Data Science com Python

Análise Exploratória de Dados

Prof.: Lucas Roberto Correa

LEMBRETE: Fazer o import dos datasets usados no ambiente do colab antes de executar os comandos.

Import de pacotes

```
!pip install sweetviz
```

```
Collecting sweetviz
  Downloading sweetviz-2.1.3-py3-none-any.whl (15.1 MB)
     |████████████████████████████████| 15.1 MB 2.9 MB/s
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.7/dist-package
Requirement already satisfied: matplotlib>=3.1.3 in /usr/local/lib/python3.7/dist-pac
Requirement already satisfied: pandas!=1.0.0,!=1.0.1,!=1.0.2,>=0.25.3 in /usr/local/l
Requirement already satisfied: tqdm>=4.43.0 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: jinja2>=2.11.1 in /usr/local/lib/python3.7/dist-packag
Requirement already satisfied: importlib-resources>=1.2.0 in /usr/local/lib/python3.7
Requirement already satisfied: zipp>=3.1.0 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: MarkupSafe>=0.23 in /usr/local/lib/python3.7/dist-pack
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-pac
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7/dist-
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.7/dist-pac
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-packages (fr
Installing collected packages: sweetviz
Successfully installed sweetviz-2.1.3
```

```
import sweetviz as sv
```

```
import pandas as pd
```

```
import seaborn as sns
```

```
import matplotlib.pyplot as plt
```

```
from IPython import display
```

```
pd.set_option('display.max_rows', 500)
pd.set_option('display.max_columns', 500)
pd.set_option('display.max_colwidth', 10000)
```

Import da base

Fonte dos dados: https://www.kaggle.com/rashmiranu/banking-dataset-classification?select=new_train.csv

```
metadata = pd.read_excel('metadata.xlsx')
```

```
metadata
```

	Feature	Feature_Type	
0	age	numeric	
1	job	Categorical,nominal	type of job ('admin.','blue-collar','entrepreneur','l employed','services','stude
2	marital	categorical,nominal	marital status ('divorced','married','single','unknown'; note:
3	education	categorical,nominal	('basic.4y','basic.6y','basic.9y','high.school','illiterate','professiona
4	default	categorical,nominal	ha
5	housing	categorical,nominal	
6	loan	categorical,nominal	h
7	contact	categorical,nominal	contact co
8	month	categorical,ordinal	last contact month
9	dayofweek	categorical,ordinal	last contact da
10	duration	numeric	last contact duration, in seconds . Important note: this attribute
11	campaign	numeric	number of contacts performed during this campaign a
12	pdays	numeric	number of days that passed by after the client was last co mea
13	previous	numeric	number of contacts performed

```
df = pd.read_csv('new_train.csv', sep=',')
```

```
df.head()
```

	age	job	marital	education	default	housing	loan	contact	month
0	49	blue-collar	married	basic.9y	unknown	no	no	cellular	nov

```
# Explorar o output da biblioteca sweetviz em uma outra janela, com análise descritiva e g

report = sv.analyze(df)

report.show_html('Analise.html')
```

Done! Use 'show' commands to display/save.

```
Report Analise.html was generated! NOTEBOOK/COLAB USERS: the web browser MAY not pop
```

Estatísticas básicas

```
# Método 'info' retorna diversas informações relacionadas ao Dataframe, dentre elas número

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32950 entries, 0 to 32949
Data columns (total 16 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   age          32950 non-null  int64 
 1   job          32950 non-null  object
 2   marital      32950 non-null  object
 3   education    32950 non-null  object
 4   default      32950 non-null  object
 5   housing      32950 non-null  object
 6   loan         32950 non-null  object
 7   contact      32950 non-null  object
 8   month        32950 non-null  object
 9   day_of_week  32950 non-null  object
 10  duration     32950 non-null  int64 
 11  campaign     32950 non-null  int64 
 12  pdays        32950 non-null  int64 
 13  previous     32950 non-null  int64 
 14  poutcome     32950 non-null  object
 15  y            32950 non-null  object
dtypes: int64(5), object(11)
memory usage: 4.0+ MB
```

```
# Número de linhas e colunas do Dataframe

df.shape
```

```
(32950, 16)
```

```
# Função len (length) para Dataframes retorna o número de linhas

len(df)
```

```
32950
```

```
# Método nunique retorna os valores únicos para cada variável (análogo ao "remover duplica

df.nunique()
```

```
age              75
job              12
marital           4
education         8
default           3
housing           3
loan              3
contact           2
month            10
day_of_week       5
duration       1467
campaign         40
pdays            27
previous          8
poutcome          3
y                 2
dtype: int64
```

Análise Univariada

```
# Retornar as 5 primeiras linhas do Dataframe (5 é o default, é possível alterar esse núme

df['age'].head()
```

```
0    49
1    37
2    78
3    36
4    59
Name: age, dtype: int64
```

```
# Retornar as 5 últimas linhas do Dataframe (mesmo default do 'head')

df['age'].tail()
```

```
32945    28
32946    52
32947    54
32948    29
32949    35
Name: age, dtype: int64
```

```
# Soma de todos os valores de uma coluna (no caso, coluna "age")

df['age'].sum()
```

```
1318465
```

```python
# Valor mínimo observado para determinada coluna

df['age'].min()
```

```
17
```

```python
# Valor médio

df['age'].mean()
```

