GABRIEL VINICIUS BOIN FREITAS
LEONARDO CARDOSO SANTOS

Inicio - Análise descritiva da série temporal

1. Seleção de Dados: • Os alunos devem escolher um conjunto de dados com características temporais relevantes para o problema proposto. Exemplos incluem séries temporais financeiras, dados meteorológicos, registros de vendas, entre outros.

```
!pip install pmdarima
!pip install tensorflow
!pip install keras
!pip install numpy pandas statsmodels deap
!pip install yfinance
```

```
import pandas as pd
import numpy as np
import sklearn as sk
from sklearn import metrics
from pandas.plotting import autocorrelation_plot
from statsmodels.tsa.filters.hp_filter import hpfilter
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.stattools import adfuller
import tensorflow as tf
from sklearn import preprocessing

from pmdarima import auto_arima

import yfinance as yf
yf.pdr_override()

from pandas_datareader import data as pdr

import datetime
from datetime import date
from datetime import timedelta

import warnings
warnings.filterwarnings("ignore")

import matplotlib.pyplot as plt
%matplotlib inline

import seaborn as sns

import plotly.graph_objects as go
import plotly.express as px
import plotly.io as pio
import plotly.figure_factory as ff
import plotly.offline as py
from plotly.subplots import make_subplots

from sklearn import preprocessing
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Flatten,TimeDistributed,RepeatVector
from tensorflow.keras.layers import Conv1D
from tensorflow.keras.layers import MaxPool1D
from tensorflow.keras.layers import Dropout

tf.random.set_seed(123)
np.random.seed(123)
import random
random.seed(123)
```

```
def get(tickers,startdate,enddate):
   def data(ticker):
       return(pdr.get_data_yahoo(ticker, start=startdate,end=enddate))
   datas = map(data,tickers)
   all_data = pd.concat(datas, keys=tickers, names=['Ticker', 'Date'])
   return all_data
```

```
tickers = ["MGLU3.SA"]
startdate = date(2020,1,1)
enddate = date.today()

data = get(tickers,startdate,enddate)

asset = tickers[0]
data.loc[asset].tail()
```

```
[*********************100%%**********************]  1 of 1 completed
```

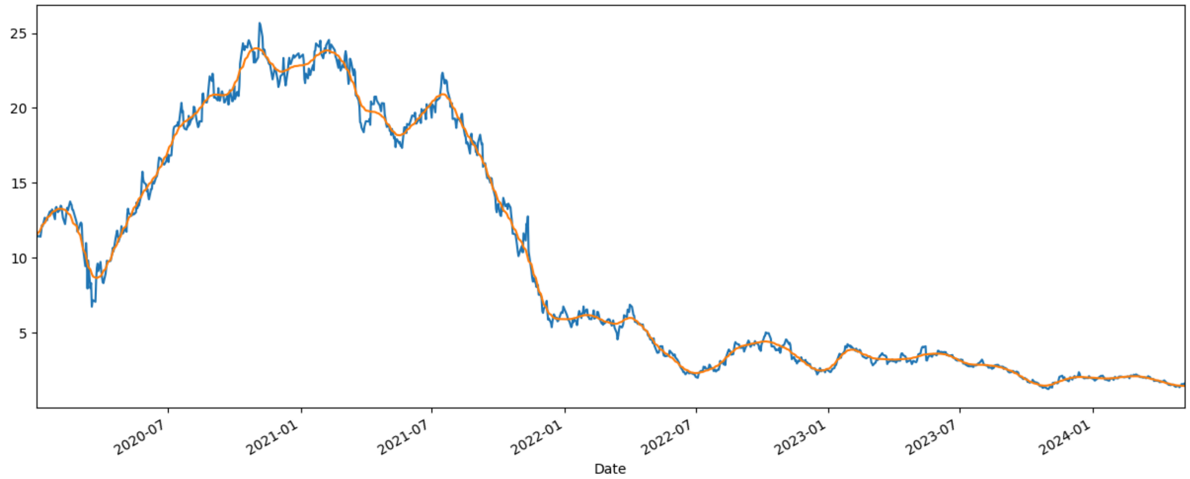
Date	Open	High	Low	Close	Adj Close	Volume
2024-04-30	1.43	1.45	1.34	1.36	1.36	104966200
2024-05-02	1.40	1.48	1.39	1.46	1.46	129948300
2024-05-03	1.50	1.58	1.50	1.57	1.57	173467500
2024-05-06	1.58	1.61	1.54	1.57	1.57	97166300
2024-05-07	1.58	1.65	1.57	1.61	1.61	83097400

Escolhida série de preços das ações do Magazine Luiza S.A. na bolsa de valores brasileira, B3.

2. Pré-processamento de Dados: • Realizar a limpeza e preparação dos dados, incluindo tratamento de valores ausentes, normalização e codificação de variáveis categóricas, se necessário.

Analisando apenas a tendência.

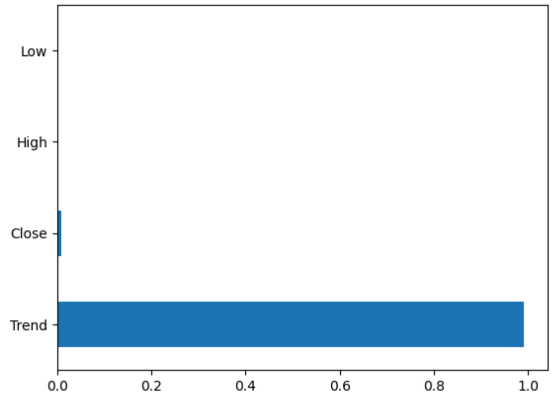
```
df = data.loc[asset,["Close","High","Low"]]
df_cycle,df_trend = hpfilter(df["Close"], lamb=1600)
df["Close"].plot(figsize=(15,6)).autoscale(axis='x',tight=True)
df_trend.plot(figsize=(15,6)).autoscale(axis='x',tight=True)
df["Trend"] = df_trend
df_close = df["Close"]
```



Analisando se seria interessante utilizar outra séria de dados em apoio à previsão da tendência, além da própria tendência passada.

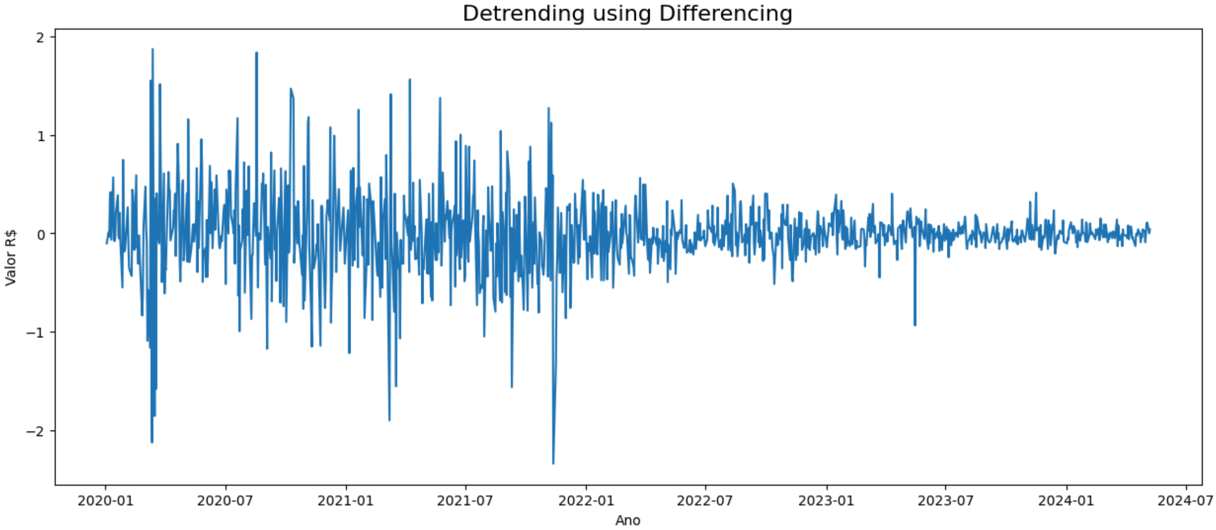
```
from numpy import loadtxt
from xgboost import XGBRegressor
from matplotlib import pyplot

model = XGBRegressor()
model.fit(df[["High","Low",'Close','Trend']],df['Trend'])

(pd.Series(model.feature_importances_, index=df[["High","Low",'Close','Trend']].columns)
   .nlargest(7)
   .plot(kind='barh'))
```

```
<Axes: >
```



