BITCOIN PRICE PREDICTION



Group Name: DataEureka

/Agenda

Bitcoin Price Prediction

- Data collection
- Data cleaning and preprocessing
- Basic LSTM Model baseline
- Features Engineering
- Modeling and optimization



/Data Input

Collected from:

Downloading open-source database
Web crawler

Collated to be: structured sequenced in time series.

Dated Between: 2020/9/16 ~ 2021/9/17

1 Bitcoin property and network

Bitcoin Daily Average Prices, Hash Rate, Miner Rewards, Miner Reserves,...

2 Bitcoin Marketing and trading

Number of Large Transactions, Average Transaction Size, Average Balance, Average Time Between Transactions, ...

3 Global economic indicators

Gold price, US dollar index, Dow Jones Commodity index, ...

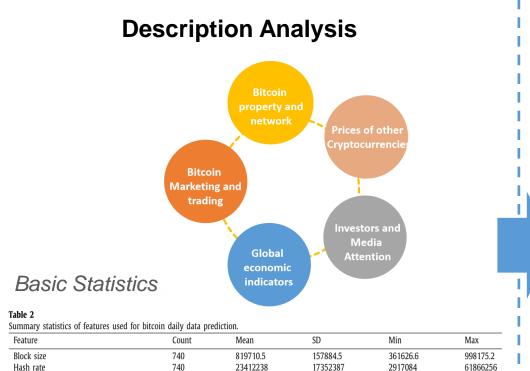
4 Investors and Media Attention

Google trend, Twitter positive, Twitter negative, ...

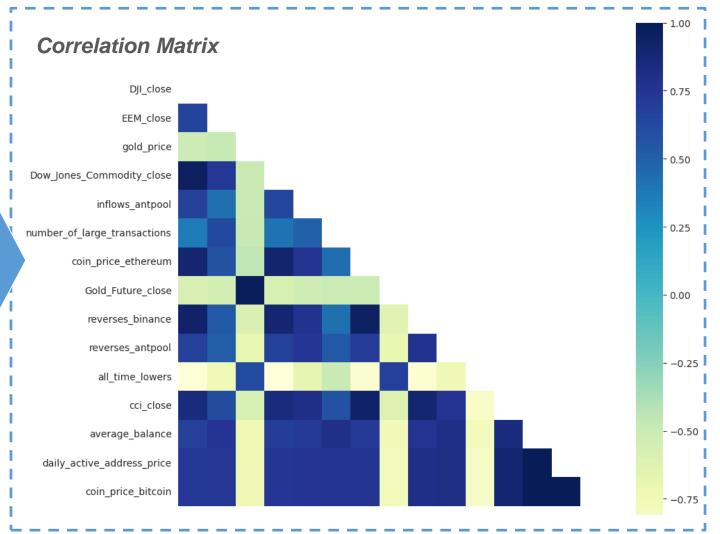
5 Prices of Other Cryptocurrencies and BTC Index

Ethereum, Dogecoin, CCI30*

/Data Preprocessing



Feature	Count	Mean	SD	Min	Max
Block size	740	819710.5	157884.5	361626.6	998175.2
Hash rate	740	23412238	17352387	2917084	61866256
Mining difficulty	740	3.18E+12	2.41E+12	4.22E+11	7.45E+12
Number of transactions	740	255215.8	57038.29	131875	490644
Confirmed transactions per Day	740	255694.5	57012.15	131875	490644
Mempool transaction Count	740	255215.8	57038.29	131875	490644
Mempool size	740	26489513	35357624	35369.5	1.37E+08
Market capitalization	740	9.87E+10	6.1E+10	1.53E+10	3.23E+11
Estimated transaction value	740	193095	96494.26	37558.21	629491.3
Total transaction fees	740	165.9894	192.5094	11.2287	1495.946
Google trend search volume index	740	8.452703	10.53606	2	100
Gold spot price	740	1268.682	43.20863	1174.2	1357.91



/Data Preprocessing

Data Cleaning

Imputation:

Google trend, Titter trend Too many missing values dropped

US index, Gold price, etc, Impute by Friday numbers

Redundancy:

Miners related features
Drop similar miner pools

BTC price similarity
High correlation but no
contribution - dropped

Data Normalization

Min-Max Scaler to normalize the data.

