UNIVERSIDADE DE FORTALEZA

MBA em Ciência de Dados

Introdução ao Aprendizado de Máquina - Professor Erneson Oliveira.

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1. Introdução

Este trabalho tem como objetivo desenvolver um sistema de aprendizagem de máquina capaz de fazer previsões de salários dos jogadores da NBA, a partir de um conjunto de dados disponibilizado. Bem como, após todas as análises e predições, verificar se o valor do salário real do jogador Stephen Curry é justo.

2. Metodologia

Primeiramente, será realizada uma higienização dos dados no DataFrame para remover valores que não possuem relevância para a análise. Após isso, serão realizadas análises de algumas características como média de minutos na quadra, pontos por jogo na ultima temporada, eficiência, número de rotatividade por jogo, etc. Em seguida, será feita uma correlação para análisar as melhores características. Por último, serão criados alguns modelos como Regressão Linear, Floresta aleatória, Árvore de Decisão, para que seja verificada a melhor predição.

3. Obtenção dos Dados para Análise

In [718]:

```
# Importação das bibliotecas Pandas e Pyplot import pandas as pd import matplotlib.pyplot as plt
```

In [719]:

```
#Leitura e criação do DataFrame que será utilizado ao longo deste trabalho.
df = pd.read_csv('NBA_Players.csv',sep=',',encoding='utf-8', skipinitialspace=True)
#retirar espaço em branco no inicio do nome das colunas.
df.columns = [c.strip().upper().replace(' ', '') for c in df.columns]
```

In [720]:

```
df.head(10)
```

Out[720]:

	TEAM	NAME	EXPERIENCE	URL	POSITION	AGE
0	Boston Celtics	Aron Baynes	6	http://www.espn.com/nba/player/_/id/2968439	SF	31
1	Boston Celtics	Justin Bibbs	0	http://www.espn.com/nba/player/_/id/3147500	G	22
2	Boston Celtics	Jabari Bird	1	http://www.espn.com/nba/player/_/id/3064308	SG	24
3	Boston Celtics	Jaylen Brown	2	http://www.espn.com/nba/player/_/id/3917376	F	21
4	Boston Celtics	PJ Dozier	1	http://www.espn.com/nba/player/_/id/3923250	PG	21
5	Boston Celtics	Marcus Georges- Hunt	2	http://www.espn.com/nba/player/_/id/2982261	SG	24
6	Boston Celtics	Gordon Hayward	8	http://www.espn.com/nba/player/_/id/4249	SF	28
7	Boston Celtics	Al Horford	11	http://www.espn.com/nba/player/_/id/3213	PF	32
8	Boston Celtics	Kyrie Irving	7	http://www.espn.com/nba/player/_/id/6442	PG	26
9	Boston Celtics	Nick King	0	http://www.espn.com/nba/player/_/id/3057182	F	23

10 rows × 30 columns

In [721]:

```
#Removendo colunas que não serão úteis na análise:
df = df.drop(columns=["URL", "COLLEGE"])
```

In [722]:

```
#Formatação do campo Salário
df["SALARY"] = df["SALARY"].replace("Not signed",0)
#df["SALARY"].str.replace(',','.')
df["SALARY"] = df["SALARY"].str.replace(',','').astype(float)
df["SALARY"] = df["SALARY"].fillna(0)
df['SALARY'] = df['SALARY']/1000000
```

In [723]:

```
df["PPG_LAST_SEASON"] = df["PPG_LAST_SEASON"].fillna(0)
df["PER_LAST_SEASON"] = df["PER_LAST_SEASON"].fillna(0)
df["APG_LAST_SEASON"] = df["APG_LAST_SEASON"].fillna(0)
df["RPG_LAST_SEASON"] = df["RPG_LAST_SEASON"].fillna(0)
```

In [724]:

```
#df.head(100)
# deletar linhas que possuem salário zerado
df.drop(df[df["SALARY"] == 0.000].index, inplace=True)
# deletar linhas que possuem idade = '-'
df.drop(df[df["AGE"] == '-'].index, inplace=True)
# Deletar linhas com eficiência menor que 0
df.drop(df[df["PER_LAST_SEASON"] <= 0].index, inplace=True)</pre>
```

In [725]:

```
#Análise geral dos dados do Stephen Curry

df[df.NAME == "Stephen Curry"]
```

Out[725]:

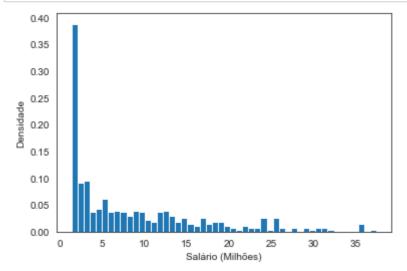
_		TEAM	NAME	EXPERIENCE	POSITION	AGE	НТ	WT	SALARY	PPG_LAST_S
	103	Golden State Warriors	Stephen Curry	9	PG	30	190.5	85.97	37.457154	

1 rows × 28 columns

←

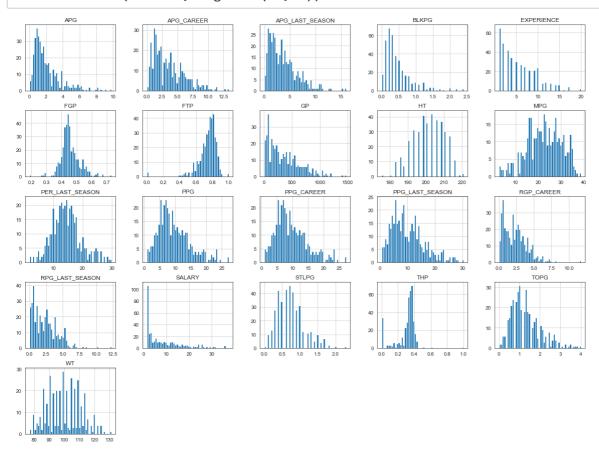
In [726]:

```
# Histograma de Salários
plt.hist(df['SALARY'], density=True, bins=50)
plt.xlabel('Salário (Milhões)')
plt.ylabel('Densidade')
plt.show()
```



In [727]:

hist = df.hist(bins=50, figsize=(20,15))



In [729]:

```
# Minutos por jogo na quadra.
df.sort_values(by="MPG", ascending=False, inplace=True)
df[["NAME","MPG","SALARY"]].head(20)
```

Out[729]:

	NAME	MPG	SALARY
147	LeBron James	38.8	35.654150
105	Kevin Durant	37.1	30.000000
518	Damian Lillard	36.4	27.977689
493	Andrew Wiggins	36.2	25.467250
295	Carmelo Anthony	35.9	1.512601
457	John Wall	35.9	19.169800
310	Chris Paul	35.3	35.654150
230	Blake Griffin	35.0	32.088932
492	Karl-Anthony Towns	34.9	7.839435
338	Anthony Davis	34.8	25.434263
479	Luol Deng	34.7	1.512601
352	LaMarcus Aldridge	34.6	22.347015
361	Rudy Gay	34.6	10.087200
418	Dwyane Wade	34.5	1.512601
446	Dwight Howard	34.5	5.337000
290	Dirk Nowitzki	34.4	5.000000
510	Russell Westbrook	34.4	35.654150
103	Stephen Curry	34.4	37.457154
138	Lonzo Ball	34.2	7.461960
109	Andre Iguodala	34.1	16.000000

In [730]:

```
# Pontos por jogo na ultima temporada
#df.describe()
df.sort_values(by="PPG_LAST_SEASON", ascending=False, inplace=True)
df[["NAME","PPG_LAST_SEASON", "SALARY"]].head(10)
```

Out[730]:

	NAME	PPG_LAST_SEASON	SALARY
306	James Harden	30.4	35.650150
338	Anthony Davis	28.1	25.434263
147	LeBron James	27.5	35.654150
518	Damian Lillard	26.9	27.977689
259	Giannis Antetokounmpo	26.9	24.157303
105	Kevin Durant	26.4	30.000000
103	Stephen Curry	26.4	37.457154
510	Russell Westbrook	25.4	35.654150
102	DeMarcus Cousins	25.2	5.337000
161	Devin Booker	24.9	3.314365

In [731]:

```
# Eficiência por jogo na última temporada
df.sort_values(by="PER_LAST_SEASON", ascending=False, inplace=True)
df[["NAME", "PER_LAST_SEASON", "SALARY"]].head(10)
```

Out[731]:

	NAME	PER_LAST_SEASON	SALARY
306	James Harden	29.87	35.650150
338	Anthony Davis	28.98	25.434263
147	LeBron James	28.65	35.654150
103	Stephen Curry	28.32	37.457154
259	Giannis Antetokounmpo	27.37	24.157303
468	Monte Morris	27.14	1.349383
317	MarShon Brooks	26.40	1.656092
105	Kevin Durant	26.05	30.000000
88	Kawhi Leonard	26.03	23.114067
129	Boban Marjanovic	25.98	7.000000

In [732]:

```
# Idade dos jogadores
df.sort_values(by="AGE", ascending=False, inplace=True)
df[["NAME","AGE", "SALARY"]].head(50)
```

Out[732]:

