# ANÁLISE PREDITIVA DE POPULARIDADE DE NOTÍCIAS ONLINE

Arthur de Assis

Luciana Lima

# ARTHUR DE ASSIS

Cientista de Dados na A3Data

## FORMAÇÃO

- Sistemas de Informação
- Mestrado em Ciência da Computação

## INTERESSES

- Metaheurísticas
- Cozinhar
- Séries
- Machine Learning
- Twitter
- Lecionar

# LUCIANA LIMA

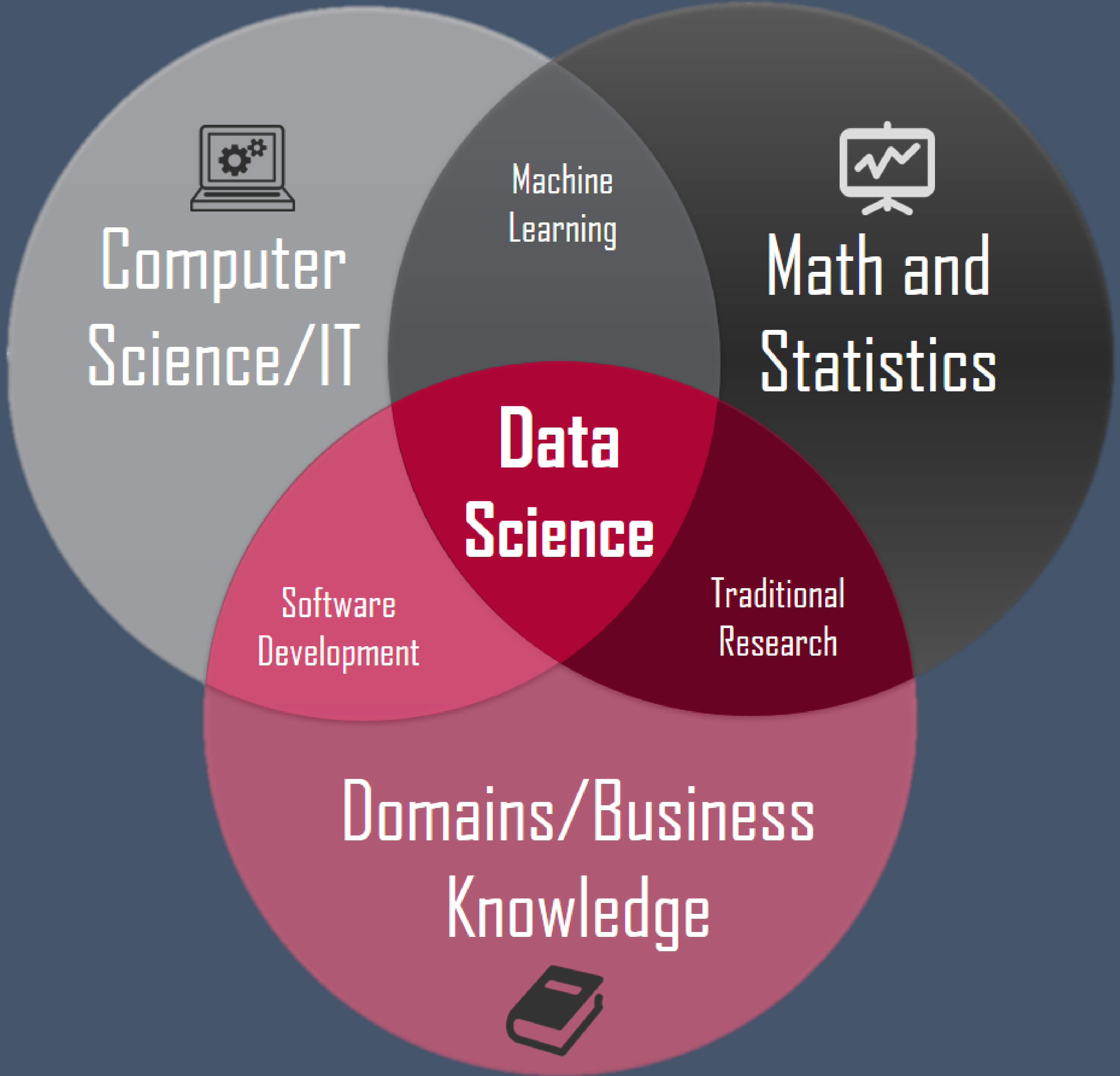
Cientista de Dados na A3Data

## FORMAÇÃO

- Estatística
- Pós-graduação em Business Intelligence

## INTERESSES

- Ciência de Dados
- Futuro de Trabalho
- Séries
- Trekking
- Viagem
- Gatos



Computer Science/IT

Machine Learning

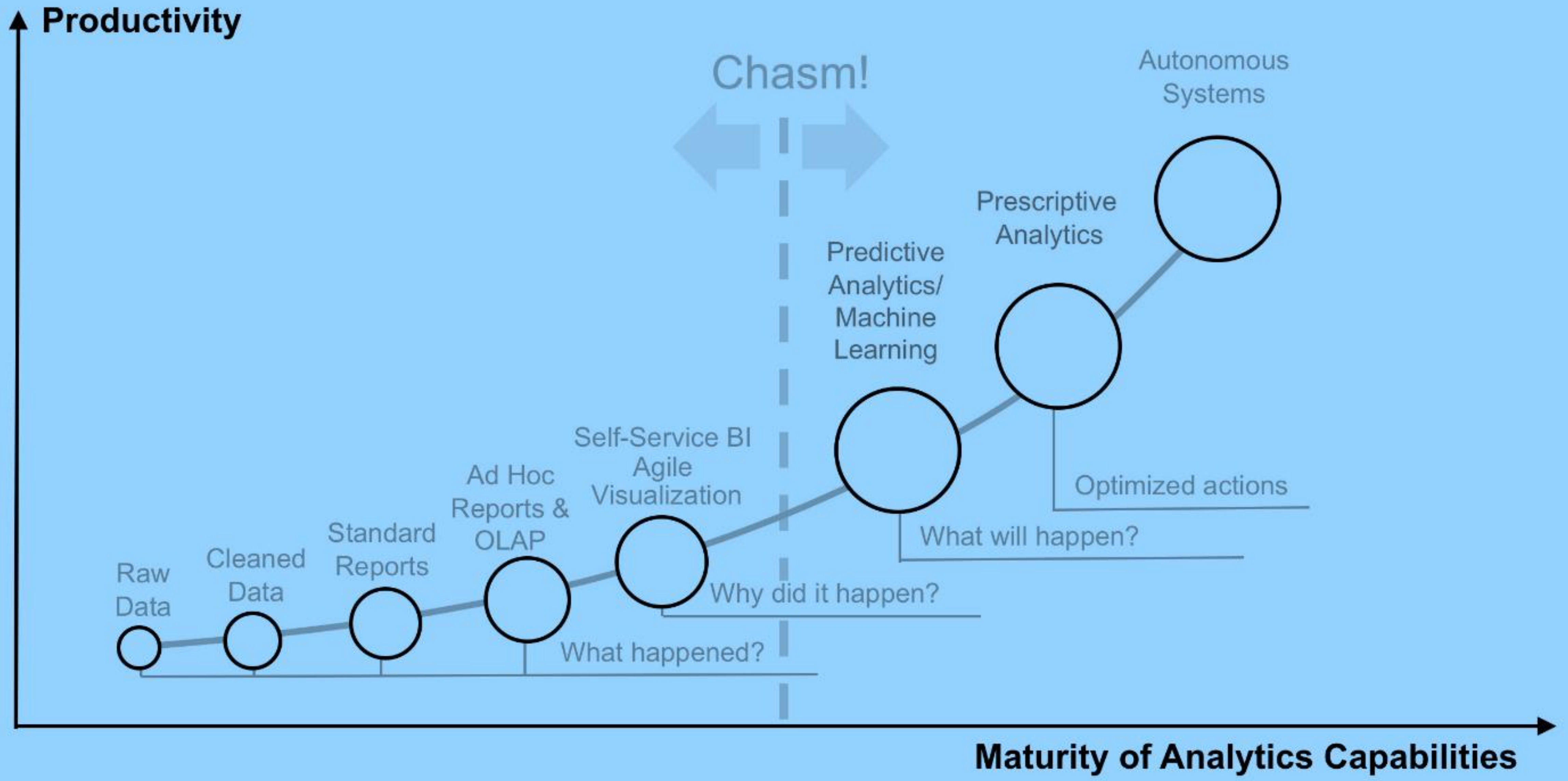
Math and Statistics

Data Science

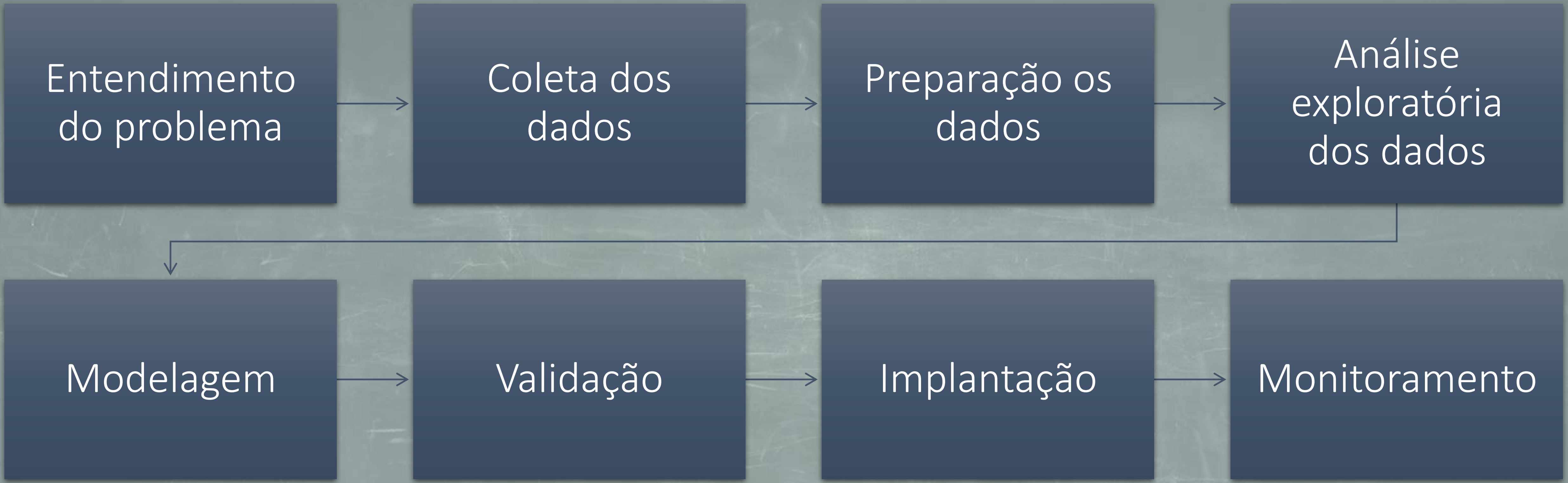
Software Development

Traditional Research

Domains/Business Knowledge


Productivity
Chasm!
Autonomous Systems
Prescriptive Analytics
Predictive Analytics/ Machine Learning
Self-Service BI Agile Visualization
Ad Hoc Reports & OLAP
Standard Reports
Cleaned Data
Raw Data
Optimized actions
What will happen?
Why did it happen?
What happened?
Maturity of Analytics Capabilities

