# Data Science com Python

## Análise Exploratória de Dados

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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](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
```

```
# Valor mínimo observado para determinada coluna

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

```
17
```

```
# Valor médio

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

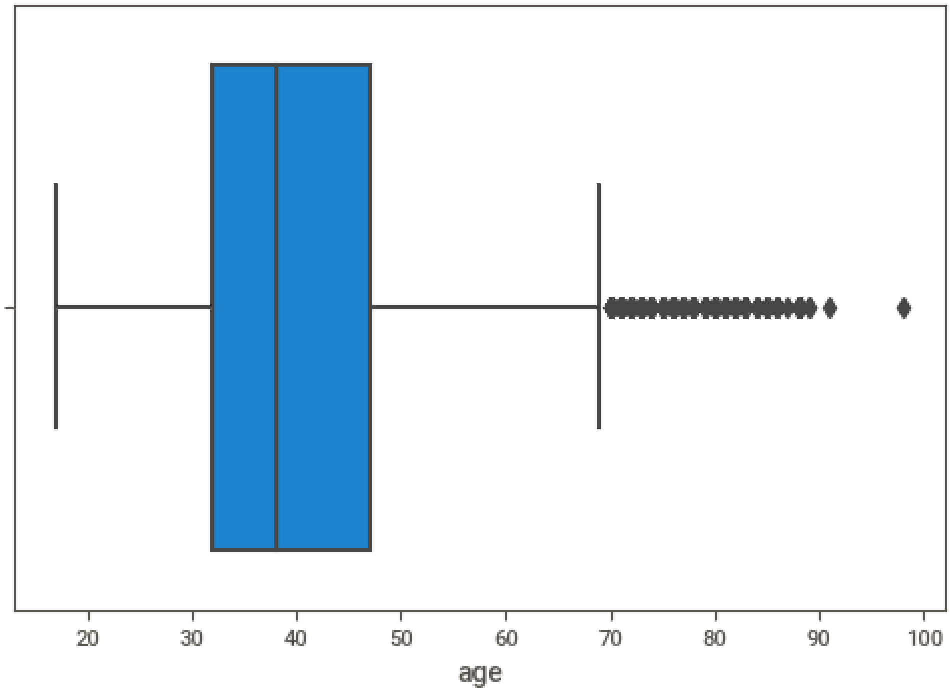
```
40.01411229135053
```