	NAME	AGE	SALARY
374	Vince Carter	41	1.512601
290	Dirk Nowitzki	40	5.000000
407	Udonis Haslem	38	1.512601
360	Pau Gasol	38	16.800000
189	Zach Randolph	37	11.692308
213	Kyle Korver	37	7.560000
225	Jose Calderon	37	1.512601
308	Nene	36	3.651480
418	Dwyane Wade	36	1.512601
164	Tyson Chandler	36	13.585000
400	Tony Parker	36	5.000000
209	Channing Frye	35	1.512601
284	Devin Harris	35	1.512601
109	Andre Iguodala	34	16.000000
548	Thabo Sefolosha	34	5.250000
238	Zaza Pachulia	34	1.512601
125	Marcin Gortat	34	13.565218
278	J.J. Barea	34	3.710850
500	Raymond Felton	34	1.512601
295	Carmelo Anthony	34	1.512601
75	JJ Redick	34	12.250000
352	LaMarcus Aldridge	33	22.347015
220	JR Smith	33	14.720000
54	Courtney Lee	33	12.253780
314	PJ Tucker	33	7.969537
491	Anthony Tolliver	33	4.750000
479	Luol Deng	33	1.512601
322	Marc Gasol	33	24.119025
467	Paul Millsap	33	29.230769
157	Trevor Ariza	33	15.000000
113	Shaun Livingston	33	8.307692
26	Jared Dudley	33	9.530000
310	Chris Paul	33	35.654150
147	LeBron James	33	35.654150
481	Taj Gibson	33	14.000000
193	Omer Asik	32	11.286516
333	Garrett Temple	32	8.000000

	NAME	AGE	SALARY
361	Rudy Gay	32	10.087200
210	George Hill	32	19.000000
456	Jason Smith	32	5.450000
289	Salah Mejri	32	1.512601
89	Kyle Lowry	32	31.200000
402	Marvin Williams	32	14.087500
7	Al Horford	32	28.928709
305	Gerald Green	32	1.512601
353	Marco Belinelli	32	6.153846
437	Timofey Mozgov	32	16.000000
21	DeMarre Carroll	32	15.400000
405	Goran Dragic	32	18.109175
446	Dwight Howard	32	5.337000

4. Conjunto de treinamento e conjunto de testes.

4.1 Amostragem aleatória

In [733]:

In [734]:

```
train_set.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 305 entries, 248 to 235
Data columns (total 28 columns):
TEAM
                   305 non-null object
NAME
                   305 non-null object
                   305 non-null int64
EXPERIENCE
POSITION
                   305 non-null object
                   305 non-null object
AGE
HT
                   305 non-null float64
                   305 non-null float64
WT
                   305 non-null float64
SALARY
                   305 non-null float64
PPG LAST SEASON
APG_LAST_SEASON
                   305 non-null float64
RPG LAST SEASON
                   305 non-null float64
PER_LAST_SEASON
                   305 non-null float64
                   305 non-null float64
PPG_CAREER
APG_CAREER
                   305 non-null float64
RGP CAREER
                   305 non-null float64
                   305 non-null int64
GΡ
                   305 non-null float64
MPG
                   305 non-null object
FGM_FGA
                   305 non-null float64
FGP
THM THA
                   305 non-null object
THP
                   305 non-null float64
                   305 non-null object
FTM FTA
FTP
                   305 non-null float64
                   305 non-null float64
APG
                   305 non-null float64
BLKPG
STLPG
                   305 non-null float64
TOPG
                   305 non-null float64
PPG
                   305 non-null float64
dtypes: float64(19), int64(2), object(7)
```

memory usage: 69.1+ KB

In [735]:

```
test set.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 77 entries, 371 to 285
Data columns (total 28 columns):
TEAM
                   77 non-null object
NAME
                   77 non-null object
EXPERIENCE
                   77 non-null int64
POSITION
                   77 non-null object
AGE
                   77 non-null object
                   77 non-null float64
HT
                   77 non-null float64
WT
SALARY
                   77 non-null float64
                   77 non-null float64
PPG LAST SEASON
                   77 non-null float64
APG_LAST_SEASON
RPG LAST SEASON
                   77 non-null float64
                   77 non-null float64
PER_LAST_SEASON
PPG_CAREER
                   77 non-null float64
APG CAREER
                   77 non-null float64
                   77 non-null float64
RGP CAREER
                   77 non-null int64
GP
MPG
                   77 non-null float64
FGM_FGA
                   77 non-null object
FGP
                   77 non-null float64
                   77 non-null object
THM THA
                   77 non-null float64
THP
FTM FTA
                   77 non-null object
FTP
                   77 non-null float64
APG
                   77 non-null float64
                   77 non-null float64
BLKPG
STLPG
                   77 non-null float64
                   77 non-null float64
TOPG
PPG
                   77 non-null float64
dtypes: float64(19), int64(2), object(7)
```

4.2 Amostragem estratificada

memory usage: 17.4+ KB

In [736]:

```
import numpy as np

df["EFICIENCIA_CAT"]= np.ceil(df["PER_LAST_SEASON"]/2) # Limitando o numero de categori
as
df["EFICIENCIA_CAT"].where(df["EFICIENCIA_CAT"]<8,8.0, inplace=True)</pre>
```

In [737]:

In [738]:

```
S_overall = df['EFICIENCIA_CAT'].value_counts()/len(df)
S_overall.rename('EFICIENCIA_CAT_OVERALL', inplace=True)
```

Out[738]:

```
8.0
       0.502618
7.0
       0.188482
6.0
       0.123037
5.0
       0.104712
4.0
       0.047120
3.0
       0.023560
2.0
       0.005236
1.0
       0.005236
```

Name: EFICIENCIA_CAT_OVERALL, dtype: float64

In [739]:

Out[739]:

```
8.0 0.389610

7.0 0.298701

5.0 0.155844

6.0 0.116883

4.0 0.038961

Name: EFICIENCIA_CAT_RANDOM, dtype: float64
```

In [740]:

```
# Proporções da categoria de eficiencia no conjunto de testes gerados usando amostragem
stratificada
S_stratified=strat_test_set["EFICIENCIA_CAT"].value_counts()/len(strat_test_set)
S_stratified.rename('EFICIENCIA_CAT_STRATIFIED', inplace=True)
```

Out[740]:

```
8.0 0.506494
7.0 0.194805
6.0 0.116883
5.0 0.103896
4.0 0.051948
3.0 0.025974
Name: EFICIENCIA CAT STRATIFIED, dtype: float64
```

In [741]:

```
# Comparação entre as proporções
pd.concat([S_overall, S_random, S_stratified], axis=1).sort_index()
```

Out[741]:

	EFICIENCIA_CAT_OVERALL	EFICIENCIA_CAT_RANDOM	EFICIENCIA_CAT_STRATIFIED
1.0	0.005236	NaN	NaN
2.0	0.005236	NaN	NaN
3.0	0.023560	NaN	0.025974
4.0	0.047120	0.038961	0.051948
5.0	0.104712	0.155844	0.103896
6.0	0.123037	0.116883	0.116883
7.0	0.188482	0.298701	0.194805
8.0	0.502618	0.389610	0.506494

In [742]:

```
# Removendo o atributo EFICIENCIA_CAT
strat_train_set = strat_train_set.drop('EFICIENCIA_CAT', axis=1)
strat_test_set = strat_test_set.drop('EFICIENCIA_CAT', axis=1)
```

5. Visualização dos dados

5.1 Explorando o conjunto de treinamentos

In [743]:

```
nba=strat_train_set.copy()
print(nba.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 305 entries, 401 to 508
Data columns (total 28 columns):
TEAM
                   305 non-null object
NAME
                   305 non-null object
                   305 non-null int64
EXPERIENCE
                   305 non-null object
POSITION
AGE
                   305 non-null object
                   305 non-null float64
HT
                   305 non-null float64
WT
                   305 non-null float64
SALARY
PPG_LAST_SEASON
                   305 non-null float64
APG_LAST_SEASON
                   305 non-null float64
RPG_LAST_SEASON
                   305 non-null float64
PER_LAST_SEASON
                   305 non-null float64
PPG_CAREER
                   305 non-null float64
APG CAREER
                   305 non-null float64
RGP_CAREER
                   305 non-null float64
                   305 non-null int64
GP
MPG
                   305 non-null float64
FGM FGA
                   305 non-null object
                   305 non-null float64
FGP
                   305 non-null object
THM_THA
                   305 non-null float64
THP
FTM_FTA
                   305 non-null object
FTP
                   305 non-null float64
                   305 non-null float64
APG
BLKPG
                   305 non-null float64
                   305 non-null float64
STLPG
TOPG
                   305 non-null float64
PPG
                   305 non-null float64
dtypes: float64(19), int64(2), object(7)
memory usage: 69.1+ KB
```

5.1.1 Buscando correlações

None

In [744]:

```
# Selecionando as características que julguei mais importantes para correlacionar.
import seaborn as sns

#sns.set_style("white")
plt.figure(figsize=(12,8))
heatmap_per = nba[["SALARY", "MPG", "PPG_LAST_SEASON", "APG_LAST_SEASON", "RPG_LAST_SEA
SON", "TOPG", "BLKPG", "STLPG", "AGE", "PER_LAST_SEASON"]]
df_heat = heatmap_per.corr()
sns.heatmap(df_heat, annot=True, cmap=plt.cm.Reds)
plt.show()

#Analisando as características é possível perceber que o campo MPG ("Minutos por jogo e m quadra") e
# ("TOPG: Rotatividade por jogo") e PPG_LAST_SEASON ("Pontos por jogo na ultima tempora da")
# são os atributos que mais se cocrelacionam
```



