```
import os
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score, mean_squared_error, r2_score
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report
from sklearn.linear_model import LogisticRegression
```

```
from google.colab import drive
drive.mount('/content/drive')
```

Mounted at /content/drive

data = pd.read_csv("/content/drive/MyDrive/Colab Notebooks/card_transdata.csv")

data.head()

8		distance_from_home	distance_from_last_transaction	ratio_to_median_purchase_pric
	0	57.877857	0.311140	1.94594
	1	10.829943	0.175592	1.29421
	2	5.091079	0.805153	0.42771
	3	2.247564	5.600044	0.36266
	4	44.190936	0.566486	2.22276
	\prec			•

print(data.shape)

(1000000, 8)

```
onlycredit = data[(data['used_chip'] == 1.0)]
print(onlycredit.shape)
```

(350399, 8)

```
onlyonline = onlycredit[(onlycredit['online_order'] == 1.0)]
print(onlyonline.shape)
```

(227903, 8)

```
onlyonline.isnull().any().any()
```

False

```
X = onlyonline.drop(['fraud'], axis=1)
Y = onlyonline['fraud']
print(X, Y)
              distance_from_home
                                   distance_from_last_transaction
     3
                        2.247564
                                                           5.600044
     4
                       44.190936
                                                           0.566486
     10
                       14.263530
                                                           0.158758
     11
                                                           0.240540
                       13.592368
     15
                      179.665148
                                                           0.120920
     . . .
                              . . .
                                                                 . . .
     999982
                        3.805818
                                                           0.685528
     999987
                       12.539374
                                                           1.773940
     999990
                       20.334489
                                                          11.437333
     999997
                        2.914857
                                                           1.472687
     999999
                       58.108125
                                                           0.318110
              ratio_to_median_purchase_price repeat_retailer used_chip \
     3
                                     0.362663
                                                             1.0
                                                                         1.0
     4
                                     2.222767
                                                             1.0
                                                                         1.0
     10
                                     1.136102
                                                             1.0
                                                                         1.0
     11
                                     1.370330
                                                             1.0
                                                                         1.0
     15
                                     0.535640
                                                             1.0
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     . . .
                                                             . . .
                                                                         . . .
     999982
                                     0.336647
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     999987
                                     0.792166
                                                             1.0
                                                                         1.0
     999990
                                     0.699527
                                                             1.0
                                                                         1.0
     999997
                                     0.218075
                                                             1.0
                                                                         1.0
     999999
                                     0.386920
                                                             1.0
                                                                         1.0
              used_pin_number
                                online order
     3
                           0.0
                                          1.0
     4
                           0.0
                                          1.0
     10
                           0.0
                                          1.0
     11
                           0.0
                                          1.0
     15
                           1.0
                                          1.0
                           . . .
     999982
                           0.0
                                          1.0
     999987
                           0.0
                                          1.0
     999990
                           0.0
                                          1.0
     999997
                           0.0
                                          1.0
     999999
                                          1.0
                           0.0
     [227903 rows x 7 columns] 3
                                            0.0
     4
                0.0
     10
                0.0
     11
                0.0
     15
                0.0
               . . .
     999982
                0.0
     999987
                0.0
     999990
                0.0
     999997
                0.0
     999999
                0.0
     Name: fraud, Length: 227903, dtype: float64
```

X_train, X_test, Y_train, Y_test = train_test_split(X,Y, test_size=0.2, random_state | B 2

```
lr = LogisticRegression(max_iter=1000)
lr.fit(X_train, Y_train)
pred = lr.predict(X_test)
acc = accuracy_score(Y_test, pred)
f'Acurácia:{acc * 100:.2f}'
```

'Acurácia:99.24'

```
only_real = onlyonline.fraud
only_total = onlyonline.drop(['fraud'], axis=1)
only_total
```

	distance_from_home	distance_from_last_transaction	ratio_to_median_purchase
3	2.247564	5.600044	0.
4	44.190936	0.566486	2.
10	14.263530	0.158758	1.
11	13.592368	0.240540	1.
15	179.665148	0.120920	0.
999982	3.805818	0.685528	0.
999987	12.539374	1.773940	0.
999990	20.334489	11.437333	0.
999997	2.914857	1.472687	0.
999999	58.108125	0.318110	0.

