REPORT FOR PROJECT 3

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1 Introduction

We aim to use the historical minute-level data of open, high, low, close, and volume for four major cryptocurrencies,including Bitcoin, Ethereum, EOS, and Tron, to simulate the trading strategy, including Long Short-Term Memory(LSTM) model, reinforcement learning model, exponential moving average strategy, and factor models. The training data is from 2019-01-31 16:00:00 to 2021-04-18 23:59:00, and the testing data is from 2021-04-19 00:00:00 to 2021-11-27 06:19:00. Our backtest considers the transaction rate of five basis points per action. Finally, the structured reversal factor model wins with the Sharpe Ratio of 3.07566, and LSTM model wins with the total return of 0.29234. In addition, we utilized the LSTM strategy for the currency in the extension part; without changing any parameter, the Sharpe Ratio and total return could reach 2.01025 and 0.49159.

2 AI Strategy

2.1 Long Short-Term Memory Model

Financial time series prediction is one difficult predictive modeling problem. Unlike the classification model, time series adds the complexity of a sequential dependence among input variables. One of powerful neural networks designed to handle this issue is named recurrent neural networks(RNN), LSTM is one type of RNN used in the deep learning.

After turning parameters of the model by the loss diagram, we set the learning rate, epochs, batch size, hidden size, dropout, and number of layers equal to 0.005, 50, 150, 50, 0.1, and 3 separately.

The validation loss will be tested after every two epochs. Below are train and validation loss diagrams.

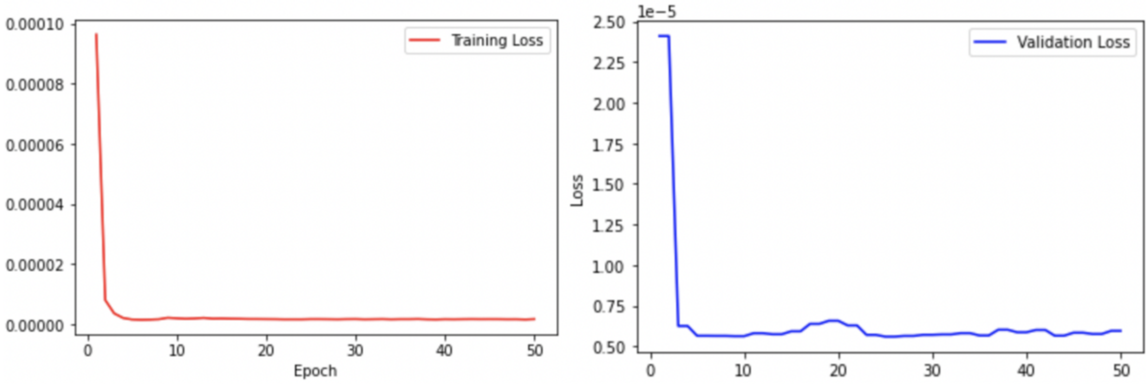

Figure 1: Train/Validation Loss

When the time arrives each 540 minutes, we put the 540-minute k-line data including open, high, low, close price, and combined volume for every crypto currency into trained LSTM model. Higher predicted return from the model, more investment capital to the underlying asset limited to $20,000 in total for each time. However, as the cash balance is lower than $20,000, we only short the asset with negative predicted return due to the cash limit by the rule.

Below is the balance curve and performance statistics for our strategy.

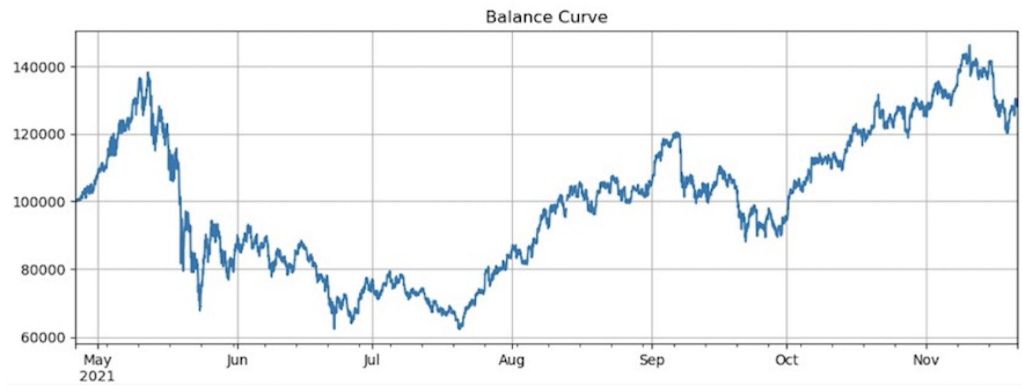

Figure 2: Balance Curve of LSTM Strategy

Total Return: 0.29234	Average Daily Return: 0.00225
Sharpe Ratio: 0.95638	Maximum Drawdown: -0.55499

2.2 Reinforcement Learning Model

In addition, we tried the package of Finrl introduced in class to train our strategy model. Although we overcame the difficulty that authors' codes needed to be changed to train our model, other obstacles included long training and testing time as well as not ideal performance in the test data.