```
# Valor máximo

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

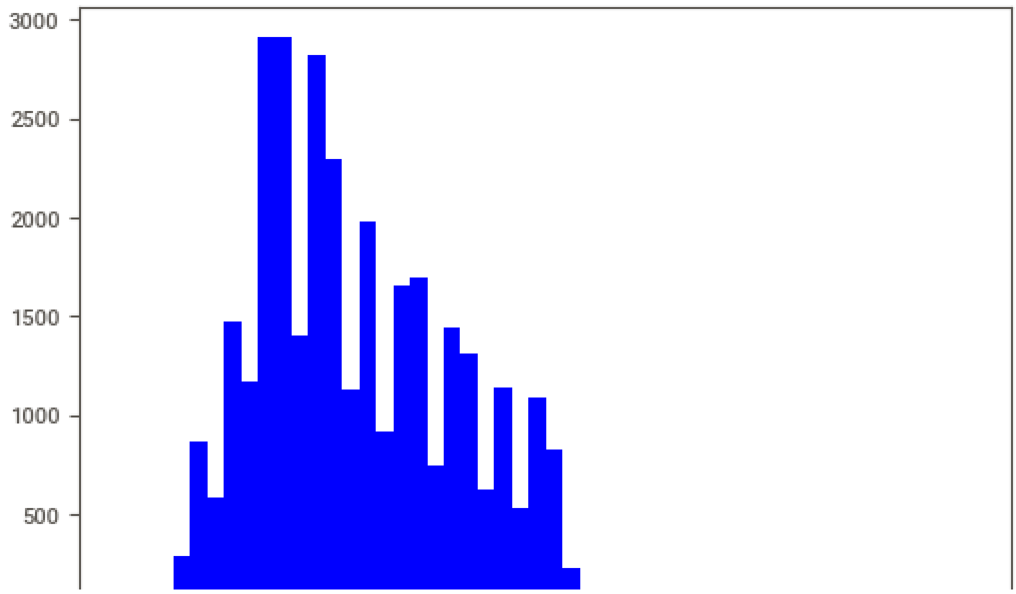
```
98
```

```
# 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>
```




```
# 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 |

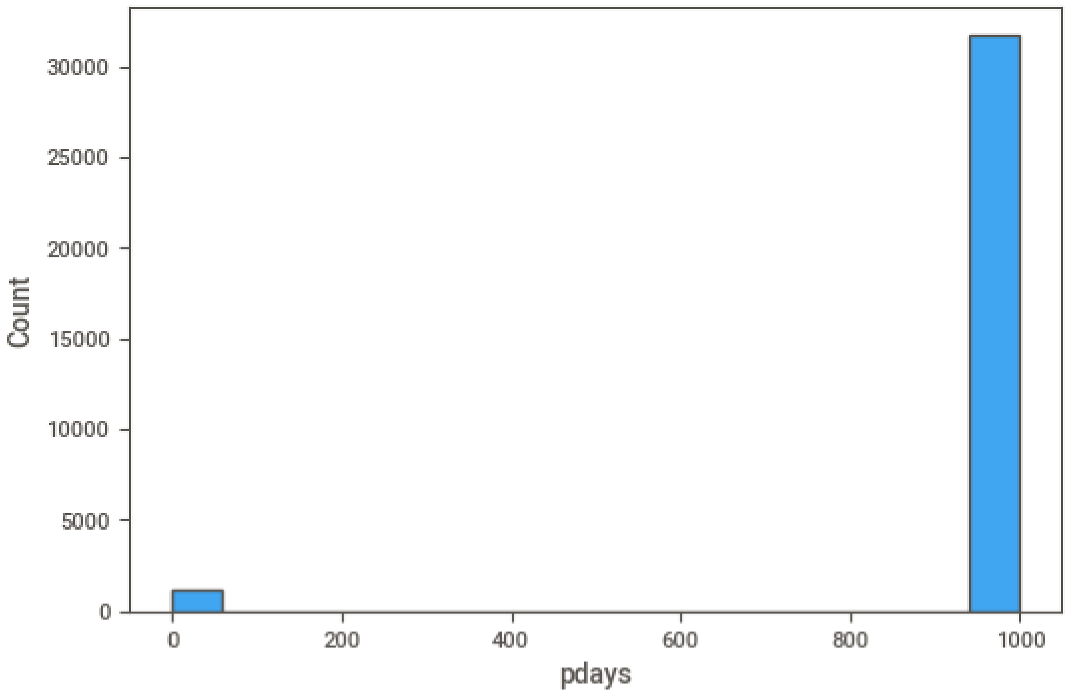
# Histograma

```
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
```

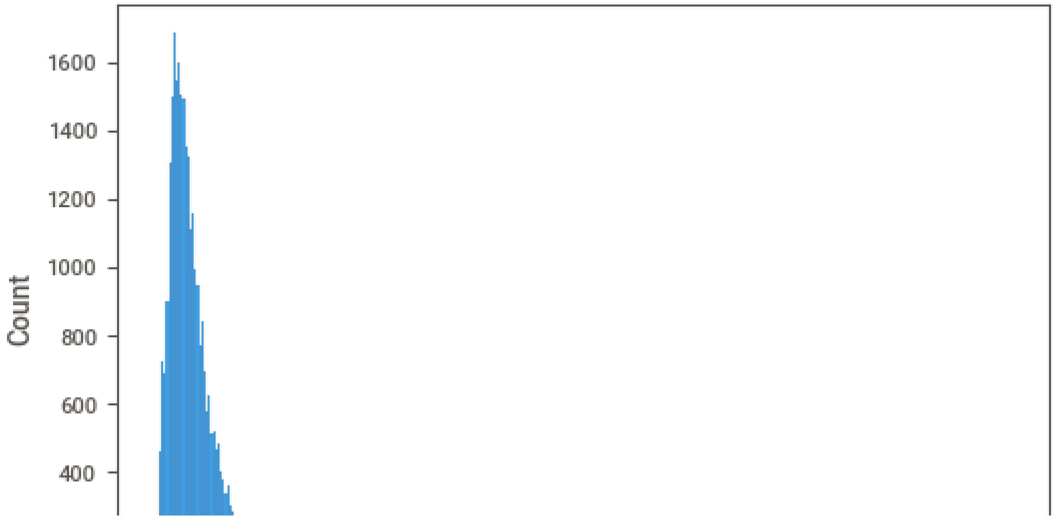
```
sns.histplot(data=df, x="pdays")
```