# 8 PASSOS PARA UM PROJETO DE CIÊNCIA DE DADOS



Entendimento do problema

Coleta dos dados

Preparação os dados

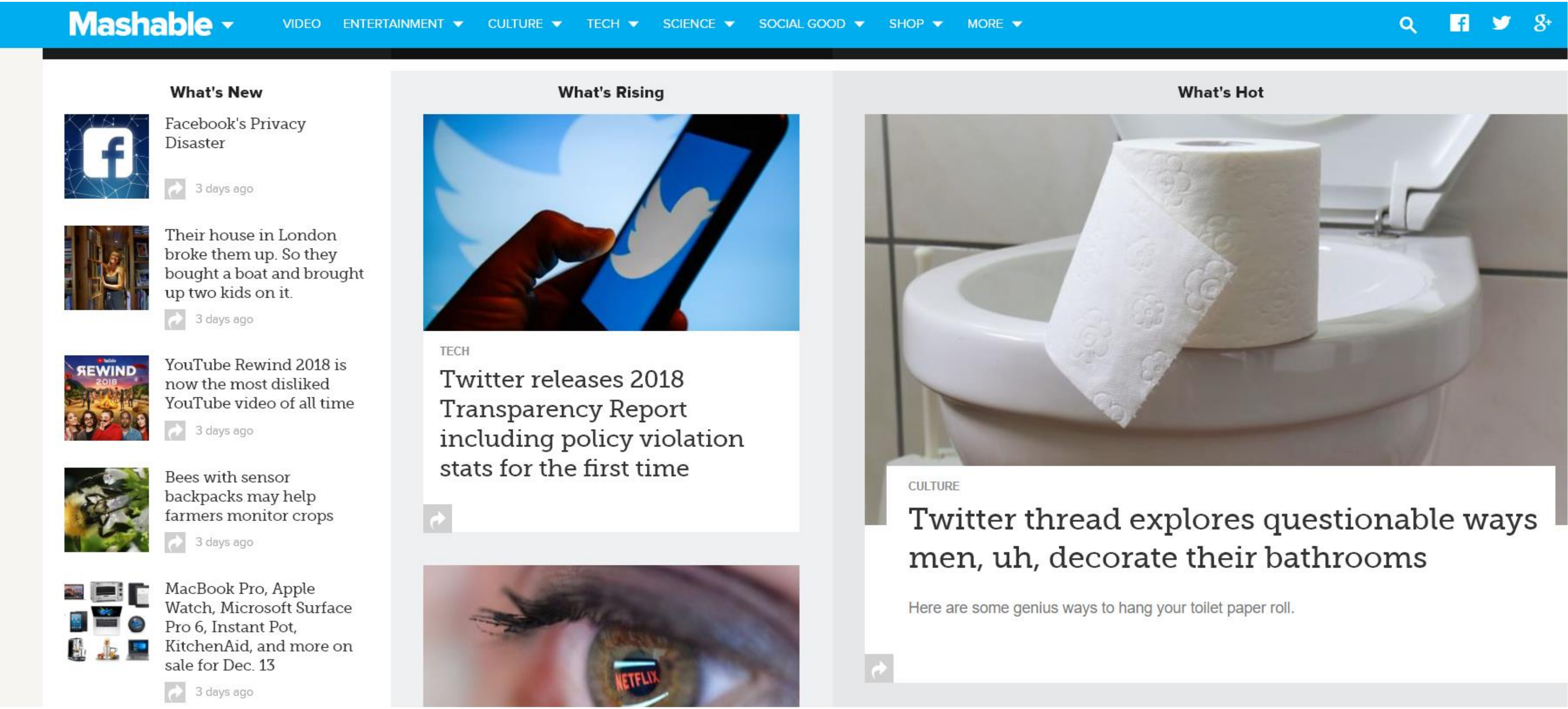
Análise exploratória dos dados

Modelagem

Validação

Implantação

Monitoramento



**What's New**

Facebook's Privacy Disaster

3 days ago

Their house in London broke them up. So they bought a boat and brought up two kids on it.

3 days ago

YouTube Rewind 2018 is now the most disliked YouTube video of all time

3 days ago

Bees with sensor backpacks may help farmers monitor crops

3 days ago

MacBook Pro, Apple Watch, Microsoft Surface Pro 6, Instant Pot, KitchenAid, and more on sale for Dec. 13

3 days ago

**What's Rising**

TECH

Twitter releases 2018 Transparency Report including policy violation stats for the first time

**What's Hot**

CULTURE

Twitter thread explores questionable ways men, uh, decorate their bathrooms

Here are some genius ways to hang your toilet paper roll.

Days between the article publication and the dataset acquisition

Number of words in the title and content

Rate of unique and stopwords words in the content

Number of links, images and videos

Average length of the words in the content

Number of keywords in the metadata

Channel: Lifestyle, Entertainment, Business, Social Media, Tech, World?

Worst keyword (min, max, avg shares)

Best keyword (min, max, avg shares)

Avg. keyword (min, max, avg shares)

Referenced articles in Mashable (min, max, avg shares)

Day of week the article  was published

Text subjectivity and sentiment polarity

Rate of positive and negative words in the content

Rate of positive and negative words among non-neutral tokens

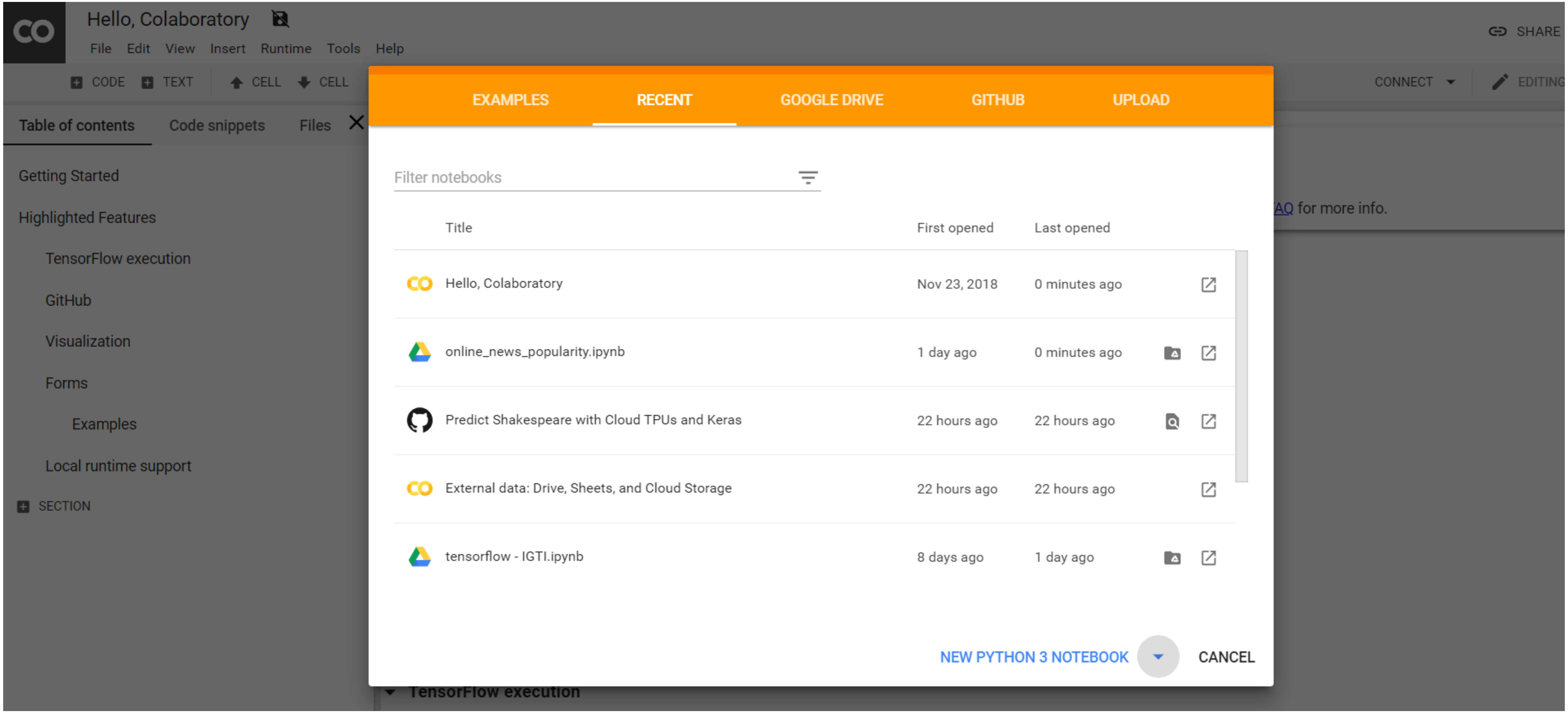
Polarity of positive/negative words (min, max, avg)

