

final

July 1, 2025

importing important libraries:

```
[156]: import pandas as pd
import numpy as np
import statsmodels.api as sm
from statsmodels.tsa.stattools import adfuller
from itertools import combinations
import tqdm
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.stattools import kpss
import warnings
from statsmodels.stats.diagnostic import acorr_ljungbox
from statsmodels.sandbox.stats.runs import runstest_1samp
from scipy.stats import shapiro, anderson, kstest
import numpy as np
from statsmodels.stats.diagnostic import het_arch
import backtrader as bt
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from IPython.display import Image
```

```
[126]: data = pd.read_csv('data/daily_close.csv', index_col=[0])
X = data['HDFCBANK'] #some random time series, just for an example
```

```
[155]: Image(filename='handwritten notes/intro1.png')
```

```
[155]:
```

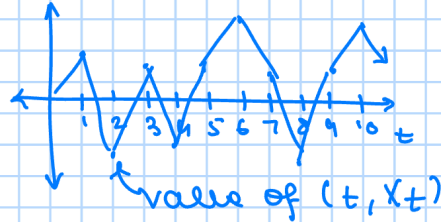
Let's start with random variables

what are random variables

- Random (dumb)

$X \sim N(0,1)$ this means X is a Normal random variable
mean 0, var 1

$X_t \sim N(0,1) \forall t \in \text{fixed time space}$ then:



[157]: Image(filename='handwritten notes/intro2.png')

[157]:

why are we interested in $N(0,1)$?

cause it has a nice mean reversion behavior
and also fixed variance, so $N(0,1) \Rightarrow$ stationary

How will we pick pairs?

This is the most important problem to
solve.

say: S_1, S_2 are prices (time series)

by fitting a linear regression
we get:

$$E[S_2] = \alpha S_1 + \beta$$

← this is just a constant term

we call
Expectation this slope or hedge ratio
of S_2

$$\text{But: } S_2 = \alpha S_1 + \beta + \varepsilon_t$$

← some error per t

$$\varepsilon = \{\varepsilon_1, \varepsilon_2, \dots\}$$

← one more series

If this ε_t is stationary then we select this pair

[158]: Image(filename='handwritten notes/intro3.png')

[158]:

Test for Stationarity:

① ADF: Augmented Dickey-Fuller

→ this checks for unit root (the non-stationary)
the ADF test is for non-stationarity, statistically if we get p-value < 0.05 (5%)
we reject the fact that something is non-stationary
⇒ something is stationary
(we will not go much into the math, but I have attached papers and videos below on ADF and other test too)

② KPSS test: this test confirms the stationarity from other side so p-value > 0.05 is what we are looking for

```
[127]: with warnings.catch_warnings():  
        warnings.simplefilter("ignore")  
        print("ADF p-value:", adfuller(X)[1])  
        print("KPSS p-value:", kpss(X, regression='c')[1])
```

ADF p-value: 0.5838533381000819

KPSS p-value: 0.01

```
[159]: Image(filename='handwritten notes/intro4.png')
```

[159]:

Is this enough? No.
we should do more test on $\varepsilon = S_2 - \alpha \cdot S_1 - \beta$
→ how "close" a sequence is to its previous values
Test for autocorrelation / independence:

① Ljung-Box test: checks if residual is white noise or not
again we want to pass here so p-value > 0.05

② Runs Test: checks for randomness above / below
some, p-value > 0.05

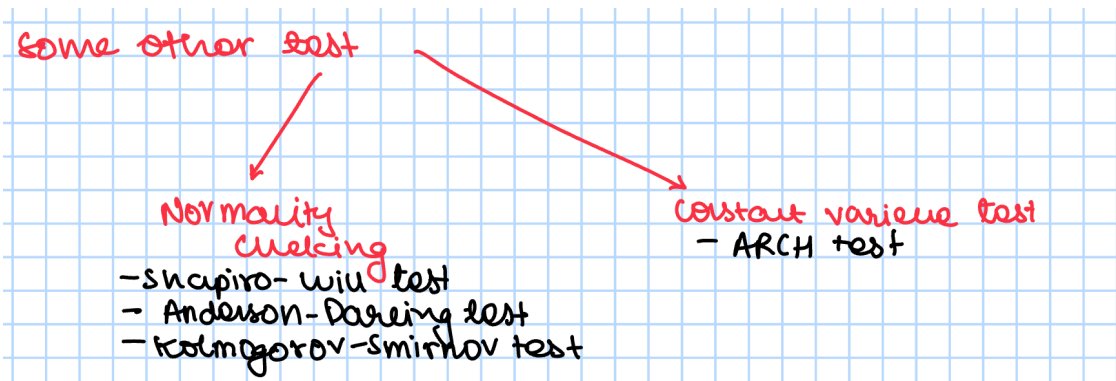
```
[128]: print("Ljung-Box p-value:", acorr_ljungbox(X, lags=[10],  
        ↪return_df=True)['lb_pvalue'].iloc[0])  
        print("Runs Test p-value:", runstest_1samp(X)[1])
```

Ljung-Box p-value: 0.0

Runs Test p-value: 5.734341803692584e-266

```
[160]: Image(filename='handwritten notes/intro5.png')
```

[160]:



```
[129]: print("Shapiro p-value:", shapiro(X)[1])
print("Anderson p-value:", anderson(X, dist='norm').significance_level[0])
mu, sigma = np.mean(X), np.std(X)
print("K-S p-value:", kstest((X - mu)/sigma, 'norm')[1])
```

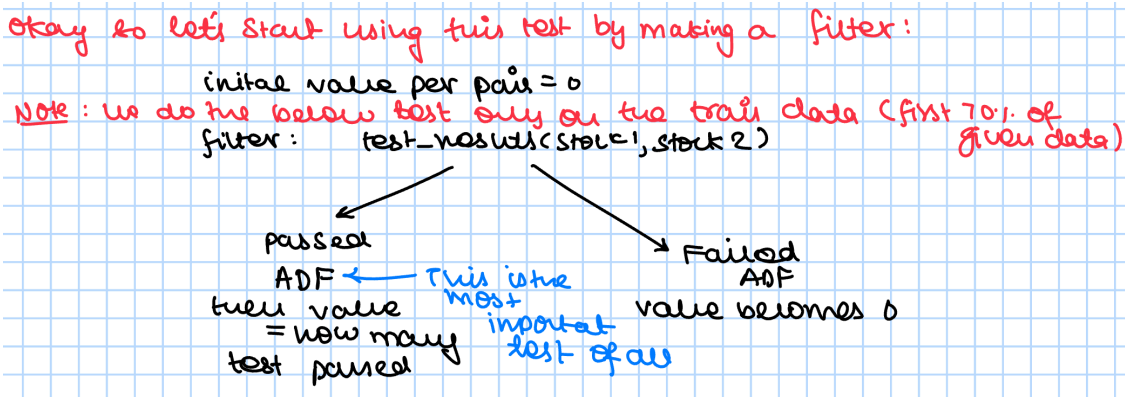
Shapiro p-value: 2.4550930606901267e-21

Anderson p-value: 15.0

K-S p-value: 3.062135942541275e-12

```
[161]: Image(filename='handwritten notes/intro6.png')
```

[161]:



```
[130]: def return_metric_given_spread(spread_X):
    X = spread_X
    p_values = []
    with warnings.catch_warnings():
        warnings.simplefilter("ignore")
        p_values.append(("ADF", adfuller(X)[1], adfuller(X)[1] < 0.05))
        p_values.append(("KPSS", kpss(X, regression='c')[1], kpss(X,
        ↪ regression='c')[1] > 0.05))
```

```

        p_values.append(("Ljung-Box", acorr_ljungbox(X, lags=[10],
↪return_df=True)['lb_pvalue'].iloc[0], acorr_ljungbox(X, lags=[10],
↪return_df=True)['lb_pvalue'].iloc[0] > 0.05))
        p_values.append(("Runs Test", runstest_1samp(X)[1],
↪runstest_1samp(X)[1] > 0.05))
        p_values.append(("Shapiro", shapiro(X)[1], shapiro(X)[1] > 0.05))
        p_values.append(("Anderson", anderson(X, dist='norm').
↪significance_level[0], anderson(X, dist='norm').significance_level[0] > 0.
↪05))
        mu, sigma = np.mean(X), np.std(X)
        p_values.append(("K-S", kstest((X - mu)/sigma, 'norm')[1], kstest((X -
↪mu)/sigma, 'norm')[1] > 0.05))
        p_values.append(("ARCH Test", het_arch(X)[1], het_arch(X)[1] > 0.05))
    return p_values

```

```

[131]: def return_metric(ticker1, ticker2):
        S1 = data[:int(len(data)*0.7)][ticker1]
        S2 = data[:int(len(data)*0.7)][ticker2]
        X = sm.add_constant(S2)
        model = sm.OLS(S1, X).fit()
        spread_X = model.resid
        return return_metric_given_spread(spread_X)

