Trabalho 3

A partir do material visto nas aulas, utilizar técnicas de aprendizado de máquina para criar algoritmos de alocação ou trading sistemático.

- Devem ser apresentadas duas estratégias, baseadas em técnicas de aprendizado de máquina diferentes (Redes Neurais MLP, Árvores de Decisão ou outras técnicas não vistas na aula).
- Os algoritmos desenvolvidos devem utilzar conjuntos dados de entrada e saída diferentes daqueles usados nas aulas. No caso da alocação sistemática, outras classes de ativos devem ser utilizados ou adicionadas às entradas e saídas dos algoritmos. No caso do trading sistemático, outros indicadores devem ser utilizados ou adicionadas às entradas dos algoritmos.
- Apresentar os resultados de ambos os conjuntos de dados de treinamento e validação.

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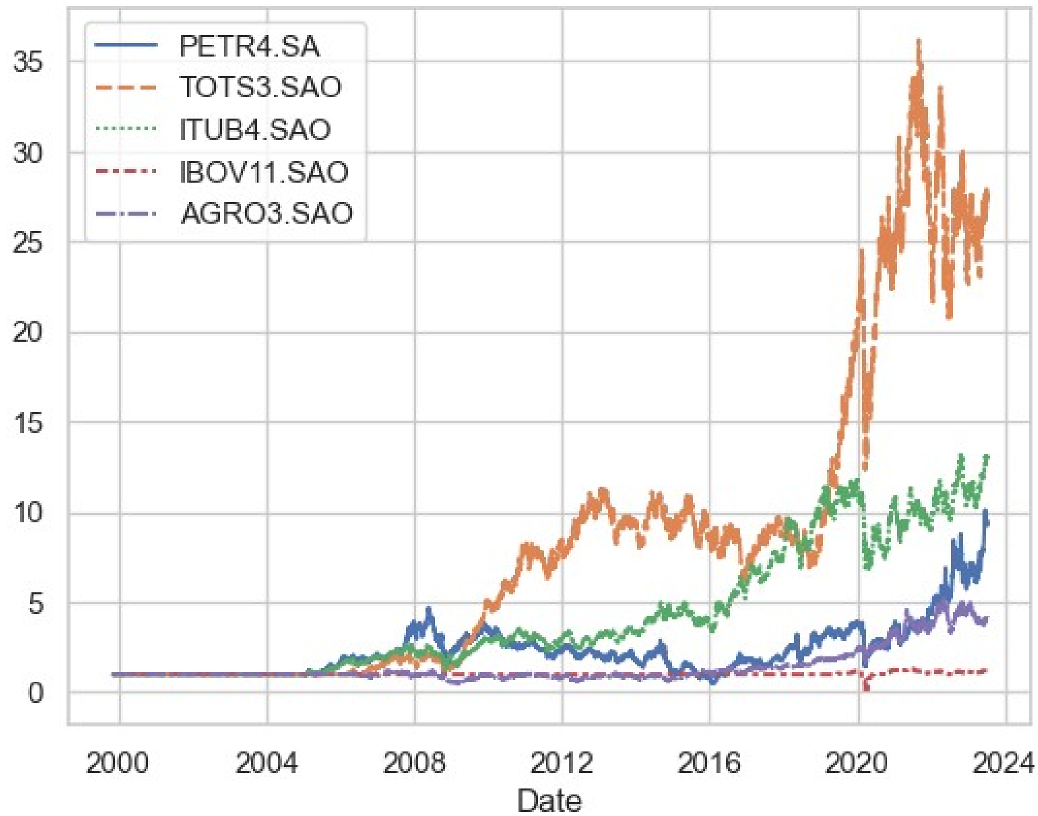
Alocação Sistemática

```
import requests
import os

import numpy
import pandas
import seaborn
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import accuracy_score

seaborn.set(style='whitegrid')

def get_adjusted(symbol):
    if os.path.exists(f"{symbol}_close.csv"):
        try:
            security = pandas.read_csv(f"{symbol}_close.csv",
index_col=0, parse_dates=True)
            security.index = pandas.to_datetime(security.index)
            return security
        except pandas.errors.EmptyDataError:
            pass
    if not symbol or symbol == "":
        raise ValueError("Invalid symbol: ", symbol)
```

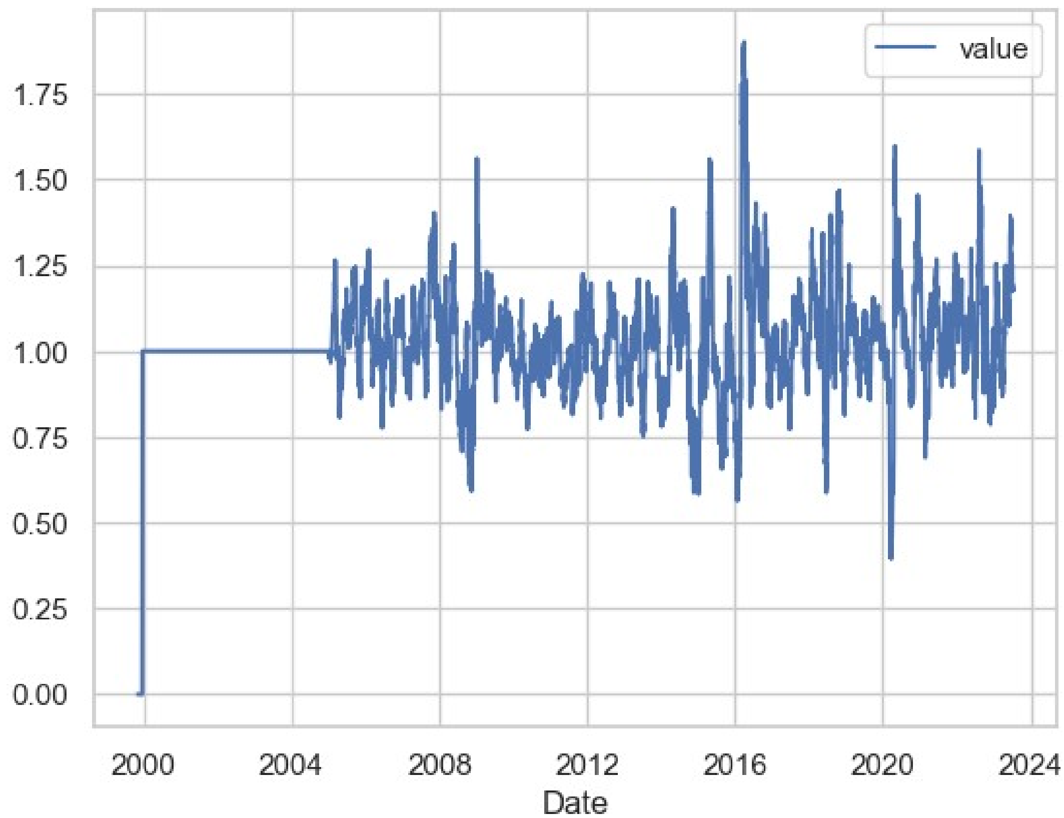
```
    try:
        url = f"https://www.alphavantage.co/query?
function=TIME_SERIES_DAILY_ADJUSTED&symbol={symbol}&outputsize=full&ap
ikey=U93DVTNCTOO1DTTI"
        response = requests.get(url)

        data = pandas.DataFrame(response.json())
    except ValueError:
        print("Possible retry with: ", symbol)
        return get_adjusted(symbol)
    formatted_data = data[data.keys()[1]][5:]
    adjusted = pandas.DataFrame.from_records(formatted_data.values)
["5. adjusted close"]
    security = pandas.DataFrame(adjusted.values.astype(float),
columns=["value"],

index=formatted_data.index).sort_index()
    security.index.name = "Date"
    security.to_csv(f"{symbol}_close.csv")
    return get_adjusted(symbol)


def changes(security: pandas.DataFrame):
    return security.values / security.values[0]

def create_portfolio(symbols=None):
    if not symbols:
        symbols = ["AAPL", "GOOGL", "IBM", "VOO"]
    portfolio = {
        symbol: get_adjusted(symbol) for symbol in symbols
    }

    portfolio_df = pandas.concat(portfolio,
axis=1).fillna(method="bfill")
    changes_df = portfolio_df.apply(changes)

    return portfolio_df, changes_df

# https://www.alphavantage.co/query?
function=SYMBOL_SEARCH&keywords=IBOV&apikey=$key
portfolio_df, changes_df = create_portfolio(
    symbols=["IBM", "SPY", "USD", "PETR4.SA", "TOTS3.SAO",
"ITUB4.SAO", "IBOV11.SAO", "AGRO3.SAO"])

sample = changes_df[["PETR4.SA", "TOTS3.SAO", "ITUB4.SAO",
"IBOV11.SAO", "AGRO3.SAO"]]

seaborn.lineplot(sample)
```