Title subjectivity and sentiment polarity

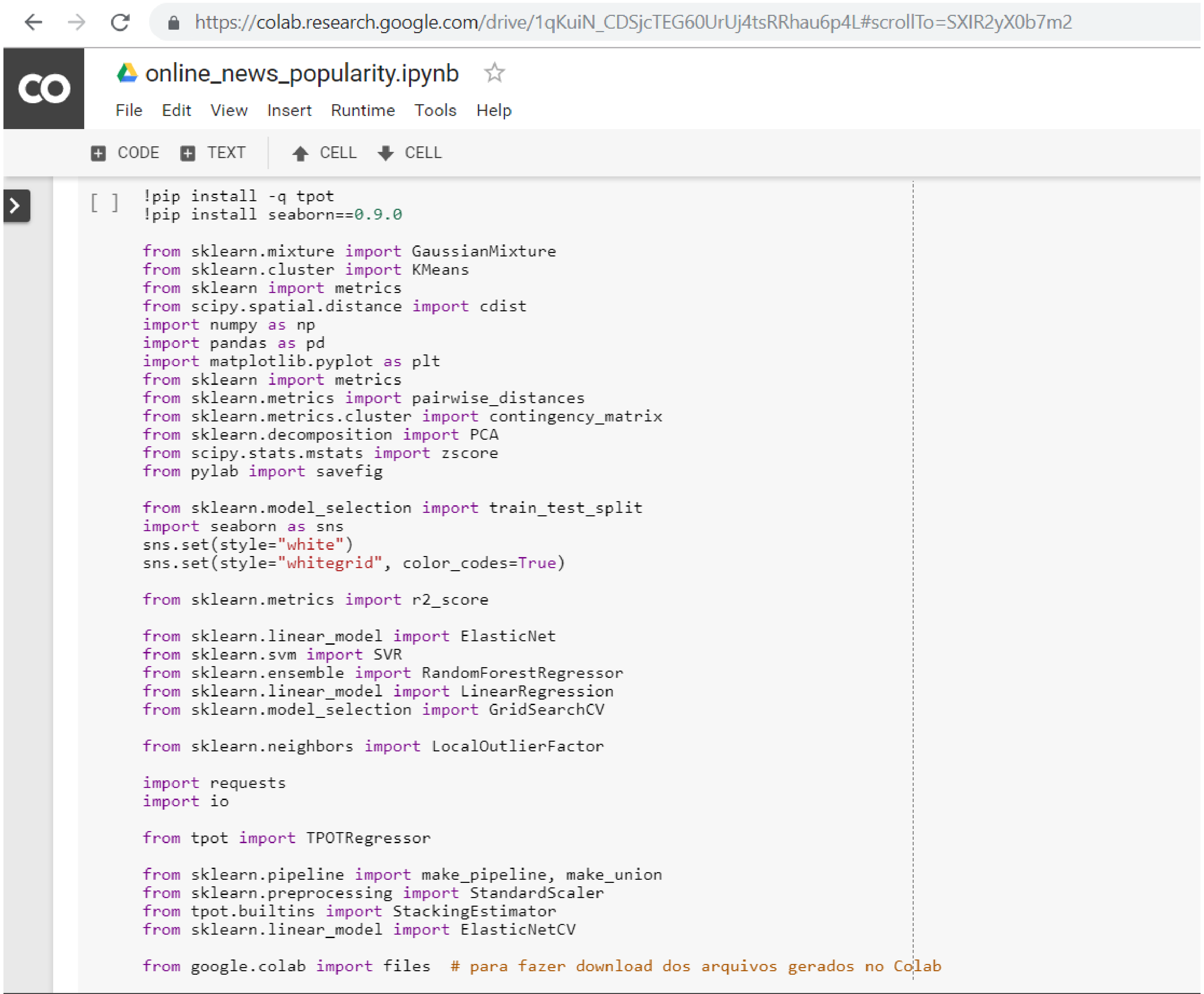
Absolute subjectivity and sentiment polarity

# VAMOS PRO HANDS ON?

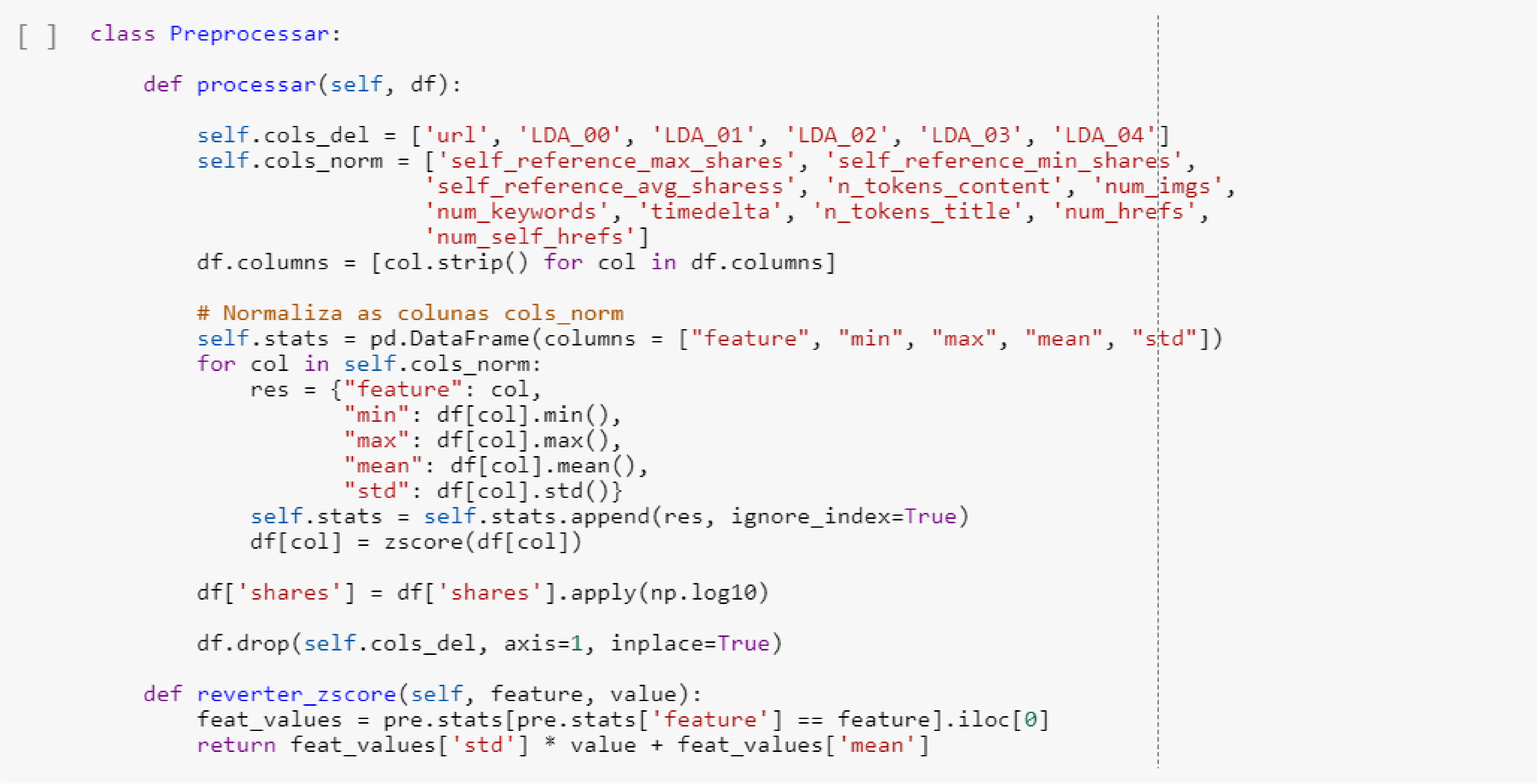
https://colab.research.google.com/



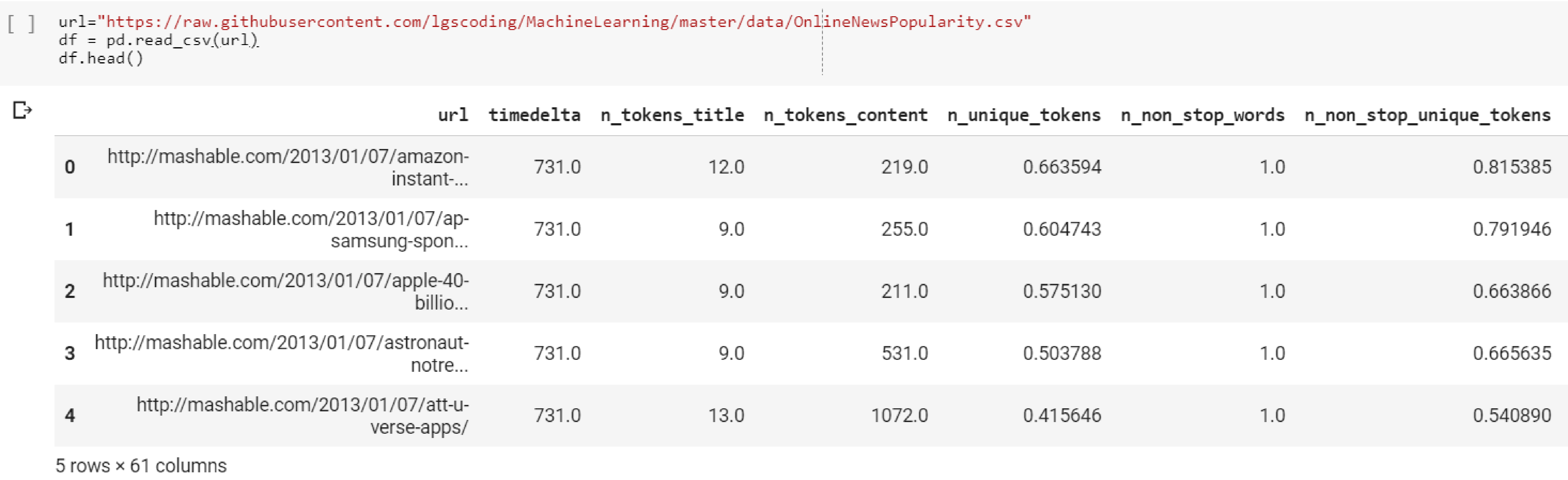
| Title | First opened | Last opened |
|---|---|---|
| Hello, Colaboratory | Nov 23, 2018 | 0 minutes ago |
| online_news_popularity.ipynb | 1 day ago | 0 minutes ago |
| Predict Shakespeare with Cloud TPUs and Keras | 22 hours ago | 22 hours ago |
| External data: Drive, Sheets, and Cloud Storage | 22 hours ago | 22 hours ago |
| tensorflow - IGTI.ipynb | 8 days ago | 1 day ago |


https://colab.research.google.com/drive/1qKuiN_CDSjcTEG60UrUj4tsRRhau6p4L#scrollTo=SXIR2yX0b7m2
CO
online_news_popularity.ipynb
File
Edit
View
Insert
Runtime
Tools
Help
CODE
TEXT
CELL
CELL
[ ]

```
!pip install -q tpot
!pip install seaborn==0.9.0

from sklearn.mixture import GaussianMixture
from sklearn.cluster import KMeans
from sklearn import metrics
from scipy.spatial.distance import cdist
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn import metrics
from sklearn.metrics import pairwise_distances
from sklearn.metrics.cluster import contingency_matrix
from sklearn.decomposition import PCA
from scipy.stats.mstats import zscore
from pylab import savefig

from sklearn.model_selection import train_test_split
import seaborn as sns
sns.set(style="white")
sns.set(style="whitegrid", color_codes=True)

from sklearn.metrics import r2_score

from sklearn.linear_model import ElasticNet
from sklearn.svm import SVR
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import GridSearchCV

from sklearn.neighbors import LocalOutlierFactor

import requests
import io

from tpot import TPOTRegressor

from sklearn.pipeline import make_pipeline, make_union
from sklearn.preprocessing import StandardScaler
from tpot.builtins import StackingEstimator
from sklearn.linear_model import ElasticNetCV

from google.colab import files  # para fazer download dos arquivos gerados no Colab
```



