LionQuant

IEORE4576
Final Presentation
Fall 2022

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Agenda

- Framework
- Approach to Ranking
- Approach to Portfolio Construction
- Other methodologies
- Q&A

Our Guiding Principle:

Delegate as many decisions as possible to the algorithm because we feel human biases restrict us from making the optimal decisions.

Our intervention was thus limited to finding the external data sources to feed into the algorithm and determining the appropriate model to be used in the exercise.

Informed by our analysis over the weeks, we chose an algorithm that uses the LSTM framework to predict the future daily prices of assets using external datasets that consisted of market indices, commodity prices, calendar events and various sentiment indicators.

To rank assets among different buckets, we relied on simulations built upon Brownian Motions. The PyPortfolioOpt library was used in determining portfolio weights.

Algorithm Snapshot:

Create Indexes for the 3 asset classes:

- Stocks
- ETFs
- Cryptocurrencies

Gathering Datasets:

- Market Indices
- Commodity Prices
- Sentiment Indicators
- Calendar Events

Identifying datasets that have predictive power using correlation matrix

Feeding the selected datasets into a LSTM model and
run model separately for each asset class to predict future daily prices and use PyPortfolioOpt library to determine optimal portfolio weights for all 110 assets

Rank the assets into 5 buckets (bucket 1 showing probability of being in the bottom 20% of returns) using 5,000 Brownian Motion simulations for each asset

Submission

Approach to Ranking

Week 1: Assumed that the historical categorization of individual asset returns across the 5 ranks would hold in the future. Historical window length of 1 year.

Weeks 2 to 5: Imposed a normal distribution on historical returns of individual assets. Z-Scores were then used to determine the ranking.

Weeks 6 to 8: Assumed all rankings are equally likely for each individual asset

Weeks 9 to 11: Ran 5,000 simulations for each asset and calculated the weekly returns at each epoch. The ranking of these returns for each asset per epoch was then used to determine the probability of each ranking for individual assets.

Approach to Portfolio Construction

Week 1: Assumed that weekly returns are normally distributed. Ran 1,000 simulations and took the mean of the simulations as the forecasted return. Long only portfolio.

Week 2: Modeled daily price movements as Brownian Motions. Ran 5,000 simulations and took the mean of the simulations as the forecasted return. Long only portfolio.

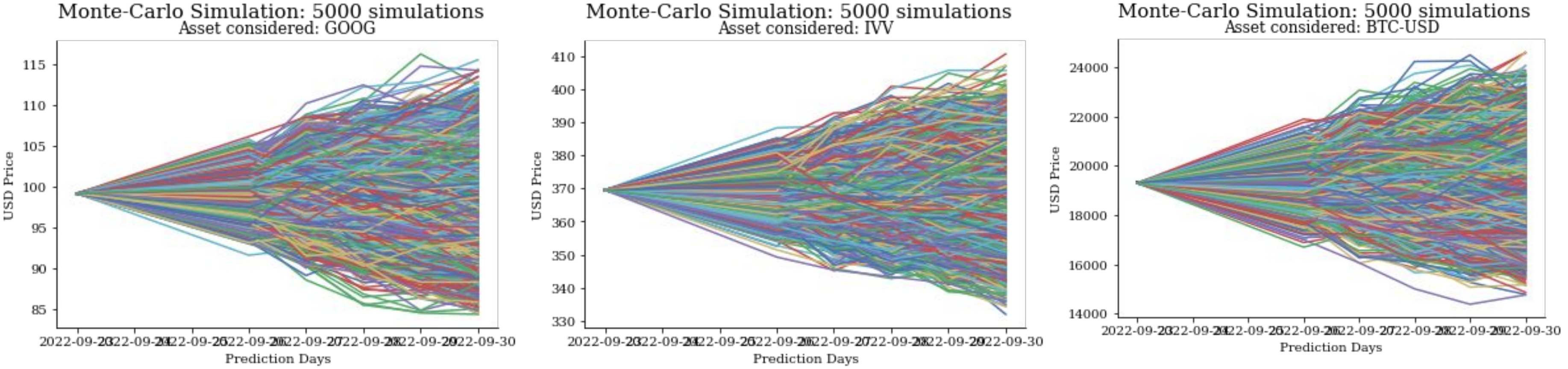

Fig 1: 5,000 simulations of the asset price over the forecast period for GOOG, IVV and BTC-USD

Approach to Portfolio Construction

Week 3: Used ARMA model to predict daily future prices. Long only portfolio.