227903 rows × 7 columns

```
pred = lr.predict(only_total)
only_val = pd.DataFrame({'real':only_real, 'previsao':pred})
only_val.head(n=30)
```

	real	previsao
3	0.0	0.0
4	0.0	0.0
10	0.0	0.0
11	0.0	0.0
15	0.0	0.0
28	0.0	0.0
30	0.0	0.0
31	0.0	0.0
35	1.0	1.0
39	0.0	0.0
42	0.0	0.0
43	0.0	0.0
51	0.0	0.0
52	0.0	0.0
55	0.0	0.0
67	0.0	0.0
72	0.0	0.0
77	0.0	0.0
78	0.0	0.0
79	0.0	0.0
81	0.0	0.0
91	0.0	0.0
95	0.0	0.0
00	0 0	0.0

```
only_val.previsao.value_counts()
```

0.0 1456501.0 14093

Name: previsao, dtype: int64

only_val.real.value_counts()

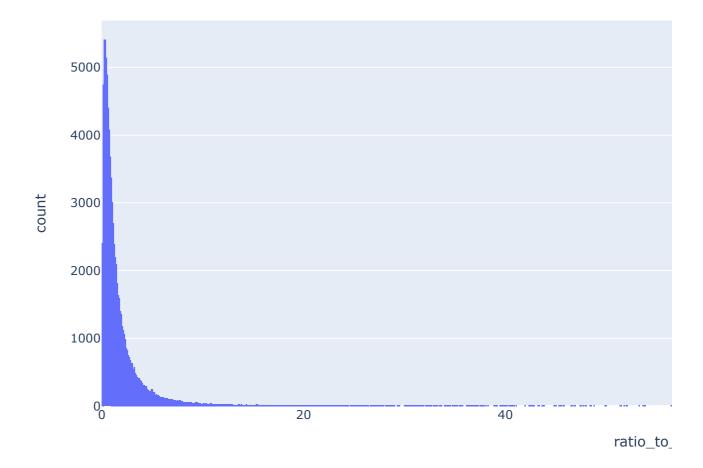
0.0 144670

1.0 15073

Name: real, dtype: int64

 $\hbox{import plotly.} \\ \hbox{express as px}$

px.histogram(onlyonline, x = 'ratio_to_median_purchase_price')



```
data['credit_and_online'] = np.where (
    (data['used_chip'] == 1.0) & (data['used_pin_number'] == 1.0) & (data['online_order']
    'yes',
    'no'
)
```

data

		distance_from_home	distance_from_last_transaction	ratio_to_median_purchase
	0	57.877857	0.311140	1.
	1	10.829943	0.175592	1.
	2	5.091079	0.805153	0.
<pre>data2 = data[data.credit_and_online != 'no'] data2</pre>				

	distance_from_home	distance_from_last_transaction	ratio_to_median_purchase
15	179.665148	0.120920	0.
51	43.281314	3.367793	0.
55	24.268906	0.136521	1.
98	6.136181	2.579574	1.
138	5.169928	0.534060	1.
700792	54.018855	0.215318	0.
700843	11.077239	3.175977	2.
700848	3.687145	9.964012	1.
700962	5.914416	0.008577	0.
701063	3.000823	0.148435	0.

15909 rows × 9 columns

```
data2 = data2.drop([('used_chip')], axis=1)
data2
```

```
KeyError
                                          Traceback (most recent call last)
<ipython-input-32-ff96b3bf7ca0> in <module>
----> 1 data2 = data2.drop([('used_chip')], axis=1)
      2 data2
                                   4 frames -
/usr/local/lib/python3.7/dist-packages/pandas/core/indexes/base.py in drop(self, labe
                if mask.any():
   6015
                    if errors != "ignore":
   6016
                        raise KeyError(f"{labels[mask]} not found in axis")
-> 6017
   6018
                    indexer = indexer[~mask]
                return self.delete(indexer)
   6019
KeyError: "['used_chip'] not found in axis"
 SEARCH STACK OVERFLOW
```

В

data2 = data2.drop([('used_pin_number')], axis=1)
data2

	distance_from_home	distance_from_last_transaction	ratio_to_median_purchase
15	179.665148	0.120920	0.
51	43.281314	3.367793	0.
55	24.268906	0.136521	1.
98	6.136181	2.579574	1.
138	5.169928	0.534060	1.
700792	54.018855	0.215318	0.
700843	11.077239	3.175977	2.
700848	3.687145	9.964012	1.
700962	5.914416	0.008577	0.
701063	3.000823	0.148435	0.

15909 rows × 7 columns

data2 = data2.drop([('online_order')], axis=1)
data2

	<pre>distance_from_home</pre>	distance_from_last_transaction	ratio_to_median_purchase
15	179.665148	0.120920	0.
51	43.281314	3.367793	0.
55	24.268906	0.136521	1.
98	6.136181	2.579574	1.
138	5.169928	0.534060	1.
700792	54.018855	0.215318	0.
700843	11.077239	3.175977	2.
700848	3.687145	9.964012	1.
700962	5.914416	0.008577	0.
701063	3.000823	0.148435	0.