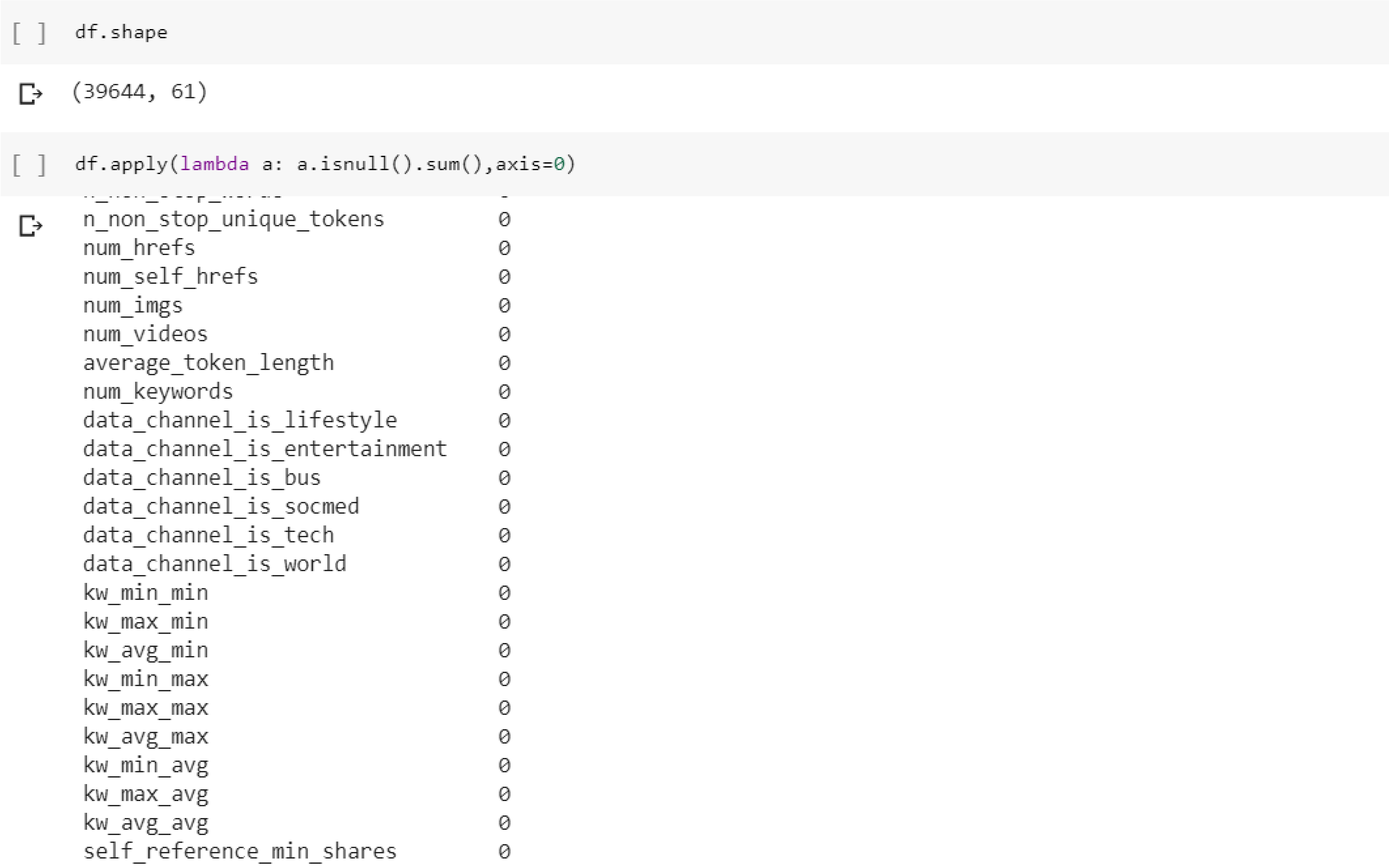
```
class Preprocessar:

    def processar(self, df):

        self.cols_del = ['url', 'LDA_00', 'LDA_01', 'LDA_02', 'LDA_03', 'LDA_04']
        self.cols_norm = ['self_reference_max_shares', 'self_reference_min_shares',
                         'self_reference_avg_sharess', 'n_tokens_content', 'num_imgs',
                         'num_keywords', 'timedelta', 'n_tokens_title', 'num_hrefs',
                         'num_self_hrefs']
        df.columns = [col.strip() for col in df.columns]

        # Normaliza as colunas cols_norm
        self.stats = pd.DataFrame(columns = ["feature", "min", "max", "mean", "std"])
        for col in self.cols_norm:
            res = {"feature": col,
                   "min": df[col].min(),
                   "max": df[col].max(),
                   "mean": df[col].mean(),
                   "std": df[col].std()}
            self.stats = self.stats.append(res, ignore_index=True)
            df[col] = zscore(df[col])

        df['shares'] = df['shares'].apply(np.log10)

        df.drop(self.cols_del, axis=1, inplace=True)

    def reverter_zscore(self, feature, value):
        feat_values = pre.stats[pre.stats['feature'] == feature].iloc[0]
        return feat_values['std'] * value + feat_values['mean']
```



```
url="https://raw.githubusercontent.com/lgscoding/MachineLearning/master/data/OnlineNewsPopularity.csv"
df = pd.read_csv(url)
df.head()
```

| | url | timedelta | n_tokens_title | n_tokens_content | n_unique_tokens | n_non_stop_words | n_non_stop_unique_tokens |
|---|---|---|---|---|---|---|---|
| **0** | http://mashable.com/2013/01/07/amazon-instant-... | 731.0 | 12.0 | 219.0 | 0.663594 | 1.0 | 0.815385 |
| **1** | http://mashable.com/2013/01/07/ap-samsung-spon... | 731.0 | 9.0 | 255.0 | 0.604743 | 1.0 | 0.791946 |
| **2** | http://mashable.com/2013/01/07/apple-40-billio... | 731.0 | 9.0 | 211.0 | 0.575130 | 1.0 | 0.663866 |
| **3** | http://mashable.com/2013/01/07/astronaut-notre... | 731.0 | 9.0 | 531.0 | 0.503788 | 1.0 | 0.665635 |
| **4** | http://mashable.com/2013/01/07/att-u-verse-apps/ | 731.0 | 13.0 | 1072.0 | 0.415646 | 1.0 | 0.540890 |

5 rows × 61 columns

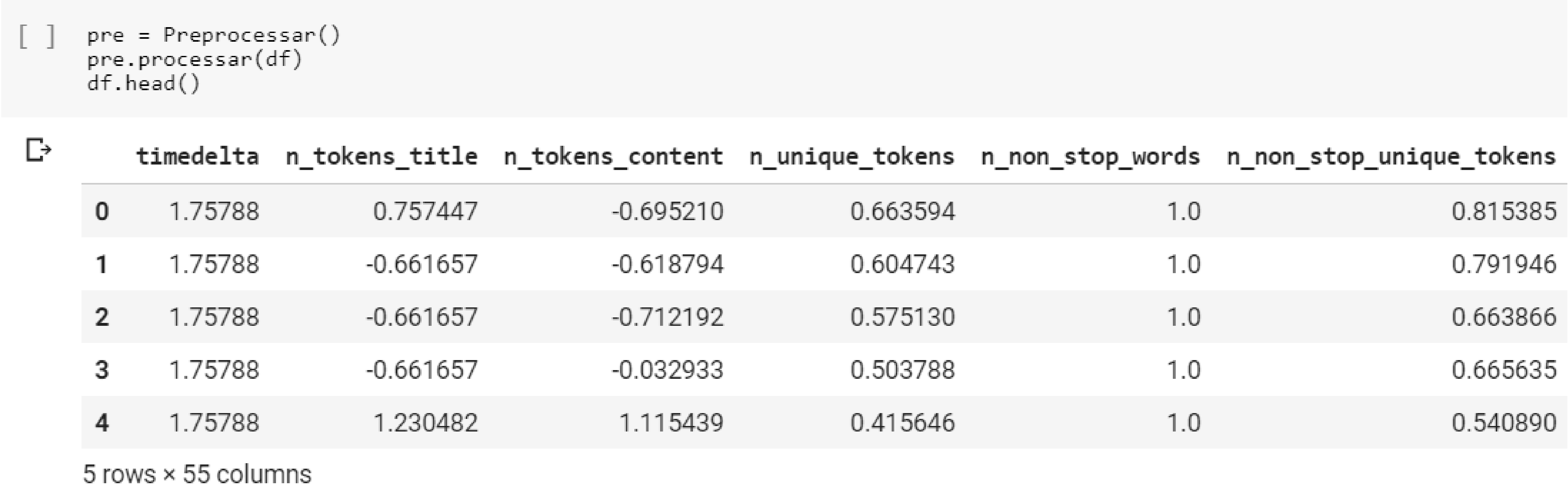


```
[ ]  df.shape
```

```
(39644, 61)
```

```
[ ]  df.apply(lambda a: a.isnull().sum(),axis=0)
```

```
n_non_stop_words                0
n_non_stop_unique_tokens        0
num_hrefs                       0
num_self_hrefs                  0
num_imgs                        0
num_videos                      0
average_token_length            0
num_keywords                    0
data_channel_is_lifestyle       0
data_channel_is_entertainment   0
data_channel_is_bus             0
data_channel_is_socmed          0
data_channel_is_tech            0
data_channel_is_world           0
kw_min_min                      0
kw_max_min                      0
kw_avg_min                      0
kw_min_max                      0
kw_max_max                      0
kw_avg_max                      0
kw_min_avg                      0
kw_max_avg                      0
kw_avg_avg                      0
self_reference_min_shares       0
```

