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DSC 423: Data Analysis and Regression

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Bitcoin Price Predictor Regression Model

Trading Bitcoin is often driven by profiting from its price fluctuations or hedging against inflation. However, the highly volatile nature of Bitcoin's value can be tricky to anticipate, forcing many to shy away from it. Despite this, cryptocurrency is undeniably the future and gaining a deeper understanding of its behaviour via a variety of market, economic and social factors is a must. Understanding the drivers of Bitcoin's price is essential to assessing the crypto market in order to reap the benefits of a good Bitcoin investment.

This project utilises regression models to predict the Bitcoin price by working with quantitative and sentiment-based indicators to see if they play an important role in Bitcoin price movements. The model can assist in forecasting the overall future trend for Bitcoin prices, helping with the bigger picture for a variety of clients, such as Trading Firms, Hedge Funds, Crypto exchanges, Fintech startups and more. It looks out for issues such as multicollinearity and overfitting while assessing which top five predictors have the most impact on Bitcoin's price movements.

Data Selection and Preparation

The dataset being used has been downloaded from Kaggle. It spans 17'515 rows and 131 columns, which includes open, high, low, close and volume data for several cryptocurrency pairs such as BTC/USDT, ETH, USDT, etc. It also includes information about commodities such as crude oil, gold, corn and global stock indices like NASDAQ, DAX, S&P 500. Furthermore, there are some sentiment variables such as the fear and greed index, open interest and Google Trends data. Overall, the quality of the dataset is high and can be used to focus on crypto-market behaviour analysis or create a Bitcoin Price Predictor model.

Data Preparation

The Data Preparation section took a significant time, where special attention was given to handling missing and irrelevant values. This helped improve model accuracy and stability. Features with mostly or entirely "NaN" values were deleted altogether. For the most part, these features were volume-based columns. It was justifiable to drop these columns as they did not provide helpful information for building the model. Additionally, they would have contributed to the noise and computational overhead.

Time stamps were turned into features in order to extract trading activity during different times from the original datetime column. Numeric columns were normalised using the min-max technique, as the Regression model is sensitive to feature magnitude. This helped ensure that predictors with larger numeric ranges do not dominate the model training.

The "BTC_USDT_1h_close" was selected as the target variable. It refers to the price of one Bitcoin in Tether at the end of each hourly interval. These steps helped retrieve an information-rich and complete dataset, which was ready for the next step.

Data Analysis

Visualisation and Data Statistics

Throughout the paper, different visualisation methods were used, such as correlation heatmaps, boxplots, time series plots and more.

Variable Selections and Multicollinearity

The most relevant predictors were identified by first doing a correlation analysis. The top ten variables most positively correlated with the target were identified. Out of which, three BTC-related variables (BTC_USDT_1h_open, high, and low) were dropped as they were too close to the target variable being predicted. Keeping them would have caused multicollinearity and overfitting issues. The remaining variables showed a strong correlation with SOL and S&P 500 values, enhancing predictive value and hence were retained.

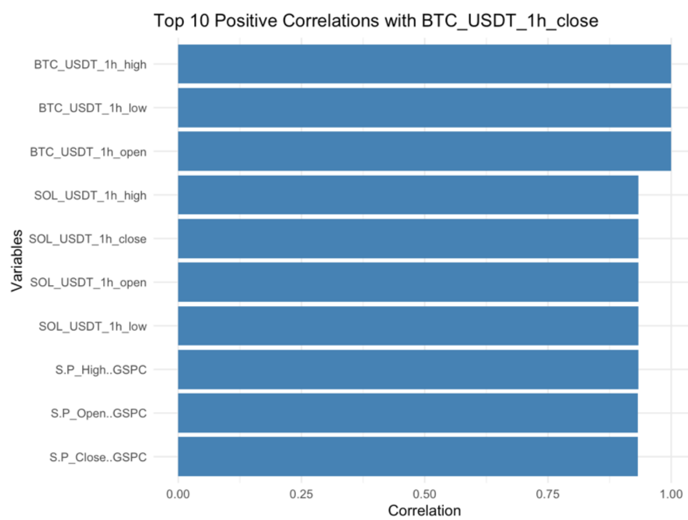

Fig 1. Top 10 positively correlated Variables with Target variable.

Then the VIF values were assessed, where features with a VIF value of more than 10 were removed. This process resulted in 30 predictors, which were used to build a robust model from all the available predictors.

Model Building

First Model: Normal Linear Model

Analysis and Results

The first model was built using a standard linear regression model with the selected predictors. The model summary showed a strong model performance with an Adjusted R^2 of 0.8622. This meant that 86.22% of the variation in the hourly Bitcoin closing price could be explained by the selected predictors. Some of the highly significant predictors included "funding_rate", "google_trends_buy_crypto" and "cattle.Close.LE.F".

Cross Validation and Residual Analysis

A 10-fold cross-validation was conducted to assess the model's generalisation. It achieved an RMSE of 0.108 and an MAE of 0.0854, which further validated the model's strong performance. The R^2 value (0.8608445) was almost identical to the model's Adjusted R^2 (0.8622), suggesting low chances of overfitting. The Residual Analysis, however, shed light on the more problematic aspects of the model, which needed instant attention.

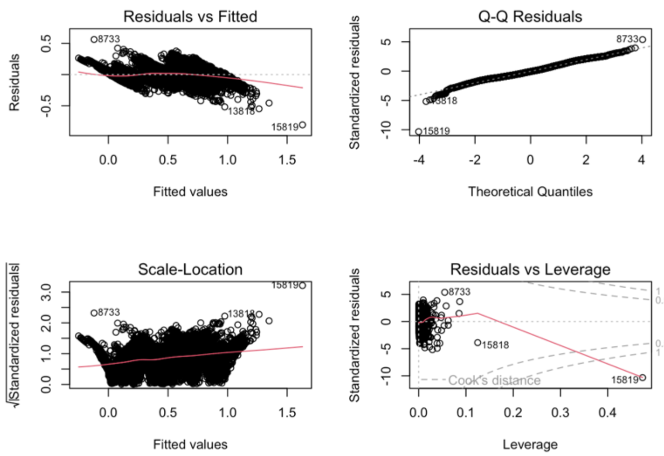

Fig 2. Residual Analysis of Model 1.

The results clearly revealed that the model was violating the linear model assumptions. The Residual vs. Fitted graph shows a clear pattern rather than a random scatter, which suggests heteroscedasticity and slight non-linearity. The Q-Q Residuals revealed there are major outliers present in the dataset, which explains why the residuals are not normally distributed.

This indicated the next necessary steps to be taken. These included taking care of outliers and dealing with the non-linearity. However, the first linear model provided a solid baseline to work on due to the strong predictive accuracy and the strong feature set.

Second Model: Piecewise linear model

Analysis

When addressing the mild non-linearity, a piecewise linear model was considered appropriate. Initially, a piecewise model with one knot at 0.277 was created using the predictor "funding_rate"; however, a better fit was a model with two knots estimated at 0.277 and 0.550 to deal with the trend of the data. This divided the data into three parts. It helped capture these distinct behavioural phases:

1. Sharp negative slope (approximately -6.71) below 0.277
2. Upwards trend (approximately +1.01) between 0.277 and 0.550
3. Moderate decline (approximately -1.11) above 0.550

Residual Analysis and Results

After this segmented model was expanded over to all 30 selected predictors using the "funding_rate" breakpoints, the model showed significant improvement. The Adjusted R^2 increased to 0.883.

