Probabilistic Forecasts for Cryptocurrency

Jake Taylor, Samuel Wong
jakee417@stanford.edu, samwwong@stanford.edu

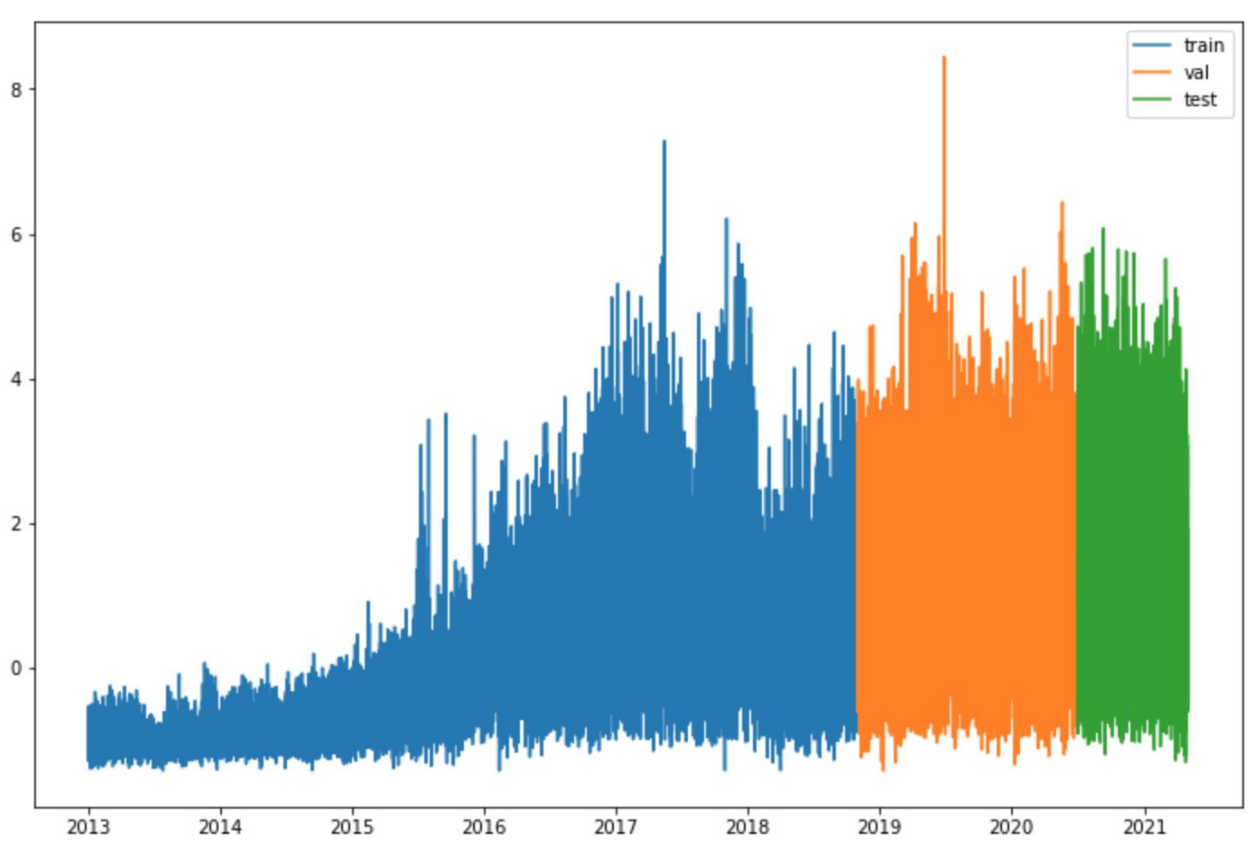
Introduction

- **Forecast-** Given the past information about the transaction volume of Bitcoin, what can we say about the transaction volume of the Bitcoin blockchain in the future?
- **Anomaly-** Looking at the past, can we tell if significant events occurred and the transaction volume was anomalous? What occurred at these time points?