5.1.1.2 Correlação entre pontos por jogo e salário

In [745]:

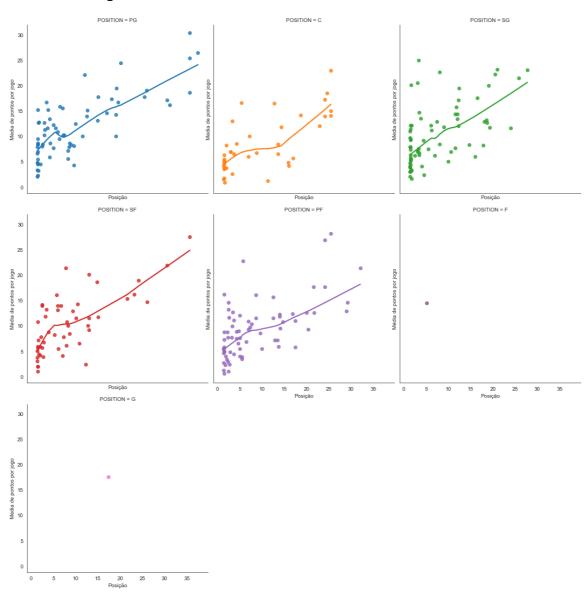
```
sns.lmplot(x="SALARY", y="PPG_LAST_SEASON", hue="POSITION", col="POSITION", col_wrap=3,
data=nba, lowess=True).set(xlabel='Posição', ylabel='Média de pontos por jogo')
```

C:\Users\Thiago\Anaconda3\lib\site-packages\statsmodels\nonparametric\smoo
thers_lowess.py:165: RuntimeWarning: invalid value encountered in true_div
ide

res = _lowess(y, x, frac=frac, it=it, delta=delta)

Out[745]:

<seaborn.axisgrid.FacetGrid at 0x1cf863bd88>

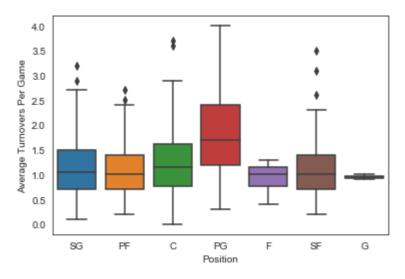


In [746]:

#Qual posição é mais propensa a rotatividade?
sns.boxplot(x="POSITION", y="TOPG", data=df).set(xlabel="Position", ylabel="Average Tur
novers Per Game")

Out[746]:

[Text(0, 0.5, 'Average Turnovers Per Game'), Text(0.5, 0, 'Position')]

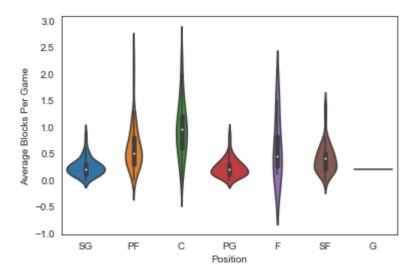


In [747]:

Qual posição tem os maiores bloqueios?
sns.violinplot(x="POSITION", y="BLKPG", data=df).set(xlabel="Position", ylabel="Average
Blocks Per Game")

Out[747]:

[Text(0, 0.5, 'Average Blocks Per Game'), Text(0.5, 0, 'Position')]



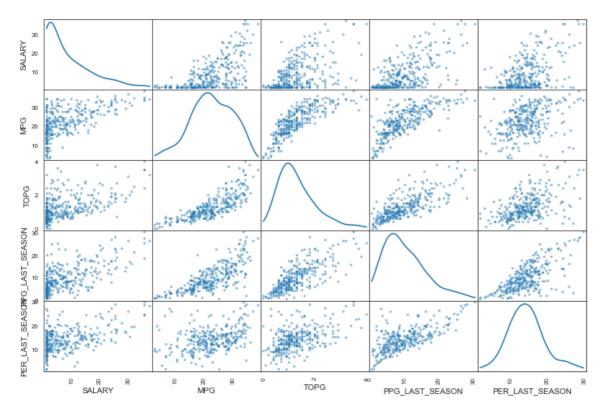
In [696]:

```
from pandas.plotting import scatter_matrix

atributes = ["SALARY", "MPG", "TOPG", "PPG_LAST_SEASON", "PER_LAST_SEASON"]
scatter_matrix(heatmap_per[atributes], figsize=(12,8), diagonal='kde')
```

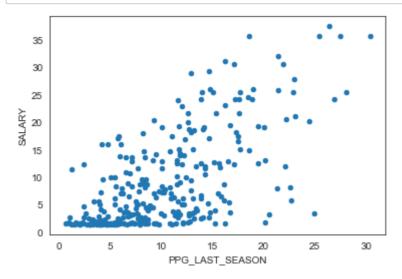
Out[696]:

```
array([[<matplotlib.axes. subplots.AxesSubplot object at 0x0000001CF884C54
8>,
         <matplotlib.axes. subplots.AxesSubplot object at 0x0000001CF8BD340</pre>
8>,
         <matplotlib.axes._subplots.AxesSubplot object at 0x0000001CF8C0AC0</pre>
8>,
         <matplotlib.axes. subplots.AxesSubplot object at 0x0000001CF8C43A0</pre>
8>,
         <matplotlib.axes._subplots.AxesSubplot object at 0x0000001CF9CACB0</pre>
8>],
        [<matplotlib.axes._subplots.AxesSubplot object at 0x0000001CF9CE5C0</pre>
8>,
         <matplotlib.axes. subplots.AxesSubplot object at 0x0000001CF9D1DCC</pre>
8>,
         <matplotlib.axes._subplots.AxesSubplot object at 0x0000001CF9D55DC</pre>
8>,
         <matplotlib.axes._subplots.AxesSubplot object at 0x0000001CF9D619C</pre>
8>,
         <matplotlib.axes. subplots.AxesSubplot object at 0x0000001CF9D99B8</pre>
8>],
        [<matplotlib.axes. subplots.AxesSubplot object at 0x0000001CF9E0514</pre>
8>,
         <matplotlib.axes._subplots.AxesSubplot object at 0x0000001CF9E3E20</pre>
8>,
         <matplotlib.axes. subplots.AxesSubplot object at 0x0000001CF9E7734</pre>
8>,
         <matplotlib.axes. subplots.AxesSubplot object at 0x0000001CF9EAE44</pre>
8>,
         <matplotlib.axes._subplots.AxesSubplot object at 0x0000001CF9EE654</pre>
8>],
        (<matplotlib.axes. subplots.AxesSubplot object at 0x0000001CF9F24E8)</pre>
8>,
         <matplotlib.axes._subplots.AxesSubplot object at 0x0000001CF9F5770</pre>
8>,
         <matplotlib.axes._subplots.AxesSubplot object at 0x0000001CF9F9080</pre>
8>,
         <matplotlib.axes._subplots.AxesSubplot object at 0x0000001CF9FC890</pre>
8>,
         <matplotlib.axes. subplots.AxesSubplot object at 0x0000001CFA001A4</pre>
8>],
        [<matplotlib.axes. subplots.AxesSubplot object at 0x0000001CFA03AB4</pre>
8>,
         <matplotlib.axes. subplots.AxesSubplot object at 0x0000001CFA075C0</pre>
8>,
         <matplotlib.axes. subplots.AxesSubplot object at 0x0000001CFA0AED4</pre>
8>,
         <matplotlib.axes._subplots.AxesSubplot object at 0x0000001CFA0E5E4</pre>
8>,
         <matplotlib.axes. subplots.AxesSubplot object at 0x0000001CFA11FF4</pre>
8>]],
      dtype=object)
```



In [748]:

g=heatmap_per.plot(kind='scatter',x='PPG_LAST_SEASON', y="SALARY")



In [749]:

```
corr_matrix=nba.corr()
corr_matrix['SALARY'].sort_values(ascending=False)
```

Out[749]:

```
SALARY
                    1.000000
PPG_LAST_SEASON
                    0.658278
PPG
                    0.606026
PPG_CAREER
                    0.606026
MPG
                    0.597137
APG_LAST_SEASON
                    0.517157
                    0.514620
STLPG
TOPG
                    0.498969
PER_LAST_SEASON
                    0.498125
APG CAREER
                    0.468525
GP
                    0.433706
APG
                    0.409380
                    0.389446
EXPERIENCE
RPG_LAST_SEASON
                    0.310001
BLKPG
                    0.273259
RGP_CAREER
                    0.266624
FGP
                    0.173544
FTP
                    0.155398
                    0.134140
THP
WT
                    0.080882
HT
                    0.012826
Name: SALARY, dtype: float64
```

6. Preparar modelos de AM

6.1 Limpeza dos dados

```
In [750]:
```

```
nba=strat_train_set.drop('SALARY', axis=1) # X
nba_labels=strat_train_set['SALARY'].copy() # y
```

