# Modulo_8_Tarea_1

April 1, 2022

## 1 S8 T01:Feature Engineering

Gestion de parámetros _____

#### 1.0.1 Exercice 1: Getting dummies of the categorical variables.

---

[287]:
```
#Importing the librarys:
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import os
```

[288]:
```
#Print the first two rows:
df = pd.read_csv('Michael_Jordan_Data.csv')
df.head(2)
```

[288]:
```
   EndYear  Rk  G        Date  Years  Days        Age   Tm  Home  Opp  …  \
0     1985   1  1  10/26/1984     21   252  21.689938  CHI     1  WSB  …
1     1985   2  2  10/27/1984     21   253  21.692676  CHI     0  MIL  …

   ORB  DRB  TRB  AST  STL  BLK  TOV  PF  PTS  GmSc
0    1    5    6    7    2    4    5   2   16  12.5
1    3    2    5    5    2    1    3   4   21  19.4

[2 rows x 33 columns]
```

[289]:
```
#Show some info:
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1072 entries, 0 to 1071
Data columns (total 33 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   EndYear   1072 non-null   int64
 1   Rk        1072 non-null   int64
```

```
 2   G        1072 non-null   int64
 3   Date     1072 non-null   object
 4   Years    1072 non-null   int64
 5   Days     1072 non-null   int64
 6   Age      1072 non-null   float64
 7   Tm       1072 non-null   object
 8   Home     1072 non-null   int64
 9   Opp      1072 non-null   object
 10  Win      1072 non-null   int64
 11  Diff     1072 non-null   int64
 12  GS       1072 non-null   int64
 13  MP       1072 non-null   int64
 14  FG       1072 non-null   int64
 15  FGA      1072 non-null   int64
 16  FG_PCT   1072 non-null   float64
 17  3P       1072 non-null   int64
 18  3PA      1072 non-null   int64
 19  3P_PCT   742 non-null    float64
 20  FT       1072 non-null   int64
 21  FTA      1072 non-null   int64
 22  FT_PCT   1042 non-null   float64
 23  ORB      1072 non-null   int64
 24  DRB      1072 non-null   int64
 25  TRB      1072 non-null   int64
 26  AST      1072 non-null   int64
 27  STL      1072 non-null   int64
 28  BLK      1072 non-null   int64
 29  TOV      1072 non-null   int64
 30  PF       1072 non-null   int64
 31  PTS      1072 non-null   int64
 32  GmSc     1072 non-null   float64
dtypes: float64(5), int64(25), object(3)
memory usage: 276.5+ KB
```

[290]:
```
#Knowing for example that Opp column is a categorical variable, we will get the
↪unique values of the column opponent to transform in dummies for handle the
↪data better:
df['Opp'].unique()
```

[290]:
```
array(['WSB', 'MIL', 'KCK', 'DEN', 'DET', 'NYK', 'IND', 'SAS', 'BOS',
       'PHI', 'SEA', 'POR', 'GSW', 'PHO', 'LAC', 'LAL', 'NJN', 'DAL',
       'HOU', 'ATL', 'CLE', 'UTA', 'SAC', 'MIA', 'CHH', 'MIN', 'ORL',
       'TOR', 'VAN', 'WAS', 'MEM', 'CHI', 'NOH'], dtype=object)
```

[291]:
```
#Assing a variable df_dmm that will be cointain our dummies:
df_dumm = pd.get_dummies(df, columns=['Opp'], prefix= "dmmi" )
df_dumm.head()
```

```
[291]:    EndYear  Rk  G        Date  Years  Days        Age   Tm  Home  Win  …  \
0     1985   1  1  10/26/1984     21   252  21.689938  CHI     1    1  …
1     1985   2  2  10/27/1984     21   253  21.692676  CHI     0    0  …
2     1985   3  3  10/29/1984     21   255  21.698152  CHI     1    1  …
3     1985   4  4  10/30/1984     21   256  21.700890  CHI     0    1  …
4     1985   5  5   11/1/1984     21   258  21.706366  CHI     0    0  …

   dmmi_PHO  dmmi_POR  dmmi_SAC  dmmi_SAS  dmmi_SEA  dmmi_TOR  dmmi_UTA  \
0         0         0         0         0         0         0         0
1         0         0         0         0         0         0         0
2         0         0         0         0         0         0         0
3         0         0         0         0         0         0         0
4         0         0         0         0         0         0         0

   dmmi_VAN  dmmi_WAS  dmmi_WSB
0         0         0         1
1         0         0         0
2         0         0         0
3         0         0         0
4         0         0         0

[5 rows x 65 columns]
```

**Basically what the function will do is create a column for each different value of each cell, separating them by the character that we specify, and fill that column with zeros and ones.**