```
<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
```

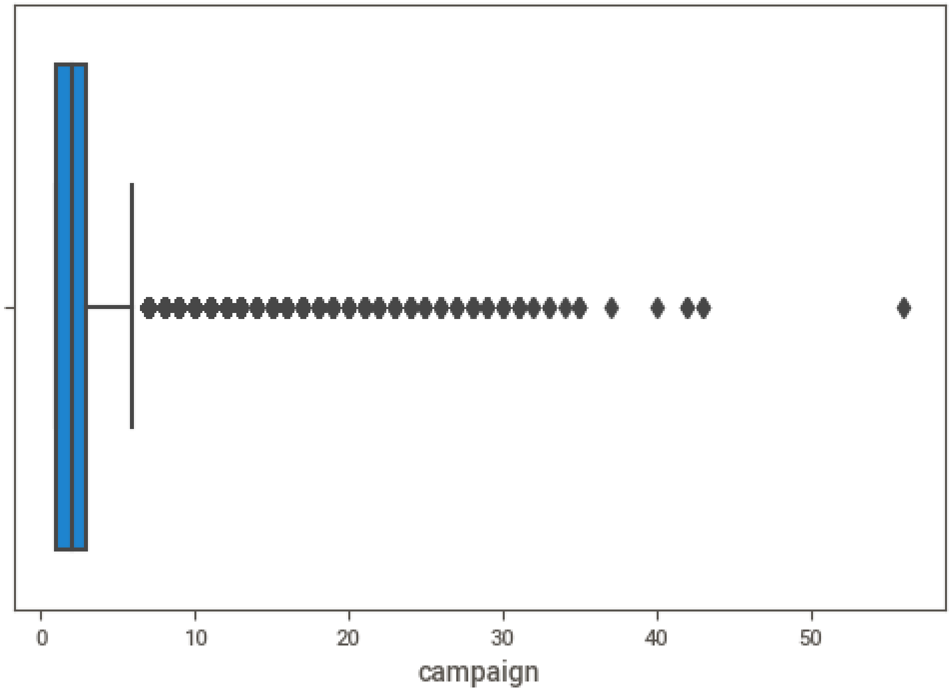
```
sns.histplot(data=df, x="campaign")
```

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


## Boxplot

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

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

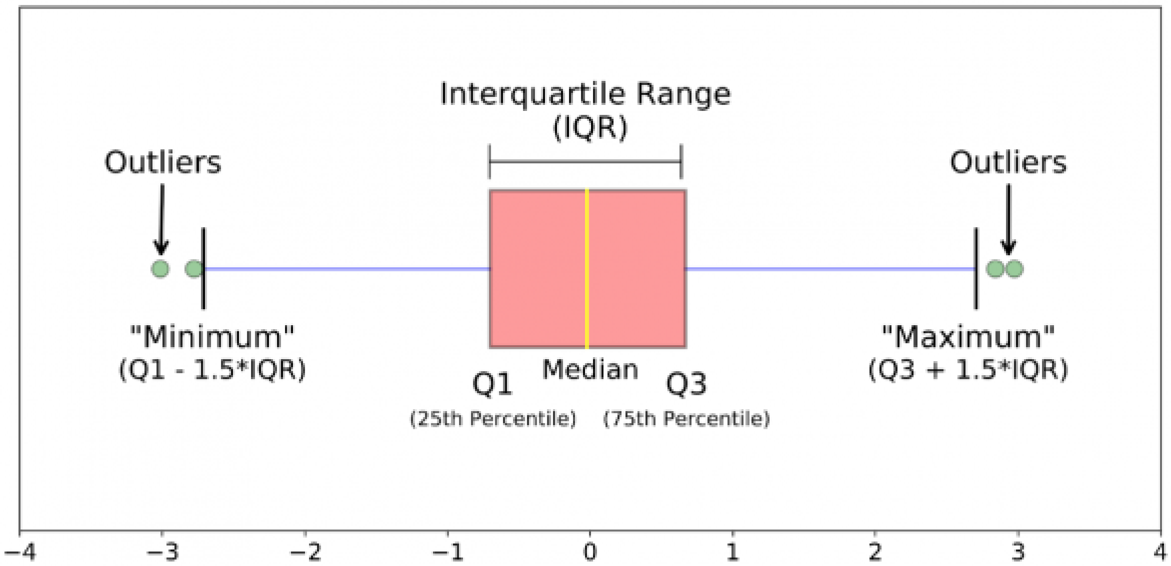