```

```

[132]: def value(ticker1, ticker2):
        passes = 0;
        matrix = return_metric(ticker1, ticker2)
        for _, _, result in matrix:
            if matrix[0][2] == True:
                if result == True:
                    passes+=1
        return passes

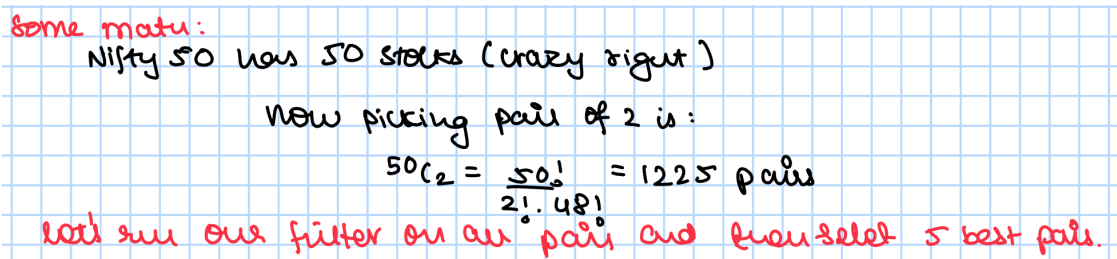
```

```

[162]: Image(filename='handwritten notes/intro7.png')

```

[162]:



Some math:

Nifty 50 has 50 stocks (crazy right)

Now picking pair of 2 is:

$$50C_2 = \frac{50!}{2! \cdot 48!} = 1225 \text{ pairs}$$

Let's run our filter on each pair and then select 5 best pairs.

```

[133]: stock_pairs = list(combinations(data.columns, 2))
        n = len(data.columns)

```

```
print(f"50C2 = {int(n*(n-1)/2)}")
print(f"total stock pairs using combinations = {len(stock_pairs)}")
```

50C2 = 1225

total stock pairs using combinations = 1225

```
[134]: value_matrix = pd.DataFrame(np.zeros((50, 50), dtype=int), columns=data.
    ↪columns, index=data.columns)
list_of_pairs = []
for stock1, stock2 in tqdm.tqdm(stock_pairs):
    value_matrix.loc[stock1, stock2] = value(stock1, stock2)
    value_matrix.loc[stock2, stock1] = value_matrix.loc[stock1, stock2]
    if value_matrix.loc[stock1, stock2] > 0:
        list_of_pairs.append((stock1, stock2, value_matrix.loc[stock1, stock2]))
```

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```
[135]: print([pair for pair in sorted(list_of_pairs, key=lambda x: x[2], reverse=True)
    ↪if pair[2] >= 0])
```

```
[('ADANI_PORTS', 'GRASIM', 4), ('ADANI_PORTS', 'TATACONSUM', 4), ('ASIANPAINT',
'GRASIM', 4), ('ASIANPAINT', 'TATACONSUM', 4), ('BAJFINANCE', 'GRASIM', 4),
('BAJFINANCE', 'HINDALCO', 4), ('BAJFINANCE', 'TATAMOTORS', 4), ('BPCL',
'POWERGRID', 4), ('BHARTIARTL', 'POWERGRID', 4), ('BHARTIARTL', 'SUNPHARMA', 4),
('BHARTIARTL', 'TITAN', 4), ('EICHERMOT', 'ICICIBANK', 4), ('EICHERMOT', 'M&M',
4), ('HCLTECH', 'TATACONSUM', 4), ('HDFCBANK', 'JSWSTEEL', 4), ('HINDUNILVR',
'LT', 4), ('HINDUNILVR', 'NESTLEIND', 4), ('HINDUNILVR', 'TATAMOTORS', 4),
('HINDUNILVR', 'ULTRACEMCO', 4), ('NESTLEIND', 'SUNPHARMA', 4), ('SBILIFE',
'SBIN', 4), ('TCS', 'TATACONSUM', 4), ('ADANI_PORTS', 'APOLLOHOSP', 3),
('ADANI_PORTS', 'ASIANPAINT', 3), ('ADANI_PORTS', 'BAJFINANCE', 3), ('ADANI_PORTS',
'CIPLA', 3), ('ADANI_PORTS', 'HINDALCO', 3), ('ADANI_PORTS', 'JSWSTEEL', 3),
('APOLLOHOSP', 'GRASIM', 3), ('APOLLOHOSP', 'HINDALCO', 3), ('APOLLOHOSP',
'JSWSTEEL', 3), ('APOLLOHOSP', 'LTIM', 3), ('APOLLOHOSP', 'TCS', 3),
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3), ('AXISBANK', 'MARUTI', 3), ('BAJAJ-AUTO', 'HINDUNILVR', 3), ('BAJFINANCE',
'BAJAJFINSV', 3), ('BAJFINANCE', 'JSWSTEEL', 3), ('BAJFINANCE', 'TATASTEEL', 3),
('BAJAJFINSV', 'HINDALCO', 3), ('BPCL', 'BHARTIARTL', 3), ('BPCL', 'M&M', 3),
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('BRITANNIA', 'M&M', 3), ('CIPLA', 'RELIANCE', 3), ('DIVISLAB', 'WIPRO', 3),
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'HDFCBANK', 3), ('HCLTECH', 'HINDALCO', 3), ('HCLTECH', 'JSWSTEEL', 3),
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('HINDUNILVR', 'ITC', 3), ('HINDUNILVR', 'JSWSTEEL', 3), ('HINDUNILVR', 'M&M',
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'SHRIRAMFIN', 3), ('HINDUNILVR', 'SBIN', 3), ('HINDUNILVR', 'SUNPHARMA', 3),
('HINDUNILVR', 'TCS', 3), ('HINDUNILVR', 'TATACONSUM', 3), ('HINDUNILVR',
```

'TATASTEEL', 3), ('HINDUNILVR', 'TITAN', 3), ('ICICIBANK', 'ONGC', 3),
 ('ICICIBANK', 'POWERGRID', 3), ('ICICIBANK', 'TITAN', 3), ('INDUSINDBK', 'M&M',
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 ('MARUTI', 'POWERGRID', 3), ('MARUTI', 'SBIN', 3), ('MARUTI', 'SUNPHARMA', 3),
 ('MARUTI', 'TITAN', 3), ('NESTLEIND', 'POWERGRID', 3), ('NESTLEIND',
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 'SUNPHARMA', 3), ('POWERGRID', 'TITAN', 3), ('RELIANCE', 'TATACONSUM', 3),
 ('RELIANCE', 'TITAN', 3), ('SBILIFE', 'SUNPHARMA', 3), ('SBILIFE', 'TATAMOTORS',
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 ('APOLLOHOSP', 'BAJFINANCE', 2), ('APOLLOHOSP', 'HCLTECH', 2), ('APOLLOHOSP',
 'HDFCBANK', 2), ('APOLLOHOSP', 'ONGC', 2), ('APOLLOHOSP', 'POWERGRID', 2),
 ('APOLLOHOSP', 'SBILIFE', 2), ('APOLLOHOSP', 'SBIN', 2), ('APOLLOHOSP',
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 2), ('APOLLOHOSP', 'ULTRACEMCO', 2), ('ASIANPAINT', 'BAJFINANCE', 2),
 ('ASIANPAINT', 'BAJAJFINSV', 2), ('ASIANPAINT', 'HCLTECH', 2), ('ASIANPAINT',
 'LTIM', 2), ('ASIANPAINT', 'ONGC', 2), ('ASIANPAINT', 'POWERGRID', 2),
 ('ASIANPAINT', 'TCS', 2), ('ASIANPAINT', 'TATASTEEL', 2), ('ASIANPAINT',
 'ULTRACEMCO', 2), ('AXISBANK', 'HDFCBANK', 2), ('AXISBANK', 'INDUSINDBK', 2),
 ('BAJAJ-AUTO', 'SHRIRAMFIN', 2), ('BAJFINANCE', 'SBILIFE', 2), ('BAJFINANCE',
 'TCS', 2), ('BAJFINANCE', 'KOTAKBANK', 2), ('BAJAJFINSV', 'ONGC', 2),
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 2), ('BHARTIARTL', 'ONGC', 2), ('BHARTIARTL', 'SBILIFE', 2), ('BHARTIARTL',
 'SBIN', 2), ('BRITANNIA', 'ITC', 2), ('BRITANNIA', 'NTPC', 2), ('DIVISLAB',
 'INFY', 2), ('EICHERMOT', 'HDFCBANK', 2), ('EICHERMOT', 'HINDUNILVR', 2),
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 'SBILIFE', 2), ('HDFCBANK', 'SHRIRAMFIN', 2), ('HDFCBANK', 'TCS', 2),
 ('HDFCBANK', 'TATASTEEL', 2), ('HDFCBANK', 'KOTAKBANK', 2), ('HDFCLIFE',
 'HEROMOTOCO', 2), ('HINDALCO', 'TCS', 2), ('HINDALCO', 'TATAMOTORS', 2),
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 2), ('NESTLEIND', 'SBIN', 2), ('NESTLEIND', 'ULTRACEMCO', 2), ('POWERGRID',
 'SBILIFE', 2), ('POWERGRID', 'TATAMOTORS', 2), ('RELIANCE', 'SBILIFE', 2),

