```
# Cargue de Librerías básicas
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Importar tensorflow
import tensorflow as tf
print("TF version   : ", tf.__version__)

# Necesitaremos GPU
print("GPU available: ", tf.config.list_physical_devices('GPU'))

# keras version is 2.11.0
import keras
print("Keras version   : ", keras.__version__)
```

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

```
#--------------------------------------------#
#       debido a que estoy usando COLAB      #
#--------------------------------------------#

from google.colab import drive
drive.mount('/content/drive') #/content/drive/MyDrive/pec2/data/xl.pickle
print("GPU available: ", tf.config.list_physical_devices('GPU'))
```

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

```
import pandas as pd

home =  '/content/drive/MyDrive/TFM/'

file_path = home + "2017_2023DSTrabajo.xlsx"

dsXls = pd.read_excel(file_path)
dsXls.head(5)
dsXls.info()

####################################
```

```
# LIMPIEZA DE DATOS
####################################
#1. validar duplicados
dsXls.nunique()

#2. validar nulos, rellenar valores faltantes con la mediana
#dsXls.isnull().sum()
dsXls['Dist'].fillna(dsXls['Dist'].median(), inplace=True)
dsXls['Attendance'].fillna(dsXls['Attendance'].median(), inplace=True)
dsXls.isnull().sum()


####################################
# ESTADISTICAS
####################################
#dsXls.describe().T
dsXls.iloc[:,1:].describe()

