Portfolio Construction and Forecasting Using Regression

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Project Context

Construct an optimal portfolio from an investment universe consisting of 50 stocks, 50 ETFs, and 10 cryptocurrencies.

Explore datasets that can be used in a model to predict the expected weekly return and familiarize ourselves with different trading strategies

We chose to focus on a linear regression model for the predictive aspect of this project and then played around with different weighting methodologies

Data	**Description**
~~Gas prices~~	~~Used as a proxy for inflation~~
~~News sentiment~~	~~This is a proprietary data field from Bloomberg and is computed using natural language processing. The field assigns a score between -1 and 1 where -1 indicates the maximum amount of negative sentiment and vice versa.~~
20 Day Bollinger Pct	The difference between the current asset value and its 20D lower bollinger band divided by the difference between the 20D upper bollinger band and the current asset value. Filtered for Fridays
14 Day RSI	The average gain over the 14D period divided by the average loss over the 14D period. Periods with price losses are counted as zero in the calculations of average gain. Periods with price increases are counted as zero in the calculations of average loss. The formula uses a positive value for the average loss. Filtered for Fridays
VIX Values	Weekly values for the VIX Index, filtered for Fridays

Datasets Explored

Momentum Strategy

- "Momentum strategies exploit a tendency for a stock's prior returns and prior news about its earnings to predict future returns."
- Pro: Potential to generate high profits over shorter periods of time
- Con: High turnover and very sensitive to market swings
- Datasets:
  - 1 Week Return (%)
  - 1 Month Return (%)
  - 3 Month Return (%)
  - 20 Day Bollinger Pct
  - 14 Day RSI
  - VIX Values

Forecasting Returns Using Regression

Iteration 1

Simple Linear Regression model using historical stock data

- Dependent variable is the percent change in the current week and the decision variables are the 7 day % change and the 28 day % change previous to that week

Iteration 2

Added news sentiment, gas prices, and VIX data as independent variables to the regression

Iteration 3

Focused on a momentum strategy and split up the multivariable regression into a single variable regression for each factor

- Computed the weighted average Mean Squared Error (MSE) to incorporate in the weighted average predicted return

Iteration 4

Introduced a Lasso multivariable regression and split up our data into a train and test set

- Variables: 7 day % change, 28 day % change, 168 day % change, 20 day Bollinger band, 14 day RSI, VIX

Lasso Regression Framework

Input Variables

- Universe 1-week return
- Universe 1-month return
- Universe 6-month return
- 20-day Bollinger Bands
- 14-day RSI
- VIX 1-week return

Train & Validation

- Split the data into train and test sets and feed into the lasso regression
- The lasso regression method desensitizes our model on the training data to prevent overfitting, and leads to more accurate predictions

Run Model

- We used the scikit-learn package to perform the lasso regression analysis and calculate the mse, to quantify our models performance

Optimization and Ranking Methodologies

Optimization

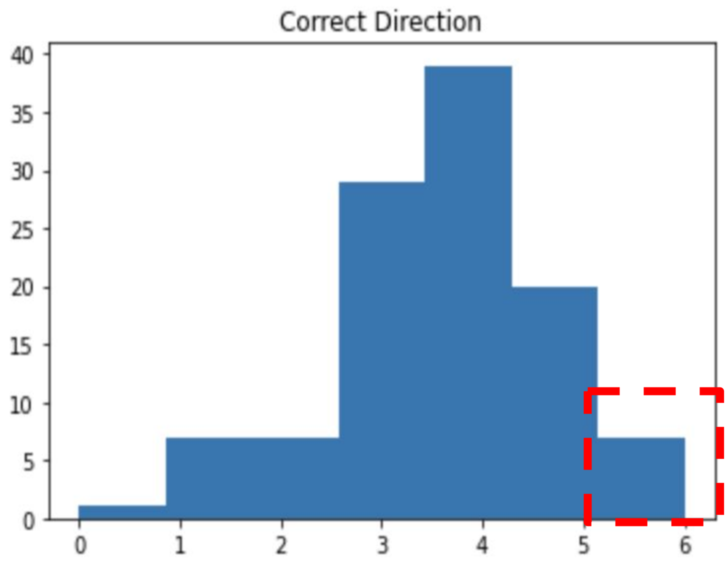
We tested several packages for our optimization model but the code that worked the best for us was running a simulation on 10,000 portfolios and selecting the portfolio weights that yielded the highest Sharpe Ratio

Rankings

Initially we calculated the rank columns by looking at the expected returns computed from our regression model and bucketing them into quintiles. We then leveraged the norm function from the scipy package to calculate each asset's probabilities.