Weeks 4 & 5: Used LSTM model by identifying appropriate external datasets using indexes for the 3 asset classes. The external datasets consisted of commodity prices and the VIX Index. Long and short portfolio.

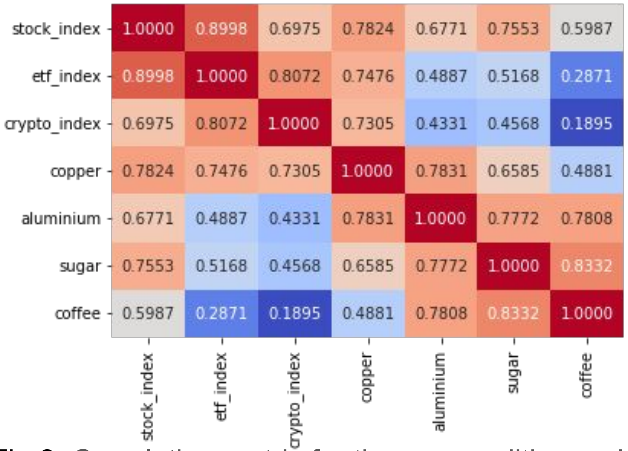

Fig 2: Correlation matrix for the commodities and custom asset indexes

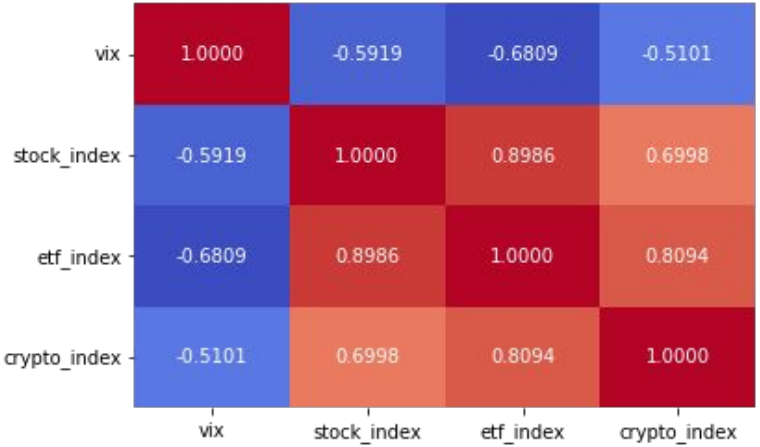

Fig 3: Correlation matrix for the VIX index and custom asset indexes

Approach to Portfolio Construction

Week 6: Used the same LSTM model. However, we had issues with accessing the previous datasets. Switched to new external datasets that consisted of the VIX Index, S&P 500, Effective Federal Funds Rate, and the 5-Year Forward Inflation Rate.