Data outcome

1 Date + 61 features

2020/9/14 0.001356 0.009181 0.000392 0.988841 0.710623 0.000547 1 0.0056 0.061118 0.011497 0.664999 0.610892 0.68680 2020/9/15 0.006322 0.009409 0.00045 0.955364 0.670118 0.000542 0.991071 0.011379 0.120176 0.017194 0.647389 0.544633 0.53474 2020/9/16 0.008669 0.007594 0.00045 1 0.711456 0.000536 0.982143 0.013402 0.133448 0.019472 0.6847 0.659941 0.67154 2020/9/17 0.008614 0.012067 0.000421 0.908207 0.720404 0.000528 0.973214 0.01426 0.05226 0.036946 0.693398 0.70955 0.80784 2020/9/18 0.009204 0.012717 0.000406 0.960763 0.637174 0.000522 0.973214 0.01462 0.089609 0.035739 0.602966 0.549028 0.5752 2020/9/20 0.009163 0.010657 0.000392 0.960763 0.379195 0.000513 0.964286 0.014599 0.173299 0.020891 0.374923 0.35941 0.45825 2020/10/7 0.00361 0.001308 0.000116 0.721742 0.743837 0.000429 0.883929 0.004767 0.132894 2020/10/8 0.006005 0.002476 0.000131 0.732541 0.617524 0.000425 0.883929 0.007841 0.112618 0.002869 0.630755 0.624564 0.65402 2020/10/9 0.010335 0.005686 0.000189 0.861411 0.663186 0.00042 0.883929 0.012778 0.183096 0.015369 0.635882 0.585608 0.6101 020/10/13 0.019179 0.01219 0.000218 0.74622 0.666387 0.000393 0.883929 0.023116 0.10008 0.009595 0.67607 0.647587 0.6993 020/10/15 0.018452 0.010777 0.000145 0.74838 0.686771 0.000381 0.883929 0.022308 0.153186 0.014845 0.678822 0.626231 0.6581 020/10/16 0.017529 0.008936 0.000102 0.795896 0.642938 0.000376 0.883929 0.020666 0.13207 0.011896 0.630752 0.565477 0.5891 020/10/17 0.017145 0.008361 0.000102 0.795896 0.432153 0.000371 0.883929 0.019475 0.121282 0.021079 0.455306 0.402591 0.46358 020/10/18 0.018707 0.009838 0.000116 0.795896 0.277694 0.000368 0.883929 0.02137 0.279954 0.023837 0.33182 0.264805 0.32376 020/10/19 0.021526 0.010941 0.000116 0.797696 0.550715 0.000359 0.883929 0.024847 0.281394 0.037398 0.583848 0.499682 0.4778

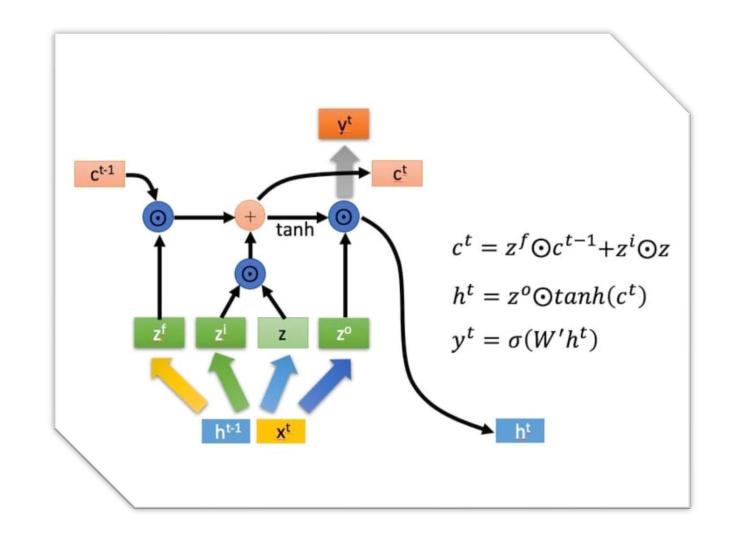
365 days

/Long short-term memory(LSTM)

