84      0.86      0.85       260

[[214  12]
 [ 24  10]]
------------------------------------------------------------
('Random Forest', 0.8615384615384616)
             precision    recall  f1-score   support

          0       0.89      0.96      0.92       226
          1       0.43      0.18      0.25        34
```

```
avg / total       0.83      0.86      0.84       260

[[218   8]
 [ 28   6]]
------------------------------------------------------------
('AdaBoost', 0.8769230769230769)
             precision    recall  f1-score   support

          0       0.90      0.97      0.93       226
          1       0.56      0.26      0.36        34

avg / total       0.85      0.88      0.86       260

[[219   7]
 [ 25   9]]
------------------------------------------------------------
('Naive Bayes', 0.8576923076923076)
             precision    recall  f1-score   support

          0       0.87      0.98      0.92       226
          1       0.20      0.03      0.05        34

avg / total       0.78      0.86      0.81       260

[[222   4]
 [ 33   1]]
------------------------------------------------------------
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

1.5 Conclusión

Después de probar los diferentes métodos y buscar clasificar todas las categorías de participación individualmente, se obtuvieron los siguientes resultados.

Método de Clasificación
Etiqueta1
Etiqueta2
Etiqueta3
Etiqueta4
Nearest Neighbors
.758
.969
.862
.846
Linear SVM
.527
.919

.904
.869
RBF SVM
.742
.973
.858
.835
Gaussian Process
.796
.969
.904
.892
Decision Tree
.735
.969
.896
.862
Random Forest
.8
.954
.892
.865
AdaBoost
.781
.969
.9
.877
Naive Bayes
.650
.977
.904
.858

Se puede concluir que con los datos de edad y sexo del participante y el género del Filme, se puede precisar si la participación del concursante es en la categoría Juvenil. En cambio, para identificar las otras categorías, los datos proporcionados otorgaron al clasificador una precisión a lo más del 79.6% para las demás categorías.

--05 de junio 2019-- Luis Angel Gutiérrez Rodríguez 1484412