**Bitcoin Price Analysis**

Yulong Yang, Yaqin Tang

**ABSTRACT**

In this paper, we discuss different methods for predicting price variation of Bitcoin, a recently popularized virtual, cryptographic currency. First, we apply two traditional way of doing stock market analysis – Bayesian regression and support vector machines (SVM). And compare the performance on Bitcoin and Google’s stock price, of which the relative error rate of the former one is larger than the latter. Based on this, we use moving average trend classifier to predict the trend of Bitcoin and try two new methods – Google trend analysis and news sentimental analysis, in order to improve the accuracy of the classifier. Results shown that SVM outperforms Bayesian curve fitting in terms of large number of datasets, and those traditional way of doing stock market analysis cannot be directly applied to Bitcoin price analysis due to its large and unpredictable price variation.

***Keywords***: Bitcoin, Bayesian regression, SVM, Google trend analysis, news sentimental analysis

1. **INTRODUCTION**

Bitcoin is a new currency that was created in 2009 by an unknown person using the alias Satoshi Nakamoto. Transactions are made with no middle men – meaning, no banks! There are no transaction fees and no need to give your real name. More merchants are beginning to accept them: You can buy web hosting services, pizza or even manicures. Bitcoins can be used to buy merchandise anonymously. In addition, international payments are easy and cheap because Bitcoins are not tied to any country or subject to regulation. Small businesses may like them because there are no credit card fees. Some people just buy Bitcoins as an investment, hoping that they’ll go up in value. People can send Bitcoins to each other using mobile apps or their computers. It’s similar to sending cash digitally. Bitcoins are stored in a “digital wallet,” which exists either in the cloud or on a user’s computer. The wallet is a kind of virtual bank account that allows users to send or receive Bitcoins, pay for goods or save their money. Unlike bank accounts, Bitcoin wallets are not insured by the FDIC. Though each Bitcoin transaction is recorded in a public log, names of buyers and sellers are never revealed – only their wallet IDs. While that keeps Bitcoin users’ transactions private, it also lets them buy or sell anything without easily tracing it back to them [1].

No one knows what will become of Bitcoin. However, since Bitcoin is such a new type of currency and is of great difference than traditional stock market with such a worldwide concern, it’s an interesting topic to research if we can do some analysis on Bitcoin price prediction.

Moreover, the Bitcoin market Cap is shown below in figure 1, it’s worth an effort to dig into this problem.

Figure 1 Bitcoin Market Cap

1. **BAYESIAN REGRESSION**
   1. **Data Preprocessing**

As can be seen from figure 2, we get the Bitcoin historical data from the *COINBASE* website in US dollar. Then sort the data based on time and choose the closed price of each day as the data we use in Bayesian curve fitting.

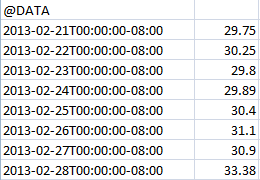
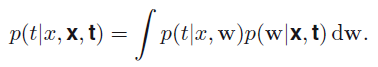


Figure 2 Dataset Example

* 1. **Algorithms**

In the curve fitting problem, we are given the training data **x** and **t**, along with a new test point x, and our goal is to predict the value of t, we therefore wish to evaluate the predictive distribution p(t|x,**x**,**t**). Here we shall assume that the parameters α and β are fixed and known in advance. A Bayesian treatment simply corresponds to a consistent application of the sum and product rules of probability, which allow the predictive distribution to be written in the form [3]

 (Eq. 1)

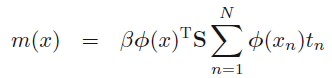
Here p(t|x,w) is given by Eq. 2, and we have omitted the dependence on α and β to simplify the notation. Here p(w|**x**,**t**) is the posterior distribution over parameters, and can be found by normalizing the right-hand side of Eq. 3. For problems such as the curve fitting, this posterior distribution is a Gaussian and can be evaluated analytically. Similarly, the integration in Eq. 1 can also be performed analytically with the result that the predictive distribution is given by a Gaussian of the form in Eq. 4.

 (Eq. 2)

 (Eq. 3)

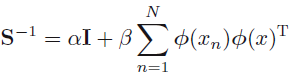
 (Eq. 4)

Where the mean and variance are given by

 (Eq. 5)

 (Eq. 6)

Here the matrix S is given by

 (Eq. 7)

Where I is the unit matrix, and we have defined the vector ф(x) with elements фi(x) = x^i for I = 0, …, M. We see that the variance, as well as the mean, of the predictive distribution in Eq. 4 is dependent on x. the first term in Eq. 6 represents the uncertainty in the predicted value of t due to the noise on the target variables and was expressed already in the maximum likelihood predictive distribution. However, the second term arises from the uncertainty in the parameters w and is a consequence of the Bayesian treatment.