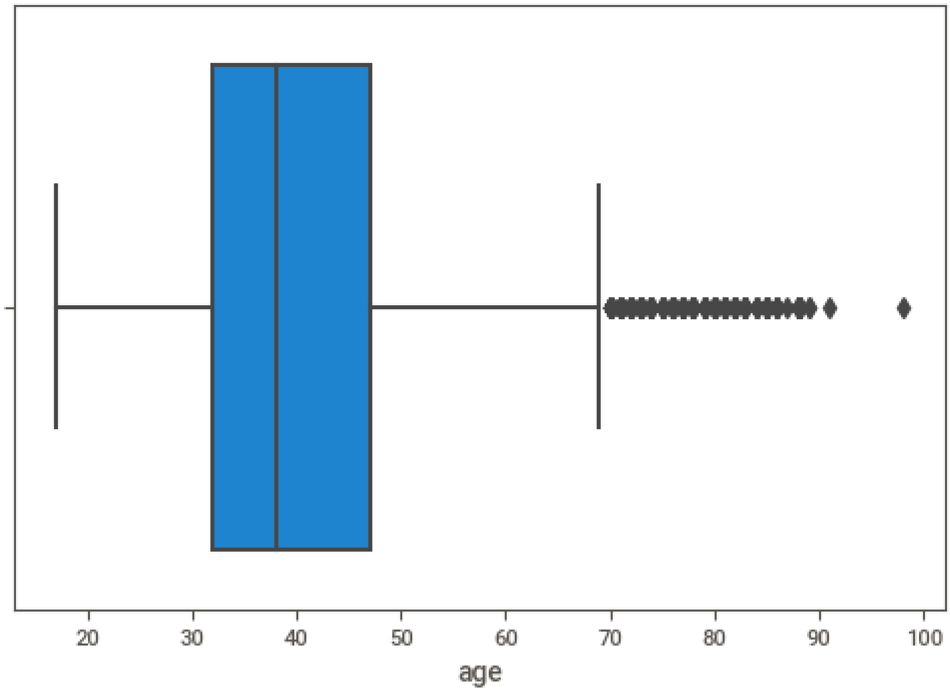
```
40.01411229135053
```

```python
# Valor máximo

df['age'].max()
```

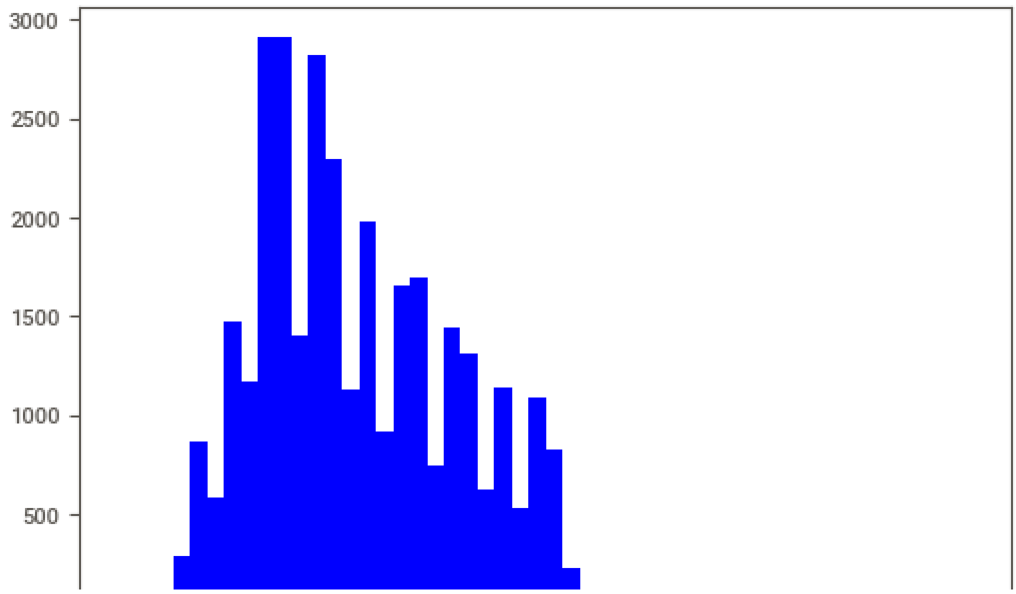
```
98
```

```python
# Boxplot dos dados referentes à coluna "Age". É possível observar onde estão dispostos os

sns.boxplot(x=df["age"])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9a334c6050>
```




```python
# O histograma também facilita a visualização da distribuição dos dados, fundamental na es

plt.hist(df['age'], 50, facecolor='b')
plt.show()
```



Medidas descritivas básicas

```
df.describe(include='int64')
```

	age	duration	campaign	pdays	previous
count	32950.000000	32950.000000	32950.000000	32950.000000	32950.000000
mean	40.014112	258.127466	2.560607	962.052413	0.174719
std	10.403636	258.975917	2.752326	187.951096	0.499025
min	17.000000	0.000000	1.000000	0.000000	0.000000
25%	32.000000	103.000000	1.000000	999.000000	0.000000
50%	38.000000	180.000000	2.000000	999.000000	0.000000
75%	47.000000	319.000000	3.000000	999.000000	0.000000
max	98.000000	4918.000000	56.000000	999.000000	7.000000

```
df.describe(include='object')
```

	job	marital	education	default	housing	loan	contact	month	day_
count	32950	32950	32950	32950	32950	32950	32950	32950	
unique	12	4	8	3	3	3	2	10	
top	admin.	married	university.degree	no	yes	no	cellular	may	
freq	8314	19953	9736	26007	17254	27131	20908	11011	

