Programmatic Equity Trading Research

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Hypothesis

If the price of a share/stock falls significantly in a relatively short period of time, the price will rebound significantly in the near future.

The purpose of this research is to quantify the terms ‘falls significantly’, ‘short period’ and ‘near future’ and to identify a pattern.

Data & Technologies Used

Share prices from the last one year (June 2020 - June 2021) of the 100 largest companies by market cap in India listed on the Bombay Stock Exchange were used for this analysis. The same analysis was also conducted on the 100 largest companies by market cap based in the USA listed on the Nasdaq. Data was procured through MarketStack’s API.

The software for this research was built using Python, Pandas and Matplotlib.

Defining Terms

Fall Window : The number of trading days the share price of a given stock has been falling for.

Fall Percentage : The absolute percentage by which the share price fell within the observed fall window.

Gain Window : The number of trading days a long position on a stock is held for.

Methodology

The idea was to find an optimal combination of these three factors - Fall Window, Fall Percentage and Gain Window - which when applied to any given stock, yields the maximum amount of return. For example, if the Fall Window is 15 trading days, Fall Percentage is 10 percentage points and Gain Window is 35 trading days, then this combination is denoted as [15, 10, 35]. This means, if the share price of a stock has fallen

10 percentage points in the last 15 trading days, then on the 16th day, a long position on that stock should be opened and held for the next 35 trading days for maximising short term returns.

Below are the steps used to arrive at this Optimal Combination for the Indian and US stock markets.

<u>Defining All Possible Combinations</u> :

To find the optimal combination of the three factors mentioned above, first, a set of all possible combinations was defined.

The *Fall Window* could take on a range of values between 10 - 60 trading days. The rationale behind this was that only those price falls were considered that were due to some sort of immediate shock/correction in the market (the bounce back of the price was hypothesized to be the highest for stocks that fell due to these reasons). A firm ailing for months and therefore seeing it's share price decline for a long period of time was not considered for this analysis.

The *Fall Percentage* could take on values ranging between 10% - 50%. 10 was chosen as the lower limit as price falls lower than that can't really be considered a true shock/correction. 50 was the upper limit as price falls greater than that are relatively rare in such a short period of time. The algorithm wouldn't be of much use if it only looked for massive price falls that occurred very rarely in the market.

The *Gain Window* could take on values ranging between 5 - 80 trading days. The lower limit was selected as 5, since at least a week of market activity was required to see any significant movements in price. 80 was the upper limit since ample time was to be given to the long positions to observe price increases.

Thus, the Fall Window could take on 50 unique integer values, Fall Percentage could take on 40 unique integer values and the Gain Window could take on 75 unique integer values. In total, there were **150,000 possible permutations** of these three factors.

<u>Applying Combinations To Stocks</u>

'Applying' a combination to a stock entails the below:

- Say the combination [10, 20, 30] is applied to Reliance Ltd. All 10-day windows (in the last 1 trading year) will be identified in which Reliance share price fell at least 20 percentage points. Each such window identified is also defined as an 'occurence' of the combination for that stock.
- Then, the price of the share 30 days from the 11th day is retrieved and the change in price between the 11th day and 30 days hence (representing the long position) was calculated and stored. This price change was noted as the return on that long position.
- Once all such fall windows were identified and the return was calculated on each such price fall occurrence, the average was calculated for each long position for that given combination on the given stock. In other words, if for the combination [10,20,30], there were 6 occurrences for Reliance, then the average return of the 6 corresponding 30-day long positions was calculated and stored.