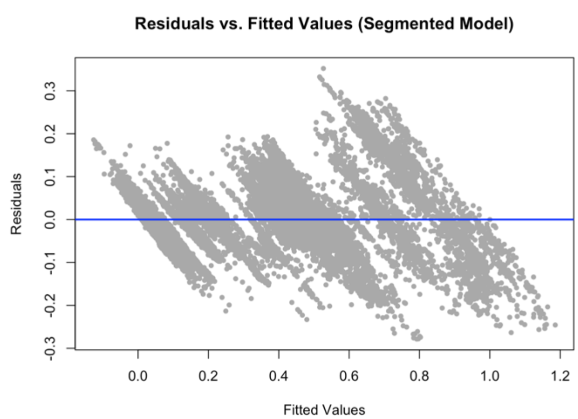

Fig 3. Residual Analysis of Model 2.

The updated residuals vs. Fitted Values plot for the segmented model showed improvement in homoscedasticity compared to the initial model. However, further improvement was needed, as a striped pattern remained visible. The segmented model was a great next step in improving the model.

Third Model: Cleaned Piecewise linear model

Analysis

The next issue which needed to be addressed was the presence of outliers, which negatively impacted the distribution of residuals. To improve the normality in the residuals, Cook's Distance was used. It helped identify high-leverage observations. Any datapoints above the threshold of 4/n were removed from the dataset. The scatterplot below highlights the specific data points which were removed from the dataset.

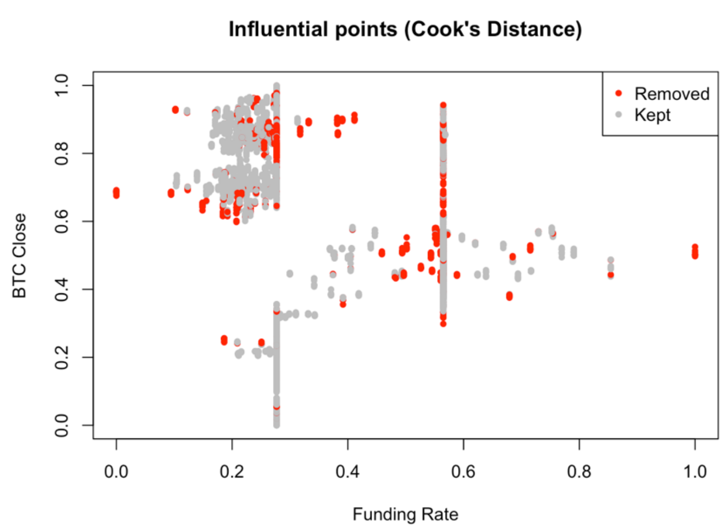

Fig 4. Influential points removed by using Cook's Distance

Residual Analysis and Results

After assessing the summary of the piecewise linear model created by using the updated and cleaned dataset, it was evident that the model had improved. The R^2 value increased to 0.920, and the estimated breakpoints shifted to 0.335 and 0.562 based on the cleaned dataset. The distinct behavioural phases in this case were:

1. Sharp negative slope below 0.335

2. Upwards trend between 0.335 and 0.562
3. Sharper decline above 0.562

This model continued to highlight “google_trends_buy_crypto”, “cattle_Close.LE.F”, and “fear_greed_index” as the most influential predictors in predicting the target variable. The new Residual Plot further gave reassurance that the new model, indeed, was better than the previous one. The diagonal pattern seemed to have lessened, indicating improved linear fit and lower bias.

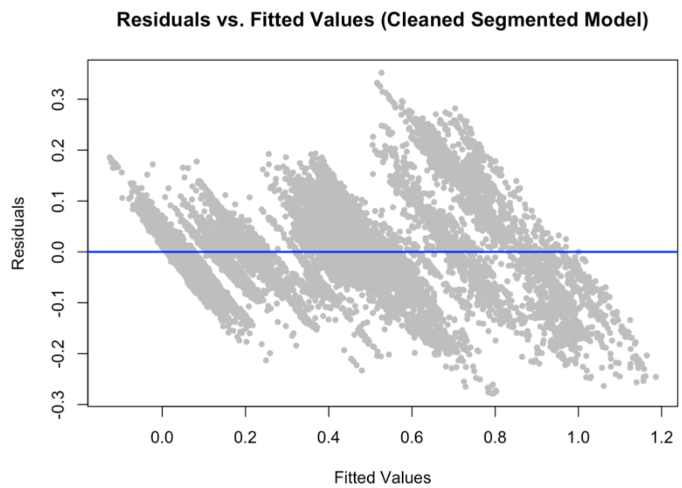

Fig 5. Residual Analysis of Model 3.

Fourth Model: Cleaned Piecewise linear model and Interaction Terms

Analysis

In the next attempt to address the diagonal residual pattern, adding interaction terms proved effective. This is because interaction terms can help detect missing interaction effects between predictors. However, adding too many interaction terms can harm the model by exposing it to the risk of overfitting or multicollinearity. Therefore, only three interaction terms were added to the chosen predictors:

1. “funding_rate” * “fear_gread_index” may indicate how the funding rate may affect prices

2. “funding_rate” * “weekend” may indicate how the funding rate is affected over the weekend
3. “google_trends_buy_crypto” * “fear_gread_index” may indicate how public interest has an effect on fear/greed periods based on psychology.

Residual Analysis and Results

The fitted model yields an adjusted R^2 of 0.9366. This was an improvement compared to the previous model. The strong predictors remain the same as before. The new interaction terms were strongly significant with a p-value of less than 0.001. This confirms that adding these enhancements to the model improves its performance.

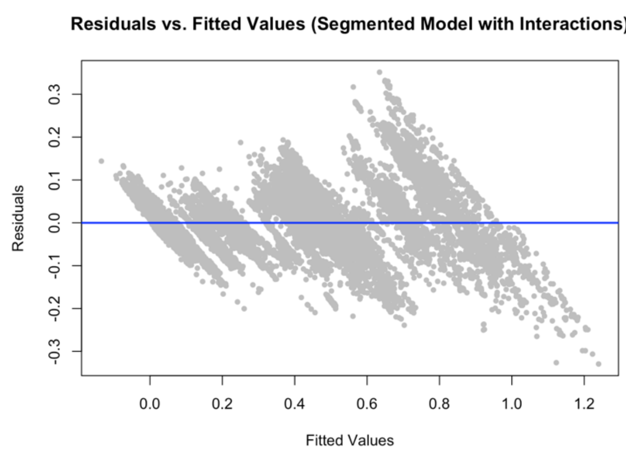

Fig 4. Residual Analysis of Model 4.

Despite the fanning pattern being better than before, it was still persistent. However, its reduction indicates that the interaction terms were indeed helpful. This highlights the complexity of crypto market dynamics, which depend on predictors that are not always independent or linear.

Fifth Model: Cleaned Piecewise linear model with Interaction and Nonlinear terms

Analysis and Results

As a final attempt to address this model's residual pattern issue, a nonlinear term was added to the predictors. The term added to the regression formula was "(funding_rate)^2". This quadratic term was added in hopes of capturing the curvature in the relationship between funding rate and BTC closing price. The term "funding_rate" was specifically chosen as it already has breakpoints through the segmented model, and adding the "(funding_rate)^2" was expected to introduce curvature to those segments, reducing the structured residual pattern observed from the Residual Analysis of Model 4. The newest and final model also retained the interaction terms from the previous attempt, based on its positive performance.

Residual Analysis and Results

The non-linear term was highly significant with a p value <0.001 and a strong negative coefficient of -3.277. This confirmed the concave nature of the relationship. Furthermore, the Adjusted R^2 value increased to 0.9416, which was the highest till now. This suggested an improved model compared to the ones created before. The residual standard error was also reduced to 0.06821. Through the Cross-Validation (10-fold) results, the RMSE was noted as 0.0807, which shows that the predictions made are closer to the actual value on average. The R^2 was noted as 0.9183, meaning that more variance in the target variable can be explained than ever before. Lastly, the lower MAE further reflects improved model accuracy. These findings indicate strong generalisation performance and a reduced prediction error.