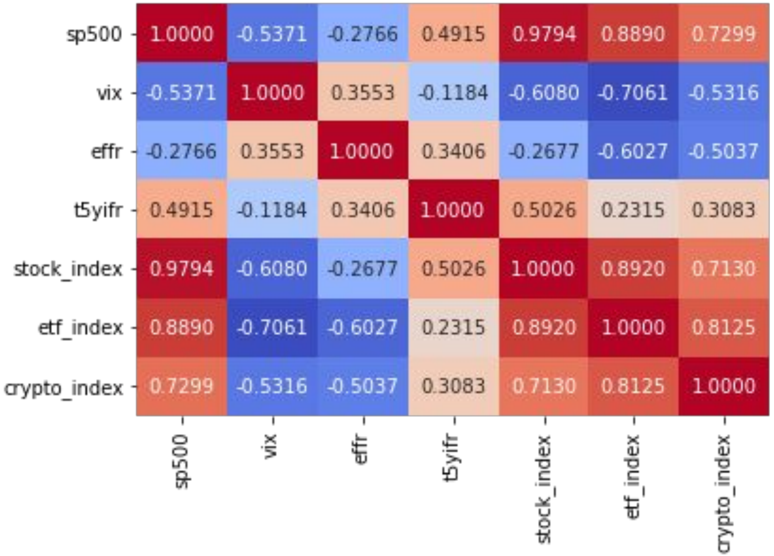

Fig 4: Correlation matrix for the updated datasets and custom asset indexes

Approach to Portfolio Construction

Weeks 7 & 8: Web scraped calendar events and used this to exaggerate weights for the individual stocks in the portfolio. 5.0% of the weight from the stock with the largest weight that do not have an event tied to it was transferred to stocks with an event. Stocks were first categorized into ones with long positions and ones with short positions before the transfer.

We also added the U.S. Dollar Index and the GBP/USD exchange rate into our external dataset to account for the market volatility stemming from cryptocurrencies and government changes in the U.K.