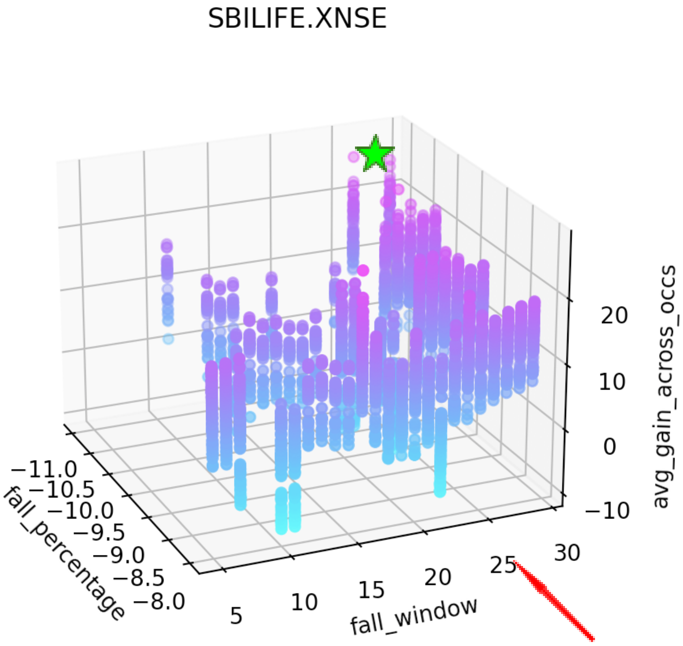
This was repeated 150,000 times as each combination was applied to each stock being analysed. Then the results were sorted by the average return per combination applied. The output for each stock looked like this -

```
(venv) Vibhus-MacBook-Pro:strats vibhumahendru$ python new_strat.py
3742 LEN
           ticker  fall_window  gain_window  fall_percentage  occurrences  avg_buy_price  avg_gain_across_occs
346   SBILIFE.XNSE          10           53               -8            1         839.30             -9.269629
532   SBILIFE.XNSE          11           53               -8            1         839.30             -9.269629
348   SBILIFE.XNSE          10           55               -8            1         839.30             -8.727511
534   SBILIFE.XNSE          11           55               -8            1         839.30             -8.727511
347   SBILIFE.XNSE          10           54               -8            1         839.30             -8.358156
...            ...         ...          ...              ...          ...            ...                   ...
2467  SBILIFE.XNSE          25           95              -10            1         780.80             24.398053
3706  SBILIFE.XNSE          29           91              -11            2         766.25             24.759158
2818  SBILIFE.XNSE          26           94              -11            1         770.70             26.028286
2819  SBILIFE.XNSE          26           94              -10            1         770.70             26.028286
1010  SBILIFE.XNSE          16           90               -8            1         761.50             27.550886
```

To better visualise this output, 3D graphs for each stock were generated. After analysing the raw data and graphs, the optimal combinations were identified as below.

1. Indian Stock Market : [25, 13, 43]
2. US Stock Market : [15, 16, 52]

The optimal values are highlighted by the red arrows and the peak gains are marked by the green star.


