```
# 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()

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

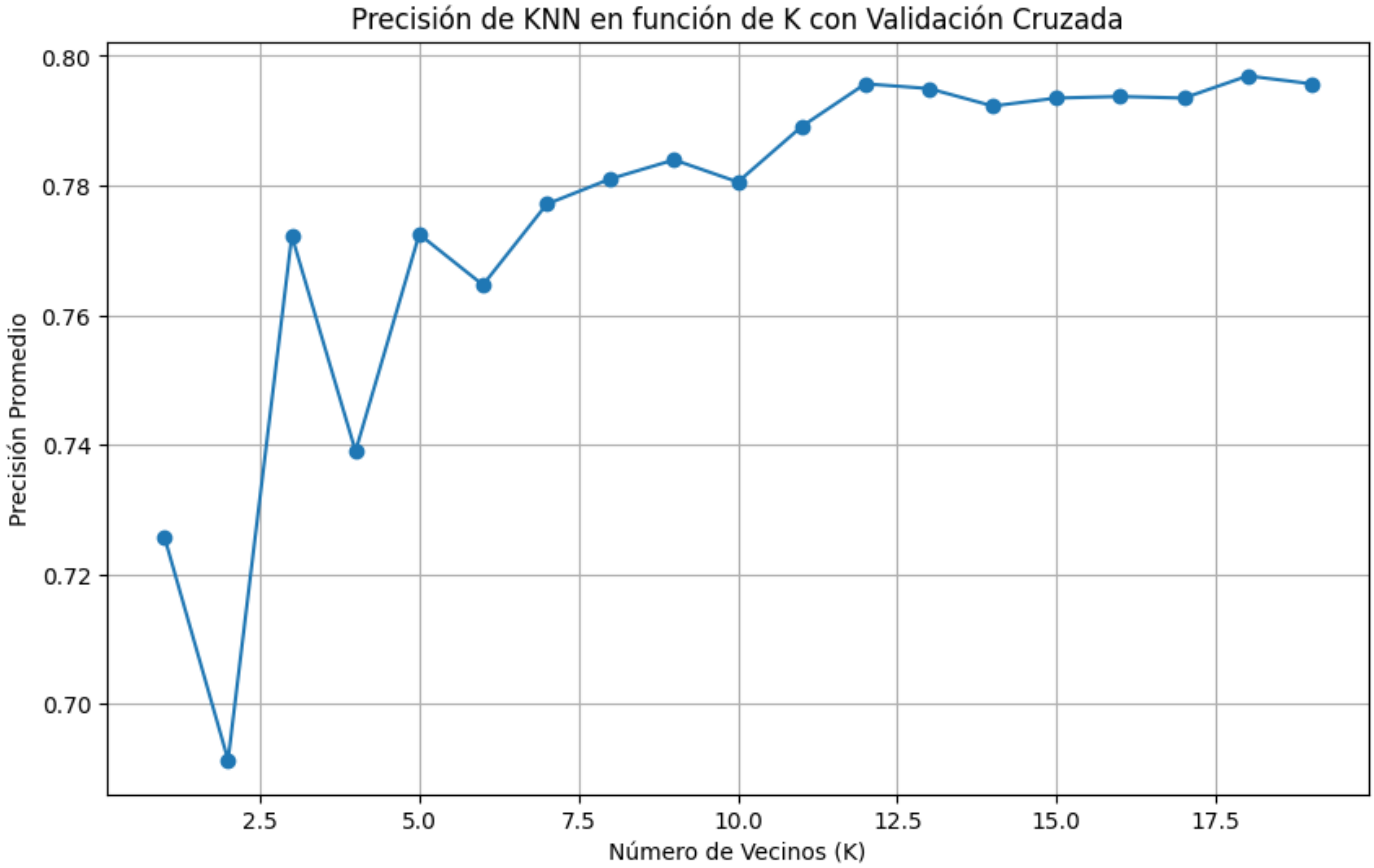
```
# LIMPIEZA DE DATOS
####################################
#1. validar duplicados
dsXls.nunique()

#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(

```
#BUSCAR NUMERO OPTIMO DE VECINOS
from sklearn.model_selection import cross_val_score
```

```
3
4  k_values = range(1, 20)
5  cross_val_scores = []
6
7  for k in k_values:
8      knn = KNeighborsClassifier(n_neighbors=k, metric='euclidean')
9      scores = cross_val_score(knn, X_scaled, y, cv=5, scoring='accuracy')  # Us
10     cross_val_scores.append(scores.mean())
11
12 plt.figure(figsize=(10, 6))
13 plt.plot(k_values, cross_val_scores, marker='o')
14 plt.title('Precisión de KNN en función de K con Validación Cruzada')
15 plt.xlabel('Número de Vecinos (K)')
16 plt.ylabel('Precisión Promedio')
17 plt.grid(True)
18 plt.show()
```




```
# APLICAR KNN
from sklearn.preprocessing import OneHotEncoder, MinMaxScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline


from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score

# Selecciono columnas categóricas y numéricas
categorical_features = ['Day', 'Venue', 'Opponent']
numeric_features = ['GF', 'GA', 'xG', 'xGA', 'Poss', 'Sh', 'SoT', 'Dist', 'SC

