Mineração de Dados

Conjunto de dados: Diamonds Prices

https://www.kaggle.com/datasets/nancyalaswad90/diamonds-prices

Marcos Geraldo Braga Emiliano 19.1.4012

Contexto geral dos dados: Dados relativos a 53,940 diamantes de corte redondo negociados em 2022, onde são descritas 10 caracteristicas sobre eles, carat, cut, color, clarity, depth, table, price, x, y, e z, descrição detalhada a frente.

Carregando os dados:

```
from google.colab import drive
drive.mount('/content/drive')
import pandas as pd
import numpy as np
import math
import pylab as plt
import seaborn as sns
from scipy import stats
from pandas.api.types import is_string_dtype
from pandas.api.types import is_numeric_dtype
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn import preprocessing
from sklearn.preprocessing import PolynomialFeatures
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import metrics
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.linear_model import ElasticNet
from sklearn.ensemble import RandomForestRegressor

%matplotlib inline
```

```
    Mounted at /content/drive
```

```
data = pd.read_csv('/content/drive/My Drive/TPDataMining/DiamondsPrices2022.csv')
```

```
data.shape
```

```
(53943, 11)
```

Removendo uma coluna com valores de indice

```
data.drop('Unnamed: 0', axis=1, inplace=True)
```

```
numData = data.select_dtypes('number')
catData = data.select_dtypes('O')
for c in catData.columns:
    print(catData[c].unique())
```

```
['Ideal' 'Premium' 'Good' 'Very Good' 'Fair']
['E' 'I' 'J' 'H' 'F' 'G' 'D']
['SI2' 'SI1' 'VS1' 'VS2' 'VVS2' 'VVS1' 'I1' 'IF']
```

```
instances, features = data.shape
```

Pequeno Exemplo:

```
data.head(20)
```

	carat	cut	color	clarity	depth	table	price	x	y	z
0	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43
1	0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31
2	0.23	Good	E	VS1	56.9	65.0	327	4.05	4.07	2.31
3	0.29	Premium	I	VS2	62.4	58.0	334	4.20	4.23	2.63

Descrição dos Atributos:

1) index - indice numerico que indentifica a entidade, dado Discreto

2) carat - quilate, unidade de medida baseada no peso, dado Continuo

3) cut - classificação do corte da pedra preciosa, dado categorico

4) color - cor da pedra, dado categorico

5) clarity - clareza da pedra, dado categorico

6) depth - "altura" da pedra, continuo

7) table - "largura" do topo da pedra, continuo

8) price - preço da pedra em dolar, continuo

9) x - medida no eixo x da pedra em mm, continuo

10) y - medida no eixo y da pedra em mm, continuo

11) z - medida no eixo z da pedra em mm, continuo

Avaliando os valores contidos no banco de dados:

Quilate

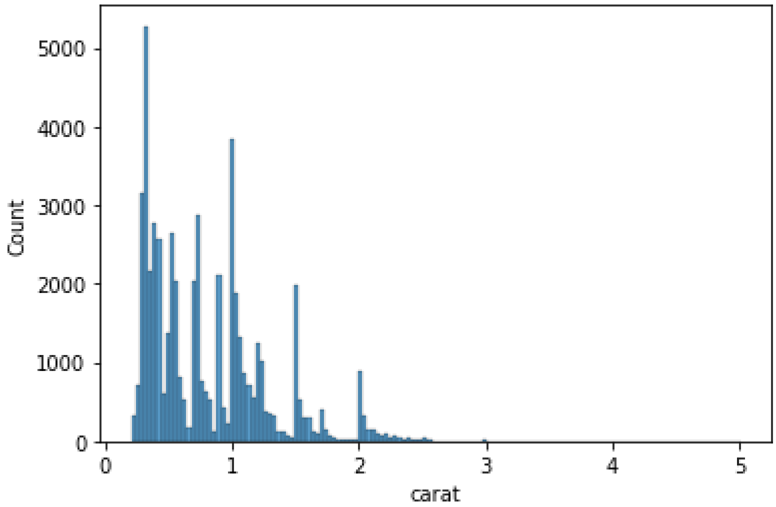
```
min = np.min(data['carat'])
max = np.max(data['carat'])
```

```
media = sum(data['carat'])/instances
desv= math.sqrt(np.sum((data['carat']-media)**2)/instances)
inter=max-min
out=[]

print("Carat:")
print("Minimo: ",min)
print("Maximo: ",max)
print("Media: ",media)
print("Desvio Padrao: ", desv)
print("Intervalo: ", inter)
```

```
Carat:
Minimo:  0.2
Maximo:  5.01
Media:  0.7979346717831621
Desvio Padrao:  0.4739941595630074
Intervalo:  4.81
```

```
sns.histplot(numData['carat'].sort_values())
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f0fae9373d0>
```



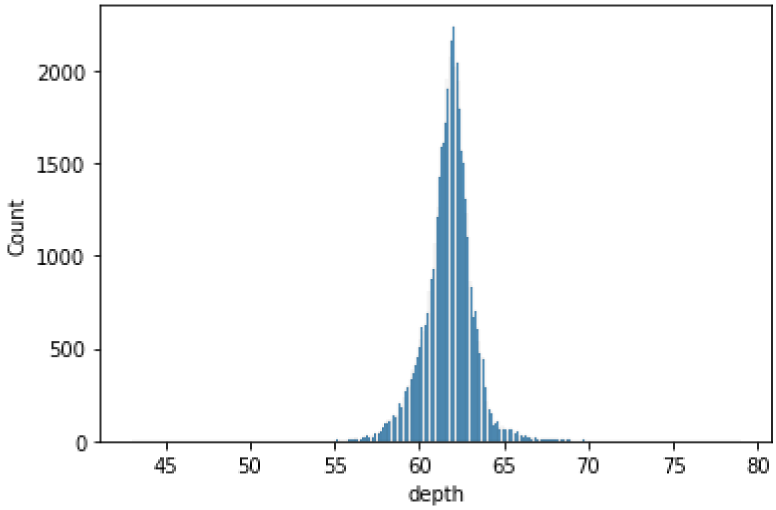
"Altura"

```
min = np.min(data['depth'])
max = np.max(data['depth'])
media = sum(data['depth'])/instances
desv= math.sqrt(np.sum((data['depth']-media)**2)/instances)
inter=max-min
out=[]

print("Depth:")
print("Minimo: ",min)
print("Maximo: ",max)
print("Media: ",media)
print("Desvio Padrao: ", desv)
print("Intervalo: ", inter)
```

```
Depth:
Minimo:  43.0
Maximo:  79.0
Media:  61.74932243293768
Desvio Padrao:  1.4326129869036368
Intervalo:  36.0
```

```
sns.histplot(numData['depth'].sort_values())
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f0fae22d610>
```



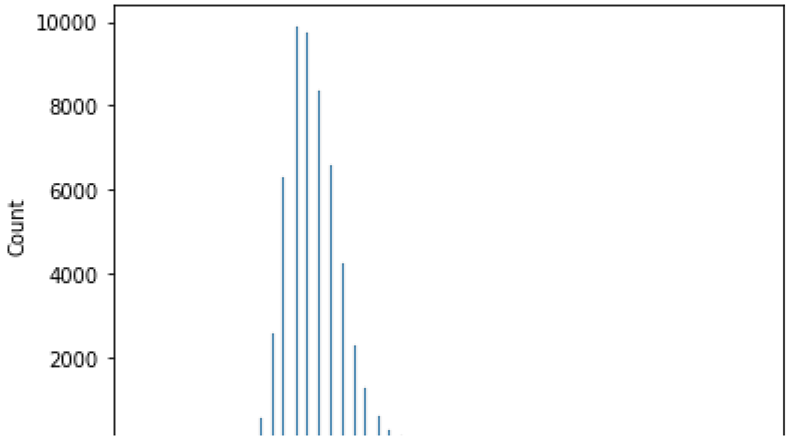
"Largura"

```
min = np.min(data['table'])
max = np.max(data['table'])
media = sum(data['table'])/instances
desv= math.sqrt(np.sum((data['table']-media)**2)/instances)
inter=max-min
out=[]

print("Table:")
print("Minimo: ",min)
print("Maximo: ",max)
print("Media: ",media)
print("Desvio Padrao: ", desv)
print("Intervalo: ", inter)
```

```
Table:
Minimo:  43.0
Maximo:  95.0
Media:  57.45725117253402
Desvio Padrao:  2.2345282410474523
Intervalo:  52.0
```

```
sns.histplot(numData['table'].sort_values())
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f0fadc28c10>
```