Purpose

capable of learning long-term dependencies

use prior
experience to
inform future
outcomes

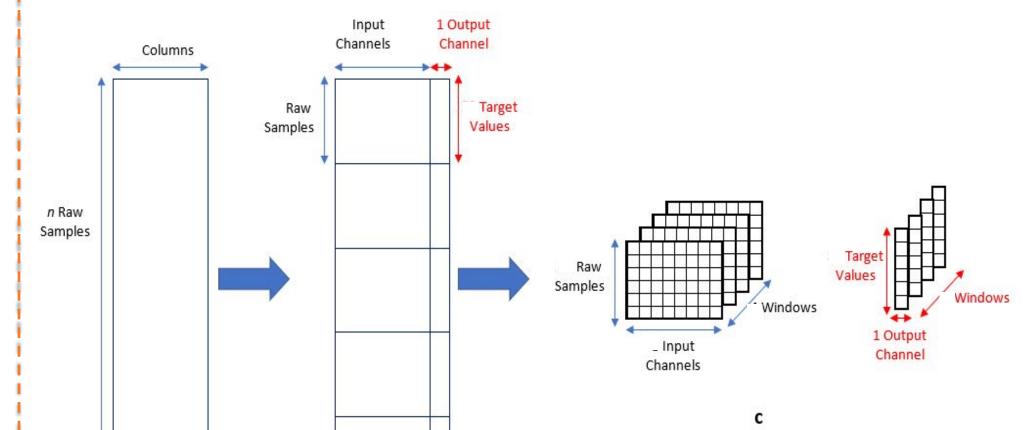


/Data Split

Train Test Split

split ratio = 0.2

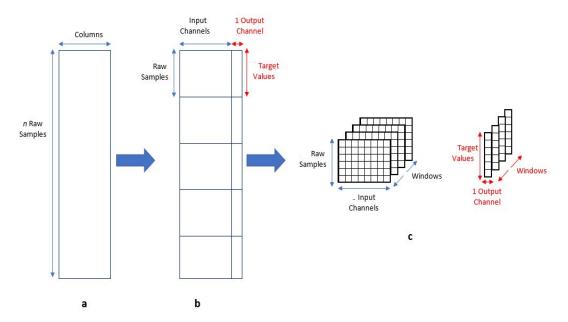
Extract data windows



b

/Data Preprocessing

Extract data windows

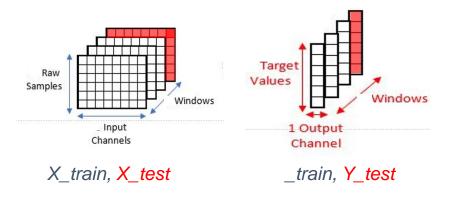


We decided to combine data of a certain time window as input to predict bitcoin price of next day.

After experiments, we found that the time window of 10 would be a reasonable choice.

Train Test Split

We used a **ratio of 0.2** to split train and test sets. So the data of last 60+ days was used for testing.



Original data shape

X: (366 * 61) Y: (366 * 1)

After concatenating

X: (366 * 10 * 61) Y: (366 * 1)

After splitting

X_train: (300 * 10 * 61) X_test: (66 * 10 * 61)