```

```
# uso transformadores en las transformaciones de codificación y escalado
categorical_transformer = OneHotEncoder(sparse=False)
numeric_transformer = MinMaxScaler()

# Combinar transformadores
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numeric_features),
        ('cat', categorical_transformer, categorical_features)
    ])

# Aplicando las transformaciones
X = dsXls.drop(['Date', 'Round', 'Result', 'Team'], axis=1)
# campo objetivo jam
y = dsXls['Result']

# Pipeline de transformaciones
pipeline = Pipeline(steps=[('preprocessor', preprocessor),
                           ('classifier', KNeighborsClassifier(n_neighbors=10

# Divido los datos en entrenamiento y de prueba relacion 80/20
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rand

# Entrenar
pipeline.fit(X_train, y_train)

# Evaluando el modelo
y_pred = pipeline.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f'Precisión de KNN: {accuracy:.2f}')

#Precision con 5 vecinos = 59%
#Precision con 2 vecinos = 47%
#Precision con 4 vecinos = 55%
#Precision con 6 vecinos = 57%
#Precision con 10 vecinos = 62%
```

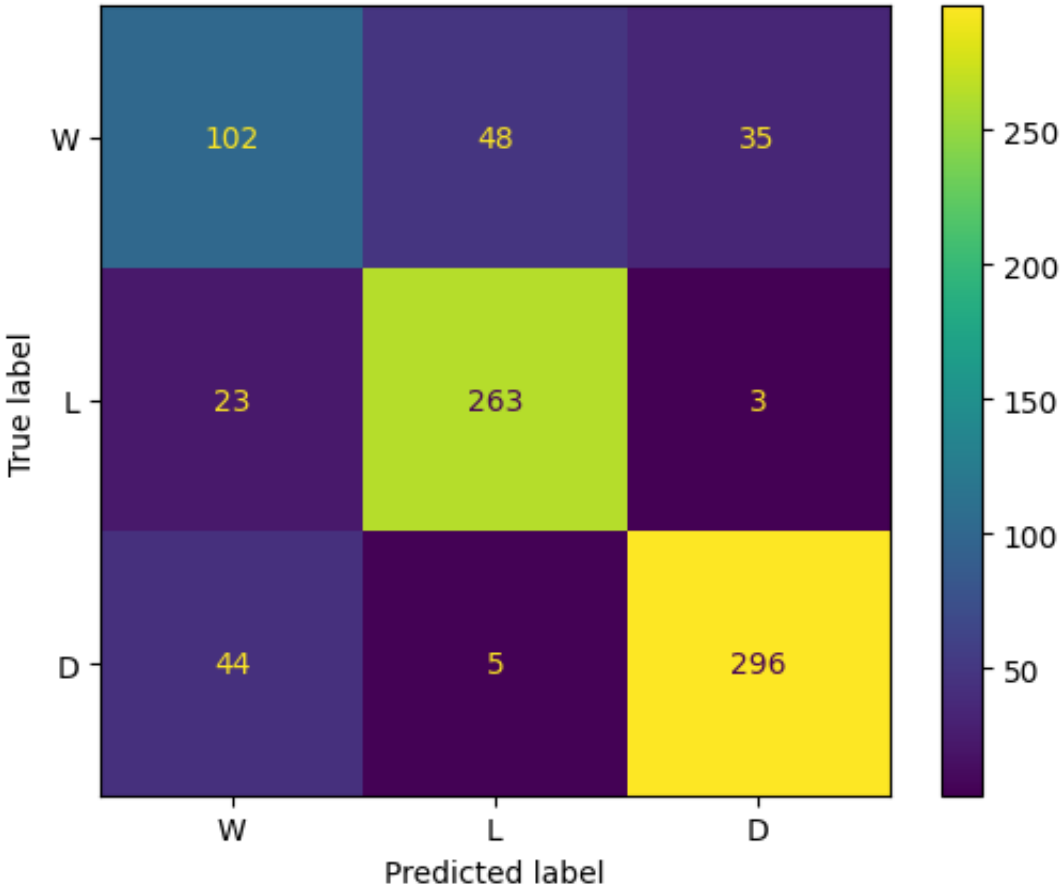
```
Precisión de KNN: 0.62
/usr/local/lib/python3.10/dist-packages/sklearn/preprocessing/_encoders.py:868
  warnings.warn(
```

```
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: 0.8070818070818071



Classification Report:

	precision	recall	f1-score	support
D	0.60	0.55	0.58	185
L	0.83	0.91	0.87	289
W	0.89	0.86	0.87	345
accuracy			0.81	819
macro avg	0.77	0.77	0.77	819
weighted avg	0.80	0.81	0.80	819

Cross-validated Accuracy: 0.7939789863356742