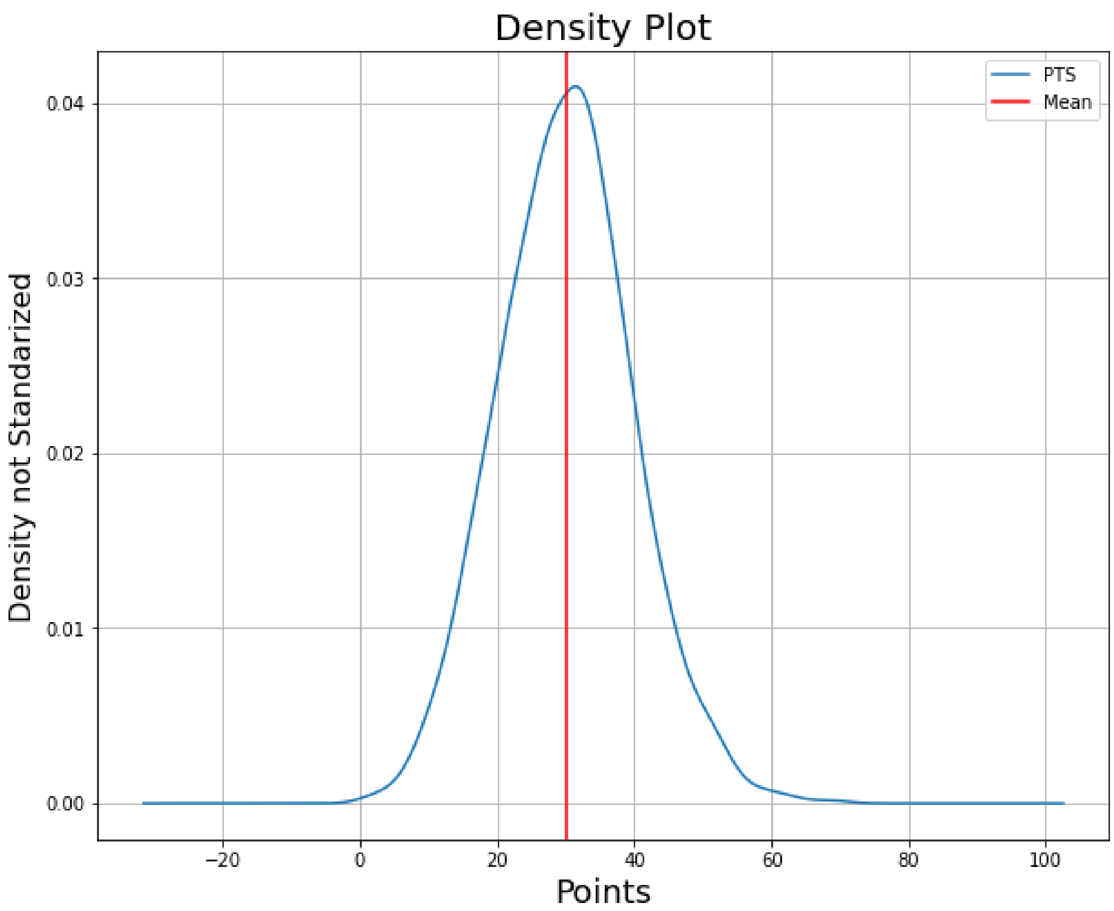
### 1.0.2 Exercice 1 Part 2: Standarized the numerical variables:

---

```
[292]: #Grab the column Puntos, and take the mean:
df_puntos_mean= df['PTS'].mean()
df_puntos_mean
```

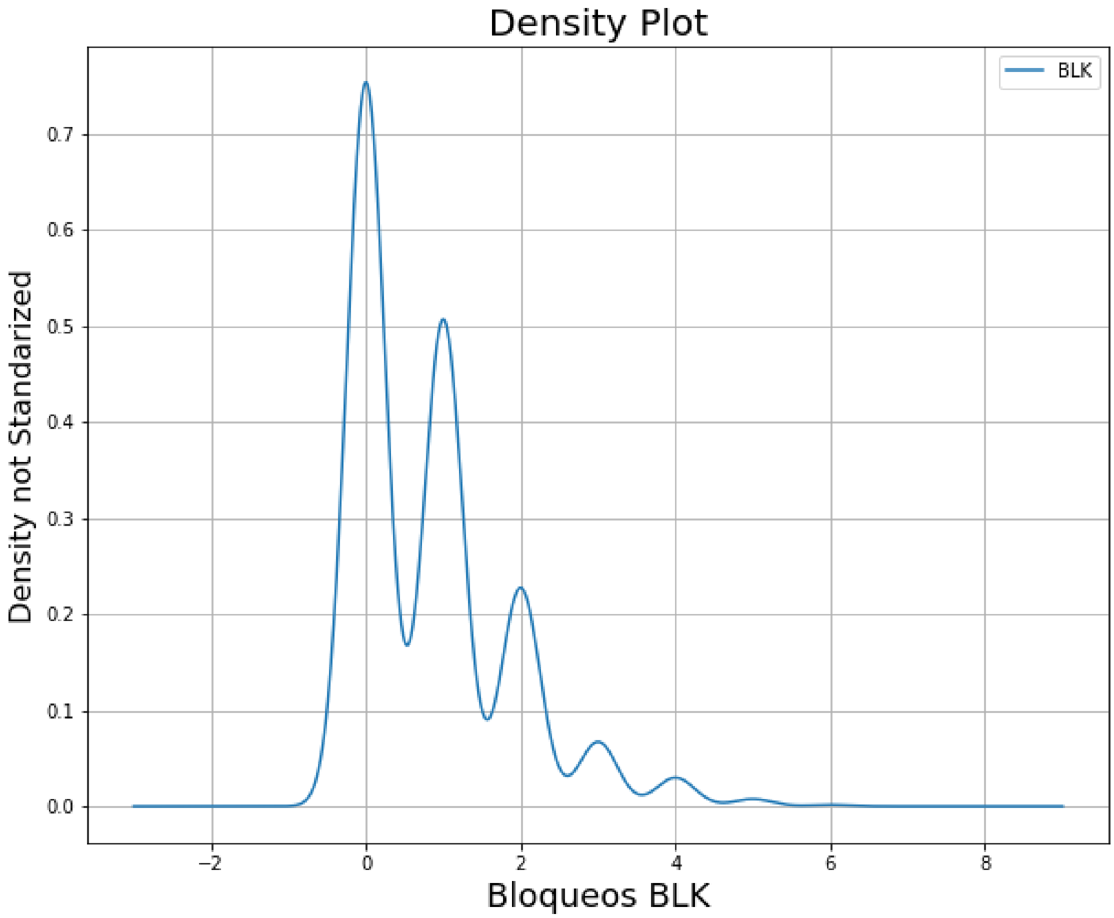
```
[292]: 30.12313432835821
```

```
[293]: plt.figure(figsize=(10,8))
df['PTS'].plot.kde()
plt.title("Density Plot",  fontsize=20)
plt.xlabel("Points", fontsize=18)
plt.ylabel("Density not Standarized", fontsize=16)
plt.grid()
plt.axvline(x=df_puntos_mean, color='red', label='Mean')
plt.legend()
plt.show()
```