Análise de missings

```
df.isnull().sum()
```

```
age            0
job            0
marital        0
education      0
default        0
housing        0
loan           0
contact        0
month          0
day_of_week    0
duration       0
campaign       0
pdays          0
previous       0
poutcome       0
y              0
dtype: int64
```

Tabela de Frequencia

```
df['poutcome'].value_counts()
```

```
nonexistent    28416
failure         3429
success         1105
Name: poutcome, dtype: int64
```

```
df['contact'].value_counts()
```

```
cellular     20908
telephone    12042
Name: contact, dtype: int64
```

```
df['age'].value_counts().hist()
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f9a31f76490>

```
prev_y = pd.crosstab(index=df["previous"], columns=df["y"],margins=True)
prev_y
```

y	no	yes	All
previous			
0	25915	2501	28416
1	2889	784	3673
2	324	282	606
3	74	101	175
4	29	31	60
5	4	10	14
6	2	3	5
7	1	0	1
All	29238	3712	32950

```
job_y = pd.crosstab(index=df["job"], columns=df["y"],margins=True)
job_y
```

y	no	yes	All
job			
admin.	7244	1070	8314
blue-collar	6926	515	7441
entrepreneur	1060	100	1160
housemaid	769	86	855
management	2076	269	2345
retired	1018	348	1366
self-employed	980	119	1099
services	2942	254	3196
student	494	217	711
technician	4815	585	5400
unemployed	682	116	798
unknown	232	33	265
All	29238	3712	32950

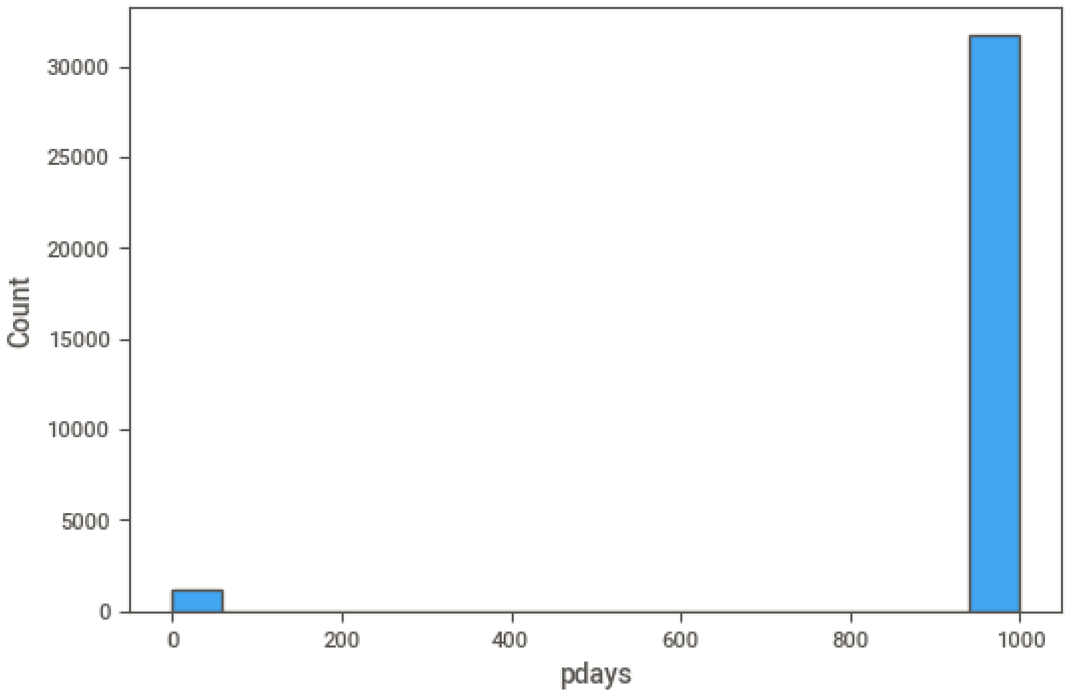
Histograma