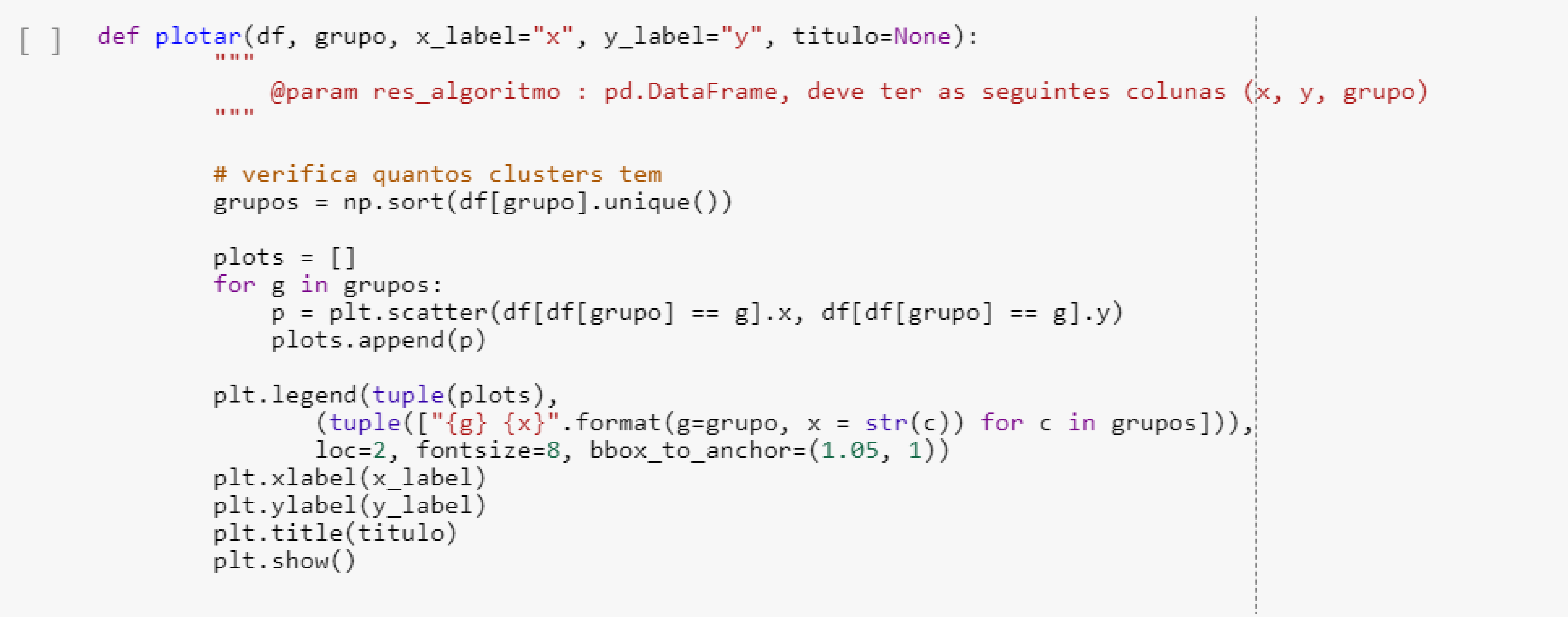


```
pre = Preprocessar()
pre.processar(df)
df.head()
```

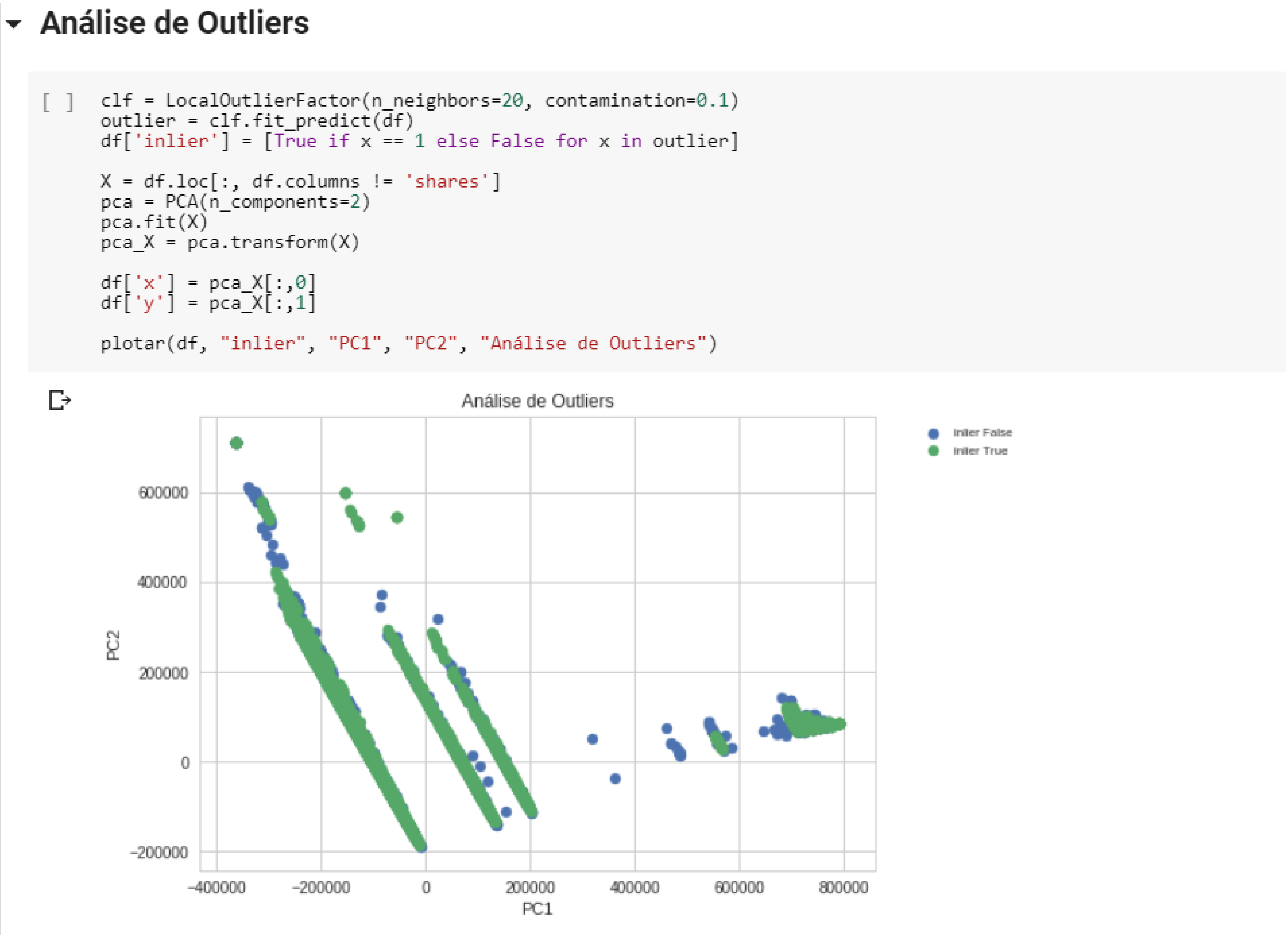
|   | timedelta | n_tokens_title | n_tokens_content | n_unique_tokens | n_non_stop_words | n_non_stop_unique_tokens |
|---|---|---|---|---|---|---|
| **0** | 1.75788 | 0.757447 | -0.695210 | 0.663594 | 1.0 | 0.815385 |
| **1** | 1.75788 | -0.661657 | -0.618794 | 0.604743 | 1.0 | 0.791946 |
| **2** | 1.75788 | -0.661657 | -0.712192 | 0.575130 | 1.0 | 0.663866 |
| **3** | 1.75788 | -0.661657 | -0.032933 | 0.503788 | 1.0 | 0.665635 |
| **4** | 1.75788 | 1.230482 | 1.115439 | 0.415646 | 1.0 | 0.540890 |

5 rows × 55 columns

# Função para plotar os outliers existentes na base

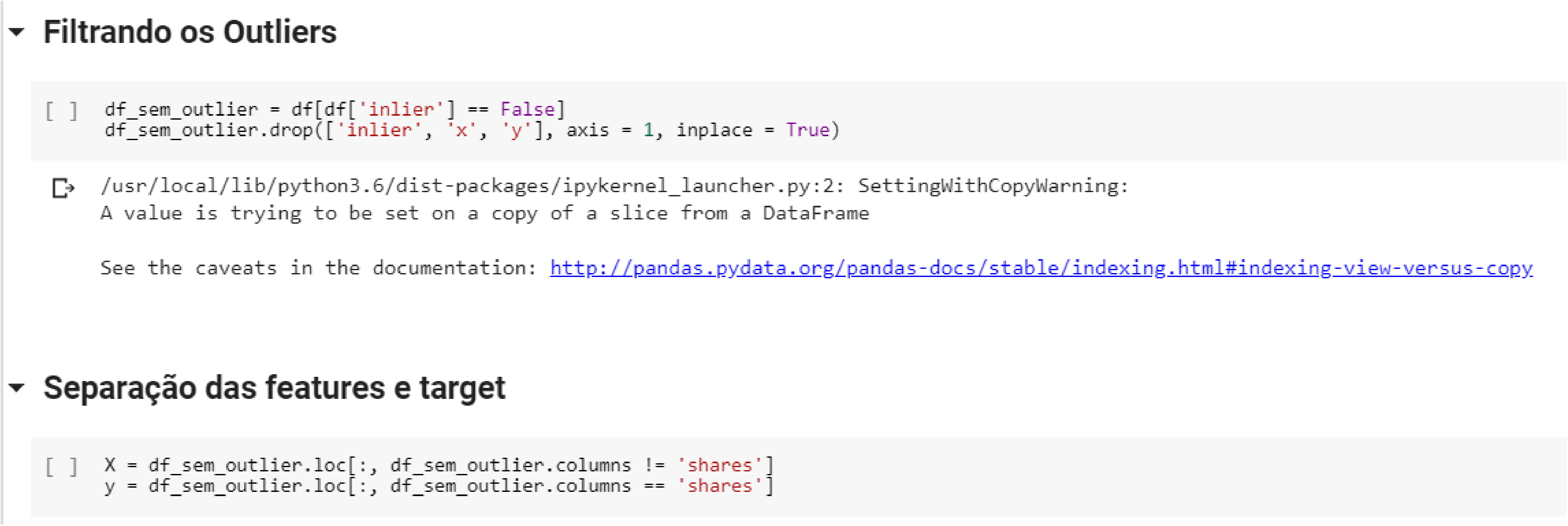


```
[ ]  def plotar(df, grupo, x_label="x", y_label="y", titulo=None):
             """
                 @param res_algoritmo : pd.DataFrame, deve ter as seguintes colunas (x, y, grupo)
             """

             # verifica quantos clusters tem
             grupos = np.sort(df[grupo].unique())

             plots = []
             for g in grupos:
                 p = plt.scatter(df[df[grupo] == g].x, df[df[grupo] == g].y)
                 plots.append(p)

             plt.legend(tuple(plots),
                    (tuple(["{g} {x}".format(g=grupo, x = str(c)) for c in grupos])),
                    loc=2, fontsize=8, bbox_to_anchor=(1.05, 1))
             plt.xlabel(x_label)
             plt.ylabel(y_label)
             plt.title(titulo)
             plt.show()
```



## Análise de Outliers

```
[ ]  clf = LocalOutlierFactor(n_neighbors=20, contamination=0.1)
     outlier = clf.fit_predict(df)
     df['inlier'] = [True if x == 1 else False for x in outlier]

     X = df.loc[:, df.columns != 'shares']
     pca = PCA(n_components=2)
     pca.fit(X)
     pca_X = pca.transform(X)

     df['x'] = pca_X[:,0]
     df['y'] = pca_X[:,1]

     plotar(df, "inlier", "PC1", "PC2", "Análise de Outliers")
```