/ Model Evaluation

train and test the model 5 rounds

calculate their average RMSE as a indicator of its performance

fixed the random seed in each round to ensure it can be reproduced

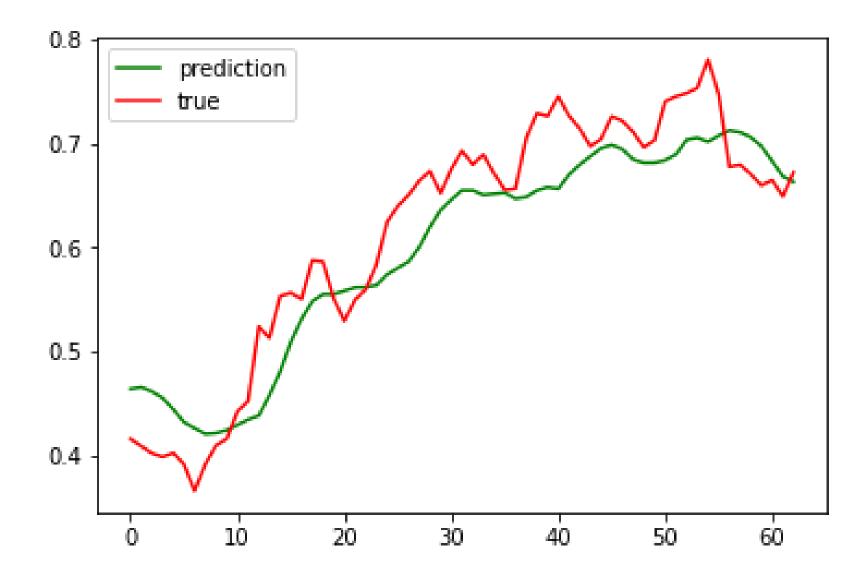
```
Training epoch 0 MSE: 0.3618645668029785
Training epoch 20 MSE: 0.018359770998358727
Training epoch 40 MSE: 0.0027389577589929104
Training epoch 60 MSE:
                        0.003316698130220175
Training epoch 80 MSE: 0.0028881970793008804
train 5 rounds in total, this is the 0 th round, RMSE is0.043214183300733566
Training epoch 0 MSE: 0.34949031472206116
Training epoch 20 MSE: 0.009240277111530304
Training epoch 40 MSE: 0.0054707834497094154
Training epoch 60 MSE:
                       0.0029721681494265795
Training epoch 80 MSE: 0.002721790922805667
train 5 rounds in total, this is the 1 th round, RMSE is0.04568817466497421
Training epoch 0 MSE: 0.33345314860343933
Training epoch 20 MSE: 0.015268449671566486
Training epoch 40 MSE: 0.004078330937772989
Training epoch 60 MSE:
                       0.0033113863319158554
Training epoch 80 MSE: 0.0027421447448432446
train 5 rounds in total, this is the 2 th round, RMSE is0.047878626734018326
Training epoch 0 MSE: 0.2620851397514343
Training epoch 20 MSE: 0.014127722941339016
Training epoch 40 MSE: 0.0031828766223043203
Training epoch 60 MSE: 0.002784544602036476
Training epoch 80 MSE: 0.002620649291202426
train 5 rounds in total, this is the 3 th round, RMSE is0.04254891350865364
Training epoch 0 MSE: 0.22142408788204193
Training epoch 20 MSE: 0.006789344362914562
Training epoch 40 MSE: 0.0036627124063670635
Training epoch 60 MSE:
                       0.002691515488550067
Training epoch 80 MSE: 0.00261324574239552
train 5 rounds in total, this is the 4 th round, RMSE is0.04782906174659729
```

Baseline Model

First Attempt

All features are used for modeling

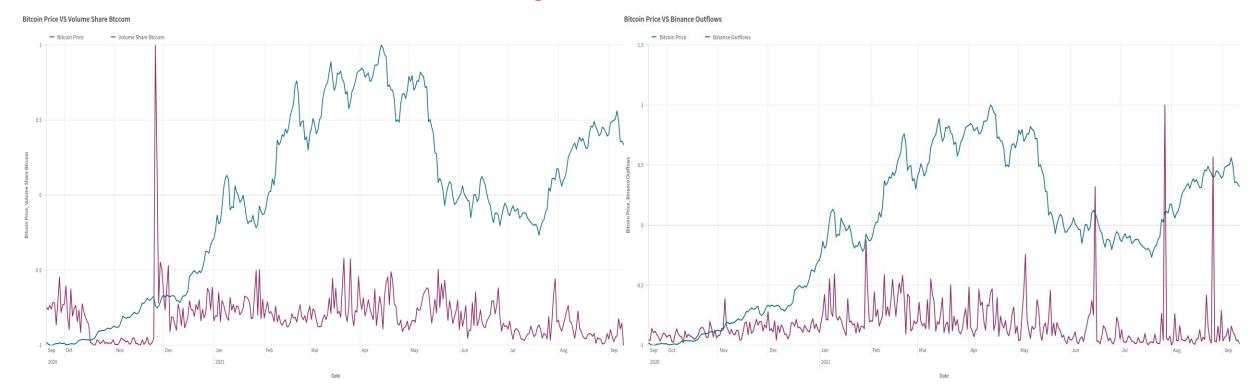
AvgMSE=0.0454



1. Noise



Need criteria to drop **columns** with low significance!