However, as we moved towards an equal weight / mixed weight approach - we revised our rank columns to all be equal to 0.2.

Backtest Results: How many times did our regression model correctly predict direction over the past 7 weeks?



Security	Name	Sector / Asset Focus	Correct Direction
IEAA L	iShares Core € Corp Bond UCITS ETF	Corporate Bonds	6
TLT	iShares 20 Plus Year Treasury Bond ETF	Government Bonds	6
IEF	iShares 7-10 Year Treasury Bond ETF	Government Bonds	6
MCHI	iShares MSCI China ETF	Chinese Stocks	6
META	Meta	Technology	6
EWH	iShares MSCI Hong Kong ETF	Hong Kong Stocks	6
ADA USD	Cardano	Crypto	6

Weekly Movement for Top Securities (Normalized)

Backtest Results: Top 10 assets with the lowest MSE

Security	Name	Sector / Asset Focus	MSE
SHY	iShares 1-3 Year Treasury Bond ETF	Government Bonds	0.000008
IEAA L	iShares Core € Corp Bond UCITS ETF	Corporate Bonds	0.000094
IEF	iShares 7-10 Year Treasury Bond ETF	Government Bonds	0.000137
SEGA L	iShares Core € Govt Bond UCITS ETF	Government Bonds	0.000154
HIGH L	iShares € High Yield Corp Bond UCITS ETF	Corporate Bonds	0.000157
IEFM L	iShares Edge MSCI Europe Momentum Factor UCITS ETF	Momentum Stocks	0.000241
LQD	iShares iBoxx $ Inv Grade Corporate Bond ETF	Corporate Bonds	0.000270
IAU	iShares Gold Trust	Commodity	0.000377
HYG	iShares iBoxx $ High Yield Corporate Bond ETF	Corporate Bonds	0.000388
MVEU L	iShares Edge MSCI Europe Minimum Volatility UCITS ETF	Low Vol European Stocks	0.000536

Week	Forecast Performance	Decision Performance	Weekly Rank
9/11/2022	0.16	-7.80	4.75
9/18/2022	0.16	-16.48	5.25
9/25/2022	0.16	-5.75	6.25
10/2/2022	0.16	2.36	3.25
10/9/2022	0.16	-3.81	7.50
10/16/2022	0.16	7.41	5.50
10/23/2022	0.16	15.17	4.00
10/30/2022	0.16	-2.53	5.50
11/6/2022	0.16	3.76	3.75
11/13/2022	0.16	-10.1	5.25
11/20/2022	0.16	13.57	3.25

In a perfect world...

	18-Sep	25-Sep	2-Oct	9-Oct	16-Oct	23-Oct	30-Oct	6-Nov	13-Nov	20-Nov	**Overall**
DorsiaV3	5.25	6.25	3.25	7.5	5.5	4	5.5	3.75	5.25	3.25	**4.95**
LionQuant	10	4	2	3	6	6	3	9	7.5	2	**5.25**
NullCapitalLLC	1	1	6	2	5.5	3.5	14	14	1.5	7	**5.55**
Jamesville	3.5	8	4.5	13	2	4.5	4.5	9	5.5	7.5	**6.2**
random	4.25	4.25	11.25	4.75	9.25	9.75	4.25	8.25	4.75	12	**7.275**
EW	6.25	5.25	2.75	8	6	3	4.5	5.25	7.25	25	**7.325**
LionsofColumbia	7.5	6.5	6.5	6.5	7	10.5	12	4.5	6.5	7	**7.45**
RaccoonCapital	5.5	8	12	4	6	6	10.5	8	8	6.5	**7.45**
sp500	5.75	8.25	7.75	7.75	6.25	9.25	8.75	4.75	8.75	9.75	**7.7**
Yuan	10	12	6.5	11	6	10	6.5	3.25	6.25	6	**7.75**
quantzz	10	12	8.5	7	6.5	8.5	6.5	11	8.25	11.5	**8.975**
finmily	10	8	9.5	7	13.5	6.5	10.5	7	14	9.5	**9.55**
Dorsia	10	12	14	13	12	13.5	7.5	4.75	9.5	3.25	**9.95**
last_value	6	6.5	10.5	9.5	13.5	10	7	12.5	12	12.5	**10**

In a perfect world...

Takeaways and Extensions

- ★ Important to be diligent and careful when trading securities and sending out trades (ticker symbol changes, fat finger amounts, etc.)
- ★ Starting out simple with an equal weighted approach and slowly modifying it would have yielded the best results
- ★ Looking forward, we would like to integrate our backtest results further into our model
- ★ Incorporate more sophisticated constraints into our optimization model such as beta neutrality or corporate actions information (i.e if a company is going to report)

Thank you! Questions?