```

```
<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
```

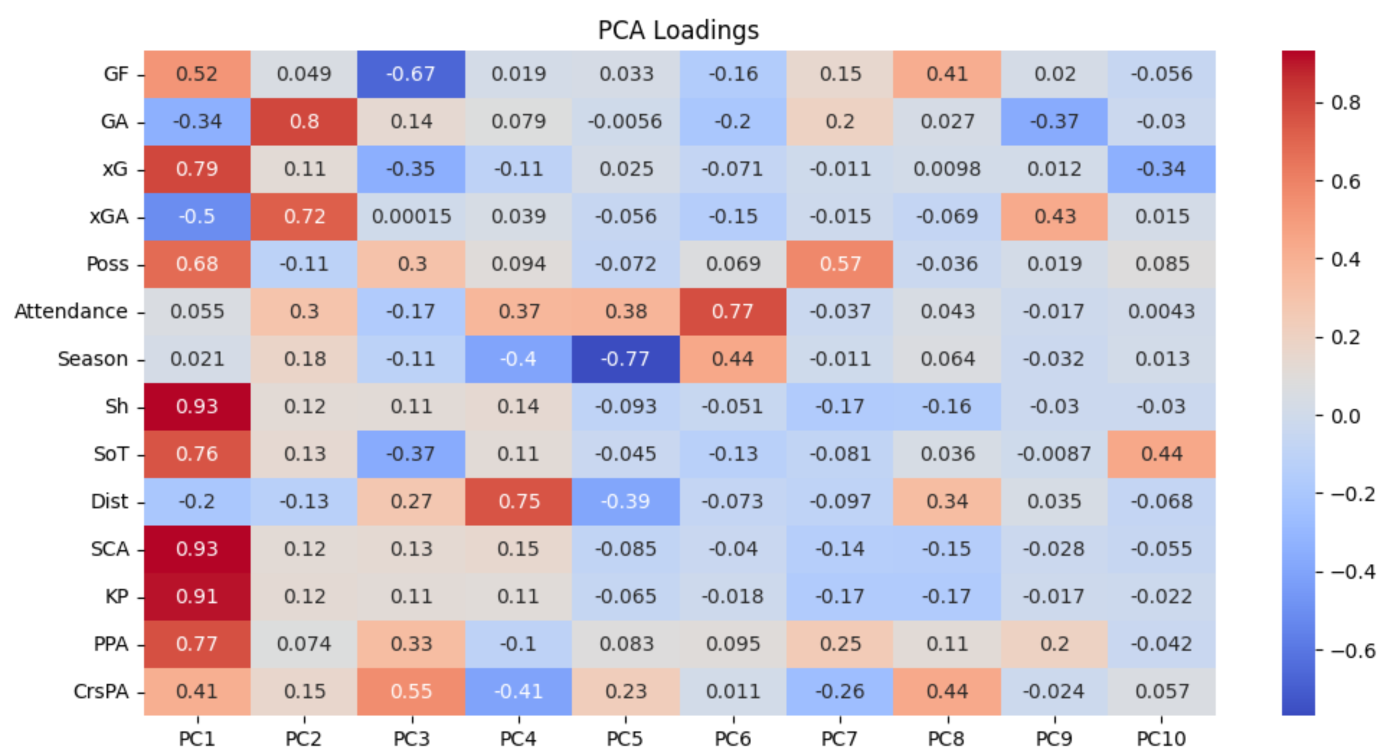
	GF	GA	xG	xGA	Poss	Attendance	
count	4092.000000	4092.000000	4092.000000	4092.000000	4092.000000	4092.000000	4(
mean	1.377810	1.377810	1.346163	1.346163	50.001222	36912.650049	2(
std	1.277631	1.277631	0.796551	0.796551	12.726702	15301.262664	
min	0.000000	0.000000	0.000000	0.000000	18.000000	2000.000000	2(
25%	0.000000	0.000000	0.700000	0.700000	41.000000	29296.000000	2(
50%	1.000000	1.000000	1.200000	1.200000	50.000000	32092.500000	2(
75%	2.000000	2.000000	1.800000	1.800000	59.000000	51237.000000	2(
max	9.000000	9.000000	5.900000	5.900000	82.000000	83222.000000	2(

```
#APLICAR PCA
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
import numpy as np

# Preparando los datos para PCA, excluyendo columnas no numéricas y la variabl
features = dsXls.select_dtypes(include=[np.number])

# Normalizando los datos antes de aplicar PCA
scaler = StandardScaler()
features_scaled = scaler.fit_transform(features)

# Aplicando PCA
pca = PCA(n_components=0.95)  # Conservar el 95% de la varianza explicada
principal_components = pca.fit_transform(features_scaled)

# Porcentaje de varianza explicada por cada componente principal
explained_variance = pca.explained_variance_ratio_
cumulative_variance = pca.explained_variance_ratio_.cumsum()

# Creando un DataFrame para los resultados de PCA
pca_results = pd.DataFrame({
    'Componente': range(1, len(explained_variance) + 1),
    'Explained Variance': explained_variance,
    'Cumulative Variance': cumulative_variance
})

print(pca_results)
print("Número de componentes principales:", principal_components.shape[1])
```

```
   Componente  Explained Variance  Cumulative Variance
0           1            0.404537             0.404537
1           2            0.100658             0.505195
2           3            0.099203             0.604398
3           4            0.080980             0.685378
4           5            0.070068             0.755446
5           6            0.066543             0.821989
6           7            0.044109             0.866098
7           8            0.041575             0.907673
8           9            0.025706             0.933379
9          10            0.024218             0.957597
Número de componentes principales: 10
```

```
import pandas as pd
import numpy as np
```

```
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler

# features es el DataFrame de variables numéricas
scaler = StandardScaler()
features_scaled = scaler.fit_transform(features)

# Aplicando PCA conservando primeros 10 componentes
pca = PCA(n_components=10)
principal_components = pca.fit_transform(features_scaled)

# Cargando la matriz
loadings = pca.components_.T * np.sqrt(pca.explained_variance_)

# Creando un DataFrame para visualizar mejor los loadings
loading_matrix = pd.DataFrame(loadings, columns=['PC1', 'PC2', 'PC3', 'PC4', '

# Visualizando los loadings para las primeras cinco componentes
plt.figure(figsize=(12, 6))
sns.heatmap(loading_matrix, annot=True, cmap='coolwarm')
plt.title('PCA Loadings')
plt.show()

# Imprimiendo los loadings
print(loading_matrix)
```