```
df['campaign'].value_counts()
```

```
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

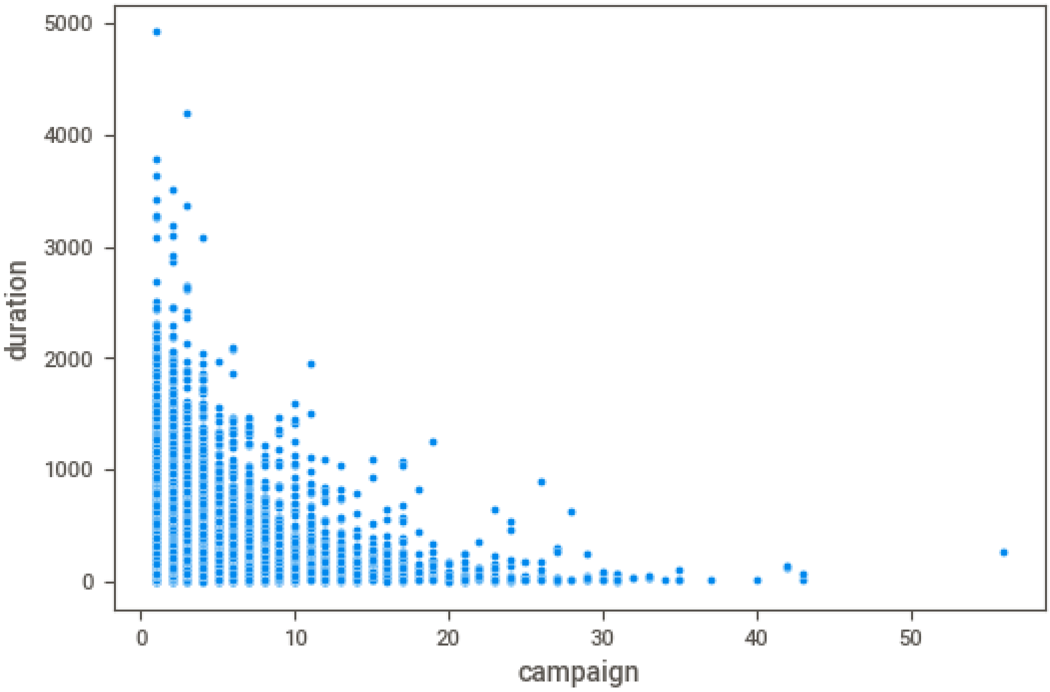
```
df.dtypes
```

```
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
```