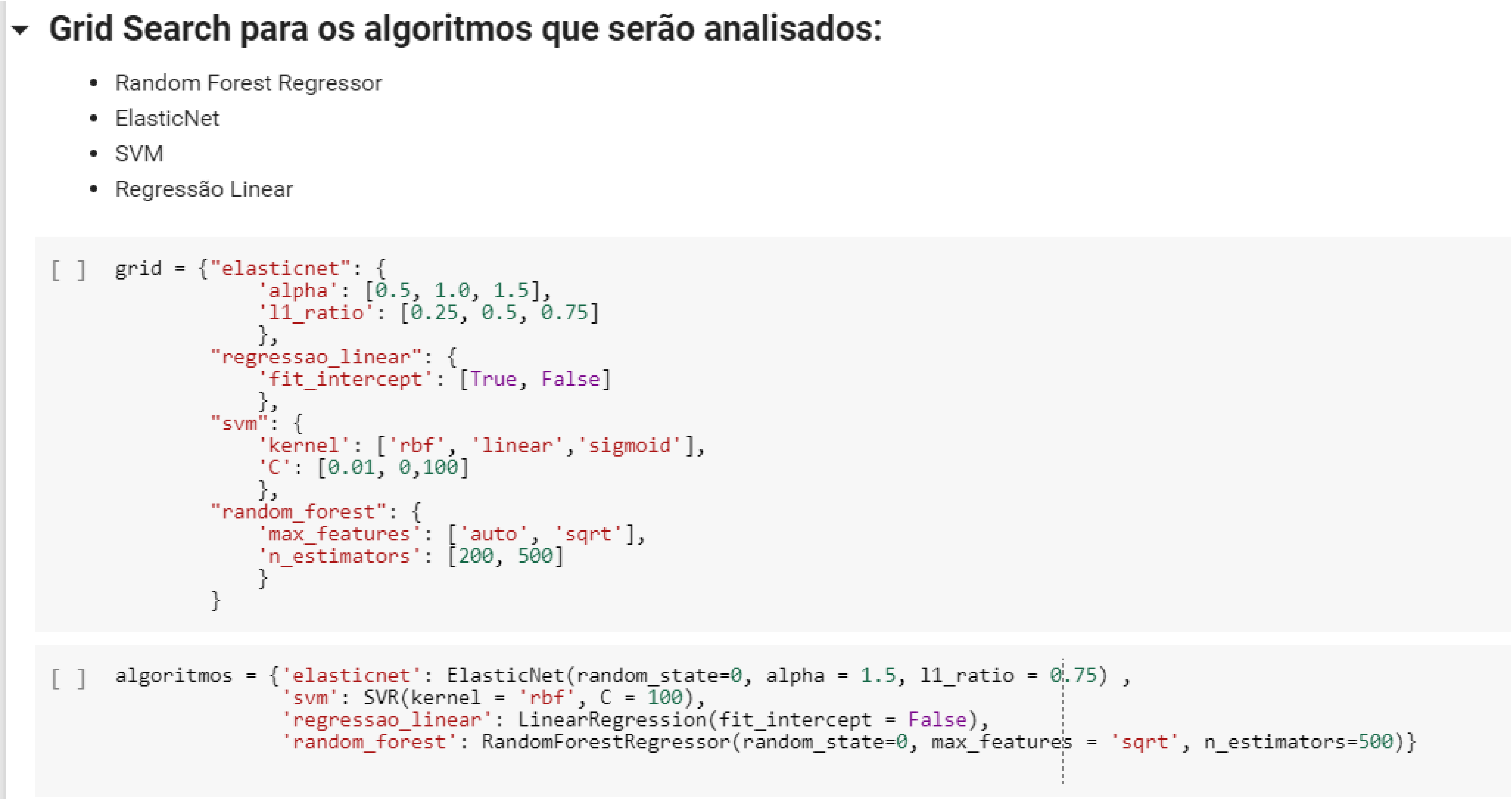
## Filtrando os Outliers

```
[ ] df_sem_outlier = df[df['inlier'] == False]
    df_sem_outlier.drop(['inlier', 'x', 'y'], axis = 1, inplace = True)
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

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

## Separação das features e target

```
[ ] X = df_sem_outlier.loc[:, df_sem_outlier.columns != 'shares']
    y = df_sem_outlier.loc[:, df_sem_outlier.columns == 'shares']
```

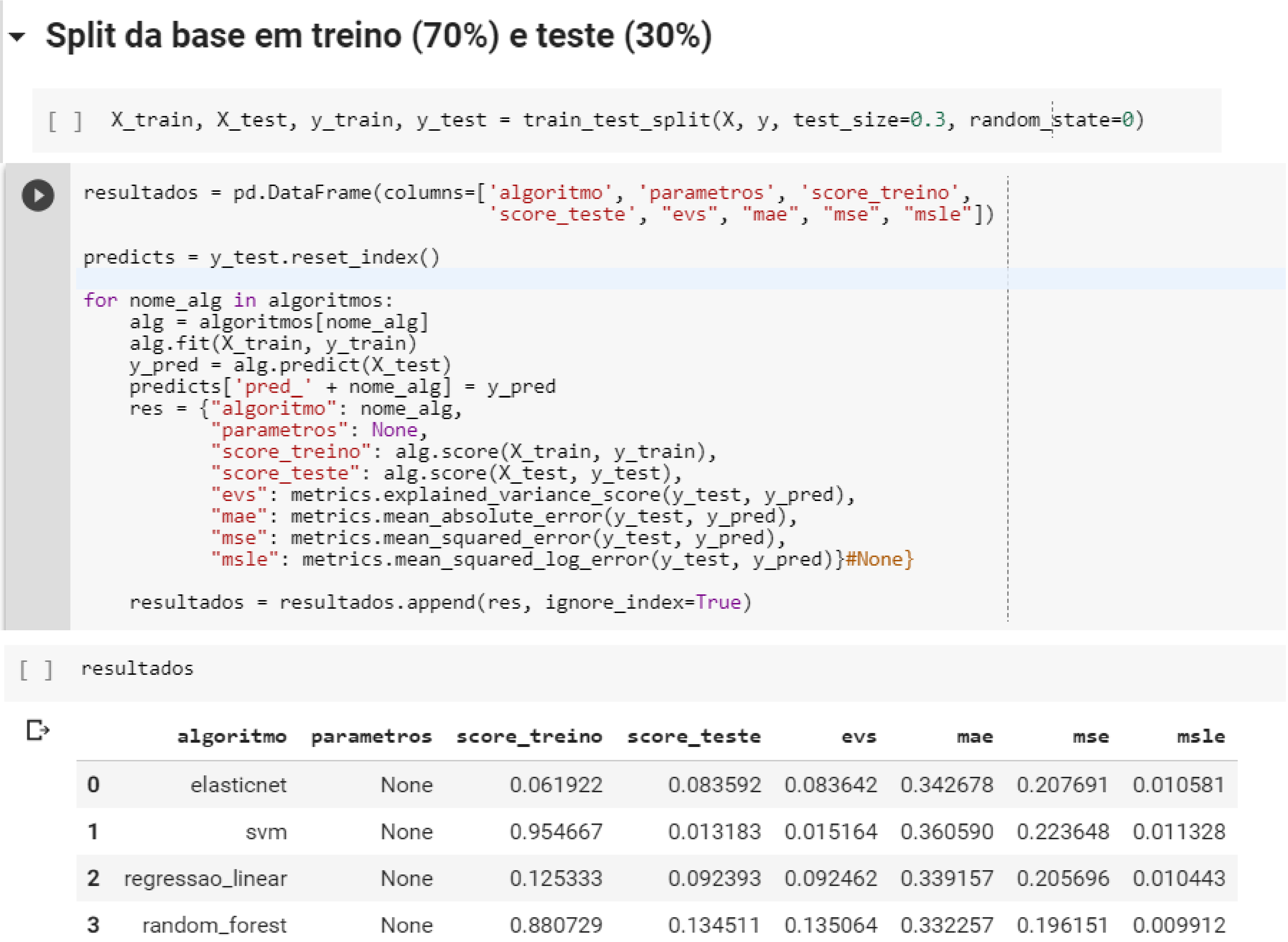


## Grid Search para os algoritmos que serão analisados:

- Random Forest Regressor
- ElasticNet
- SVM
- Regressão Linear

[ ]
```
grid = {"elasticnet": {
            'alpha': [0.5, 1.0, 1.5],
            'l1_ratio': [0.25, 0.5, 0.75]
            },
        "regressao_linear": {
            'fit_intercept': [True, False]
            },
        "svm": {
            'kernel': ['rbf', 'linear','sigmoid'],
            'C': [0.01, 0,100]
            },
        "random_forest": {
            'max_features': ['auto', 'sqrt'],
            'n_estimators': [200, 500]
            }
        }
```

[ ]
```
algoritmos = {'elasticnet': ElasticNet(random_state=0, alpha = 1.5, l1_ratio = 0.75) ,
              'svm': SVR(kernel = 'rbf', C = 100),
              'regressao_linear': LinearRegression(fit_intercept = False),
              'random_forest': RandomForestRegressor(random_state=0, max_features = 'sqrt', n_estimators=500)}
```



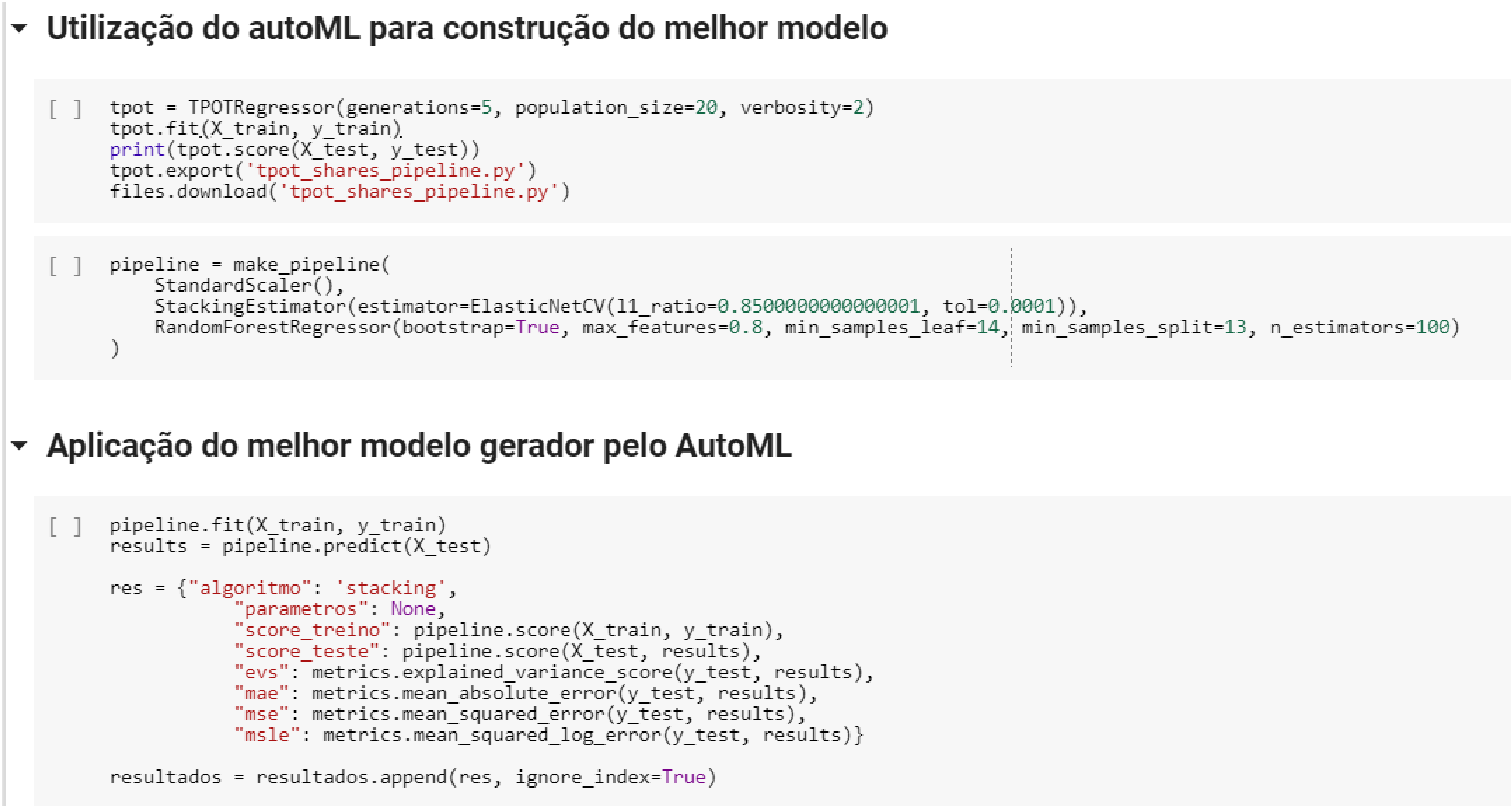
## Split da base em treino (70%) e teste (30%)