```
('RELIANCE', 'SUNPHARMA', 2), ('RELIANCE', 'TCS', 2), ('SUNPHARMA', 'TITAN', 2),
('TCS', 'KOTAKBANK', 2), ('TATAMOTORS', 'TATASTEEL', 2)]
```

```
[163]: Image(filename='handwritten notes/intro8.png')
```

```
[163]:
```

one big issue here:
 so many pairs, now we need to use some fundamentals
 to select best pairs from all this. For my research, I have
 found a lot of links to support why only this 3 pairs.
 All links given below at last.

Overall picks:

- ① SBIN & SBILIFE (Both same family)
- ② BAJFINANCE & BAJAJFINSV (same family)
- ③ INFY & TCS (major IT companies)
- ④ RELIANCE & BPCL (Energy sector stocks)
- ⑤ POWERGRID & NTP (gov owned, power sector)

some functions I made

```
[136]: def get_hedge_ratio(ticker1, ticker2, data):
    X = sm.add_constant(data[ticker1])
    y = data[ticker2]
    model = sm.OLS(y, X).fit()
    hedge_ratio = model.params[ticker1]

    return hedge_ratio #this is the alpha in our calculation

def spread(ticker1, ticker2, data, hedge_ratio):
    S2_bought = 100
    S1_bought = int(100*hedge_ratio)
    spread_v = 100*data[ticker2].iloc[-1] - int(100*hedge_ratio)*data[ticker1].
    ↪iloc[-1]
    return spread_v, -1*S1_bought, S2_bought #this is the beta + epsilon per day

def plot_spread(ticker1, ticker2, data, hedge_ratio):
    t_values = range(0, len(data) - int(len(data)*0.7))
    spread_values_list = []
    dates = []

    for t in tqdm.tqdm(t_values):
        spread_values_list.append(spread(ticker1, ticker2, data[:
    ↪int(len(data)*0.7) + t], hedge_ratio)[0])
        dates.append(data[:int(len(data)*0.7) + t].index[-1])

    plt.figure(figsize=(12, 6))
    plt.plot(dates, spread_values_list)
```



```

plt.title(f'Spread between {ticker1} and {ticker2}')
plt.xlabel('Date')
plt.ylabel('Spread Value')
plt.grid(True)
plt.xticks(rotation=90)
plt.xticks(dates[::len(dates)//50])
plt.tight_layout()
plt.show() #here we have made sure that we only plot the last 30% of the
data for the spread

```

```

[137]: ticker1 = 'SBIN'
       ticker2 = 'SBILIFE'

       hedge_ratio = get_hedge_ratio(ticker1,ticker2, data[:int(len(data)*0.7)])
       _, quantity_S1, quantity_S2 = spread(ticker1,ticker2, data[:int(len(data)*0.
       ↪7)], hedge_ratio)

       rev_hedge_ratio = get_hedge_ratio(ticker2,ticker1, data[:int(len(data)*0.7)])
       _, r_quantity_S1, _ = spread(ticker2, ticker1, data[:int(len(data)*0.7)],
       ↪rev_hedge_ratio)

       if r_quantity_S1 < quantity_S1:
           ticker1, ticker2 = ticker2, ticker1
           hedge_ratio = get_hedge_ratio(ticker1,ticker2, data[:int(len(data)*0.7)])
           _, quantity_S1, quantity_S2 = spread(ticker1,ticker2, data[:int(len(data)*0.
           ↪7)], hedge_ratio)

       plot_spread(ticker1, ticker2, data, hedge_ratio)

```

100% | 421/421 [00:00<00:00, 10829.09it/s]

<IPython.core.display.Javascript object>

<IPython.core.display.HTML object>

```

[164]: Image(filename='handwritten notes/intro9.png')

```

```

[164]:

```

okay now how do we trade?

$$S_2 = \alpha \cdot S_1 + \beta + \varepsilon$$

α is fixed \leftarrow we have this with us
so for other 30% of data:

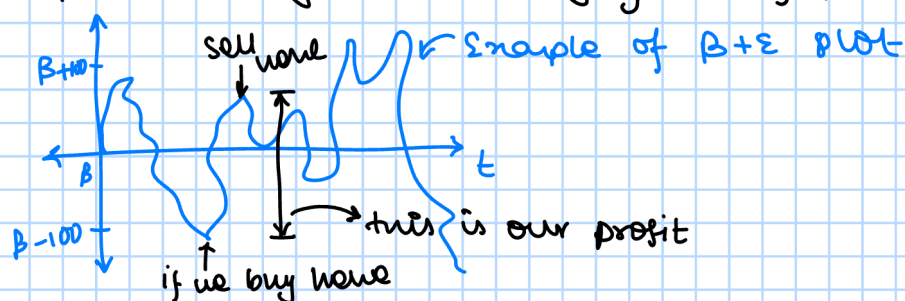
$$S_2 - \alpha \cdot S_1 = \beta + \varepsilon$$

β is fixed \leftarrow error term

what do we want to do?

we want to buy S_2 and sell $\alpha \cdot S_1$
or vice versa

so, theoretically we are buying/selling $\beta + \varepsilon$



[165]: Image(filename='handwritten notes/intro10.png')

[165]:

how do we get signals?

Traditionally (when I say traditionally, I mean that in a lot of papers and other resources I referred, this technique was mentioned in almost all classic resources) we have something called "Z-score"

Z-score?

mathematically

$$Z\text{-score} = (\text{1 day } \text{MAV}(x) - \text{30 day } \text{MAV}(x)) / \text{30 day var}$$

\leftarrow moving average

\leftarrow Rolling Period

so if $Z\text{-score} > 2$ we buy else sell

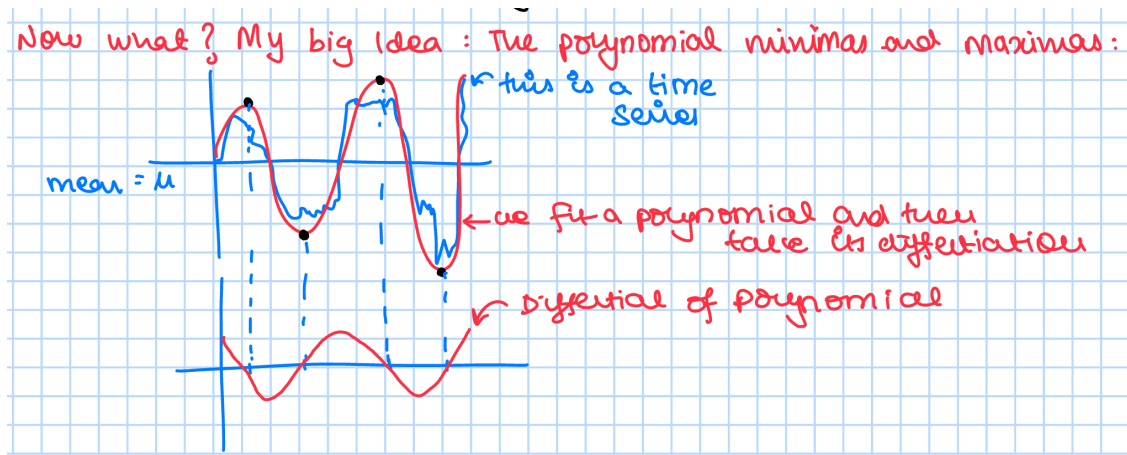
I am not going to do Z-score method.

why?

It works but not always. My issue is that Z-score doesn't really well tell the signal, it is little bit delayed and I just don't like that.

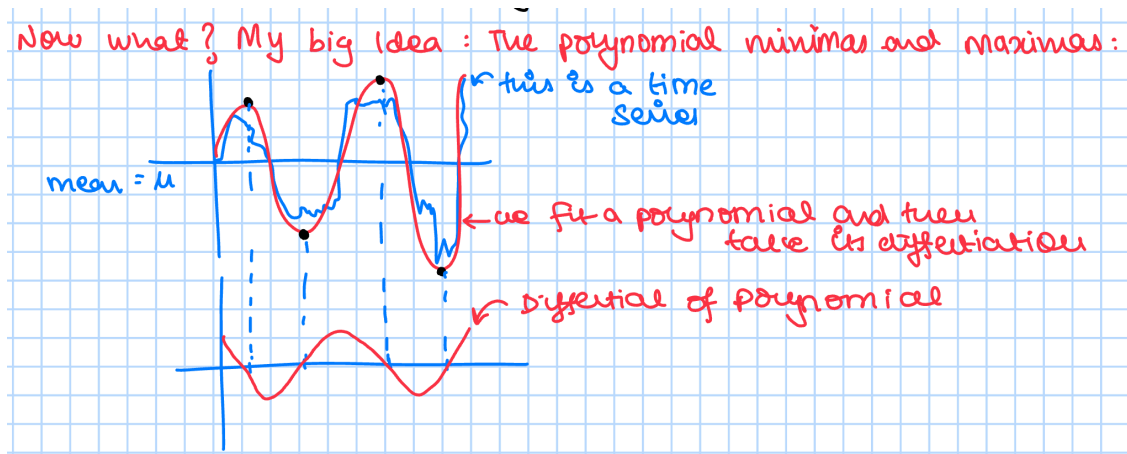
[166]: Image(filename='handwritten notes/intro11.png')

[166]:



[167]: Image(filename='handwritten notes/intro11.png')

[167]:



[168]: Image(filename='handwritten notes/intro12.png')

[168]:

buy rule: if previous day slope was negative and today's slope is positive, we buy

sell rules: if previous day slope was positive and today's slope is negative, we sell.

mathematically let $p(t)$ be polynomial

$$\left. \begin{array}{l} p'(t_0) = 0 \\ p''(t_0) < 0 \end{array} \right\} \text{local maxima}$$

$$\left. \begin{array}{l} p'(t_0) = 0 \\ p''(t_0) > 0 \end{array} \right\} \text{local minima}$$

this is just differentiation test