**As we can see the mean is 30 points**

[294]:
```
plt.figure(figsize=(10,8))
df['BLK'].plot.kde()
plt.title("Density Plot",  fontsize=20)
plt.xlabel("Bloqueos BLK", fontsize=18)
plt.ylabel("Density not Standarized", fontsize=16)
plt.grid()

plt.legend()
plt.show()
```




[319]:
```
#Assing to df2 just the columns that we will work with:
df2 = df[['PTS','AST', 'BLK']]
```

[296]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1072 entries, 0 to 1071
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   PTS     1072 non-null   int64
 1   AST     1072 non-null   int64
 2   BLK     1072 non-null   int64
dtypes: int64(3)
memory usage: 25.2 KB
```

### 1.0.3 We use Standar Scaler to transform our variables and set the mean to 0 and the standard deviation to 1 to have a better scale.

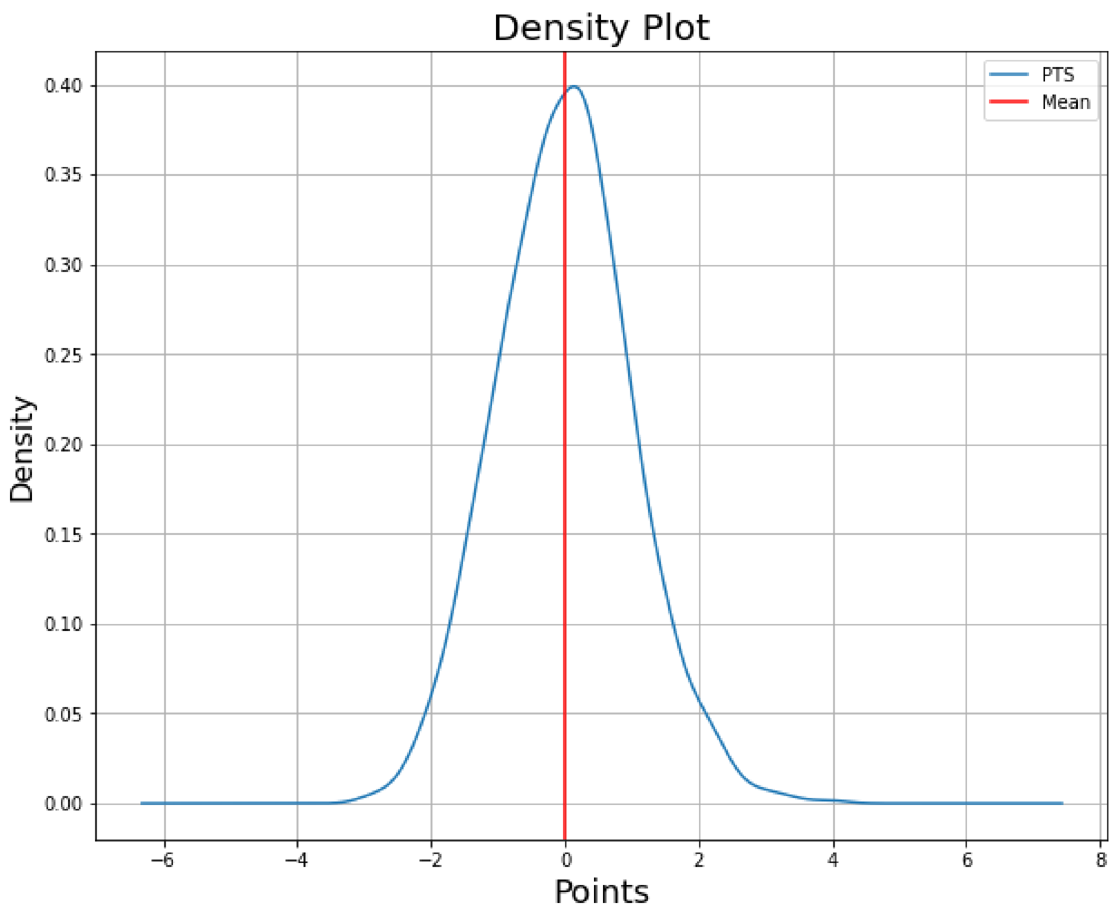
[297]:
```
#Import the library and standarized the variables PTS, AST, BLK(Puntos,␣
↪Asistencias, Bloqueos)
from sklearn.preprocessing import StandardScaler