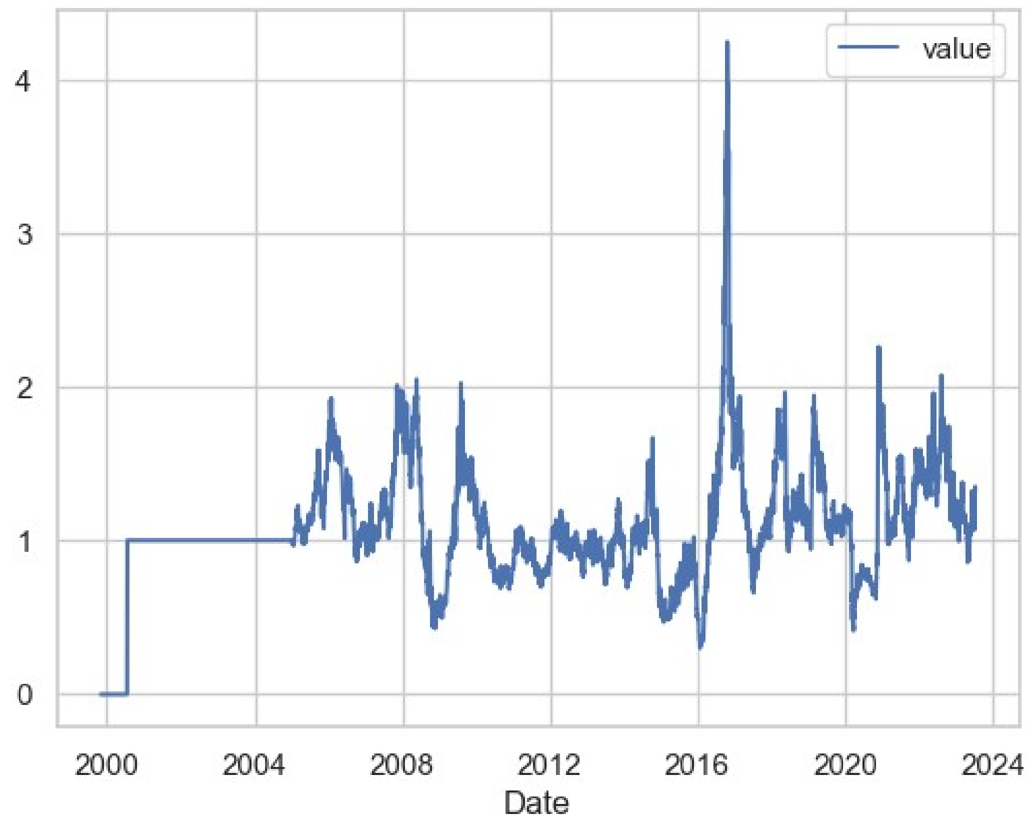
```
<AxesSubplot:xlabel='Date'>
```



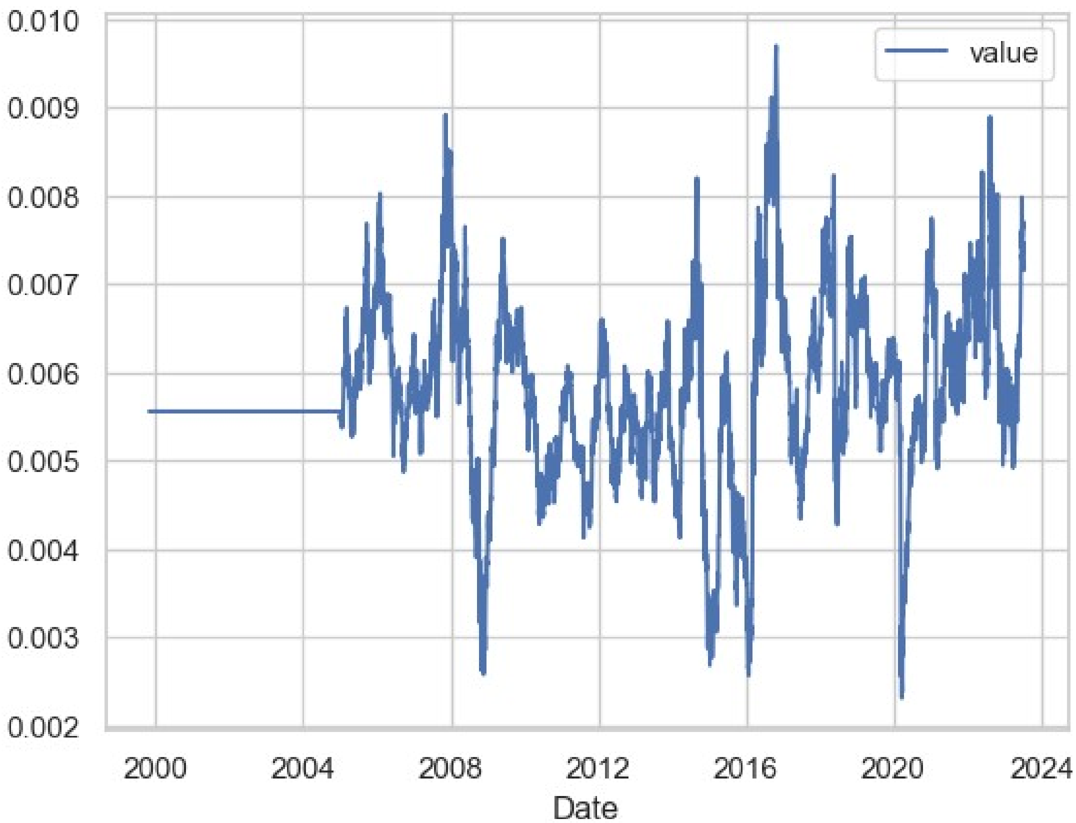

```
def momentum(security, T):
    momentum_T = security.copy()
    momentum_T[0:T] = 0

    for i in range(T, len(momentum_T.values)):
        momentum_T.iloc[i] = security.iloc[i] / security.iloc[i - T]

    return momentum_T


def price_size(security, T):
    pcs = security / security.rolling(T).sum()

    return pcs.fillna(method='bfill')

def vol_rolling(security, T):
    vol = security.pct_change().rolling(T).std(ddof=0)

    return vol.fillna(method='bfill')

petr4 = portfolio_df["PETR4.SA"]

momentum_1T = momentum(petr4, 30)
momentum_3T = momentum(petr4, 90)
momentum_6T = momentum(petr4, 180)
```