6.1.1 Tratando os valores faltantes com o Scikit-Learn

In [751]:

```
nba=strat_train_set.drop('SALARY', axis=1) #X
nba_num = nba.drop(['TEAM','NAME','POSITION','AGE','FGM_FGA','THM_THA','FTM_FTA'], axi
s=1)
from sklearn.impute import SimpleImputer # Estimador
imputer = SimpleImputer(strategy="mean") # Objeto da classe Imputer
# Imputer é um estimador
imputer.fit(nba_num)
print(imputer.statistics_) # Média de cada coluna do nba_num
print(nba_num.mean().values)
#Imputer é também um "Transformador": Parametros estimados + dado de entrada -> dado tr
ansformado
X=imputer.transform(nba num)
# dado de entrada -> parâmetros estimados; parametros estimados + dado de entrada -> da
do transformado
#X=imputer.fit_transform(nba_num)
nba_num_transformed=pd.DataFrame(X,columns=nba_num.columns) # de nDarray para DataFrame
nba_num_transformed.info()
```

```
[5.59016393e+00 2.00884852e+02 9.93933115e+01 1.01524590e+01
 3.70885246e+00 2.33016393e+00 1.43281639e+01 9.68918033e+00
 3.67475410e+00 2.32229508e+00 3.57675410e+02 2.28216393e+01
 4.54806557e-01 3.06718033e-01 7.40616393e-01 2.12000000e+00
 4.61639344e-01 7.50819672e-01 1.32196721e+00 9.68918033e+00]
[5.59016393e+00 2.00884852e+02 9.93933115e+01 1.01524590e+01
 3.70885246e+00 2.33016393e+00 1.43281639e+01 9.68918033e+00
 3.67475410e+00 2.32229508e+00 3.57675410e+02 2.28216393e+01
 4.54806557e-01 3.06718033e-01 7.40616393e-01 2.12000000e+00
 4.61639344e-01 7.50819672e-01 1.32196721e+00 9.68918033e+00]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 305 entries, 0 to 304
Data columns (total 20 columns):
                   305 non-null float64
EXPERIENCE
HT
                   305 non-null float64
WT
                   305 non-null float64
PPG_LAST_SEASON
                   305 non-null float64
APG_LAST_SEASON
                   305 non-null float64
RPG_LAST_SEASON
                   305 non-null float64
                   305 non-null float64
PER LAST SEASON
PPG_CAREER
                   305 non-null float64
                   305 non-null float64
APG_CAREER
RGP_CAREER
                   305 non-null float64
GP
                   305 non-null float64
                   305 non-null float64
MPG
FGP
                   305 non-null float64
                   305 non-null float64
THP
                   305 non-null float64
FTP
                   305 non-null float64
APG
                   305 non-null float64
BLKPG
STLPG
                   305 non-null float64
TOPG
                   305 non-null float64
                   305 non-null float64
PPG
dtypes: float64(20)
```

memory usage: 47.8 KB

6.2 Manipulando texto e atributos categóricos

In [752]:

```
nba = strat_train_set.drop('SALARY', axis=1) #X
nba_cat = nba[['TEAM', 'POSITION']] # Apenas atributos categoricos
nba_cat.head(10)
```

Out[752]:

	TEAM	POSITION
401	Charlotte Hornets	PG
444	Washington Wizards	С
187	Sacramento Kings	PG
351	New Orleans Pelicans	SG
539	Utah Jazz	SF
431	Orlando Magic	PF
361	San Antonio Spurs	SF
279	Dallas Mavericks	SF
13	Boston Celtics	PG
229	Detroit Pistons	SG