"Preço"

```
min = np.min(data['price'])
max = np.max(data['price'])
media = sum(data['price'])/instances
desv= math.sqrt(np.sum((data['price']-media)**2)/instances)
inter=max-min
out=[]

print("Price:")
print("Minimo: ",min)
print("Maximo: ",max)
print("Media: ",media)
print("Desvio Padrao: ", desv)
print("Intervalo: ", inter)
```

```
Price:
Minimo:  326
Maximo:  18823
Media:  3932.734293606214
Desvio Padrao:  3989.301469302266
Intervalo:  18497
```

```
sns.histplot(numData['price'].sort_values())
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f0fad82f750>

Medidas x, y e z

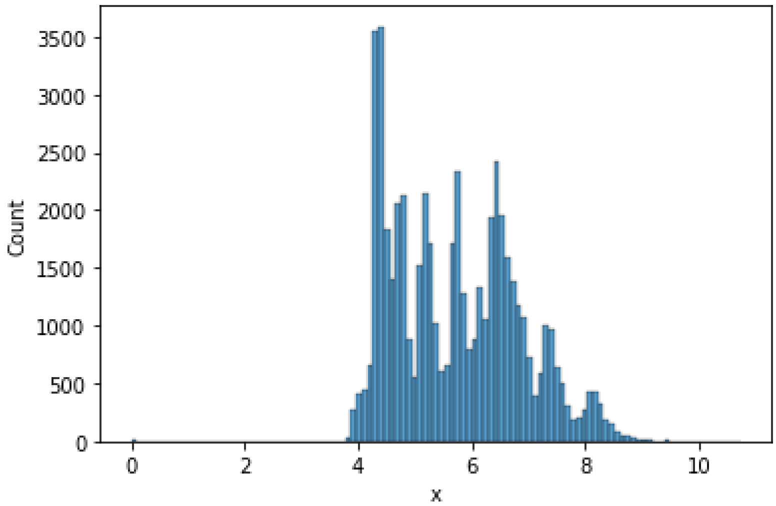
```
min = np.min(data['x'])
max = np.max(data['x'])
media = sum(data['x'])/instances
desv= math.sqrt(np.sum((data['x']-media)**2)/instances)
inter=max-min
out=[]

print("\nEixo x:")
print("Minimo: ",min)
print("Maximo: ",max)
print("Media: ",media)
print("Desvio Padrao: ", desv)
print("Intervalo: ", inter)

min = np.min(data['y'])
max = np.max(data['y'])
media = sum(data['y'])/instances
desv= math.sqrt(np.sum((data['y']-media)**2)/instances)
inter=max-min
out=[]

print("\n--------------------\n")

print("Eixo y:")
print("Minimo: ",min)
print("Maximo: ",max)
print("Media: ",media)
print("Desvio Padrao: ", desv)
print("Intervalo: ", inter)

print("\n--------------------\n")


min = np.min(data['z'])
max = np.max(data['z'])
media = sum(data['z'])/instances
desv= math.sqrt(np.sum((data['z']-media)**2)/instances)
inter=max-min
out=[]

print("Eixo z:")
print("Minimo: ",min)
print("Maximo: ",max)
print("Media: ",media)
print("Desvio Padrao: ", desv)
print("Intervalo: ", inter)
```

```
Eixo x:
```

```
Minimo:  0.0
Maximo:  10.74
Media:  5.731158074263461
Desvio Padrao:  1.121719188381892
Intervalo:  10.74

--------------------

Eixo y:
Minimo:  0.0
Maximo:  58.9
Media:  5.734526444580299
Desvio Padrao:  1.1420923330316735
Intervalo:  58.9

--------------------

Eixo z:
Minimo:  0.0
Maximo:  31.8
Media:  3.5387295849324203
Desvio Padrao:  0.7056729303858117
Intervalo:  31.8
```

```
sns.histplot(numData['x'].sort_values())
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f0fad74d6d0>
```

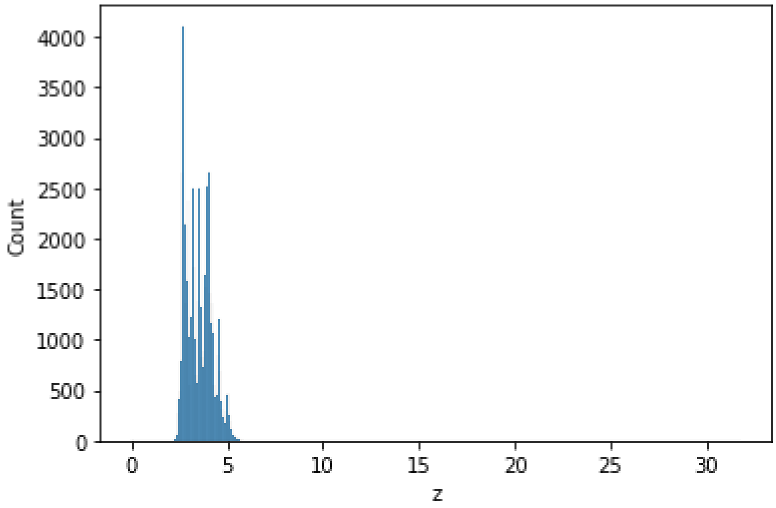



```
sns.histplot(numData['y'].sort_values())
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f0fadd73e10>
```


```
sns.histplot(numData['z'].sort_values())
```

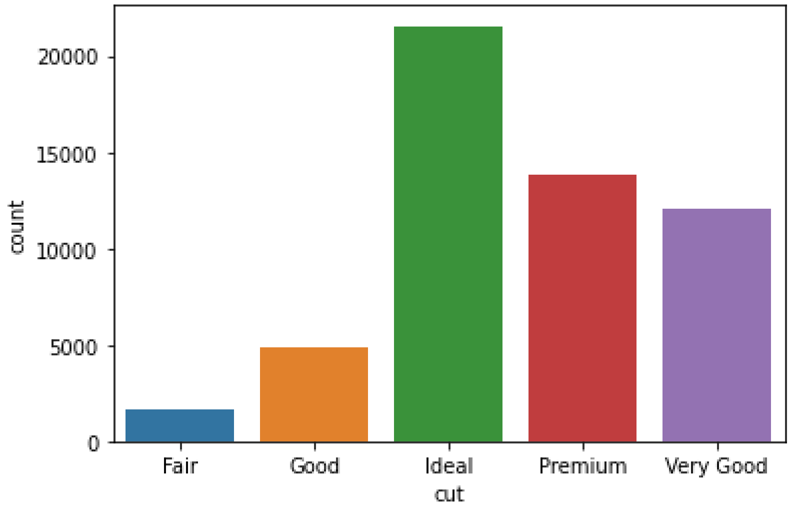
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f0facdb4390>
```



Qualidade do Corte

```
sns.countplot(catData['cut'].sort_values())
```

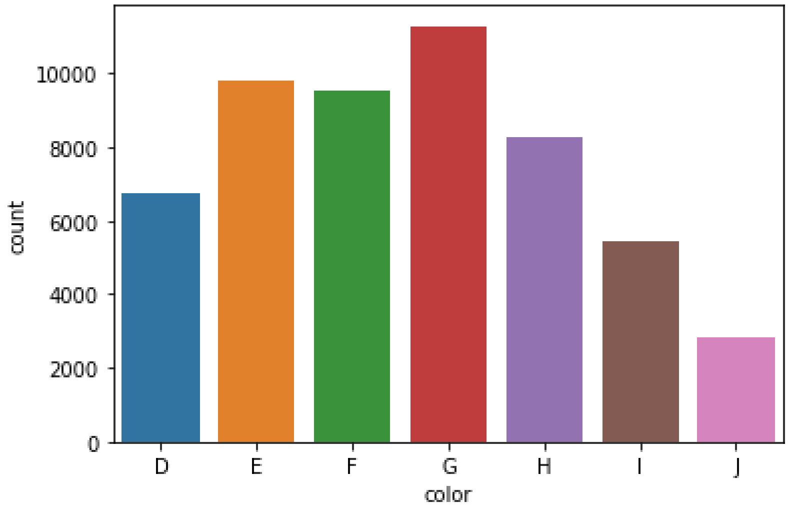
```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pas
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f0fac772410>
```



Cor

```
sns.countplot(catData['color'].sort_values())
```

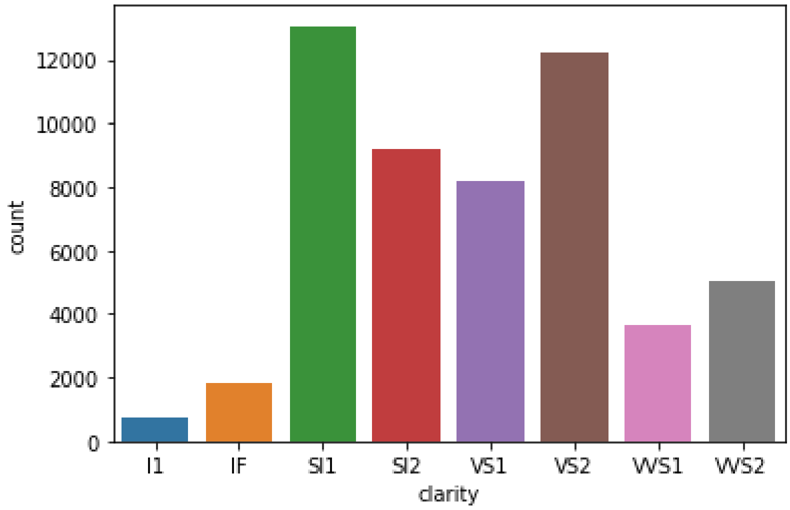
```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pas:
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f0facefdfd0>
```



Clareza

```
sns.countplot(catData['clarity'].sort_values())
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pas:
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f0facd50150>
```



Limpeza de Dados

```
print(data.isnull().any())
print()
```

```
carat      False
cut        False
color      False
clarity    False
depth      False
table      False
```

```
price      False
x          False
y          False
z          False
dtype: bool
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 53943 entries, 0 to 53942
Data columns (total 10 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   carat    53943 non-null  float64
 1   cut      53943 non-null  object
 2   color    53943 non-null  object
 3   clarity  53943 non-null  object
 4   depth    53943 non-null  float64
 5   table    53943 non-null  float64
 6   price    53943 non-null  int64
 7   x        53943 non-null  float64
 8   y        53943 non-null  float64
 9   z        53943 non-null  float64
dtypes: float64(6), int64(1), object(3)
memory usage: 4.1+ MB
```