SBILIFE.XNSE
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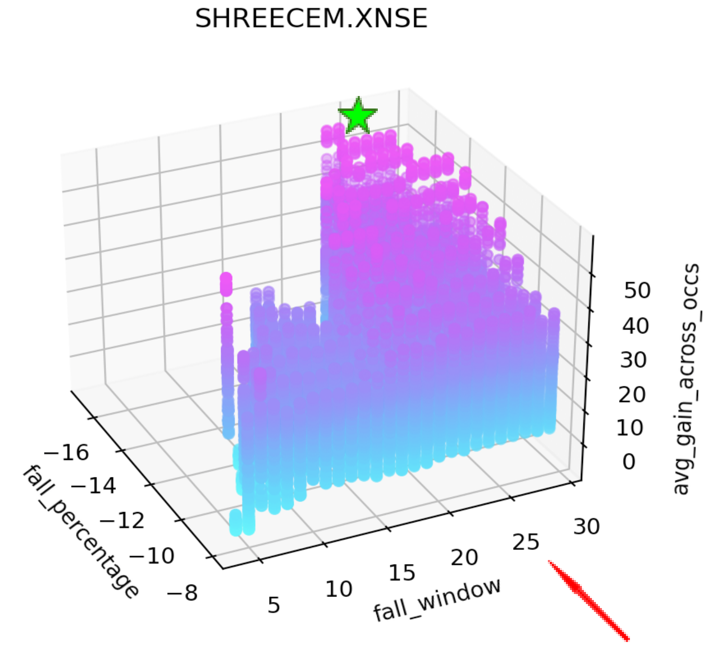
fall_window
avg_gain_across_occs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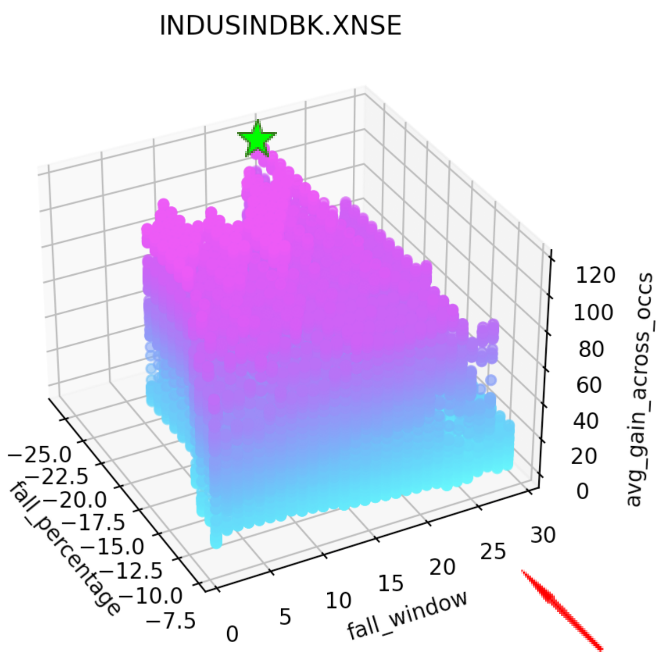
avg_gain_across_occs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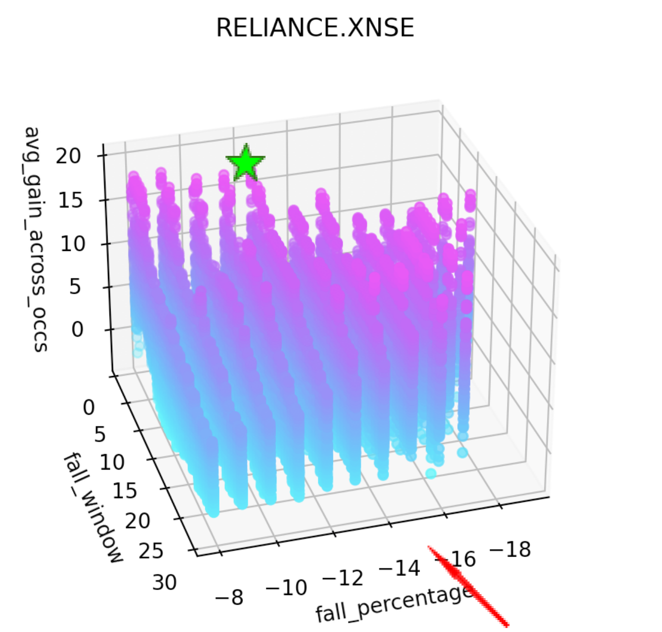
fall_percentage
fall_window
avg_gain_across_occs