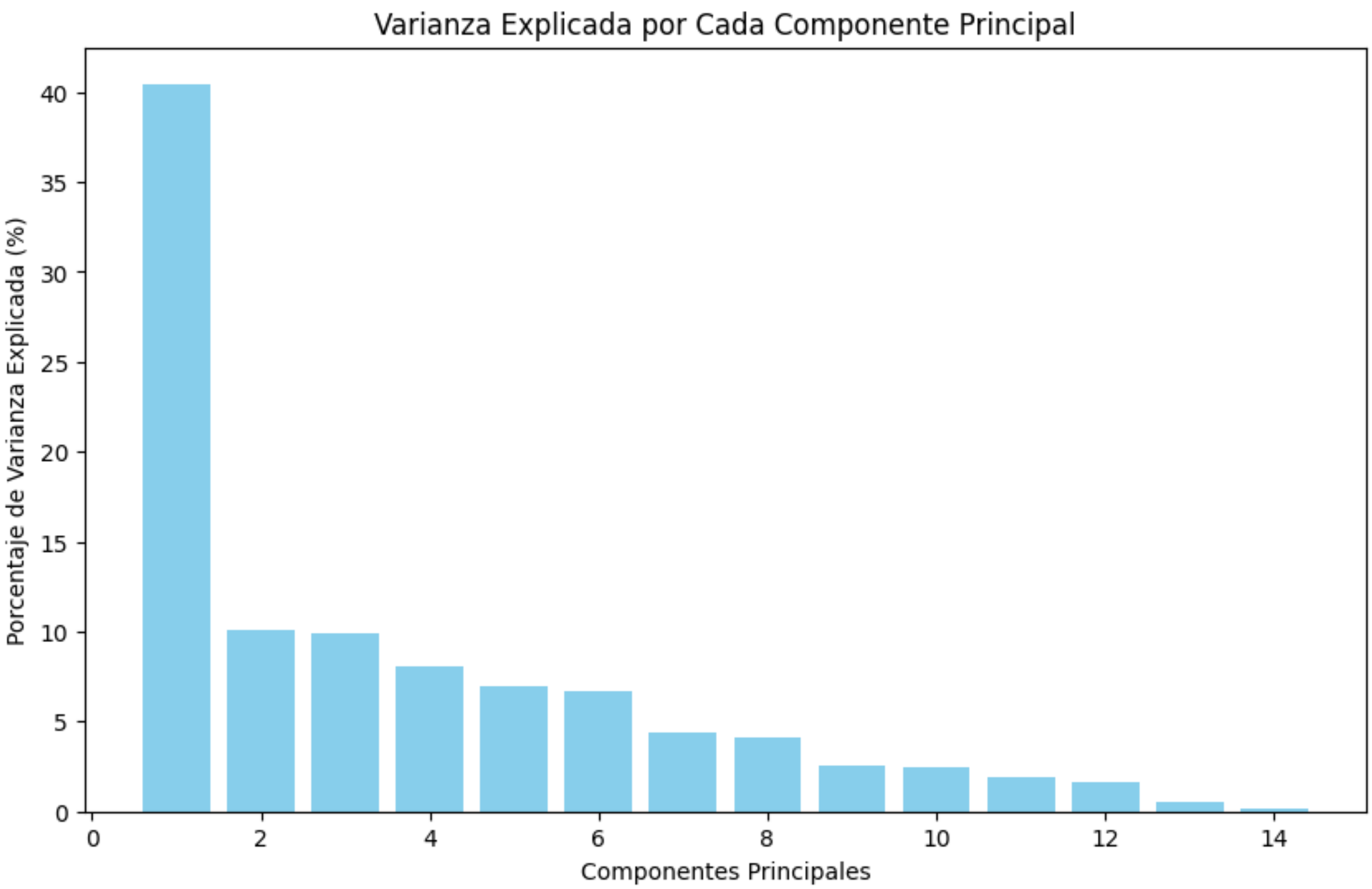


```
                 PC1       PC2       PC3       PC4       PC5       PC6  \
GF          0.518957  0.048783 -0.666046  0.018556  0.033161 -0.161368
GA         -0.340169  0.797295  0.136528  0.079332 -0.005586 -0.204991
xG          0.794587  0.114307 -0.351056 -0.105445  0.025049 -0.070701
xGA        -0.504854  0.720574  0.000147  0.038831 -0.055531 -0.152533
Poss        0.684264 -0.112295  0.302805  0.094130 -0.072134  0.069099
Attendance  0.055375  0.297137 -0.168285  0.370409  0.376225  0.772818
Season      0.021273  0.178692 -0.108585 -0.399230 -0.770466  0.444412
Sh          0.925240  0.116836  0.110905  0.139268 -0.093101 -0.050760
SoT         0.757153  0.133350 -0.368912  0.107265 -0.045426 -0.130394
Dist       -0.203574 -0.130605  0.274611  0.754660 -0.394007 -0.072572
SCA         0.930257  0.116548  0.132500  0.147059 -0.085477 -0.039803
KP          0.908465  0.122749  0.111658  0.105117 -0.064749 -0.017976
PPA         0.770612  0.073877  0.334235 -0.101472  0.082740  0.095452
CrsPA       0.408126  0.154175  0.553484 -0.407298  0.227309  0.010713

                 PC7       PC8       PC9      PC10
GF          0.147854  0.414199  0.020427 -0.055723
GA          0.199415  0.026805 -0.366835 -0.029726
xG         -0.011218  0.009837  0.012241 -0.343443
xGA        -0.014511 -0.068538  0.425605  0.014795
Poss        0.573262 -0.035994  0.018695  0.084743
Attendance -0.037478  0.043305 -0.016982  0.004307
Season     -0.011274  0.064010 -0.032028  0.012695
Sh         -0.165947 -0.162927 -0.030221 -0.030435
SoT        -0.080635  0.035678 -0.008706  0.442140
Dist       -0.097305  0.338153  0.034717 -0.068335
SCA        -0.143690 -0.150752 -0.027559 -0.054815
KP         -0.172417 -0.172072 -0.016517 -0.022139
PPA         0.252168  0.107760  0.195521 -0.041721
CrsPA      -0.260922  0.437878 -0.024068  0.057363
```

```python
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
import pandas as pd


# Estandarizando los datos
```

```
scaler = StandardScaler()
features_scaled = scaler.fit_transform(features)

# Aplicando PCA
pca = PCA()
principal_components = pca.fit(features_scaled)

# Obteniendo la varianza explicada
explained_variance_ratio = pca.explained_variance_ratio_

# Convirtiendo la varianza explicada en porcentaje
explained_variance_percent = explained_variance_ratio * 100

# Creando un DataFrame para visualizar la varianza explicada por cada componen
variance_df = pd.DataFrame({
    'Component': range(1, len(explained_variance_percent) + 1),
    'Explained Variance (%)': explained_variance_percent
})

print(variance_df)


import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
plt.bar(variance_df['Component'], variance_df['Explained Variance (%)'], color
plt.xlabel('Componentes Principales')
plt.ylabel('Porcentaje de Varianza Explicada (%)')
plt.title('Varianza Explicada por Cada Componente Principal')
plt.show()
```

```
    Component  Explained Variance (%)
0           1               40.453701
1           2               10.065772
2           3                9.920342
3           4                8.097951
4           5                7.006828
5           6                6.654295
6           7                4.410897
7           8                4.157499
8           9                2.570607
9          10                2.421779
10         11                1.917171
11         12                1.672561
12         13                0.512914
13         14                0.137685
```