Nenhum valor nulo encontrado

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 53943 entries, 0 to 53942
Data columns (total 10 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   carat    53943 non-null  float64
 1   cut      53943 non-null  object
 2   color    53943 non-null  object
 3   clarity  53943 non-null  object
 4   depth    53943 non-null  float64
 5   table    53943 non-null  float64
 6   price    53943 non-null  int64
 7   x        53943 non-null  float64
 8   y        53943 non-null  float64
 9   z        53943 non-null  float64
dtypes: float64(6), int64(1), object(3)
memory usage: 4.1+ MB
```

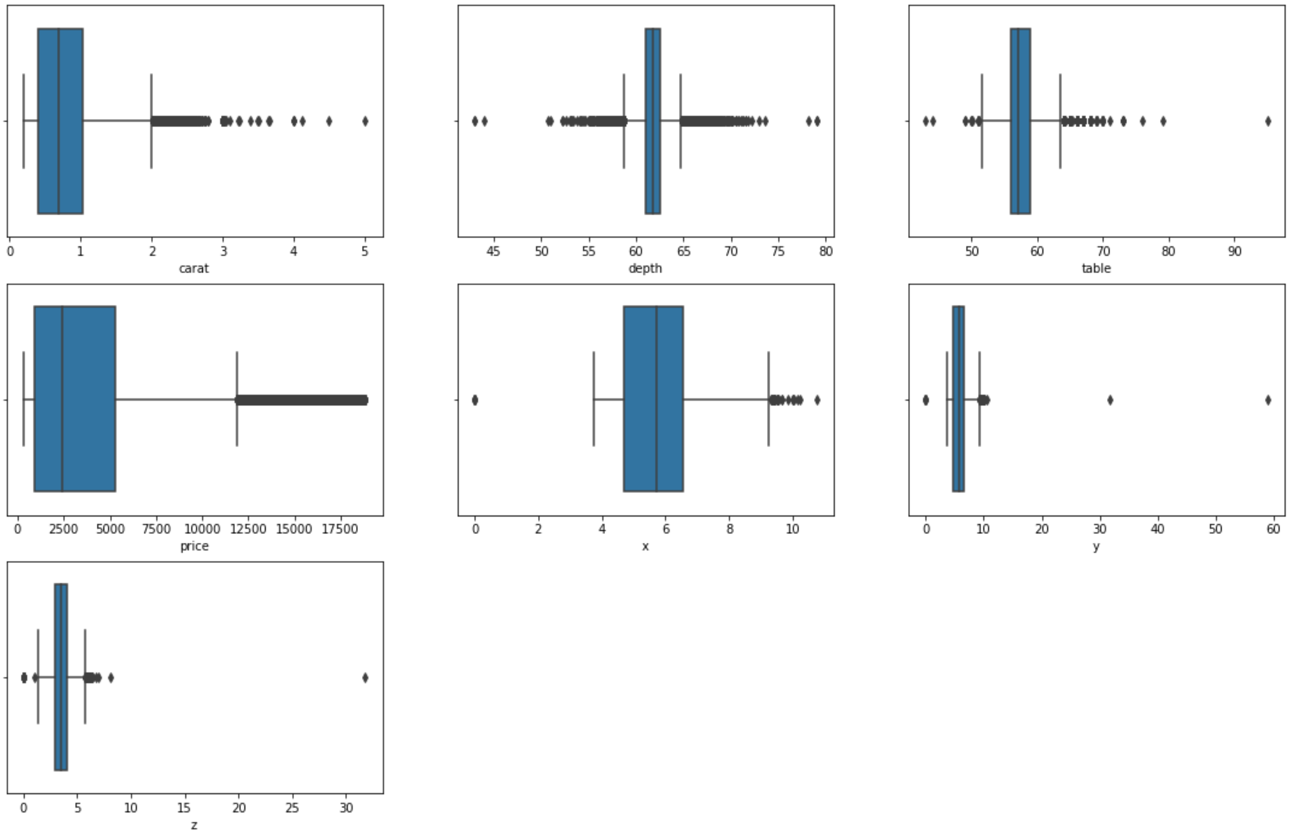
Buscando valores duplicados

```
print(f'The number of duplicate rows : {data.duplicated().sum()}')
```

```
The number of duplicate rows : 149
```

Buscando Outliers

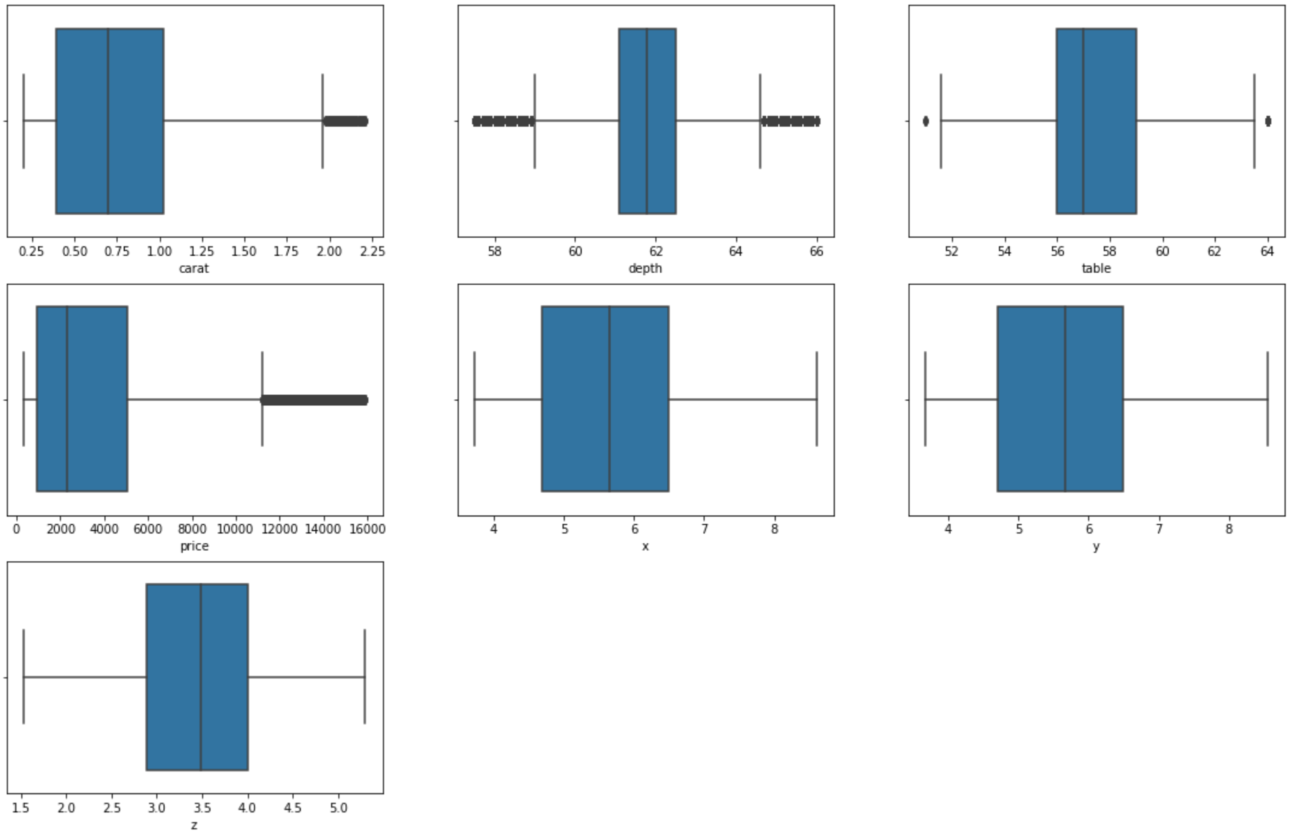
```
i = 1
plt.figure(figsize=(19, 12))
for c in numData.columns:
    plt.subplot(3, 3, i)
    sns.boxplot(x=data[c])
    i+=1
```



Fazendo o tratamento dos Outliers

```
data = data[(np.abs(stats.zscore(numData)) < 3).all(axis=1)]
```

```
data = data[(np.abs(stats.zscore(numData)) < 3).all(axis=1)]


numData = data.select_dtypes('number')
i = 1
plt.figure(figsize=(19, 12))
for c in numData.columns:
    plt.subplot(3, 3, i)
    sns.boxplot(x=data[c])
    i+=1
```



Correlação dos demais atributos com o preço