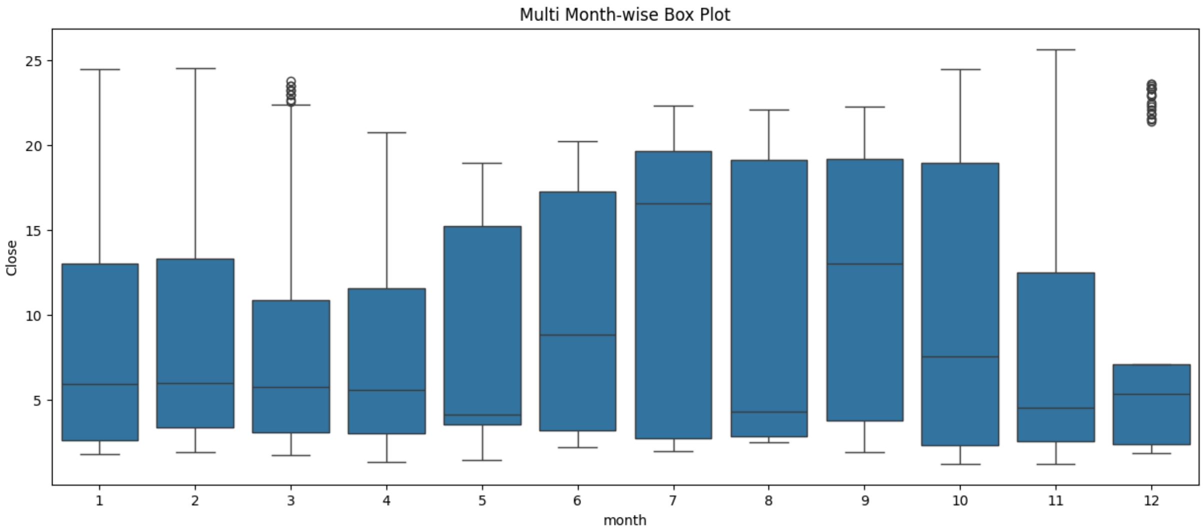
Olhando os dados sem a tendência.

```
diff = df["Close"].diff()
plt.figure(figsize=(15,6))
plt.plot(diff)
plt.title('Detrending using Differencing', fontsize=16)
plt.xlabel('Ano')
plt.ylabel('Valor R$')
plt.show()
```



Procurando por sasonalidade.

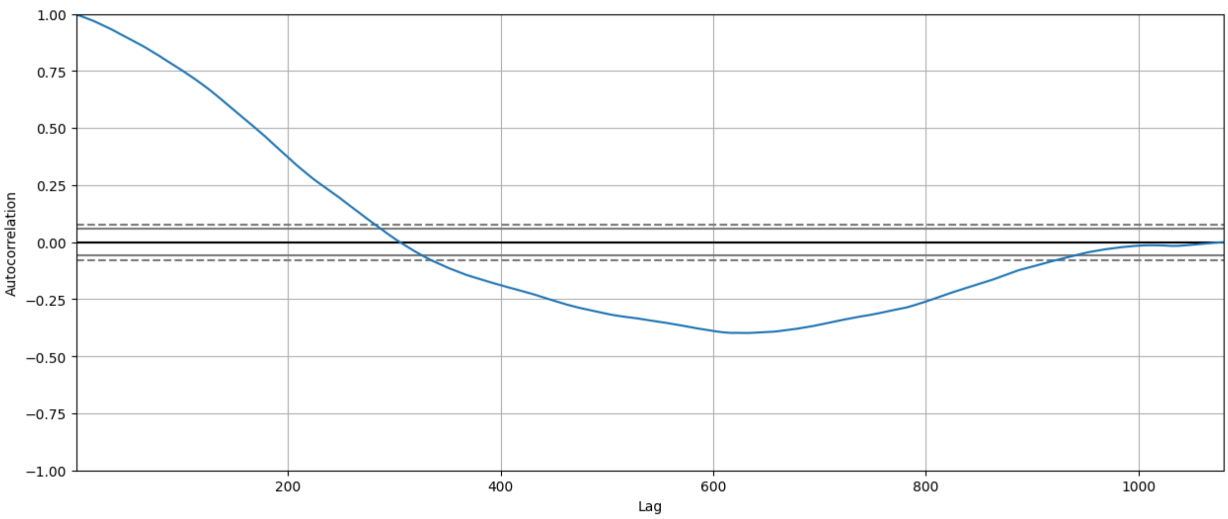
```
df2 = pd.DataFrame(df["Close"])
df2['Date'] = pd.to_datetime(df2.index)
df2['month'] = df2['Date'].dt.strftime('%b')
df2['year'] = [d.year for d in df2.Date]
df2['month'] = [d.month for d in df2.Date]
years = df2['year'].unique()
plt.figure(figsize=(15,6))
sns.boxplot(x='month', y="Close", data=df2).set_title("Multi Month-wise Box Plot")
plt.show()
```



Analisando a autocorrelação nos dados.

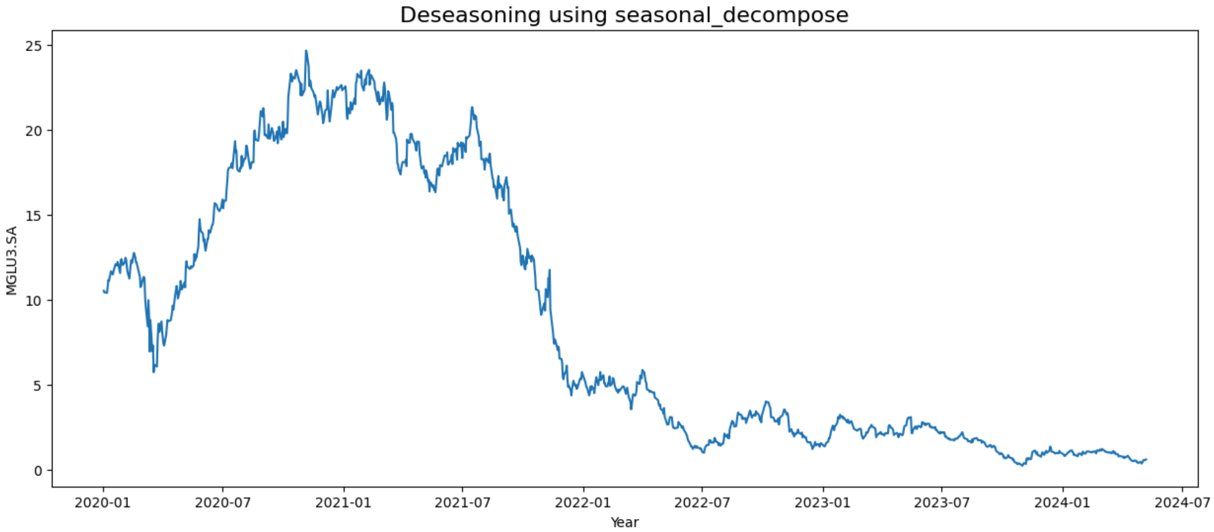
```
plt.rcParams.update({'figure.figsize':(15,6), 'figure.dpi':100})
autocorrelation_plot(df["Close"].tolist())
```

```
<Axes: xlabel='Lag', ylabel='Autocorrelation'>
```