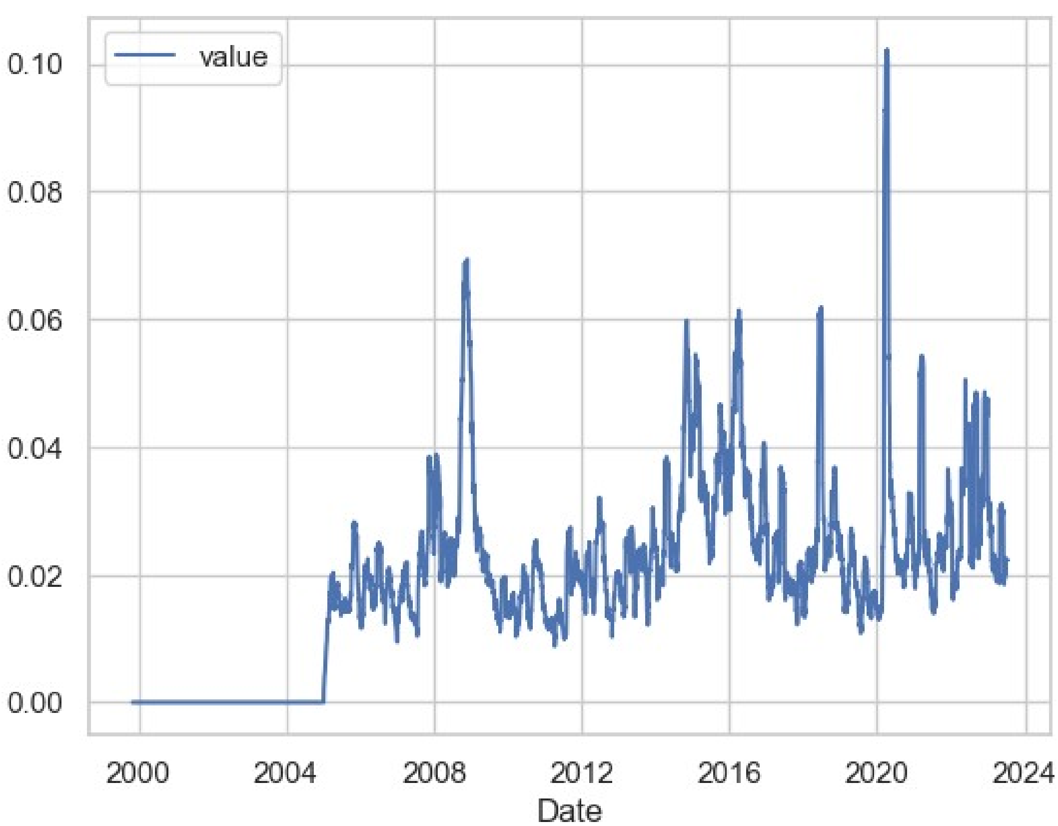
```
pcs_1T, pcs_6T, vol_1T, vol_6T = [
    price_size(petr4, 30), price_size(petr4, 180),
    vol_rolling(petr4, 30), vol_rolling(petr4, 180)
]

seaborn.lineplot(momentum_1T, color="r")
plt.show()
seaborn.lineplot(momentum_6T, color="b")
plt.show()
```






```
seaborn.lineplot(pcs_6T)
plt.show()
seaborn.lineplot(vol_1T)
plt.show()
```


0.010
0.009
0.008
0.007
0.006
0.005
0.004
0.003
0.002
value
2000
2004
2008
2012
2016
2020
2024
Date


0.10
0.08
0.06
0.04
0.02
0.00
value
2000
2004
2008
2012
2016
2020
2024
Date

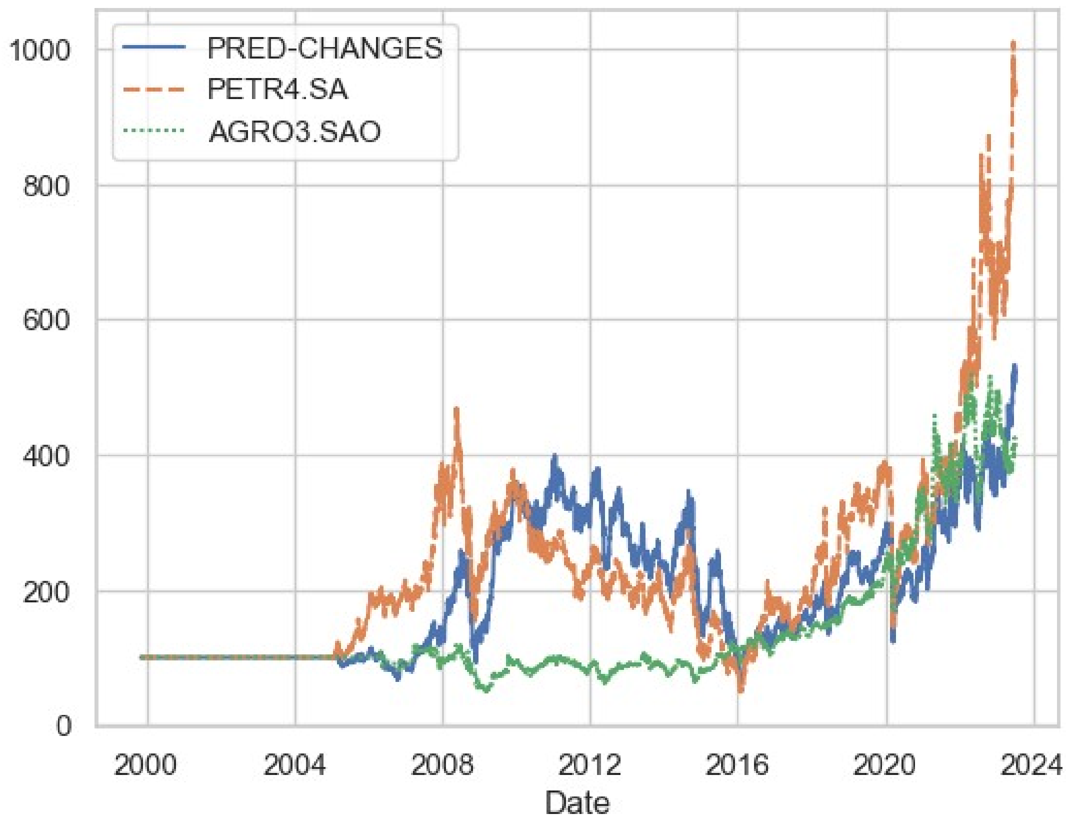
```
def train_test_split(features, labels, percentage):
    size = int(len(features) * percentage)

    train = {"x": features[10:size], "y": labels[10:size].flatten()}
    test = {"x": features[size:], "y": labels[size:].flatten()}

    return train, test

def simulate_trade_allocation(title, y_pred, basis):
    y_pred_portfolio = numpy.array([1 - y_pred, y_pred]).T
    basis['BUY-PRED'] = numpy.argmin(y_pred_portfolio, axis=1)
    basis['SELL-PRED'] = numpy.argmax(y_pred_portfolio, axis=1)

    basis['BUY-PRED'] = basis['BUY-PRED'].shift(1).fillna(1)
    basis['SELL-PRED'] = basis['SELL-PRED'].shift(1).fillna(0)

    basis['PRED-PERCENTAGE'] = basis['PETR4.SA'].to_numpy().flatten()
* basis['BUY-PRED'].to_numpy() + \
                           basis['AGRO3.SAO'].to_numpy().flatten() *
basis['SELL-PRED'].to_numpy()
    changes_df['PRED-CHANGES'] = (1 + basis['PRED-
PERCENTAGE'].fillna(0).to_numpy()).cumprod()

    print(title)
    seaborn.lineplot(100 * changes_df[['PRED-CHANGES', "PETR4.SA",
"AGRO3.SAO"]])
    return changes_df["PRED-CHANGES"], \
        (changes_df["PRED-CHANGES"].iloc[-1] - changes_df["PRED-
CHANGES"].iloc[0]) / changes_df["PRED-CHANGES"].iloc[0]  # final value
- starting value  / starting value
```

Alocação por classe para Momento (Usando RandomForest e MLP)

```
basis = changes_df[["PETR4.SA", "AGRO3.SAO"]].copy()
basis = basis.pct_change()
basis['1T'] = momentum_1T
basis['3T'] = momentum_3T
basis['6T'] = momentum_6T

basis["BUY"] = numpy.argmin(basis[["PETR4.SA",
"AGRO3.SAO"]].to_numpy(), axis=1)

features = basis[["1T", "3T", "6T"]].to_numpy()
labels = basis[["BUY"]].to_numpy()

train, test = train_test_split(features, labels, 0.5)
```