```
data.corrwith(data.price)
```

```
    carat    0.922409
```

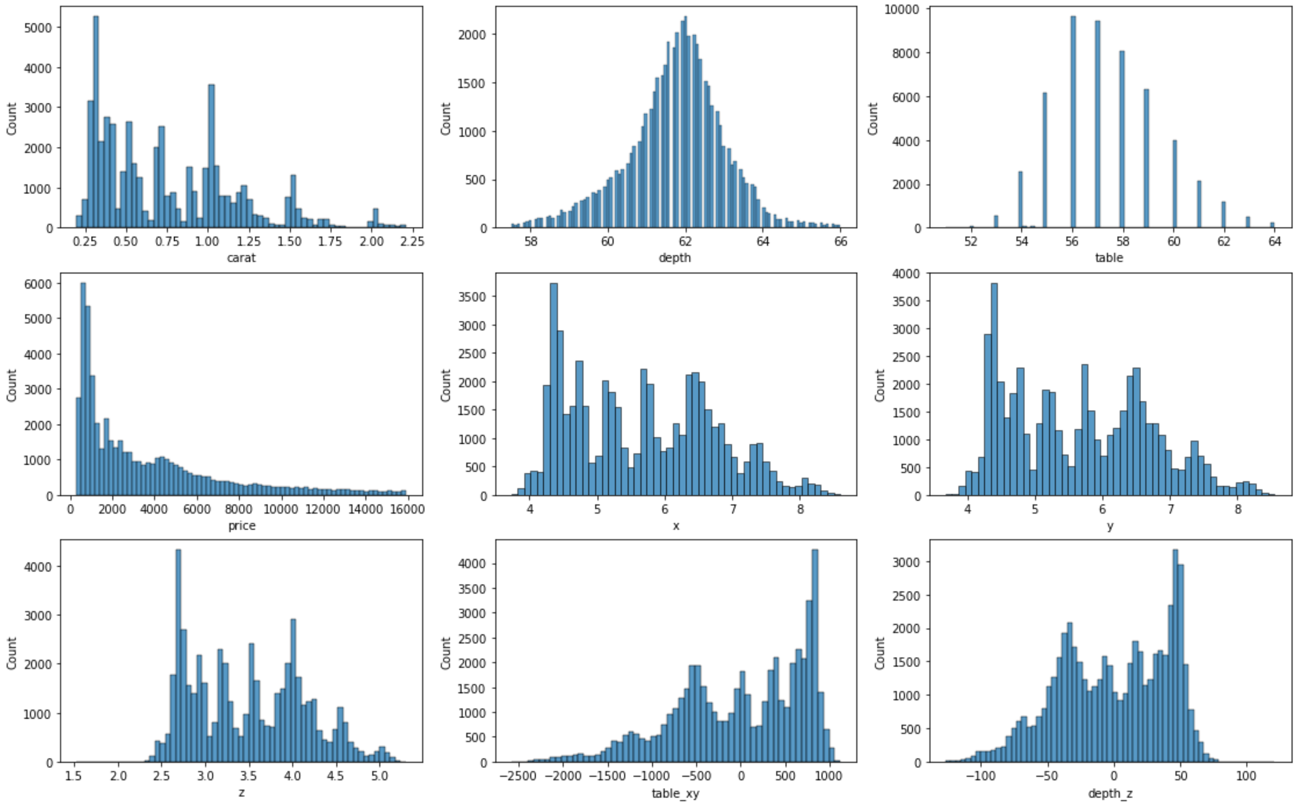
```
depth   -0.001882
table    0.131667
price    1.000000
x        0.890451
y        0.891716
z        0.887339
dtype: float64
```

```
data['table_xy'] = (data['table'].mean()*(data['x']*data['y']).mean()-data['table']*(data[
data['depth_z'] = (data['depth'].mean()*data['z'].mean()-data['depth']*data['z'])

print("\n",data['table_xy'])
print("\n---------------------------------------------------\n")
print("\n",data['depth_z'])
```

```
 0        1036.549639
1         990.011039
3         870.776639
4         806.222639
5        1011.867839
             ...
53938    -281.799361
53939      18.989139
53940      73.301639
53941    -137.987761
53942     -39.281761
Name: table_xy, Length: 51593, dtype: float64

---------------------------------------------------


 0        66.359088
1        77.666088
3        51.692088
4        41.729088
5        60.060088
           ...
53938   -12.335912
53939   -10.603912
53940     4.659088
53941    10.690088
53942     5.869088
Name: depth_z, Length: 51593, dtype: float64
```

Distribuição de valores

```
numData = data.select_dtypes('number')
i = 1
plt.figure(figsize=(19, 12))
for c in numData.columns:
    plt.subplot(3, 3, i)
    sns.histplot(x = data[c])
    i+=1
```



Fazendo o tratamento dos atributos categoricos

```
data['cut'] = data['cut'].map({'Fair':0, 'Good':1, 'Very Good':2, 'Premium':3, 'Ideal':4})
data['color'] = data['color'].map({'J':0, 'I':1, 'H':2, 'G':3, 'F':4, 'E':5, 'D':6})
data['clarity'] = data['clarity'].map({'I1':0, 'SI2':1, 'SI1':2, 'VS2':3, 'VS1':4, 'VVS2':
```

Resultado das operações

```
data.describe()
```

	carat	cut	color	clarity	depth	tal
count	51593.000000	51593.000000	51593.000000	51593.000000	51593.000000	51593.000
mean	0.759929	2.952532	3.433625	3.086950	61.752751	57.369
std	0.424971	1.070644	1.694679	1.642551	1.269271	2.100
min	0.200000	0.000000	0.000000	0.000000	57.500000	51.000
25%	0.390000	2.000000	2.000000	2.000000	61.100000	56.000
50%	0.700000	3.000000	3.000000	3.000000	61.800000	57.000
75%	1.020000	4.000000	5.000000	4.000000	62.500000	59.000

```
data.head()
```

	carat	cut	color	clarity	depth	table	price	x	y	z	table_xy	de
0	0.23	4	5	1	61.5	55.0	326	3.95	3.98	2.43	1036.549639	66.3
1	0.21	3	5	2	59.8	61.0	326	3.89	3.84	2.31	990.011039	77.6
3	0.29	3	1	3	62.4	58.0	334	4.20	4.23	2.63	870.776639	51.6
4	0.31	1	0	1	63.3	58.0	335	4.34	4.35	2.75	806.222639	41.7
5	0.24	2	0	5	62.8	57.0	336	3.94	3.96	2.48	1011.867839	60.0

```
print(data.sort_values('carat', ascending=False).head(5)['carat'])
print(data.sort_values('carat', ascending=True).head(5)['carat'])
```

```
25250    2.21
24072    2.21
24922    2.21
26321    2.21
25506    2.21
Name: carat, dtype: float64
31598    0.2
31591    0.2
31592    0.2
31593    0.2
31594    0.2
Name: carat, dtype: float64
```

```
print(data.sort_values('depth', ascending=False).head(5)['depth'])
print(data.sort_values('depth', ascending=True).head(5)['depth'])
```

```
2534     66.0
1523     66.0
46742    66.0
15331    66.0
1097     66.0
Name: depth, dtype: float64
5481     57.5
50486    57.5
11639    57.5
34938    57.5
```

```
50211    57.5
Name: depth, dtype: float64
```

```
print(data.sort_values('table', ascending=False).head(5)['table'])
print(data.sort_values('table', ascending=True).head(5)['table'])
```

```
4582     64.0
10570    64.0
20481    64.0
24787    64.0
3595     64.0
Name: table, dtype: float64
46040    51.0
47630    51.0
33586    51.0
3979     51.0
45798    51.0
Name: table, dtype: float64
```

```
print(data.sort_values('price', ascending=False).head(5)['price'])
print(data.sort_values('price', ascending=True).head(5)['price'])
```

```
26393    15898
26392    15897
26391    15897
26390    15897
26389    15889
Name: price, dtype: int64
0    326
1    326
3    334
4    335
5    336
Name: price, dtype: int64
```

```
print(data.sort_values('x', ascending=False).head(5)['x'])
print(data.sort_values('x', ascending=True).head(5)['x'])
```

```
24739    8.60
22140    8.57
25562    8.57
25749    8.54
23121    8.52
Name: x, dtype: float64
31596    3.73
31600    3.73
31598    3.74
31599    3.76
31601    3.77
Name: x, dtype: float64
```

```
print(data.sort_values('y', ascending=False).head(5)['y'])
print(data.sort_values('y', ascending=True).head(5)['y'])
```

```
26242    8.55
24739    8.53
25717    8.53
22140    8.53
26223    8.51
Name: y, dtype: float64
31600    3.68
31598    3.71
31596    3.71
31601    3.72
31599    3.73
Name: y, dtype: float64
```

```
print(data.sort_values('z', ascending=False).head(5)['z'])
print(data.sort_values('z', ascending=True).head(5)['z'])
```

```
23194    5.30
23690    5.23
13118    5.23
25305    5.23
23513    5.23
Name: z, dtype: float64
20694    1.53
39246    2.06
31592    2.24
47138    2.25
31591    2.26
Name: z, dtype: float64
```

Tratamento dos dados continuos para intervalos

Carat

```
bins=1000
min = np.min(data['carat'])
max = np.max(data['carat'])
inter=max-min
print("\nIntervalo dos Valores:",inter)
gaps=inter/bins
print("\nTamanho das Bins:",gaps)
data['carat'] = data['carat'] //gaps
print("\n",(data.sort_values('carat', ascending=True).head(10)['carat']))
print("\n",(data.sort_values('carat', ascending=False).head(10)['carat']))
```

```
Intervalo dos Valores: 2.01

Tamanho das Bins: 0.0020099999999999996

 31598    99.0
31591    99.0
31592    99.0
31593    99.0
```

```
31594    99.0
31595    99.0
31596    99.0
31597    99.0
31599    99.0
31600    99.0
Name: carat, dtype: float64

 25250    1099.0
24072    1099.0
24922    1099.0
26321    1099.0
25506    1099.0
25106    1099.0
25306    1099.0
24153    1099.0
25330    1099.0
25089    1099.0
Name: carat, dtype: float64
```

Depth