The residual vs. fitted plot for the final model shows a much less severe pattern compared to the initial one, indicating that all the additions made to the model have helped the plot better align with the assumptions of a linear model, as there is no extreme heteroscedasticity or curvature present. The final model obtained is the best one so far, with a lower residual error and minimised systematic bias in residuals.

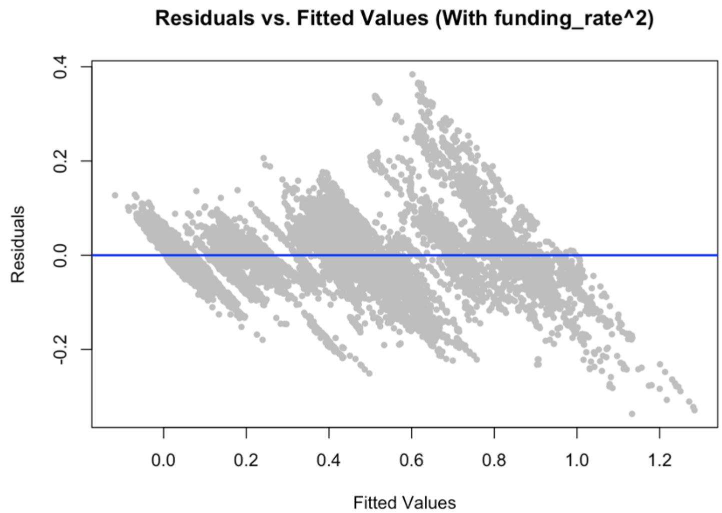

Fig 5. Residual Analysis of Model 5.

Comparison of Results

Comparisons of Model Summaries

Methodology	**Residual Std. Error**	**Adjusted R^2**	**Breakpoints (Funding Rate)**
Model 1: Basic Linear Model	0.1075	0.8622	-
Model 2: Segmented Model	0.099	0.8832	0.333, 0.565
Model 3: Segmented Cleaned Model	0.0798	0.9200	0.335, 0.562

Model 4: Segmented Model with Interaction Terms	0.0711	0.9366	0.328, 0.560
Model 5: Segmented Model with Interaction and Non-Linear Terms	0.0682	0.9416	0.276, 0.278

Model Discussions

The "Comparisons of Model Summaries" table clearly shows that there was a consistent progression in the model in terms of both statistical robustness and real-world interpretability. Model 1 served as a strong foundational starting point, however, it was limited by linear simplicity. It failed to capture the complex, non-linear relationships that the predictors may exhibit. This was reflected by the residual pattern and a relatively lower R^2 (when compared to the future models). Model 2 was an improvement of the previous model, which introduced segmentation on the "funding_rate" predictor. However, the model was still severely impacted by influential outliers. Model 3 utilised Cook's distance to remove these high-leverage data points and tightened the residual spread. This offered a more reliable representation of the possible underlying relationships between predictors. Model 4 further advanced the previous model by incorporating three interaction terms. These helped mimic real market indicators, which impacted the model heavily. Lastly, Model 5 became the most comprehensive model, as it combined segmentation, interaction terms and a non-linear, quadratic term. This model was able to accurately predict the hourly Bitcoin closing rate, which closely aligned with the sentiment-driven and volatile nature of the cryptocurrency market.

Comparisons of Model 1 and Model 5's Cross Validation

Metric	**Model 1**	**Model 5**
RMSE	0.1081	0.0807
R^2	0.8608	0.9183
MAE	0.0854	0.0613

The "Comparisons of Model 1 and Model 5's Cross Validation" table highlights the superiority of Model 5 in generalizability and real-world forecasting utility compared to the initial Model 1. Model 1 had an RMSE of 0.1081 and an R^2 of 0.8608, which then improved to 0.0807 and 0.9183, respectively, for Model 5. This improvement represents an increase of over 25% in predictive accuracy. In terms of a real-world application, such an improvement can significantly benefit clients utilising this model for trading strategies or portfolio management.

Discussion and Conclusions

The final model is a valuable tool for traders, risk managers or high-frequency crypto markets as it demonstrates strong predictive skills and statistical integrity. The time series line plot compares the actual vs predicted BTC price over time. The BTC closing time is normalised to be scaled between 0-1. The predicted values closely follow the actual BTC trend, visually showing the model's accuracy rate. The smoothed actual vs. predicted plot gives a more user-friendly insight into the model's performance. It helps reinforce the fact that the model is capable of generalising well over time. The predicted BTC price against funding rate provides clear breakpoints that illustrate the model's ability to adapt to sharp behavioural shifts in market sentiment, specifically around the funding rate range of 0.276 to 0.278.

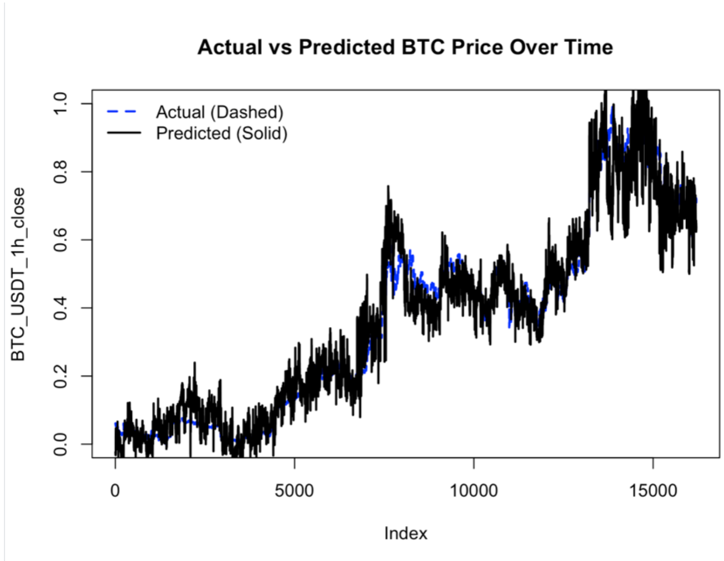

Fig 6. Actual vs Predicted BTC Price Over Time time series line plot

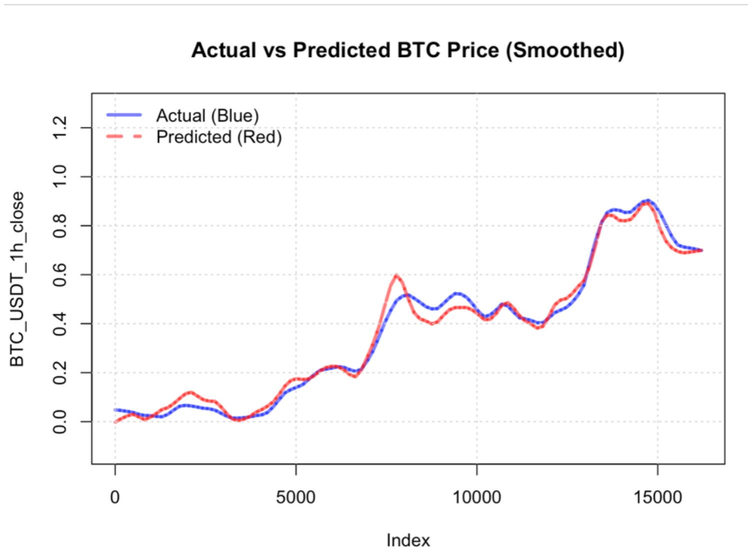

Fig 7. Actual vs Predicted BTC Price (Smoothed)