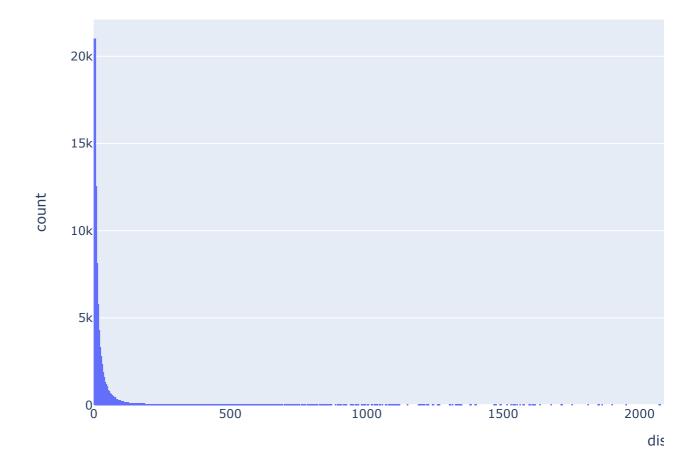
15909 rows × 6 columns

print(data2.shape)

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(15909, 6)

```
import plotly.express as px
px.histogram(onlyonline, x = 'distance_from_home')
```

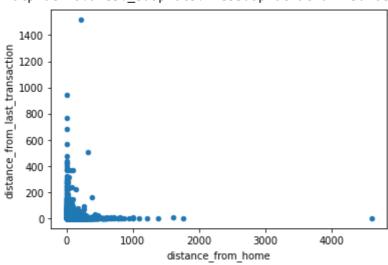


```
import plotly.express as px
px.histogram(onlyonline, x = 'distance_from_last_transaction')
```

```
50k
             40k
import matplotlib.pyplot as plt
```

data2.plot.scatter('distance_from_home', 'distance_from_last_transaction')

<matplotlib.axes._subplots.AxesSubplot at 0x7f5a1cedb650>



from sklearn.tree import DecisionTreeClassifier

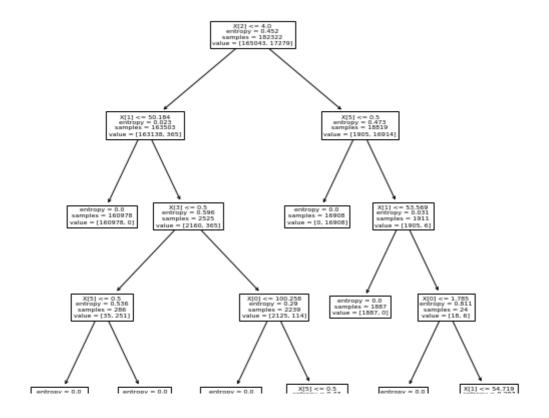
tree.plot_tree(arvore)

```
arvore = DecisionTreeClassifier(criterion='entropy')
arvore.fit(X_train, Y_train)
```

DecisionTreeClassifier(criterion='entropy')

```
arvore.feature_importances_
     array([0.00739904, 0.02765845, 0.84669187, 0.00851158, 0.
            0.10973907, 0.
                                  1)
from sklearn import tree
figura, eixos = plt.subplots(nrows = 1, ncols = 1, figsize = (10,10))
```

```
[\text{Text}(0.4230769230769231, 0.91666666666666666, 'X[2] <= 4.0 \neq 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.452 = 0.4
 [165043, 17279]'),
      Text(0.23076923076923078, 0.75, 'X[1] \le 50.184 \cdot py = 0.023 \cdot py = 163503 \cdot py = 0.023 \cdot py = 163503 \cdot py = 1635
      Text(0.15384615384615385, 0.583333333333334, 'entropy = 0.0\nsamples = 160978\nvalue
01'),
      Text(0.3076923076923077, 0.5833333333333334, 'X[3] <= 0.5\nentropy = 0.596\nsamples
 [2160, 365]'),
      Text(0.15384615384615385, 0.4166666666666667, 'X[5] <= 0.5\nentropy = 0.536\nsamples
 [35, 251]'),
      Text(0.07692307692307693, 0.25, 'entropy = 0.0 \times = 251 \times = [0, 251]'),
      Text(0.23076923076923078, 0.25, 'entropy = 0.0\nsamples = 35\nvalue = [35, 0]'),
      Text(0.46153846153846156, 0.41666666666666667, 'X[0] <= 100.258 \nentropy = 0.29 \nsample | 100.258 \nentropy | 100.258 \nen
= [2125, 114]'),
      Text(0.38461538461, 0.25, 'entropy = 0.0\nsamples = 2114\nvalue = [2114, 0]'),
      Text(0.5384615384615384, 0.25, 'X[5] <= 0.5\nentropy = 0.43\nsamples = 125\nvalue =
      Text(0.6153846153846154, 0.75, X[5] <= 0.5 \neq 0.473 = 0.473 = 18819 = 18819
      Text(0.5384615384615384, 0.583333333333333, 'entropy = 0.0\nsamples = 16908\nvalue
      Text(0.6923076923076923, 0.5833333333333333333, 'X[1] <= 53.569 \setminus nentropy = 0.031 \setminus ne
= [1905, 6]'),
      [18, 6]'),
      Text(0.6923076923076923, 0.25, 'entropy = 0.0 \nsamples = 5 \nvalue = [0, 5]'),
      Text(0.8461538461538461, 0.25, 'X[1] <= 54.719\nentropy = 0.297\nsamples = 19\nvalue
      Text(0.7692307692307693, 0.08333333333333333, 'entropy = 0.0\nsamples = 1\nvalue = |
```



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