

```

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'))

```

```

↔ 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
```

	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 ####REGRESIÓN LINEAL #####
2 from sklearn.decomposition import PCA
```

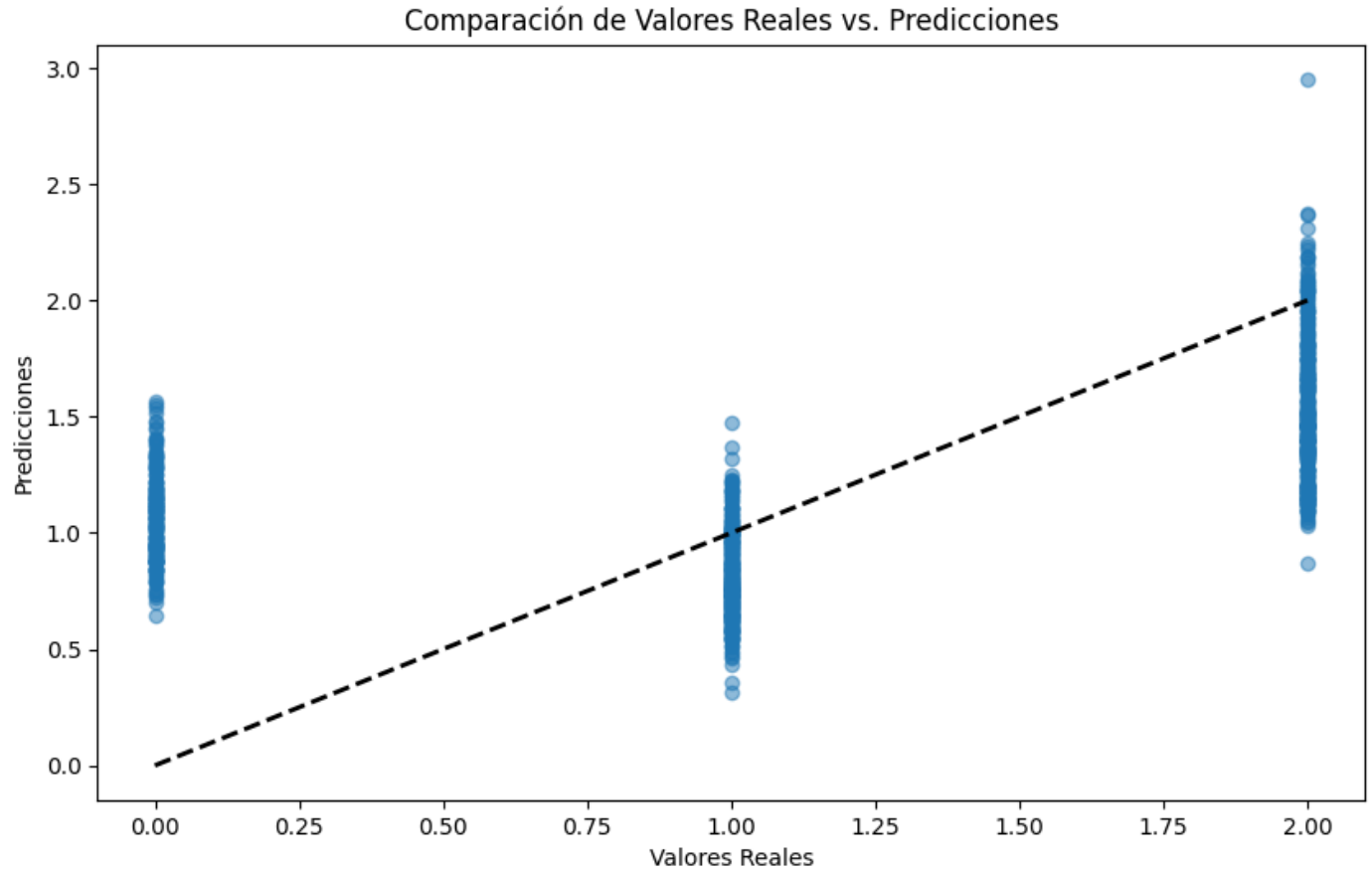
```
3 from sklearn.preprocessing import StandardScaler
4 from sklearn.linear_model import LogisticRegression, LinearRegression
5 from sklearn.model_selection import train_test_split
6 from sklearn.metrics import mean_squared_error, r2_score
7 from sklearn.preprocessing import LabelEncoder
8
9 dataReg = dsXls.drop(['Date', 'Round', 'Day', 'Venue', 'Result', 'Team', 'Opp
10
11 from sklearn.preprocessing import OneHotEncoder
12 # Estandarizando los datos
13 scaler = StandardScaler()
14
15 # Aplicando PCA
16 pca = PCA()
17 X_pcaReg = pca.fit_transform(dataReg)
18
19 from sklearn.model_selection import train_test_split
20
21 # Codificar las etiquetas categóricas
22 encoderREG = LabelEncoder()
23 y_encodedReg = encoderREG.fit_transform(dsXls[['Result']]) #dsXls['Result'] #
24
25
26 # Dividir el dataset
27 X_trainReg, X_testReg, y_trainReg, y_testReg = train_test_split(X_pcaReg, y_e
28
29 # Crear el modelo de regresión logística para multiclase
30 #model = LogisticRegression(max_iter=10000, multi_class='ovr')
31 model = LinearRegression()
32 model.fit(X_trainReg, y_trainReg) #model.fit(X_train, y_train)
33 y_predReg = model.predict(X_testReg)
34
35 #print("dats",y_predReg)
36 #labels = ['D', 'L', 'W']
37 #plt.xticks([0, 1, 2], labels)
38 plt.figure(figsize=(10, 6))
39 plt.scatter(y_testReg, y_predReg, alpha=0.5)
40 plt.xlabel('Valores Reales')
41 plt.ylabel('Predicciones')
42 plt.title('Comparación de Valores Reales vs. Predicciones')
43 plt.plot([y_testReg.min(), y_testReg.max()], [y_testReg.min(), y_testReg.max(
44 plt.show()
45
46
47 from sklearn.metrics import classification_report, confusion_matrix, accuracy
```