```
[138]: def get_polynomial_slope(spread_values_list, dates, closness):
    degree = min(int(len(dates) / closness) + 1, len(dates)-1)
    x = np.arange(len(dates))
    y = np.array(spread_values_list)

    coeffs = np.polyfit(x, y, degree)
    polynomial = np.poly1d(coeffs)

    slope = polynomial.deriv()(x[-1])
    return slope #we get the last day's slope

def make_slope_curve(spread_values_list, dates, closness):
    slopes = []
    for i in range(10, len(spread_values_list)):
        slope = get_polynomial_slope(spread_values_list[0:i], dates[0:i],
↪closness)
        slopes.append(slope)
    plt.figure(figsize=(12, 8))
    plt.plot(dates[10:], slopes)
    plt.xlabel('time')
    plt.ylabel('Slope Value')
    plt.grid(True)
    plt.xticks(rotation=90)
    plt.xticks(dates[::len(dates)//50])
    plt.tight_layout()
    plt.show() #plotting the slope curve for my method
```

```
[139]: t_values = range(0, len(data) - int(len(data)*0.7))
spread_values_list = []
dates = []

for t in tqdm.tqdm(t_values):
    spread_values_list.append(spread(ticker1,ticker2, data[:int(len(data)*0.7),
↪ t], hedge_ratio)[0])
    dates.append(data[:int(len(data)*0.7) + t].index[-1])
```

100%| | 421/421 [00:00<00:00, 20305.91it/s]

```
[140]: make_slope_curve(spread_values_list, dates, 30) #closness of 30 means that
↪after every 30 days, we change the degree of polynomial, we can see nice
↪periodic value of slopes below
```

<IPython.core.display.Javascript object>

<IPython.core.display.HTML object>

[169]: Image(filename='handwritten notes/intro13.png')

[169]:

let me predict what the reader is thinking right now:
But if we cannot use past slopes to trade right?
Yes, but there is a turnaround
let's divide no. of trading days / 30 = degree of polynomial
and now for every day, from the
70%th data day to this day we plot a
polynomial for that day we get its value
and save it. As polynomials are continuous functions
theoretically this will work.
Note: Below attached are some graphs which will help us
visualise what is happening and also the first difference curve.

```
[141]: def get_signals(spread_values_list, dates, closeness, quantity_S1, quantity_S2):
    slopes = []
    signals = []
    order_book = []
    for i in range(10, len(spread_values_list)):
        slope = get_polynomial_slope(spread_values_list[0:i], dates[0:i],
        ↪ closeness)
        if len(slopes) > 0:
            if slopes[-1] > 0 and slope < 0:
                signals.append((dates[i], "buy", spread_values_list[i]))
                order_book.append((dates[i], quantity_S1, quantity_S2))
            if slopes[-1] < 0 and slope > 0:
                signals.append((dates[i], "sell", spread_values_list[i]))
                order_book.append((dates[i], -1*quantity_S1, -1*quantity_S2))
        slopes.append(slope)
    return signals, order_book #getting signals, again I have not used future
    ↪ data in anyway
```

[170]: Image(filename='handwritten notes/intro14.png')

[170]:

lets trade on minima and maxima, also some other things before we
read the result is that
① to calculate profit
no. of buys = no. of sells
② at end my portfolio does not have any
stock as either we sell, then buy
or we buy then sell then $\beta + \epsilon$
with this explanation out the way, let's visualise our strategy:

```

[142]: def final_metrics(ticker1, ticker2, data, closeness, verbos = True):
    hedge_ratio = get_hedge_ratio(ticker1,ticker2, data[:int(len(data)*0.7)])
    _, quantity_S1, quantity_S2 = spread(ticker1,ticker2, data[:int(len(data)*0.
    ↪7)], hedge_ratio)

    rev_hedge_ratio = get_hedge_ratio(ticker2,ticker1, data[:int(len(data)*0.
    ↪7)])
    _, r_quantity_S1, _ = spread(ticker2, ticker1, data[:int(len(data)*0.7)],
    ↪rev_hedge_ratio)

    if r_quantity_S1 < quantity_S1:
        ticker1, ticker2 = ticker2, ticker1
        hedge_ratio = get_hedge_ratio(ticker1,ticker2, data[:int(len(data)*0.
    ↪7)])
    _, quantity_S1, quantity_S2 = spread(ticker1,ticker2, data[:
    ↪int(len(data)*0.7)], hedge_ratio)

    t_values = range(0, len(data) - int(len(data)*0.7))
    spread_values_list = []
    dates = []

    for t in tqdm.tqdm(t_values):
        spread_values_list.append(spread(ticker1,ticker2, data[:int(len(data)*0.
    ↪7) + t], hedge_ratio)[0])
        dates.append(data[:int(len(data)*0.7) + t].index[-1])

    if verbos:
        print(f"spread is made up of {quantity_S1}*{ticker1} +
    ↪{quantity_S2}*{ticker2}")
        signals, _ = get_signals(spread_values_list, dates, closeness, quantity_S1,
    ↪quantity_S2)

    if verbos:
        plt.figure(figsize=(12, 6))
        plt.plot(dates, spread_values_list)

        for date, signal, price in signals:
            if signal == 'buy':
                plt.scatter(date, price, color='green', marker='^', s=100)
            elif signal == 'sell':
                plt.scatter(date, price, color='red', marker='v', s=100)

        plt.xlabel('Date')
        plt.ylabel('Spread')
        plt.grid(True)

```

```

plt.xticks(rotation=90)
plt.xticks(dates[::len(dates)//50])
plt.tight_layout()
plt.show()

total_profit = 0
for date, signal, price in signals:
    if signal == "sell":
        total_profit += price
    if signal == "buy":
        total_profit -= price

    if signals[0][1] == "buy" and signals[-1][1] == "buy":
        total_profit += signals[-1][2]
        if verbos:
            print("haven't counted the last buy trade in final profit_
↪calculation to equate number of buys = number of sells")

    if signals[0][1] == "sell" and signals[-1][1] == "sell":
        total_profit -= signals[-1][2]
        if verbos:
            print("haven't counted the last sell trade in final profit_
↪calculation to equate number of buys = number of sells")

    if verbos:
        print(f"total profit: {total_profit}")
        for date, signal, price in signals:
            print(f"on {date}, {signal} at {price}")

return total_profit

```

```
[143]: print(final_metrics('SBILIFE', 'SBIN', data, 30, verbos=True))
```

```
100%|      | 421/421 [00:00<00:00, 21498.25it/s]
```

```
spread is made up of -119*SBIN + 100*SBILIFE
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

```

total profit: 26498.798809999998
on 2023-09-26 09:15:00, buy at 58236.39761999999
on 2023-10-18 09:15:00, sell at 67489.64761999999
on 2023-12-18 09:15:00, buy at 67523.5
on 2024-01-23 09:15:00, sell at 65543.10238000001
on 2024-02-15 09:15:00, buy at 54692.69881
on 2024-02-28 09:15:00, sell at 65662.5