RELIANCE.XNSE
avg_gain_across_occs
fall_window
fall_percentage

Getting Stock Recommendations

With the optimal combinations identified, a program was run to identify all stocks whose price had been falling in the last 50 trading days. The output of this program is as below. The stocks highlighted in red matched closest to the optimal combination.

```
(venv) Vibhus-MacBook-Pro:strats vibhumahendru$ python what_to_buy.py
             ticker                  prev_date  prev_price  latest_price  percentage_diff  fall_window  fall_percentage
27     FINPIPE.XNSE  2021-04-12T00:00:00+0000      676.10        173.65       -74.315930           49              -40
10       IRCON.XNSE  2021-05-19T00:00:00+0000       97.35         48.35       -50.333847           25              -40
0     AARTIIND.XNSE  2021-05-26T00:00:00+0000     1664.25        864.40       -48.060688           20              -40
1          VBL.XNSE  2021-05-26T00:00:00+0000     1016.40        753.45       -25.870720           20              -25
     INDIAMART.XNSE  2021-04-29T00:00:00+0000     8815.40       7142.70       -18.974749           38              -18
2     GRAPHITE.XNSE  2021-05-26T00:00:00+0000      758.65        629.55       -17.017070           20              -17
       FINEORG.XNSE  2021-05-25T00:00:00+0000     3397.10       2936.90       -13.546849           21              -13
7   ADANITRANS.XNSE  2021-05-24T00:00:00+0000     1526.50       1321.45       -13.432689           22              -13
14  NATIONALUM.XNSE  2021-05-11T00:00:00+0000       79.50         69.00       -13.207547           30              -13
25    ASTRAZEN.XNSE  2021-04-27T00:00:00+0000     4223.50       3667.10       -13.173908           40              -13
15    GRANULES.XNSE  2021-05-11T00:00:00+0000      359.90        314.35       -12.656293           30              -12
3        AFFLE.XNSE  2021-05-26T00:00:00+0000     5249.05       4597.60       -12.410817           20              -12
12  JINDALSTEL.XNSE  2021-05-18T00:00:00+0000      439.40        385.20       -12.335002           26              -12
      JSWSTEEL.XNSE  2021-05-10T00:00:00+0000      758.65        665.50       -12.278389           31              -12
8   GMMPFAUDLR.XNSE  2021-05-24T00:00:00+0000     5317.50       4676.20       -12.060179           22              -12
20   VAKRANGEE.XNSE  2021-05-06T00:00:00+0000       51.55         45.35       -12.027158           33              -12
26       JCHAC.XNSE  2021-04-16T00:00:00+0000     2553.25       2246.25       -12.023891           46              -12
13        NMDC.XNSE  2021-05-12T00:00:00+0000      202.95        178.80       -11.899483           29              -11
     BAJAJELEC.XNSE  2021-05-11T00:00:00+0000     1177.70       1040.35       -11.662563           30              -11
16        SAIL.XNSE  2021-05-11T00:00:00+0000      140.40        124.10       -11.609687           30              -11
    LINDEINDIA.XNSE  2021-05-11T00:00:00+0000     1793.15       1588.00       -11.440761           30              -11
22  CANFINHOME.XNSE  2021-04-30T00:00:00+0000      581.45        514.95       -11.436925           37              -11
6         BHEL.XNSE  2021-05-25T00:00:00+0000       74.50         66.05       -11.342282           21              -11
23        STAR.XNSE  2021-04-30T00:00:00+0000      864.75        767.05       -11.298063           37              -11
      SYMPHONY.XNSE  2021-04-30T00:00:00+0000     1176.65       1043.95       -11.277780           37              -11
    ADANIGREEN.XNSE  2021-05-25T00:00:00+0000     1314.25       1166.15       -11.268784           21              -11
11        VEDL.XNSE  2021-05-19T00:00:00+0000      282.70        251.25       -11.124867           25              -11
9       VARROC.XNSE  2021-05-21T00:00:00+0000      419.35        372.85       -11.088589           23              -11
(venv) Vibhus-MacBook-Pro:strats vibhumahendru$
```