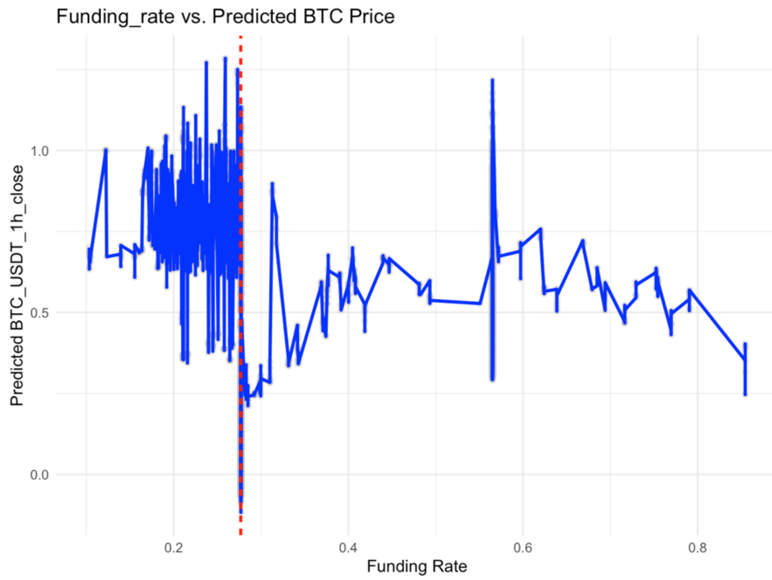

Fig 8. Funding_rate vs. Predicted BTC Price

Evaluating coefficient magnitudes of standardised predictors revealed the five most influential variables: “google_trends_buy_crypto”, “cattle_Close.LE.F”, “S.P_Volume..GSPC”, “google_trends_buy_crypto:fear_gread_index” and “Dow_Volume..DJI”. These predictors show that the multifactorial nature of BTC price movements depends on funding mechanisms, sentiment, global macroeconomic indicators and commodities.

Recommendations and Future Work

Despite the model being robust and dynamic thanks to its flexible design, which allows it to adapt to evolving market behaviours, from a business perspective, specifically in the realm of financial forecasting, even small differences in predictions can result in significant real-world consequences.

Currently, the final model’s RMSE is 0.081. This is strong in theoretical terms; however, it may correspond to real BTC prices scaled over $50’000. This translates to a potential deviation of $4,000 per prediction. Such a deviation is substantial for trading decisions or risk assessment. The error in the model can trigger false buy/sell signals or lead to inefficient hedging. It also creates a risk of losing opportunity cost. For example, if BTC is bought based on the current final model predicting the BTC price to rise, but it falls in reality, profit is lost due to the bad trade and due to better options getting skipped.

To further polish this final model, feature engineering should be used to include lagged BTC prices. This can help with improving the model's directional accuracy. This will require modifying the dataset to include rolling window statistics. Incorporating an LSTM will allow the model to predict long-term patterns present in a financial time series. Furthermore, including profit and loss simulations can help with the financial usefulness of the model. The model can be integrated with real-time data streams by utilising APIs, which can be visualised through a live dashboard. A model of this quality would be more practical and realistic for real-world use.

References

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"RPubs - Cook's Distance." Rpubs.com, rpubs.com/DragonflyStats/introduction-to-cooks-distance.

Holtz, Yan. "Time Series | the R Graph Gallery." R-Graph-Gallery.com, r-graph-gallery.com/time-series.html.

Appendix

R-Studio Outputs used to write this report:

Looking at Correlated Predictors:

```
> print(sort(cor_target, decreasing = TRUE)[2:11])
 BTC_USDT_1h_high   BTC_USDT_1h_low  BTC_USDT_1h_open  SOL_USDT_1h_high
SOL_USDT_1h_close
       0.9999426        0.9999382        0.9998947        0.9338509        0.9337587
 SOL_USDT_1h_open   SOL_USDT_1h_low    S.P_High..GSPC    S.P_Open..GSPC
S.P_Close..GSPC
       0.9337462        0.9337448        0.9332708        0.9324650        0.9324298
>
```

Looking at Aliased Predictors:

```
> alias(vif_model)
Model :
BTC_USDT_1h_close ~ BNB_USDT_1h_open + BNB_USDT_1h_high +
BNB_USDT_1h_low +
   BNB_USDT_1h_close + BNB_USDT_1h_volume + BTC_USDT_1h_volume +
   DOGE_USDT_1h_open + DOGE_USDT_1h_high + DOGE_USDT_1h_low +
   DOGE_USDT_1h_close + DOGE_USDT_1h_volume + ETH_USDT_1h_open +
   ETH_USDT_1h_high + ETH_USDT_1h_low + ETH_USDT_1h_close +
   ETH_USDT_1h_volume + SOL_USDT_1h_open + SOL_USDT_1h_high +
   SOL_USDT_1h_low + SOL_USDT_1h_close + SOL_USDT_1h_volume +
   XRP_USDT_1h_open + XRP_USDT_1h_high + XRP_USDT_1h_low +
XRP_USDT_1h_close +
   XRP_USDT_1h_volume + cattle_Close.LE.F + cattle_High.LE.F +
   cattle_Low.LE.F + cattle_Open.LE.F + cattle_Volume.LE.F +
   corn_Close.ZC.F + corn_High.ZC.F + corn_Low.ZC.F + corn_Open.ZC.F +
   corn_Volume.ZC.F + crude_Close.CL.F + crude_High.CL.F + crude_Low.CL.F +
   crude_Open.CL.F + crude_Volume.CL.F + gold_Close.GC.F + gold_High.GC.F +
   gold_Low.GC.F + gold_Open.GC.F + gold_Volume.GC.F + silver_Close.SI.F +
   silver_High.SI.F + silver_Low.SI.F + silver_Open.SI.F + silver_Volume.SI.F +
   soybeans_Close.ZS.F + soybeans_High.ZS.F + soybeans_Low.ZS.F +
   soybeans_Open.ZS.F + soybeans_Volume.ZS.F + wheat_Close.ZW.F +
   wheat_High.ZW.F + wheat_Low.ZW.F + wheat_Open.ZW.F + wheat_Volume.ZW.F +
   CAC_Close..FCHI + CAC_High..FCHI + CAC_Low..FCHI + CAC_Open..FCHI +
   DAX_Close..GDAXI + DAX_High..GDAXI + DAX_Low..GDAXI + DAX_Open..GDAXI +
   Dow_Close..DJI + Dow_High..DJI + Dow_Low..DJI + Dow_Open..DJI +
   Dow_Volume..DJI + EURO_Close..STOXX50E + EURO_High..STOXX50E +
   EURO_Low..STOXX50E + EURO_Open..STOXX50E + FTSE_Close..FTSE +
   FTSE_High..FTSE + FTSE_Low..FTSE + FTSE_Open..FTSE + IBOVESPA_Close..BVSP +
   IBOVESPA_High..BVSP + IBOVESPA_Low..BVSP + IBOVESPA_Open..BVSP +
   IPC_Close..MXX + IPC_High..MXX + IPC_Low..MXX + IPC_Open..MXX +
   IPC_Volume..MXX + NASDAQ_Close..IXIC + NASDAQ_High..IXIC +
   NASDAQ_Low..IXIC + NASDAQ_Open..IXIC + NASDAQ_Volume..IXIC +
   Russell_Close..RUT + Russell_High..RUT + Russell_Low..RUT +
   Russell_Open..RUT + S.P_Close..GSPC + S.P_High..GSPC + S.P_Low..GSPC +
   S.P_Open..GSPC + S.P_Volume..GSPC + S.P_Close..GSPTSE + S.P_High..GSPTSE +
   S.P_Low..GSPTSE + S.P_Open..GSPTSE + S.P_Volume..GSPTSE +
   VIX_Close..VIX + VIX_High..VIX + VIX_Low..VIX + VIX_Open..VIX +
   funding_rate + fear_gread_index + open_interest + google_trends_buy_crypto +
   google_trends_bitcoin + hour + day_of_week + weekend

Complete :
        (Intercept)   BNB_USDT_1h_open  BNB_USDT_1h_high  BNB_USDT_1h_low
weekend         2/7                  0                 0                0
```