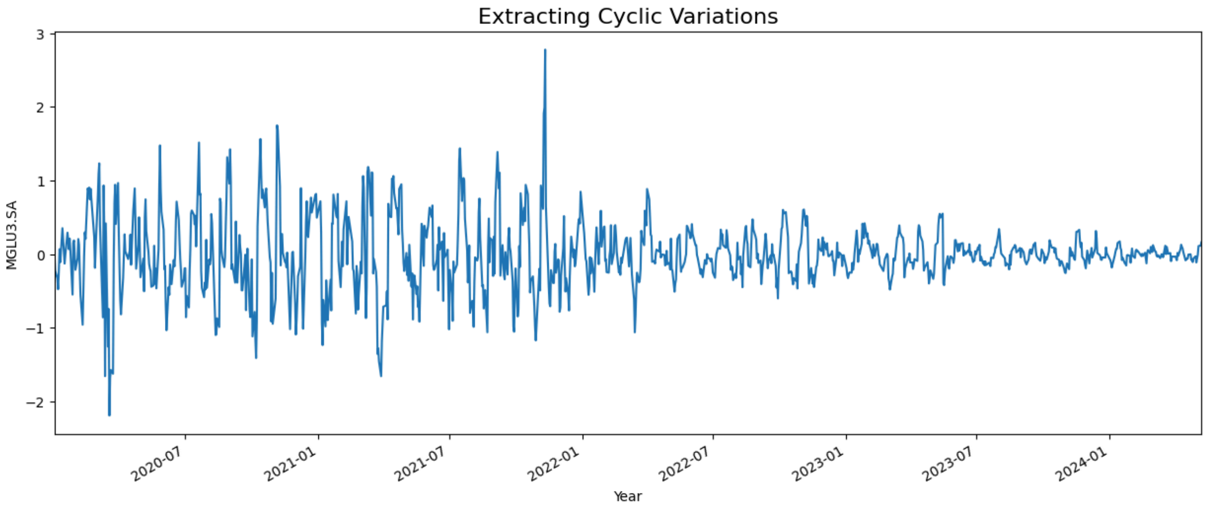
Tirando a sasonalidade.

```
result_mul = seasonal_decompose(df["Close"], model='multiplicative', period=12, extrapolate_trend='freq')
deseason = df["Close"] - result_mul.seasonal
plt.figure(figsize=(15,6))
plt.plot(deseason)
plt.title('Deseasoning using seasonal_decompose', fontsize=16)
plt.xlabel('Year')
plt.ylabel(f'{asset}')
plt.show()
```



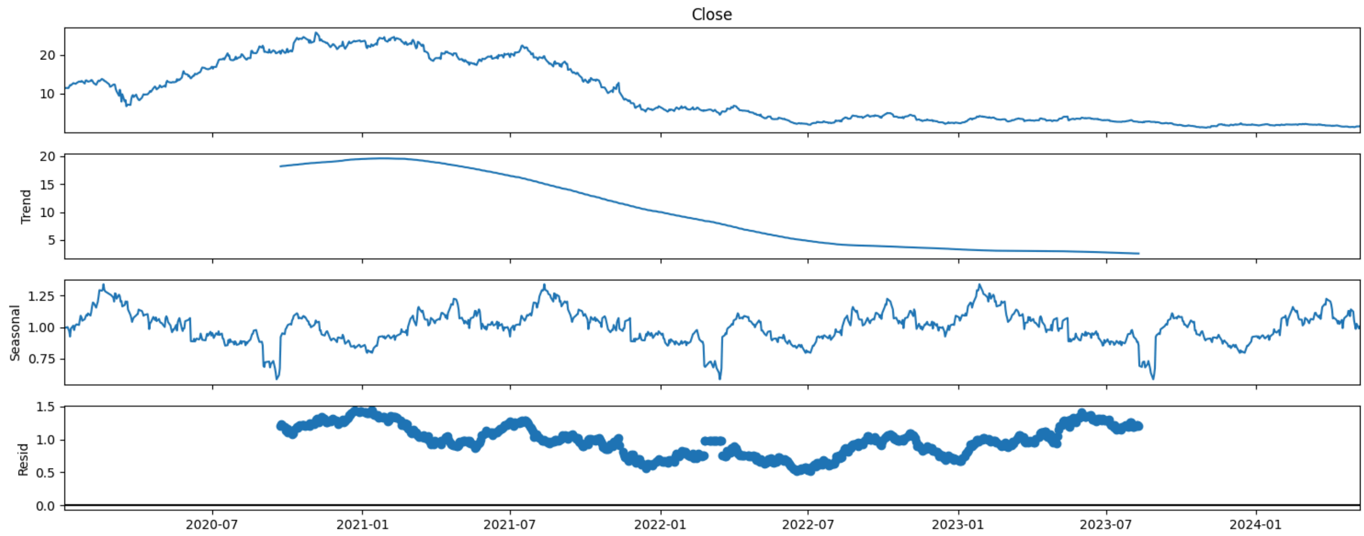
Tirando variações cíclicas.

```
df_cycle, df_trend = hpfilter(df["Close"], lamb=1600)
df_cycle.plot(figsize=(15,6)).autoscale(axis='x',tight=True)
plt.title('Extracting Cyclic Variations', fontsize=16)
plt.xlabel('Year')
plt.ylabel(f'{asset}')
plt.show()
```



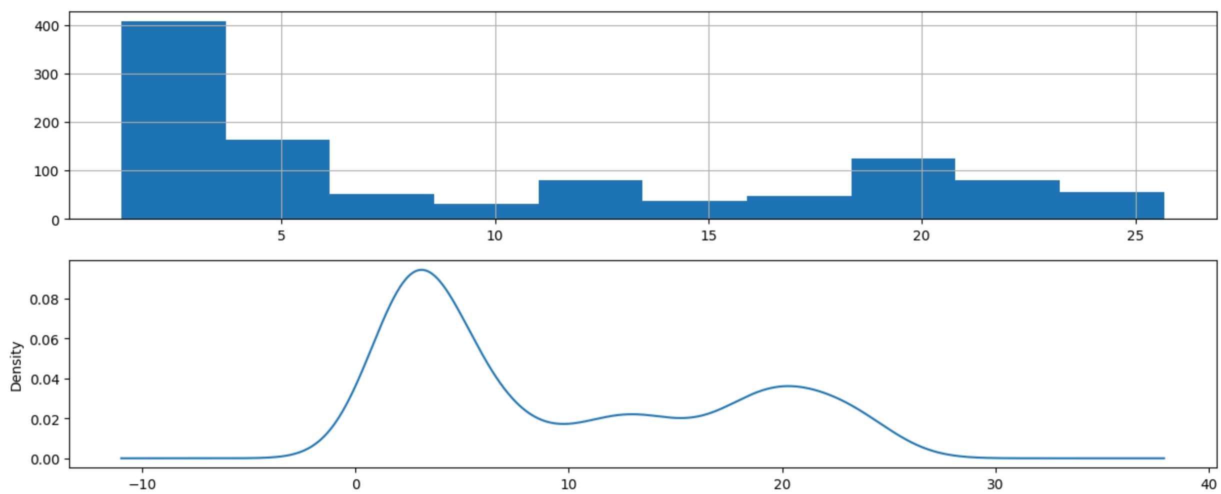
Análise decomposta multiplicativa da série.

```
result = seasonal_decompose(df["Close"], period=365, model='mul')
result.plot();
```



Analisando qual a distribuição dos valores da ação ao longo do tempo.

```
plt.figure(1, figsize=(15,6))
plt.subplot(211)
df["Close"].hist()
plt.subplot(212)
df["Close"].plot(kind='kde')
plt.show()
```