Data

Time Series Data

- Public blockchain data
  - Obtained block header in query-able form from BigQuery
- Time Series data
  - Hourly volume information (each Bitcoin block is mined on average every 10 min)
  - Preprocessed to remove data prior to 2013



Model/Features

Forecast Distribution- Approximated by conditionally independent distribution with a continuous latent factor and autoregressive parameters

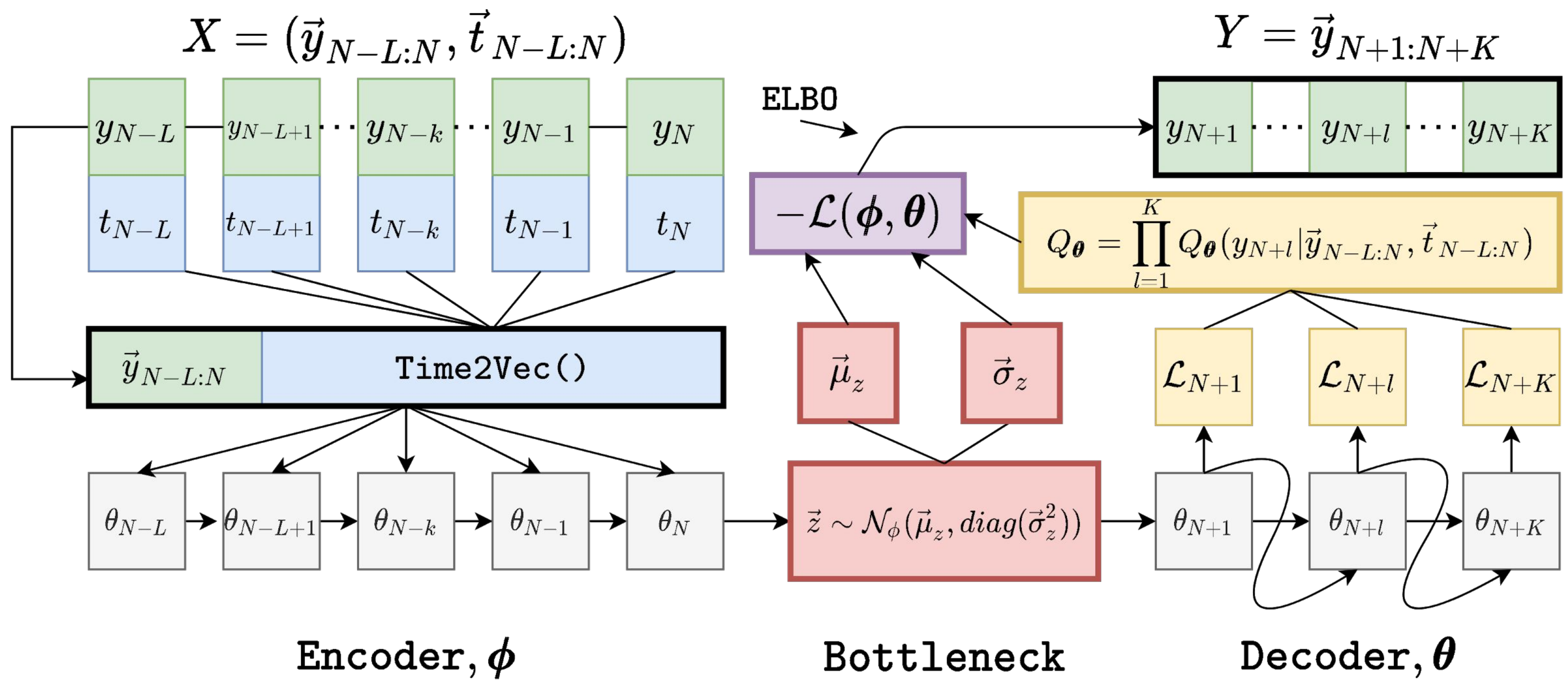
$$\mathbb{P}(\vec{y}_{N+1:N+K}|\vec{t}_{1:N},\vec{y}_{1:N}) \approx \prod_{l=1}^{K} Q_{\vec{\theta}}(y_{N+l}|\vec{y}_{N-L:N},\vec{t}_{N-L:N}) = \int \prod_{l=1}^{K} Q_{\vec{\theta}}(y_{N+l}|\vec{y}_{N-L:N},\vec{t}_{N-L:N},\vec{z})p(\vec{z})d\vec{z}$$