	BNB_USDT_1h_close	BNB_USDT_1h_volume	BTC_USDT_1h_volume	DOGE_USDT_1h_open
weekend	0	0	0	0

	DOGE_USDT_1h_high	DOGE_USDT_1h_low	DOGE_USDT_1h_close	DOGE_USDT_1h_volume
weekend	0	0	0	0

	ETH_USDT_1h_open	ETH_USDT_1h_high	ETH_USDT_1h_low	ETH_USDT_1h_close
weekend	0	0	0	0

	ETH_USDT_1h_volume	SOL_USDT_1h_open	SOL_USDT_1h_high	SOL_USDT_1h_low
weekend	0	0	0	0

	SOL_USDT_1h_close	SOL_USDT_1h_volume	XRP_USDT_1h_open	XRP_USDT_1h_high
weekend	0	0	0	0

	XRP_USDT_1h_low	XRP_USDT_1h_close	XRP_USDT_1h_volume	cattle_Close.LE.F
weekend	0	0	0	0

	cattle_High.LE.F	cattle_Low.LE.F	cattle_Open.LE.F	cattle_Volume.LE.F
weekend	0	0	0	0

	corn_Close.ZC.F	corn_High.ZC.F	corn_Low.ZC.F	corn_Open.ZC.F
weekend	0	0	0	0

	corn_Volume.ZC.F	crude_Close.CL.F	crude_High.CL.F	crude_Low.CL.F
weekend	0	0	0	0

	crude_Open.CL.F	crude_Volume.CL.F	gold_Close.GC.F	gold_High.GC.F
weekend	0	0	0	0

	gold_Low.GC.F	gold_Open.GC.F	gold_Volume.GC.F	silver_Close.SI.F
weekend	0	0	0	0

	silver_High.SI.F	silver_Low.SI.F	silver_Open.SI.F	silver_Volume.SI.F
weekend	0	0	0	0

	soybeans_Close.ZS.F	soybeans_High.ZS.F	soybeans_Low.ZS.F	soybeans_Open.ZS.F
weekend	0	0	0	0

	soybeans_Volume.ZS.F	wheat_Close.ZW.F	wheat_High.ZW.F	wheat_Low.ZW.F
weekend	0	0	0	0

	wheat_Open.ZW.F	wheat_Volume.ZW.F	CAC_Close..FCHI	CAC_High..FCHI
weekend	0	0	0	0

	CAC_Low..FCHI	CAC_Open..FCHI	DAX_Close..GDAXI	DAX_High..GDAXI
weekend	0	0	0	0

	DAX_Low..GDAXI	DAX_Open..GDAXI	Dow_Close..DJI	Dow_High..DJI
weekend	0	0	0	0

	Dow_Low..DJI	Dow_Open..DJI	Dow_Volume..DJI	EURO_Close..STOXX50E
weekend	0	0	0	0

	EURO_High..STOXX50E	EURO_Low..STOXX50E	EURO_Open..STOXX50E	FTSE_Close..FTSE
weekend	0	0	0	0

```
        FTSE_High..FTSE     FTSE_Low..FTSE      FTSE_Open..FTSE
IBOVESPA_Close..BVSP
weekend                0                0                0                0
        IBOVESPA_High..BVSP IBOVESPA_Low..BVSP  IBOVESPA_Open..BVSP
IPC_Close..MXX
weekend                0                0                0                0
        IPC_High..MXX      IPC_Low..MXX       IPC_Open..MXX      IPC_Volume..MXX
weekend                0                0                0                0
        NASDAQ_Close..IXIC  NASDAQ_High..IXIC   NASDAQ_Low..IXIC
NASDAQ_Open..IXIC
weekend                0                0                0                0
        NASDAQ_Volume..IXIC Russell_Close..RUT  Russell_High..RUT   Russell_Low..RUT
weekend                0                0                0                0
        Russell_Open..RUT   S.P_Close..GSPC    S.P_High..GSPC      S.P_Low..GSPC
weekend                0                0                0                0
        S.P_Open..GSPC      S.P_Volume..GSPC    S.P_Close..GSPTSE   S.P_High..GSPTSE
weekend                0                0                0                0
        S.P_Low..GSPTSE     S.P_Open..GSPTSE    S.P_Volume..GSPTSE  VIX_Close..VIX
weekend                0                0                0                0
        VIX_High..VIX       VIX_Low..VIX        VIX_Open..VIX       funding_rate
weekend                0                0                0                0
        fear_gead_index    open_interest       google_trends_buy_crypto
weekend                0                0                0
        google_trends_bitcoin hour             day_of_week.L       day_of_week.Q
weekend                0                  0                0 133465168/122322847
        day_of_week.C       day_of_week^4       day_of_week^5       day_of_week^6
weekend                0        10296/21295                0  41306188/627799705

>
```

VIF values for predictors:

```
> print(sort(vif_final, decreasing = TRUE))
        S.P_High..GSPTSE          S.P_Low..GSPTSE           gold_High.GC.F
            45062.364466             42681.821590             38594.259093
        S.P_Open..GSPTSE        S.P_Close..GSPTSE          gold_Close.GC.F
            38250.326015             38071.375892             27740.684413
        Russell_Low..RUT        Russell_High..RUT       Russell_Close..RUT
            19636.092390             19256.738180             16754.006491
          gold_Open.GC.F          silver_High.SI.F        Russell_Open..RUT
            16151.192454             16082.343196             15775.709177
       silver_Close.SI.F         silver_Open.SI.F            gold_Low.GC.F
             9558.634182              7279.193167              3833.702511
         silver_Low.SI.F           crude_Low.CL.F           crude_High.CL.F
             3253.645297              2916.855841              2745.095641
```

```
   crude_Close.CL.F        S.P_Close..GSPC        IPC_High..MXX
       2735.192924            2592.134807          2573.525233
    crude_Open.CL.F        IPC_Close..MXX          IPC_Low..MXX
       2392.714075            2263.263982          2222.828311
  soybeans_Low.ZS.F         IPC_Open..MXX     soybeans_High.ZS.F
       1775.486434            1695.260138          1557.109908
 soybeans_Open.ZS.F     soybeans_Close.ZS.F     NASDAQ_Close..IXIC
       1379.232021            1260.909861           901.985706
     corn_High.ZC.F          VIX_Close..VIX          corn_Low.ZC.F
        829.650511             719.695143           684.884730
       VIX_Low..VIX          cattle_Low.LE.F          VIX_High..VIX
        673.729403             587.788784           577.521335
      VIX_Open..VIX          corn_Close.ZC.F         corn_Open.ZC.F
        518.692349             417.309705           415.314582
   cattle_Close.LE.F          Dow_Close..DJI    EURO_Close..STOXX50E
        408.775955             390.913564           378.228793
    wheat_High.ZW.F          wheat_Low.ZW.F        DAX_Close..GDAXI
        315.779497             268.876050           261.880520
   cattle_Open.LE.F        cattle_High.LE.F        wheat_Close.ZW.F
        246.030094             241.405443           164.179852
    wheat_Open.ZW.F       BNB_USDT_1h_close        CAC_Close..FCHI
        157.169520              85.129668            74.655461
  SOL_USDT_1h_close       XRP_USDT_1h_close      DOGE_USDT_1h_close
         58.238743              35.408813            34.805363
  ETH_USDT_1h_close          FTSE_Close..FTSE           funding_rate
         31.524488              28.662007            13.706464
IBOVESPA_Close..BVSP google_trends_buy_crypto        S.P_Volume..GSPC
         13.281095              10.526003            10.311260
    Dow_Volume..DJI    google_trends_bitcoin        fear_gread_index
          9.647653               7.276298             5.210554
   silver_Volume.SI.F        gold_Volume.GC.F      ETH_USDT_1h_volume
          4.931500               4.231139             3.581374
 BTC_USDT_1h_volume      S.P_Volume..GSPTSE      SOL_USDT_1h_volume
          3.382286               3.137585             3.088642
DOGE_USDT_1h_volume      XRP_USDT_1h_volume         IPC_Volume..MXX
          2.775466               2.281155             2.173568
  wheat_Volume.ZW.F        corn_Volume.ZC.F     soybeans_Volume.ZS.F
          2.130700               2.122796             2.060684
 BNB_USDT_1h_volume      NASDAQ_Volume..IXIC                weekend
          1.975205               1.947214             1.767749
  crude_Volume.CL.F       cattle_Volume.LE.F                   hour
          1.454454               1.371445             1.291225
      open_interest
          1.254570
>
```