```
[ ]  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=0)
```

```
resultados = pd.DataFrame(columns=['algoritmo', 'parametros', 'score_treino',
                                   'score_teste', "evs", "mae", "mse", "msle"])

predicts = y_test.reset_index()

for nome_alg in algoritmos:
    alg = algoritmos[nome_alg]
    alg.fit(X_train, y_train)
    y_pred = alg.predict(X_test)
    predicts['pred_' + nome_alg] = y_pred
    res = {"algoritmo": nome_alg,
           "parametros": None,
           "score_treino": alg.score(X_train, y_train),
           "score_teste": alg.score(X_test, y_test),
           "evs": metrics.explained_variance_score(y_test, y_pred),
           "mae": metrics.mean_absolute_error(y_test, y_pred),
           "mse": metrics.mean_squared_error(y_test, y_pred),
           "msle": metrics.mean_squared_log_error(y_test, y_pred)}#None}

    resultados = resultados.append(res, ignore_index=True)
```

```
[ ]  resultados
```

| | algoritmo | parametros | score_treino | score_teste | evs | mae | mse | msle |
|---|---|---|---|---|---|---|---|---|
| 0 | elasticnet | None | 0.061922 | 0.083592 | 0.083642 | 0.342678 | 0.207691 | 0.010581 |
| 1 | svm | None | 0.954667 | 0.013183 | 0.015164 | 0.360590 | 0.223648 | 0.011328 |
| 2 | regressao_linear | None | 0.125333 | 0.092393 | 0.092462 | 0.339157 | 0.205696 | 0.010443 |
| 3 | random_forest | None | 0.880729 | 0.134511 | 0.135064 | 0.332257 | 0.196151 | 0.009912 |



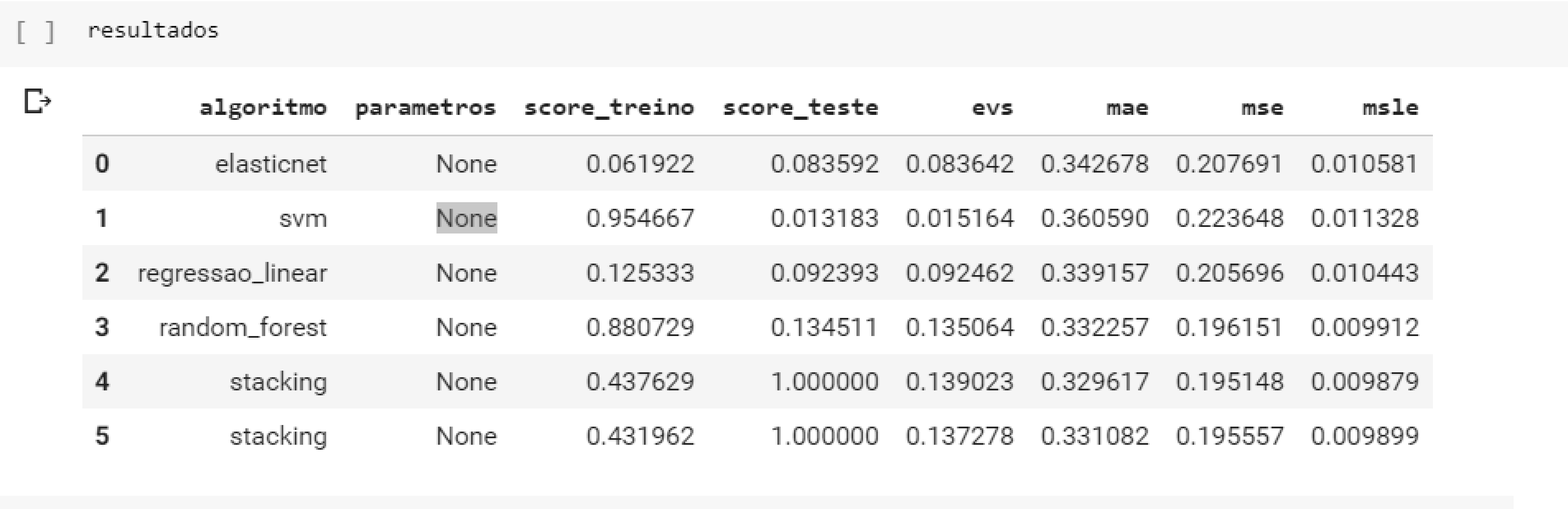
## Utilização do autoML para construção do melhor modelo

```
tpot = TPOTRegressor(generations=5, population_size=20, verbosity=2)
tpot.fit(X_train, y_train)
print(tpot.score(X_test, y_test))
tpot.export('tpot_shares_pipeline.py')
files.download('tpot_shares_pipeline.py')
```

```
pipeline = make_pipeline(
    StandardScaler(),
    StackingEstimator(estimator=ElasticNetCV(l1_ratio=0.8500000000000001, tol=0.0001)),
    RandomForestRegressor(bootstrap=True, max_features=0.8, min_samples_leaf=14, min_samples_split=13, n_estimators=100)
)
```

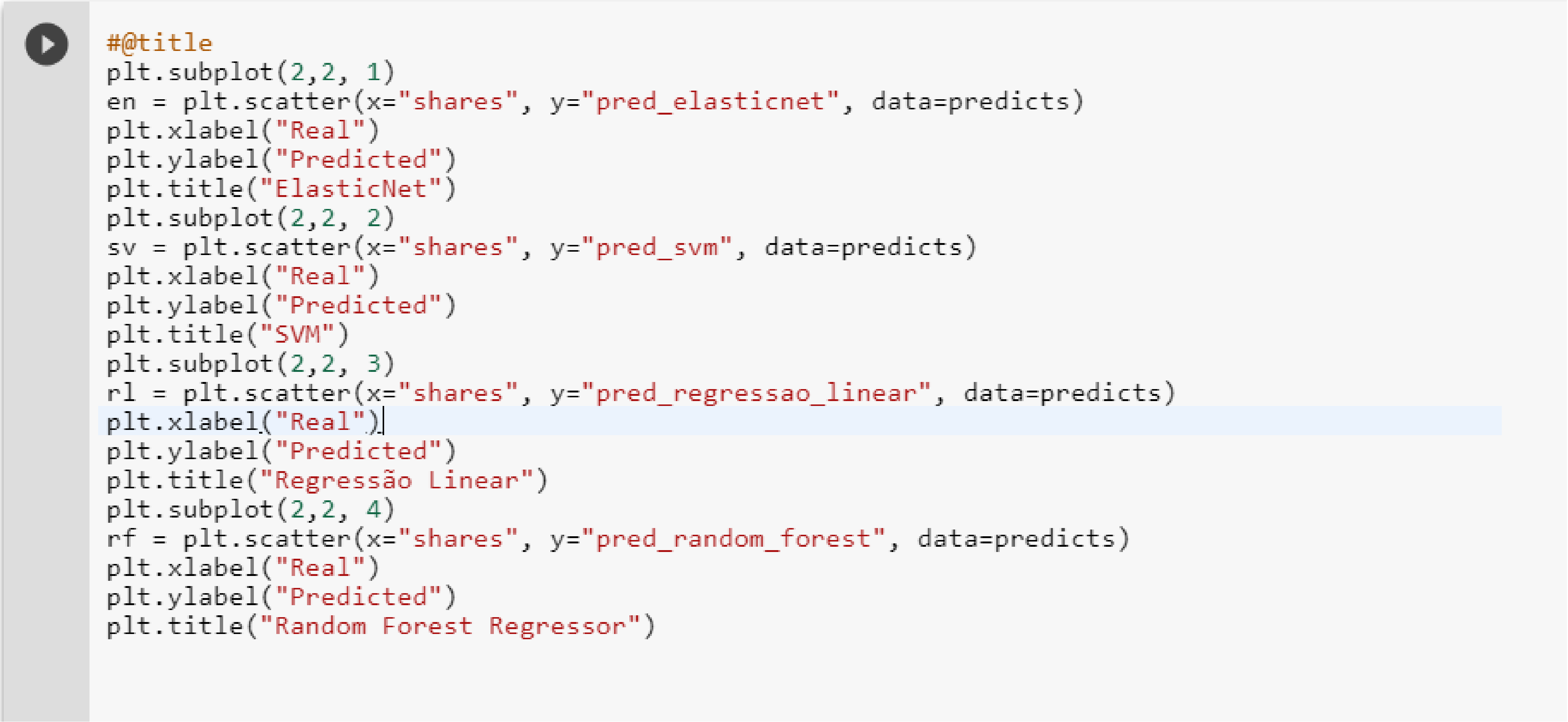
## Aplicação do melhor modelo gerador pelo AutoML