Criando função para avaliação dos modelos a serem criados.

```
def timeseries_evaluation_metrics_func(y_true, y_pred):

    def mean_absolute_percentage_error(y_true, y_pred):
        y_true, y_pred = np.array(y_true), np.array(y_pred)
        return np.mean(np.abs((y_true - y_pred) / y_true)) * 100
    MSE = metrics.mean_squared_error(y_true, y_pred)
    MAE = metrics.mean_absolute_error(y_true, y_pred)
    RMSE = np.sqrt(metrics.mean_squared_error(y_true, y_pred))
    MAPE = mean_absolute_percentage_error(y_true, y_pred)
    R2 = metrics.r2_score(y_true, y_pred)
    print('Evaluation metric results:-')
    print(f'MSE is : {MSE}')
    print(f'MAE is : {MAE}')
    print(f'RMSE is : {RMSE}')
    print(f'MAPE is : {MAPE}')
    print(f'R2 is : {R2}',end='\n\n')
    return  {"MSE":[MSE],"MAE":[MAE],"RMSE":[RMSE],"MAPE":[MAPE],"R2":[R2]}
```

```
resultados = pd.DataFrame(columns=["MSE","MAE","RMSE","MAPE","R2"])
```

Criando função com o teste de Dickey Fuller para verificar se a série é estacionária ou não.

```
def Augmented_Dickey_Fuller_Test_func(series , column_name):
    print (f'Results of Dickey-Fuller Test for column: {column_name}')
    dftest = adfuller(series, autolag='AIC')
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','No Lags Used','Number of Observations Used'])
    for key,value in dftest[4].items():
       dfoutput['Critical Value (%s)'%key] = value
    print (dfoutput)
    if dftest[1] <= 0.05:
        print("Conclusion:====>")
        print("Reject the null hypothesis")
        print("Data is stationary")
    else:
        print("Conclusion:====>")
        print("Fail to reject the null hypothesis")
        print("Data is non-stationary")
```

```
Augmented_Dickey_Fuller_Test_func(df["Close"],'Close')
```

```
Results of Dickey-Fuller Test for column: Close
Test Statistic                   -0.444392
p-value                           0.902419
No Lags Used                      1.000000
Number of Observations Used    1078.000000
Critical Value (1%)              -3.436431
Critical Value (5%)              -2.864225
Critical Value (10%)             -2.568200
dtype: float64
Conclusion:====>
```

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[ ] ↳ *33 células ocultas*

Primeiro modelo - Auto - ARIMA:

Separando dados de treino, validação e teste.

```
X = df["Close"]
train, val, test = X[0:-90], X[-90:-30], X[-30:]
```

Utilizando o auto-arima para identificar a melhor modelagem a ser usada com Arima.

```
stepwise_model = auto_arima(train,start_p=1, start_q=1,
    max_p=100, max_q=100, seasonal=True,
    d=None, trace=True,error_action='ignore',suppress_warnings=True, stepwise=True)
```

```
Performing stepwise search to minimize aic
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=1019.943, Time=1.26 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=1019.767, Time=0.30 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=1018.298, Time=0.22 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=1018.403, Time=0.36 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=1018.331, Time=0.13 sec
 ARIMA(2,1,0)(0,0,0)[0] intercept   : AIC=1020.069, Time=0.47 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=1021.942, Time=1.68 sec
 ARIMA(1,1,0)(0,0,0)[0]             : AIC=1016.932, Time=0.11 sec
 ARIMA(2,1,0)(0,0,0)[0]             : AIC=1018.684, Time=0.26 sec
 ARIMA(1,1,1)(0,0,0)[0]             : AIC=1018.561, Time=0.50 sec
 ARIMA(0,1,1)(0,0,0)[0]             : AIC=1017.039, Time=0.20 sec
 ARIMA(2,1,1)(0,0,0)[0]             : AIC=1020.559, Time=0.51 sec

Best model:  ARIMA(1,1,0)(0,0,0)[0]
Total fit time: 6.040 seconds
```

Modelo criado:

```
stepwise_model.summary()
```

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	990
Model:	SARIMAX(1, 1, 0)	**Log Likelihood**	-506.466
Date:	Wed, 08 May 2024	**AIC**	1016.932
Time:	17:03:31	**BIC**	1026.725
Sample:	0 - 990	**HQIC**	1020.656
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.0586	0.019	-3.159	0.002	-0.095	-0.022
sigma2	0.1630	0.004	41.862	0.000	0.155	0.171

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	1074.65
Prob(Q):	0.99	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.07	**Skew:**	-0.18
Prob(H) (two-sided):	0.00	**Kurtosis:**	8.09

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

Gerando previsões para comparar com a validação e em seguida com a base teste.

```
forecast1,conf_int1 = stepwise_model.predict(n_periods=60,return_conf_int=True)
forecast1 = pd.DataFrame(forecast1,columns=['close_pred'])
```

```
df_conf1 = pd.DataFrame(conf_int1,columns= ['Upper_bound','Lower_bound'])
df_conf1["new_index"] = df.index[-90:-30]
df_conf1 = df_conf1.set_index("new_index")
```

Avaliação da previsão em relação a base de validação.

```
timeseries_evaluation_metrics_func(val, forecast1)
```

```
Evaluation metric results:-
MSE is : 0.010607713259458251
MAE is : 0.085461682579874
RMSE is : 0.1029937534972789
MAPE is : 4.234445972626502
R2 is : -0.09410281436280643

{'MSE': [0.010607713259458251],
 'MAE': [0.085461682579874],
 'RMSE': [0.1029937534972789],
 'MAPE': [4.234445972626502],
 'R2': [-0.09410281436280643]}
```

```
forecast2,conf_int2 = stepwise_model.predict(n_periods=30,return_conf_int=True)
forecast2 = pd.DataFrame(forecast2,columns=['close_pred'])
```

```
df_conf2 = pd.DataFrame(conf_int2,columns= ['Upper_bound','Lower_bound'])
df_conf2["new_index"] = df.index[-30:]
df_conf2 = df_conf2.set_index("new_index")
```

Avaliação da previsão em relação à base teste.

```
resultados = pd.concat([resultados,pd.DataFrame(data=timeseries_evaluation_metrics_func(test, forecast2))],axis=0)
```

```
Evaluation metric results:-
MSE is : 0.15368944251529093
MAE is : 0.36099563583100974
RMSE is : 0.39203245084468574
MAPE is : 23.379816248523316
R2 is : -5.576387494937645
```

```
forecast1["new_index"] = df.index[-90:-30]
forecast1 = forecast1.set_index("new_index")

forecast2["new_index"] = df.index[-30:]
forecast2 = forecast2.set_index("new_index")
```

Plotando as previsões e seus intervalos de onfiança e comparando com o que ocorreu de fato.

```
import matplotlib.pyplot as plt
%matplotlib inline
plt.rcParams["figure.figsize"] = [15,7]
plt.plot( train[-300:], label='Train ')
plt.plot( val, label='Val ')
plt.plot(test, label='Test ')
plt.plot(forecast1, label='Predicted val')
plt.plot(forecast2, label='Predicted test')
#plt.plot(df_conf1['Upper_bound'], label='Confidence Interval Upper bound ')
#plt.plot(df_conf1['Lower_bound'], label='Confidence Interval Lower bound ')
plt.plot(df_conf2['Upper_bound'], label='Confidence Interval Upper bound ')
plt.plot(df_conf2['Lower_bound'], label='Confidence Interval Lower bound ')
plt.legend(loc='best')
plt.show()
```

Segundo modelo - LSTM

[ ] ↳ 29 células ocultas

Terceiro modelo - Algoritmo Genético para melhorar ARIMA

[ ] ↳ 10 células ocultas

Comparação entre os modelos

[ ] ↳ 1 célula oculta

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[ ] ↳ *33 células ocultas*

Primeiro modelo - Auto - ARIMA:

[ ] ↳ *18 células ocultas*

Segundo modelo - LSTM

Criando função para preparar os dados para envio ao Tensorflow.

```
def custom_ts_multi_data_prep(dataset, target, start, end, window, horizon):
    X = []
    y = []
    start = start + window
    if end is None:
        end = len(dataset) - horizon

    for i in range(start, end):
        indices = range(i-window, i)
        X.append(dataset[indices])

        indicey = range(i+1, i+1+horizon)
        y.append(target[indicey])
    return np.array(X), np.array(y)
```

Guardando dados de teste.

```
h = 90
predition_X = df.tail(h)
uni_data = df.drop(df.tail(h).index)
```

Normalizando os dados para facilitar o treinamento e sua convergência. As colunas utilizadas para a previsão da série são "Close","High","Low" e "Trend". Se tenta prever a "Trend", e não o valor de "Close", para a previsão ser mais suavizada.

```
x_scaler = preprocessing.StandardScaler()
y_scaler = preprocessing.StandardScaler()
dataX = x_scaler.fit_transform(df)
dataY = y_scaler.fit_transform(df[['Trend']]) #y_scaler.fit_transform(np.array(df).reshape(-1, 1))
```

Fazendo o split dos dados de Treino e Validação, deixando 20% para validação e 80% para treino. Para o teste, será realizada uma previsão de horizonte de 90 períodos. Ajustando o índice de calendário para apenas os dias comerciais, já que só tem-se dados em dias em que há o pregão da Bolso de Valores. A janela de deslizante de dados que treina a previsão de cada horizonte de 90 dias é de 60 dias. O modelo sempre olha 60 dias pra traz para prever os próximos 90 dias.

```
tamanho = len(df["Close"])
hist_window = 60
horizon = h

index_prev = data.loc[asset].index[-h:]
index_prev

from pandas.tseries.holiday import USFederalHolidayCalendar
from pandas.tseries.offsets import CustomBusinessDay
us_bd = CustomBusinessDay(calendar=USFederalHolidayCalendar())
index_prev_oficial = pd.period_range(start=index_prev[-1], periods=h+1, freq=us_bd)[1:]


TRAIN_SPLIT = int((tamanho-h)*0.80)

x_train_multi, y_train_multi = custom_ts_multi_data_prep(
    dataX, dataY, 0, TRAIN_SPLIT, hist_window, horizon)
x_val_multi, y_val_multi= custom_ts_multi_data_prep(
    dataX, dataY, TRAIN_SPLIT, None, hist_window, horizon)
```

```
TRAIN_SPLIT
```

```
792
```

Exemplo de coleta de 60 pregões das 4 features de interesse ("Close","High","Low" e "Trend") e geração da previsão de 90 dias de Trend.

```
print ('Single window of past history')
print(x_train_multi[0])
print ('\n Target horizon')
print (y_train_multi[0])
```

```
Single window of past history
[[ 2.46784952e-01  2.12363095e-01  2.29663506e-01  2.48367008e-01]
 [ 2.33583393e-01  2.12363095e-01  2.47665441e-01  2.63046809e-01]
 [ 2.34783580e-01  2.11772434e-01  2.32409429e-01  2.77726062e-01]
 [ 2.30583050e-01  2.08523918e-01  2.53767671e-01  2.92386220e-01]
 [ 2.75588074e-01  2.42485486e-01  2.53767671e-01  3.06982318e-01]
 [ 3.29294081e-01  2.98005220e-01  3.12350179e-01  3.21431174e-01]
 [ 3.20893267e-01  3.22221241e-01  3.31572634e-01  3.35630477e-01]
 [ 3.93801396e-01  3.57068800e-01  3.65135461e-01  3.49483418e-01]
 [ 3.86900692e-01  3.81284821e-01  4.09377348e-01  3.62884551e-01]
 [ 3.76699477e-01  3.60907977e-01  3.97172762e-01  3.75756829e-01]
 [ 3.70698791e-01  3.71539395e-01  3.69712165e-01  3.88038908e-01]
 [ 3.97401710e-01  3.62975170e-01  3.94121585e-01  3.99670705e-01]
```

```
 [ 4.46907309e-01  4.09340019e-01  4.23107584e-01  4.10581960e-01]
 [ 4.44206890e-01  4.31193516e-01  4.70705903e-01  4.20701706e-01]
 [ 4.37606356e-01  4.41824934e-01  4.46906743e-01  4.29982475e-01]
 [ 4.64309275e-01  4.30602855e-01  4.49957921e-01  4.38392284e-01]
 [ 4.51407763e-01  4.40348401e-01  4.82605482e-01  4.45904695e-01]
 [ 3.80899884e-01  3.88667844e-01  4.13954176e-01  4.52510299e-01]
 [ 4.76610693e-01  4.38576538e-01  4.21887188e-01  4.58203928e-01]
 [ 4.85611600e-01  4.71061453e-01  5.02438073e-01  4.62936342e-01]
 [ 4.61909025e-01  4.30012314e-01  4.52703968e-01  4.66670652e-01]
 [ 4.40906623e-01  4.43301586e-01  4.58196187e-01  4.69385011e-01]
 [ 4.62809164e-01  4.37395216e-01  4.72231554e-01  4.71055417e-01]
 [ 4.96712833e-01  4.88189902e-01  5.17083700e-01  4.71640858e-01]
 [ 4.85911647e-01  4.93210281e-01  5.14032523e-01  4.71095996e-01]
 [ 4.41806763e-01  4.72833437e-01  4.76503127e-01  4.69392045e-01]
 [ 3.93801396e-01  4.07272825e-01  4.06326170e-01  4.66510349e-01]
 [ 3.38295232e-01  3.95460085e-01  3.46523391e-01  4.62415800e-01]
 [ 3.95001460e-01  3.73901798e-01  3.52320616e-01  4.57028549e-01]
 [ 4.45107030e-01  4.25582476e-01  4.29209939e-01  4.50191774e-01]
 [ 4.78410850e-01  4.47731304e-01  4.24633235e-01  4.41710594e-01]
 [ 4.56808356e-01  4.67222397e-01  4.82605482e-01  4.31387742e-01]
 [ 5.32416903e-01  5.25104535e-01  5.17693961e-01  4.19049744e-01]
 [ 5.13514828e-01  5.00888514e-01  5.28373020e-01  4.04539829e-01]
 [ 5.02713642e-01  4.94982264e-01  5.31729327e-01  3.87773030e-01]
 [ 4.63109088e-01  4.72242655e-01  4.77418518e-01  3.68733406e-01]
 [ 4.60408792e-01  4.63087769e-01  4.64298542e-01  3.47477751e-01]
 [ 3.53296825e-01  3.51752971e-01  3.53235757e-01  3.24122673e-01]
 [ 2.74388010e-01  3.32557328e-01  3.00145469e-01  2.98856179e-01]
 [ 2.82488900e-01  2.47505864e-01  2.14712873e-01  2.71885145e-01]
 [ 3.43395779e-01  3.33738650e-01  2.94043238e-01  2.43401641e-01]
 [ 3.52396686e-01  3.73901798e-01  3.50489834e-01  2.13604869e-01]
 [ 3.40395436e-01  3.63861162e-01  3.56592189e-01  1.82757142e-01]
 [ 2.00579742e-01  2.91212858e-01  1.95795424e-01  1.51208145e-01]
 [ 1.26771474e-01  1.26130309e-01  8.74789355e-02  1.19406695e-01]
 [-2.23451737e-02  6.52661616e-03 -4.28060555e-02  8.78328243e-02]
 [ 1.76576997e-01  1.43849299e-01  6.39849064e-02  5.69713952e-02]
 [ 5.92639378e-02  1.36761727e-01 -8.63284318e-03  2.72383678e-02]
 [-2.13166578e-01 -9.77206107e-02 -2.93307052e-01 -8.75228669e-04]
 [ 2.68603794e-02  1.83392358e-02 -1.82244517e-01 -2.68582434e-02]
 [-2.11066313e-01 -6.58263569e-02 -1.86516090e-01 -5.03325879e-02]
 [-1.66061350e-01 -1.31682178e-01 -2.23740418e-01 -7.08865518e-02]
 [-3.68883943e-01 -2.51581202e-01 -4.18405017e-01 -8.82092600e-02]
 [-3.16678230e-01 -3.18027684e-01 -4.63257288e-01 -1.02049618e-01]
 [-3.13677765e-01 -1.79228349e-01 -2.90866073e-01 -1.12332611e-01]
 [-3.26879262e-01 -2.71958106e-01 -3.24123895e-01 -1.19117933e-01]
 [-1.32757530e-01 -1.28433663e-01 -1.97195211e-01 -1.22591679e-01]
```