1. **SVM FOR REGRESSION**
   1. **Data Preprocessing**

Choosing a suitable forecasting horizon is the first step in financial forecasting. From the trading aspect, the forecasting horizon should be sufficiently long so that the over-trading resulting in excessive transaction costs could be avoided. From the prediction aspect, the forecasting horizon should be short enough as the persistence of financial time series is of limited duration. As suggested by Thomason [5] a forecasting horizon of five days is a suitable choice for the daily data. As the precise values of the daily prices is often not as meaningful to trading as its relative magnitude, and also the high-frequency components in financial data are often more difficult to successfully model, the original closing price is transformed into a five-day relative difference in percentage of price (RDP). The input variables are determined from four lagged RDP values based on five-day periods (RDP-5, RDP-10, RDP-15, and RDP-20) and one transformed closing price which is obtained by subtracting a 15-day exponential moving average (EMA15) from the closing price. The subtraction is performed to eliminate the trend in price as the maximum value and the minimum value is in the ratio of about 2: 1 in all the five data sets. The optimal length of the moving day is not critical, but it should be longer than the forecasting horizon of five days. EMA15 is used to maintain as much of the information contained in the original closing price as possible since the application of the RDP transform to the original closing price may remove some useful information. The output variable RDP+5 is obtained by first smoothing the closing price with a three-day exponential moving average, because the application of a smoothing transform to the dependent variable generally enhances the prediction performance of neural networks.

* 1. **Algorithms**

Given a set of training data {(x1, y1), …, (xl, yl)}, where each xi belongs to X and X belongs to R^n. (X denotes the input space of the sample) and corresponding target value yi belongs to R for I = 1, …, l (where l corresponds to the size of the training data), the objective of the regression problem is to determine a function that can approximate the value of y for an x not in the training set [4].

The estimating function f is taken in the form:

f(x) = ( w\*ф(x)) + b (Eq. 8)

where w belongs to R^m, b belongs to R is the bias and ф denotes a non-linear function from R^n to high dimensianl space R^m (m>n). The objective is to find the value of w and b such that values of f(x) can be determined by minimizing the risk.

 (Eq. 9)

Where L is the extension of insensitive loss function originally proposed by Vapnik [6] and defined as:

 (Eq. 10)

For those αi and αi\* for which the xi’s corresponding to 0 < αi < C and 0 < αi\* < C are called support vectors. f(x) is computed as in Eq. 11.



 (Eq. 11)

It is to be noted that we do not require function ф to compute f(x) which is one the advantage of using the kernel.

1. **MOVING AVERAGE TREND CLASSIFIER**

The moving average algorithm is to calculate the average value within a window size and then move to the next time period for the fixed size. Combining the moving average and any short-term price prediction algorithm, we are able to classify Bit-coin price trend weekly and monthly, which works as follows:

* sample the historical data weekly, which means the sample rate is 7;
* predict each day's price for next week;
* calculate moving average this week go back N ave\_now and next week go back N ave\_future;
* if ave\_now > ave\_future, predict 0: decrease, otherwise 1: increase;
* from results of each day next week, vote for the trend next week;
* Similarly vote for monthly trend with weight [0.6; 0.25; 0.1; 0.05].

1. **GOOGLE TREND ANALYSIS**
   1. **Data Preprocessing**
   2. **Algorithms**
2. **NEWS SENTIMENTAL ANALYSIS**
   1. **Data Preprocessing**
   2. **Algorithms**
3. **EXPERIMENTS AND RESULTS**

The experiments are conducted through all the historical datasets starting from November 2011 to November 2014. And below figure 3 and 4 show the results for Bayesian curve fitting and supporting vector separately.



Figure 3 Comparison of actual price and predict price by Bayesian curve fitting



Figure 4 Comparison of actual price and predict price by support vector

Blow in table 1 is the evaluation for both methods.

Table 1 performance evaluation

|  |  |  |
| --- | --- | --- |
| Algorithms | MSE | RMSE |
| Bayesian | 26.76 | 0.08 |
| SVM | 21.39 | 0.07 |
| Google stock | 16.79 | 0.03 |

From the table, we can see that the relative mean square error for Google stock is smaller than any of the algorithms applied to Bayesian or SVM, the reason could because Bitcoin price is fluctuating a lot and we calculate the variance of Bitcoin is 27 times that of Google stock price in figure 5.