```
pipeline.fit(X_train, y_train)
results = pipeline.predict(X_test)

res = {"algoritmo": 'stacking',
           "parametros": None,
           "score_treino": pipeline.score(X_train, y_train),
           "score_teste": pipeline.score(X_test, results),
           "evs": metrics.explained_variance_score(y_test, results),
           "mae": metrics.mean_absolute_error(y_test, results),
           "mse": metrics.mean_squared_error(y_test, results),
           "msle": metrics.mean_squared_log_error(y_test, results)}

resultados = resultados.append(res, ignore_index=True)
```

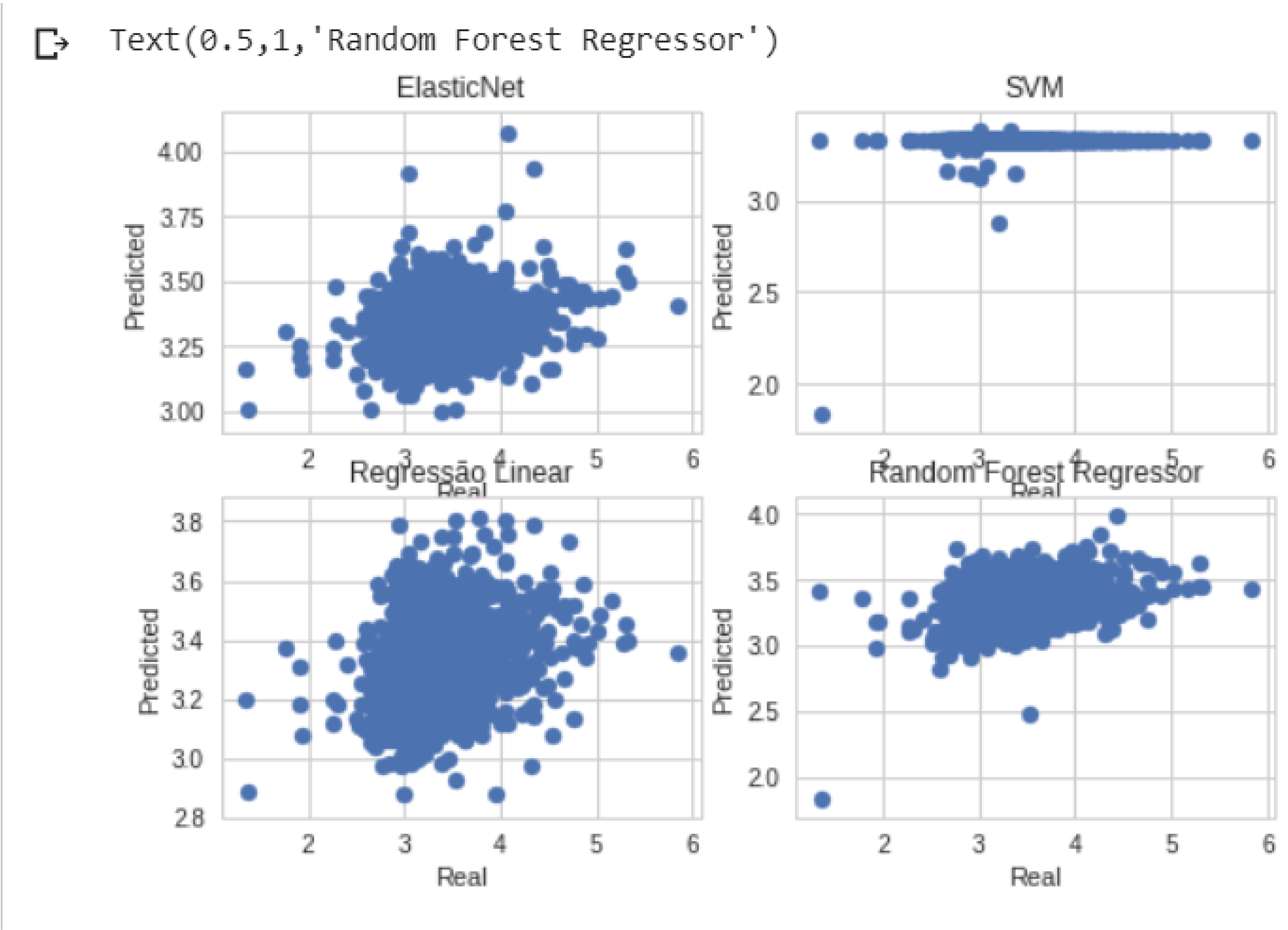


```
resultados
```

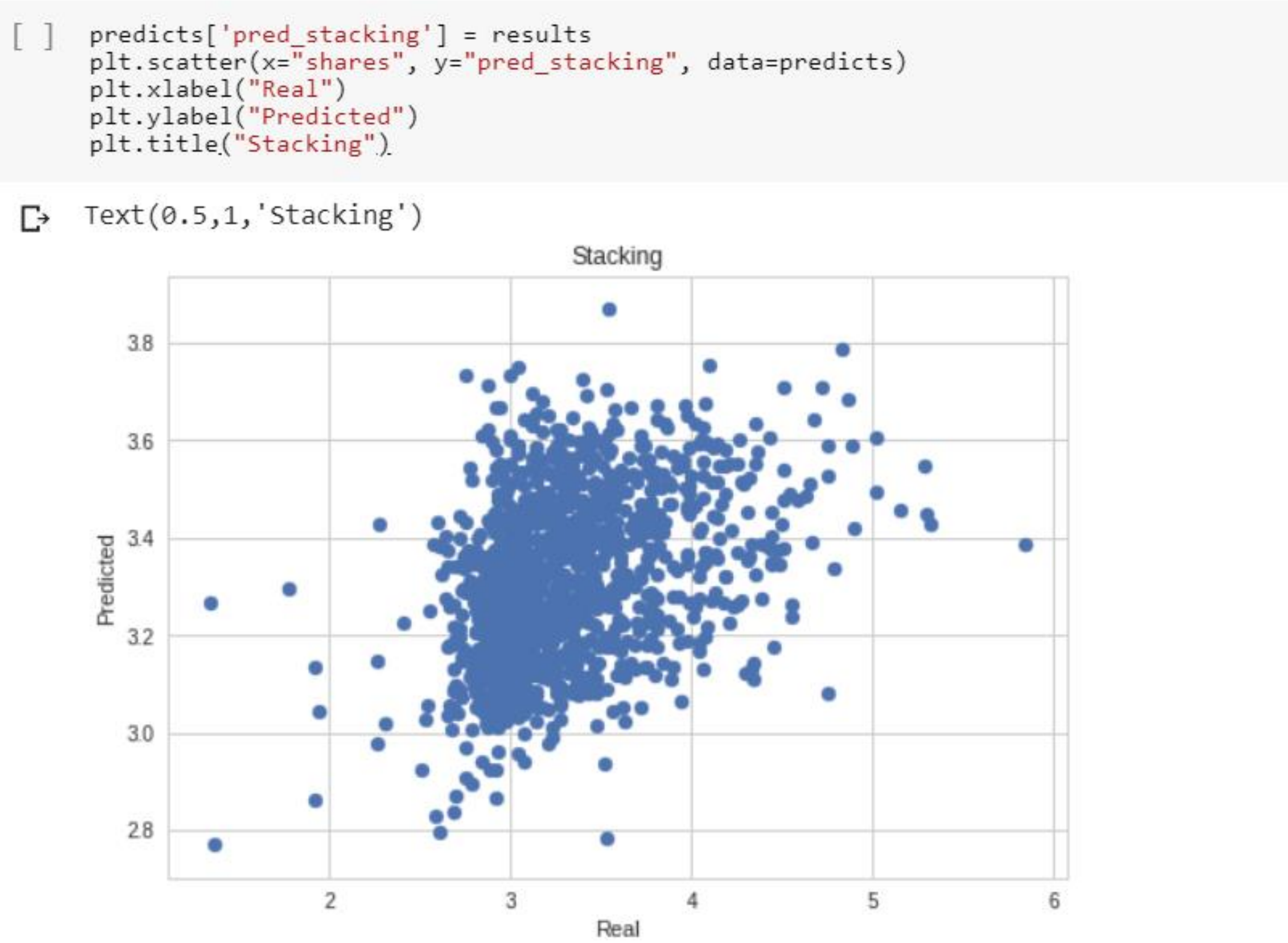
|   | algoritmo | parametros | score_treino | score_teste | evs | mae | mse | msle |
|---|---|---|---|---|---|---|---|---|
| **0** | elasticnet | None | 0.061922 | 0.083592 | 0.083642 | 0.342678 | 0.207691 | 0.010581 |
| **1** | svm | None | 0.954667 | 0.013183 | 0.015164 | 0.360590 | 0.223648 | 0.011328 |
| **2** | regressao_linear | None | 0.125333 | 0.092393 | 0.092462 | 0.339157 | 0.205696 | 0.010443 |
| **3** | random_forest | None | 0.880729 | 0.134511 | 0.135064 | 0.332257 | 0.196151 | 0.009912 |
| **4** | stacking | None | 0.437629 | 1.000000 | 0.139023 | 0.329617 | 0.195148 | 0.009879 |
| **5** | stacking | None | 0.431962 | 1.000000 | 0.137278 | 0.331082 | 0.195557 | 0.009899 |



```
#@title
plt.subplot(2,2, 1)
en = plt.scatter(x="shares", y="pred_elasticnet", data=predicts)
plt.xlabel("Real")
plt.ylabel("Predicted")
plt.title("ElasticNet")
plt.subplot(2,2, 2)
sv = plt.scatter(x="shares", y="pred_svm", data=predicts)
plt.xlabel("Real")
plt.ylabel("Predicted")
plt.title("SVM")
plt.subplot(2,2, 3)
rl = plt.scatter(x="shares", y="pred_regressao_linear", data=predicts)
plt.xlabel("Real")
plt.ylabel("Predicted")
plt.title("Regressão Linear")
plt.subplot(2,2, 4)
rf = plt.scatter(x="shares", y="pred_random_forest", data=predicts)
plt.xlabel("Real")
plt.ylabel("Predicted")
plt.title("Random Forest Regressor")
```



```
Text(0.5,1,'Random Forest Regressor')
```



```
[ ]  predicts['pred_stacking'] = results
     plt.scatter(x="shares", y="pred_stacking", data=predicts)
     plt.xlabel("Real")
     plt.ylabel("Predicted")
     plt.title("Stacking")
```

```
Text(0.5,1,'Stacking')
```

# CONSIDERAÇÕES FINAIS

# OBRIGADO(A)!

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