Montagem dos dados de treino e validação para poder realizar o treinamento do modelo. Os dados de teste já foram separados para depois de o modelo pronto, poder-se testar com dados ainda não vistos.

```
BATCH_SIZE = 60
BUFFER_SIZE = 60

train_data_multi = tf.data.Dataset.from_tensor_slices((x_train_multi, y_train_multi))
train_data_multi = train_data_multi.cache().batch(BATCH_SIZE).repeat()

val_data_multi = tf.data.Dataset.from_tensor_slices((x_val_multi, y_val_multi))
val_data_multi = val_data_multi.batch(BATCH_SIZE).repeat()
```

Muitas configurações de rede foram testadas, tendo sido esta última a que melhor performou nos testes realizados. Diferentes número de camadas também foram utilizados. Alterou-se também o dropout. EX:

LSTM_model = tf.keras.models.Sequential([tf.keras.layers.LSTM(60, input_shape=x_train_multi.shape[-2:],return_sequences=True), tf.keras.layers.LSTM(units=60,return_sequences=True), tf.keras.layers.LSTM(units=60), tf.keras.layers.Dropout(0.2), tf.keras.layers.Dense(units=horizon),]) LSTM_model.compile(optimizer='adam', loss='mse')

LSTM_model = tf.keras.models.Sequential([tf.keras.layers.LSTM(360, input_shape=x_train_multi.shape[-2:],return_sequences=True), tf.keras.layers.LSTM(units=360,return_sequences=True), tf.keras.layers.LSTM(units=360), tf.keras.layers.Dropout(0.2), tf.keras.layers.Dense(units=horizon),]) LSTM_model.compile(optimizer='adam', loss='mse')

LSTM_model = tf.keras.models.Sequential([tf.keras.layers.LSTM(120, input_shape=x_train_multi.shape[-2:],return_sequences=True), tf.keras.layers.LSTM(units=120,return_sequences=True), tf.keras.layers.LSTM(units=120), tf.keras.layers.Dropout(0.3), tf.keras.layers.Dense(units=horizon),]) LSTM_model.compile(optimizer='adam', loss='mse')

LSTM_model = tf.keras.models.Sequential([tf.keras.layers.LSTM(30, input_shape=x_train_multi.shape[-2:],return_sequences=True), tf.keras.layers.LSTM(units=60,return_sequences=True), tf.keras.layers.LSTM(units=120), tf.keras.layers.Dropout(0.3), tf.keras.layers.Dense(units=horizon),]) LSTM_model.compile(optimizer='adam', loss='mse')

LSTM_model = tf.keras.models.Sequential([tf.keras.layers.LSTM(30, input_shape=x_train_multi.shape[-2:],return_sequences=True), tf.keras.layers.LSTM(units=60,return_sequences=True), tf.keras.layers.LSTM(units=30), tf.keras.layers.Dropout(0.2), tf.keras.layers.Dense(units=horizon),]) LSTM_model.compile(optimizer='adam', loss='mse')

LSTM_model = tf.keras.models.Sequential([tf.keras.layers.LSTM(60, input_shape=x_train_multi.shape[-2:],return_sequences=True), tf.keras.layers.LSTM(units=30,return_sequences=True), tf.keras.layers.LSTM(units=15), tf.keras.layers.Dropout(0.2), tf.keras.layers.Dense(units=horizon),]) LSTM_model.compile(optimizer='adam', loss='mse')

LSTM_model = tf.keras.models.Sequential([tf.keras.layers.LSTM(60, input_shape=x_train_multi.shape[-2:],return_sequences=True), tf.keras.layers.LSTM(units=20,return_sequences=True),
tf.keras.layers.LSTM(units=10), tf.keras.layers.Dropout(0.2), tf.keras.layers.Dense(units=horizon),]) LSTM_model.compile(optimizer='adam', loss='mse')

LSTM_model = tf.keras.models.Sequential([tf.keras.layers.LSTM(60, input_shape=x_train_multi.shape[-2:],return_sequences=True), tf.keras.layers.LSTM(units=30,return_sequences=True), tf.keras.layers.LSTM(units=15,return_sequences=True), tf.keras.layers.LSTM(units=5), tf.keras.layers.Dropout(0.2), tf.keras.layers.Dense(units=horizon),]) LSTM_model.compile(optimizer='adam', loss='mse')

LSTM_model = tf.keras.models.Sequential([tf.keras.layers.LSTM(30, input_shape=x_train_multi.shape[-2:],return_sequences=True), tf.keras.layers.LSTM(units=15,return_sequences=True), tf.keras.layers.LSTM(units=5,return_sequences=True), tf.keras.layers.LSTM(units=1), tf.keras.layers.Dropout(0.2), tf.keras.layers.Dense(units=horizon),]) LSTM_model.compile(optimizer='adam', loss='mse')

LSTM_model = tf.keras.models.Sequential([tf.keras.layers.LSTM(30, input_shape=x_train_multi.shape[-2:],return_sequences=True), tf.keras.layers.LSTM(units=15,return_sequences=True), tf.keras.layers.LSTM(units=5,return_sequences=True), tf.keras.layers.LSTM(units=1), tf.keras.layers.Dropout(0.1), tf.keras.layers.Dense(units=horizon),]) LSTM_model.compile(optimizer='adam', loss='mse')

```
LSTM_model = tf.keras.models.Sequential([
    tf.keras.layers.LSTM(30, input_shape=x_train_multi.shape[-2:],return_sequences=True),
    tf.keras.layers.LSTM(units=15,return_sequences=True),
    tf.keras.layers.LSTM(units=5,return_sequences=True),
    tf.keras.layers.LSTM(units=1),
    tf.keras.layers.Dropout(0.1),
    tf.keras.layers.Dense(units=horizon),
])
LSTM_model.compile(optimizer='adam', loss='mse')
```

```
model_path = f'drive/MyDrive/modelos_ia_prev_acoes/{asset[:5]}.h5'
```