Time2Vec- Sine function for modeling periodicity

$$\text{Time2Vec}(\tau)[i] = \begin{cases} w_i\tau + \varphi_i, & \text{if } i = 0 \\ \sin(w_i\tau + \varphi_i), & \text{if } 1 \leq i \leq k \end{cases}$$

Likelihood Models- Try various and fit with Tensorflow Probability (TFP)

$$\mathcal{L} = \{\mathcal{N}(\lambda, \sqrt{|\lambda|}), \mathcal{N}(\mu, \sigma^2), t(\mu, \tau^2, \nu), \text{Laplace}(\mu, b), \text{Mixture}, \text{HMM}\}$$



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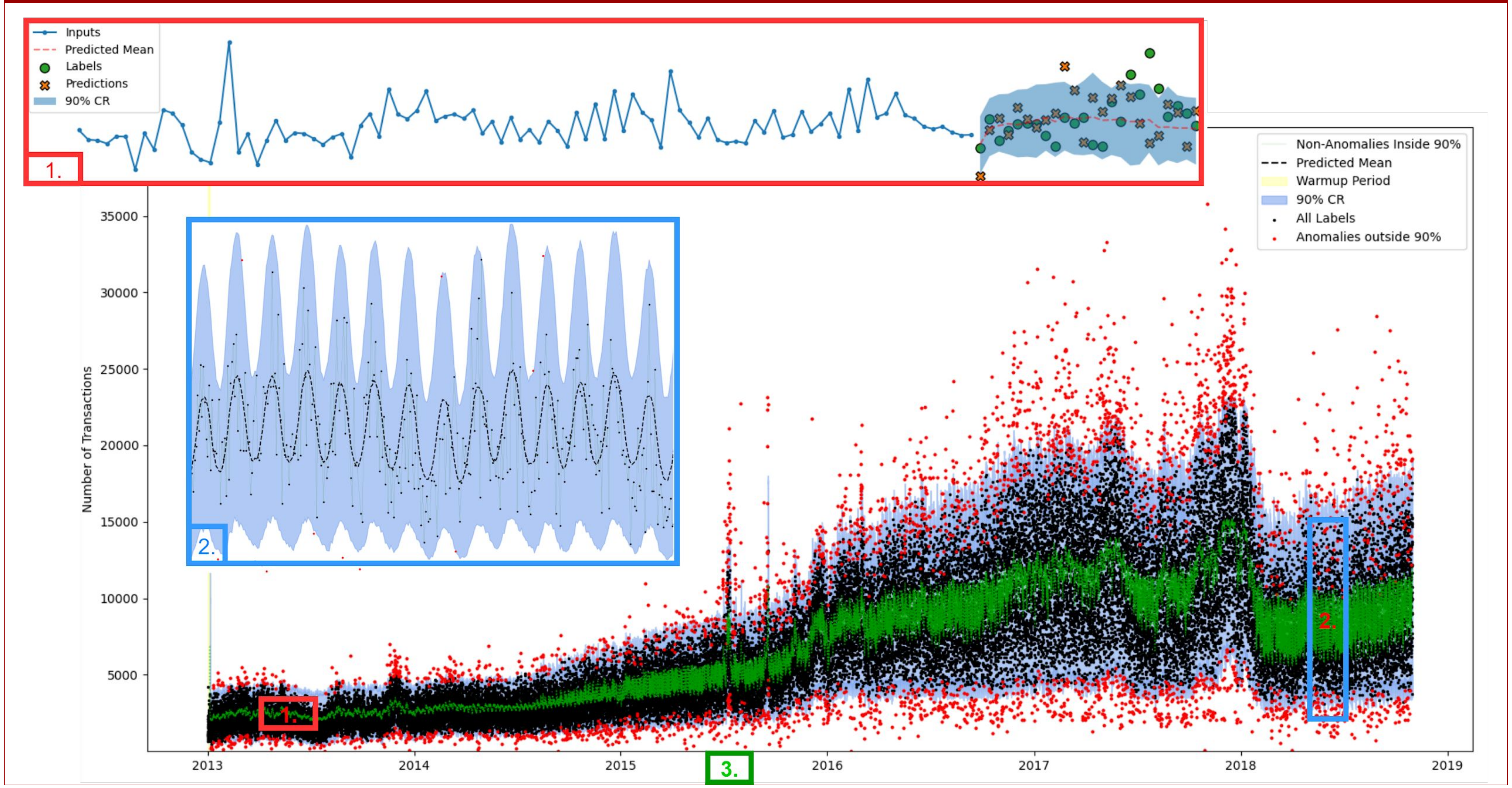
Forecasted Distribution with (1.) Training Batch (2.) Learned Periodicity (3.) Detected Anomaly



