

```

1 # Cargue de Librerías básicas
2 import pandas as pd
3 import matplotlib.pyplot as plt
4 import seaborn as sns
5
6 # Importar tensorflow
7 import tensorflow as tf
8 print("TF version  : ", tf.__version__)
9
10 # Necesitaremos GPU
11 print("GPU available: ", tf.config.list_physical_devices('GPU'))
12
13 # keras version is 2.11.0
14 import keras
15 print("Keras version  : ", keras.__version__)

```

```

⇒ TF version  :  2.15.0
   GPU available:  []
   Keras version  :  2.15.0

```

```

1 #-----#
2 #      debido a que estoy usando COLAB      #
3 #-----#
4
5 from google.colab import drive
6 drive.mount('/content/drive') #/content/drive/MyDrive/pec2/data/xl.pickle
7 print("GPU available: ", tf.config.list_physical_devices('GPU'))

```

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⇒ Drive already mounted at /content/drive; to attempt to forcibly remount, call
   GPU available:  []

```

```

1 import pandas as pd
2
3 home =  '/content/drive/MyDrive/TFM/'
4
5 file_path = home + "2017_2023DSTrabajo.xlsx"
6
7 dsXls = pd.read_excel(file_path)
8 dsXls.head(5)
9 dsXls.info()
10
11 #####

```

```
12 # LIMPIEZA DE DATOS
13 #####
14 #1. validar duplicados
15 dsXls.nunique()
16
17 #2. validar nulos, rellenar valores faltantes con la mediana
18 #dsXls.isnull().sum()
19 dsXls['Dist'].fillna(dsXls['Dist'].median(), inplace=True)
20 dsXls['Attendance'].fillna(dsXls['Attendance'].median(), inplace=True)
21 dsXls.isnull().sum()
22
23
24 #####
25 # ESTADISTICAS
26 #####
27 #dsXls.describe().T
28 dsXls.iloc[:,1:].describe()
29
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4092 entries, 0 to 4091
Data columns (total 21 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Date                   4092 non-null   datetime64[ns]
1   Round                  4092 non-null   object
2   Day                    4092 non-null   object
3   Venue                  4092 non-null   object
4   Result                 4092 non-null   object
5   GF                     4092 non-null   float64
6   GA                     4092 non-null   float64
7   Opponent               4092 non-null   object
8   xG                     4092 non-null   float64
9   xGA                    4092 non-null   float64
10  Poss                   4092 non-null   float64
11  Attendance              3212 non-null   float64
12  Season                  4092 non-null   int64
13  Team                   4092 non-null   object
14  Sh                      4092 non-null   float64
15  SoT                     4092 non-null   float64
16  Dist                    4089 non-null   float64
17  SCA                     4092 non-null   float64
18  KP                      4092 non-null   float64
19  PPA                     4092 non-null   float64
20  CrsPA                   4092 non-null   float64
dtypes: datetime64[ns](1), float64(13), int64(1), object(6)
memory usage: 671.5+ KB

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	GF	GA	xG	xGA	Poss	Attendance	
count	4092.000000	4092.000000	4092.000000	4092.000000	4092.000000	4092.000000	4092.000000
mean	1.377810	1.377810	1.346163	1.346163	50.001222	36912.650049	2000.000000
std	1.277631	1.277631	0.796551	0.796551	12.726702	15301.262664	2000.000000
min	0.000000	0.000000	0.000000	0.000000	18.000000	2000.000000	2000.000000
25%	0.000000	0.000000	0.700000	0.700000	41.000000	29296.000000	2000.000000
50%	1.000000	1.000000	1.200000	1.200000	50.000000	32092.500000	2000.000000
75%	2.000000	2.000000	1.800000	1.800000	59.000000	51237.000000	2000.000000
max	9.000000	9.000000	5.900000	5.900000	82.000000	83222.000000	2000.000000

```

1 import numpy as np
2 import pandas as pd