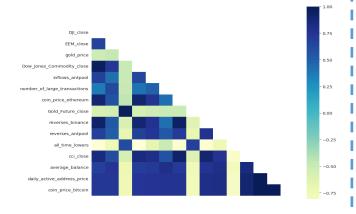
BTC Price V.S. Volume share Btccom

BTC Price V.S. Binance outflows

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/Features Engineering





2 Regularization

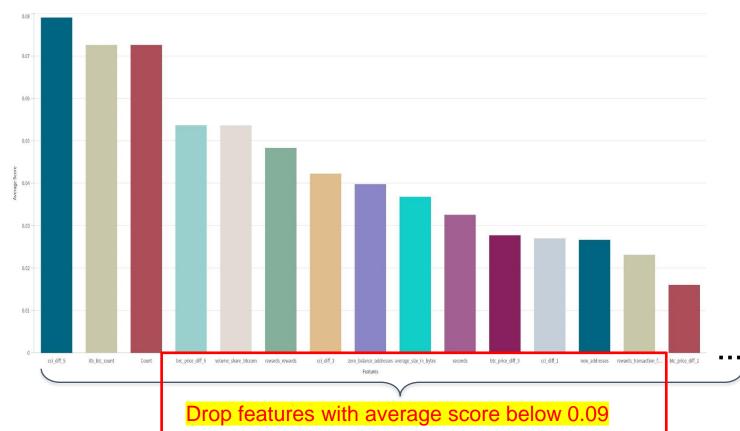
2-1 Ridge, alpha=5

2-2 Random forest regressor

Tuning coefficients of data that suffers from multicollinearity

Features scoring

Calculate the average of three methods results after scaling.



2. Add Lagging Effect Features

• 1-day lag Bitcoin Price return rate:

$$Return_{1-day} = \frac{Price_t - Price_{t-1}}{Price_{t-1}}$$

• 3-day lag Bitcoin Price return rate:

$$Return_{1-day} = \frac{Price_t - Price_{t-3}}{Price_{t-3}}$$

• 5-day lag Bitcoin Price return rate:

$$Return_{1-day} = \frac{Price_t - Price_{t-5}}{Price_{t-5}}$$

3. Add Lagging Effect Features

lagging Crypto Currency Index (CCI)

• 1-day lag CCI increase rate:

• 3-day lag CCI increase rate:

• 5-day lag CCI increase rate:

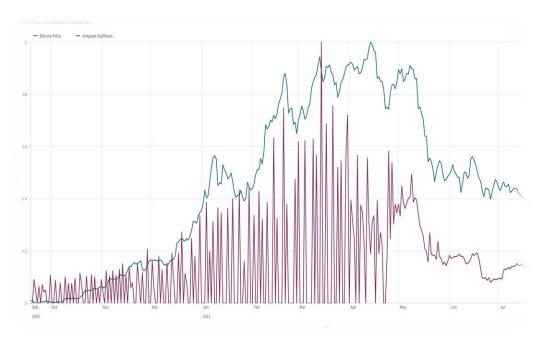
$$\widehat{CCI}_{1-day} = \frac{CCI_t - CCI_{t-1}}{CCI_{t-1}}$$

$$\widehat{CCI}_{3-day} = \frac{CCI_t - CCI_{t-3}}{CCI_{t-3}}$$

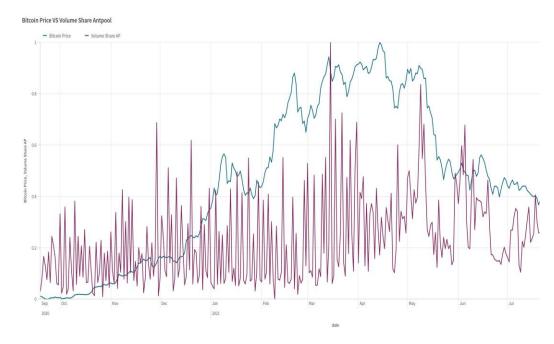
$$\widehat{CCI}_{5-day} = \frac{CCI_t - CCI_{t-5}}{CCI_{t-5}}$$

High Volatility Features

Visualized High Volatility Features



Bitcoin Price VS Antpool Outflows



Bitcoin Price VS Volume Share Antpool

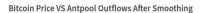
Good trend!

