Applications of Graph Theory in Context of Indian Markets.

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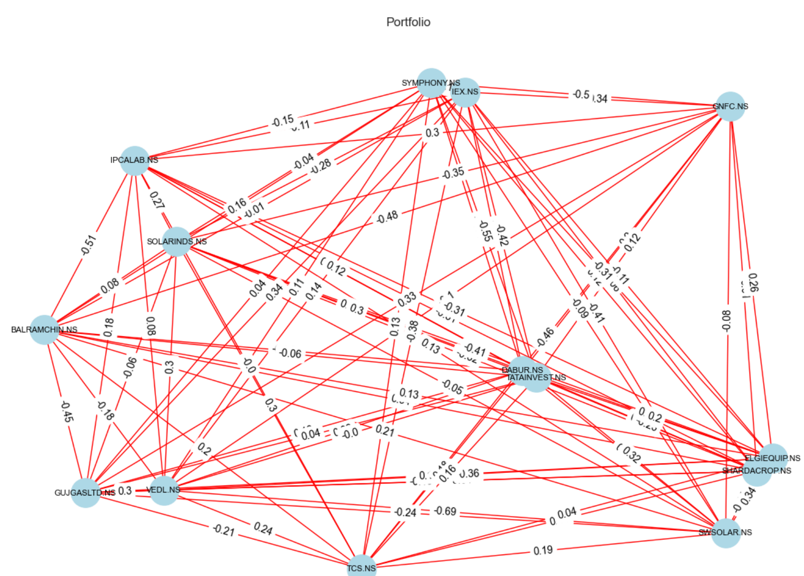


The Below Quantitative Research Report is based on the Paper “The Applications of Graph Theory to Investing” by Joseph Attia of the Brooklyn Technical High School.

The Main Idea of the Paper:

We try to explain the pros and cons of Building portfolios based on correlations of stocks. Where we explore diversified and undiversified portfolios in various market conditions. The paper uses stocks from the S&P 500, which we will replace with Nifty 50.

Rules for building the portfolio:

For building the portfolio, we will follow the paper initially, i.e., a back window of 4 years and making a portfolio holding it for four years and then rebalancing after the four years.

So now we have two portfolios.

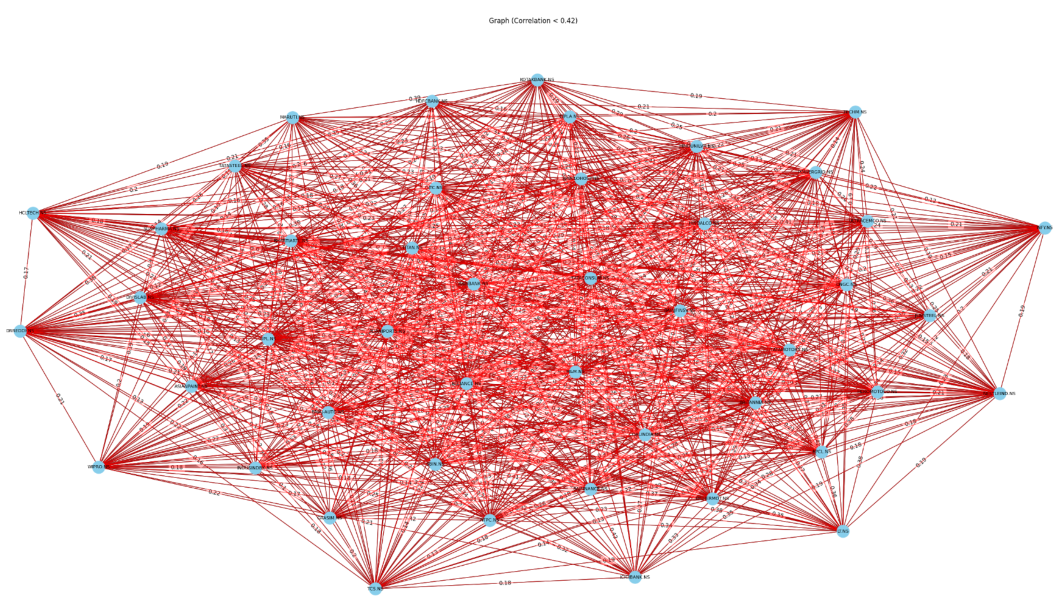
- Higher Correlation Portfolio
- Lower Correlation Portfolio