6.2.2 OneHotEncoder

In [753]:

```
from sklearn.preprocessing import OneHotEncoder # Transformador

nba_cat_reshaped=nba_cat.to_numpy().reshape(-1,1)
print(nba_cat_reshaped)

encoder=OneHotEncoder()
nba_cat_1hot = encoder.fit_transform(nba_cat_reshaped) # A Saída é um scipy sparse matr
ix

print(nba_cat_1hot.toarray())
```

```
[['Charlotte Hornets']
['PG']
['Washington Wizards']
 ['C']
 ['Sacramento Kings']
 ['PG']
 ['New Orleans Pelicans']
 ['SG']
['Utah Jazz']
['SF']
['Orlando Magic']
['PF']
 ['San Antonio Spurs']
 ['SF']
 ['Dallas Mavericks']
 ['SF']
['Boston Celtics']
 ['PG']
 ['Detroit Pistons']
 ['SG']
 ['Miami Heat']
 ['SG']
['Boston Celtics']
['F']
['Detroit Pistons']
 ['SF']
 ['LA Clippers']
 ['SF']
 ['Dallas Mavericks']
 ['SG']
['Miami Heat']
['PG']
 ['Minnesota Timberwolves']
['PG']
 ['Houston Rockets']
 ['SG']
 ['LA Clippers']
 ['SG']
['Utah Jazz']
 ['PF']
 ['Chicago Bulls']
 ['PF']
 ['New York Knicks']
 ['SG']
 ['Houston Rockets']
 ['SF']
 ['Los Angeles Lakers']
 ['PG']
 ['Memphis Grizzlies']
 ['C']
 ['Atlanta Hawks']
 ['SG']
 ['Houston Rockets']
['PG']
 ['Indiana Pacers']
 ['PF']
 ['Portland Trail Blazers']
 ['PG']
 ['New Orleans Pelicans']
 ['SG']
 ['Golden State Warriors']
```

```
['SG']
['Chicago Bulls']
['PG']
['Sacramento Kings']
['PF']
['Charlotte Hornets']
['PF']
['Los Angeles Lakers']
['C']
['Orlando Magic']
['PF']
['LA Clippers']
['PF']
['Atlanta Hawks']
['C']
['Detroit Pistons']
['PF']
['Toronto Raptors']
['SG']
['Sacramento Kings']
['SG']
['Denver Nuggets']
['SG']
['Atlanta Hawks']
['SG']
['New Orleans Pelicans']
['SF']
['Philadelphia 76ers']
['PG']
['Phoenix Suns']
['PG']
['Minnesota Timberwolves']
['SF']
['Memphis Grizzlies']
['SG']
['Denver Nuggets']
['PF']
['Toronto Raptors']
['SF']
['Sacramento Kings']
['SF']
['Milwaukee Bucks']
['PF']
['Utah Jazz']
['PG']
['Philadelphia 76ers']
['SG']
['Memphis Grizzlies']
['PG']
['Milwaukee Bucks']
['C']
['Memphis Grizzlies']
['SG']
['Philadelphia 76ers']
['PF']
['Brooklyn Nets']
['PG']
['Golden State Warriors']
['C']
['Boston Celtics']
['PG']
```

```
['Utah Jazz']
['C']
['Detroit Pistons']
['SG']
['Chicago Bulls']
['SG']
['Miami Heat']
['PF']
['Houston Rockets']
['PF']
['Chicago Bulls']
['C']
['Utah Jazz']
['PG']
['Denver Nuggets']
['PG']
['Utah Jazz']
['SF']
['Memphis Grizzlies']
['SG']
['Los Angeles Lakers']
['SG']
['Milwaukee Bucks']
['SG']
['Phoenix Suns']
['SF']
['Golden State Warriors']
['PG']
['Indiana Pacers']
['PF']
['Denver Nuggets']
['PF']
['Cleveland Cavaliers']
['SF']
['Brooklyn Nets']
['SF']
['Golden State Warriors']
['PF']
['Cleveland Cavaliers']
['PG']
['San Antonio Spurs']
['SG']
['Orlando Magic']
['C']
['Dallas Mavericks']
['PG']
['Atlanta Hawks']
['SG']
['Miami Heat']
['SG']
['LA Clippers']
['SG']
['Milwaukee Bucks']
['SG']
['Phoenix Suns']
['PF']
['Atlanta Hawks']
['SF']
['Orlando Magic']
['PF']
['Indiana Pacers']
```

```
['PF']
['Oklahoma City Thunder']
['SF']
['Oklahoma City Thunder']
['SF']
['Charlotte Hornets']
['SF']
['Toronto Raptors']
['PG']
['San Antonio Spurs']
['PG']
['Portland Trail Blazers']
['SF']
['Brooklyn Nets']
['SF']
['Portland Trail Blazers']
['PF']
['Dallas Mavericks']
['PF']
['LA Clippers']
['C']
['Utah Jazz']
['SF']
['Philadelphia 76ers']
['PG']
['Oklahoma City Thunder']
['SF']
['New Orleans Pelicans']
['PG']
['Oklahoma City Thunder']
['SG']
['Denver Nuggets']
['PG']
['New York Knicks']
['G']
['Sacramento Kings']
['SG']
['Philadelphia 76ers']
['PF']
['Minnesota Timberwolves']
['PF']
['Washington Wizards']
['SF']
['Portland Trail Blazers']
['SG']
['Toronto Raptors']
['SF']
['Miami Heat']
['SG']
['Orlando Magic']
['C']
['Milwaukee Bucks']
['PF']
['Phoenix Suns']
['SG']
['LA Clippers']
['SF']
['Atlanta Hawks']
['SF']
['Washington Wizards']
['C']
```

```
['Utah Jazz']
['SG']
['Detroit Pistons']
['PG']
['San Antonio Spurs']
['C']
['Phoenix Suns']
['C']
['Boston Celtics']
['PF']
['Denver Nuggets']
['PF']
['LA Clippers']
['PF']
['Denver Nuggets']
['SF']
['Cleveland Cavaliers']
['PF']
['San Antonio Spurs']
['SF']
['New Orleans Pelicans']
['SF']
['Boston Celtics']
['PF']
['Memphis Grizzlies']
['PF']
['Milwaukee Bucks']
['SG']
['Minnesota Timberwolves']
['SG']
['Minnesota Timberwolves']
['PG']
['Sacramento Kings']
['C']
['Indiana Pacers']
['PF']
['Golden State Warriors']
['PG']
['LA Clippers']
['PG']
['Denver Nuggets']
['SG']
['New Orleans Pelicans']
['PF']
['Miami Heat']
['SG']
['Washington Wizards']
['PG']
['New York Knicks']
['PG']
['Boston Celtics']
['SG']
['Memphis Grizzlies']
['SG']
['Brooklyn Nets']
['PF']
['Washington Wizards']
['PF']
['Toronto Raptors']
['PF']
['Golden State Warriors']
```

```
['SG']
['Portland Trail Blazers']
['SG']
['Washington Wizards']
['SG']
['Toronto Raptors']
['PF']
['Detroit Pistons']
['C']
['Brooklyn Nets']
['PG']
['Portland Trail Blazers']
['PF']
['New York Knicks']
['PG']
['Charlotte Hornets']
['SG']
['Washington Wizards']
['SF']
['Memphis Grizzlies']
['PG']
['LA Clippers']
['SG']
['Portland Trail Blazers']
['PF']
['Indiana Pacers']
['SF']
['Utah Jazz']
['SG']
['Brooklyn Nets']
['SG']
['Los Angeles Lakers']
['SF']
['Washington Wizards']
['SF']
['Milwaukee Bucks']
['PF']
['Phoenix Suns']
['SG']
['Charlotte Hornets']
['SG']
['Detroit Pistons']
['SG']
['Toronto Raptors']
['PG']
['LA Clippers']
['PG']
['Toronto Raptors']
['SF']
['Philadelphia 76ers']
['SF']
['Dallas Mavericks']
['C']
['Dallas Mavericks']
['PG']
['Indiana Pacers']
['SG']
['Milwaukee Bucks']
['PG']
['Detroit Pistons']
['PF']
```

```
['LA Clippers']
['PG']
['Brooklyn Nets']
['C']
['San Antonio Spurs']
['SG']
['Detroit Pistons']
['PG']
['Golden State Warriors']
['PG']
['Orlando Magic']
['SF']
['Charlotte Hornets']
['C']
['Los Angeles Lakers']
['C']
['Detroit Pistons']
['C']
['Indiana Pacers']
['PG']
['Boston Celtics']
['PF']
['Golden State Warriors']
['PF']
['Detroit Pistons']
['PG']
['Denver Nuggets']
['C']
['Miami Heat']
['C']
['Los Angeles Lakers']
['SG']
['Phoenix Suns']
['PG']
['Minnesota Timberwolves']
['PG']
['Utah Jazz']
['PF']
['Charlotte Hornets']
['PG']
['Houston Rockets']
['PF']
['Atlanta Hawks']
['SG']
['Dallas Mavericks']
['SF']
['Cleveland Cavaliers']
['SG']
['Chicago Bulls']
['C']
['Charlotte Hornets']
['SG']
['Washington Wizards']
['SG']
['LA Clippers']
['C']
['Boston Celtics']
['SF']
['Chicago Bulls']
['PF']
['Dallas Mavericks']
```

```
['PG']
['Philadelphia 76ers']
['SG']
['Milwaukee Bucks']
['SG']
['Indiana Pacers']
['SG']
['Oklahoma City Thunder']
['PG']
['San Antonio Spurs']
['SF']
['New York Knicks']
['SF']
['New Orleans Pelicans']
['PF']
['LA Clippers']
['SF']
['Los Angeles Lakers']
['SF']
['Cleveland Cavaliers']
['SG']
['Sacramento Kings']
['PG']
['Dallas Mavericks']
['PF']
['Los Angeles Lakers']
['PG']
['Houston Rockets']
['C']
['Chicago Bulls']
['PG']
['Cleveland Cavaliers']
['C']
['Utah Jazz']
['PG']
['Miami Heat']
['C']
['Detroit Pistons']
['PF']
['Toronto Raptors']
['PG']
['Oklahoma City Thunder']
['C']
['Milwaukee Bucks']
['SF']
['San Antonio Spurs']
['SG']
['Oklahoma City Thunder']
['PF']
['Philadelphia 76ers']
['C']
['Sacramento Kings']
['PG']
['New York Knicks']
['PF']
['Washington Wizards']
['C']
['Dallas Mavericks']
['C']
['Houston Rockets']
['PG']
```

```
['San Antonio Spurs']
['PG']
['Philadelphia 76ers']
['C']
['Indiana Pacers']
['SF']
['Phoenix Suns']
['PF']
['New York Knicks']
['SG']
['Orlando Magic']
['PG']
['New Orleans Pelicans']
['PF']
['Atlanta Hawks']
['C']
['Cleveland Cavaliers']
['PF']
['Philadelphia 76ers']
['PG']
['Denver Nuggets']
['PF']
['New Orleans Pelicans']
['PG']
['Miami Heat']
['PF']
['New York Knicks']
['PG']
['Houston Rockets']
['SF']
['Orlando Magic']
['C']
['Cleveland Cavaliers']
['PF']
['Sacramento Kings']
['SG']
['Minnesota Timberwolves']
['PF']
['Miami Heat']
['PF']
['Houston Rockets']
['PF']
['New York Knicks']
['C']
['Orlando Magic']
['SF']
['Charlotte Hornets']
['PF']
['Cleveland Cavaliers']
['SG']
['Denver Nuggets']
['SG']
['New Orleans Pelicans']
['PF']
['New Orleans Pelicans']
['C']
['Miami Heat']
['SF']
['Golden State Warriors']
['PF']
['New York Knicks']
```

```
['PF']
['Portland Trail Blazers']
['SG']
['Memphis Grizzlies']
['SG']
['Denver Nuggets']
['PG']
['Brooklyn Nets']
['PF']
['Memphis Grizzlies']
['PF']
['New York Knicks']
['SG']
['Charlotte Hornets']
['C']
['Milwaukee Bucks']
['PG']
['Miami Heat']
['SG']
['Boston Celtics']
['PF']
['Washington Wizards']
['PG']
['Milwaukee Bucks']
['PF']
['Utah Jazz']
['C']
['Minnesota Timberwolves']
['SF']
['Dallas Mavericks']
['PF']
['Washington Wizards']
['PF']
['Sacramento Kings']
['PF']
['Charlotte Hornets']
['PF']
['Chicago Bulls']
['PG']
['Houston Rockets']
['PG']
['Cleveland Cavaliers']
['PG']
['Brooklyn Nets']
['SG']
['Toronto Raptors']
['PG']
['Phoenix Suns']
['SF']
['Orlando Magic']
['PG']
['Oklahoma City Thunder']
['SF']
['LA Clippers']
['SG']
['Memphis Grizzlies']
['SF']
['Los Angeles Lakers']
['SF']
['Oklahoma City Thunder']
['SG']]
```

```
[[0. 0. 0. ... 0. 0. 0.]

[0. 0. 0. ... 0. 0. 0.]

[0. 0. 0. ... 0. 0. 1.]

...

[0. 0. 0. ... 0. 0. 0.]

[0. 0. 0. ... 0. 0. 0.]
```

6.3 Escalonamento das características

6.3.1 Normalização

In [754]:

```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
nba_num_normalized=scaler.fit_transform(nba_num) #NormLizado

nba_num_normalized
```

Out[754]:

```
array([[0.31578947, 0.22222222, 0.0782241 , ..., 0.56521739, 0.525 , 0.68441065],
[0. , 0.77777778, 0.63482606, ..., 0.04347826, 0.025 , 0.02281369],
[0. , 0.11111111, 0.13030944, ..., 0.30434783, 0.325 , 0.2661597 ],
...,
[0.42105263, 0.666666667, 0.43474918, ..., 0.26086957, 0.25 , 0.26996198],
[0.47368421, 0.666666667, 0.52162214, ..., 0.26086957, 0.425 , 0.4486692 ],
[0.21052632, 0.55555556, 0.30424755, ..., 0.39130435, 0.15 , 0.14068441]])
```

6.3.2 Padronização

In [755]:

```
from sklearn.preprocessing import StandardScaler # Bom para outliers, ruim para redes n
eurais

scaler=StandardScaler()
nba_num_standardized=scaler.fit_transform(nba_num)

nba_num_standardized
```

Out[755]:

```
array([[ 0.340599 , -1.78246822, -1.48638384, ..., 1.39275141, 1.07285695, 1.83061476], [-1.10892698, 1.14511825, 1.18174019, ..., -1.65051436, -1.68501385, -1.62756789], [-1.10892698, -2.36798552, -1.23670787, ..., -0.12888147, -0.03029137, -0.35559267], ..., [ 0.82377433,  0.55960096,  0.22265279, ..., -0.38248695, -0.44397199, -0.33571805], [ 1.06536199,  0.55960096,  0.63908651, ..., -0.38248695,  0.52128279,  0.59838876], [ -0.14257633, -0.02591634, -0.40291911, ...,  0.37832949, -0.99554615, -1.01145489]])
```