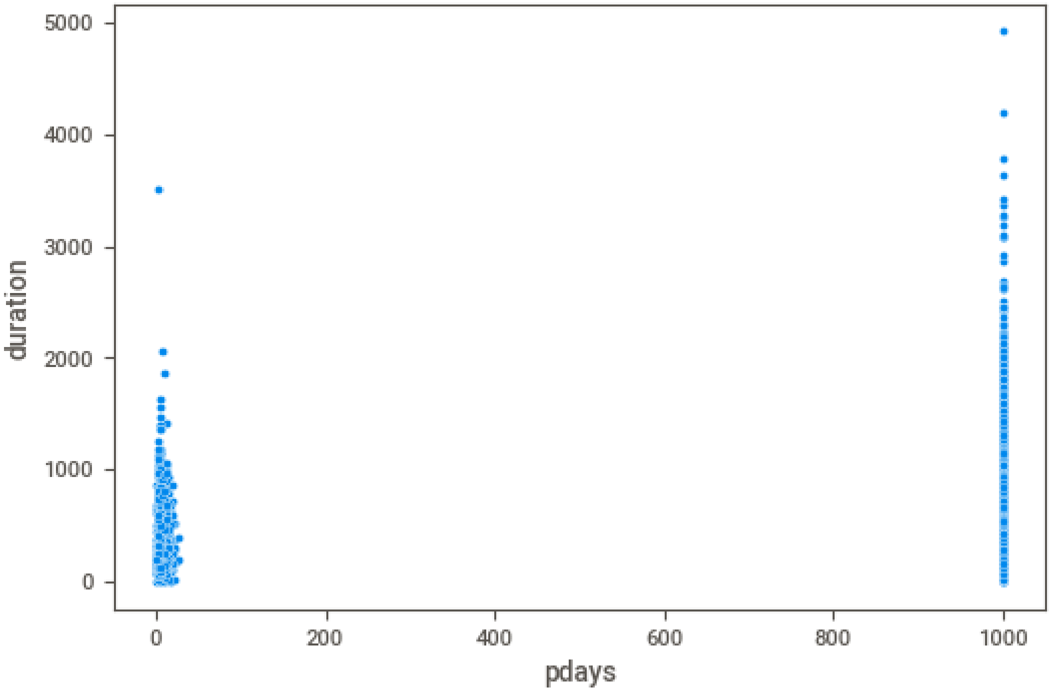
```
sns.scatterplot(data=df, x="campaign", y="duration")
```

```
<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>
```