Final selected predictors for the model:

```
predictors <- c(
  "funding_rate", "google_trends_buy_crypto", "S.P_Volume..GSPC",
  "Dow_Volume..DJI", "IBOVESPA_Close..BVSP", "IPC_Close..MXX",
  "google_trends_bitcoin", "cattle_Close.LE.F", "wheat_Close.ZW.F",
  "silver_Volume.SI.F", "crude_Close.CL.F", "gold_Volume.GC.F",
  "fear_gread_index", "ETH_USDT_1h_volume", "BTC_USDT_1h_volume",
  "SOL_USDT_1h_volume", "S.P_Volume..GSPTSE", "DOGE_USDT_1h_volume",
  "XRP_USDT_1h_volume", "BNB_USDT_1h_volume", "corn_Volume.ZC.F",
  "soybeans_Volume.ZS.F", "NASDAQ_Volume..IXIC", "IPC_Volume..MXX",
  "weekend", "wheat_Volume.ZW.F", "crude_Volume.CL.F", "hour",
  "cattle_Volume.LE.F", "open_interest"
)
```

Model 1 Summary

```
> summary(model)

Call:
lm(formula = formula, data = data)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.80591 -0.07640 -0.00775  0.06827  0.56265 

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)    
(Intercept)             -0.1527883  0.0183932  -8.307  < 2e-16 ***
funding_rate             0.4945077  0.0074065  66.767  < 2e-16 ***
google_trends_buy_crypto  0.4608822  0.0095963  48.027  < 2e-16 ***
S.P_Volume..GSPC        -0.7899567  0.0227391 -34.740  < 2e-16 ***
Dow_Volume..DJI          0.8595052  0.0257362  33.397  < 2e-16 ***
IBOVESPA_Close..BVSP     0.0173484  0.0062818   2.762 0.005756 ** 
IPC_Close..MXX           0.0875248  0.0053494  16.362  < 2e-16 ***
google_trends_bitcoin   -0.0150222  0.0089614  -1.676 0.093692 .  
cattle_Close.LE.F        0.6582502  0.0061855 106.419  < 2e-16 ***
wheat_Close.ZW.F        -0.1733724  0.0070257 -24.677  < 2e-16 ***
silver_Volume.SI.F       0.0184067  0.0302966   0.608 0.543493    
crude_Close.CL.F        -0.4023568  0.0066635 -60.383  < 2e-16 ***
gold_Volume.GC.F        -0.1343124  0.0283930  -4.730 2.26e-06 ***
fear_gread_index         0.1440804  0.0056548  25.479  < 2e-16 ***
ETH_USDT_1h_volume       1.8322320  0.1033039  17.736  < 2e-16 ***
```

```
BTC_USDT_1h_volume        0.2605170  0.0347280   7.502 6.60e-14 ***
SOL_USDT_1h_volume       -0.3561217  0.0329605 -10.805  < 2e-16 ***
S.P_Volume..GSPTSE        0.5179156  0.0241567  21.440  < 2e-16 ***
DOGE_USDT_1h_volume      -0.6539133  0.0521240 -12.545  < 2e-16 ***
XRP_USDT_1h_volume       -0.5564845  0.0394857 -14.093  < 2e-16 ***
BNB_USDT_1h_volume        0.3631873  0.0309391  11.739  < 2e-16 ***
corn_Volume.ZC.F         -0.0399288  0.0157930  -2.528 0.011472 *
soybeans_Volume.ZS.F      0.0990395  0.0127709   7.755 9.31e-15 ***
NASDAQ_Volume..IXIC       0.5094268  0.0222089  22.938  < 2e-16 ***
IPC_Volume..MXX          -0.3513624  0.0155310 -22.623  < 2e-16 ***
weekend                  -0.0079322  0.0022843  -3.472 0.000517 ***
wheat_Volume.ZW.F         0.0572555  0.0085473   6.699 2.17e-11 ***
crude_Volume.CL.F        -0.1423679  0.0145704  -9.771  < 2e-16 ***
hour                     -0.0009491  0.0001313  -7.229 5.07e-13 ***
cattle_Volume.LE.F       -0.0206075  0.0093448  -2.205 0.027451 *
open_interest             0.0849756  0.0249282   3.409 0.000654 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1075 on 17484 degrees of freedom
Multiple R-squared:  0.8625,  Adjusted R-squared:  0.8622
F-statistic:  3654 on 30 and 17484 DF,  p-value: < 2.2e-16

>
```

Model 1 Cross Validation

```
> print(cv_model)
Linear Regression

17515 samples
   30 predictor

No pre-processing
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 15763, 15764, 15764, 15764, 15764, 15763, ...
Resampling results:

  RMSE       Rsquared   MAE
  0.1080941  0.8608445  0.08542452

Tuning parameter 'intercept' was held constant at a value of TRUE

>
```

Finding the two breakpoints for a segmented model:

```
> print(bp)
                Initial     Est.      St.Err
psi1.funding_rate      NA 0.2768802 0.003124869
psi2.funding_rate      NA 0.5497754 0.026803268
```