3 Exponential Moving Average Strategy

The Exponential Moving Average indicator(EMA) is an indicator of the moving average. Unlike simple arithmetic moving averages, the average calculated by EMA uses exponential decline weighting to calculate the mean. When it comes closer to the current time, the weight becomes greater.

The formula for EMA of N minutes:

$$EMA(N) = Close(N) * alpha + EMA(N-1) * (1 - alpha) \tag{1}$$

Close(N) shows the close price of the Nth minute. Alpha is a smoothing coefficient lies between 0 and 1 used to smooth the average. Larger the value, greater the weight on the recent close price and smaller the weight on the forward price.

Our double EMA strategy, when the short-term EMA crosses the long-term EMA from bottom to top, the long signal is generated. Otherwise, when the short-term EMA crosses the long-term EMA from top to bottom, the short signal is generated.

But if we generate the signal in every minute, the revenue may not cover the transaction cost. So, after tuning the parameters, we decide to capture the signal in every thirty minutes, and set the alpha as 0.7. Short-term and long-term correspond to five minutes and twenty minutes respectively.

The specific trading strategy is that if the trading order is generated, each currency will be traded with $2,500 dollars per time. When the cash balance is less than $20,000 dollars, the position will be automatically cleared, and wait for the next signal.

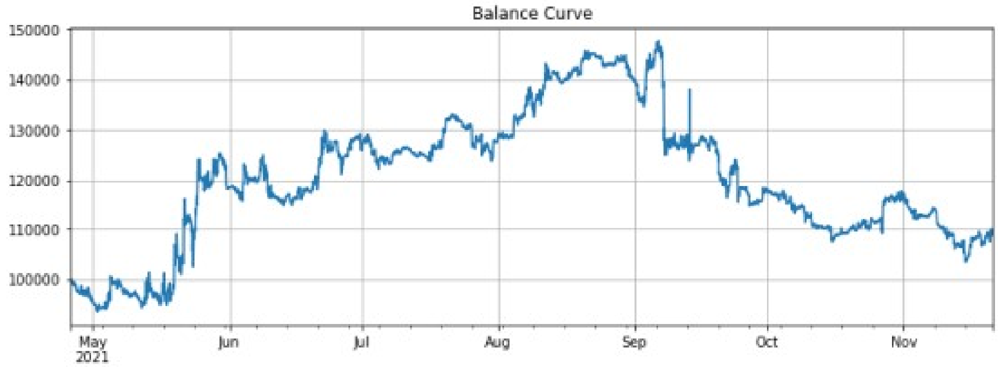

Figure 3: Balance Curve of EMA Strategy

Total Return: 0.09275	Average Daily Return: 0.00068
Sharpe Ratio: 0.56920	Maximum Drawdown: -0.30259

Interestingly, we found that this strategy cannot capture the upward trend of the market, but when the market trend goes down, the strategy can make the profit. This strategy performs quite well in the former period, but performs badly after September. It may not be a good idea to use this strategy to make the decision.

4 Factor Model

4.1 Volatility Range Indicator

As the cryptocurrency is more volatile than other assets, in this part, we backtested some factors constructed by the volatility. However, the result is not as good as we thought. It performed stable when it is a bull market while it cannot avoid the going down with the market's plunge.

We calculated the VRI factors as below, we buy the asset if the VRI is smaller than the lower bound and sell the position if the VRI is higher than the upper bound. For lower and upper bounds, we set 0.01 and 0.95 quantile of VRI of the last thirty minutes. We use open price minus close price as the difference term, then take the difference between the smallest low price and largest high price of last three bars as ExtremeRange term. The volatility is calculated by the standard deviation of the close price with five rolling windows.

$$VRI = \frac{Difference * Volatility}{ExtremeRange} \tag{2}$$

Below is the result for the testing data using this strategy. We can see that it shares the same trend with the market and loses some money when the price goes down. The max drawdown is a little high and it does not perform as good as we thought. For the further exploration, we can combine the volatility factors