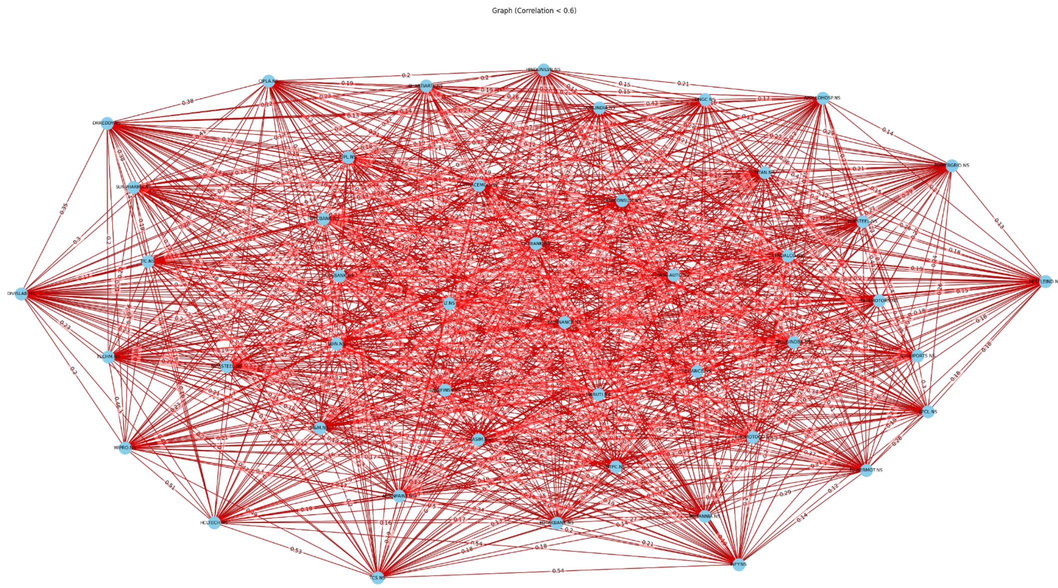
We can use the threshold values used in the paper for the first test. The Graph will be built in two ways.

- The Higher correlation Portfolio with threshold =0.46
- The Lower correlation Portfolio with threshold =0.33

The Graph will consist of Stocks as nodes and their correlations as the edges. In the case of the portfolios, we will connect all nodes with values greater than the threshold value and vice versa in the case of the lowest correlation portfolio.

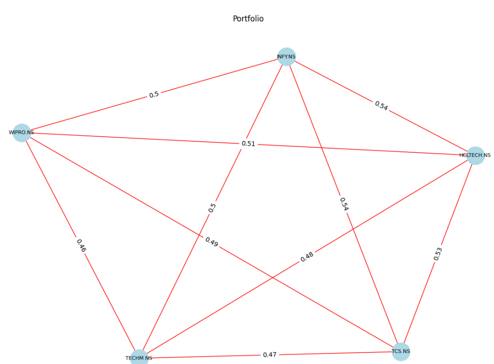
This is what the graphs will look like.

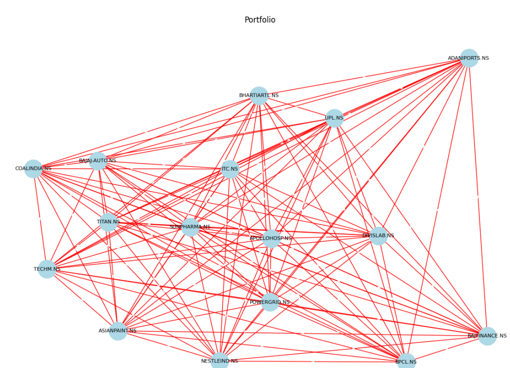




The first graph shows the lower correlation portfolio graph, and the latter shows the higher.