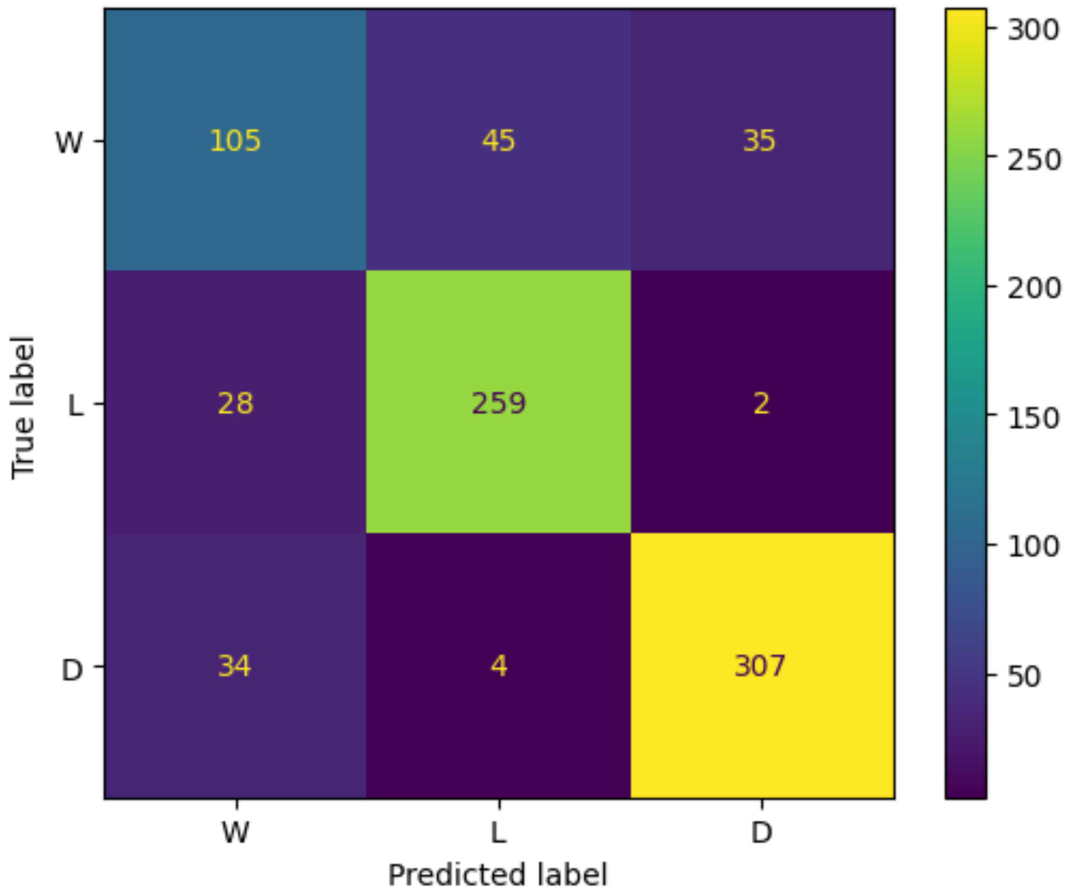



```
from sklearn.model_selection import train_test_split
```

