

2017 Bitcoin Price Prediction Report

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0.1 Experimental Settings

For price prediction of 2017, we have tried all these experimental settings defined in Table 1 and we demonstrate the RMSE values of models.

| Explanation | Values |
|------------------------------|--------------------------------|
| window length | 3, 5, 7 |
| dimension reduction with PCA | 5, 10, 15, 20 |
| horizon | 1, 2, 5, 7, 10, 15, 20, 25, 30 |
| training length | 25, 50, 100, 200 |
| filtration threshold | 0, 10, 20, 30, 40, 50 |
| betti threshold | 50, 100, 200, 400 |

Table 1: Model parameter descriptions and values.

0.2 Baseline Models and RMSE Values

In this experimental settings, we have tried different training lengths in the optimization of the models on bitcoin price prediction. We have chosen *training_length* as 100 and reported the results of the models in this report.

| Model | Input | Output | Explanation |
|-------|----------------|--------|---|
| arima | Price, TotalTx | Price | ARIMA Model |
| rf | Price, TotalTx | Price | Random Forest Regressor Model |
| xgbt | Price, TotalTx | Price | Extreme Gradient Boosting Regressor Model |
| enet | Price, TotalTx | Price | Elastic Net Regressor Model |
| gp | Price, TotalTx | Price | Gaussian Process Based Regression Model |

Table 2: Baseline Model Descriptions

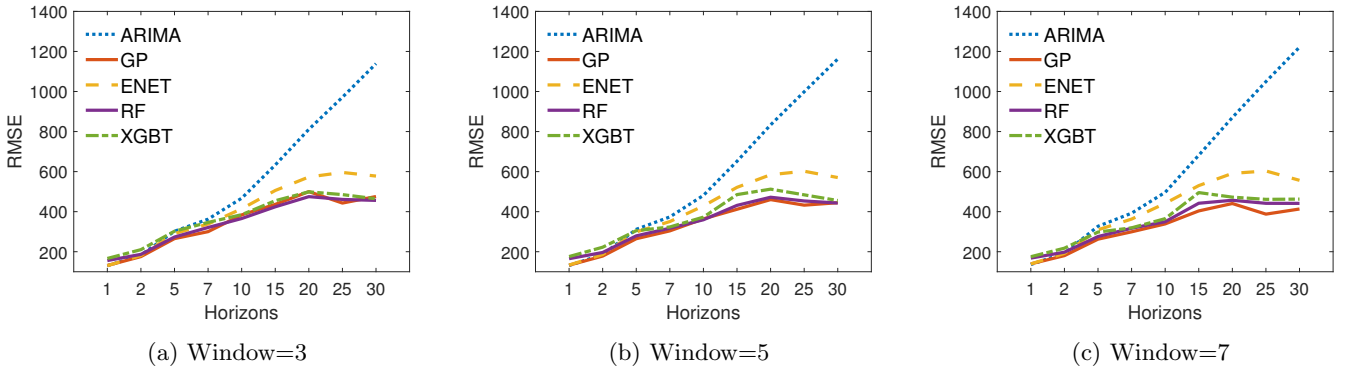


Figure 1: Line graphs of Figure 1 with different window and horizon values.

0.3 Random Forest Models and Gain Percentage Based on ARIMA

In our analysis, we report the percentage predictive gain, or decrease in $RMSE$ for a specific model m w.r.t. a baseline model m_0 as

$$\Delta_m(h) = 100 \times \left(1 - \frac{RMSE_m(h)}{RMSE_0(h)} \right), \quad (1)$$

where $RMSE_0(h)$ and $RMSE_m(h)$ are delivered by a baseline model m_0 and a competing model m , respectively.

