Kharagpur Data Science Hackathon 2024

Final Report

Team #include<team.h>

1 Introduction

Our journey starts as we face the unique challenges of the BTC/USDT cryptocurrency market in the world of algorithmic trading. This field operates in a fast-paced environment where every moment can either bring opportunities or risks. As active participants, we embrace the complexity of the digital landscape and focus on creating trading techniques. These techniques aim not only to withstand market ups and downs but also to achieve returns that surpass benchmarks. Our combined efforts result in a mix of innovation and strategic thinking. We develop and use algorithms specifically designed to navigate the intricacies of the BTC/USDT market. Beyond the potential for profits, we also prioritize the crucial aspect of managing risks, which is especially important in the unpredictable world of cryptocurrency trading. Cryptocurrencies are always changing, requiring us to stay flexible and aware of market trends. As contributors, we present this report not just as a summary of our work but as a part of the ongoing story of innovation and expertise in BTC/USDT algorithmic trading. We hope our work sparks new ideas, encourages teamwork, and promotes methodologies where algorithms play a key role in maximizing returns and controlling risks.

2 Final Strategy

2.1 Strategy Intuition and Hypothesis

In the realm of BTC/USDT trading, where trends are prominent and market volatility is high, the problem at hand necessitates a pursuit of a Drawdown that leans towards higher end and not the lower end. The emphasis lies on identifying scenarios characterized by robust trend strength and minimal volatility. The assurance of a strong trend translates to favorable returns, while the commitment to low volatility mitigates risk. The idea of Dual Thrust is similar to a typical breakout system, however dual thrust uses the historical price to construct update the look back period - theoretically making it more stable in any given period.

The hypothesis proposes a trading strategy for Bitcoin based on:

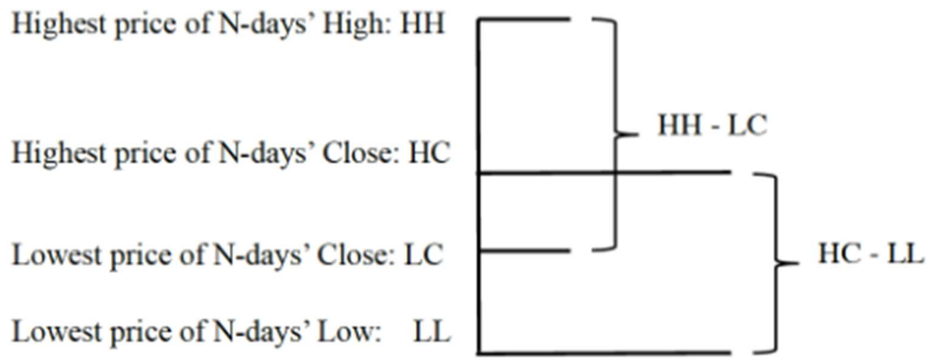
1. the historical price is used to calculate the range based on the close, high, and low over the most recent *N* days.
2. A position is opened when the market moves a certain range from the opening price.

2.2 Implementation of Algorithm

In order to calculate the range, each trading day we need the close, high, and low price data over the most recent *N* days. In addition, the open price of the current day is required in order to generate the signals. Then the range is calculated by

$$range=max(HH-LC,HC-LL)$$

In this implementation, we choose N=4. It is less than one week and the range would reflect the recent price change.