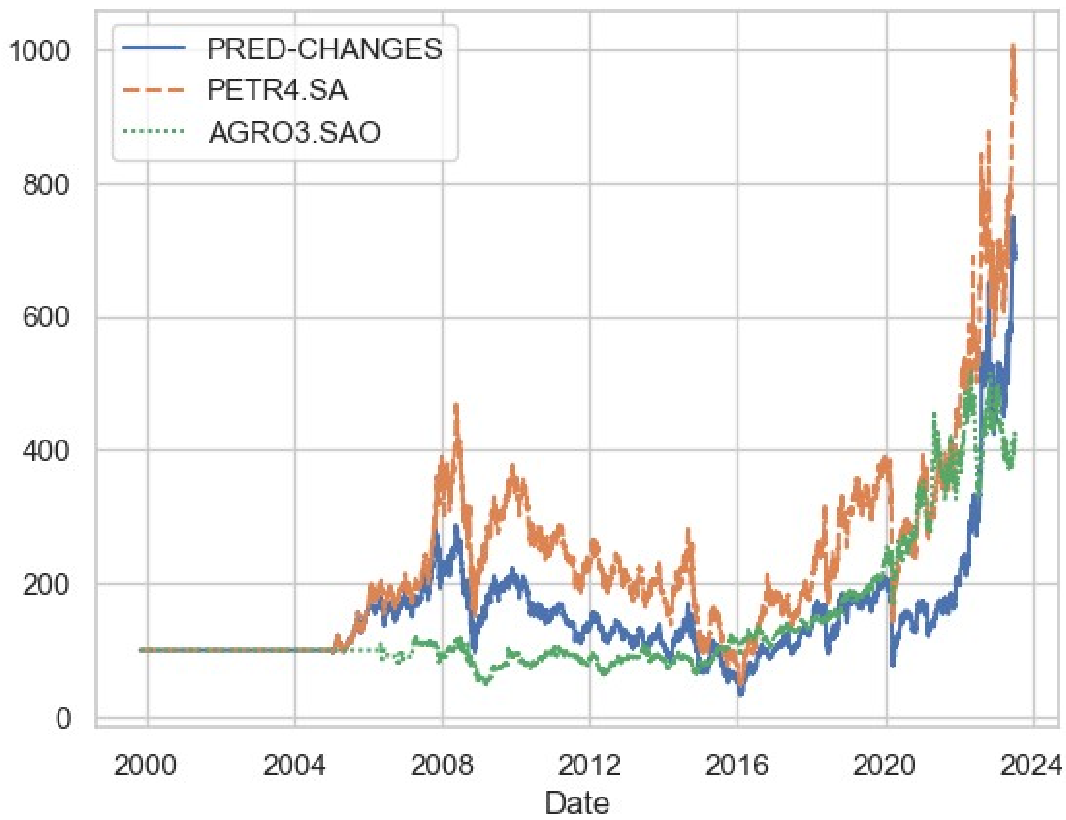
```python
clf = RandomForestClassifier()
clf.fit(train["x"], train["y"])

y_pred_train = clf.predict(train["x"])
y_pred_val = clf.predict(test["x"])
y_pred = clf.predict(features)

pred_changes, returns = simulate_trade_allocation("RandomForest for 1, 
3 and 6 months Momentum class", y_pred, basis)
print(pred_changes, f"\nReturns: {returns}")
print("Accuracy train:", accuracy_score(train["y"], y_pred_train))
print("Accuracy validation:", accuracy_score(test["y"], y_pred_val))
```

```
RandomForest for 1, 3 and 6 months Momentum class
Date
1999-11-01    1.000000
1999-11-02    1.000000
1999-11-03    1.000000
1999-11-04    1.000000
1999-11-05    1.000000
                ...
2023-07-06    5.246646
2023-07-07    5.220103
2023-07-10    5.228950
2023-07-11    5.158169
2023-07-12    5.069131
Name: PRED-CHANGES, Length: 6080, dtype: float64
Returns: 4.069130571286874
Accuracy train: 0.999009900990099
Accuracy validation: 0.5398026315789474
```




```
clf = MLPClassifier(hidden_layer_sizes=(3, ), max_iter=1000,
activation='tanh')
clf.fit(train["x"], train["y"])

y_pred_train = clf.predict(train["x"])
y_pred_val = clf.predict(test["x"])
y_pred = clf.predict(features)

pred_changes, returns = simulate_trade_allocation("MLP (3 layered) for
1, 3 and 6 months Momentum class", y_pred, basis)
print(pred_changes, f"\nReturns: {returns}")
print("Accuracy train:", accuracy_score(train["y"], y_pred_train))
print("Accuracy validation:", accuracy_score(test["y"], y_pred_val))

MLP (3 layered) for 1, 3 and 6 months Momentum class
Date
1999-11-01    1.000000
1999-11-02    1.000000
1999-11-03    1.000000
1999-11-04    1.000000
1999-11-05    1.000000
                ...
2023-07-06    6.974326
2023-07-07    6.939043
```

```
2023-07-10    6.950804
2023-07-11    6.856715
2023-07-12    6.861420
Name: PRED-CHANGES, Length: 6080, dtype: float64
Returns: 5.861419857341457
Accuracy train: 0.7184818481848185
Accuracy validation: 0.5348684210526315
```

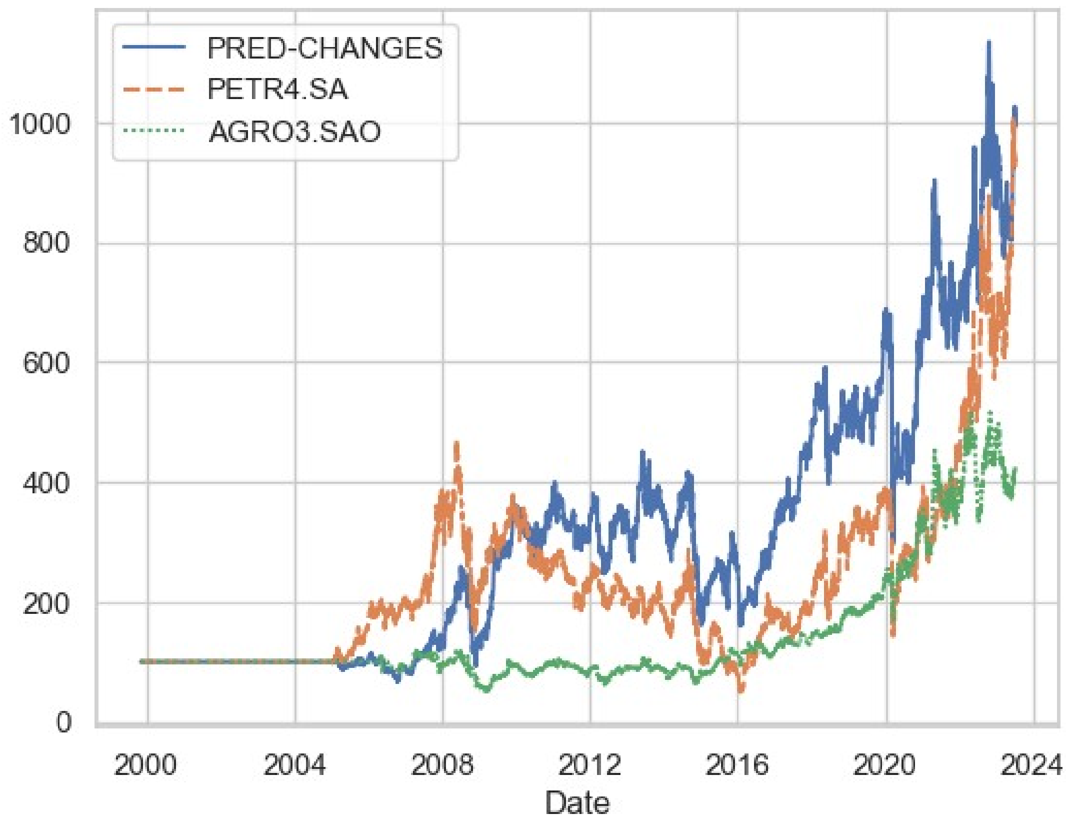


Alocação por Classe usando PCS (Price per Size) e Volatilidade

```
basis = changes_df[["PETR4.SA", "AGRO3.SAO"]].copy()
basis = basis.pct_change()
basis['PCS_1T'] = pcs_1T
basis['PCS_6T'] = pcs_6T
basis['VOL_1T'] = vol_1T
basis['VOL_6T'] = vol_6T

basis["BUY"] = numpy.argmin(basis[["PETR4.SA",
"AGRO3.SAO"]].to_numpy(), axis=1)

features = basis[["PCS_1T", "PCS_6T", "VOL_1T", "VOL_6T"]].to_numpy()
labels = basis[["BUY"]].to_numpy()
```