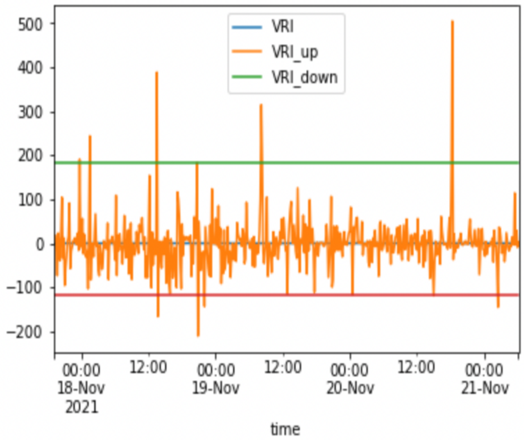

Figure 4: VRI Bound

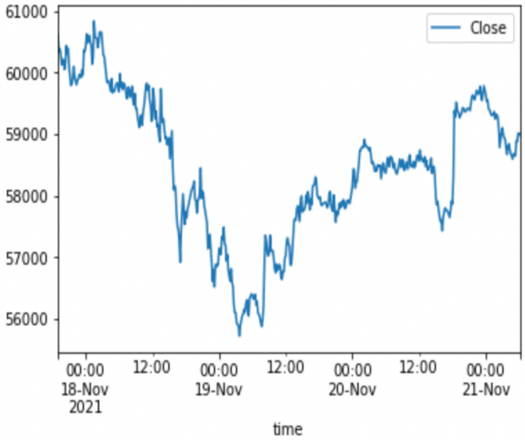

Figure 5: Close Price

with other strategies like Bollinger Bands as an additional condition for opening or closing positions, instead of taking it as a single factor. We also tried other factors which can distinguish positive volatility and negative volatility and build strategy based on them; however, they follow the market trend as well.

Figure 6: Balance Curve of VRI Factors

Total Return: 0.11551	Average Daily Return: 0.00060
Sharpe Ratio: 0.92713	Maximum Drawdown: -0.18097

4.2 Structured Reversal Factor

In traditional financial market, momentum and reversal factors are often used to construct a strategy to select stocks or futures to long or short. The momentum strategy is a trading rule that buying winners and selling losers, whereby the rank is obtained from the historical data based on their log-returns during the formation period. The portfolio is constructed by taking long positions on the winners, while short selling the losers. On the contrary, a reversal strategy buys the worst and sells the best performers based on a historical ranking.

We make some improvements in this strategy and apply this improved model to trade cryptocurrency. Momentum and reversal effect can be combined together to produce signals.

First, for each specific formation period, the data are sorted by the trading volume from the lowest to the highest. A critical volume point is chosen to split the period into momentum period and reversal period. Take the period whose trade volume lower than this point as the momentum period and the period whose trade volume larger than this point as the reversal momentum.

Momentum factor, reversal factor and combined structured factor can be calculated by formula(3) , formula (4), and formula(5) respectively.

$$FACTOR_{momentum} = \sum_{i=1}^{peirod_{momentum}} \omega_i * \ln \frac{Open_{t-i+1}}{Open_{t-1}}, \omega_i \propto \frac{1}{volume_i} \tag{3}$$

$$FACTOR_{reversal} = \sum_{i=1}^{peirod_{reversal}} \omega_i * \ln \frac{Open_{t-i+1}}{Open_{t-1}}, \omega_i \propto volume_i \tag{4}$$

$$FACTOR_{structure} = FACTOR_{momentum} - FACTOR_{reversal} \tag{5}$$

Below is the balance curve and performance statistics for this improved strategy.

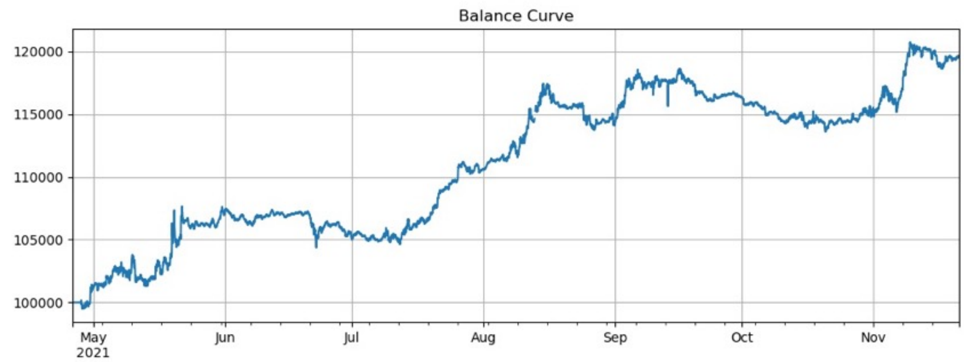

Figure 7: Balance Curve of Combined Momentum and Reversal Strategy

Total Return: 0.19485	Average Daily Return: 0.00086
Sharpe Ratio: 3.07566	Maximum Drawdown: -0.04359

4.3 Smart Money Factor

The smart money factor is designed to find the "Smart" trades.