Approach to Portfolio Construction

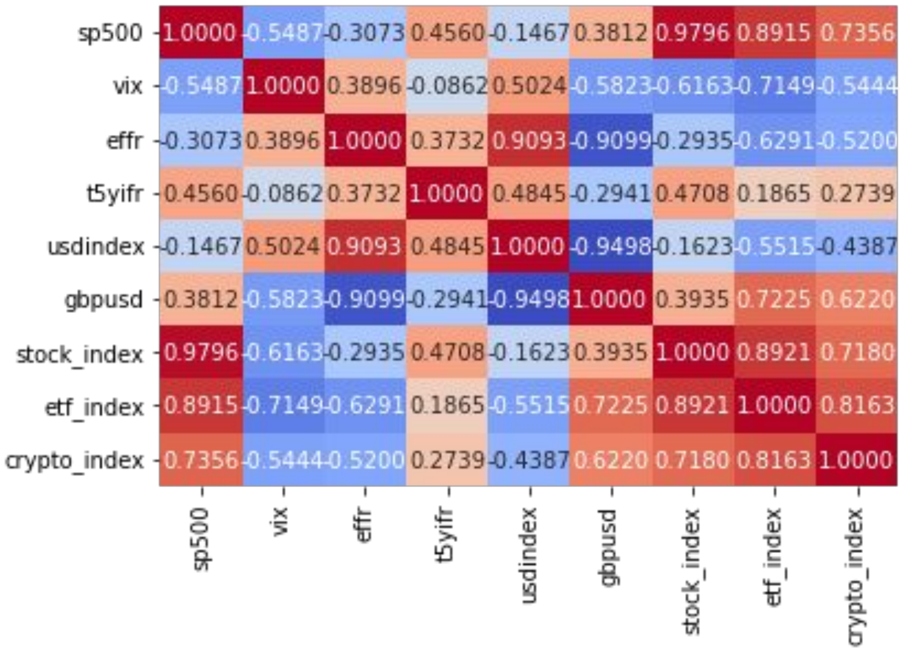

Fig 5: Correlation matrix for the updated datasets and custom asset indexes

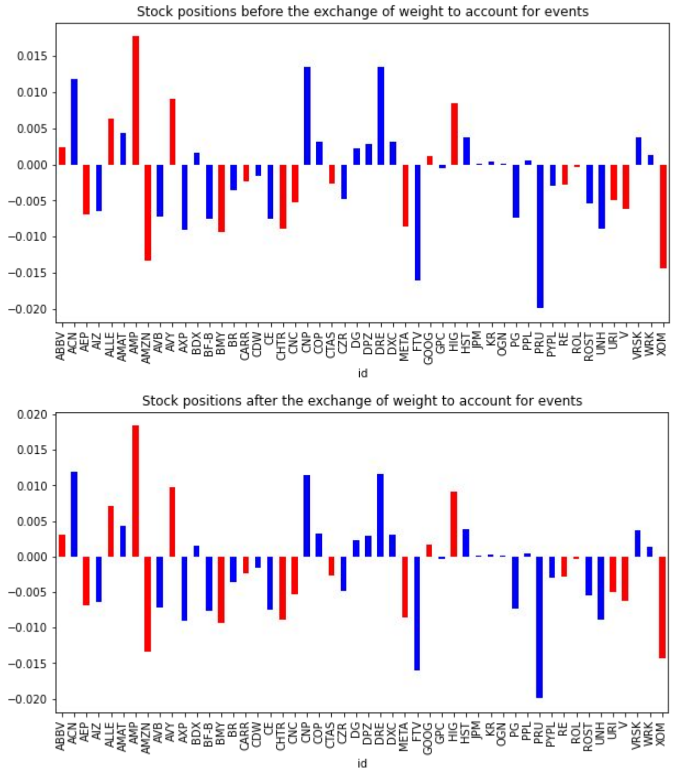

Fig 6: Weights of the 50 public equities in the portfolio separated into those with events (red) and no events (blue) during the forecast period before (top) and after the reallocation of weights for week 7

Approach to Portfolio Construction

Weeks 9 to 11: We were able to access the commodity dataset from the previous weeks again. This was added to the existing dataset to run the LSTM model with the most comprehensive dataset.

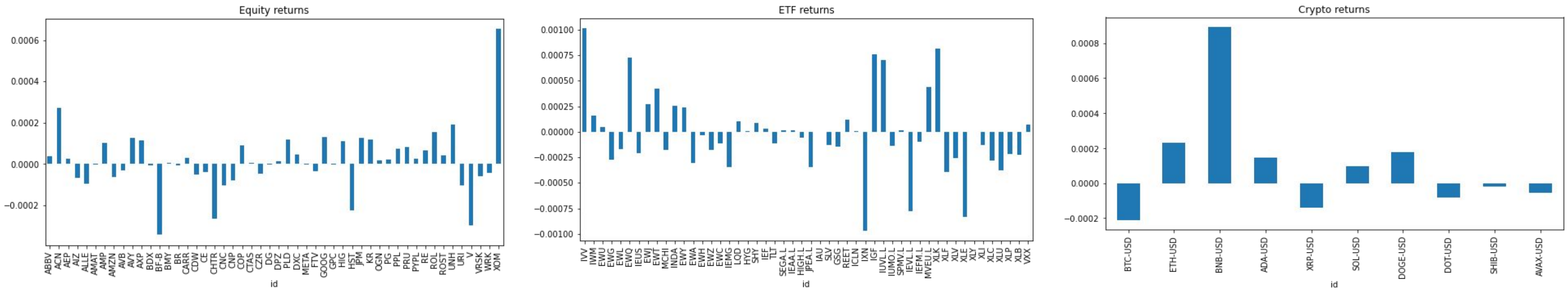

Fig 7: Attribution of portfolio return across the 110 individual assets spanning equities, ETFs, and cryptocurrencies for Week 11

Other Methodologies

We also explored several other methods to supplement our prediction of the individual asset prices. However, we ran into complications when trying to use them in our model as outlined below:

- Integrating Twitter sentiment for cryptocurrencies as a time series - *could not use as the extraction process is extremely time consuming.*
- Training a Convolutional Neural Network to visually identify patterns in asset prices - *training the model involved capturing screenshots of the path asset prices across various time intervals.*
- Extracting news sentiment as a time series - *faced issues with API calls.*

Performance Summary

Week	Ranking	Comments
Week 1	1	Only team to utilize simulations in ranking
Week 2	5	Tied for 5th (last) position. Error in submission file format
Week 3	2	Only instance of using the ARMA model
Week 4	1	Started shorting assets
Week 5	1	Algorithm unchanged from previous week
Week 6	4	Lost access to commodity database
Week 7	3	Initiated our event-driven modification for stock weights
Week 8	1	Exhausted our event-driven modification for stock weights
Week 9	6	Impacted by tech layoffs and cryptocurrency volatility
Week 10	5	Adverse market news moved the market in opposite direction
Week 11	1	Used the most comprehensive dataset