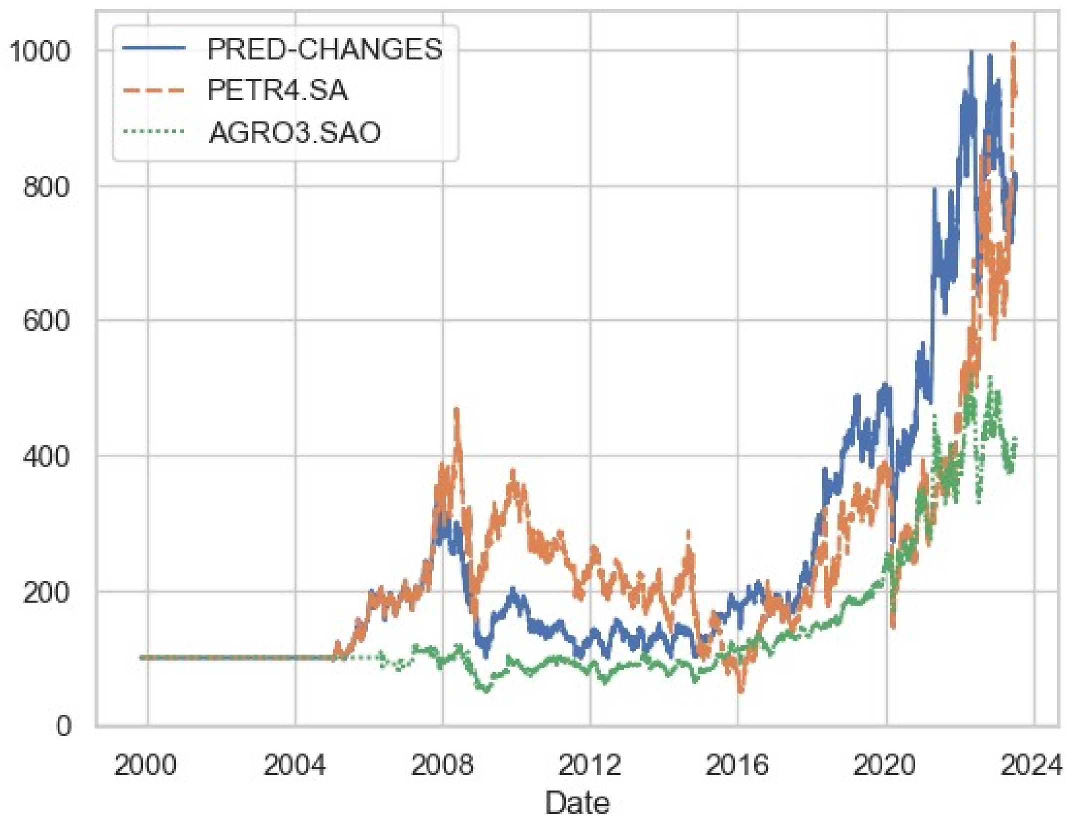
```python
train, test = train_test_split(features, labels, 0.5)

clf = RandomForestClassifier()
clf.fit(train["x"], train["y"])

y_pred_train = clf.predict(train["x"])
y_pred_val = clf.predict(test["x"])
y_pred = clf.predict(features)

pred_changes, returns = simulate_trade_allocation("RandomForest for 1 and 6 months PCS + Vol classes", y_pred, basis)
print(pred_changes, f"\nReturns: {returns}")
print("Accuracy train:", accuracy_score(train["y"], y_pred_train))
print("Accuracy validation:", accuracy_score(test["y"], y_pred_val))
```

```
RandomForest for 1 and 6 months PCS + Vol classes
Date
1999-11-01     1.000000
1999-11-02     1.000000
1999-11-03     1.000000
1999-11-04     1.000000
1999-11-05     1.000000
                 ...
2023-07-06    10.152843
2023-07-07    10.259965
2023-07-10    10.180615
2023-07-11    10.113168
2023-07-12     9.938598
Name: PRED-CHANGES, Length: 6080, dtype: float64
Returns: 8.938597615231103
Accuracy train: 0.9996699669966996
Accuracy validation: 0.5588815789473685
```




```
clf = MLPClassifier(hidden_layer_sizes=(20,), max_iter=2000,
activation='tanh')
clf.fit(train["x"], train["y"])

y_pred_train = clf.predict(train["x"])
y_pred_val = clf.predict(test["x"])
y_pred = clf.predict(features)

pred_changes, returns = simulate_trade_allocation("MLP (6 layered) for
1 and 6 months PCS + Vol class", y_pred, basis)
print(pred_changes, f"\nReturns: {returns}")
print("Accuracy train:", accuracy_score(train["y"], y_pred_train))
print("Accuracy validation:", accuracy_score(test["y"], y_pred_val))

MLP (6 layered) for 1 and 6 months PCS + Vol class
Date
1999-11-01    1.000000
1999-11-02    1.000000
1999-11-03    1.000000
1999-11-04    1.000000
1999-11-05    1.000000
                 ...
2023-07-06    8.095649
2023-07-07    8.181066
```

```
2023-07-10    8.117794
2023-07-11    8.064013
2023-07-12    7.924814
Name: PRED-CHANGES, Length: 6080, dtype: float64
Returns: 6.9248144709385295
Accuracy train: 0.7125412541254126
Accuracy validation: 0.4930921052631579
```

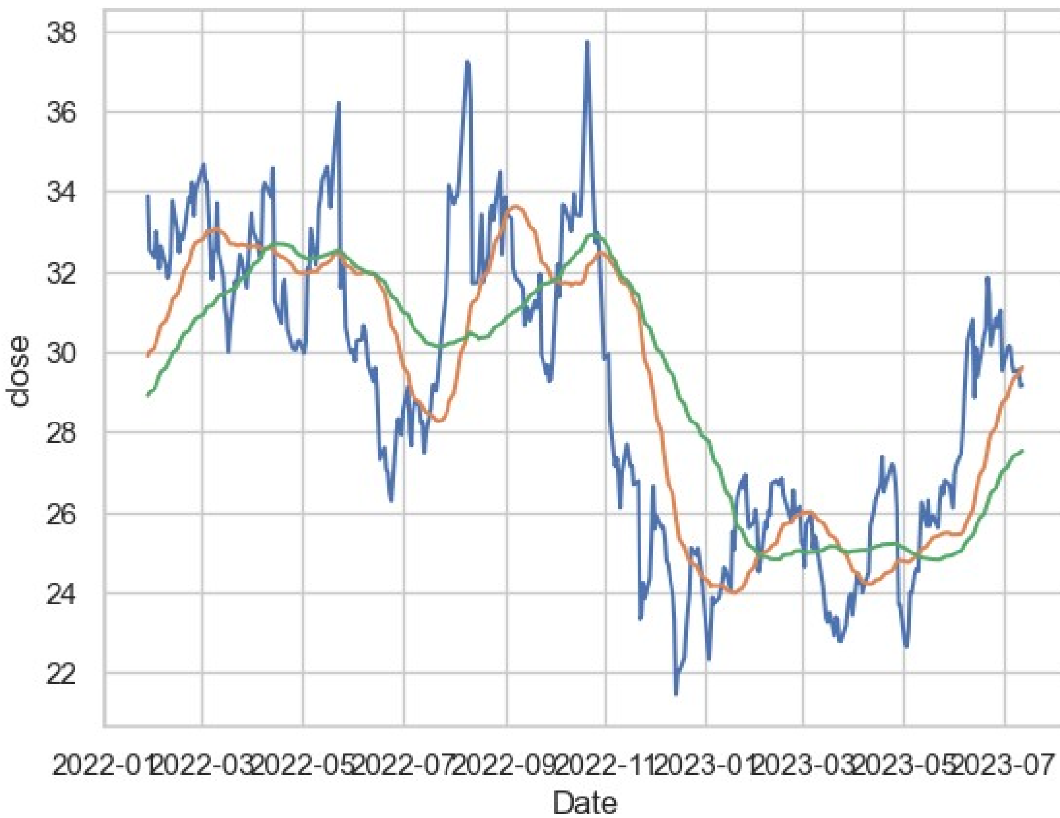


Trading Sistemático

```
def get_series(symbol):
    if os.path.exists(f"{symbol}.csv"):
        try:
            security = pandas.read_csv(f"{symbol}.csv", index_col=0, 
parse_dates=True)
            security.index = pandas.to_datetime(security.index)
            return security
        except pandas.errors.EmptyDataError:
            pass
    if not symbol or symbol == "":
        raise ValueError("Invalid symbol: ", symbol)
    try:
        url = f"https://www.alphavantage.co/query?
```