```
df.dtypes
```

```
age               int64
job              object
marital          object
education        object
default          object
housing          object
loan             object
contact          object
month            object
day_of_week      object
duration          int64
campaign          int64
pdays             int64
previous          int64
poutcome         object
y                object
dtype: object
```

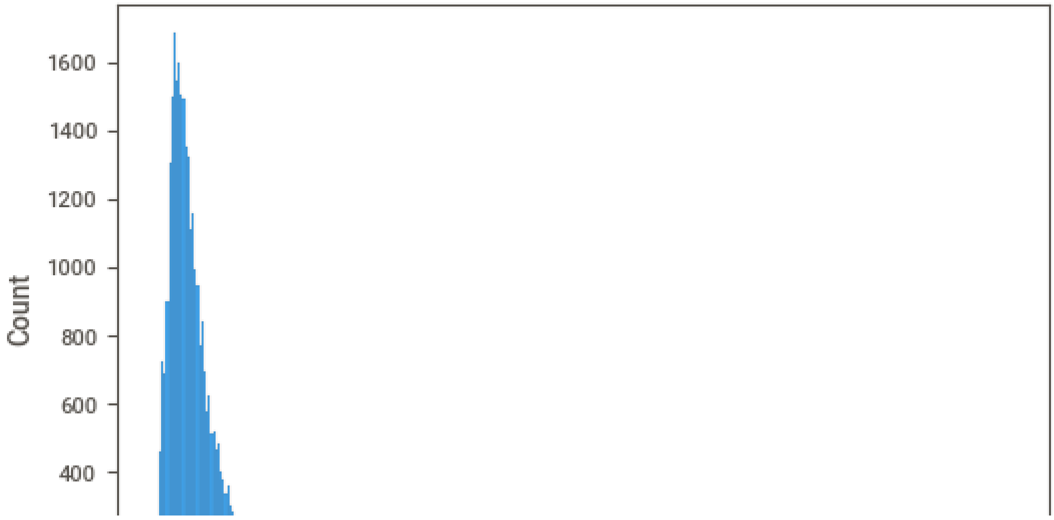
```
sns.histplot(data=df, x="pdays")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9a31ea48d0>
```




```
sns.histplot(data=df, x="duration")
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f9a31e146d0>




```
df['duration'].describe()
```

```
count    32950.000000
mean       258.127466
std        258.975917
min          0.000000
25%        103.000000
50%        180.000000
75%        319.000000
max       4918.000000
Name: duration, dtype: float64
```

```
df['duration'].median()
```

```
180.0
```

```
df['duration'].mode()
```

```
0    90
dtype: int64
```

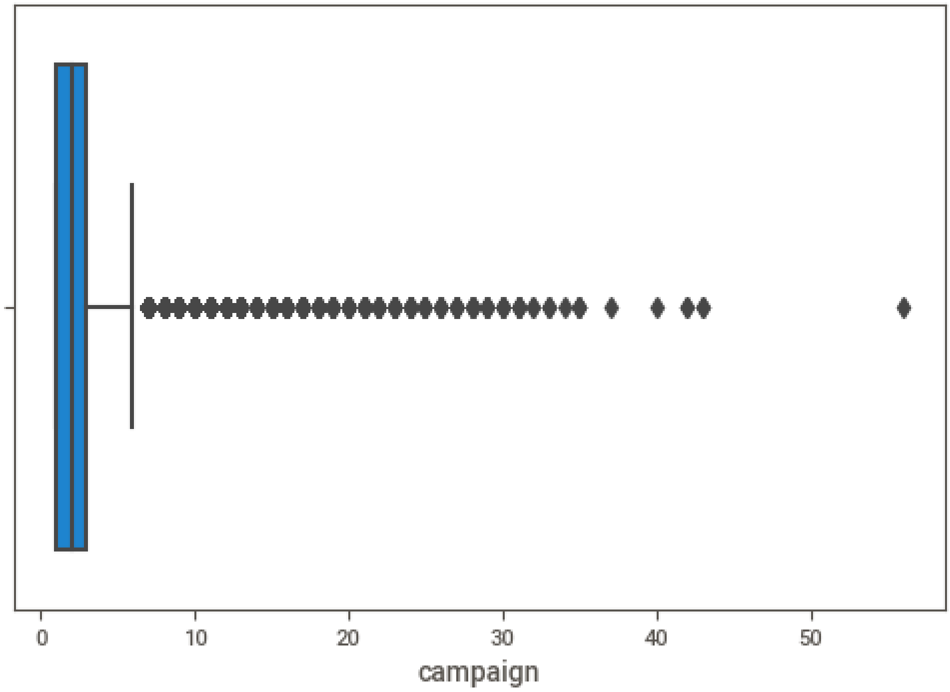
```
sns.histplot(data=df, x="campaign")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9a33900790>
```

Boxplot

```
sns.boxplot(x=df["campaign"])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9a338915d0>
```




```
df['campaign'].value_counts()
```

```
1     14121
2      8469
3      4300
4      2116
5      1255
6       773
7       493
8       329
9       220
10      187
11      142
12       92
13       74
14       52
17       51
15       45
16       42
18       27
20       22
21       20
19       16
```

```
22     13
24     12
23     12
27      9
25      8
26      7
31      7
29      7
28      6
30      6
35      4
33      3
43      2
32      2
42      2
34      1
37      1
40      1
56      1
Name: campaign, dtype: int64
```

```
display.Image("IQR.png")
```