* Ranking relative to 9 teams

Performance Summary

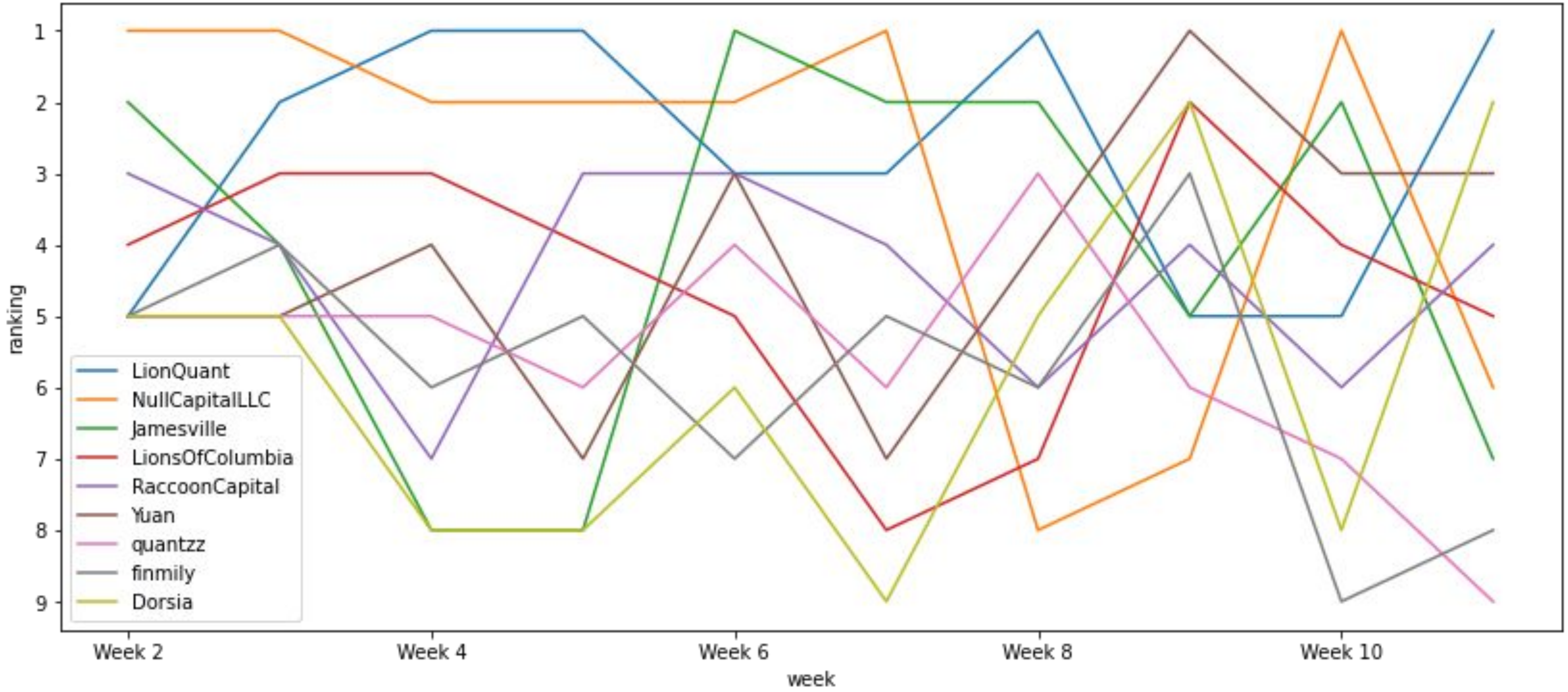

Fig 8: Rankings of each team across the 11 weeks of the competition

Q&A

Thank you!