The portfolio will consist of the largest complete subgraph from both graphs, which will look similar.





As we can see, the higher correlation portfolio will have more constituents than the former.

What do the backtest results suggest?

The portfolios certainly show interesting results.

For starters, here are a few metrics of both the portfolios over
2017-10-04 To 2023-08-25

	CAGR	Absolute Returns	Max Drawdown	Calmar Ratio	Sharpe Ratio
Market	19.71%	245%	-38.45%	1.66	0.7
Higher correlation portfolio	21.6%	261%	-35.2%	1.9	0.72
Lower correlation portfolio	23.9%	285%	-37.87%	2.49	0.69

* Due to a lack of market data and to avoid forward-looking biases, “Market” is considered an equal-weight index portfolio of all the stocks in the testing universe.

Looking a little deeper...

These are the stats before the COVID-19 crash.

	CAGR	Absolute Returns	Max Drawdown	Calmar Ratio	Sharpe Ratio
Market	12.64%	126%	-14.47%	5.64	0.82
Higher correlation portfolio	13.07%	127%	-14.62%	5.12	0.84
Lower correlation portfolio	18.02%	139%	-14.23%	6.04	0.77

The difference in the two approaches is much larger but is masked by the COVID-19 pandemic black swan event.

Variation with Correlation…

Let us extend the research further and experiment with a range of threshold values.
Let's build graphs with threshold values of [0.5,0.4,0.3,0.2].

The Portfolios at 0.2 and 0.3 values show incredible outperformance.

	CAGR	Absolute Returns	Max Drawdown	Calmar Ratio	Sharpe Ratio
0.2 portfolio	26.6%	325%	-14.6%	4.64	0.63
0.3 Portfolio	19%	275%	-14.23%	2.59	0.72

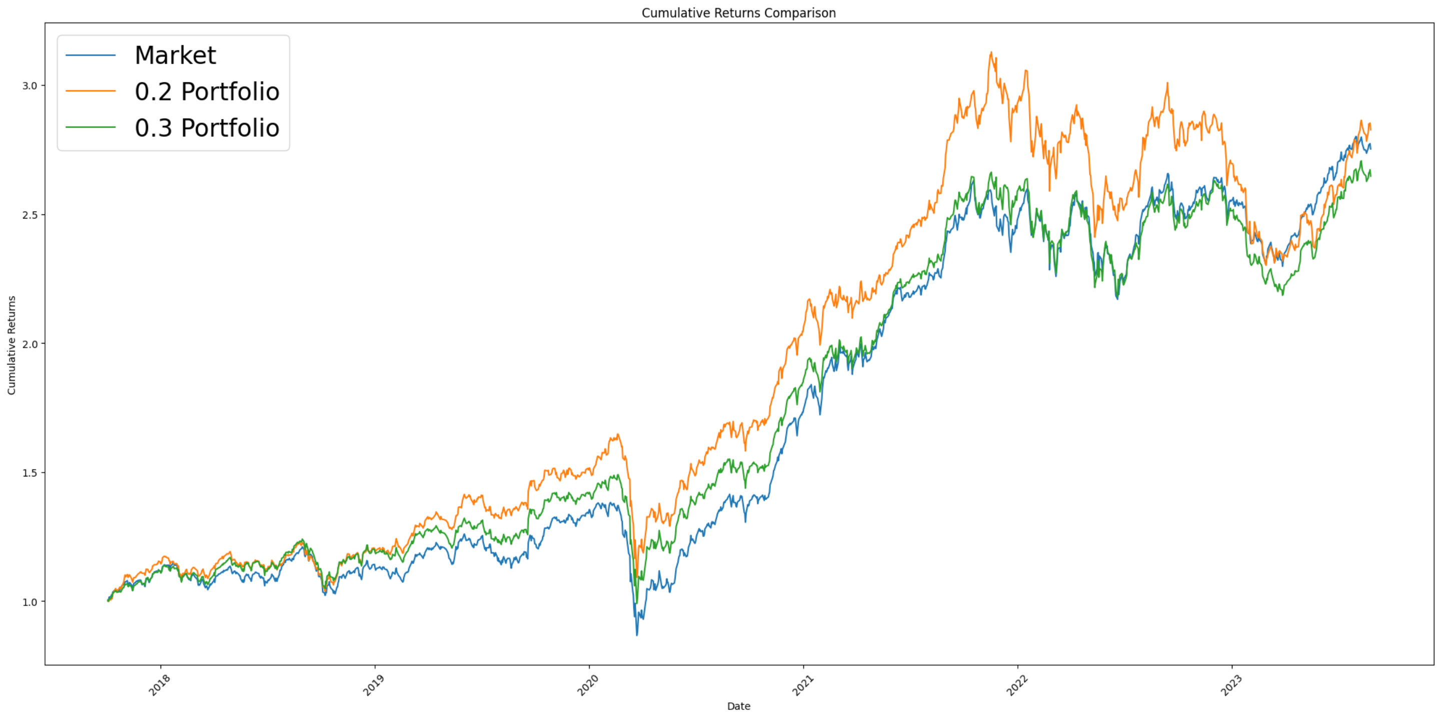
Although lesser in the Sharpe Ratio, the 0.2 threshold shows significant outperformance in the Calmar ratio.

