

Multi-step ahead Bitcoin Price Forecasting Based on VMD and Ensemble Learning Methods

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Agenda

- Introduction
- Dataset
- Methodology
- Results
- Conclusion
- Acknowledgments













Introduction



A cryptocurrency is a digital asset designed to work as a exchange that uses strong cryptography to secure financial transactions.



Bitcoin is considered the first decentralized cryptocurrency, and it was first released as open-source software in 2009.



With the emergence of the cryptocurrency market, the Bitcoin, its leading currency, has captured global attention.













Introduction

Bitcoin price time series has a high volatility

Forecasting Bitcoin price as accurate as possible is a challenge

Hybrid ensemble learning models can handle this volatility

Variational mode decomposition (VMD) and Stacking-ensemble learning (STACK)













Introduction

Objective

- To develop a heterogeneous stacking-ensemble learning model for Bitcoin price forecasting multi-step ahead (one, two and three days ahead).
- The proposed model is composed by VMD and STACK approaches, and heterogeneous forecasting models.













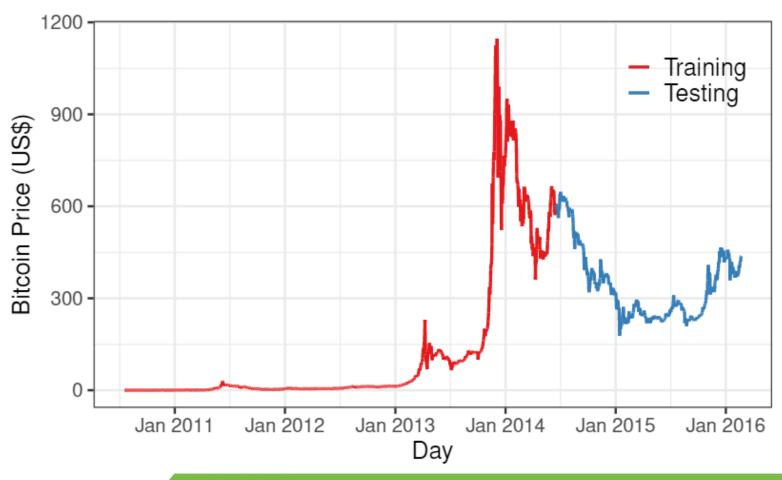
Dataset

 Daily observations from July 28th 2010 to
 February 21st 2016

• Observations number: 2045

TABLE I INPUTS AND OUTPUT OF THE SYSTEM

Type	Description	Unit Measure
Input	Opening Price	
Input	High Price	ΠCΦ
Input	Low Price	US\$
Output	Closing Price	









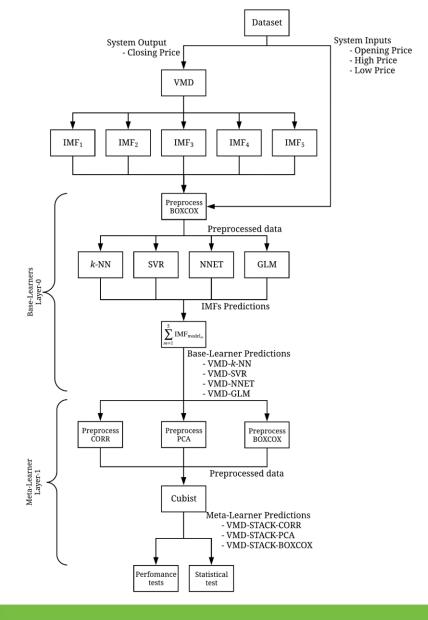






Methodology

- VMD decomposed the data into 5 components;
- A Box-Cox transformation as preprocess;
- Four different algorithms (models) as base-learners:
 - **k-NN** (k-Nearest Neighbor)
 - SVR (Support Vector Regression with Linear kernel)
 - NNET (Feed-forward Neural Network)
 - **GLM** (Generalized Linear Model)
- Base-learners predictions were preprocessed by:
 - **CORR** (Correlation Matrix)
 - PCA (Principal Component Analysis)
 - Box-Cox transformation
- Stacking meta-learner:
 - Cubist Regression















Methodology

Performance measures:

$$ext{RRMSE} = rac{\sqrt{rac{1}{n}\sum_{i=1}^{n}\left(y_i-\hat{y}_i
ight)^2}}{rac{1}{n}\sum_{i=1}^{n}y_i}, \quad ext{sMAPE} = rac{1}{n}\sum_{i=1}^{n}\left|rac{\hat{y}_i-y_i}{\left(|y_i|+|\hat{y}_i|/2
ight)}
ight|, \quad ext{APE} = rac{|y_i-\hat{y_i}|}{y_i}$$

· Statistical test:

$$ext{DM} = rac{rac{\sum_{n}^{i-1} \left[d_i
ight]}{n}}{\sqrt{rac{ ext{var}(d_i)}{n-1}}}$$