```

```

on 2024-04-03 09:15:00, buy at 54325.05119
on 2024-05-22 09:15:00, sell at 45308.75
on 2024-07-04 09:15:00, buy at 50898.30119
on 2024-07-26 09:15:00, sell at 72463.44881
on 2024-08-12 09:15:00, buy at 73800.60238000001
on 2024-08-22 09:15:00, sell at 81909.30119
on 2024-09-30 09:15:00, buy at 90639.90000000001
on 2024-11-14 09:15:00, sell at 60524.25
on 2024-11-26 09:15:00, buy at 50786.40000000001
on 2024-12-27 09:15:00, sell at 45371.65000000001
on 2025-01-24 09:15:00, buy at 55486.15000000001
on 2025-02-11 09:15:00, sell at 54899.09999999999
on 2025-03-07 09:15:00, buy at 53962.75
on 2025-03-21 09:15:00, sell at 65009.2
on 2025-04-02 09:15:00, buy at 63646.95
on 2025-04-29 09:15:00, sell at 76316.55
26498.79880999998

```

```
[144]: print(final_metrics('BAJFINANCE', 'BAJAJFINSV', data, 30, verbos=True))
```

```
100%|      | 421/421 [00:00<00:00, 21759.46it/s]
```

```
spread is made up of -379*BAJAJFINSV + 100*BAJFINANCE
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

```

total profit: 112334.669999999969
on 2023-09-14 09:15:00, sell at 161638.88
on 2023-10-19 09:15:00, buy at 164584.72999999998
on 2023-12-20 09:15:00, sell at 112333.92000000004
on 2024-01-31 09:15:00, buy at 69543.29000000004
on 2024-03-18 09:15:00, sell at 52763.04000000004
on 2024-05-03 09:15:00, buy at 76403.30000000005
on 2024-06-07 09:15:00, sell at 124981.68999999994
on 2024-07-16 09:15:00, buy at 94980.55000000005
on 2024-08-09 09:15:00, sell at 70504.21999999997
on 2024-08-19 09:15:00, buy at 73768.10999999999
on 2024-09-30 09:15:00, sell at 22381.400000000023
on 2024-10-17 09:15:00, buy at 1761.8000000000466
on 2024-10-22 09:15:00, sell at 14924.599999999977
on 2024-11-12 09:15:00, buy at 22646.75
on 2024-12-27 09:15:00, sell at 92220.30000000005
on 2025-01-14 09:15:00, buy at 84083.5
on 2025-01-17 09:15:00, sell at 81243.65000000002
on 2025-02-17 09:15:00, buy at 124511.84999999998
on 2025-03-24 09:15:00, sell at 191122.14999999999
on 2025-04-01 09:15:00, buy at 135659.10000000001

```



```
on 2025-04-08 09:15:00, sell at 160912.19999999995
on 2025-05-12 09:15:00, buy at 124748.40000000002
112334.669999999969
```

```
[145]: print(final_metrics('INFY', 'TCS', data, 30, verbos=True))
```

```
100%|      | 421/421 [00:00<00:00, 20251.18it/s]
spread is made up of -156*INFY + 100*TCS
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

```
total profit: 14052.830000000133
on 2023-10-13 09:15:00, buy at 133825.61
on 2023-10-16 09:15:00, sell at 128677.59999999998
on 2023-10-17 09:15:00, buy at 125682.79999999999
on 2023-11-24 09:15:00, sell at 121475.60999999999
on 2024-01-09 09:15:00, buy at 130419.19
on 2024-02-15 09:15:00, sell at 148809.42000000004
on 2024-04-05 09:15:00, buy at 167185.40000000002
on 2024-05-22 09:15:00, sell at 156251.2
on 2024-05-23 09:15:00, buy at 159650.59999999998
on 2024-06-13 09:15:00, sell at 154758.78999999998
on 2024-07-11 09:15:00, buy at 134548.8
on 2024-07-16 09:15:00, sell at 148511.02000000002
on 2024-07-31 09:15:00, buy at 147088.00999999995
on 2024-08-21 09:15:00, sell at 163008.8
on 2024-08-30 09:15:00, buy at 152157.8
on 2024-10-03 09:15:00, sell at 127904.59999999998
on 2024-10-15 09:15:00, buy at 106029.20000000001
on 2024-10-21 09:15:00, sell at 118956.0
on 2024-11-14 09:15:00, buy at 123720.19999999995
on 2025-01-01 09:15:00, sell at 117575.0
on 2025-02-06 09:15:00, buy at 109433.59999999998
on 2025-03-24 09:15:00, sell at 114426.0
on 2025-04-15 09:15:00, buy at 102364.0
on 2025-04-21 09:15:00, sell at 105804.0
14052.830000000133
```

```
[146]: print(final_metrics('RELIANCE', 'BPCL', data, 30, verbos=True))
```

```
100%|      | 421/421 [00:00<00:00, 19801.54it/s]
spread is made up of 6*RELIANCE + 100*BPCL
```

```
<IPython.core.display.Javascript object>
```

<IPython.core.display.HTML object>

```
total profit: 8892.544599999972
on 2023-09-28 09:15:00, buy at 24199.8008000000005
on 2023-11-06 09:15:00, sell at 25329.5
on 2024-01-09 09:15:00, buy at 30739.0005000000002
on 2024-02-02 09:15:00, sell at 36663.698699999999
on 2024-03-12 09:15:00, buy at 40125.0508000000005
on 2024-04-25 09:15:00, sell at 38929.851
on 2024-06-06 09:15:00, buy at 37797.101
on 2024-07-19 09:15:00, sell at 39710.899
on 2024-07-23 09:15:00, buy at 39527.4
on 2024-07-26 09:15:00, sell at 41934.149
on 2024-09-12 09:15:00, buy at 43308.8
on 2024-10-03 09:15:00, sell at 43326.85
on 2024-10-07 09:15:00, buy at 41724.35
on 2024-11-12 09:15:00, sell at 38625.5
on 2024-12-24 09:15:00, buy at 36536.5
on 2025-02-06 09:15:00, sell at 33944.3
on 2025-03-04 09:15:00, buy at 31963.4
on 2025-03-05 09:15:00, sell at 32637.6
on 2025-03-24 09:15:00, buy at 35856.6
on 2025-04-29 09:15:00, sell at 39568.2
8892.544599999972
```

```
[147]: print(final_metrics('POWERGRID', 'NTPC', data, 30, verbos=True))
```

```
100%|      | 421/421 [00:00<00:00, 18965.71it/s]
spread is made up of -100*POWERGRID + 100*NTPC
```

<IPython.core.display.Javascript object>

<IPython.core.display.HTML object>

haven't counted the last buy trade in final profit calculation to equate number of buys = number of sells

```
total profit: 479.99999999999636
on 2023-10-06 09:15:00, buy at 3850.0
on 2023-11-24 09:15:00, sell at 4344.999
on 2024-01-09 09:15:00, buy at 7745.0
on 2024-02-21 09:15:00, sell at 5599.999999999996
on 2024-04-23 09:15:00, buy at 6179.9980000000003
on 2024-05-29 09:15:00, sell at 4689.999999999993
on 2024-07-15 09:15:00, buy at 4175.0
on 2024-07-16 09:15:00, sell at 3800.0
on 2024-07-19 09:15:00, buy at 3244.9979999999996
on 2024-07-25 09:15:00, sell at 5269.998
on 2024-08-14 09:15:00, buy at 6285.000999999997
```

```

on 2024-09-20 09:15:00, sell at 8310.0
on 2024-11-04 09:15:00, buy at 8550.0
on 2024-12-10 09:15:00, sell at 4125.0
on 2025-01-14 09:15:00, buy at 2014.9999999999964
on 2025-01-15 09:15:00, sell at 2270.0000000000073
on 2025-02-06 09:15:00, buy at 3165.0000000000036
on 2025-02-14 09:15:00, sell at 4300.0
on 2025-02-17 09:15:00, buy at 3915.0000000000036
on 2025-02-21 09:15:00, sell at 6435.000000000004
on 2025-03-11 09:15:00, buy at 6300.0
on 2025-03-24 09:15:00, sell at 7509.999999999996
on 2025-04-07 09:15:00, buy at 6040.000000000004
on 2025-04-09 09:15:00, sell at 5595.000000000004
on 2025-04-11 09:15:00, buy at 5599.999999999996
on 2025-04-28 09:15:00, sell at 5295.0
on 2025-05-07 09:15:00, buy at 3094.9999999999964
479.99999999999636

```

```
[171]: Image(filename='handwritten notes/intro15.png')
```

[171]:

Of course this is not enough (nothing is ready), so now let's make the function required with inputs:

- ① PnL plot
- ② total returns
- ③ Average returns
- ④ maximum drawdown
- ⑤ Sharpe ratio $\left(\frac{\bar{R} - R_{ff}}{\sigma_R} \right)$
 - ← Mean returns
 - ← Risk-free rate
 - ← Std dev of returns
- ⑥ Win rate
- ⑦ No of trades
- ⑧ Avg holding period

```

[185]: def general_function(ticker1, ticker2, data, com=0.0005, slippage=0.0001,
    ↪ risk_free_rate = 0.05): #0.05% and 0.01%
    hedge_ratio = get_hedge_ratio(ticker1, ticker2, data[:int(len(data)*0.7)])
    _, quantity_S1, quantity_S2 = spread(ticker1, ticker2, data[:int(len(data)*0.
    ↪ 7)], hedge_ratio)

    rev_hedge_ratio = get_hedge_ratio(ticker2, ticker1, data[:int(len(data)*0.
    ↪ 7)])

```

```

_, r_quantity_S1, _ = spread(ticker2, ticker1, data[:int(len(data)*0.7)],
↪rev_hedge_ratio)

if r_quantity_S1 < quantity_S1:
    ticker1, ticker2 = ticker2, ticker1
    hedge_ratio = get_hedge_ratio(ticker1,ticker2, data[:int(len(data)*0.
↪7)])

_, quantity_S1, quantity_S2 = spread(ticker1,ticker2, data[:
↪int(len(data)*0.7)], hedge_ratio)
    #this is like our nomenclature, I just use (s1, s2) or (s2, s1) depending
↪on hedge ratio
    #I did this to ensure that (s1, s2) or (s2, s1) will get same answer

t_values = range(0, len(data) - int(len(data)*0.7))
spread_values_list = []
dates = []

for t in tqdm.tqdm(t_values):
    spread_values_list.append(spread(ticker1,ticker2, data[:int(len(data)*0.
↪7) + t], hedge_ratio)[0])
    dates.append(data[:int(len(data)*0.7) + t].index[-1])

signals, _ = get_signals(spread_values_list, dates, 30, quantity_S1,
↪quantity_S2)

signals = signals
prices = spread_values_list
dates = dates

first_buy_date = signals[0][0]
second_buy_date = signals[1][0]

initial_portfolio = abs(quantity_S1 * data.loc[first_buy_date, ticker1]) +
↪abs(quantity_S2 * data.loc[first_buy_date, ticker2])
    #this is just |total buy| + |total sell| on the first day

if initial_portfolio < max(spread_values_list):
    initial_portfolio = max(spread_values_list) + 1000

df = pd.DataFrame({
    "datetime": pd.to_datetime(dates),
    "open": prices,
    "high": prices,

```

```

        "low": prices,
        "close": prices,
        "volume": [1000] * len(prices) #not going to use anyway, just to
↪satisfy bt
    })

df.set_index("datetime", inplace=True)
df["signal"] = 0
signal_map = {
    "buy": 1,
    "sell": -1
}

for date, signal, _ in signals:
    dt = pd.to_datetime(date)
    if dt in df.index:
        df.at[dt, "signal"] = signal_map[signal]

class SignalStrategy(bt.SignalStrategy):
    def __init__(self):
        self.signal_add(bt.SIGNAL_LONG, self.data.signal)

class PandasSignalData(bt.feeds.PandasData):
    lines = ('signal',)
    params = (('signal', -1),)

data = PandasSignalData(dataname=df)

cerebro = bt.Cerebro()
cerebro.addstrategy(SignalStrategy)
cerebro.adddata(data)
cerebro.broker.set_cash(initial_portfolio)

cerebro.broker.setcommission(commission=com)
cerebro.broker.set_slippage_perc(slippage)

cerebro.addanalyzer(bt.analyzers.DrawDown, _name='drawdown')
cerebro.addanalyzer(bt.analyzers.TradeAnalyzer, _name='ta')
cerebro.addanalyzer(bt.analyzers.TimeReturn, _name='timereturn')

results = cerebro.run()
strat = results[0]

dd = strat.analyzers.drawdown.get_analysis()
ta = strat.analyzers.ta.get_analysis()

```

```

returns = strat.analyzers.timereturn.get_analysis()

initial_cash = initial_portfolio
final_value = cerebro.broker.getvalue()
total_return = (final_value - initial_cash) / initial_cash #percentage
↳ returns

daily_returns = pd.Series(returns)
average_return = daily_returns.mean() #this is also percentage returns

excess_daily_returns = daily_returns - (risk_free_rate / 252)

mean_excess_return = excess_daily_returns.mean()
std_excess_return = excess_daily_returns.std(ddof=1)

sharpe_ratio = (mean_excess_return / std_excess_return) * np.sqrt(252) if
↳ std_excess_return != 0 else 0

total_trades = ta.total.closed if 'total' in ta and 'closed' in ta.total
↳ else 0
win_trades = ta.won.total if 'won' in ta else 0
win_rate = win_trades / total_trades if total_trades > 0 else 0

avg_holding = ta.len.average if 'len' in ta and 'average' in ta.len else 0

performance_metrics = {
    "Total Return": f"{total_return * 100:.2f}%",
    "Average Daily Return": f"{average_return * 100:.4f}%",
    "Sharpe Ratio": f"{sharpe_ratio:.2f}",
    "Max Drawdown": f"{(dd.max.drawdown):.2f}%",
    "Total Trades": str(total_trades),
    "Win Rate": f"{win_rate * 100:.2f}%",
    "Avg Holding Period": f"{avg_holding:.2f} days"
}

cumulative_returns = (1 + daily_returns).cumprod()
plt.figure(figsize=(12, 6))
plt.plot(cumulative_returns.index, cumulative_returns.values, linewidth=2,
↳ color='#2E86C1')
plt.title("Cumulative PnL", fontsize=14, pad=15)
plt.xlabel("Date", fontsize=12, labelpad=10)
plt.ylabel("Cumulative Returns", fontsize=12, labelpad=10)
plt.grid(True, linestyle='--', alpha=0.7)
plt.gca().spines['top'].set_visible(False)
plt.gca().spines['right'].set_visible(False)
plt.tight_layout()
plt.savefig('cumulative_returns.png', dpi=300, bbox_inches='tight')

```

```
plt.close()

plt.figure(figsize=(12, 8))
cerebro.plot(style='line', barup='green', bardown='red', volume=False)
plt.xlabel('Date', fontsize=8, labelpad=5)
plt.ylabel('Portfolio Value', fontsize=8, labelpad=5)
plt.tight_layout()
plt.savefig('cerebro.png', dpi=300, bbox_inches='tight')
plt.close()

from IPython.display import Image, display

display(Image('cumulative_returns.png'))
display(Image('cerebro.png'))

return performance_metrics
```

```
[181]: general_function('SBIN', 'SBILIFE', data, com=0, slipage=0, risk_free_rate=0)
```

```
100%|      | 421/421 [00:00<00:00, 14045.51it/s]
```

```
<IPython.core.display.Javascript object>
```

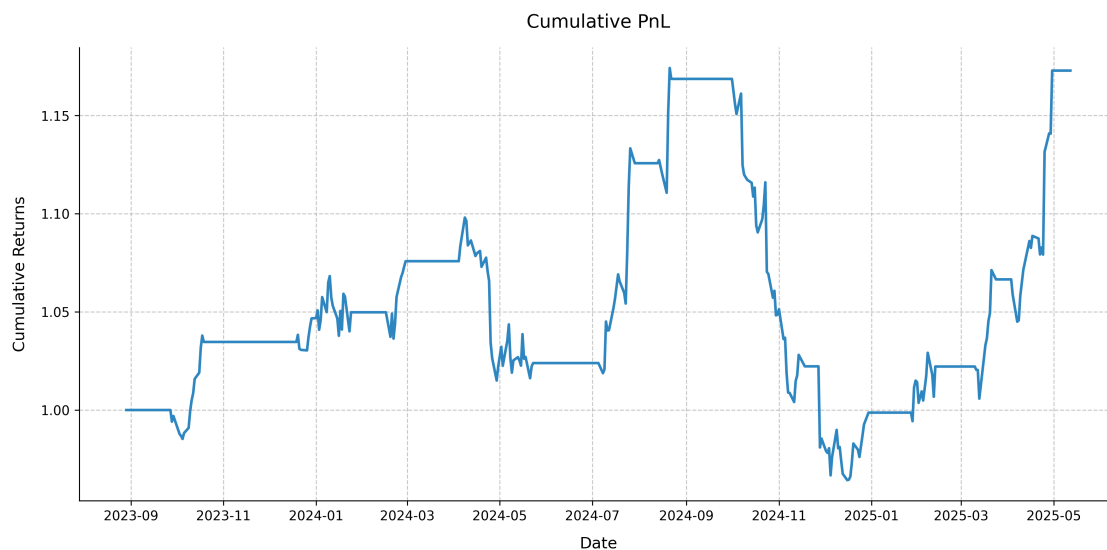
```
<IPython.core.display.HTML object>
```