Threshold values are Robust or Just a coincidence?

As we saw earlier, the outperformance of the 0.2 and 0.3 parameters is a mere coincidence or a robust factor in the Indian context.

For this, let's look at portfolios with these parameters from indices like nifty100 and nifty200.

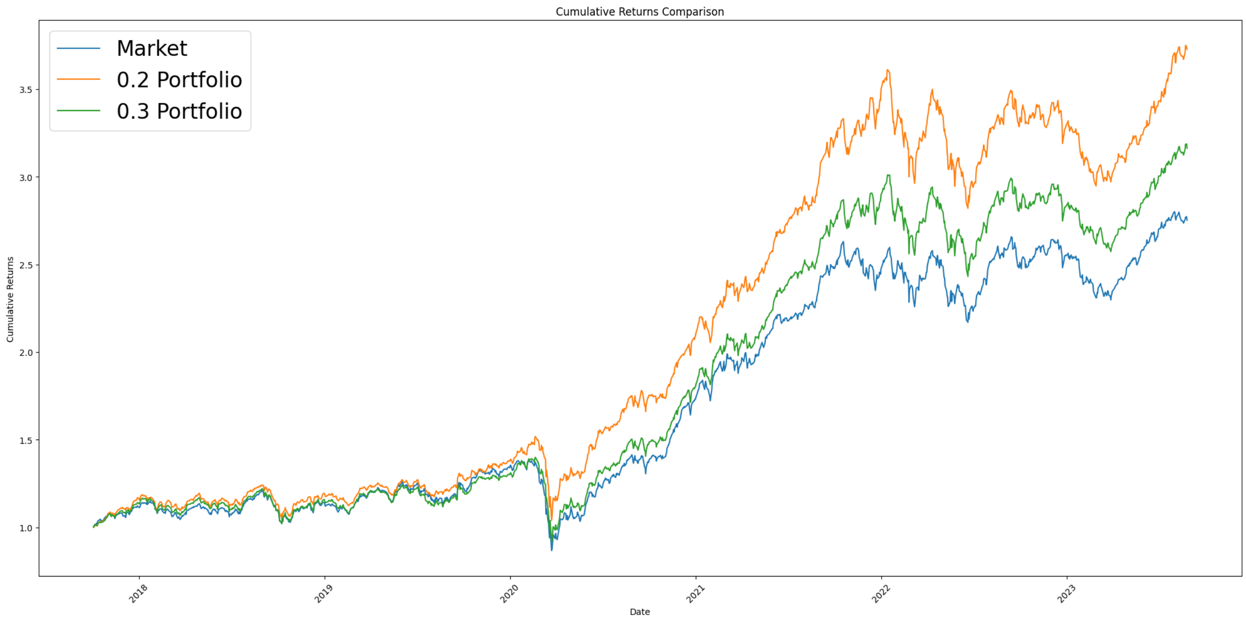
Nifty 100:



	CAGR	Absolute Returns	Max Drawdown	Calmar Ratio	Sharpe Ratio
Market	18.57%	272%	-15.5%	6.18	6.98
0.2 portfolio	18.19%	267%	-14.6%	9.56	4.45
0.3 Portfolio	17.2%	255%	-14.23%	7.8	5.59

Both the threshold values again show better performance than the market.