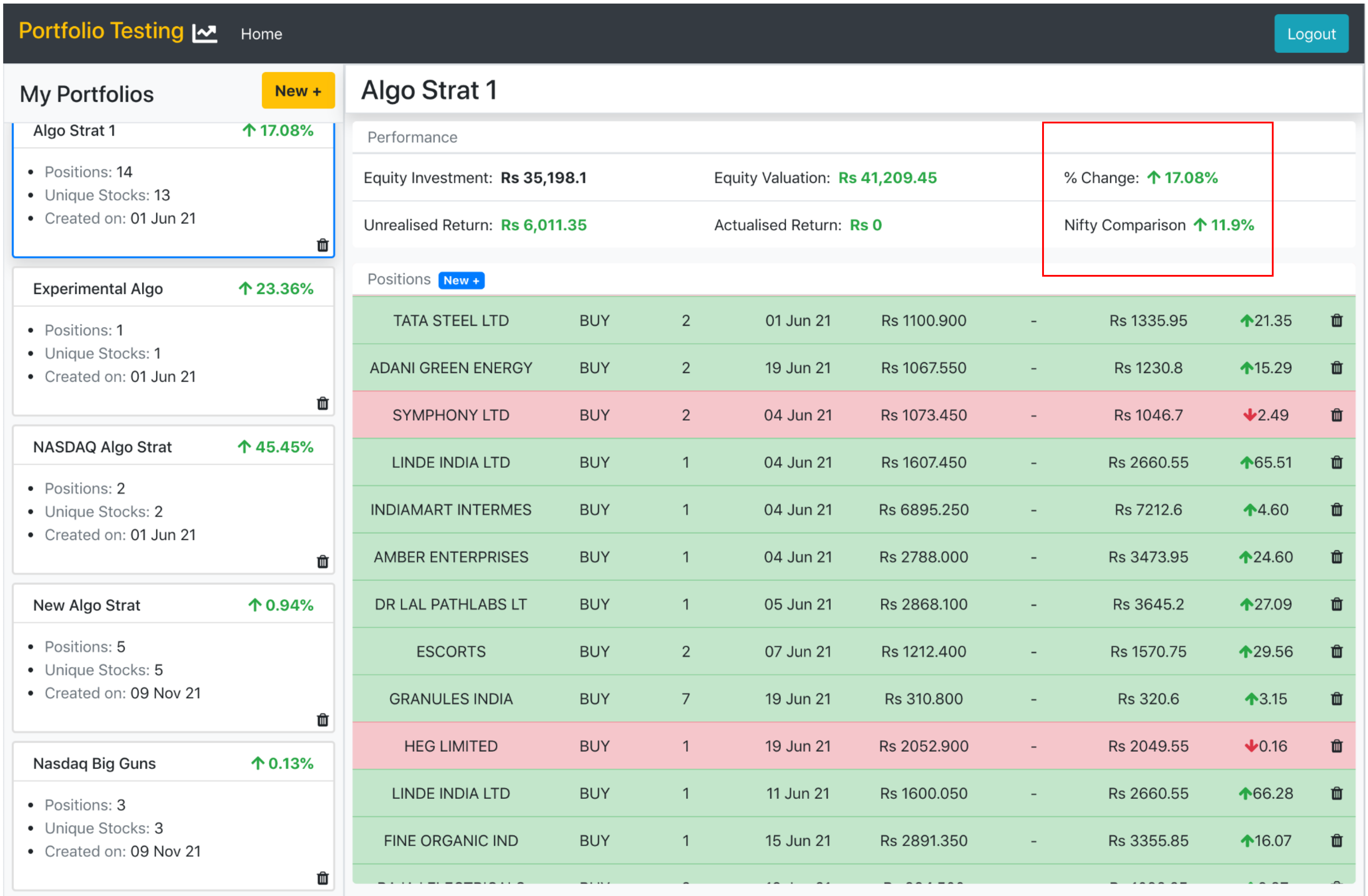
Building a Portfolio Using This Strategy