```
bins=1000
min = np.min(data['depth'])
max = np.max(data['depth'])
inter=max-min
print("\nIntervalo dos Valores:",inter)
gaps=inter/bins
print("\nTamanho das Bins:",gaps)
data['depth'] = data['depth'] //gaps
print("\n",(data.sort_values('depth', ascending=True).head(10)['depth']))
print("\n",(data.sort_values('depth', ascending=False).head(10)['depth']))
```

```
Intervalo dos Valores: 8.5

Tamanho das Bins: 0.0085

 5481     6764.0
50486    6764.0
11639    6764.0
34938    6764.0
50211    6764.0
34024    6764.0
46085    6764.0
25562    6764.0
12641    6764.0
12692    6764.0
Name: depth, dtype: float64

 2534     7764.0
1523     7764.0
46742    7764.0
15331    7764.0
1097     7764.0
15139    7764.0
17716    7764.0
```

```
49151    7764.0
49328    7764.0
3115     7764.0
Name: depth, dtype: float64
```

Table

```
bins=1000
min = np.min(data['table'])
max = np.max(data['table'])
inter=max-min
print("\nIntervalo dos Valores:",inter)
gaps=inter/bins
print("\nTamanho das Bins:",gaps)
data['table'] = data['table'] //gaps
print("\n",(data.sort_values('table', ascending=True).head(10)['table']))
print("\n",(data.sort_values('table', ascending=False).head(10)['table']))
```

```
Intervalo dos Valores: 13.0

Tamanho das Bins: 0.013

 46040    3923.0
47630    3923.0
33586    3923.0
3979     3923.0
45798    3923.0
1515     3923.0
26387    3923.0
4150     3923.0
24815    3969.0
5144     4000.0
Name: table, dtype: float64

 4582     4923.0
10570    4923.0
20481    4923.0
24787    4923.0
3595     4923.0
17781    4923.0
13749    4923.0
14861    4923.0
30409    4923.0
19089    4923.0
Name: table, dtype: float64
```

Price

```
bins=1000
min = np.min(data['price'])
max = np.max(data['price'])
inter=max-min
print("\nIntervalo dos Valores:",inter)
```

```
gaps=inter/bins
print("\nTamanho das Bins:",gaps)
data['price'] = data['price'] //gaps
print("\n",(data.sort_values('price', ascending=True).head(10)['price']))
print("\n",(data.sort_values('price', ascending=False).head(10)['price']))
```

```
Intervalo dos Valores: 15572

Tamanho das Bins: 15.572

 0     20.0
1     20.0
11    21.0
10    21.0
9     21.0
8     21.0
12    21.0
6     21.0
5     21.0
4     21.0
Name: price, dtype: float64

 26393    1020.0
26392    1020.0
26391    1020.0
26390    1020.0
26389    1020.0
26387    1020.0
26386    1020.0
26382    1019.0
26383    1019.0
26381    1019.0
Name: price, dtype: float64
```

X

```
bins=1000
min = np.min(data['x'])
max = np.max(data['x'])
inter=max-min
print("\nIntervalo dos Valores:",inter)
gaps=inter/bins
print("\nTamanho das Bins:",gaps)
data['x'] = data['x'] //gaps
print("\n",(data.sort_values('x', ascending=True).head(10)['x']))
print("\n",(data.sort_values('x', ascending=False).head(10)['x']))
```

```
Intervalo dos Valores: 4.869999999999999

Tamanho das Bins: 0.004869999999999999

 31596    765.0
31600    765.0
31598    767.0
```

```
31599    772.0
31601    774.0
31591    778.0
14       778.0
31592    782.0
31593    782.0
31597    782.0
Name: x, dtype: float64

 24739    1765.0
22140    1759.0
25562    1759.0
25749    1753.0
23121    1749.0
22251    1749.0
26242    1747.0
25250    1747.0
24211    1743.0
25717    1741.0
Name: x, dtype: float64
```

Y

```
bins=1000
min = np.min(data['y'])
max = np.max(data['y'])
inter=max-min
print("\nIntervalo dos Valores:",inter)
gaps=inter/bins
print("\nTamanho das Bins:",gaps)
data['y'] = data['y'] //gaps
print("\n",(data.sort_values('y', ascending=True).head(10)['y']))
print("\n",(data.sort_values('y', ascending=False).head(10)['y']))
```

```
Intervalo dos Valores: 4.870000000000001

Tamanho das Bins: 0.004870000000000001

 31600    755.0
31598    761.0
31596    761.0
31601    763.0
31599    765.0
14       770.0
31591    774.0
31597    774.0
31593    776.0
38276    776.0
Name: y, dtype: float64

 26242    1755.0
24739    1751.0
25717    1751.0
22140    1751.0
26223    1747.0
22251    1745.0
```

```
25749    1743.0
26133    1743.0
25562    1741.0
26321    1741.0
Name: y, dtype: float64
```

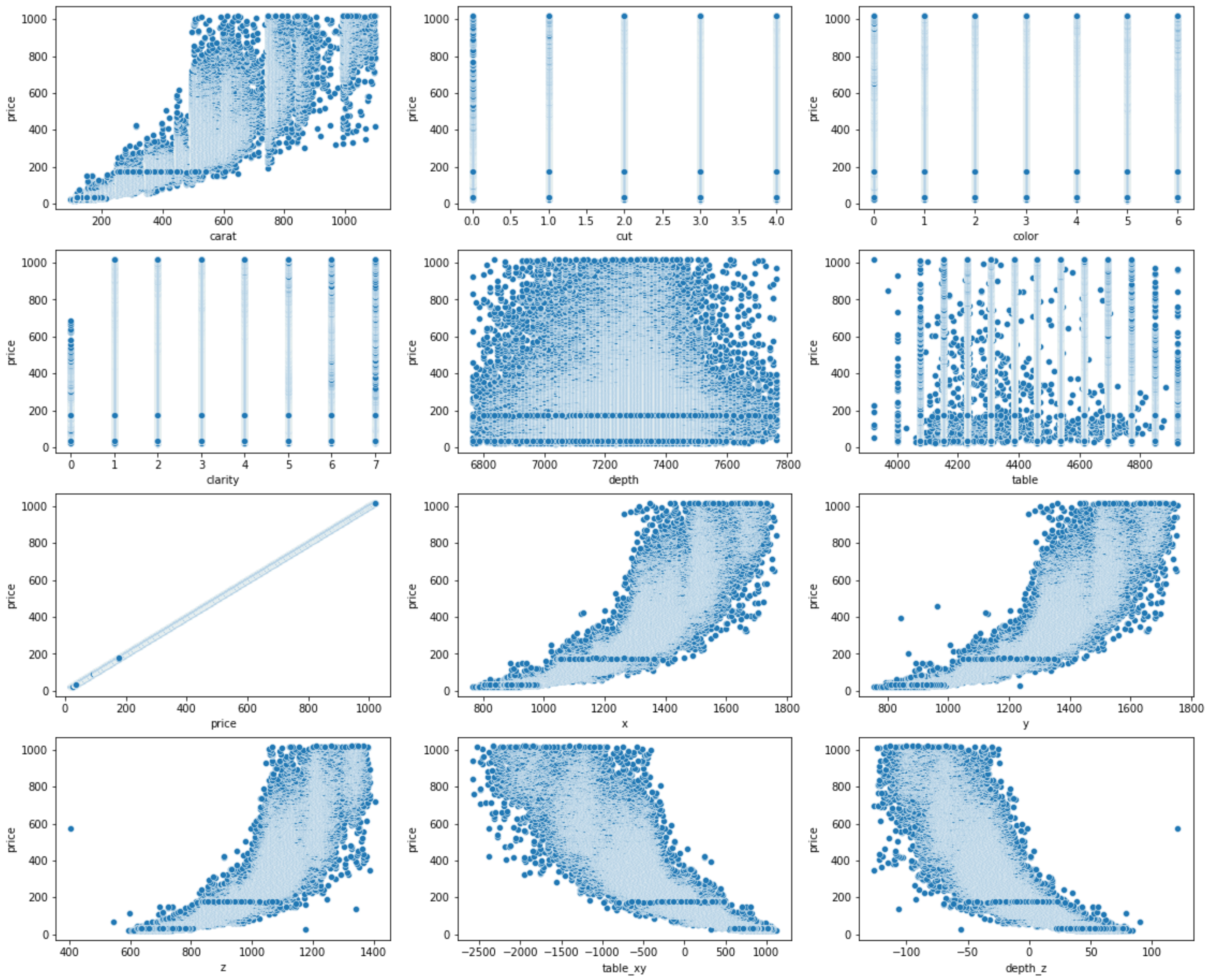
Z

```
bins=1000
min = np.min(data['z'])
max = np.max(data['z'])
inter=max-min
print(inter)
gaps=inter/bins
print(gaps)
data['z'] = data['z'] //gaps
print((data.sort_values('z', ascending=True).head(10)['z']))
print((data.sort_values('z', ascending=False).head(10)['z']))
```

```
3.7699999999999996
0.0037699999999999995
20694    405.0
39246    546.0
31592    594.0
47138    596.0
31591    599.0
14       602.0
31594    604.0
38278    607.0
31595    610.0
38279    610.0
Name: z, dtype: float64
23194    1405.0
23690    1387.0
13118    1387.0
25305    1387.0
23513    1387.0
24536    1387.0
24396    1384.0
24857    1384.0
25225    1384.0
23841    1381.0
Name: z, dtype: float64
```

Relação entre o preço e os demais atributos