Nifty 200:



	CAGR	Absolute Returns	Max Drawdown	Calmar Ratio	Sharpe Ratio
Market	22.44%	275%	-37.3%	2.12	0.63
0.3 Portfolio	25.89%	316%	-34.6%	3.06	0.6
0.2 portfolio	30.1%	372%	-31.5%	4.64	0.62

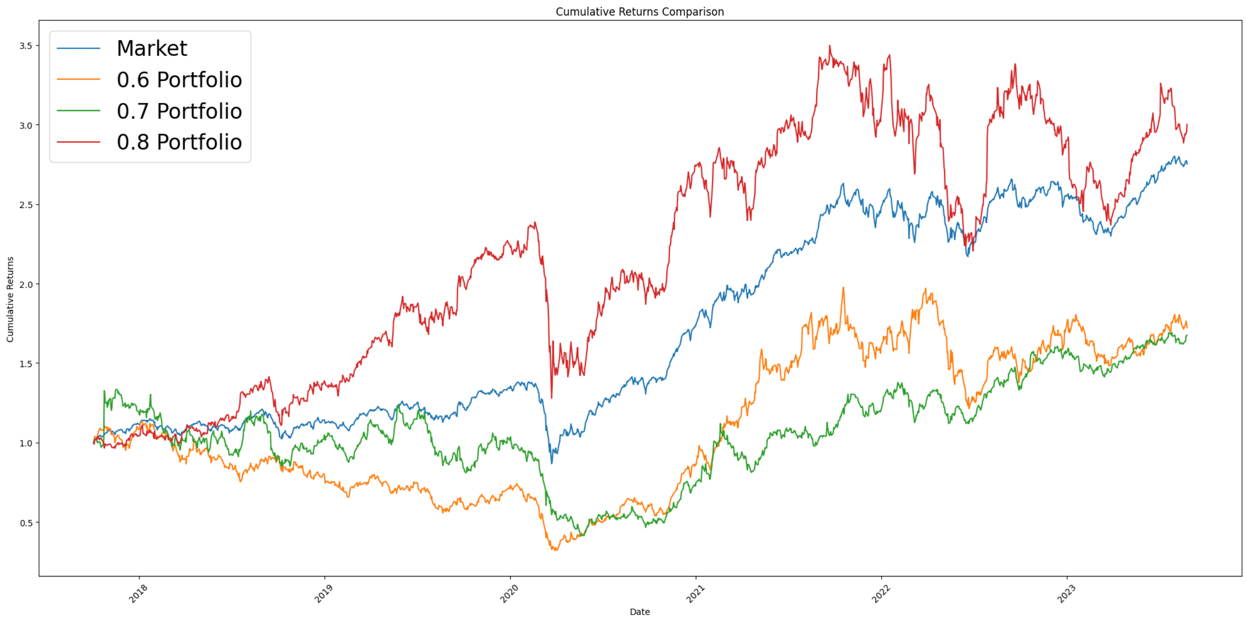
Looking at results from both the indices it can be concluded that the 0.2 and 0.3 thresholds do seem to build powerful portfolios that have the potential to beat the markets.

A new potential direction:

As an experiment, what if we only selected highly correlated stocks and did the polar opposite of what the paper recommends us to do?!

The new condition for the graph would now be connecting all the nodes to nodes correlated to each other above a certain threshold value.

For the sake of simplicity, let's take three values [0.6,0.7,0.8] on Nifty100.