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report, confusion_matrix, accuracy
from sklearn.model_selection import cross_val_score


#y = dsXls['Result']
#X_pca = pca.fit_transform(X_scaled)

# Dividir los datos en conjuntos de entrenamiento y prueba
#X_train, X_test, y_train, y_test = train_test_split(X_pca, y, test_size=0.2,



X = features_scaled
y = dsXls['Result']

# Estandarización de los datos
scaler = StandardScaler()
X_scaled = pca.fit_transform(X)   #scaler.fit_transform(X)

# Dividir los datos en entrenamiento y prueba
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.

# Crear el modelo KNN con distancia Euclidiana
knn = KNeighborsClassifier(n_neighbors=13, metric='euclidean')
#10 0.7851037851037851
#8 0.7924297924297924
#5 0.7887667887667887
#2 0.7081807081807082

# Entrenar el modelo
knn.fit(X_train, y_train)

# Predecir y evaluar el modelo
y_pred = knn.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

# debido a que y_pred y y_test definidos
```

```
# Matriz de confusión
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['W','L','D
disp.plot()
plt.show()

# Reporte de clasificación
print("Classification Report:\n", classification_report(y_test, y_pred))

# Validación cruzada
cross_val_accuracy = cross_val_score(knn, X_scaled, y, cv=13, scoring='accura
print("Cross-validated Accuracy:", cross_val_accuracy.mean())
```

```
Accuracy: 0.8192918192918193
```




```
Classification Report:
              precision    recall  f1-score   support

           D       0.63      0.57      0.60       185
           L       0.84      0.90      0.87       289
           W       0.89      0.89      0.89       345

    accuracy                           0.82       819
   macro avg       0.79      0.78      0.79       819
weighted avg       0.81      0.82      0.82       819

Cross-validated Accuracy: 0.8105947131424838
```