```
i = 1
plt.figure(figsize=(19, 16))
for c in data.columns:
    plt.subplot(4, 3, i)
    sns.scatterplot(x=data[c], y=data['price'])
    i+=1
```



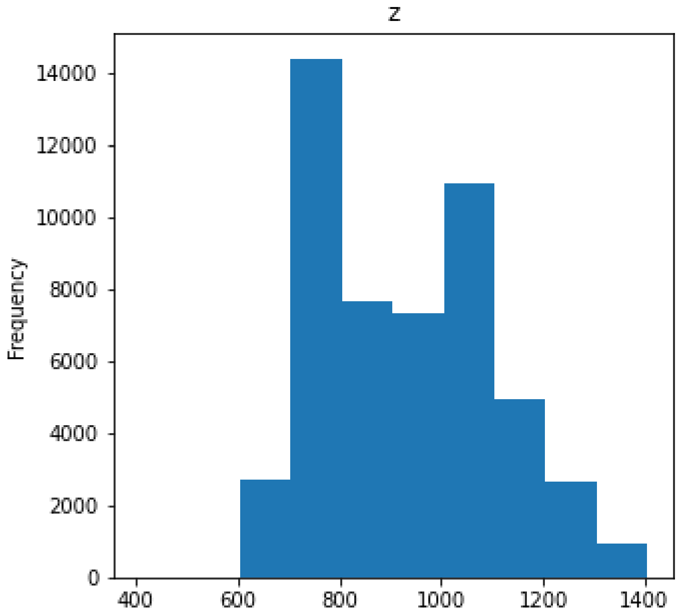
Inicio da Fase 2

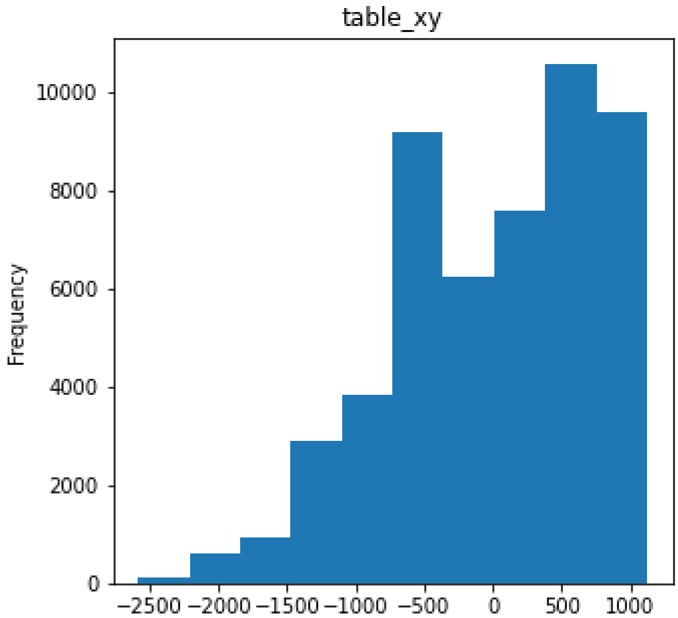
```
data.head
```

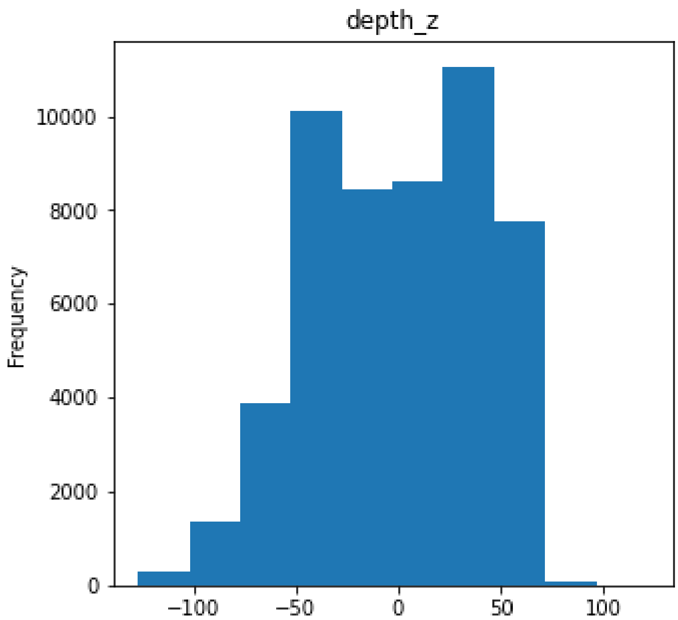
```
<bound method NDFrame.head of        carat  cut  color  clarity   depth   table
price      x      y  \
0      114.0    4      5       1  7235.0  4230.0   20.0   811.0   817.0
1      104.0    3      5       2  7035.0  4692.0   20.0   798.0   788.0
3      144.0    3      1       3  7341.0  4461.0   21.0   862.0   868.0
4      154.0    1      0       1  7447.0  4461.0   21.0   891.0   893.0
5      119.0    2      0       5  7388.0  4384.0   21.0   809.0   813.0
...      ...  ...    ...     ...     ...     ...    ...     ...     ...
53938  427.0    3      2       1  7176.0  4461.0  177.0  1262.0  1256.0
53939  373.0    4      6       1  7317.0  4230.0  177.0  1197.0  1205.0
53940  353.0    3      5       2  7117.0  4230.0  176.0  1188.0  1178.0
53941  353.0    3      4       2  7035.0  4769.0  176.0  1178.0  1176.0
53942  348.0    2      5       3  7117.0  4538.0  177.0  1172.0  1182.0

           z     table_xy    depth_z
0      644.0  1036.549639  66.359088
1      612.0   990.011039  77.666088
3      697.0   870.776639  51.692088
4      729.0   806.222639  41.729088
5      657.0  1011.867839  60.060088
...      ...          ...        ...
53938  992.0  -281.799361 -12.335912
53939  965.0    18.989139 -10.603912
53940  925.0    73.301639   4.659088
53941  909.0  -137.987761  10.690088
53942  920.0   -39.281761   5.869088

[51593 rows x 12 columns]>
```

```
num_col=[]
cat_col=[]
for col in data.columns:
    plt.figure(col, figsize=(5,5))
    plt.title(col)
    if is_numeric_dtype(data[col]):
        data[col].plot(kind="hist")
        num_col.append(col)
    if is_string_dtype(data[col]):
        sns.countplot(x=col, data=data, order=data[col].value_counts().index)
        plt.show()
        cat_col.append(col)
```


0
800
1000
1200
1400
1600
1800


z
Frequency
14000
12000
10000
8000
6000
4000
2000
0
400
600
800
1000
1200
1400


table_xy
Frequency
10000
8000
6000
4000
2000
0
−2500 −2000 −1500 −1000 −500 0 500 1000


depth_z
Frequency
10000
8000
6000
4000
2000
0
−100
−50
0
50
100

Como vamos utilziar regressão devemos transformas as variaveis de categoricas para numericas

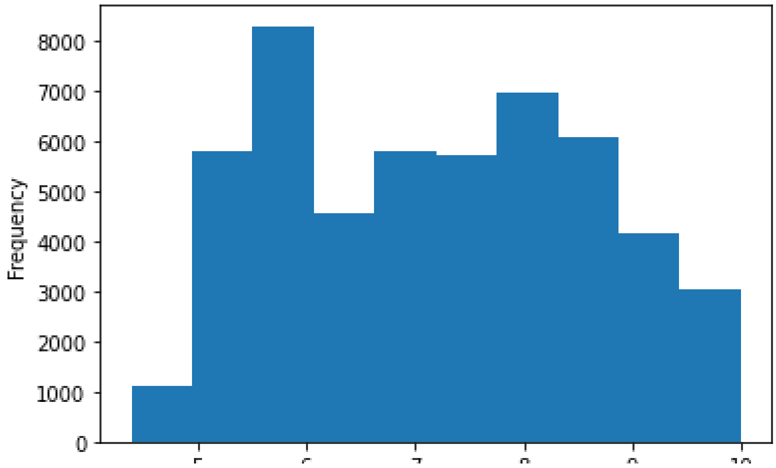
```
for i in cat_col:
    data[i]=data().fit_transform(data[i])
print(data.head())
```