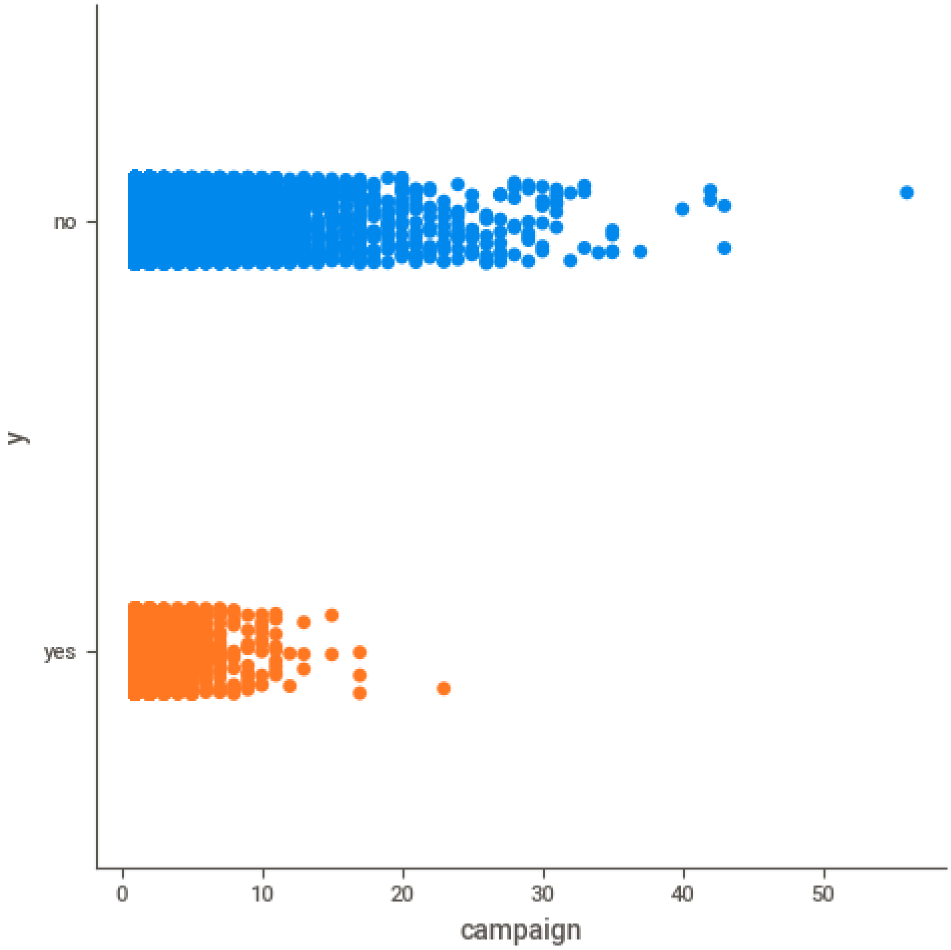

## Plot de variáveis categoricas

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

<seaborn.axisgrid.FacetGrid at 0x7f9a2dd82750>

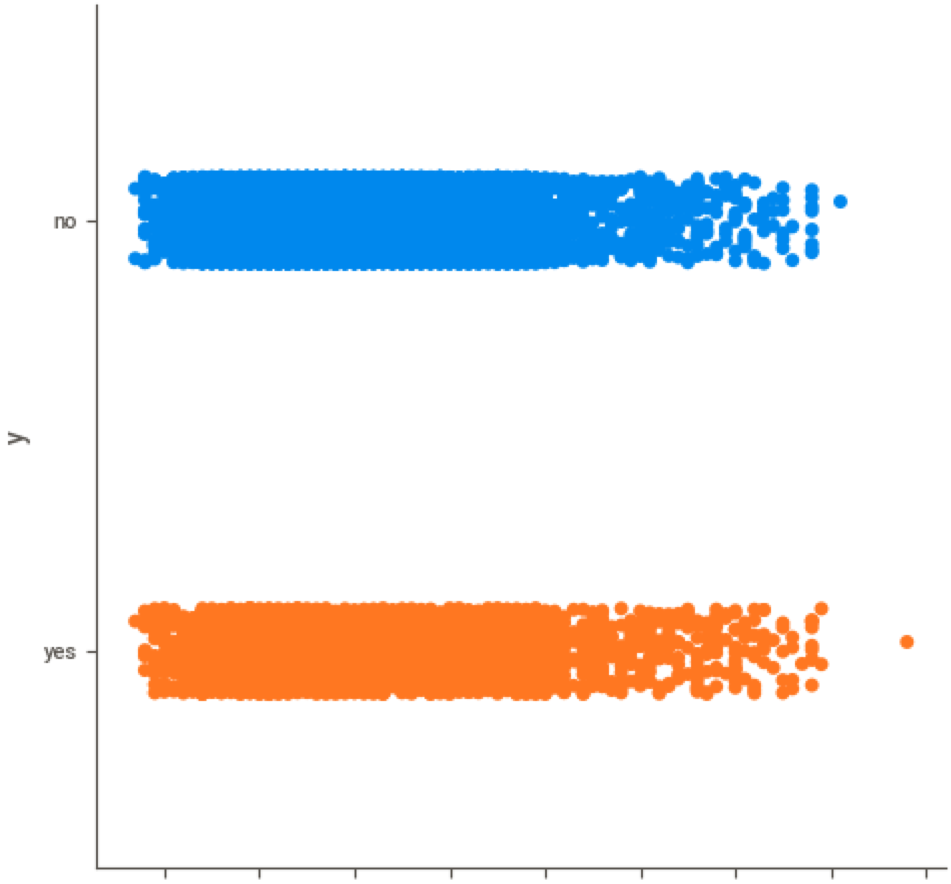

```
sns.catplot(x="campaign", y="y", data=df)
```