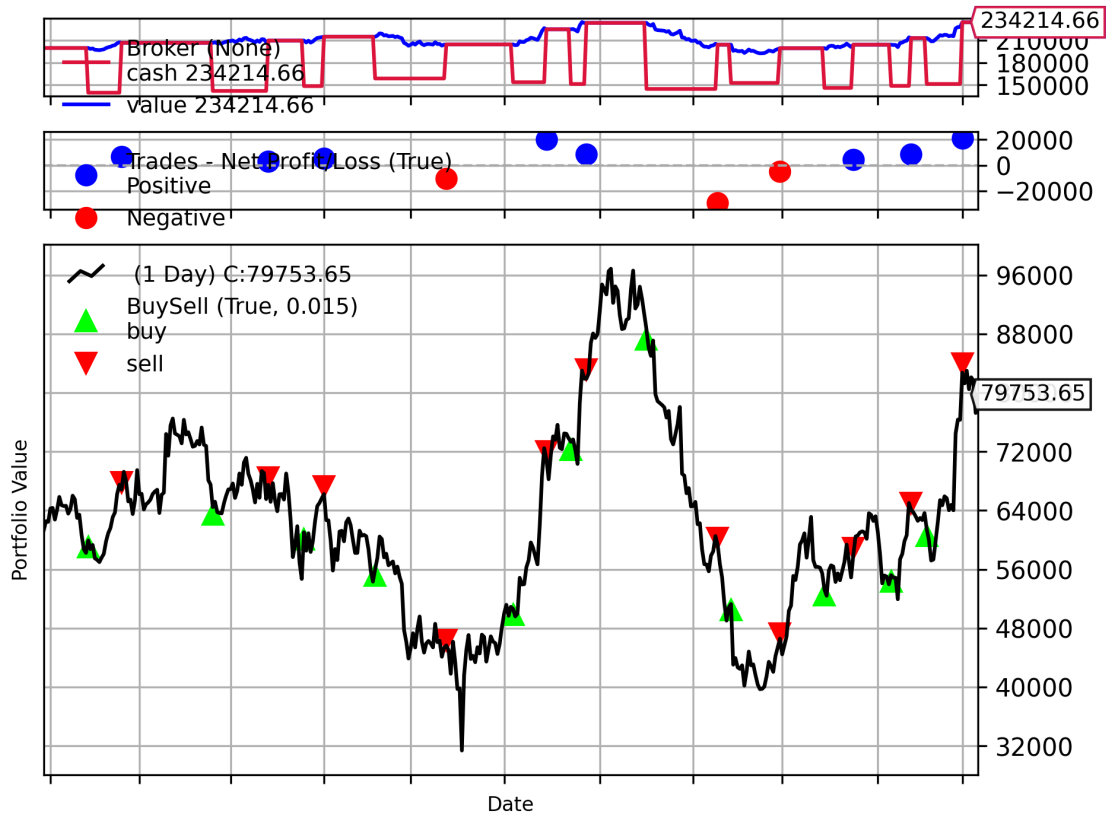
```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```





```
[181]: {'Total Return': '17.28%',
        'Average Daily Return': '0.0408%',
        'Sharpe Ratio': '0.84',
        'Max Drawdown': '17.87%',
        'Total Trades': '11',
        'Win Rate': '72.73%',
        'Avg Holding Period': '17.73 days'}
```

```
[174]: general_function('BAJFINANCE', 'BAJAJFINSV', data, com=0, slippage=0,
        ↪risk_free_rate=0)
```

```
100% | 421/421 [00:00<00:00, 19823.77it/s]
```

```
<IPython.core.display.Javascript object>
```

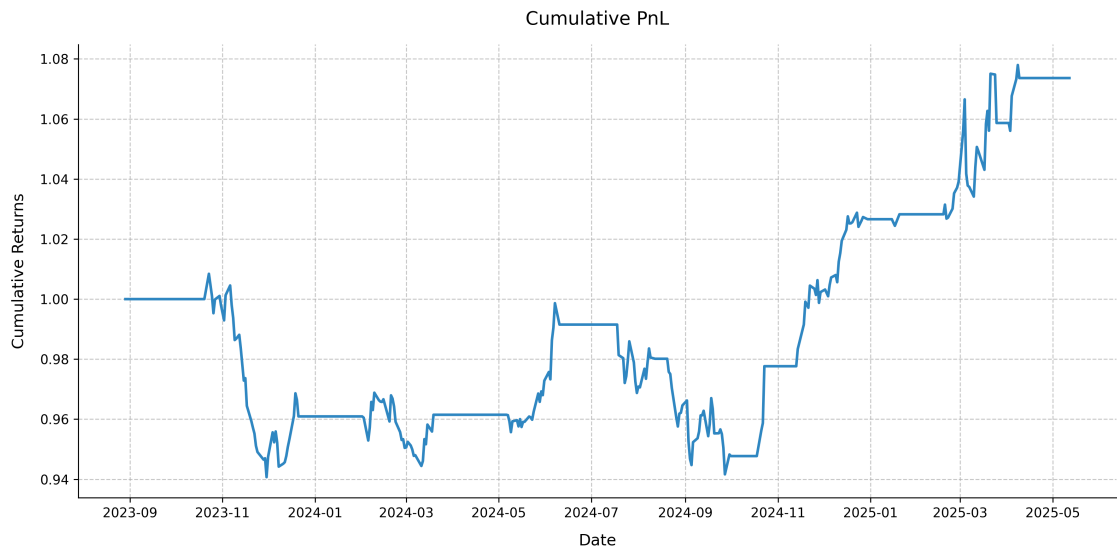
```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

```
[174]: {'Total Return': '7.36%',  
        'Average Daily Return': '0.0177%',
```

```

'Sharpe Ratio': '0.70',
'Max Drawdown': '6.72%',
'Total Trades': '10',
'Win Rate': '70.00%',
'Avg Holding Period': '21.10 days'

```

```
[175]: general_function('INFY', 'TCS', data, com=0, slippage=0, risk_free_rate=0)
```

```
100% | 421/421 [00:00<00:00, 16004.44it/s]
```

```
<IPython.core.display.Javascript object>
```

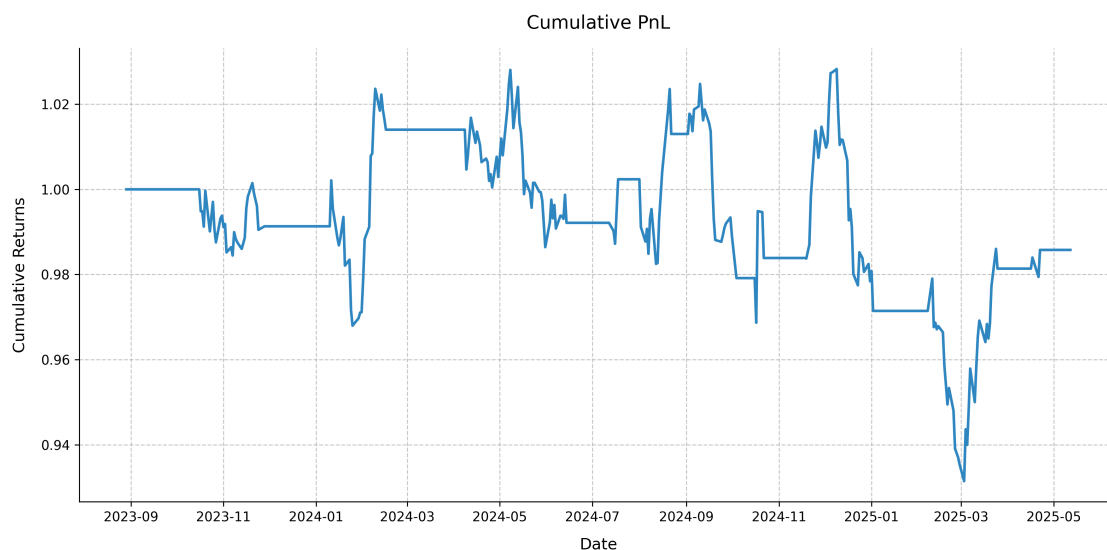
```
<IPython.core.display.HTML object>
```