```
   carat  cut  color  clarity   depth   table  price      x      y      z  \
0  114.0    4      5        1  7235.0  4230.0   20.0  811.0  817.0  644.0
1  104.0    3      5        2  7035.0  4692.0   20.0  798.0  788.0  612.0
3  144.0    3      1        3  7341.0  4461.0   21.0  862.0  868.0  697.0
4  154.0    1      0        1  7447.0  4461.0   21.0  891.0  893.0  729.0
5  119.0    2      0        5  7388.0  4384.0   21.0  809.0  813.0  657.0

      table_xy    depth_z
0  1036.549639  66.359088
1   990.011039  77.666088
3   870.776639  51.692088
4   806.222639  41.729088
5  1011.867839  60.060088
```

Distribuição de valores de Preços

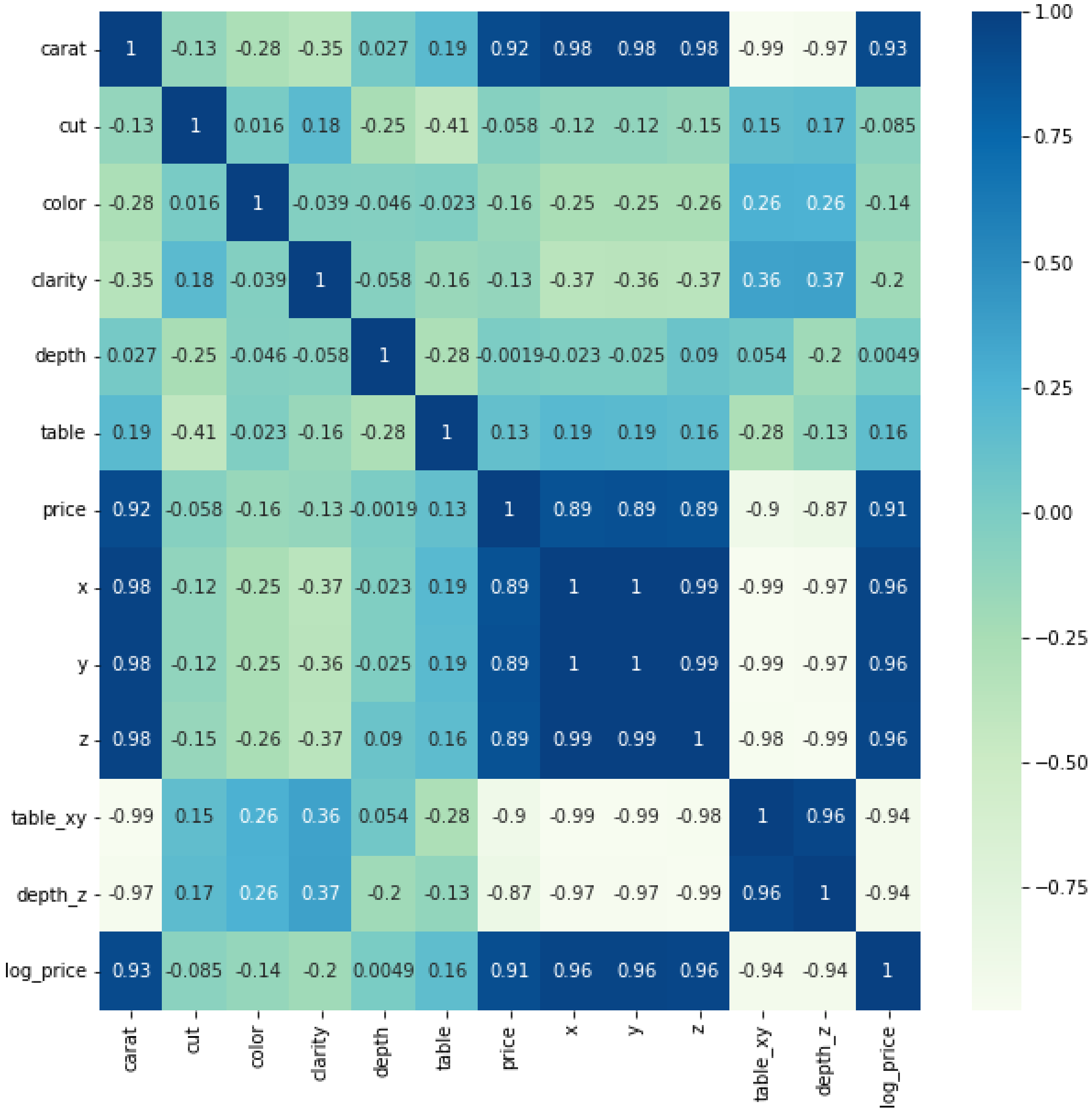
```
data["log_price"]=np.log2(data["price"]+1)
data["log_price"].plot(kind="hist")
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f0fabf6acd0>



Analise de Correlação

```
plt.figure(figsize=(10,10))
sns.heatmap(data.corr(), annot=True, cmap="GnBu")
plt.show()
```



	carat	cut	color	clarity	depth	table	price	x	y	z	table_xy	depth_z	log_price
carat	1	-0.13	-0.28	-0.35	0.027	0.19	0.92	0.98	0.98	0.98	-0.99	-0.97	0.93
cut	-0.13	1	0.016	0.18	-0.25	-0.41	-0.058	-0.12	-0.12	-0.15	0.15	0.17	-0.085
color	-0.28	0.016	1	-0.039	-0.046	-0.023	-0.16	-0.25	-0.25	-0.26	0.26	0.26	-0.14
clarity	-0.35	0.18	-0.039	1	-0.058	-0.16	-0.13	-0.37	-0.36	-0.37	0.36	0.37	-0.2
depth	0.027	-0.25	-0.046	-0.058	1	-0.28	-0.0019	-0.023	-0.025	0.09	0.054	-0.2	0.0049
table	0.19	-0.41	-0.023	-0.16	-0.28	1	0.13	0.19	0.19	0.16	-0.28	-0.13	0.16
price	0.92	-0.058	-0.16	-0.13	-0.0019	0.13	1	0.89	0.89	0.89	-0.9	-0.87	0.91
x	0.98	-0.12	-0.25	-0.37	-0.023	0.19	0.89	1	1	0.99	-0.99	-0.97	0.96
y	0.98	-0.12	-0.25	-0.36	-0.025	0.19	0.89	1	1	0.99	-0.99	-0.97	0.96
z	0.98	-0.15	-0.26	-0.37	0.09	0.16	0.89	0.99	0.99	1	-0.98	-0.99	0.96
table_xy	-0.99	0.15	0.26	0.36	0.054	-0.28	-0.9	-0.99	-0.99	-0.98	1	0.96	-0.94
depth_z	-0.97	0.17	0.26	0.37	-0.2	-0.13	-0.87	-0.97	-0.97	-0.99	0.96	1	-0.94
log_price	0.93	-0.085	-0.14	-0.2	0.0049	0.16	0.91	0.96	0.96	0.96	-0.94	-0.94	1

Abaixo estão os atributos com mais de 50% de correlação

```
# Next, Get the variables which has correlation more than 50%
diamond_corr=data.corr()[["log_price"]]
diamond_corr_hi=diamond_corr.loc[diamond_corr["log_price"]>0.5]
print(diamond_corr_hi)
```

```
           log_price
carat       0.931003
price       0.907942
x           0.961694
y           0.962143
z           0.958906
log_price   1.000000
```

Buscando por multicolinearidade

```
X=data[['carat','cut','color','clarity', 'x','y','z', 'table', 'depth']]
#VIF DataFrame

vif_data=pd.DataFrame()
vif_data['features']=X.columns

#calculating VIF for each feature
vif_data["VIF"]=[variance_inflation_factor(X.values,i) for i in range(len(X.columns))]
vif_data
```

	features	VIF
0	carat	128.610656
1	cut	11.926322
2	color	5.689119
3	clarity	5.543326
4	x	13615.173569
5	y	11572.010189
6	z	5575.561623
7	table	996.507428
8	depth	1492.813962

Inicio da implementação do modelo

```
y=data['log_price'] #Dependent variable
X=data[['carat','color','clarity', 'cut','x','y','z', 'table', 'depth']] #independent vari
```

```
# Next, we devide our dataset into training and testing datasets, in 70 and 30 ratio.
# Use model_selection.train_test_split from sklearn to split the data into training and te
X_train, X_test, y_train, y_test=train_test_split(X,y,test_size=0.3)
```

Treinando o modelo

Regressão Linear

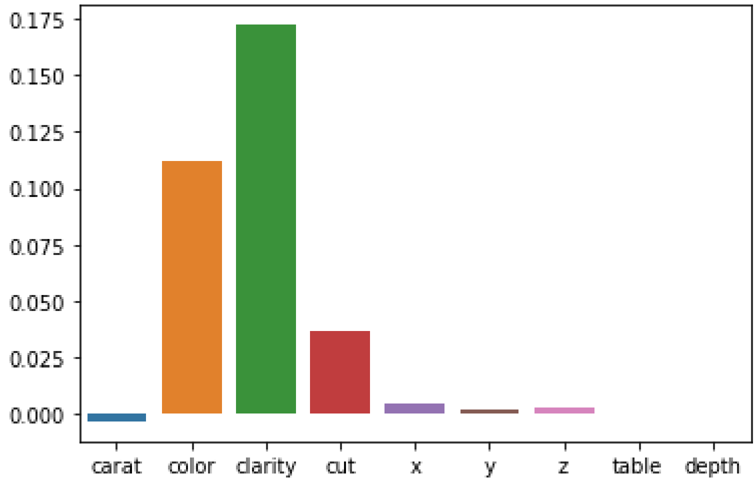
```
lr=LinearRegression(normalize=True)
lr.fit(X_train, y_train)

coeffecients = pd.DataFrame(lr.coef_,X_train.columns)
coeffecients.columns = ['Coeffecient']
print("Intercept value is {}".format(lr.intercept_))
coeffecients
```

```
Intercept value is -8.13963648753174
/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_base.py:145: FutureWarni
If you wish to scale the data, use Pipeline with a StandardScaler in a preprocessing

from sklearn.pipeline import make_pipeline

model = make_pipeline(StandardScaler(with_mean=False), LinearRegression())

If you wish to pass a sample_weight parameter, you need to pass it as a fit parameter

kwargs = {s[0] + '__sample_weight': sample_weight for s in model.steps}
model.fit(X, y, **kwargs)


  FutureWarning,
```

	Coeffecient
carat	-0.003090
color	0.112217
clarity	0.172063
cut	0.036276
x	0.005159
y	0.002592
z	0.002722
table	0.000188
depth	0.000430

```
sns.barplot(x=X_train.columns, y=lr.coef_)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f0fabfee6d0>
```