<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','<br>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<br>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 |
| 2 | 36 | 120 | 2 | 999 | 0 |

```
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_
```

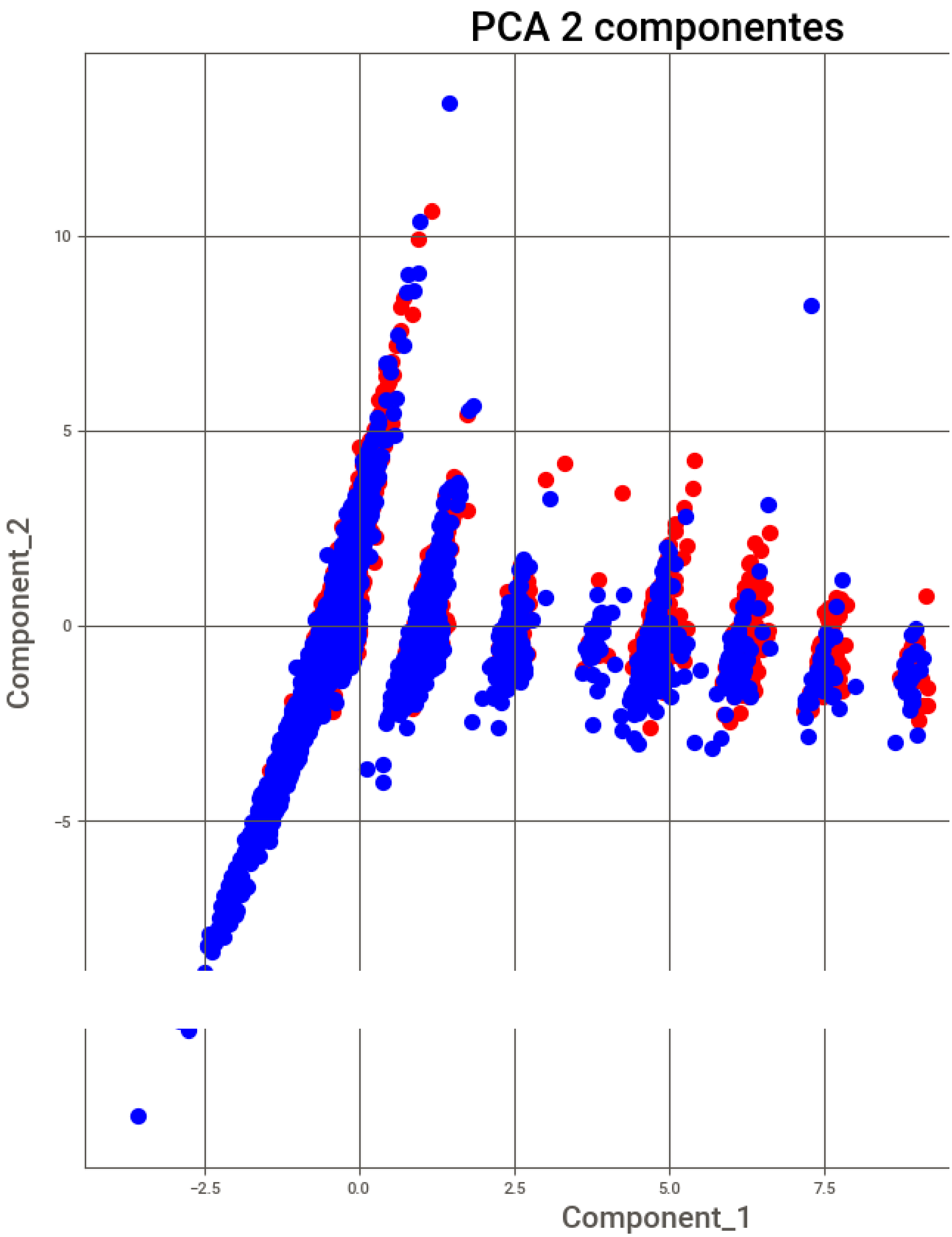
```
array([0.32246681, 0.2116934 ])
```

```
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