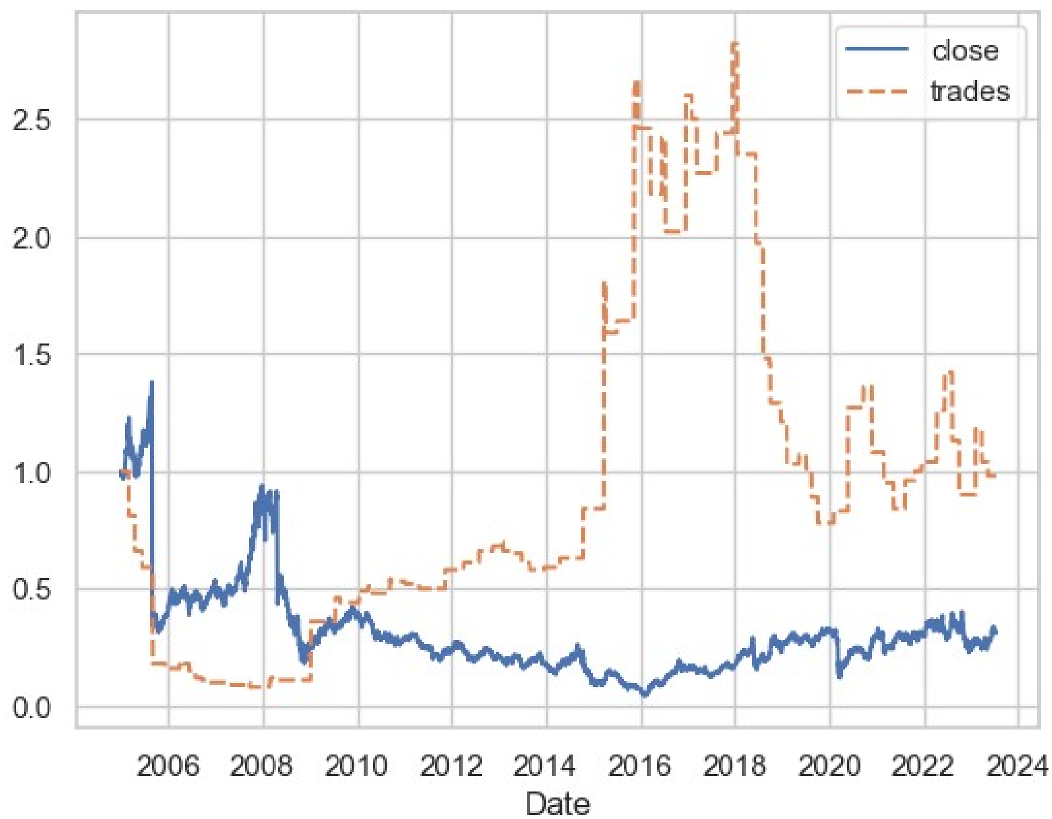
```
function=TIME_SERIES_DAILY_ADJUSTED&symbol={symbol}&outputsize=full&ap
ikey=U93DVTNCTOO1DTTI"
        response = requests.get(url)

        data = pandas.DataFrame(response.json())
    except:
        raise ValueError("Invalid symbol: ", symbol)
    formatted_data = data[data.keys()[1]][5:]

    adjusted = pandas.DataFrame.from_records(formatted_data.values)[
        ["1. open", "2. high", "3. low", "4. close", "6. volume"]
    ]
    security = pandas.DataFrame(adjusted.values.astype(float),
columns=["open", "high", "low", "close", "volume"],

index=formatted_data.index).sort_index()
    security.index.name = "Date"
    security.to_csv(f"{symbol}.csv")
    return get_adjusted(symbol)

print(get_series("PETR4.SA"))
seaborn.lineplot(get_series("PETR4.SA")["close"])

              value
Date
2005-01-03   3.1520
2005-01-04   3.1145
2005-01-05   3.1025
2005-01-06   3.1119
2005-01-07   3.1256
...             ...
2023-07-06  29.6500
2023-07-07  29.5000
2023-07-10  29.5500
2023-07-11  29.1500
2023-07-12  29.1700

[4583 rows x 1 columns]

<AxesSubplot:xlabel='Date', ylabel='close'>
```


```
def moving_average(series, T=1):
    return series.rolling(T * 30).mean().fillna(method='bfill')

sample = get_series("PETR4.SA")
sample["fast"] = moving_average(sample["close"], 1)
sample["slow"] = moving_average(sample["close"], 2)

seaborn.lineplot(sample["close"][-365:])
seaborn.lineplot(sample["fast"][-365:])
seaborn.lineplot(sample["slow"][-365:])
plt.show()
```




```
def simulate_trade(data, method, starting_wallet=1):
    data['trades'] = starting_wallet
    buy = 0
    weight = 100

    buy_value, sell_value = 1, 1

    for idx, row in data.iterrows():
        r = method(idx, row, buy, buy_value, sell_value, weight)
        if r is None:
            continue
        buy, weight, buy_value, sell_value = r
        sample.at[idx, 'trades'] = weight


def trend_follow(idx, row, buy, buy_value, sell_value, weight):
    if row['fast'] > row['slow'] and buy == 0:
        buy = 1
        buy_value = row['close']
    elif row['fast'] < row['slow'] and  buy == 1:
        buy = 0
        weight = weight * (row['close'] / buy_value)
    elif row['fast'] < row['slow'] and buy == 0:
        buy = -1
```

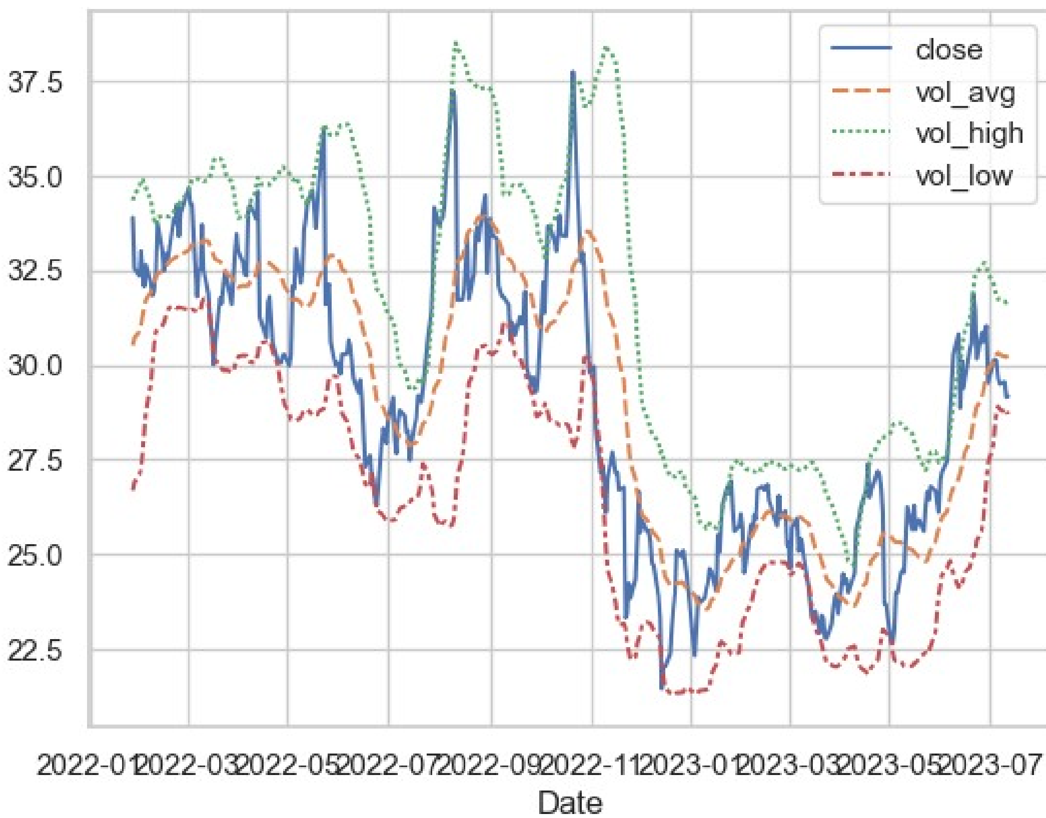
```
        sell_value = row['close']
    elif row['fast'] > row['slow'] and buy == -1:
        buy = 0
        weight = weight * (sell_value / row['close'])

    return buy, weight, buy_value, sell_value

simulate_trade(sample, trend_follow)
change = sample[['close', 'trades']] / sample[['close',
'trades']].iloc[0]

print("Profit for Trend Follow: {} u.".format(
    (change["trades"].iloc[-1] - change["close"].iloc[-1]) *
sample["close"].iloc[-1])
)
seaborn.lineplot(change)
plt.show()

Profit for Trend Follow: 19.553809129511677 u.
```




```
from ta.volatility import BollingerBands
ind_bb = BollingerBands(close=sample['close'], window=20,
window_dev=2)
```

```
sample['vol_avg'] = ind_bb.bollinger_mavg()
sample['vol_high'] = ind_bb.bollinger_hband()
sample['vol_low'] = ind_bb.bollinger_lband()

seaborn.lineplot(sample[['close', 'vol_avg', 'vol_high',
'vol_low']].iloc[-365:])
```