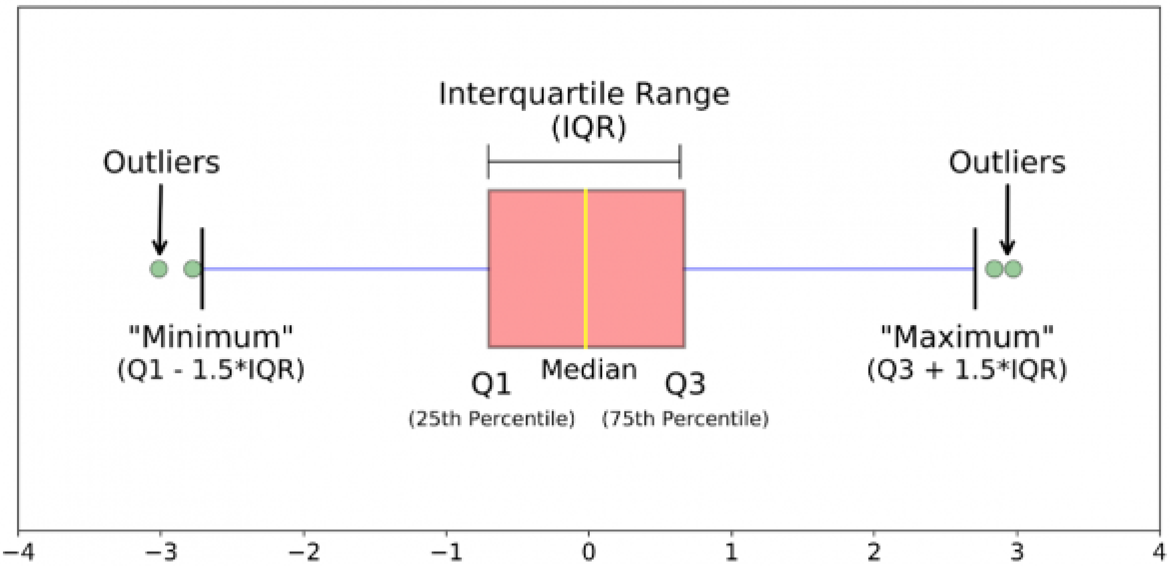


Grafico de Dispersão

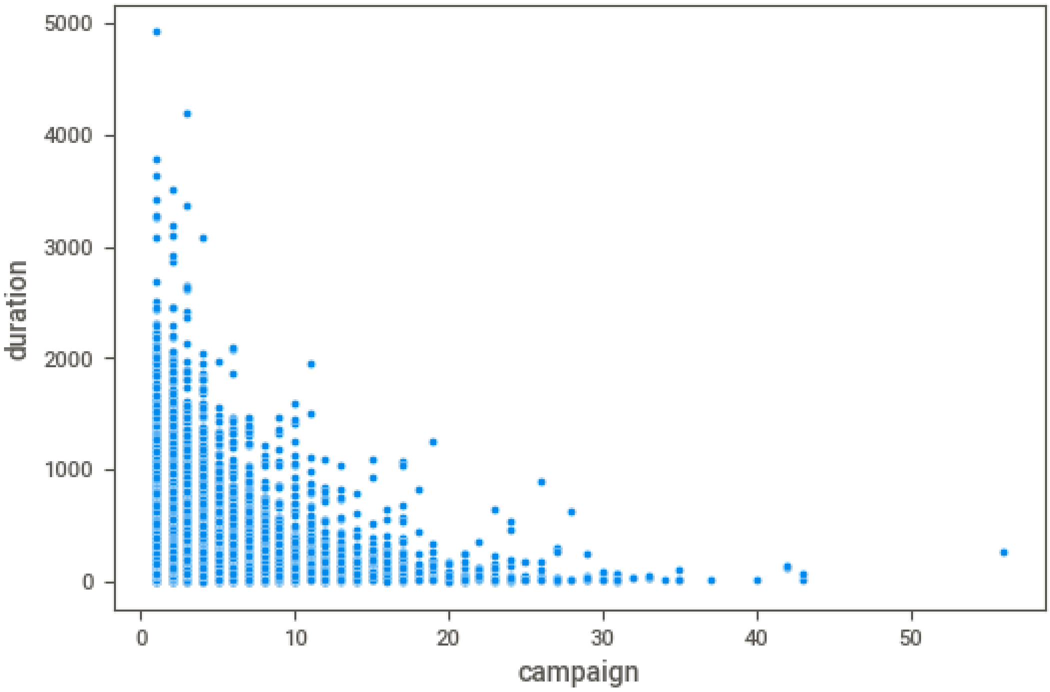
```
df.dtypes
```

```
age             int64
job            object
marital        object
education      object
default        object
housing        object
loan           object
contact        object
month          object
day_of_week    object
duration        int64
```

```
campaign        int64
pdays           int64
previous        int64
poutcome       object
y              object
dtype: object
```

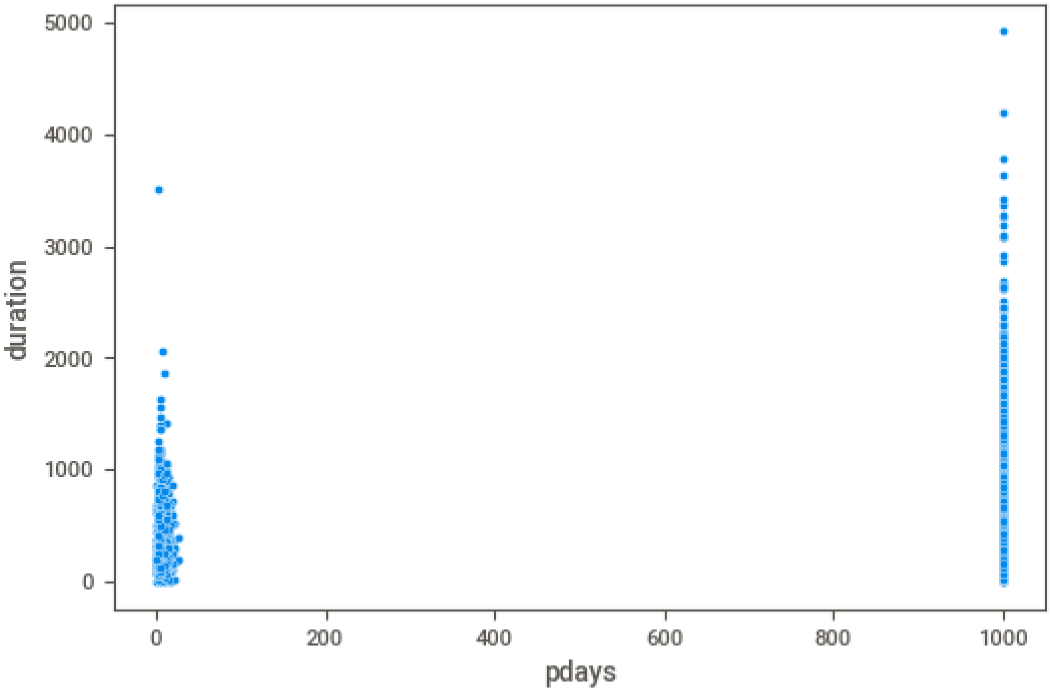
```
sns.scatterplot(data=df, x="campaign", y="duration")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9a2ddfa950>
```




```
sns.scatterplot(data=df, x="pdays", y="duration")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9a2dd7c110>
```