```

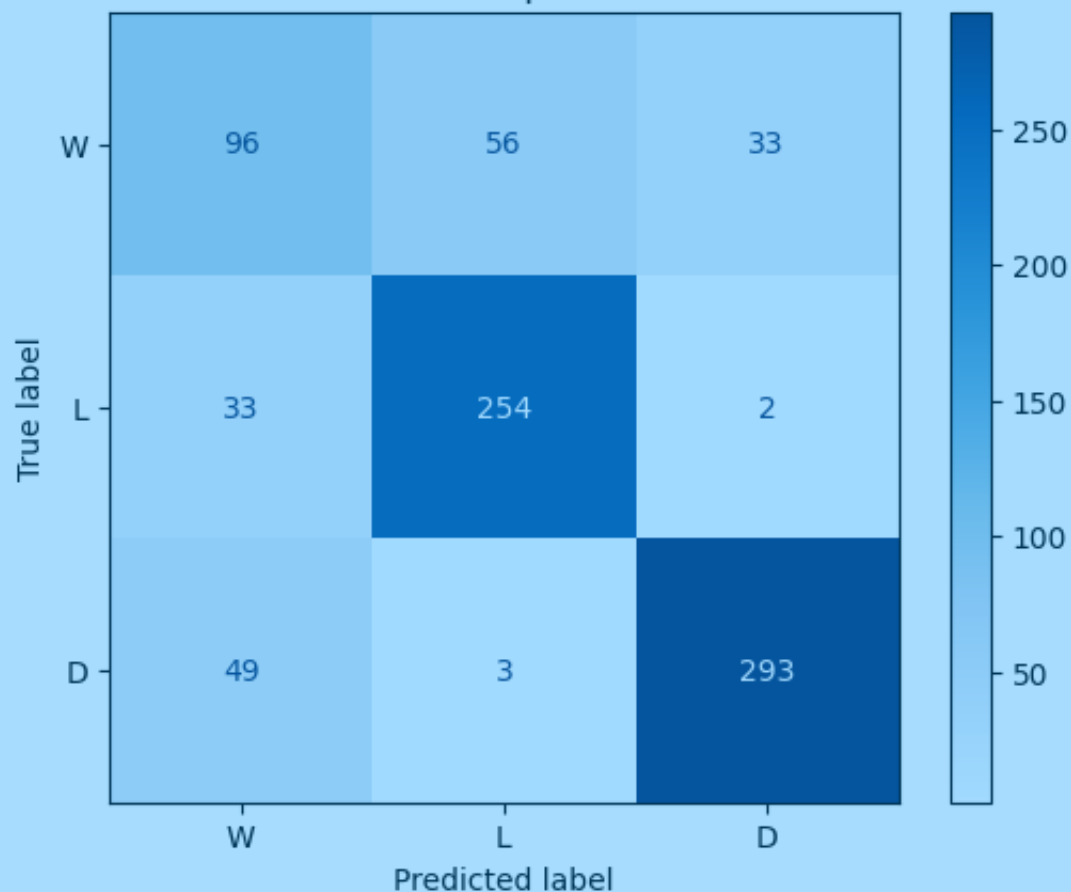
```
3 from sklearn.model_selection import train_test_split
4 from sklearn.naive_bayes import GaussianNB
5 from sklearn.metrics import accuracy_score
6 from sklearn.decomposition import PCA
7 from sklearn.preprocessing import StandardScaler
8 from sklearn.preprocessing import LabelEncoder
9 from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, classification_report
10 from sklearn.model_selection import cross_val_score
11
12
13 # Supongamos que tienes un DataFrame llamado df con tus datos
14 # y que ya has excluido las columnas que no desees incluir.
15
16 # Selección de características data = dsXls.drop(['Date', 'Round', 'Day', 'Venue', 'Result', 'Team', 'Opponent'])
17 #1 obtener datos numéricos
18 dataPCA = dsXls.drop(['Date', 'Round', 'Day', 'Venue', 'Result', 'Team', 'Opponent'])
19
20 #2 Aplicando PCA
21 pca = PCA()
22 X_pca = pca.fit_transform(dataPCA)
23
24 #3 obtener variable objetivo Result
25 y = dsXls['Result']
26 label_encoder = LabelEncoder()
27 y_encodedPCA = label_encoder.fit_transform(y)
28
29 #####X = dsXls.drop(['Date', 'Round', 'Day', 'Venue', 'Result', 'Semester', 'Team'])
30 #####y = dsXls['Result'] # La columna 'Result' es la variable objetivo
31
32 # División de los datos en entrenamiento y prueba
33 X_train, X_test, y_train, y_test = train_test_split(X_pca, y_encodedPCA, test_size=0.2, random_state=42)
34
35 # Crear el modelo Gaussian Naive Bayes
36 model = GaussianNB()
37
38 # Entrenar el modelo
39 model.fit(X_train, y_train)
40
41 # Hacer predicciones
42 y_pred = model.predict(X_test)
43
44 # Calcular la precisión
45 accuracy = accuracy_score(y_test, y_pred)
46 print(f"La precisión del modelo Naive Bayes es: {accuracy:.2f}")
47
48
```

```
48
49 #####
50
51 # Generar y mostrar la matriz de confusión
52 ###y_pred = forest.predict(X_test)
53 cm = confusion_matrix(y_test, y_pred)
54 print(cm)
55
56 disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['W', 'L', 'D'])
57 disp.plot(cmap=plt.cm.Blues)
58 plt.title("Matriz de Confusión para NAIVE BAYES")
59 plt.show()
60
61 # Reporte de clasificación
62 print("Classification Report:\n", classification_report(y_test, y_pred))
63
64 # Validación cruzada
65 cross_val_accuracy = cross_val_score(model, X_pca, y_encodedPCA, cv=5, scoring='accuracy')
66 print("Cross-validated Accuracy:", cross_val_accuracy.mean())
```

La precisión del modelo Naive Bayes es: 0.79

```
[[ 96  56  33]
 [ 33 254   2]
 [ 49   3 293]]
```

Matriz de Confusión para NAIVE BAYES



Classification Report:

	precision	recall	f1-score	support
0	0.54	0.52	0.53	185
1	0.81	0.88	0.84	289
2	0.89	0.85	0.87	345
accuracy			0.79	819
macro avg	0.75	0.75	0.75	819
weighted avg	0.78	0.79	0.78	819

Cross-validated Accuracy: 0.791295365867493