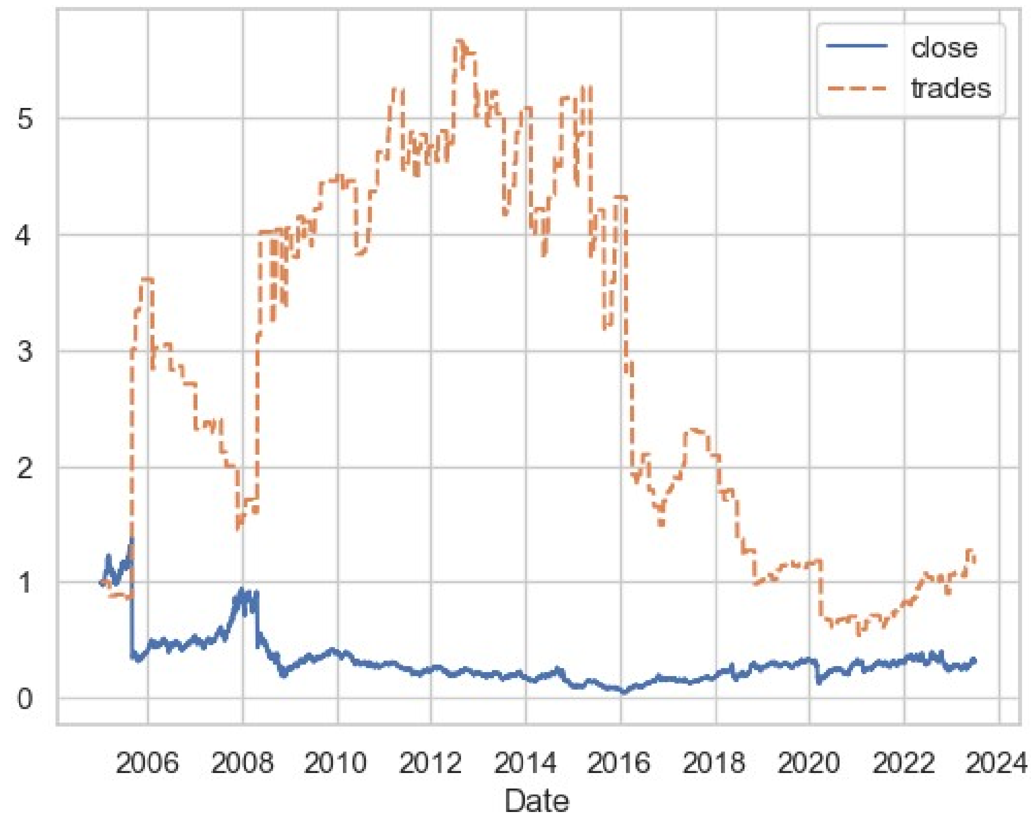
```
<AxesSubplot:xlabel='Date'>
```




```
def volatility_inversion(idx, row, buy, buy_value, sell_value,
weight):
    if row['low'] < row['vol_low'] and buy == 0:
        buy = 1
        buy_value = row['close']
    elif row['close'] > row['vol_avg'] and  buy == 1:
        buy = 0
        weight = weight * (row['close'] / buy_value)
    elif row['high'] > row['vol_high'] and buy == 0:
        buy = -1
        sell_value = row['close']
    elif row['close'] < row['vol_avg'] and buy == -1:
        buy = 0
        weight = weight * (sell_value / row['close'])
```

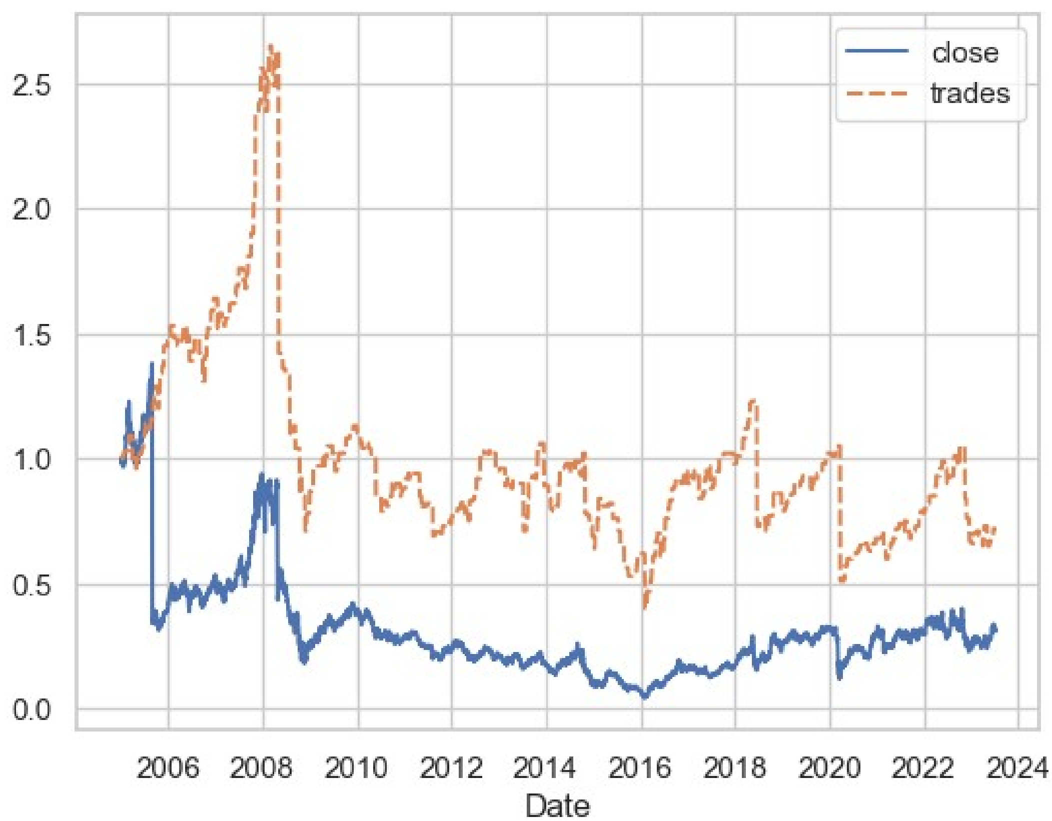
```
    return buy, weight, buy_value, sell_value

simulate_trade(sample, volatility_inversion)
change = sample[['close', 'trades']] / sample[['close',
'trades']].iloc[0]

print("Profit for Volatility Inversion: {} u.".format(
    (change["trades"].iloc[-1] - change["close"].iloc[-1]) *
sample["close"].iloc[-1])
)
seaborn.lineplot(change)
plt.show()
```

```
Profit for Volatility Inversion: 25.096109129511678 u.
```




```
from ta.momentum import RSIIndicator
indicator_rsi = RSIIndicator(close=sample['close'], window=2)
sample['RSI'] = indicator_rsi.rsi()

def rsii_low(idx, row, buy, buy_value, sell_value, weight):
    idx = sample.index.get_loc(idx)

    if idx < 2:
```