data = df2
scaler = StandardScaler()
data = scaler.fit_transform(data)
data = pd.DataFrame(data)
data['PTS'] = data[0]
data['AST'] = data[1]
data['BLK'] = data[2]
data= data[['PTS', 'AST','BLK']]
data.head()
```

[297]:

| | PTS | AST | BLK |
|---|---|---|---|
| 0 | -1.448905 | 0.641328 | 3.133382 |
| 1 | -0.935951 | -0.093577 | 0.165206 |
| 2 | 0.705504 | -0.093577 | 1.154598 |
| 3 | -0.525587 | -0.093577 | 0.165206 |
| 4 | -1.346314 | -0.093577 | 0.165206 |

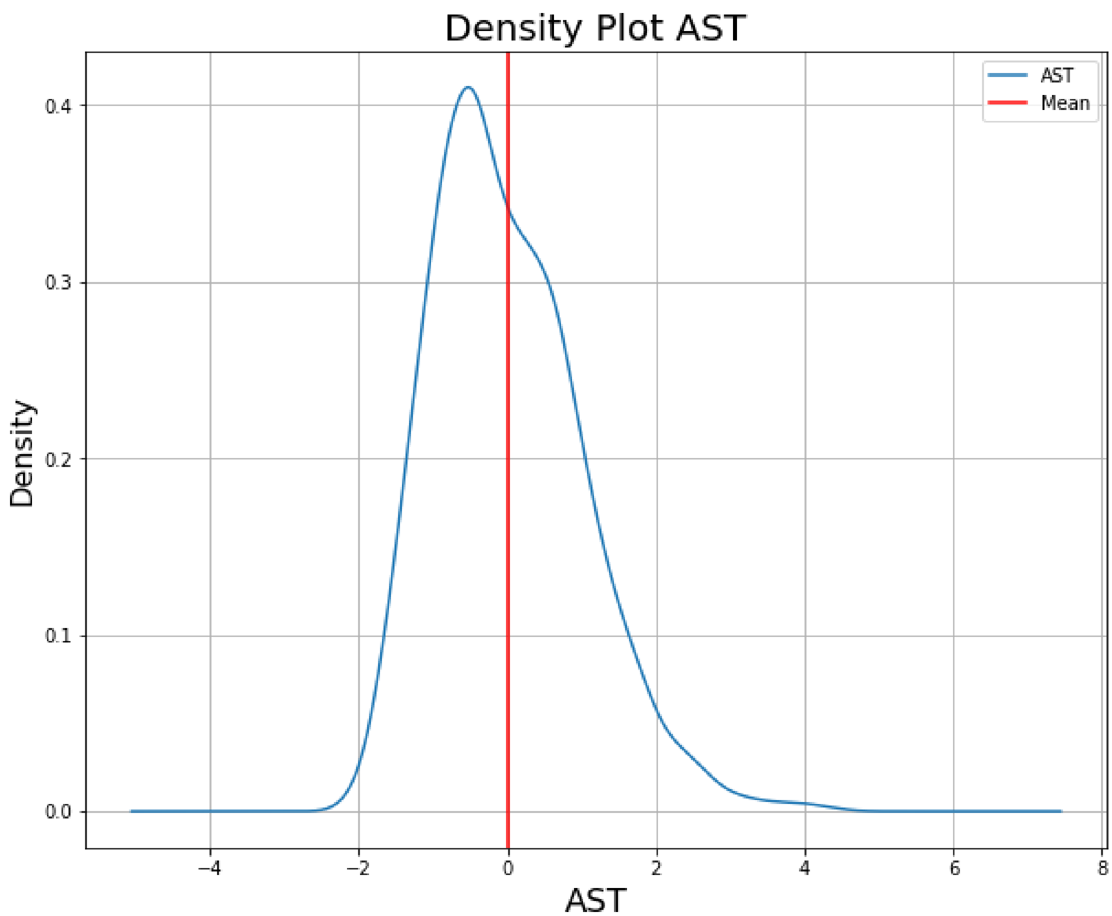
[298]:
```
data_mean_pts = data['PTS'].mean()
data_mean_ast = data['AST'].mean()
data_mean_blk = data['BLK'].mean()
```

[299]:
```
plt.figure(figsize=(10,8))
data['PTS'].plot.kde()
plt.title("Density Plot",  fontsize=20)
plt.xlabel("Points", fontsize=18)
plt.ylabel("Density", fontsize=16)
plt.grid()
plt.axvline(x=data_mean_pts, color='red', label='Mean') #show the mean line()
plt.legend()
plt.show()
```

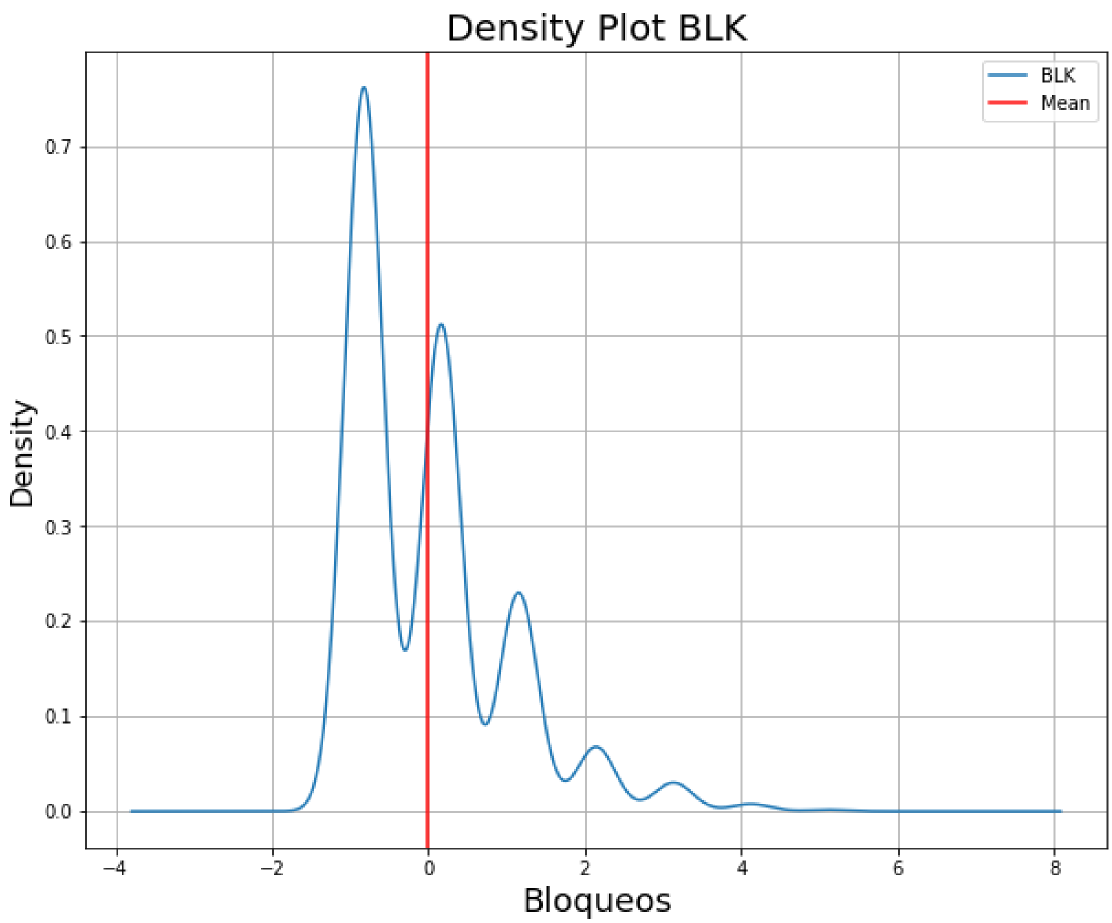



[300]:

```
plt.figure(figsize=(10,8))
data['AST'].plot.kde()
plt.title("Density Plot AST",  fontsize=20)
plt.xlabel("AST", fontsize=18)
plt.ylabel("Density", fontsize=16)
plt.grid()

plt.axvline(x=data_mean_ast, color='red', label='Mean') #Show the mean line
plt.legend()
plt.show()
```

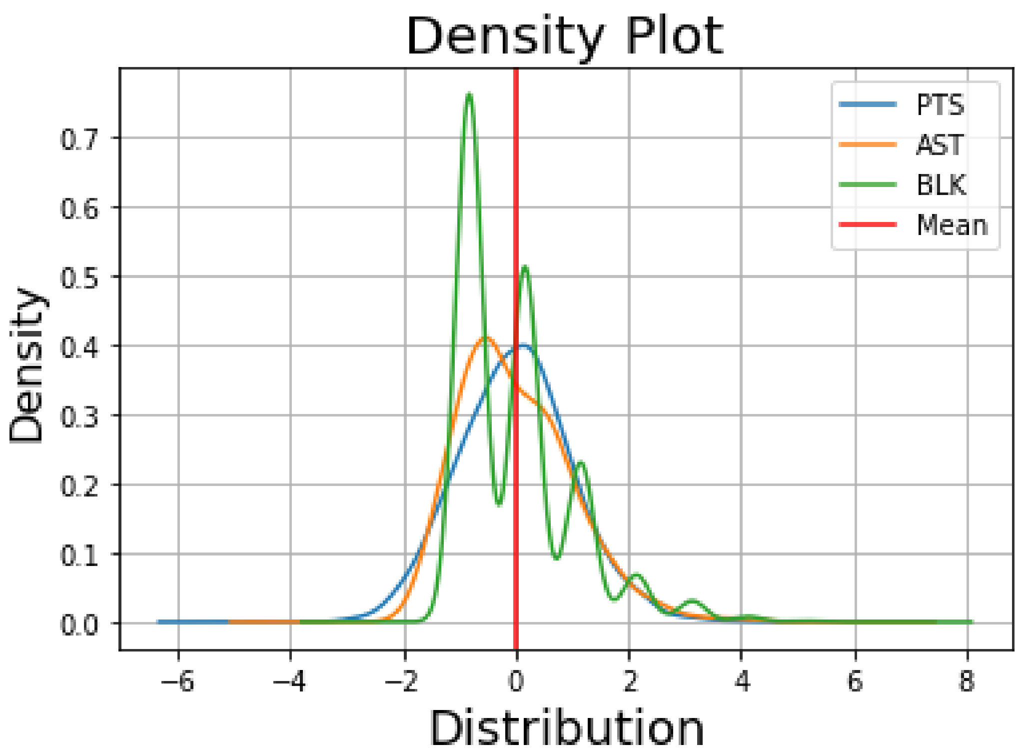



[301]:
```
plt.figure(figsize=(10,8))
data['BLK'].plot.kde()
plt.title("Density Plot BLK",  fontsize=20)
plt.xlabel("Bloqueos", fontsize=18)
plt.ylabel("Density", fontsize=16)
plt.grid()

plt.axvline(x=data_mean_blk, color='red', label='Mean')
plt.legend()
plt.show()
```




[302]:
```
plt.figure(figsize=(10,8))
data.plot.kde()
plt.title("Density Plot",  fontsize=20)
plt.xlabel("Distribution", fontsize=18)
plt.ylabel("Density", fontsize=16)
plt.grid()

plt.axvline(x=0, color='red', label='Mean')
plt.legend()
plt.show()
```

```
<Figure size 720x576 with 0 Axes>
```




---

## 1.1 Exercice 2: Apply a principal component analysis or PCA

### 1.1.1 The principal component analysis it is used to group many variables that are correlated with each other and transform it into 1 or 2 variables that contain the same information to reduce the size of the initial dataset.

### 1.1.2 Normally, it is sought to obtain a result between 90-95% variance.

[303]:
```
#Import our librarys
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
```

[304]:
```
#Assign to the variable "x_col" all the numerics variables of our data to␣
↪compile in just 2 variables:
x_col = df[['Rk','Age', 'PTS','AST', 'BLK', 'GmSc']]
```

[305]:
```
#First standarized our data x_column with Standar Scaler:
ss = StandardScaler()
x_col=ss.fit_transform(x_col)
x_col = pd.DataFrame({'Ranking': x_col[:,0], 'Edad':x_col[:,1], 'Puntos':x_col[:
↪,2], 'Asistencias':x_col[:,3], 'Bloqueos':x_col[:,4], 'GameScore':x_col[:
↪,5]})
```

```
x_col
```

[305]:

```
        Ranking      Edad    Puntos  Asistencias  Bloqueos  GameScore
0     -1.631948 -1.520719 -1.448905     0.641328  3.133382  -1.153781
1     -1.589641 -1.520208 -0.935951    -0.093577  0.165206  -0.426140
2     -1.547333 -1.519185  0.705504    -0.093577  1.154598   0.997506
3     -1.505026 -1.518673 -0.525587    -0.093577  0.165206  -0.921779
4     -1.462719 -1.517650 -1.346314    -0.093577  0.165206  -1.079962
…           …         …         …            …         …          …
1067   1.625712  1.926029 -0.935951    -1.563388 -0.824186  -0.763596
1068   1.668020  1.927052 -0.525587    -0.461030 -0.824186  -0.869052
1069   1.710327  1.927563 -1.346314     0.273876  0.165206  -0.942870
1070   1.752634  1.928586 -0.935951    -1.563388 -0.824186  -1.280327
1071   1.794942  1.929609 -1.551496    -0.461030 -0.824186  -1.575602

[1072 rows x 6 columns]
```

[306]:

```
#Transform all the variables in 2 variables:
pca2 = PCA(n_components=2, random_state=42)
pca_2= pca2.fit_transform(x_col)
pca_2
```

[306]:

```
array([[-0.02120385,  4.07094548],
       [-0.24981989,  1.94946718],
       [ 1.82556741,  1.60684466],
       …,
       [-1.91652622, -0.90514191],
       [-2.56366567, -2.05970609],
       [-2.84684497, -1.49439428]])
```

[315]:

```
#Create a dataframe with the name df3 that will contain PCA1, PCA2 column:
df3 = pd.DataFrame({'PCA1': pca_2[:,0], 'PCA2':pca_2[:,1]})
df3
```

[315]:

```
          PCA1      PCA2
0    -0.021204  4.070945
1    -0.249820  1.949467
2     1.825567  1.606845
3    -0.314756  1.866805
4    -0.875179  2.143897
…           …         …
1067 -2.255364 -2.090685
1068 -1.839546 -1.902131
1069 -1.916526 -0.905142
1070 -2.563666 -2.059706
1071 -2.846845 -1.494394
```

[1072 rows x 2 columns]

[308]:
```
#Ratio:
pca2.explained_variance_ratio_
```

[308]: array([0.38213971, 0.17800674])

[309]:
```
pca2.explained_variance_ratio_.sum()
```

[309]: 0.5601464431928321

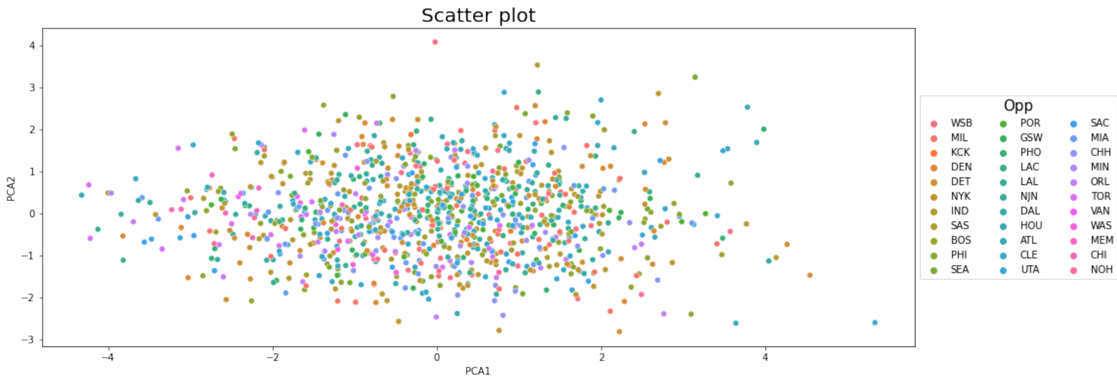
[310]:
```
#Add to the dataframe df3 the column opponent:
df3 = pd.DataFrame({'PCA1': pca_2[:,0], 'PCA2':pca_2[:,1], 'Opp':df['Opp']})
df3
```

[310]:

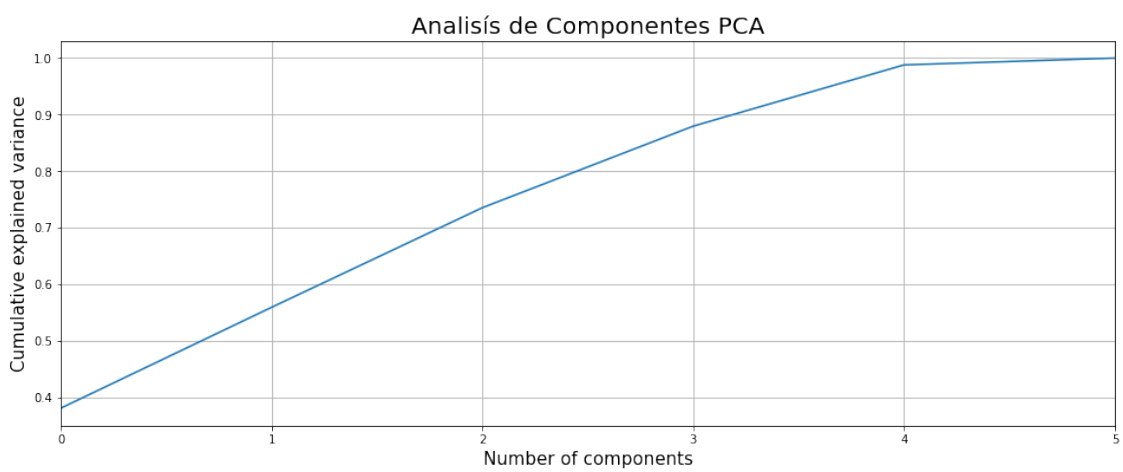
| | PCA1 | PCA2 | Opp |
|---|---|---|---|
| 0 | -0.021204 | 4.070945 | WSB |
| 1 | -0.249820 | 1.949467 | MIL |
| 2 | 1.825567 | 1.606845 | MIL |
| 3 | -0.314756 | 1.866805 | KCK |
| 4 | -0.875179 | 2.143897 | DEN |
| … | … | … | … |
| 1067 | -2.255364 | -2.090685 | BOS |
| 1068 | -1.839546 | -1.902131 | MIA |
| 1069 | -1.916526 | -0.905142 | ATL |
| 1070 | -2.563666 | -2.059706 | NYK |
| 1071 | -2.846845 | -1.494394 | PHI |

[1072 rows x 3 columns]

[311]:
```
#Lets plot a Scatter chart:
plt.figure(figsize=(16, 6))
sns.scatterplot(x='PCA1', y='PCA2', hue='Opp', data= df3)
plt.legend(title='Opp',ncol= 3,title_fontsize=15,loc='center left',␣
 ↪bbox_to_anchor=(1, 0.5))
plt.title('Scatter plot', fontsize=20)
plt.show()
```




[312]:
```python
#Lets plot the PCA:
pca = PCA().fit(x_col)
plt.figure(figsize=(16, 6))
plt.title('Analisís de Componentes PCA', size=20)
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlim(0,5,1) #Limit the x with the numbers of our components
plt.xlabel('Number of components',size=15)