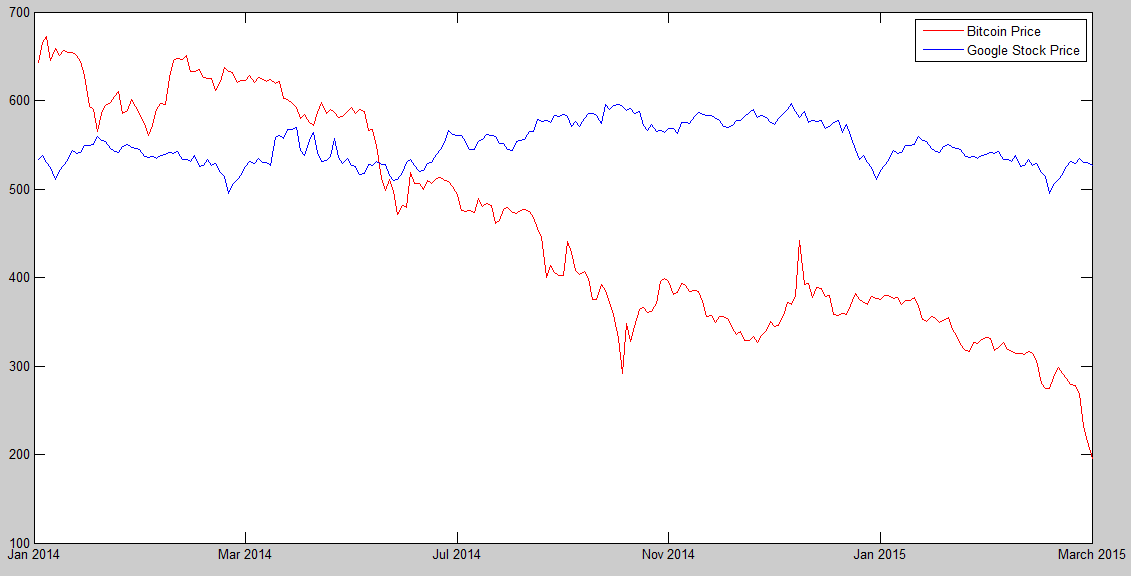


Figure 5 comparison of actual price for Bitcoin and Google stock

Also, based on the analysis for Bayesian and SVM, we evaluate the moving average trend classifier and the confusion matrix is shown below, and for Bayesian, the TPR = 0.7091; FPR = 0.5694; for SVM, the TPR = 0.7455; FPR = 0.5278.

|  |  |  |  |
| --- | --- | --- | --- |
| Bayesian  Based | Predicted Class | | |
| Actual Class |  | C\_IN | C\_DE |
| C\_IN | 78 | 32 |
| C\_DE | 41 | 31 |

|  |  |  |  |
| --- | --- | --- | --- |
| SVM  Based | Predicted Class | | |
| Actual Class |  | C\_IN | C\_DE |
| C\_IN | 82 | 28 |
| C\_DE | 38 | 34 |

1. **CONCLUSION**

In this paper, we compared the accuracy of different methods for predicting the price and trend for Bitcoin price, and results shown that SVM outperforms Bayesian curve fitting in terms of large number of datasets and these traditional methods to analyze Bitcoin price is not as good as analysis for the stock market; More care needs to be taken to analyze Bitcoin market because of its large and unpredictable price variations affected by all kinds of sources.

**REFERENCES**

[1] CNN money: http://money.cnn.com/infographic/technology/what-is-bitcoin/

[2] Devavrat Shah, Kang Zhang, “Bayesian Regression and Bitcoin”, Lab for Information and Decision Systems, Department of EECS, MIT.

[3] Pattern Recognition and Machine Learning Bishop, page 21 – 32.

[4] Shom Prasad Das, Sudarsan Padhy, “Support Vector Machines for Prediction of Futures Prices in Indian Stock Market”, International Journal of Computer Applications, Vol. 41-No.3, 2012.

[5] Thomason M., “The practitioner methods and tool”, Journal of Computational Intelligence in Finance 1999; pp.35–45.

[6] V. Vapnik., 1995, The Nature of Statistical Learning Theory. Springer, N.Y. ISBN 0-387-94559-8.