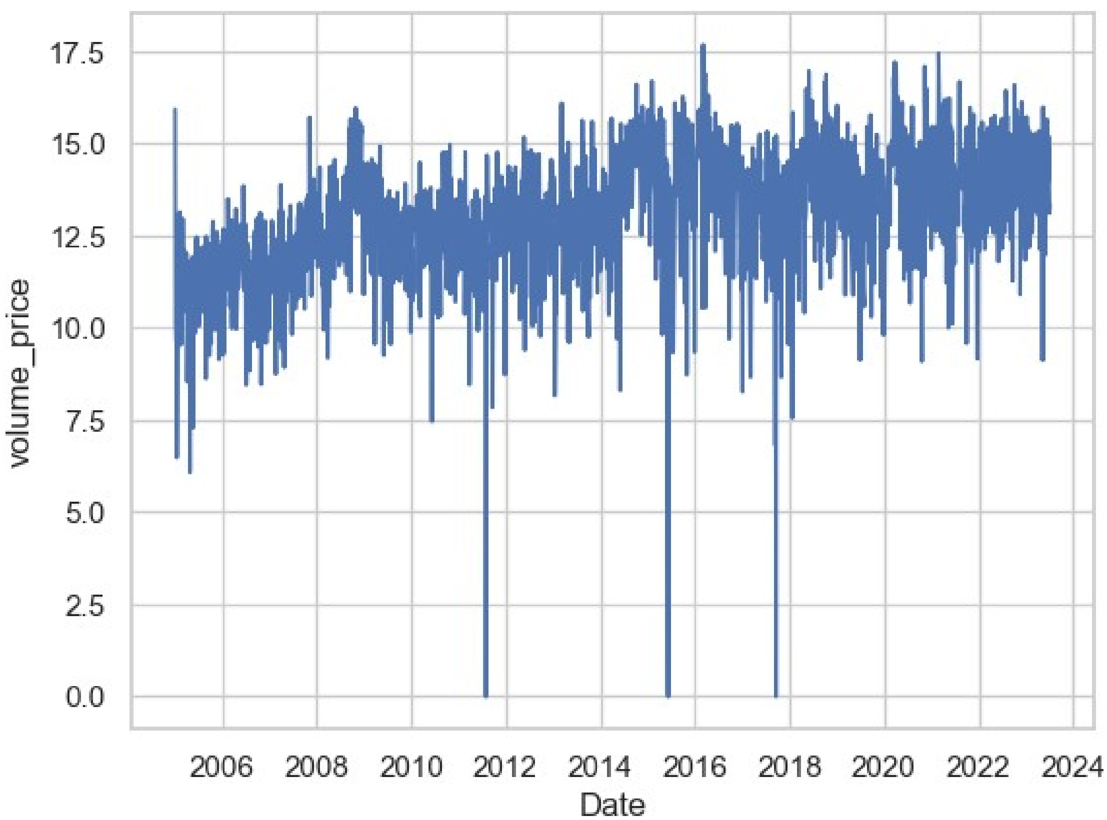
```
        return None

    if sample['RSI'].iat[idx] < 30 and buy == 0:
        buy = 1
        buy_value = sample['close'].iat[idx]
    elif sample['close'].iat[idx] > sample['high'].iat[idx - 1] and
sample['close'].iat[idx] > sample['high'].iat[idx - 2] and buy == 1:
        buy = 0
        weight = weight * (sample['close'].iat[idx] / buy_value)
    return buy, weight, buy_value, sell_value

simulate_trade(sample, rsii_low, starting_wallet=100)
change = sample[['close', 'trades']] / sample[['close',
'trades']].iloc[0]

print("Profit for Buy low RSII: {} u.".format(
    (change["trades"].iloc[-1] - change["close"].iloc[-1]) *
sample["close"].iloc[-1])
)
seaborn.lineplot(change)
plt.show()

Profit for Buy low RSII: 11.969609129511678 u.
```



```
from ta.volume import VolumePriceTrendIndicator

volume_price = VolumePriceTrendIndicator(volume=sample["volume"],
close=sample['close'], fillna=True)
sample['volume_price'] =
numpy.log(volume_price.volume_price_trend().replace(0,
1).fillna('bfill'))

seaborn.lineplot(sample['volume_price'])
```

```
c:\users\rafael.zimmer\workspace\tradingsystem\venv\lib\site-packages\
pandas\core\arraylike.py:364: RuntimeWarning: invalid value
encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

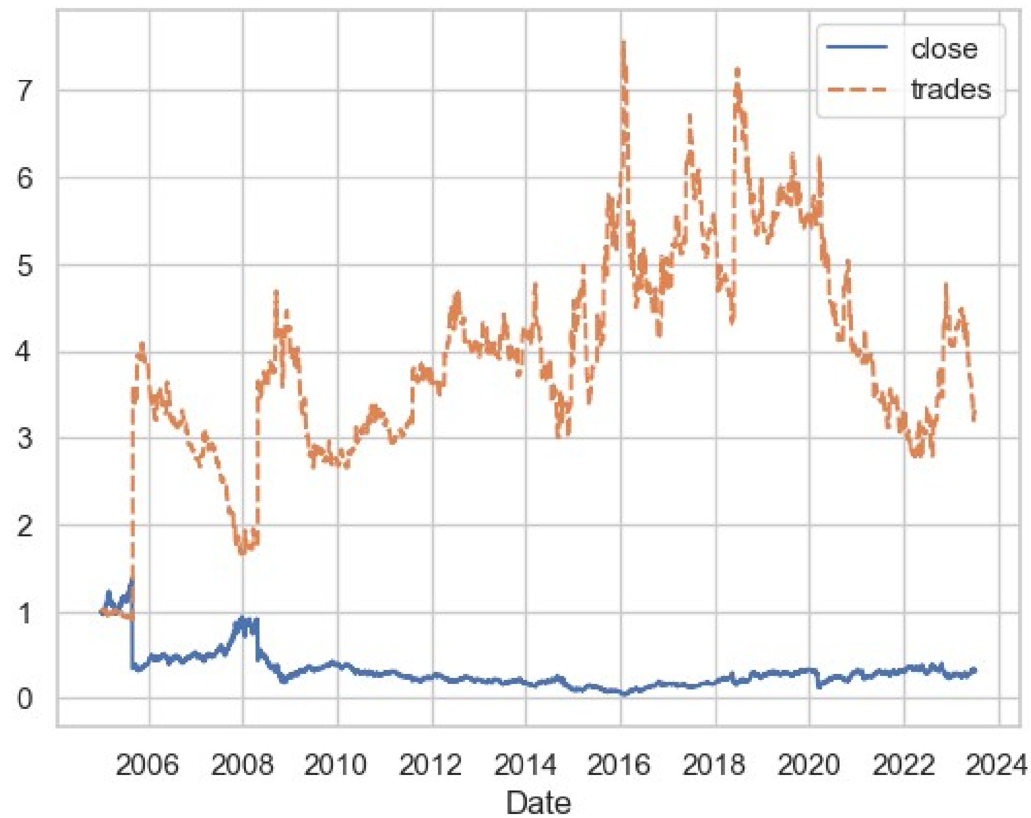
```
<AxesSubplot:xlabel='Date', ylabel='volume_price'>
```




```
def volume_high(idx, row, buy, buy_value, sell_value, weight):
    if (row['volume'] / row['close']) < row['volume_price'] and buy ==
0:
        buy = 1
        buy_value = row['close']
    elif (row['volume'] / row['close']) < row['volume_price'] and buy
== 1:
```

```
        buy = 0
        weight = weight * (row['close'] / buy_value)
    elif (row['volume'] / row['close']) > row['volume_price'] and buy
== 0:
        buy = -1
        sell_value = row['close']
    elif (row['volume'] / row['close']) > row['volume_price'] and buy
== -1:
        buy = 0
        weight = weight * (sell_value / row['close'])

    return buy, weight, buy_value, sell_value

simulate_trade(sample, volume_high)
change = sample[['close', 'trades']] / sample[['close',
'trades']].iloc[0]
print(change["trades"])
print("Profit for Volume Price: {} u.".format(
    (change["trades"].iloc[-1] - change["close"].iloc[-1]) *
sample["close"].iloc[-1])
)
seaborn.lineplot(change)
plt.show()
```

```
Date
2005-01-03    1.00
2005-01-04    1.01
2005-01-05    1.01
2005-01-06    1.01
2005-01-07    1.01
              ...
2023-07-06    3.38
2023-07-07    3.38
2023-07-10    3.38
2023-07-11    3.38
2023-07-12    3.38
Name: trades, Length: 4583, dtype: float64
Profit for Volume Price: 89.56180912951169 u.
```


close
trades
0
1
2
3
4
5
6
7
2006
2008
2010
2012
2014
2016
2018
2020
2022
2024
Date