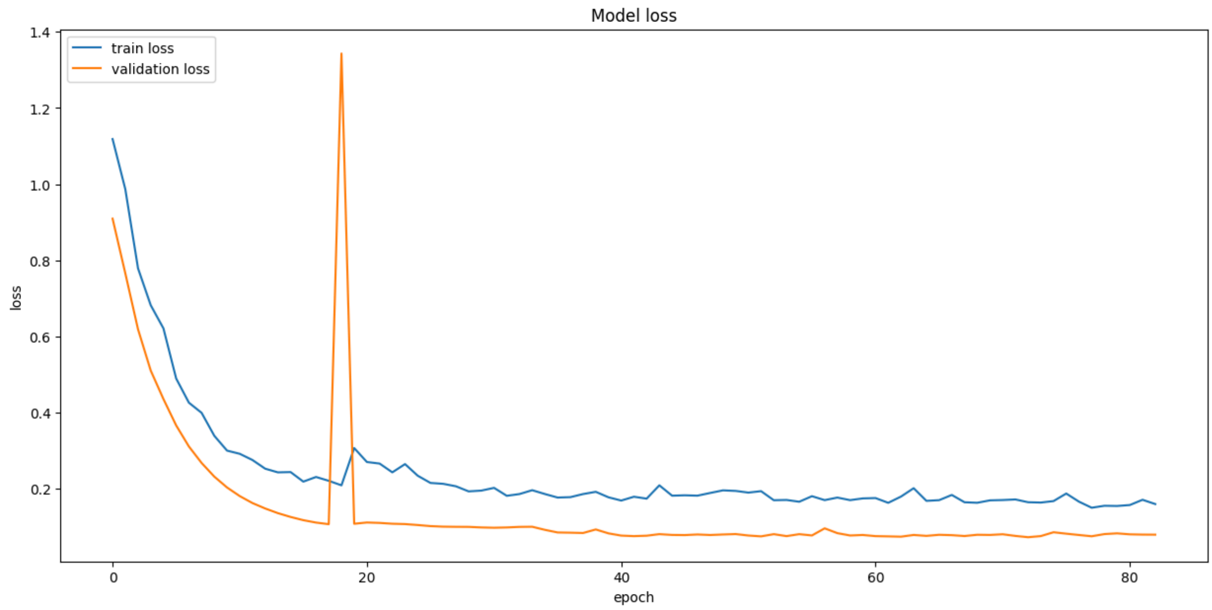
```
EVALUATION_INTERVAL = 100
EPOCHS = 150
history = LSTM_model.fit(train_data_multi, epochs=EPOCHS,steps_per_epoch=EVALUATION_INTERVAL,validation_data=val_data_multi, validation_steps=50,verbose =1,callbacks =[tf.keras.callback

Trained_model = tf.keras.models.load_model(model_path)
Trained_model.summary()
```

```
Epoch 48/150
100/100 [==============================] - 9s 91ms/step - loss: 0.1893 - val_loss: 0.0788
Epoch 49/150
100/100 [==============================] - 10s 100ms/step - loss: 0.1961 - val_loss: 0.0803
Epoch 50/150
100/100 [==============================] - 11s 105ms/step - loss: 0.1946 - val_loss: 0.0813
Epoch 51/150
100/100 [==============================] - 10s 97ms/step - loss: 0.1902 - val_loss: 0.0775
Epoch 52/150
100/100 [==============================] - 9s 94ms/step - loss: 0.1940 - val_loss: 0.0753
Epoch 53/150
100/100 [==============================] - 10s 104ms/step - loss: 0.1702 - val_loss: 0.0811
Epoch 54/150
100/100 [==============================] - 10s 105ms/step - loss: 0.1709 - val_loss: 0.0759
Epoch 55/150
100/100 [==============================] - 9s 88ms/step - loss: 0.1662 - val_loss: 0.0811
Epoch 56/150
100/100 [==============================] - 10s 104ms/step - loss: 0.1808 - val_loss: 0.0777
Epoch 57/150
100/100 [==============================] - 11s 105ms/step - loss: 0.1705 - val_loss: 0.0964
Epoch 58/150
100/100 [==============================] - 9s 90ms/step - loss: 0.1771 - val_loss: 0.0838
Epoch 59/150
100/100 [==============================] - 10s 102ms/step - loss: 0.1704 - val_loss: 0.0776
Epoch 60/150
100/100 [==============================] - 10s 103ms/step - loss: 0.1749 - val_loss: 0.0790
Epoch 61/150
100/100 [==============================] - 11s 108ms/step - loss: 0.1759 - val_loss: 0.0759
Epoch 62/150
100/100 [==============================] - 9s 88ms/step - loss: 0.1634 - val_loss: 0.0753
Epoch 63/150
100/100 [==============================] - 10s 103ms/step - loss: 0.1797 - val_loss: 0.0745
Epoch 64/150
100/100 [==============================] - 10s 105ms/step - loss: 0.2018 - val_loss: 0.0790
Epoch 65/150
100/100 [==============================] - 9s 91ms/step - loss: 0.1686 - val_loss: 0.0766
Epoch 66/150
100/100 [==============================] - 10s 101ms/step - loss: 0.1703 - val_loss: 0.0794
Epoch 67/150
100/100 [==============================] - 11s 106ms/step - loss: 0.1841 - val_loss: 0.0785
Epoch 68/150
100/100 [==============================] - 10s 97ms/step - loss: 0.1648 - val_loss: 0.0762
Epoch 69/150
100/100 [==============================] - 9s 94ms/step - loss: 0.1635 - val_loss: 0.0795
Epoch 70/150
100/100 [==============================] - 10s 103ms/step - loss: 0.1698 - val_loss: 0.0790
Epoch 71/150
100/100 [==============================] - 10s 105ms/step - loss: 0.1707 - val_loss: 0.0808
Epoch 72/150
100/100 [==============================] - 9s 90ms/step - loss: 0.1722 - val_loss: 0.0765
Epoch 73/150
100/100 [==============================] - 11s 106ms/step - loss: 0.1649 - val_loss: 0.0731
Epoch 74/150
100/100 [==============================] - 10s 103ms/step - loss: 0.1641 - val_loss: 0.0760
Epoch 75/150
100/100 [==============================] - 10s 104ms/step - loss: 0.1680 - val_loss: 0.0861
Epoch 76/150
100/100 [==============================] - 9s 88ms/step - loss: 0.1877 - val_loss: 0.0824
```

Analise de como andou o treinamento. Se não "overfitou" ou "underfitou".

```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train loss', 'validation loss'], loc='upper left')
plt.rcParams["figure.figsize"] = [16,9]
plt.show()
```



Gerando a previsão baseada no modelo criado usando treino e validação para avaliar como será a previsão na base teste.

```
data_test = x_scaler.fit_transform(uni_data.tail(hist_window))
test_rescaled = data_test.reshape(1, data_test.shape[0], data_test.shape[1])
Predicted_results = Trained_model.predict(test_rescaled)
Predicted_results
```

```
1/1 [==============================] - 2s 2s/step
array([[1.3798349, 1.3822522, 1.3846242, 1.386976 , 1.38915  , 1.391165 ,
        1.3932173, 1.3950903, 1.396866 , 1.3985856, 1.4002507, 1.4016806,
        1.4031615, 1.4044737, 1.405853 , 1.4071064, 1.4081753, 1.4091444,
        1.41017  , 1.4109517, 1.4116083, 1.4122376, 1.4128503, 1.4132684,
        1.4135373, 1.4136577, 1.4138837, 1.4137915, 1.4134946, 1.4130993,
        1.41265  , 1.4122362, 1.4114809, 1.4106877, 1.409698 , 1.4085244,
        1.4074062, 1.4060824, 1.4046102, 1.4031045, 1.401606 , 1.3999671,
        1.3981334, 1.396376 , 1.3944031, 1.3923805, 1.3903664, 1.3882334,
        1.3859324, 1.3837317, 1.3813307, 1.3788657, 1.3765055, 1.3739862,
        1.3712665, 1.3686838, 1.3659372, 1.3630866, 1.3601663, 1.3571548,
        1.3541195, 1.3508717, 1.3477671, 1.3444045, 1.3409923, 1.3374113,
        1.3338268, 1.3300115, 1.3261507, 1.3222013, 1.3182037, 1.3141421,
        1.3099003, 1.3055191, 1.3012067, 1.2966958, 1.2921377, 1.2875738,
        1.2829344, 1.2782263, 1.2734625, 1.2686415, 1.2638485, 1.2589386,
        1.2540435, 1.2490437, 1.2440346, 1.2389832, 1.2339295, 1.2288344]],
      dtype=float32)
```