6.4 Pipelines de Transformação

In [756]:

```
nba=strat_train_set.drop('SALARY', axis=1) #X
#nba_num=nba.drop(['TEAM','NAME','POSITION','AGE','FGM_FGA','THM_THA','FTM_FTA'], axis=
1)
nba_num=nba[['PPG_LAST_SEASON','PER_LAST_SEASON', 'TOPG','MPG']]
#nba_num
nba_cat=nba[['TEAM','POSITION']]
nba_num
```

Out[756]:

	PPG_LAST_SEASON	PER_LAST_SEASON	TOPG	MPG
401	22.1	20.62	2.1	33.9
444	1.5	9.89	0.1	4.8
187	7.9	13.02	1.3	18.9
351	6.3	15.18	1.0	16.9
539	11.5	14.42	1.3	23.0
503	8.4	16.19	1.0	21.9
135	3.9	8.22	0.7	15.8
319	5.7	15.56	1.0	20.7
139	13.2	17.89	1.7	23.4
508	5.0	10.90	0.6	22.5

305 rows × 4 columns

6.4.1 Pipeline para atributos numéricos

In [757]:

Out[757]:

6.4.2 Pipeline para atributos categóricos

```
In [758]:
```

Out[758]:

6.4.3 Pipeline para atributos numéricos e categóricos

In [759]:

```
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
num_attribs=["MPG", "PPG_LAST_SEASON", "PER_LAST_SEASON", "TOPG"]
cat_attribs=['TEAM', 'POSITION']
num_pipeline=Pipeline([('imputer', SimpleImputer(strategy="mean")),
                        ('scaler', StandardScaler())])
cat_pipeline=Pipeline([('imputer', SimpleImputer(strategy="constant",fill_value="missin")
g")),
                       ('encoder', OneHotEncoder(sparse=False))])
full_pipeline=ColumnTransformer(transformers=[('num_pipeline', num_pipeline, num_attrib
s),
                                              ('cat pipeline', cat pipeline, cat attrib
s)])
nba prepared=full_pipeline.fit_transform(nba)
print(nba_prepared.shape)
nba_prepared
(305, 41)
Out[759]:
                   , 2.03628394, 1.27900858, ..., 1.
array([[ 1.49332
                     0.
       [-2.429247, -1.47468532, -0.90219289, ..., 0.
                                ],
       [-0.52862176, -0.38389876, -0.26592443, ..., 1.
                   , 0.
                                ],
         0.
       [-0.28598875, -0.75885664, 0.25040845, ...,
                      0.
```

7. Selecionar e treinar o modelo de AM

, 0.

1.

7.1 Treinando e avaliando o conjunto de treinamento

0.51940887, 0.72405238, ..., 0.

], [-0.04335573, -0.87816142, -0.69687942, ..., 0.

11)

[0.07796077,

7.1.1 Modelo de Regressão Linear

$$\hat{y} = h_{oldsymbol{ heta}}(\mathbf{x}) = oldsymbol{ heta}^T \cdot \mathbf{x} = heta_0 + heta_1 x_1 + \cdots + heta_n x_n \ oldsymbol{ heta} = egin{bmatrix} heta_0 \ heta_1 \ dots \ heta_n \end{bmatrix} & \mathrm{e} \quad \mathbf{x} = egin{bmatrix} 1 \ x_1 \ dots \ x_n \end{bmatrix}$$

Aqui:

- n é o número de características de cada instância;
- θ é o vetor de parâmetros de característica;
- x é o vetor de características de instância:
- \hat{y} é o vetor de rótulos da i-ésima instância;
- $h_{\theta}(\mathbf{x})$ é a função predição (Hipótese).

Método dos mínimos quadrados:

$$\hat{oldsymbol{ heta}} = (\mathbf{X}^T \cdot \mathbf{X})^{-1} \cdot \mathbf{X}^T \cdot \mathbf{y}$$

In [760]:

```
from sklearn.linear_model import LinearRegression
lin_reg=LinearRegression()
lin_reg.fit(nba_prepared,nba_labels)
print(lin_reg.get_params())
```

```
{'copy_X': True, 'fit_intercept': True, 'n_jobs': None, 'normalize': Fals
e}
```

In [761]:

```
from sklearn.metrics import mean_squared_error

nba_predicted = lin_reg.predict(nba_prepared)
lin_reg_rmse=np.sqrt(mean_squared_error(nba_labels, nba_predicted))
print(lin_reg_rmse) #underfitting
```

5.722186186423075

7.1.2 Árvore de Decisão

In [762]:

```
from sklearn.tree import DecisionTreeRegressor

dec_tree_reg=DecisionTreeRegressor()

dec_tree_reg.fit(nba_prepared, nba_labels)
dec_tree_rmse=np.sqrt(mean_squared_error(nba_labels, nba_predicted))

print(dec_tree_reg.get_params())
print(dec_tree_rmse)

{'ccn_alpha': 0 0 _'criterion': 'mse'. 'max_denth': None. 'max_features':
```

```
{'ccp_alpha': 0.0, 'criterion': 'mse', 'max_depth': None, 'max_features': None, 'max_leaf_nodes': None, 'min_impurity_decrease': 0.0, 'min_impurity_ split': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'min_weight_f raction_leaf': 0.0, 'presort': 'deprecated', 'random_state': None, 'splitt er': 'best'}
5.722186186423075
```

7.1.3 Floresta Aleatória

In [763]:

```
from sklearn.ensemble import RandomForestRegressor

rand_forest_reg=RandomForestRegressor()

rand_forest_reg.fit(nba_prepared, nba_labels)
rand_forest_reg_rmse=np.sqrt(mean_squared_error(nba_labels, nba_predicted))

print(rand_forest_reg_rmse) # Overfitting?
print(rand_forest_reg.get_params())
```

5.722186186423075

```
{'bootstrap': True, 'ccp_alpha': 0.0, 'criterion': 'mse', 'max_depth': Non e, 'max_features': 'auto', 'max_leaf_nodes': None, 'max_samples': None, 'm in_impurity_decrease': 0.0, 'min_impurity_split': None, 'min_samples_lea f': 1, 'min_samples_split': 2, 'min_weight_fraction_leaf': 0.0, 'n_estimat ors': 100, 'n_jobs': None, 'oob_score': False, 'random_state': None, 'verb ose': 0, 'warm_start': False}
```

7.2 Validação Cruzada

7.2.1 Conjunto de Validação

In [764]:

```
from sklearn.model_selection import train_test_split
test_size=0.2 # tamanho do conjunto de teste: 20%
random state=42
strat_train_set0, strat_test_set0=train_test_split(df,
                                                    test_size=test_size,
                                                     random_state=random_state,
                                                     stratify=df['EFICIENCIA_CAT'])
valid size=0.25 # tamanho do conjunto de validação: 25% de 80% -> 20% de 100%
random_state=24
strat_train_set0, strat_valid_set0=train_test_split(strat_train_set0,
                                                    test_size=valid_size,
                                                    random_state=random_state,
                                                     stratify=strat_train_set0['EFICIENC
IA_CAT'])
strat_train_set0=strat_train_set0.drop('EFICIENCIA_CAT', axis=1)
strat_valid_set0=strat_valid_set0.drop('EFICIENCIA_CAT', axis=1)
strat_test_set0=strat_test_set0.drop('EFICIENCIA_CAT',axis=1)
print(strat_train_set0)
print(strat_valid_set0)
print(strat_test_set0)
```

384 372 254 444 258 519 214 418 292 61	Portlan Clev	Atlant Indiana hington Indiana d Trail eland Ca Mia	Pacers Blazers valiers mi Heat vericks	Kent Domanta Thom Thado CJ k Dw Dennis	Poyth Baze Sab Bas Br Beus Y McCo Cevin Jyane	ress more onis yant oung llum Love Wade Jr.	EXPERIE	NCE PO 2 6 2 1 11 5 10 15 1	SITION SF SG PF C PF SG PF SG PF	AGE 25 29 22 21 30 27 30 36 20 23	\
	НТ	WT	SALAF	RY PPG_	LAST_	SEASON	APG_L	AST_SE	ASON .		F
GP 384	\ 205.74	106.33	1.54495	51		1.0			0.1 .		0.4
50 372	195.58	90.95	18.08988	37		12.9			3.5 .	• •	0.4
22 254	210.82	108.60	2.65986	00		11.6			7.7 .		0.4
66 444	210.82	112.22	1.37824	12		1.5			1.1 .		0.3
81 258	203.20	100.00	13.96404	15		11.8			6.3 .	• •	0.4
99 ••				•							
519	190.50	85.97	25.75976	56		21.4			3.4 .		0.4
54 214	208.28	113.57	24.11902	25		17.6			9.3 .		0.4
44 418	193.04	99.55	1.51260	91		11.4			3.4 .		0.4
83 292	190.50	88.24	3.81996	50		15.2			5.2 .		0.3
95 61 44	205.74	113.12	1.51260)1		4.9			5.8 .	• •	0.4
	THM_THA		_				STLPG				
384		0.333			0.2	0.1		0.2			
372 254		0.360 0.327			1.8 1.5	0.4 0.4		1.4 1.4	8.2 8.6		
444		0.100		0.556	0.4	0.1		0.1	1.5		
258	0.4-1.3	0.326	1.4-2.1	0.675	1.6	0.4	1.5	1.4	13.4		
 519	1.9-4.7	0.408	2.2-2.6	0.842	2.9	0.3		 1.8	 17.2		
214		0.370			2.3	0.5		1.9			
418		0.287			5.5	0.9		3.2			
292		0.313				0.3		2.8			
61	0.2-0.6	0.297	0.7-1.0	0.664	0.4	0.3	0.3	0.7	4.1		
[228 rows x 28 columns] TEAM NAME EXPERIENCE POSITION AGE \											
196		Chicag	o Bulls		Kris			2	PG	24	`
67	Phi	_	a 76ers		el Em			2	C	24	
42		-	Knicks		Ron B			2	SG	25	
22		Brook1	yn Nets	All	en Cr	abbe		5	SG	26	
47			Knicks	Tim Har	daway			5	G	26	
 489	Minneso	ta Timbo	rwolves	٦٥	eff Te	ague		9	PG	30	
32	HITHIIC20		yn Nets		is Le	_		2	SG	24	
			,			- · •		_			