| Model | Input | Output |
|---------------------|--|--------|
| betti50 | Price, TotalTx, $B_0(50)$, $B_1(50)$ | Price |
| betti100 | Price, TotalTx, $B_0(100)$, $B_1(100)$ | Price |
| betti200 | Price, TotalTx, $B_0(200)$, $B_1(200)$ | Price |
| betti400 | Price, TotalTx, $B_0(400)$, $B_1(400)$ | Price |
| betti50+betti50' | Price, TotalTx, $B_0(50)$, $B_1(50)$, $B'_0(50)$, $B'_1(50)$ | Price |
| betti100+betti100' | Price, TotalTx, $B_0(100)$, $B_1(100)$, $B'_0(100)$, $B'_1(100)$ | Price |
| betti200+betti200' | Price, TotalTx, $B_0(200)$, $B_1(200)$, $B'_0(200)$, $B'_1(200)$ | Price |
| betti400+betti400' | Price, TotalTx, $B_0(400)$, $B_1(400)$, $B'_0(400)$, $B'_1(400)$ | Price |
| one_step_filtration | Price, TotalTx, 20x20 chainlet filtered with thresholds 0,10,20,30,40,50 | Price |
| deep_rf_filtration | Price, TotalTx, 20x20 chainlet filtered with thresholds 0,10,20,30,40,50 | Price |

Table 3: Random Forest Model Descriptions

| Models | Explanation |
|---------------------|--|
| one_step_filtration | Vector of chainlets are filtered with thresholds 0,10,20,30,40,50 and random forest model is run on these filtered chainlets. |
| deep_rf_filtration | Vector of chainlets are filtered with thresholds 0,10,20,30,40,50 and different random forest is run to predict the price. Results of random forest previously trained on each threshold are used on second step random forest to predict price. |

Table 4: Filtration Models Explanation

0.4 Observations

According to percentage of gain presented in Figure 2,

- among seven baseline models, arima has worst rmse for all horizon and window values.
- for window $\in \{3, 5, 7\}$ and horizon < 3 , random forest with betti numbers have best price prediction.
- for window $\in \{3, 5, 7\}$ and horizon > 3 , deep_filtration has better prediction with the exception of window=7, horizon *in* $\{11, 12\}$.
- one_step_filtration is not comparable with deep_rf_filtration and random forest with betti.

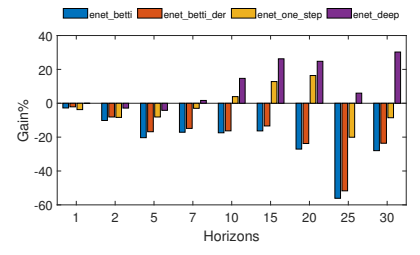
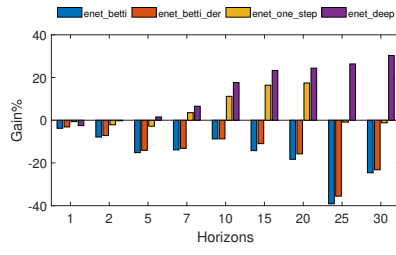
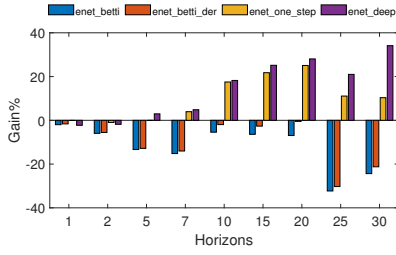


Figure 2: Enet based on gp

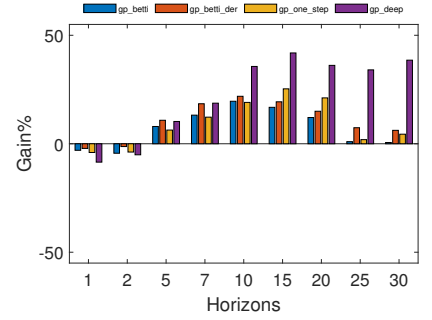
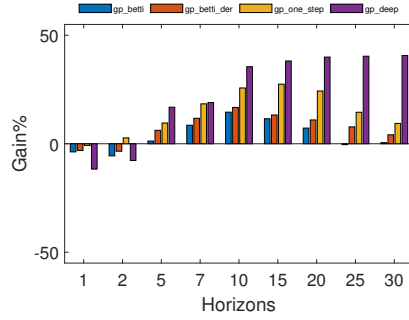
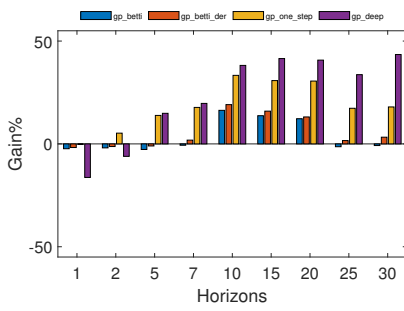