Coloando a previsão gerada em ordem de grandeza correta, desnomalizando os dados. Gerando uma tendência baseada na previsão para poder suavisar a previsão.

```
df2 = predition_X
df2_cycle,df2_trend = hpfilter(df2["Close"], lamb=1600)
df2["Trend"] = df2_trend
data_pred = x_scaler.fit_transform(df2.tail(hist_window))
pred_rescaled = data_pred.reshape(1, data_pred.shape[0], data_pred.shape[1])
Predicted_results_oficial = Trained_model.predict(pred_rescaled)
Predicted_results_oficial_Inv_trans = y_scaler.inverse_transform(Predicted_results_oficial.reshape(-1,1))
Predicted_results_oficial_Inv_trans = pd.DataFrame(Predicted_results_oficial_Inv_trans, columns=['Trend'], index=index_prev_oficial)
Predicted_results_oficial_Inv_trans_cycle,Predicted_results_oficial_Inv_trans_trend = hpfilter(Predicted_results_oficial_Inv_trans, lamb=1600)
ajuste2 = Predicted_results_oficial_Inv_trans_trend[0]-df_close.tail(h+1)[-1]
Predicted_results_oficial_Inv_trans = Predicted_results_oficial_Inv_trans-ajuste2
Predicted_results_oficial_Inv_trans_trend = Predicted_results_oficial_Inv_trans_trend-ajuste2
```

```
1/1 [==============================] - 0s 30ms/step
```

```
Predicted_results_Inv_trans = y_scaler.inverse_transform(Predicted_results.reshape(-1,1))
Predicted_results_Inv_trans = pd.DataFrame(Predicted_results_Inv_trans, columns=['Trend'], index=index_prev)
Predicted_results_Inv_trans_cycle,Predicted_results_Inv_trans_trend = hpfilter(Predicted_results_Inv_trans, lamb=1600)
ajuste = Predicted_results_Inv_trans_trend[0]-df_close.tail(h+1)[0]
Predicted_results_Inv_trans_trend = Predicted_results_Inv_trans_trend-ajuste
Predicted_results_Inv_trans = Predicted_results_Inv_trans-ajuste
```

```
test = pd.DataFrame(df_close.tail(h), columns=['Close'], index=index_prev)
```

Avaliação do Modelo na base teste.

```
resultados = pd.concat([resultados,pd.DataFrame(data=timeseries_evaluation_metrics_func(test,Predicted_results_Inv_trans_trend))],axis=0)
```

```
Evaluation metric results:-
MSE is : 0.06450614787684857
MAE is : 0.20009932065904243
RMSE is : 0.2539806053163284
MAPE is : 20.104737712205406
R2 is : -0.3365647964962464
```

Plotando a previsão.

```
plt.plot(df_close.tail(h+300))
#plt.plot( Predicted_results_Inv_trans)
#plt.plot( Predicted_results_oficial_Inv_trans)
plt.plot(Predicted_results_Inv_trans_trend)
plt.plot(Predicted_results_oficial_Inv_trans_trend)
plt
plt.title("Actual vs Predicted")
plt.ylabel(f'{asset}')
plt.legend(('Actual','test_trend','predicted_trend'))
plt.show()
```

GABRIEL VINICIUS BOIN FREITAS
LEONARDO CARDOSO SANTOS

Inicio - Análise descritiva da série temporal

[ ] ↳ *33 células ocultas*

Primeiro modelo - Auto - ARIMA:

[ ] ↳ *18 células ocultas*

Segundo modelo - LSTM

[ ] ↳ *29 células ocultas*

Terceiro modelo - Algoritmo Genético para melhorar ARIMA

```
from statsmodels.tsa.arima.model import ARIMA
from deap import base, creator, tools, algorithms
from sklearn.metrics import mean_squared_error
import random
import numpy as np
```

Dividindo os dados em treino, validação e teste.

```
data = df['Close']
train_size = int(len(data) * 0.9)
valid_size = int(len(data) * 0.05)
train, valid, test = data[0:train_size], data[train_size:train_size + valid_size], data[train_size + valid_size:]
```

Determinando melhores parâmeros para um modelo ARIMA através de Algoritmo Genético

```
# Definindo os limites dos parâmetros do modelo ARIMA
p_range = range(0, 30)  # Ordem do componente autoregressivo
d_range = range(0, 3)  # Ordem de diferenciação
q_range = range(0, 30)  # Ordem do componente de média móvel

creator.create("FitnessMin", base.Fitness, weights=(-1.0,))
creator.create("Individual", list, fitness=creator.FitnessMin)

toolbox = base.Toolbox()
toolbox.register("attr_p", random.choice, p_range)
toolbox.register("attr_d", random.choice, d_range)
toolbox.register("attr_q", random.choice, q_range)
toolbox.register("individual", tools.initCycle, creator.Individual,
                 (toolbox.attr_p, toolbox.attr_d, toolbox.attr_q), n=1)
toolbox.register("population", tools.initRepeat, list, toolbox.individual)

def evaluate(individual):
    order = (individual[0], individual[1], individual[2])
    try:
        model = ARIMA(train, order=order)
        model_fit = model.fit()
        pred = model_fit.forecast(steps=len(valid))
        mse = mean_squared_error(valid, pred)
        return (mse,)
    except:
        return (np.inf,)  # Caso o modelo falhe na convergência

toolbox.register("mate", tools.cxTwoPoint)
toolbox.register("mutate", tools.mutUniformInt, low=[0, 0, 0], up=[2, 1, 2], indpb=0.2)
toolbox.register("select", tools.selTournament, tournsize=3)
toolbox.register("evaluate", evaluate)

# Configuração do algoritmo genético
population = toolbox.population(n=50)
ngen = 5
cxpb, mutpb = 0.5, 0.2

result, log = algorithms.eaSimple(population, toolbox, cxpb, mutpb, ngen, verbose=True)

# Extraindo os melhores parâmetros
best_individual = tools.selBest(population, k=1)[0]
print('Melhores parâmetros ARIMA:', best_individual)
print('Melhor MSE:', evaluate(best_individual))
```

```
gen     nevals
0       50
1       35
2       28
3       31
4       29
5       21
Melhores parâmetros ARIMA: [28, 0, 10]
Melhor MSE: (0.014220831129557406,)
```

Analisando a performance do modelo.

```
# Construindo o modelo com os melhores parâmetros
best_order = (best_individual[0], best_individual[1], best_individual[2])
model = ARIMA(np.concatenate((train, valid)), order=best_order)
model_fit = model.fit()

# Previsão no conjunto de teste
predictions = model_fit.forecast(steps=len(test))
```

```
resultados = pd.concat([resultados,pd.DataFrame(data=timeseries_evaluation_metrics_func(test,predictions))],axis=0)
```

```
Evaluation metric results:-
MSE is : 0.19031327392428038
MAE is : 0.3479057884606748
RMSE is : 0.4362490961873507
MAPE is : 21.67818592927152
R2 is : -1.9648231025841474
```

Plotando o gráfico.

```
pred = pd.DataFrame(predictions, columns=['Close'], index=test.index)
```

```
import matplotlib.pyplot as plt
%matplotlib inline
plt.rcParams["figure.figsize"] = [15,7]
plt.plot( train[-300:], label='Train ')
plt.plot( valid, label='Val ')
plt.plot(test, label='Test ')
plt.plot(pred, label='Predicted test')
plt.legend(loc='best')
plt.show()
```

Comparação entre os modelos

[ ] ↳ *1 célula oculta*

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Inicio - Análise descritiva da série temporal

[ ] ↳ *33 células ocultas*

Primeiro modelo - Auto - ARIMA:

[ ] ↳ *18 células ocultas*

Segundo modelo - LSTM

[ ] ↳ *29 células ocultas*

Terceiro modelo - Algoritmo Genético para melhorar ARIMA

↳ *10 células ocultas*

Comparação entre os modelos

```
index = ["Auto-Arima","LSTM","AG - Arima"]
resultados.index = index
resultados.round(2)
```

	MSE	MAE	RMSE	MAPE	R2
Auto-Arima	0.15	0.36	0.39	23.38	-5.58
LSTM	0.06	0.20	0.25	20.10	-0.34
AG - Arima	0.19	0.35	0.44	21.68	-1.96