The calculation for this factor follows several steps. First, the historical trades during a specific period are sorted from the highest to lowest by an indicator S calculated by formula(6). The top trades whose volume account for twenty percent of the total trade volume are defined as "smart" trades. Then we calculate the volume weighted average price of the smart trades and the total trades respectively. Finally we can get the smart money factor by formula(8)

$$S = \frac{|Return|}{Volume^{\beta}} \tag{6}$$

$$VWAP = \frac{\sum Price * Volume}{\sum Volume} \tag{7}$$

$$FACTOR_{smart} = \frac{VWAP_{smart}}{VWAP_{all}} \tag{8}$$

Here we take β equal to -0.25. The balance curve and performance statistics for this improved strategy are shown as below.

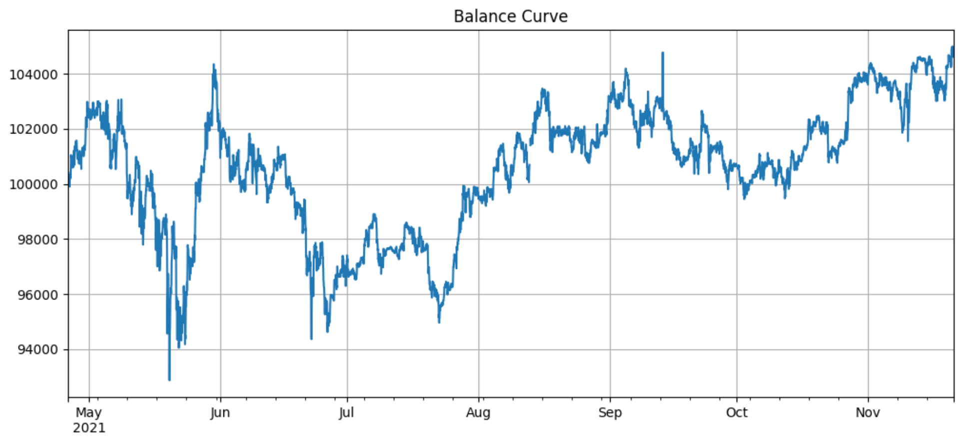

Figure 8: Balance Curve of Smart Money Strategy

Total Return: 0.04835 Average Daily Return: 0.00026
Sharpe Ratio: 0.58486 Maximum Drawdown: -0.10457

5 Extension

We utilized the LSTM strategy for the currency in the extension part; without changing any parameter, the Sharpe Ratio and total return could reach 2.01025 and 0.49159.

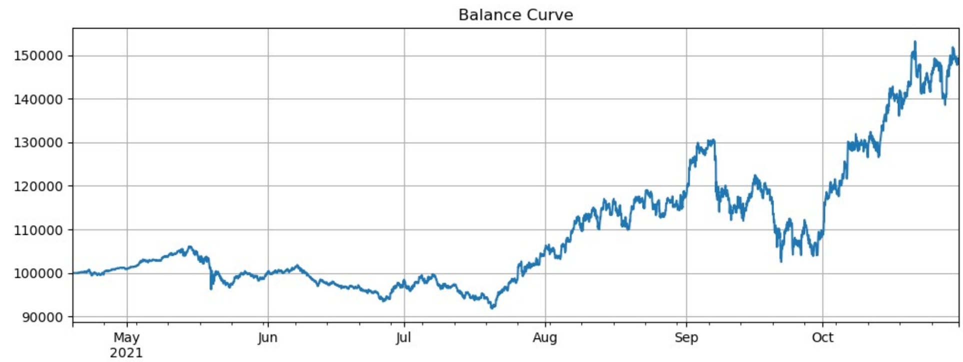

Figure 9: Balance Curve of LSTM Strategy for the Extension

Total Return: 0.49159	Average Daily Return: 0.00229
Sharpe Ratio: 2.01025	Maximum Drawdown: -0.22540

6 Conclusion

The below table compares the performance statistics for our different strategies. The structured reversal factor model wins for the Sharpe Ratio of 3.07566, and the LSTM model wins for the total return of 0.29234.

	LSTM	EMA	VRI	Smart Money	Structured Reversal
Total Return	0.29234	0.09275	0.11551	0.04835	0.19485
Sharpe Ratio	0.95638	0.56920	0.927153	0.58486	3.07566
Average Daily Return	0.00225	0.00068	0.00060	0.00026	0.00086
Maximum Drawdown	-0.55499	-0.30259	-0.18097	-0.10457	-0.04359

Table 1: Strategy Comparison