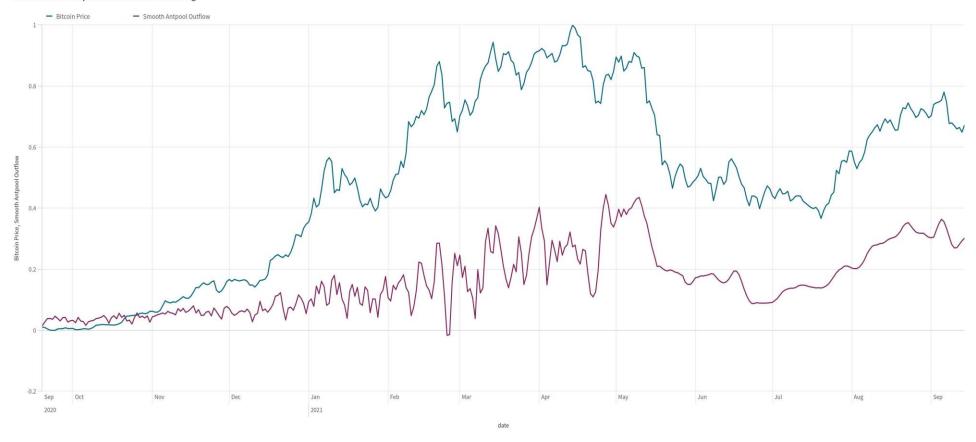


Need Smoothing

But too high Volatility!!!

After Smoothing...





/ Model Tuning

Memory Cells **Tuning Model** Architecture Hidden Layers Weight Initialization Learning Rate **Tuning Optimization** Learning Algorithm **Behavior** Regularization

In Our Case:

- 1. Hidden size and epochs size are set low to prevent over-fitting
- 2. Used GridSearchCV to find the best number of layers, learning rate, and regularization.
- Hidden Size:64,
- Epochs Size:100
- Learning Rate:0.01
- weight decay for Adam: 0.01
- Regularization:0.01

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/ Final Model Performance

•1. Performance:

RMSE = **0.02631**. not over-fitted

• 2、Results:

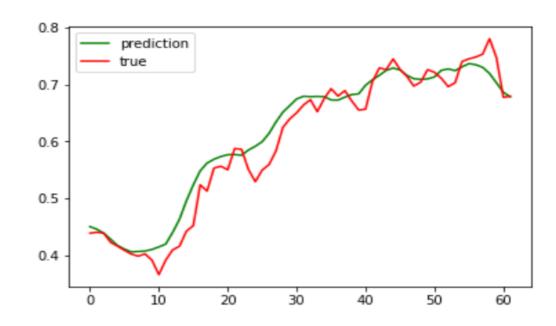
last 10 days data to predict BTC price of the next day that is not in the data set