Results

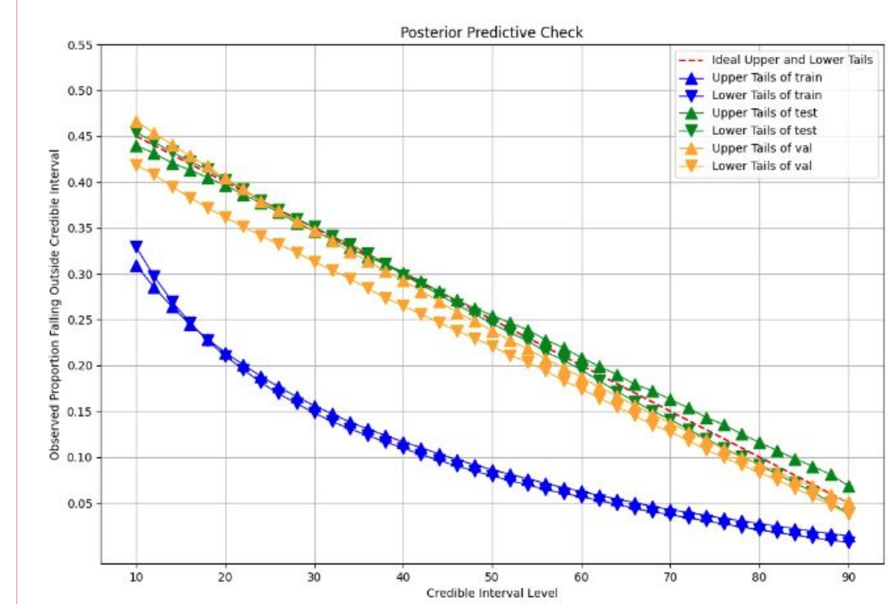


Table 1: Performance in Forecast Task

$\mathcal{L}$	train	val	test
$\mathcal{N}(\lambda, \sqrt{\lvert\lambda\rvert})$	10.48	2.06	2.75
$\mathcal{N}(\mu, \sigma^2)$	3.05	3.34	2.32
$t(\mu, \tau^2, \nu)$	1.84	4.62	5.96
Laplace(μ, b)	5.04	7.44	7.91
Mixture	5.51	4.42	3.23
HMM	13.53	10.39	7.98

Table 2: Performance in Anomaly Task

$\mathcal{L}$	train	val	test
$\mathcal{N}(\lambda, \sqrt{\lvert\lambda\rvert})$	11.8	1.52	0.55
$\mathcal{N}(\mu, \sigma^2)$	2.36	1.66	1.62
$t(\mu, \tau^2, \nu)$	0.63	3.79	4.42
Laplace(μ, b)	4.33	3.56	3.40
Mixture	5.38	3.03	3.53
HMM	13.79	4.02	3.81

Discussion

- **Distributed Denial of Service (DDoS) Detection-** in mid-2015, late-2015, late-2017, and late-2018 several attacks occured. The most notable detected attack is indicated by 3 on the Figure.
- **Concept Drift-** between December 2017 and February 2018, Bitcoin price dropped from \$20,000 to \$6,000 which affected the number of transactions. Our model learns the new distribution after this model drift change.
- **Learned Periodicity-** Time2Vec and the Autoregressive parameters learns a smooth periodicity that corresponds to Day of Week affects in traditional Time Series Analysis. This is shown by 2 in the Figure.

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