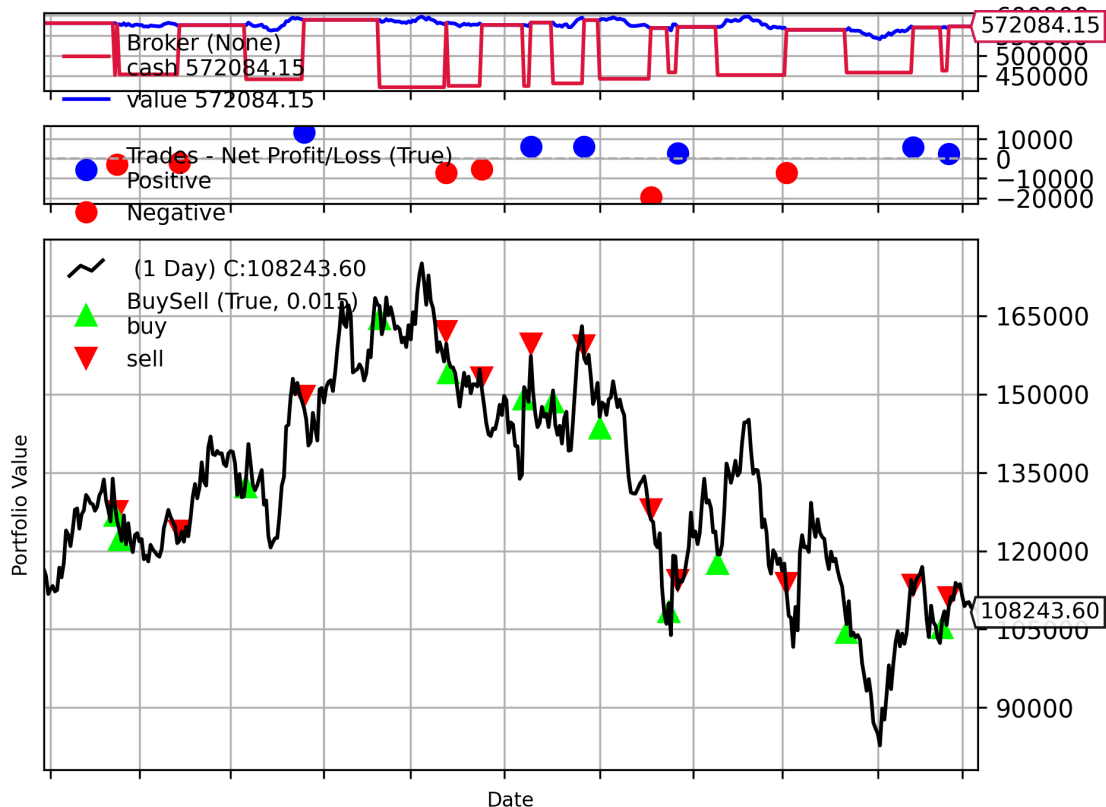
```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```





```
[175]: {'Total Return': '-1.42%',
        'Average Daily Return': '-0.0024%',
        'Sharpe Ratio': '-0.09',
        'Max Drawdown': '9.41%',
        'Total Trades': '12',
        'Win Rate': '50.00%',
        'Avg Holding Period': '17.25 days'}
```

```
[186]: general_function('BPCL', 'RELIANCE', data, com=0, slippage=0, risk_free_rate=0)
```

```
100%|      | 421/421 [00:00<00:00, 16135.77it/s]
```

```
<IPython.core.display.Javascript object>
```

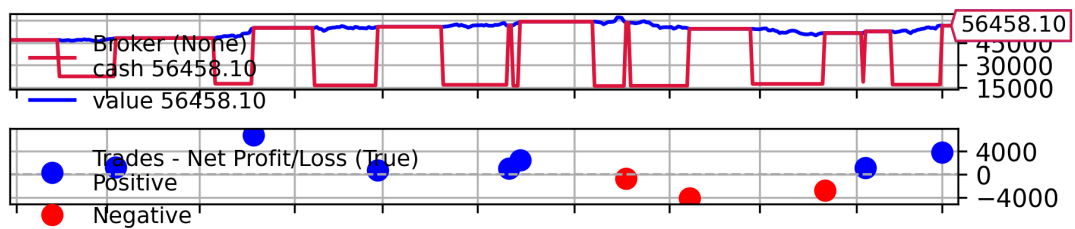
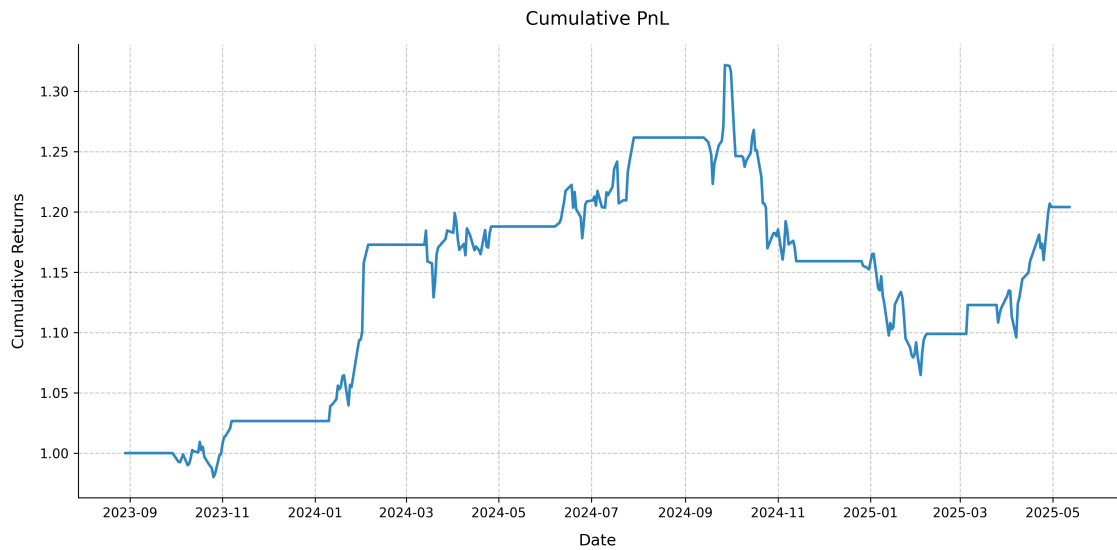
```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```



[186]: {'Total Return': '20.41%',
'Average Daily Return': '0.0473%',

```
'Sharpe Ratio': '0.94',  
'Max Drawdown': '19.46%',  
'Total Trades': '10',  
'Win Rate': '70.00%',  
'Avg Holding Period': '19.70 days'}
```

```
[177]: general_function('POWERGRID', 'NTPC', data, com=0, slippage=0, risk_free_rate=0)
```

```
100%|      | 421/421 [00:00<00:00, 19220.87it/s]
```

```
<IPython.core.display.Javascript object>
```

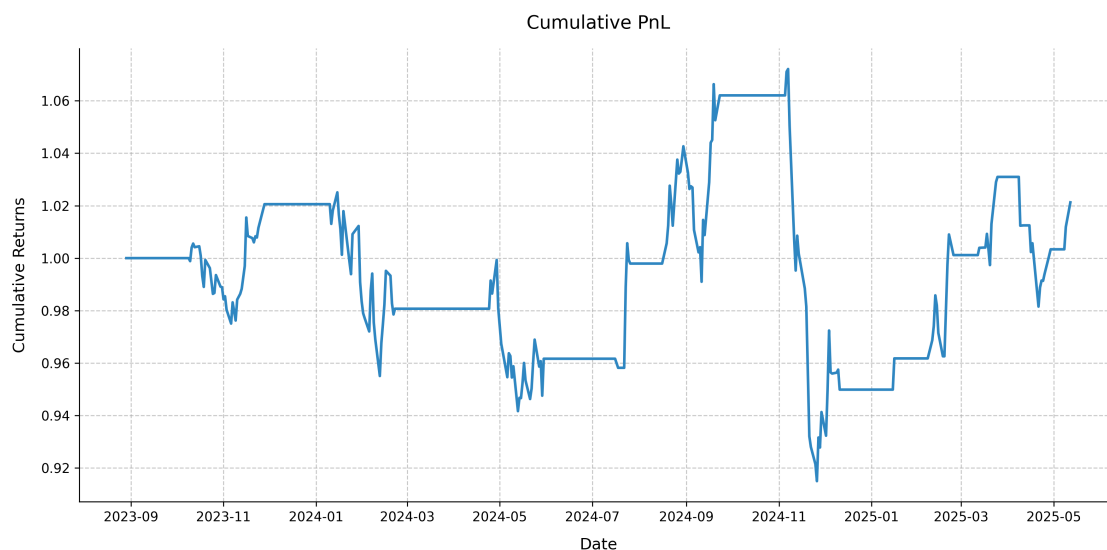
```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```





```
[177]: {'Total Return': '2.13%',
        'Average Daily Return': '0.0077%',
        'Sharpe Ratio': '0.17',
        'Max Drawdown': '14.66%',
        'Total Trades': '13',
        'Win Rate': '53.85%',
        'Avg Holding Period': '13.38 days'}
```