Correlações

```
df.corr()
```

	age	duration	campaign	pdays	previous
age	1.000000	-0.001841	0.003302	-0.032011	0.020670
duration	-0.001841	1.000000	-0.075663	-0.047127	0.022538
campaign	0.003302	-0.075663	1.000000	0.053795	-0.079051
pdays	-0.032011	-0.047127	0.053795	1.000000	-0.589601
previous	0.020670	0.022538	-0.079051	-0.589601	1.000000

```
sns.heatmap(df.corr(), annot=True, fmt="f")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9a2dd624d0>
```

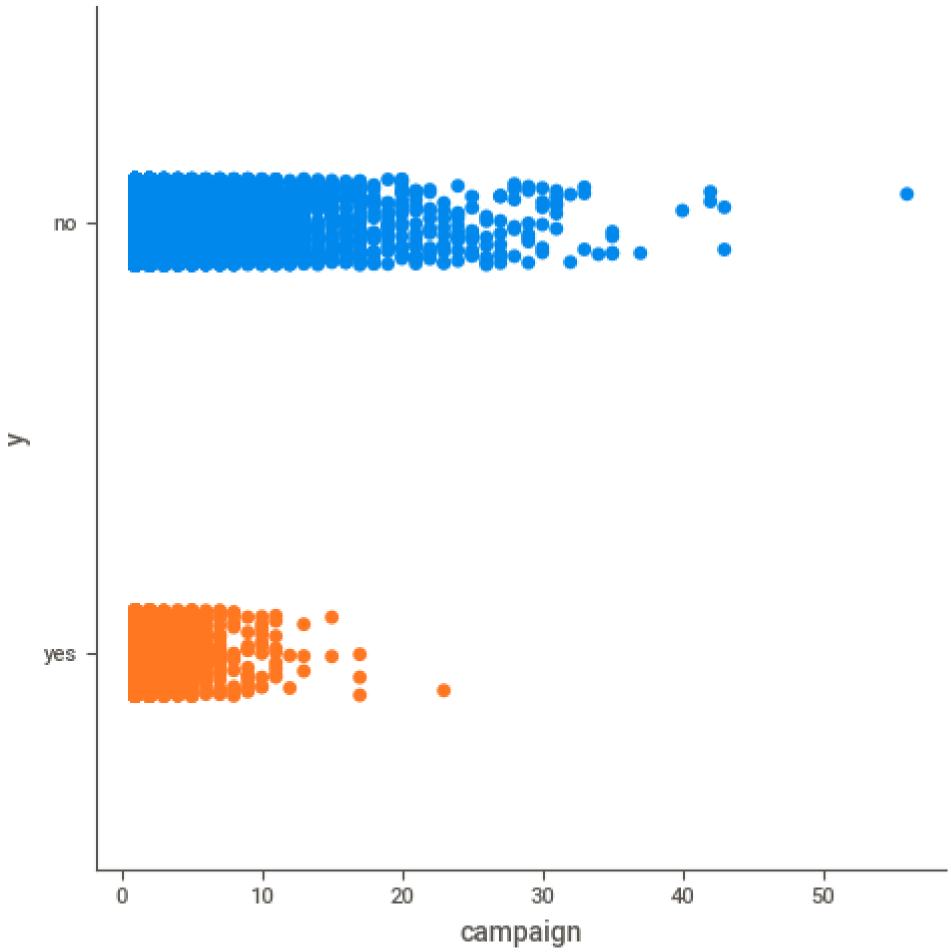
Plot de variáveis categoricas

```
sns.catplot(x="duration", y="y", data=df)
```

```
<seaborn.axisgrid.FacetGrid at 0x7f9a2dd82750>
```