```
48 from sklearn.model_selection import cross_val_score
49
50 ## Matriz de confusión
51 #cmReg = confusion_matrix(y_testReg, y_predReg)
52 #disp = ConfusionMatrixDisplay(confusion_matrix=cmReg, display_labels=['W','L
53 #disp.plot()
54 #plt.show()
55
56 ## Reporte de clasificación
57 #print("Classification Report:\n", classification_report(y_testReg, y_predReg
58
59 # Validación cruzada
60 #cross_val_accuracy = cross_val_score(model, X_pcaReg, y_encodedReg, cv=13, s
61 #print("Cross-validated Accuracy:", cross_val_accuracy.mean())
62
63 mse = mean_squared_error(y_testReg, y_predReg) #mse = mean_squared_error(y_te
64 r2 = r2_score(y_testReg, y_predReg)#r2 = r2_score(y_test, y_pred)
65
66 print(f'MSE: {mse}. R^2: {r2}')
```

```

1 /usr/local/lib/python3.10/dist-packages/sklearn/preprocessing/_label.py:116: F
y = column_or_1d(y, warn=True)

```



```

1 #regresión logística
2 from sklearn.metrics import confusion_matrix
3 from sklearn.model_selection import train_test_split
4 from sklearn.linear_model import LogisticRegression
5
6 from sklearn.metrics import accuracy_score
7 from sklearn.metrics import classification_report, confusion_matrix, accuracy_
8 from sklearn.model_selection import cross_val_score
9
10 import matplotlib.pyplot as plt
11 from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

```

```
11 from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
12 # X_pcaReg, y_encodedReg
13 #X_trainReg, X_testReg, y_trainReg, y_testReg
14
15 # Crear y ajustar el modelo de regresión logística model = LogisticRegression(
16 modelRL = LogisticRegression(max_iter=10000, multi_class='ovr')
17 modelRL.fit(X_trainReg, y_trainReg)
18
19 # Obtener predicciones de etiquetas de clase (no probabilidades)
20 y_predRL = modelRL.predict(X_testReg)
21
22 # Generar y mostrar la matriz de confusión
23 cmRL = confusion_matrix(y_testReg, y_predRL)
24 print(cmRL)
25
26 disp = ConfusionMatrixDisplay(confusion_matrix=cmRL)
27 print(disp)
28
29 #####---
30 # Reporte de clasificación
31 print("Classification Report:\n", classification_report(y_testReg, y_predRL))
32
33 # Validación cruzada
34 cross_val_accuracyRL = cross_val_score(modelRL, X_pcaReg, y_encodedReg, cv=5,
35 print("Cross-validated Accuracy:", cross_val_accuracyRL.mean())
36
37 # reporte de clasificación
38
39 reportRL = classification_report(y_testReg, y_predRL)
40
41 print(reportRL)
42
```

```

[[184  1  0]
 [ 0 289  0]
 [ 0  0 345]]
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay object at 0x7d:
Classification Report:

```

	precision	recall	f1-score	support
0	1.00	0.99	1.00	185
1	1.00	1.00	1.00	289
2	1.00	1.00	1.00	345
accuracy			1.00	819
macro avg	1.00	1.00	1.00	819
weighted avg	1.00	1.00	1.00	819

Cross-validated Accuracy: 0.9948703022052655

	precision	recall	f1-score	support
0	1.00	0.99	1.00	185
1	1.00	1.00	1.00	289
2	1.00	1.00	1.00	345
accuracy			1.00	819
macro avg	1.00	1.00	1.00	819
weighted avg	1.00	1.00	1.00	819