Figure 3: GP based on gp

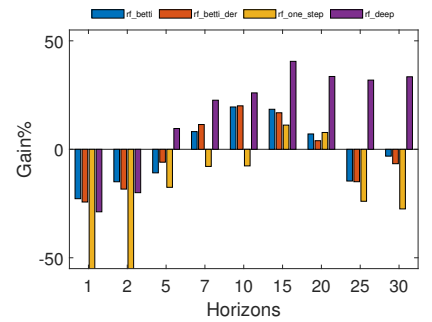
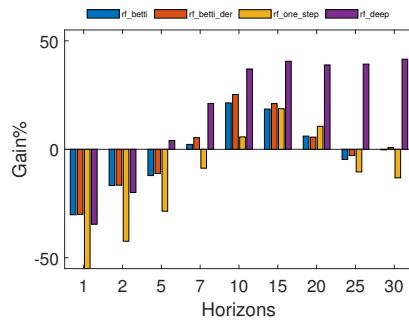
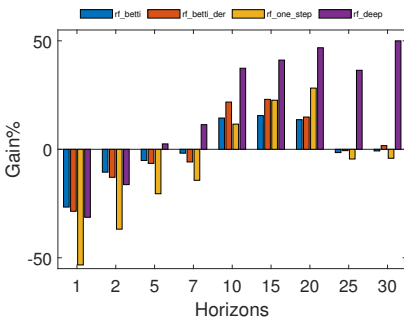


Figure 4: RF based on gp

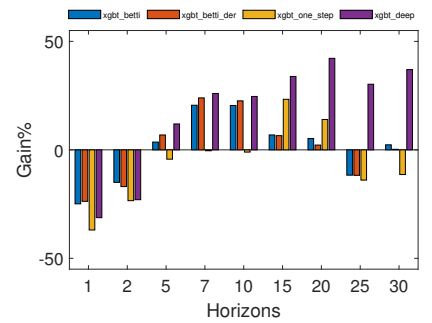
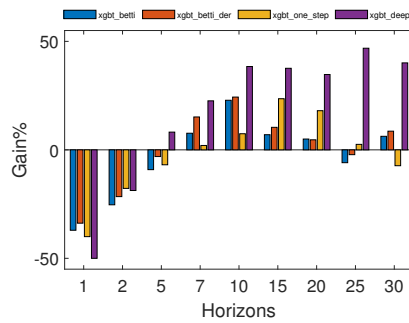
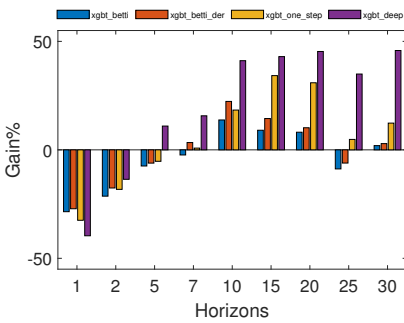
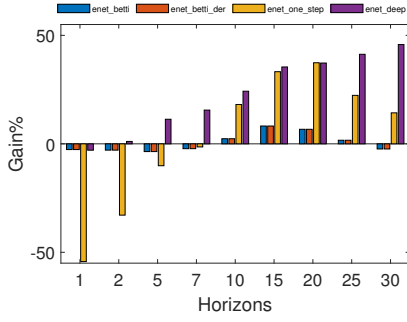
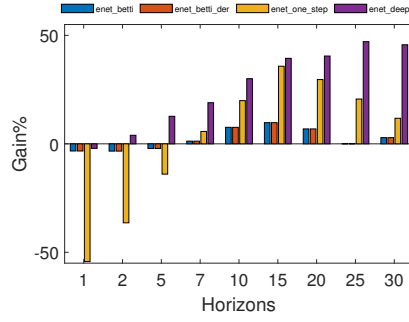