Model 2's Summary:

```
> summary(segmented_model)

          ***Regression Model with Segmented Relationship(s)***

Call:
segmented.lm(obj = full_model, seg.Z = ~funding_rate, npsi = 2)

Estimated Break-Point(s):
                   Est. St.Err
psi1.funding_rate 0.333  0.004
psi2.funding_rate 0.565  0.005

Coefficients of the linear terms:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)            0.3708233  0.0206875  17.925  < 2e-16 ***
funding_rate          -1.4875021  0.0448805 -33.144  < 2e-16 ***
google_trends_buy_crypto  0.5086978  0.0089259  56.991  < 2e-16 ***
S.P_Volume..GSPC      -0.6239059  0.0211634 -29.480  < 2e-16 ***
Dow_Volume..DJI        0.6390148  0.0240775  26.540  < 2e-16 ***
IBOVESPA_Close..BVSP   0.0046327  0.0058251   0.795 0.426445
IPC_Close..MXX         0.0821753  0.0050179  16.376  < 2e-16 ***
google_trends_bitcoin -0.0087124  0.0084441  -1.032 0.302190
cattle_Close.LE.F      0.5828224  0.0061682  94.488  < 2e-16 ***
wheat_Close.ZW.F      -0.1475747  0.0064964 -22.716  < 2e-16 ***
silver_Volume.SI.F     0.0072475  0.0279262   0.260 0.795235
crude_Close.CL.F      -0.3486811  0.0062738 -55.577  < 2e-16 ***
gold_Volume.GC.F      -0.0994571  0.0261686  -3.801 0.000145 ***
fear_gread_index       0.1631883  0.0052217  31.252  < 2e-16 ***
ETH_USDT_1h_volume     1.5827859  0.0954301  16.586  < 2e-16 ***
BTC_USDT_1h_volume     0.2480195  0.0319858   7.754 9.39e-15 ***
SOL_USDT_1h_volume    -0.2306845  0.0305022  -7.563 4.14e-14 ***
S.P_Volume..GSPTSE     0.4393188  0.0222874  19.712  < 2e-16 ***
DOGE_USDT_1h_volume   -0.6410108  0.0481467 -13.314  < 2e-16 ***
XRP_USDT_1h_volume    -0.4849265  0.0364158 -13.316  < 2e-16 ***
BNB_USDT_1h_volume     0.2631833  0.0285915   9.205  < 2e-16 ***
```

```
corn_Volume.ZC.F        -0.0322673  0.0145673  -2.215 0.026769 *
soybeans_Volume.ZS.F     0.1026714  0.0117666   8.726  < 2e-16 ***
NASDAQ_Volume..IXIC      0.4976931  0.0204572  24.329  < 2e-16 ***
IPC_Volume..MXX         -0.3043559  0.0143455 -21.216  < 2e-16 ***
weekend                 -0.0080301  0.0021037  -3.817 0.000135 ***
wheat_Volume.ZW.F        0.0399941  0.0078769   5.077 3.87e-07 ***
crude_Volume.CL.F       -0.1215570  0.0134243  -9.055  < 2e-16 ***
hour                    -0.0007686  0.0001211  -6.349 2.21e-10 ***
cattle_Volume.LE.F      -0.0200820  0.0086050  -2.334 0.019619 *
open_interest            0.0638422  0.0229528   2.781 0.005417 **
U1.funding_rate          2.6405483  0.0930375  28.382       NA
U2.funding_rate         -2.1230097  0.0943569 -22.500       NA
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.099 on 17480 degrees of freedom
Multiple R-Squared: 0.8835,  Adjusted R-squared: 0.8832

Boot restarting based on 6 samples. Last fit:
Convergence attained in 2 iterations (rel. change -1.6844e-06)
>
```

Model 3's summary:

```
> summary(segmented_model_clean)

        ***Regression Model with Segmented Relationship(s)***

Call:
segmented.lm(obj = full_model_clean, seg.Z = ~funding_rate, npsi = 2)

Estimated Break-Point(s):
                  Est. St.Err
psi1.funding_rate 0.335  0.004
psi2.funding_rate 0.562  0.010

Coefficients of the linear terms:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)              5.100e-01  1.953e-02  26.109  < 2e-16 ***
funding_rate            -2.206e+00  4.293e-02 -51.389  < 2e-16 ***
google_trends_buy_crypto  5.645e-01  8.037e-03  70.230  < 2e-16 ***
S.P_Volume..GSPC        -7.640e-01  2.039e-02 -37.468  < 2e-16 ***
Dow_Volume..DJI          7.680e-01  2.328e-02  32.990  < 2e-16 ***
IBOVESPA_Close..BVSP    -5.364e-05  4.810e-03  -0.011    0.991
IPC_Close..MXX           7.744e-02  4.213e-03  18.380  < 2e-16 ***
```

```
google_trends_bitcoin     9.635e-03  7.566e-03   1.274    0.203
cattle_Close.LE.F         4.991e-01  5.294e-03  94.261  < 2e-16 ***
wheat_Close.ZW.F         -1.486e-01  5.370e-03 -27.674  < 2e-16 ***
silver_Volume.SI.F       -1.208e-02  2.606e-02  -0.464    0.643
crude_Close.CL.F         -2.978e-01  5.231e-03 -56.924  < 2e-16 ***
gold_Volume.GC.F         -4.364e-03  2.483e-02  -0.176    0.860
fear_gread_index          1.620e-01  4.480e-03  36.165  < 2e-16 ***
ETH_USDT_1h_volume        2.784e+00  1.286e-01  21.656  < 2e-16 ***
BTC_USDT_1h_volume        1.628e-01  3.544e-02   4.593 4.40e-06 ***
SOL_USDT_1h_volume       -2.911e-01  3.137e-02  -9.279  < 2e-16 ***
S.P_Volume..GSPTSE        4.945e-01  2.095e-02  23.601  < 2e-16 ***
DOGE_USDT_1h_volume      -8.787e-01  5.059e-02 -17.370  < 2e-16 ***
XRP_USDT_1h_volume       -6.334e-01  3.945e-02 -16.058  < 2e-16 ***
BNB_USDT_1h_volume        3.349e-01  2.843e-02  11.781  < 2e-16 ***
corn_Volume.ZC.F         -6.858e-02  1.310e-02  -5.235 1.67e-07 ***
soybeans_Volume.ZS.F      1.340e-01  1.109e-02  12.084  < 2e-16 ***
NASDAQ_Volume..IXIC       6.672e-01  2.051e-02  32.536  < 2e-16 ***
IPC_Volume..MXX          -2.816e-01  1.571e-02 -17.929  < 2e-16 ***
weekend                  -1.041e-02  1.808e-03  -5.759 8.61e-09 ***
wheat_Volume.ZW.F         5.009e-02  6.779e-03   7.389 1.55e-13 ***
crude_Volume.CL.F        -2.778e-01  2.198e-02 -12.638  < 2e-16 ***
hour                     -8.775e-04  1.020e-04  -8.600  < 2e-16 ***
cattle_Volume.LE.F       -4.620e-02  7.981e-03  -5.789 7.23e-09 ***
open_interest             1.058e-01  2.184e-02   4.844 1.28e-06 ***
U1.funding_rate           3.689e+00  1.665e-01  22.151       NA
U2.funding_rate          -2.663e+00  1.688e-01 -15.774       NA
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.07979 on 16172 degrees of freedom
Multiple R-Squared: 0.9202,  Adjusted R-squared:  0.92

Boot restarting based on 6 samples. Last fit:
Convergence attained in 3 iterations (rel. change -5.7103e-08)
>
```