Price for 2021.9.15

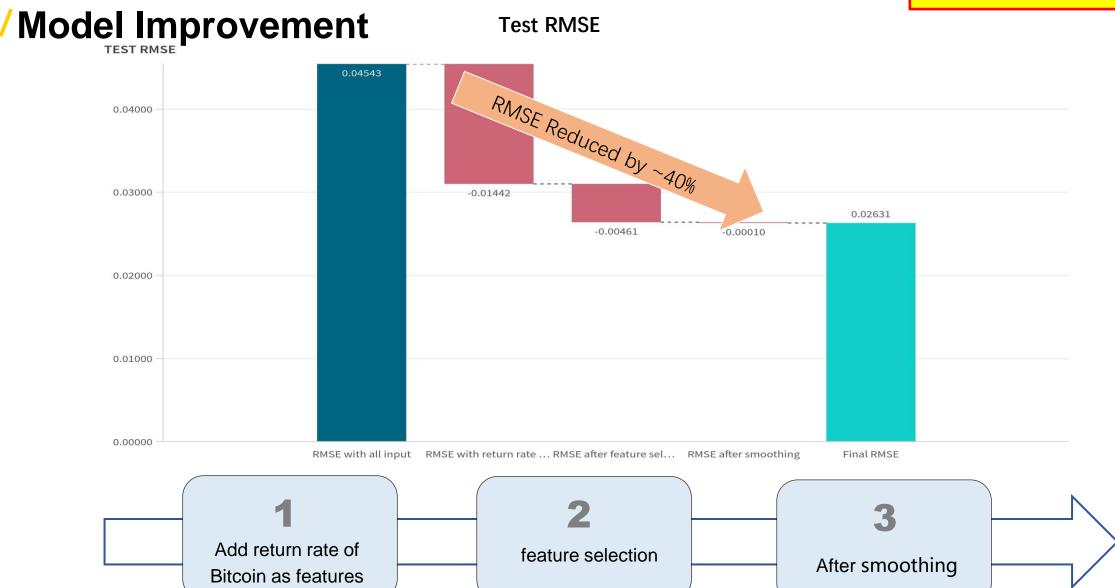
Predicted: 48847.453

True price: 48150.90.

Predict & True



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/ Model Limitation

1

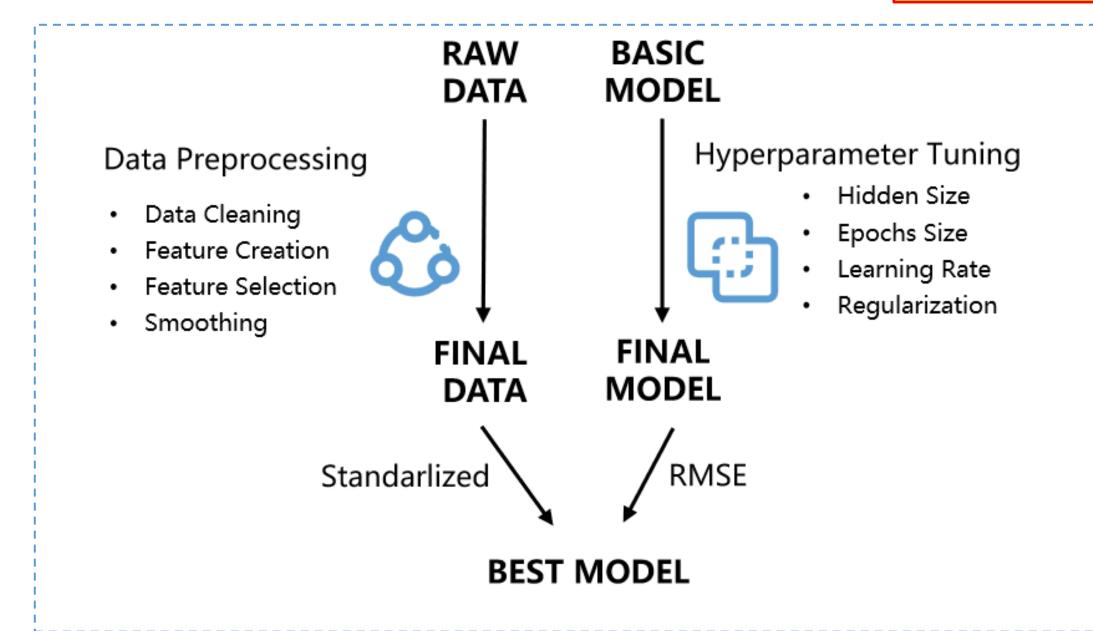
average error is low while the error of each day is sometimes significant 2

LSTM can only be used for predicting very near future

3

small dataset no validation seperation hence have risk for overfit

/ Conclusion



REFERENCE



- 1. Chen, Zheshi et al. "Bitcoin price prediction using machine learning: An approach to sample dimension engineering." J. Comput. Appl. Math. 365 (2020): n. pag.
- 2. Raju, Shobha Manival and Ali Mohammad Tarif. "Real-Time Prediction of BITCOIN Price using Machine Learning Techniques and Public Sentiment Analysis." ArXiv abs/2006.14473 (2020): n. pag.
- 3. Bollen, Johan et al. "Twitter mood predicts the stock market." ArXiv abs/1010.3003 (2011): n. pag.
- 4. Dutta, Aniruddha et al. "A Gated Recurrent Unit Approach to Bitcoin Price Prediction." arXiv: Pricing of Securities (2019): n. pag.

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