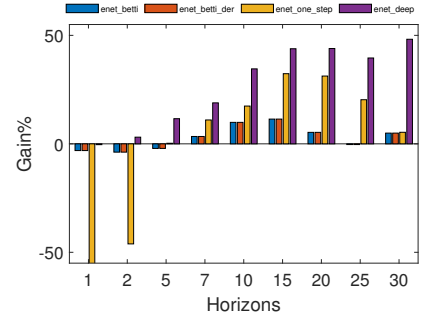
Figure 5: XGBT based on gp



(a) Window=3

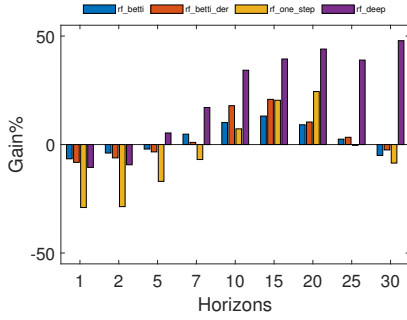


(b) Window=5

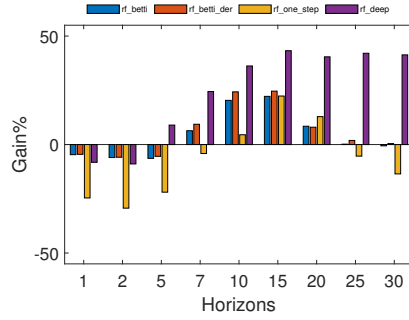


(c) Window=7

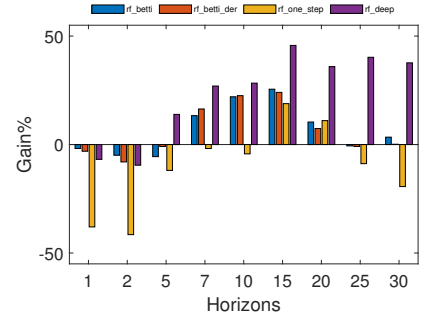
Figure 6: enet based on enet



(a) Window=3

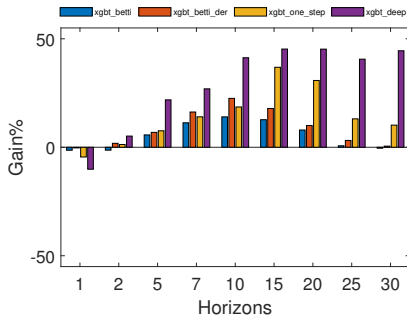


(b) Window=5

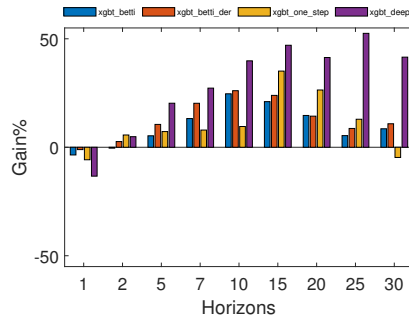


(c) Window=7

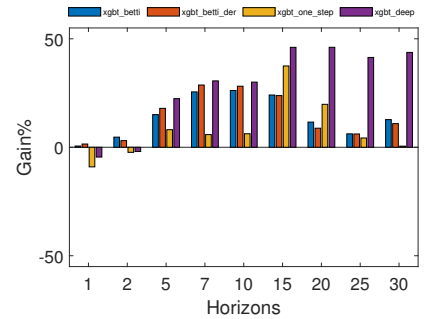
Figure 7: rf based on rf



(a) Window=3



(b) Window=5



(c) Window=7

Figure 8: xgbt based on xgbt