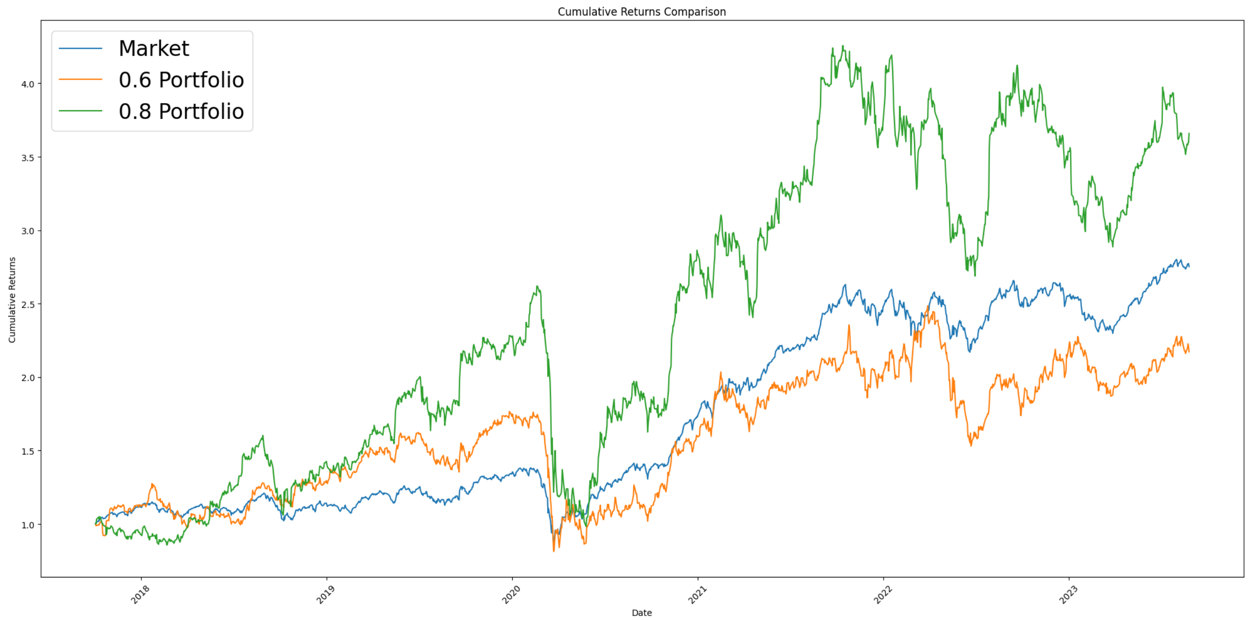


Astonishing Results!

Holding a highly correlated portfolio as expected results in poor performance in the 0.6 and 0.7 threshold values. But surprisingly, for 0.8, the results show a completely different story,

	CAGR	Absolute Returns	Max Drawdown	Calmar Ratio	Sharpe Ratio
Market	18.7%	275%	-37.3%	2.12	0.63
0.6 Portfolio	9.6%	172%	-71.63%	0.23	0.49
0.7 Portfolio	9.09%	167%	-69.05%	0.24	0.71
0.8 Portfolio	20.5%	300%	-46.44%	1.57	0.58

To check for consistency, let's backtest the same logic on the nifty50 universe:



The results seem to be consistent. The over-correlated portfolio outperformed both the market and the other strategy but the returns are very inconsistent and lumpy as this approach usually leads to very concentrated portfolios that do well during bull runs but also take the most beating when in a crash as the chart shows.

Here are the statistics for the same:

	CAGR	Absolute Returns	Max Drawdown	Calmar Ratio	Sharpe Ratio
Market	22.44%	275%	-37.3%	2.12	0.63
0.6 Portfolio	13.89%	217%	-53.99%	0.68	0.72
0.8 Portfolio	24.58%	365%	-62.52%	1.57	0.52

Conclusion:

Research in the field of graph theory offers exciting opportunities not only for long-term investing but also for short-term trading. Combining graphs with other factors can create strong models for investments that don't need constant attention. Exploring adjustments to factors like how far back you look and how long you hold onto stocks could make these models even better. Adding another way to pick out promising stocks based on fundamental factors can refine the group of stocks to consider. Mixing loosely and strongly related stocks could make the results even more dependable.