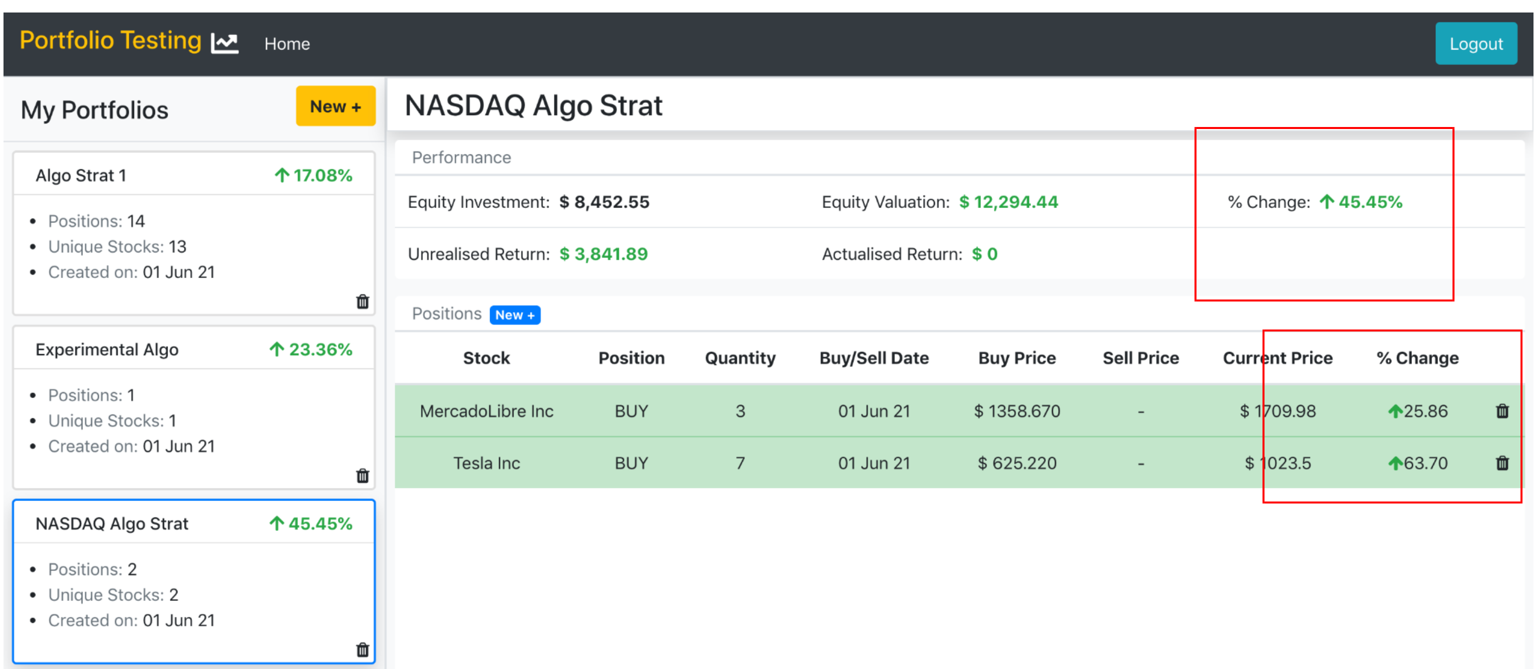
With the stock recommendations identified, it was time to build a portfolio using this strategy. I had built a [Mock Equity Portfolio] app that allows users to simulate realtime and historical trades. I opened long positions on the stocks that were recommended by the above program and monitored the portfolio for about 3 months.

As a benchmark, I compared the portfolio's performance to the Nifty50. Below are the results:

Portfolio 1 : Contained 13 unique stocks. Return over 3 months was 17.08% compared to 11.9% gain from Nifty.

Portfolio 2 : Contained two US market stocks. Average return was 45%. No benchmark available.





Outcome of Research

The strategy to go long on stocks that have been falling for some time gives higher returns as compared to the Nifty in the short run for the observed stocks. Essentially what this program is doing is that it ensures long positions are opened on stocks that have been declining. Stocks that are seeing their prices increase are never recommended. In other words, the strategy is close to ‘buying the dip’ with certain parameters quantified.

Areas of Further Research

It would be valuable to observe why certain recommendations that abide by the optimal combination still do not perform well. In the Indian stock portfolio, nearly 1out of 6 stock recommendations failed to generate a positive return, though they only further fell 7% on average.

It would also be valuable to track changes in the optimal combination itself for respective markets with time. There may well be a cyclical pattern of that the optimal combination runs through each decade.

Lastly, more backtesting of this strategy on sets that include over a year of price data would yield ever better results.