2.3 Trading Implementation

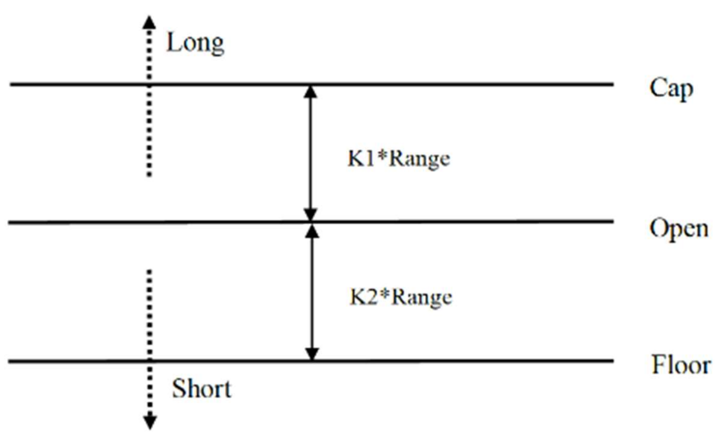
The long signal is calculated by

$$cap = open + K1 \times range$$

The short signal is calculated by

$$floor = open - K2 \times range$$

where $K1$ and $K2$ are the parameters. When $K1>K2$, it is much easier to trigger the long signal and vice versa.
we choose $K1=K2=0.5$. We can still use historical data to optimize those parameters or adjust the parameters according to the market trend. $K1$ should be small than $K2$ if you are bullish on the market and $K1$ should be much bigger if you are bearish on the market.
This system is a reversal system, so if the investor holds a short position when the price breaks the cap line, the short margin should be liquidated first before opening a long position. If the investor holds a long position when the price breaks the floor line, the long margin should be liquidated first before opening a new short position.



2.4 Further Improvement and Risk Management

Considering the fact that the BTC/USDT market shows high volatility, there is a good chance that an exit condition shows signs for immediate trend reversal to a considerable extent.

Used `MaximumDrawdownPercentPerSecurity` Risk model to limit the maximum drawdown to a specific percentage.

Note: All the Trades were limited to 8% drawdown as specified in problem statement.

2.5 Performance

- Initial Balance = 1,00,000
- Commission = 0.15 percent
- The results can be seen in Fig 1.
- The comparison between logged values of portfolio and close have been shown in Figure 2.

Metrics	Value
Return(%)	1735.15%
Compound Ann. Return(%)	51.465%
Sharpe Ratio	1.058
Treynor Ratio	0.99
Profit-Loss Ratio	3.0
Max. Drawdown	23%
Average Drawdown	8%
#Trades	436
Win Rate	37%
Annual Standard Deviation	0.44
Total Fees	$3780330.94

Fig 1

Fig 2

4 Alternate ML Based Strategies we explored

4.1 ARIMA model Time series prediction model

4.1.1 Strategy

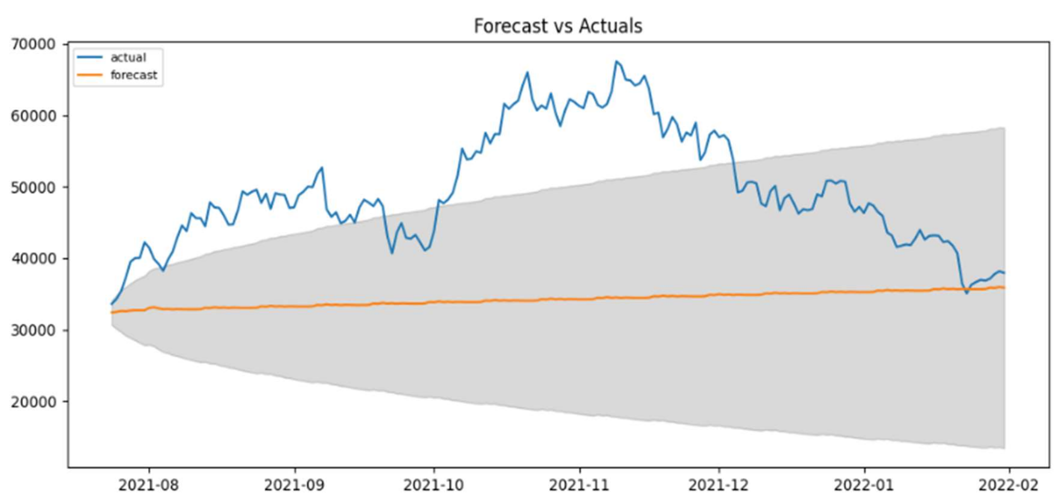
Used SARIMA model of `train,order=(3,0,0), seasonal_order=(0,1,2,12)` to predict the price of BTC with model summary as decribed below:

```
                                      SARIMAX Results
============================================================================================
Dep. Variable:                                Open   No. Observations:                 1300
Model:             SARIMAX(3, 0, 0)x(0, 1, [1, 2], 12)   Log Likelihood              -10612.130
Date:                             Thu, 04 Jan 2024   AIC                          21236.261
Time:                                     16:24:15   BIC                          21267.226
Sample:                                 01-01-2018   HQIC                         21247.884
                                      - 07-23-2021
Covariance Type:                               opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.9316      0.001   1592.290      0.000       0.930       0.933
ar.L2          0.1329      0.015      9.075      0.000       0.104       0.162
ar.L3         -0.0645      0.015     -4.423      0.000      -0.093      -0.036
ma.S.L12      -1.1156      0.016    -68.236      0.000      -1.148      -1.084
ma.S.L24       0.1159      0.012     10.021      0.000       0.093       0.139
sigma2      7.847e+05   2.15e-08   3.66e+13      0.000    7.85e+05    7.85e+05
===================================================================================
Ljung-Box (L1) (Q):                   0.14   Jarque-Bera (JB):             12354.03
Prob(Q):                              0.71   Prob(JB):                         0.00
Heteroskedasticity (H):               6.34   Skew:                            -0.46
Prob(H) (two-sided):                  0.00   Kurtosis:                        18.14
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 1.47e+28. Standard errors may be unstable.
```