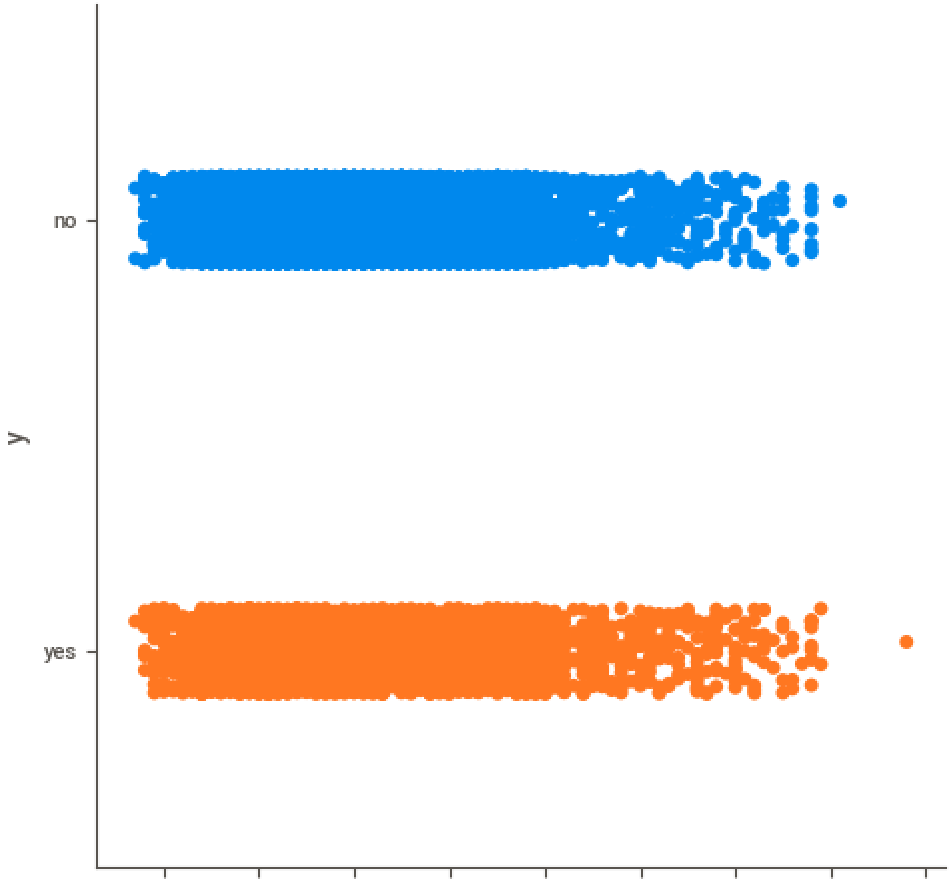

```
sns.catplot(x="campaign", y="y", data=df)
```

```
<seaborn.axisgrid.FacetGrid at 0x7f9a2dc0b650>
```




```
sns.catplot(x="age", y="y", data=df)
```

```
<seaborn.axisgrid.FacetGrid at 0x7f9a2db7ec50>
```



Análise Multivariada

```
sns.relplot(x="age", y="duration", hue="y", data=df);
```

Análise de Componentes Principais - PCA no contexto de Análise Multivariada

```
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
```

```
metadata
```

	Feature	Feature_Type	
0	age	numeric	
1	job	Categorical,nominal	type of job ('admin.','blue-collar','entrepreneur','| employed','services','stude
2	marital	categorical,nominal	marital status ('divorced','married','single','unknown'; note:
3	education	categorical,nominal	('basic.4y','basic.6y','basic.9y','high.school','illiterate','profession
4	default	categorical,nominal	ha
5	housing	categorical,nominal	
6	loan	categorical,nominal	h
7	contact	categorical,nominal	contact co
8	month	categorical,ordinal	last contact month
9	dayofweek	categorical,ordinal	last contact da
10	duration	numeric	last contact duration, in seconds . Important note: this attribute
11	campaign	numeric	number of contacts performed during this campaign a
12	pdays	numeric	number of days that passed by after the client was last co mea
13	previous	numeric	number of contacts performed
14	poutcome	categorical,nominal	outcome of the previous marketing ca

```
df_pca = df[['age', 'duration','campaign','pdays','previous']]
```

```
df_pca.head()
```

	age	duration	campaign	pdays	previous
1	37	202	2	999	1

```
pca = PCA(n_components=2, random_state=42)
```

```
df_expl_pca = StandardScaler().fit_transform(df_pca)
```

```
df_expl_pca
```

```
array([[ 0.86373877, -0.12019627,  0.52298128,  0.19658384, -0.35012691],
       [-0.28972159, -0.2167318 , -0.20368791,  0.19658384,  1.65381294],
       [ 3.65126795,  3.43617293, -0.56702251,  0.19658384, -0.35012691],
       ...,
       [ 1.34434725, -0.49089273,  0.52298128,  0.19658384, -0.35012691],
       [-1.05869515, -0.3596044 , -0.56702251,  0.19658384, -0.35012691],
       [-0.48196498,  1.10387435,  0.15964669,  0.19658384, -0.35012691]])
```

```
result_pca = pca.fit_transform(df_expl_pca)
```

```
result_pca_df = pd.DataFrame(result_pca,
                             columns=['component1','component2'])
result_pca_df
```

	component1	component2
0	-0.425175	-0.509855
1	1.005371	-0.146158
2	0.265589	2.274575
3	-0.421084	-0.115342
4	-0.197363	0.194940
...	...	...
32945	-0.379635	0.451884
32946	1.095991	-0.530097
32947	-0.433674	-0.855301
32948	-0.384307	0.361312
32949	-0.324058	0.829408

32950 rows × 2 columns

O quanto eu estou conseguindo explicar da variabilidade dos dados?

```
pca.explained_variance_ratio_
```