78 413 119	Phi	Mia	a 76ers ami Heat Clippers	Rodney	/ McGru	ıder		1 2 6	P(S(P(G 2	7
CD	НТ	WT	SALAR	XY PPG_	_LAST_S	EASON	APG_L	AST_SE	ASON	• • •	F
GP 196 13		92.76	4.22100	00		13.4			6.0	• • •	0.4
67 78	213.36	113.12	25.46725	50		22.9			11.0	• • •	0.4
42 70	193.04	99.55	4.54400	00		2.4			1.6	• • •	0.3
22 39	198.12	95.93	18.50000	00		13.2			1.6	• • •	0.4
47 25	198.12	92.76	17.32500	00		17.5			2.7	• • •	0.4
• •	•••	• • •		•		•••			•••	• • •	
489 47	187.96	88.24	19.00000	00		14.2			7.0	• • •	0.4
32 40	200.66	92.31	1.70280	00		12.1			4.2	• • •	0.4
78 45	208.28	104.07	6.43452	20		15.8			8.2	• • •	0.5
413 24	193.04	90.50	1.54495	51		5.1			0.9		0.4
119 13	185.42	83.71	5.02702	28		12.2			2.9	•••	0.4
	THM_THA		FTM_FTA				STLPG		PPG		
196	0.5-1.6					0.5		1.8	7.6		
67			5.9-7.6				0.7				
42	0.4-1.5						0.7	0.9	3.5		
22	1.6-4.0						0.6		9.5		
47	1.7-5.0	0.344	1.7-2.2	0.806	1.7	0.2	0.6	1.0	12.1		
400		0 257		0 044	 - 7	0.3	1 2		12.7		
489 32			2.8-3.3 1.6-2.2			0.3		2.3 1.7	12.7 10.4		
32 78			2.4-4.2			0.9		3.4			
			0.5-0.8				0.6		6.1		
119			1.0-1.3						9.4		
	rows x 2			0.707	3.1	0.4	1.3	,	3.4		
HT			TEAM		NAM	IE EXF	PERIENC	E POSI	TION A	AGE	
537	1	Uta	ah Jazz	Rudy	/ Gober	t		5	С	26	215.
90 198		Chicago	Bulls	Justin	Holida	y		5	SG	29	198.
12 167		Phoeni	x Suns	Richaur	n Holme	!S		3	PF	24	208.
28 53	N	ew York	Knicks	Luke	e Korne	et		1	PF	23	215.
90 545		Uta	ah Jazz	George	es Nian	g		2	SF	25	203.
20			•••	J-						• •	
 261	М	ilwaukee	Bucks M	Malcolm				2	PG	25	195.
58 383	ru.		a Hawks		_			6	C	30	210.
82		ACTUILC	1 HUWNS	111163	. Tuille			•	C	50	210.

```
26/03/2020
                                                    NBA ESPN
                Brooklyn Nets
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                                                                    PG 27
                                                                             185.
                                 Shabazz Napier
   42
   500
       Oklahoma City Thunder
                                 Raymond Felton
                                                           13
                                                                    PG
                                                                         34
                                                                             185.
   42
   11
                Boston Celtics
                                  Marcus Morris
                                                            7
                                                                    PF
                                                                         29
                                                                             205.
   74
            WT
                           PPG_LAST_SEASON APG_LAST_SEASON ...
                                                                             THM
                    SALARY
                                                                        FGP
   THA
        \
   537
        110.86
                23.241573
                                        13.5
                                                          10.7 ...
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                                                                     0.614
   0.0
   198
         81.90
                 4.384616
                                        12.2
                                                           2.1
                                                                      0.392 1.2-
   3.5
   167
                 1.600520
                                         6.5
                                                           4.4
                                                                     0.547 0.3-
        106.33
   1.0
                                                           3.2
   53
        113.12
                 1.619260
                                         6.7
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   4.0
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        104.07
                  1.512601
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                                                                      0.277 0.0-
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        103.62
                 1.544951
                                        13.0
                                                           3.2
                                                                . . .
                                                                     0.469
                                                                            1.1-
   2.9
                                                           4.1
                                                                     0.537
   383
        112.67
                12.500000
                                         4.3
                                                                . . .
                                                                             0.0-
   0.0
   35
         81.45
                 1.942422
                                         8.7
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                                                                . . .
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         92.76
                 1.512601
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                                                           2.5 ...
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        106.33
                 5.375000
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   3.6
          THP
               FTM FTA
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                                APG
                                     BLKPG STLPG TOPG
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       0.000
               2.7-4.3 0.629
                                1.2
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                                                          10.0
   537
   198
       0.350
               1.0-1.2 0.811
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                                                           7.4
   167
                         0.687
                                                           7.4
       0.257
               1.0-1.5
                                1.0
                                        0.8
                                              0.5
                                                    0.7
   53
        0.354
               0.4-0.6 0.727
                                1.3
                                        0.8
                                              0.3
                                                    0.6
                                                           6.7
   545
       0.063
               0.1-0.1
                        0.750
                                        0.0
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                                                           0.9
                                0.3
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   261
       0.395
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                                                           4.9
   383
       0.000
               0.6-1.0
                        0.544
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                                        0.8
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   35
        0.363
               1.0-1.2
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                                        0.1
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               1.8-2.3
                        0.789
                                5.4
                                        0.2
                                              1.2
                                                     2.1
                                                          11.4
        0.357
               1.6-2.1 0.731
                                1.5
                                              0.7
                                                          11.2
   11
                                        0.2
                                                     1.2
   [77 rows x 28 columns]
```

In [765]:

```
nba=strat_train_set.drop('SALARY', axis=1) # X
nba_labels=strat_train_set['SALARY'].copy() # y
nba_prepared=full_pipeline.transform(nba)
```

In [798]:

```
# Método criado para avaliar e mostrar a predição do modelo
def RegEvaluation(model, player, predict=True):
    #player_data = player_data.iloc[0:0]
    #sc_data

#player_data = nba.iloc[0:0]
#df_player

player_data=nba[nba.NAME == player]
#player_data

player_data_prepared=full_pipeline.transform(player_data)
player_data_predicted= round(model.predict(player_data_prepared)[0],6)
df_player = df.loc[df.NAME==player]
df_player['SALARIO_PREVISTO'] = player_data_predicted

#df_stephen = df.loc[df.NAME == 'Stephen Curry']
if predict:
    return df_player[['NAME', 'SALARY', 'SALARIO_PREVISTO']]
```

7.2.2.1 Regressão Linear

In [767]:

```
from sklearn.linear model import LinearRegression
from sklearn.model selection import cross val score
lin reg=LinearRegression()
scores=cross_val_score(lin_reg,
                     nba_prepared,
                     nba_labels,
                     scoring='neg_mean_squared_error', # cross_val_score expects a ut
ility function
                     cv=4)
lin reg rmse score=np.sqrt(-scores)
print(lin_reg_rmse_score)
print(lin_reg_rmse_score.mean())
print(lin reg rmse score.std())
## Predicão:
lin_reg.fit(nba_prepared, nba_labels)
#full_pipeline.transform(player_data)
RegEvaluation(lin_reg, 'Stephen Curry')
```

```
[1.37090750e+11 8.94337157e+11 6.37584419e+00 6.57184225e+00] 257856976737.6353 371709544680.20135
```

C:\Users\Thiago\Anaconda3\lib\site-packages\ipykernel_launcher.py:14: Sett
ingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

Out[767]:

NAME SALARY SALARIO_PREVISTO

103 Stephen Curry 37.457154 25.464844

7.2.2.2 Árvore de Decisão

In [768]:

```
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import cross_val_score
dec_tree_reg=DecisionTreeRegressor()
scores=cross_val_score(dec_tree_reg,
                      nba_prepared,
                      nba_labels,
                      scoring='neg_mean_squared_error',
                      cv=4)
dec_tree_reg_rmse_score=np.sqrt(-scores)
print(dec_tree_reg_rmse_score)
print(dec_tree_reg_rmse_score.mean())
print(dec_tree_reg_rmse_score.std())
## Predição:
dec_tree_reg.fit(nba_prepared, nba_labels)
RegEvaluation(dec_tree_reg, 'Stephen Curry')
```

```
[6.63285863 8.17311036 8.37852431 7.78784313]
7.743084108790161
0.6751501353379792
```