4.1.2 Drawbacks

1. ARIMA model was not able to capture the minor fluctuations
2. This resulted in low model accuracy and non-competency of prediction usage as show in fig4



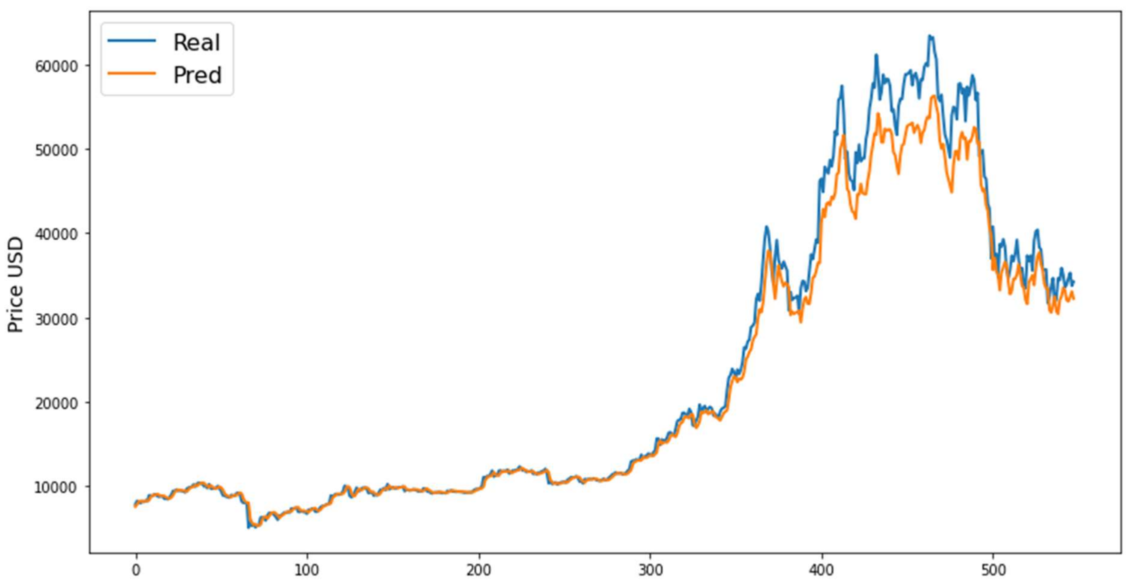
4.2 Deep Leaning model Time series prediction model

4.1.1 Strategy

Used RNN(LSTM) model to predict the price with model summary as described below:

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm (LSTM)                  (None, 100)               40800
_________________________________________________________________
dropout (Dropout)            (None, 100)               0
_________________________________________________________________
dense (Dense)                (None, 1)                 101
_________________________________________________________________
activation (Activation)      (None, 1)                 0
=================================================================
Total params: 40,901
Trainable params: 40,901
Non-trainable params: 0
_________________________________________________________________
```

Although the model was able to capture the prices quite accurately the Drawdown of the model was over 50% thatswhy we rejected this model.



5 Results, Discussion and Conclusion

During the course of 10 days, we tried several approaches, both DL based and Price Action/Indicator based. We realized that while using ML based approaches give good results on the test data, it delivers inconsistent robustness and generalization properties. This fact led us towards Price Action/Indicator based strategies. The final strategy that we used showed great performance with good robustness and consistent results. Further improvements to the same topic can be done using either Indicator-based or ML-based conditions