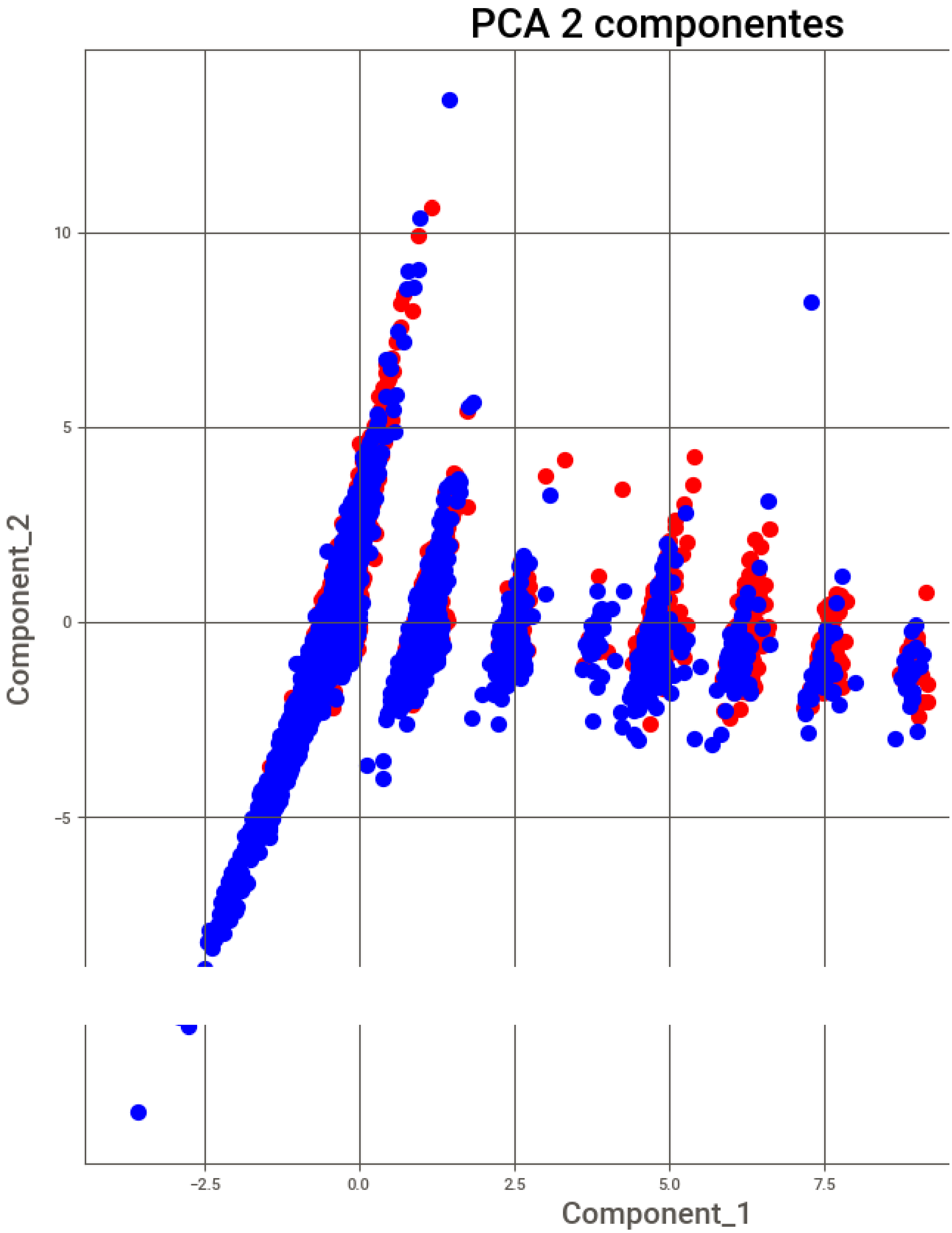
```
array([0.32246681, 0.2116934 ])
```

```
df_resp_pca = pd.concat([df['y'], result_pca_df], axis=1)
df_resp_pca
```

	y	component1	component2
0	no	-0.425175	-0.509855
1	no	1.005371	-0.146158
2	yes	0.265589	2.274575
3	no	-0.421084	-0.115342
4	no	-0.197363	0.194940
...	...	...	...
32945	no	-0.379635	0.451884
32946	no	1.095991	-0.530097
32947	no	-0.433674	-0.855301
32948	no	-0.384307	0.361312
32949	no	-0.324058	0.829408

32950 rows × 3 columns

```
fig = plt.figure(figsize= (10,10))

ax = fig.add_subplot(1,1,1)

ax.set_xlabel('Component_1', fontsize = 15)
ax.set_ylabel('Component_2', fontsize = 15)
ax.set_title('PCA 2 componentes', fontsize = 20)
targets = ['yes','no']
colors = ['r', 'b']
for target, color in zip(targets,colors):
    indicesToKeep = df_resp_pca['y'] == target
    ax.scatter(df_resp_pca.loc[indicesToKeep, 'component1']
               , df_resp_pca.loc[indicesToKeep, 'component2']
               , c = color
               , s = 50)
ax.legend(targets)
ax.grid()
```


PCA 2 componentes
10
5
0
-5
Component_2
-2.5
0.0
2.5
5.0
7.5
Component_1