Diebold-Mariano test











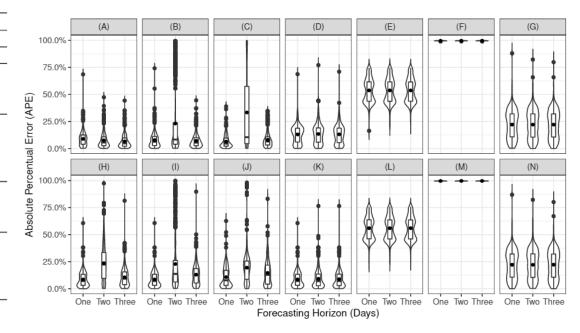


Results

TABLE IV
PERFORMANCE MEASURES RESULTS OF THE MODELS

		Forecasting Horizon								
Model		One-da	ay-ahead	Two-da	ys-ahead	Three-days-ahead				
		sMAPE	RRMSE	sMAPE	RRMSE	sMAPE	RRMSE			
(A) VMD–STACK-	-CORR*	0.0835	0.0936	0.0660	0.0943	0.0762	0.1060			
(B) VMD-STACK-	·PCA*	0.0735	0.0915	0.0708	0.0934	0.2310	0.3812			
(C) VMD–STACK–	BOXCOX*	0.0626	0.0800	0.0836	0.1003	0.5766	0.7108			
(D) VMD-k-NN**		0.1189	0.1244	0.1201	0.1274	0.1224	0.1304			
(E) VMD-SVR**		0.7506	1.5222	0.7499	1.5187	0.7497	1.5184			
(F) VMD-NNET**		1.9870	355.3495	1.9870	354.8142	1.9870	354.7863			
(G) VMD-GLM**		0.2153	0.2867	0.2151	0.2858	0.2151	0.2858			
(H) STACK-CORR	*	0.0804	0.0935	0.0976	0.1099	0.2033	0.1954			
(I) STACK-PCA*		0.0806	0.0936	0.1185	0.1263	0.2169	0.3395			
(J) STACK-BOXCO	OX*	0.0985	0.1131	0.1315	0.1596	0.3608	0.5100			
(K) k-NN**		0.0804	0.0935	0.0824	0.0985	0.0850	0.1028			
(L) SVR**		0.7925	1.6495	0.7917	1.6458	0.7916	1.6456			
(M) NNET**		1.9871	359.3776	1.9871	358.8427	1.9871	358.8427			
(N) GLM**		0.2154	0.2863	0.2152	0.2854	0.2152	0.2854			

Note: *Cubist as meta-learner; **BoxCox as pre-processing.













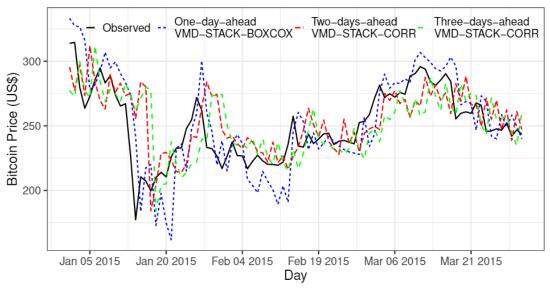


Results

Predicitions for whole dataset



Samples from Jan. 1st 2015 to Mar. 31st 2015















Results

TABLE V
DIEBOLD-MARIANO TEST RESULTS

Model	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)	(M)	(N)
Model	One-day-ahead													
(A)	-	-1.1808	3.1101*	-7.3984*	-12.0835*	-16.5659*	-8.3376*	1.8446	1.8281	-3.7099*	1.8446	-12.2978*	-16.5617*	-8.3427*
(B)	-	-	3.0229*	-5.8826*	-12.0814*	-16.5654*	-8.3103*	1.9772**	1.9679**	-1.6512	1.9772**	-12.2958*	-16.5612*	-8.3153*
(C)	-	-	-	-8.0185*	-12.0883*	-16.5674*	-8.3892*	-0.9842	-0.9961	-4.9253*	-0.9842	-12.3022*	-16.5632*	-8.3948*
Two-days-ahead														
(A)	-	0.2929	-0.2391	-5.5822*	-6.9657*	-9.5660*	-4.8075*	-2.5678**	-4.5894*	-6.8380*	-0.9036	-7.0893*	-9.5635*	-4.8115*
(B)	-	-	-0.4671	-5.6608*	-6.9654*	-9.5658*	-4.8066*	-2.8868*	-4.9356*	-6.9963*	-1.1455	-7.0891*	-9.5634*	-4.8106*
(C)	-	-	-	-4.6239*	-6.9646*	-9.5655*	-4.7984*	-1.9949**	-3.9650*	-6.4008*	-0.5822	-7.0882*	-9.5631*	-4.8024*
Three-days-ahead														
(A)	-	-13.8752*	-7.8720*	-3.5211*	-5.4017*	-7.4190*	-3.7026*	-7.0480*	-27.4156*	-13.8618*	0.1871	-5.4978*	-7.4171*	-3.7051*
(B)	-	-	-1.5640	13.9756*	-2.1187**	-6.4100*	10.3861*	13.5846*	5.7783*	-35.6064*	13.8949*	-2.4337**	-6.4087*	10.4037*
(C)	-	-	-	7.8447*	-17.5507*	-7.6499*	8.9298*	7.6728*	4.0853*	-12.5259*	7.8699*	-6.6571*	-7.6474*	8.9214*

Note: *1% significance level; **5% significance level.













Conclusion

- This study proposed a novel heterogeneous decomposition-ensemble learning model by using VMD and STACK with different preprocessing algorithms to forecast Bitcoin price multi-step-ahead.
- The stacking-ensemble was composed by k-NN, SVR, NNET and GLM, as baselearners in the first layer, and using Cubist as meta-learner in the second layer.
- Indeed, the VMD-STACK approach had a better performance than compared models in almost all forecasting horizons.

For future works

- Adopt different combinations of models in both layers of the stacking-ensemble
- Optimize the hyperparameters of the models
- Optimize the number of components to be decomposed
- Use different decomposition methods
- Increase the forecast horizon interval to more than 3 days ahead













Acknowledgments





















Thank you!