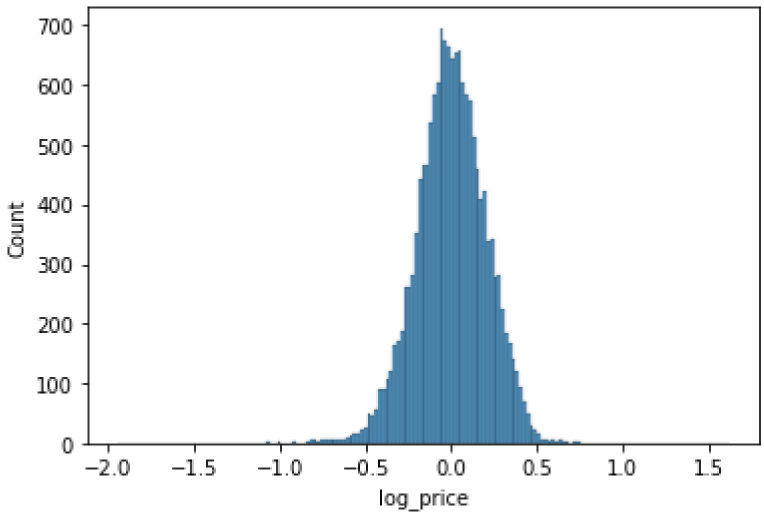

```
pred=lr.predict(X_test)
```

Mean Square Error: Erro para cada conjunto x - x', sendo x o previsto e x' o predito, onde o Mean Square Error = (x - x')**2

Root Mean Square Error: np.sqrt(Mean Square Error) R Square: Pode ser vista como a distancia entre a "curva" da regressão e os valores reais

```
plt.figure()
sns.histplot((y_test-pred))

# MAE, MSE, RMSE & R-square
lr_rsquare=metrics.r2_score(y_test, pred)
#print('Mean Square Error:',metrics.mean_absolute_error(y_test, pred))
print('Mean Square Error:',metrics.mean_squared_error(y_test, pred))
print(' Root Mean Square Error:',np.sqrt(metrics.mean_squared_error(y_test, pred)))
print('R Square:', metrics.r2_score(y_test,pred))
```

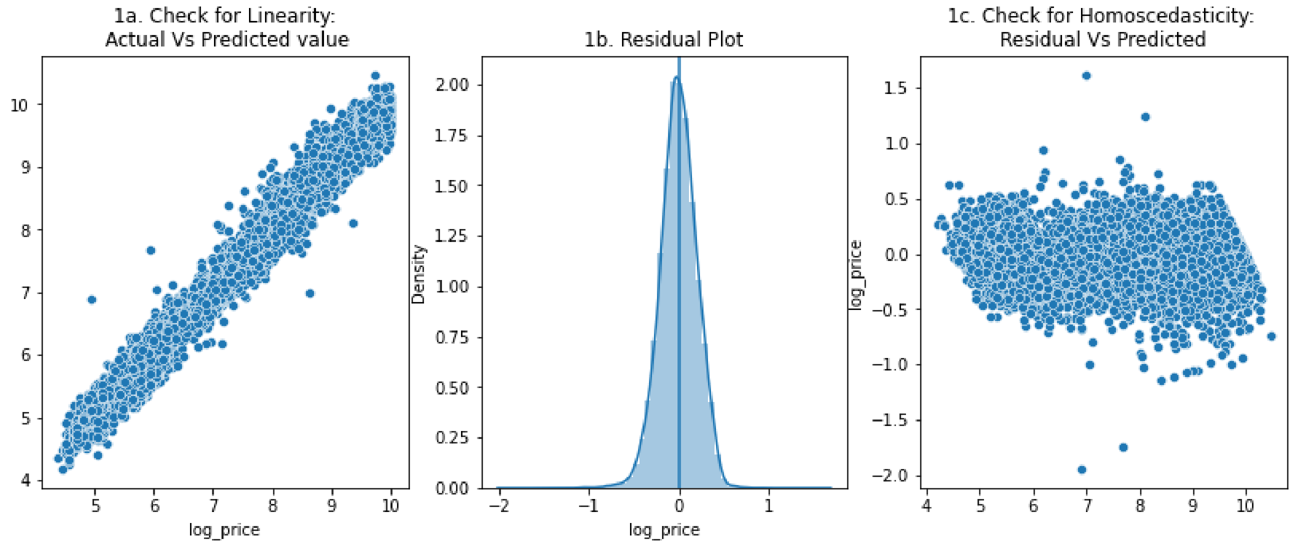
```
Mean Square Error: 0.04209241766750902
 Root Mean Square Error: 0.20516436744110567
R Square: 0.9787385471749861
```



Validação do modelo

```
#1. Plot between predicted vs actual values
f=plt.figure(figsize=(14,5))
ax=f.add_subplot(131)
sns.scatterplot(y_test, pred)
#plt.hlines(y=0, xmin= -1000, xmax=5000)
ax.set_title('1a. Check for Linearity:\n Actual Vs Predicted value')


# 2. Check for Residual normality & mean : The residual error plot should be normally dist
# & The mean of residual error should be 0 or close to 0 as much as possible

ax=f.add_subplot(132)
sns.distplot(y_test-pred)
ax.axvline((y_test-pred).mean())
ax.set_title('1b. Residual Plot')

#3 Homoscedasticity -The data are homoscedastic meaning the residuals are equal across the
#We can look at residual Vs fitted value scatter plot.
#If heteroscedastic plot would exhibit a funnel shape pattern
ax=f.add_subplot(133)
sns.scatterplot(x=pred, y=(y_test-pred))
plt.title('1c. Check for Homoscedasticity: \nResidual Vs Predicted')
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass
  FutureWarning
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning:
  warnings.warn(msg, FutureWarning)
```



Regressão Ridge

Adiciona um termo de penalização para evitar overfitting

```
ridgeReg=Ridge(alpha=0.05, normalize=True)
ridgeReg.fit(X_train, y_train)
rid_pred=ridgeReg.predict(X_test)
rid_rsquare=metrics.r2_score(y_test, rid_pred)
print('Mean Squared Error:',metrics.mean_squared_error(y_test, rid_pred))
print(' Root Mean Squared Error:',np.sqrt(metrics.mean_squared_error(y_test, rid_pred)))
print('R Squared:', metrics.r2_score(y_test,rid_pred))

#plotting

#1. Plot between predicted vs actual values
f=plt.figure(figsize=(14,5))
ax=f.add_subplot(131)
sns.scatterplot(y_test, rid_pred)
ax.set_title('1a. Check for Linearity:\n Actual Vs Predicted value')


# 2. Check for Residual normality & mean : The residual error plot should be normally dist
# & The mean of residual error should be 0 or close to 0 as much as possible

ax=f.add_subplot(132)
sns.distplot(y_test-rid_pred)
ax.axvline((y_test-rid_pred).mean())
ax.set_title('1b. Residual Plot')

#3 Homoscedasticity -The data are homoscedastic meaning the residuals are equal across the
#We can look at residual Vs fitted value scatter plot.
#If heteroscedastic plot would exhibit a funnel shape pattern
ax=f.add_subplot(133)
sns.scatterplot(x=rid_pred, y=(y_test-rid_pred))
plt.title('1c. Check for Homoscedasticity: \nResidual Vs Predicted')
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_base.py:145: FutureWarni
If you wish to scale the data, use Pipeline with a StandardScaler in a preprocessing

from sklearn.pipeline import make_pipeline

model = make_pipeline(StandardScaler(with_mean=False), Ridge())

If you wish to pass a sample_weight parameter, you need to pass it as a fit parameter

kwargs = {s[0] + '__sample_weight': sample_weight for s in model.steps}
model.fit(X, y, **kwargs)

Set parameter alpha to: original_alpha * n_samples.
  FutureWarning,
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass
  FutureWarning
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning:
  warnings.warn(msg, FutureWarning)
Mean Squared Error: 0.05832176533212648
 Root Mean Squared Error: 0.24149899654476098
R Squared: 0.9705408828716985
```

Regressão Elasticnet

Adiciona dupla penalização, um metodo hibrido entre o Ridge e o Lasso

```
ENReg=ElasticNet(alpha=0.05, l1_ratio=0.5, normalize=False)
ENReg.fit(X_train, y_train)
EN_pred=ENReg.predict(X_test)
EN_rsquare=metrics.r2_score(y_test, EN_pred)
print('Mean Squared Error:',metrics.mean_squared_error(y_test, EN_pred))
print(' Root Mean Squared Error:',np.sqrt(metrics.mean_squared_error(y_test, EN_pred)))
print('R Squared:', metrics.r2_score(y_test,EN_pred))

#Plotting

#1. Plot between predicted vs actual values
f=plt.figure(figsize=(14,5))
ax=f.add_subplot(131)
sns.scatterplot(y_test, EN_pred)
ax.set_title('1a. Check for Linearity:\n Actual Vs Predicted value')


# 2. Check for Residual normality & mean : The residual error plot should be normally dist
# & The mean of residual error should be 0 or close to 0 as much as possible

ax=f.add_subplot(132)
sns.distplot(y_test-EN_pred)
ax.axvline((y_test-EN_pred).mean())
ax.set_title('1b. Residual Plot')

#3 Homoscedasticity -The data are homoscedastic meaning the residuals are equal across the
#We can look at residual Vs fitted value scatter plot.
#If heteroscedastic plot would exhibit a funnel shape pattern
```