Model 4’s summary:

```
> summary(segmented_model_interaction)

        ***Regression Model with Segmented Relationship(s)***

Call:
segmented.lm(obj = interaction_model, seg.Z = ~funding_rate,
    npsi = 2)
```

```
Estimated Break-Point(s):
                   Est. St.Err
psi1.funding_rate 0.328  0.004
psi2.funding_rate 0.560  0.011

Coefficients of the linear terms:
                                        Estimate Std. Error t value Pr(>|t|)
(Intercept)                             2.345e-01  1.804e-02  13.002  < 2e-16 ***
funding_rate                           -1.653e+00  3.986e-02 -41.467  < 2e-16 ***
google_trends_buy_crypto                2.202e+00  2.941e-02  74.888  < 2e-16 ***
S.P_Volume..GSPC                       -7.237e-01  1.820e-02 -39.762  < 2e-16 ***
Dow_Volume..DJI                         7.372e-01  2.082e-02  35.410  < 2e-16 ***
IBOVESPA_Close..BVSP                   -1.096e-02  4.632e-03  -2.367 0.017961 *
IPC_Close..MXX                          2.508e-02  4.049e-03   6.193 6.04e-10 ***
google_trends_bitcoin                   1.051e-02  6.864e-03   1.531 0.125776
cattle_Close.LE.F                       4.877e-01  5.225e-03  93.339  < 2e-16 ***
wheat_Close.ZW.F                       -1.164e-01  4.825e-03 -24.122  < 2e-16 ***
silver_Volume.SI.F                      6.529e-02  2.329e-02   2.804 0.005060 **
crude_Close.CL.F                       -2.673e-01  4.768e-03 -56.053  < 2e-16 ***
gold_Volume.GC.F                       -4.884e-03  2.215e-02  -0.220 0.825524
fear_gread_index                        5.458e-01  1.106e-02  49.367  < 2e-16 ***
ETH_USDT_1h_volume                      1.573e+00  1.161e-01  13.552  < 2e-16 ***
BTC_USDT_1h_volume                      1.090e-01  3.181e-02   3.426 0.000614 ***
SOL_USDT_1h_volume                     -4.132e-01  2.801e-02 -14.750  < 2e-16 ***
S.P_Volume..GSPTSE                      3.384e-01  1.882e-02  17.981  < 2e-16 ***
DOGE_USDT_1h_volume                    -4.007e-01  4.592e-02  -8.727  < 2e-16 ***
XRP_USDT_1h_volume                     -4.575e-01  3.524e-02 -12.983  < 2e-16 ***
BNB_USDT_1h_volume                      3.451e-01  2.535e-02  13.614  < 2e-16 ***
corn_Volume.ZC.F                       -8.625e-02  1.169e-02  -7.380 1.67e-13 ***
soybeans_Volume.ZS.F                    7.939e-02  9.934e-03   7.992 1.42e-15 ***
NASDAQ_Volume..IXIC                     5.674e-01  1.836e-02  30.910  < 2e-16 ***
IPC_Volume..MXX                        -1.208e-01  1.422e-02  -8.494  < 2e-16 ***
weekend                                -7.198e-03  3.549e-03  -2.028 0.042581 *
wheat_Volume.ZW.F                       4.520e-02  6.113e-03   7.394 1.49e-13 ***
crude_Volume.CL.F                      -2.780e-01  1.961e-02 -14.181  < 2e-16 ***
hour                                   -5.212e-04  9.113e-05  -5.719 1.09e-08 ***
cattle_Volume.LE.F                     -6.322e-02  7.117e-03  -8.884  < 2e-16 ***
open_interest                           9.042e-02  1.952e-02   4.633 3.63e-06 ***
U1.funding_rate                         3.289e+00  1.392e-01  23.621       NA
U2.funding_rate                        -2.036e+00  1.408e-01 -14.453       NA
funding_rate:fear_gread_index          -4.909e-01  2.412e-02 -20.351  < 2e-16 ***
funding_rate:weekend                    2.221e-03  8.647e-03   0.257 0.797262
google_trends_buy_crypto:fear_gread_index -2.028e+00  3.459e-02 -58.624  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Residual standard error: 0.07107 on 16169 degrees of freedom
Multiple R-Squared: 0.9367,  Adjusted R-squared: 0.9366

Boot restarting based on 6 samples. Last fit:
Convergence attained in 3 iterations (rel. change -3.1413e-08)
>
```

Model 5’s summary:

```
> summary(segmented_model_nonlinear)

        ***Regression Model with Segmented Relationship(s)***

Call:
segmented.lm(obj = nonlinear_model, seg.Z = ~funding_rate, npsi = 2)

Estimated Break-Point(s):
                  Est. St.Err
psi1.funding_rate 0.276      0
psi2.funding_rate 0.278      0

Coefficients of the linear terms:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)             -1.115e-01  1.881e-02  -5.924 3.20e-09 ***
funding_rate             1.100e+00  7.121e-02  15.441  < 2e-16 ***
google_trends_buy_crypto 2.079e+00  2.839e-02  73.226  < 2e-16 ***
S.P_Volume..GSPC        -6.697e-01  1.754e-02 -38.183  < 2e-16 ***
Dow_Volume..DJI          6.645e-01  2.011e-02  33.048  < 2e-16 ***
IBOVESPA_Close..BVSP     1.732e-02  4.484e-03   3.862 0.000113 ***
IPC_Close..MXX           3.687e-03  3.919e-03   0.941 0.346796
google_trends_bitcoin   -1.280e-02  6.513e-03  -1.965 0.049414 *
cattle_Close.LE.F        4.087e-01  5.301e-03  77.107  < 2e-16 ***
wheat_Close.ZW.F        -9.700e-02  4.666e-03 -20.790  < 2e-16 ***
silver_Volume.SI.F       8.034e-02  2.235e-02   3.595 0.000325 ***
crude_Close.CL.F        -2.246e-01  4.690e-03 -47.882  < 2e-16 ***
gold_Volume.GC.F        -2.090e-02  2.126e-02  -0.983 0.325725
fear_gread_index         5.009e-01  1.071e-02  46.770  < 2e-16 ***
ETH_USDT_1h_volume       1.486e+00  1.114e-01  13.339  < 2e-16 ***
BTC_USDT_1h_volume       1.012e-01  3.053e-02   3.317 0.000913 ***
SOL_USDT_1h_volume      -3.456e-01  2.695e-02 -12.822  < 2e-16 ***
S.P_Volume..GSPTSE       3.016e-01  1.809e-02  16.674  < 2e-16 ***
DOGE_USDT_1h_volume     -4.319e-01  4.390e-02  -9.838  < 2e-16 ***
XRP_USDT_1h_volume      -4.819e-01  3.382e-02 -14.249  < 2e-16 ***
BNB_USDT_1h_volume       3.092e-01  2.434e-02  12.703  < 2e-16 ***
corn_Volume.ZC.F        -6.612e-02  1.122e-02  -5.892 3.88e-09 ***
```

```
soybeans_Volume.ZS.F                    6.042e-02  9.540e-03   6.333 2.47e-10 ***
NASDAQ_Volume..IXIC                     5.361e-01  1.765e-02  30.378  < 2e-16 ***
IPC_Volume..MXX                        -9.397e-02  1.368e-02  -6.871 6.61e-12 ***
weekend                                -9.013e-03  3.411e-03  -2.643 0.008235 **
wheat_Volume.ZW.F                       4.394e-02  5.868e-03   7.488 7.35e-14 ***
crude_Volume.CL.F                      -2.568e-01  1.883e-02 -13.638  < 2e-16 ***
hour                                   -3.597e-04  8.753e-05  -4.109 3.99e-05 ***
cattle_Volume.LE.F                     -6.222e-02  6.831e-03  -9.109  < 2e-16 ***
open_interest                           7.033e-02  1.875e-02   3.750 0.000177 ***
I(funding_rate^2)                      -3.277e+00  1.161e-01 -28.224  < 2e-16 ***
U1.funding_rate                        -1.479e+02  1.974e+01  -7.495       NA
U2.funding_rate                         1.510e+02  1.974e+01   7.649       NA
funding_rate:fear_gread_index          -4.125e-01  2.329e-02 -17.711  < 2e-16 ***
funding_rate:weekend                    8.469e-03  8.305e-03   1.020 0.307850
google_trends_buy_crypto:fear_gread_index -1.844e+00  3.356e-02 -54.938  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.06821 on 16168 degrees of freedom
Multiple R-Squared: 0.9417,  Adjusted R-squared: 0.9416

Boot restarting based on 10 samples. Last fit:
Convergence attained in 1 iterations (rel. change 7.3173e-07)
>
```

Model 5 Cross Validation

```
> print(cv_model_nonlinear)
Linear Regression

16207 samples
   30 predictor

No pre-processing
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 14585, 14587, 14586, 14586, 14587, 14586, ...
Resampling results:

  RMSE        Rsquared   MAE
  0.08065898  0.9183309  0.06130776

Tuning parameter 'intercept' was held constant at a value of TRUE
```

Top 5 predictors for Model 5:

```
> print(top5)
            google_trends_buy_crypto                  cattle_Close.LE.F
                  0.18091848                                0.10678396
                 S.P_Volume..GSPC google_trends_buy_crypto:fear_gread_index
                  0.08597011                                0.07800150
                 Dow_Volume..DJI
                  0.07402728
>
```