plt.ylabel('Cumulative explained variance', size=15)
plt.grid()
plt.show()
```




As we can see our 5 components are above 90-95% of variance wich is really good and mean that our components or variables are highly correlated.

## 1.2 Exercice 3: Normalizing the Data

### 1.2.1 The Normalizer convert our variables in positive numbers, inclusive if our variables have negative values:

[313]:
```
#Import the librarys and use Normalizer()
from sklearn import preprocessing
datos_normalizados= preprocessing.Normalizer().transform(df2.T)
datos_normalizados = datos_normalizados.T
datos_normalizados = pd.DataFrame({'Puntos': datos_normalizados[:,0],␣
↪'Asistencias':datos_normalizados[:,1], 'Bloqueos':datos_normalizados[:,2]})
datos_normalizados
```

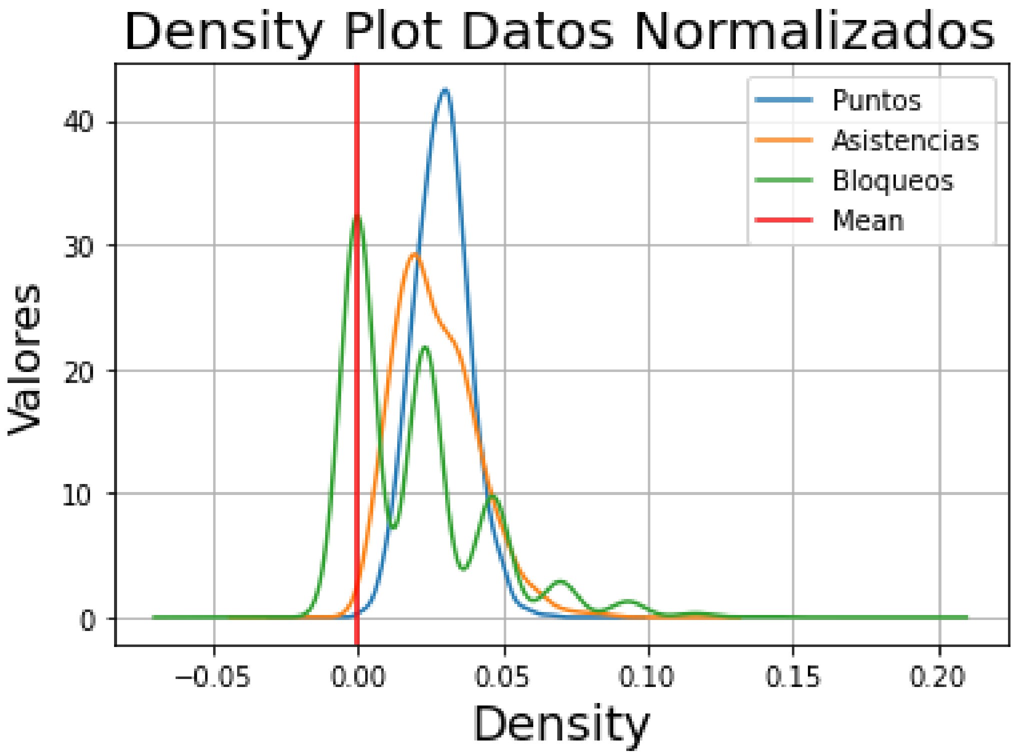
[313]:

| | Puntos | Asistencias | Bloqueos |
|---|---|---|---|
| 0 | 0.015435 | 0.036129 | 0.093276 |
| 1 | 0.020258 | 0.025806 | 0.023319 |
| 2 | 0.035693 | 0.025806 | 0.046638 |
| 3 | 0.024117 | 0.025806 | 0.023319 |
| 4 | 0.016399 | 0.025806 | 0.023319 |
| … | … | … | … |
| 1067 | 0.020258 | 0.005161 | 0.000000 |
| 1068 | 0.024117 | 0.020645 | 0.000000 |
| 1069 | 0.016399 | 0.030968 | 0.023319 |
| 1070 | 0.020258 | 0.005161 | 0.000000 |
| 1071 | 0.014470 | 0.020645 | 0.000000 |

[1072 rows x 3 columns]

[320]:
```
#Plotting our normalized data:
plt.figure(figsize=(10,8))
datos_normalizados.plot.kde()
plt.title("Density Plot Datos Normalizados",  fontsize=20)
plt.xlabel("Density", fontsize=18)
plt.ylabel("Valores", fontsize=16)

plt.grid()
plt.axvline(x=0, color='red', label='Mean')
plt.legend()
plt.show()
```

```
<Figure size 720x576 with 0 Axes>
```


Density Plot Datos Normalizados
Valores
Density
Puntos
Asistencias
Bloqueos
Mean
40
30
20
10
0
−0.05
0.00
0.05
0.10
0.15
0.20