Georgia Institute of Technology

Crypto Seems Random, But It's Chaotic: N-CATS, A Model for Cryptocurrency Price Prediction

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Problem: Crypto-currency Price Prediction

1. Crypto-currency Market
   - shows chaotic behavior, which implies that it is chaotic dynamical system[1]
   - is weakly market efficient[2]

⇒ Thus, use both **market's chaotic dynamics along with past trends of price** to predict crypto-asset price.

2. Research Question
   - **RQ1: How does baseline model perform in predicting price?**
   - **RQ2: How can we make a model learn market dynamics information?**
   - **RQ3: How does the new model perform?**

[1] 6, 4, 3, 2, 7, 1.
[2] 8.

Why is this prior knowledge possibly helpful?

- **Dynamical System**: A system whose behavior is described by predefined rules, for e.g. $x_t = f(x_{t-1}, t)$
- **Chaotic System**: A deterministic dynamical system that is *extremely sensitive to initial points* $\Rightarrow$ **Long term prediction is almost impossible**

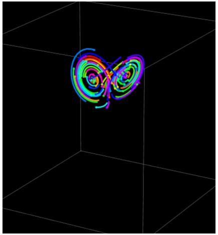


Figure: Example of Chaotic System

$\Rightarrow$ we can use **statistical measures of chaotic system**

1. to assist with training, or
2. verify if a model learned a true dynamics or not

What would learning a chaotic dynamical system from data mean?

- If a model learned
  - **a chaotic system,**
    - Auto-correlation, $\rightarrow 0$, $\Leftrightarrow$ $\lim_{t\rightarrow\infty} C(x_t, x_{t+\tau})$
    - Lyapunov exponent, $\lambda_{time-series} > 0$
  - **a correct chaotic system,**
    - Multi-step prediction error should be low

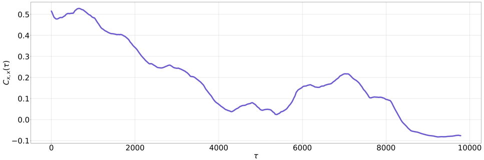


Figure: Auto-correlation of bitcoin price

- Auto-correlation $\rightarrow$ will be included in loss
- Lyapunov exponent, multi-step prediction error$\rightarrow$ will be used to verify if a model learned a chaotic system

Experiment: Data

- Data: Bitcoin Historical Dataset from Kaggle(Link)
  - Price per 1 Minute historical data of 2021, used only one feature, Closing price → univariate time series prediction
  - Size of Training Data: 7546
  - Size of Test Data: 3234
- Preprocess: Min-Max Scaling

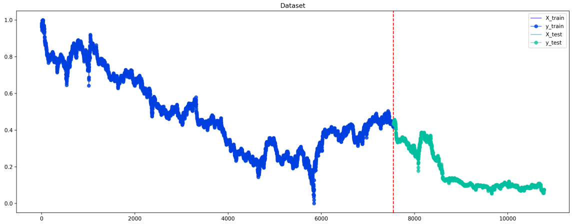


Figure: Full Dataset Visualized

Experiment Setting

1. Baseline: LSTM, Neural ODE
   - Training Algorithm: AdamW
     - Learning rate: $1e-3$, $5e-4$
     - Number of epoch: 1000
   - LSTM Setting:
     - window size = 10
     - 1 LSTM Layer, 2 Linear Layer
   - Neural ODE Setting:
     - Feed Forward Neural Network of 6 Layers for approximating ODE
2. New Model: N-CATS, Neural Chaotic Autocorrelation for Time Series
   - Training Algorithm: AdamW
     - Learning rate: $5e-4$
     - Number of epoch: 800
   - N-CATS setting:
     - 2 FFN of 2 Layers for approximating SDE (drift, diffusion)
     - latent_dim = 64

RQ1: How does baseline model perform in predicting price?

	Train loss	Test loss	Norm Diff of LE
LSTM	0.04117	0.11384	inf
Neural ODE	$3.2348e-05$	$1.0721e-05$	0.0001

Table: Baseline loss

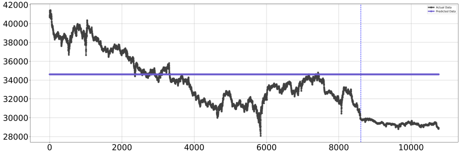


Figure: LSTM One-step Prediction

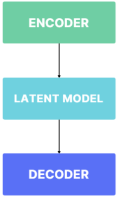
Figure: Neural ODE Multi-step Prediction

- LSTM's limitation: vanishing gradient problem[a]
- Neural ODE limitation: sensitive to noise in input data

[a] 5.

RQ2: How can we make a model learn market dynamics information?

- N-CATS: Neural Chaotic Auto-Correlation for Time Series
- Latent Model:
  - Neural SDE (⇒ N-CATS_NSDE)



$$\mathcal{L}_{new\_loss} = \mathcal{L}_{MSE} + \lambda * \mathcal{L}_{autocorrelation} \quad s.t. \lambda \in [0,1]$$

$$\mathcal{L}_{auto-correlation} = \mathbb{E}(x_t x_{t+\tau}) - \mathbb{E}(x_t)\mathbb{E}(x_{t+\tau})$$

$$= \frac{1}{T}\sum_{t\leq T} x_t x_{t+\tau} - \frac{1}{T}\sum_{t\leq T} x_t \frac{1}{T}\sum_{t\leq T} x_{t+\tau}$$

RQ3: How does N-CATS perform?

	True LE	Learned LE	Norm Diff
N-CATS	$[0.2607571, -0.1330105]$	$[0.26078153, -0.13299644]$	$2.8197e-05$

Table: LE of N-CATS

	Train Loss (One-Step) in MSE or New Loss	Test Loss (One-Step) in MSE	Multi-Step Prediction Loss	Norm Diff LE
LSTM	0.04117	0.11384	inf	
Neural ODE	$3.2348e-05$	$\mathbf{1.0721e-05}$	16.9741	0.0001
N-CATS	0.0022	0.00013	$\mathbf{6.5225}$	$\mathbf{2.8197e-05}$

Table: Loss Table

N-CATS show

- Lowest LE Norm Difference!
- Lowest Multi-Step Prediction Error!

RQ3: How does N-CATS perform?

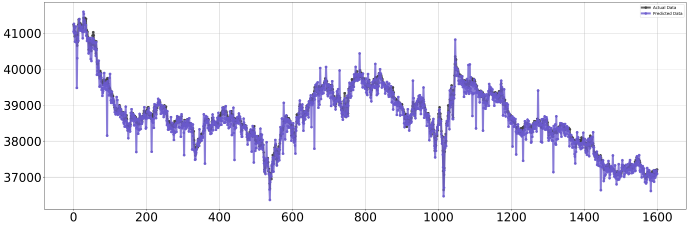


Figure: One-Step Prediction of N-CATS

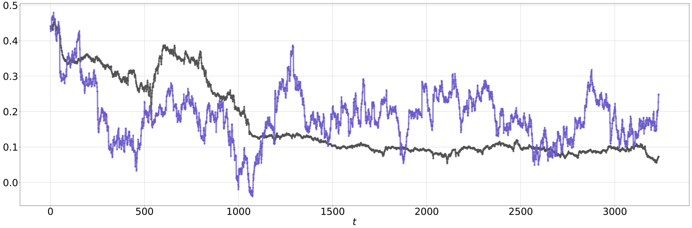


Figure: Multi-Step Prediction of N-CATS on unseen data

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Thank you for coming! Any Questions?