C:\Users\Thiago\Anaconda3\lib\site-packages\ipykernel_launcher.py:14: Sett
ingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

Out[768]:

NAME SALARY SALARIO_PREVISTO

103 Stephen Curry 37.457154

37.457154

7.2.2.3 Floresta Aleatória

In [769]:

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import cross_val_score
rand_forest_reg=RandomForestRegressor()
scores=cross_val_score(rand_forest_reg,
                       nba_prepared,
                       nba_labels,
                       scoring='neg_mean_squared_error',
                       cv=4)
rand_forest_reg_rmse_score=np.sqrt(-scores)
print(rand_forest_reg_rmse_score)
print(rand_forest_reg_rmse_score.mean())
print(rand_forest_reg_rmse_score.std()) # Bem melhor, mas ainda overfittando.
##########################
## Predição:
rand_forest_reg.fit(nba_prepared,nba_labels)
RegEvaluation(rand_forest_reg, 'Stephen Curry')
```

```
[6.10254896 6.49826555 5.58744136 6.17003873]
6.089573651034548
0.3262701684963087
```

C:\Users\Thiago\Anaconda3\lib\site-packages\ipykernel_launcher.py:14: Sett
ingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

Out[769]:

NAME SALARY SALARIO_PREVISTO

103 Stephen Curry 37.457154

33.171267

8. Ajuste do modelo

8.1 Grid Search

In [770]:

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model selection import GridSearchCV
rand forest reg=RandomForestRegressor()
param_grid=[{'n_estimators':[3,10,30], 'max_features':[2,4,6,8]}, #3x4=12
            {'bootstrap':[False], 'n_estimators':[3,10], 'max_features':[2,3,4]}] # 1x2
x3=6
grid search=GridSearchCV(rand forest reg,
                         param grid,
                         scoring='neg mean squared error',
                         refit=True,
                         cv=5,
                         return_train_score=True) # 12+6=18
grid search.fit(nba_prepared, nba_labels) # 18*5=90 rounds de treino.
print(grid_search.best_params_)
######### Predição:
RegEvaluation(grid_search, 'Stephen Curry')
```

```
{'max_features': 8, 'n_estimators': 30}
```

C:\Users\Thiago\Anaconda3\lib\site-packages\ipykernel_launcher.py:14: Sett
ingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

Out[770]:

NAME SALARY SALARIO_PREVISTO

103 Stephen Curry 37.457154

31.842928

In [771]:

```
rand_forest_reg=grid_search.best_estimator_ # methor modelo treinado em todo o conjunt
o.

#print(rand_forest_reg.get_params())
rand_forest_reg.fit(nba_prepared, nba_labels)
RegEvaluation(rand_forest_reg, 'Stephen Curry')
```

C:\Users\Thiago\Anaconda3\lib\site-packages\ipykernel_launcher.py:14: Sett
ingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

Out[771]:

NAME SALARY SALARIO PREVISTO

103 Stephen Curry 37.457154

32.710702

In [772]:

```
d=grid search.cv results
for mean_train_score, mean_test_score, params in zip(d['mean_train_score'], d['mean_test_score'])
t score'],d['params']):
    print(np.sqrt(-mean_train_score), np.sqrt(-mean_test_score), params)
3.698578677256702 7.743906023598103 {'max_features': 2, 'n_estimators': 3}
2.966646468018949 6.979407491493342 {'max_features': 2, 'n_estimators': 1
0}
2.550081889208129 6.528543790935954 {'max_features': 2, 'n_estimators': 3
3.5986670682946387 7.295956508293055 {'max features': 4, 'n estimators':
3}
2.727464141831927 6.728324229940121 {'max_features': 4, 'n_estimators': 1
0}
2.4742108095502635 6.40596043319244 {'max_features': 4, 'n_estimators': 3
3.5269428558489277 7.44668702933789 {'max_features': 6, 'n_estimators': 3}
2.7718120358177316 6.777053444041929 {'max_features': 6, 'n_estimators': 1
2.4345175318231322 6.430832255342448 {'max_features': 6, 'n_estimators': 3
0}
3.6463785341470953 7.5371374364379164 {'max_features': 8, 'n_estimators':
2.7853437447962803 6.4986533143240335 {'max_features': 8, 'n_estimators':
2.4369536491321897 6.270791588702372 {'max_features': 8, 'n_estimators': 3
0}
9.543305649517192e-09 7.461379493462362 {'bootstrap': False, 'max_feature
s': 2, 'n estimators': 3}
1.6405466901551136e-07 6.966147044774636 {'bootstrap': False, 'max_feature
s': 2, 'n_estimators': 10}
7.730666583738068e-07 7.769642141520165 {'bootstrap': False, 'max_feature
s': 3, 'n_estimators': 3}
4.0173972760727997e-07 6.832299760125102 {'bootstrap': False, 'max_feature
s': 3, 'n estimators': 10}
5.467656181278783e-07 7.143858379778542 {'bootstrap': False, 'max_feature
s': 4, 'n estimators': 3}
2.3227315745184477e-07 6.708908140642286 {'bootstrap': False, 'max_feature
s': 4, 'n_estimators': 10}
```

8.2 Randomized Search

In [773]:

```
import numpy as np
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import RandomizedSearchCV
rand forest reg=RandomForestRegressor()
param_grid=[{'n_estimators': np.arange(100), 'max_features': np.arange(1,10)},
            {'bootstrap':[False], 'n_estimators': np.arange(50), 'max_features': np.ara
nge(1,10)}] # 1x50x9=450
randomized_search=RandomizedSearchCV(rand_forest_reg,
                                     param_grid,
                                     n_iter=10, # Numero de iterações
                                     scoring='neg_mean_squared_error',
                                     refit=True.
                                     cv=10,
                                     random state=42,
                                     return_train_score=True) #900+450=1350
randomized_search.fit(nba_prepared, nba_labels) #1350*10=13500 rodadas de treinamento.
print(randomized search.best params )
RegEvaluation(randomized search, 'Stephen Curry')
```

```
{'n_estimators': 66, 'max_features': 5}
```

C:\Users\Thiago\Anaconda3\lib\site-packages\ipykernel_launcher.py:14: Sett
ingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

Out[773]:

NAME SALARY SALARIO_PREVISTO

103 Stephen Curry 37.457154

33.473709

In [779]:

```
rand_forest_reg=randomized_search.best_estimator_ # melhor modelo treinado em todo o co
njunto de treinamento

#print(rand_forest_reg.get_params())
rand_forest_reg.fit(nba_prepared, nba_labels)
df_predict = RegEvaluation(randomized_search, 'Stephen Curry')
df_predict

C:\Users\Thiago\Anaconda3\lib\site-packages\ipykernel_launcher.py:14: Sett
ingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

Out[779]:

NAME SALARY SALARIO_PREVISTO

103 Stephen Curry 37.457154 31.990118

In [775]:

```
d=randomized_search.cv_results_
for mean_train_score, mean_test_score, params in zip(d['mean_train_score'],d['mean_test
_score'], d['params']):
    print(np.sqrt(-mean_train_score), np.sqrt(-mean_test_score), params)
4.121519440739094e-07 6.4536623390772885 {'n_estimators': 26, 'max_feature
s': 5, 'bootstrap': False}
2.3680797796284114 6.241351009624532 {'n_estimators': 60, 'max_features':
3.5144361563631266e-07 6.295403583709484 {'n estimators': 44, 'max feature
s': 8, 'bootstrap': False}
2.422171173928614e-07 6.380736709400406 {'n_estimators': 30, 'max_feature
s': 5, 'bootstrap': False}
2.1780977958488306e-07 6.4300794022093415 {'n_estimators': 45, 'max_featur
es': 4, 'bootstrap': False}
1.9397949910375987e-07 6.272882363213412 {'n estimators': 44, 'max feature
s': 3, 'bootstrap': False}
2.586619436716584 6.506025482708783 {'n estimators': 21, 'max features':
2}
2.3664453556713965 6.140592292811336 {'n_estimators': 66, 'max_features':
3.436579280654067e-07 6.464522977071286 {'n estimators': 38, 'max feature
s': 7, 'bootstrap': False}
2.5042745453342334 6.4416413329084605 {'n_estimators': 30, 'max_features':
4}
```

9. Salário do Stephen Curry é justo?

```
In [796]:
```

```
# Buscando salário real do Stephen Curry
salario_real = df[df.NAME == 'Stephen Curry'].SALARY
print(salario_real)
```

103 37.457154

Name: SALARY, dtype: float64

In [797]:

```
# Salário previsto pelo modelo print(df_predict.SALARIO_PREVISTO)
```

103 31.990118

Name: SALARIO_PREVISTO, dtype: float64

In [790]:

```
# Diferença de 5.467036
dif = salario_real - df_predict.SALARIO_PREVISTO
dif
```

Out[790]:

103 5.467036 dtype: float64

In [791]:

```
# Diferença de 15% na previsão
difPercent = round(dif/salario_real * 100,00)
difPercent
```

Out[791]:

103 15.0
dtype: float64

10. Conclusão

Foi selecionado o modelo de Floresta Aleatória com o melhor estimador da busca randomizada.

Resultado da análise do SAM: É possível deduzir que o salário de Stephen Curry está acima do que seria o valor justo, de acordo com o que foi previsto no modelo.