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Stochronetics: Surpassing Time Series Forecasting Limitations using Liquid Time-stochasticity Networks

Phase 01

Problem Background

Time Series Forecasting

- TS forecasting is a significant business issue and an area where ML could create an impact (Jain, 2017).
- Although ML and DL have outperformed classical approaches for NLP and computer vision, the domain of TS still seems to be a struggle compared to classical statistical methodologies (Makridakis et al., 2018a;b).

Existing TS forecasting systems cannot adapt to incoming data streams with unexpected changes and characteristics that are different from the data on which they were trained

Existing Work

Time series forecasting algorithms

- Existing forecasting solutions are all implemented using traditional deep neural net architectures.

Existing work

- Neural ordinary differential equations (Chen et al., 2019).
- Liquid Time-Constant networks (Hasani et al., 2020), solved this to some extent.

There's a limitation here: areas with greater randomness - instantaneous, miniscule changes cannot be modelled.

Research Gap

Time series forecasting algorithms

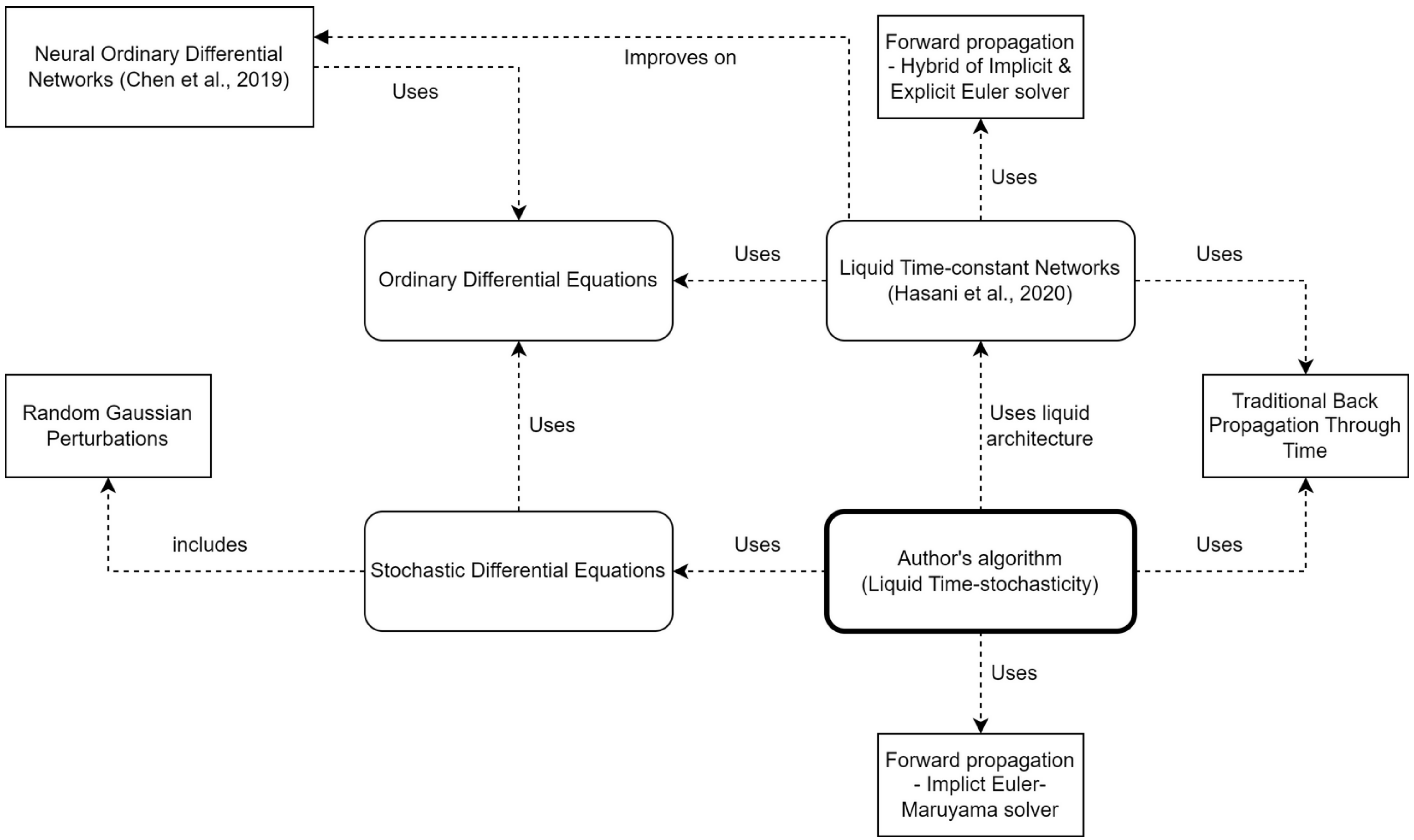
- Existing forecasting solutions are all implemented using traditional deep neural net approaches (ex: LSTM, GRU) that are static and hence have the limitation of not being able to learn and adapt during inference (Hasani et al., 2021), which results in the model's accuracy degrading overtime – a '*data drift*' (Poulopoulos, 2021).

LTC

- The proposed LTC architecture uses a sequence of linear ODEs, which are now considered obsolete and lack rapid adaptability (Duvenaud, 2021).

Algorithm Design

Stochastic differential equations can be used instead of ordinary differential equations!



Training These Networks

$$\boxed{\frac{dx(t)}{dt} = -\left[\frac{1}{\tau} + f(x(t), I(t), t, \theta) - \sigma B\right] x(t) + f(x(t), I(t), t, \theta) A}$$

To solve the state of these SDEs, implicit Euler-Maruyama solver can be used.

And for backpropogation, the traditional Backpropogation Through Time approach.

Algorithm Complexity

	BPTT	**Adjoint sensitivity**
Time	O(L)	**O(LlogL)**
Memory	O(L)	**O(1)**
Forward accuracy	High	High
Backward accuracy	**High**	Low

Algorithm Demo

Phase 02

Problem Domain

Cryptocurrencies

- The word ‘crypto’ has been an enormous buzzword recently, especially BTC. It has even come to the point where crypto and BTC are used interchangeably (Rahouti et al., 2018).
- Its a fully decentralized means of exchange/digital currency.

However, being at the forefront of the digital currency world, it has developed high volatility, making it difficult to predict future rates (Kervanci and Akay, 2020).

Research Gap

Bitcoin forecasting

- The work available on BTC forecasting has yet to consider exogenous factors that could have an impact (Roy et al., 2018; Rizwan et al., 2019; Fleisher et al., 2022). Therefore, a significant concern is that they cannot adapt well.

Factors that could influence the price are as follows (Abraham et al., 2018):

- Tweet sentiment & volume
- Google Trends

Insights

Forecasting the price of crypto is implausible without considering other factors other than the past historical prices.

Therefore, include the following factors as well:

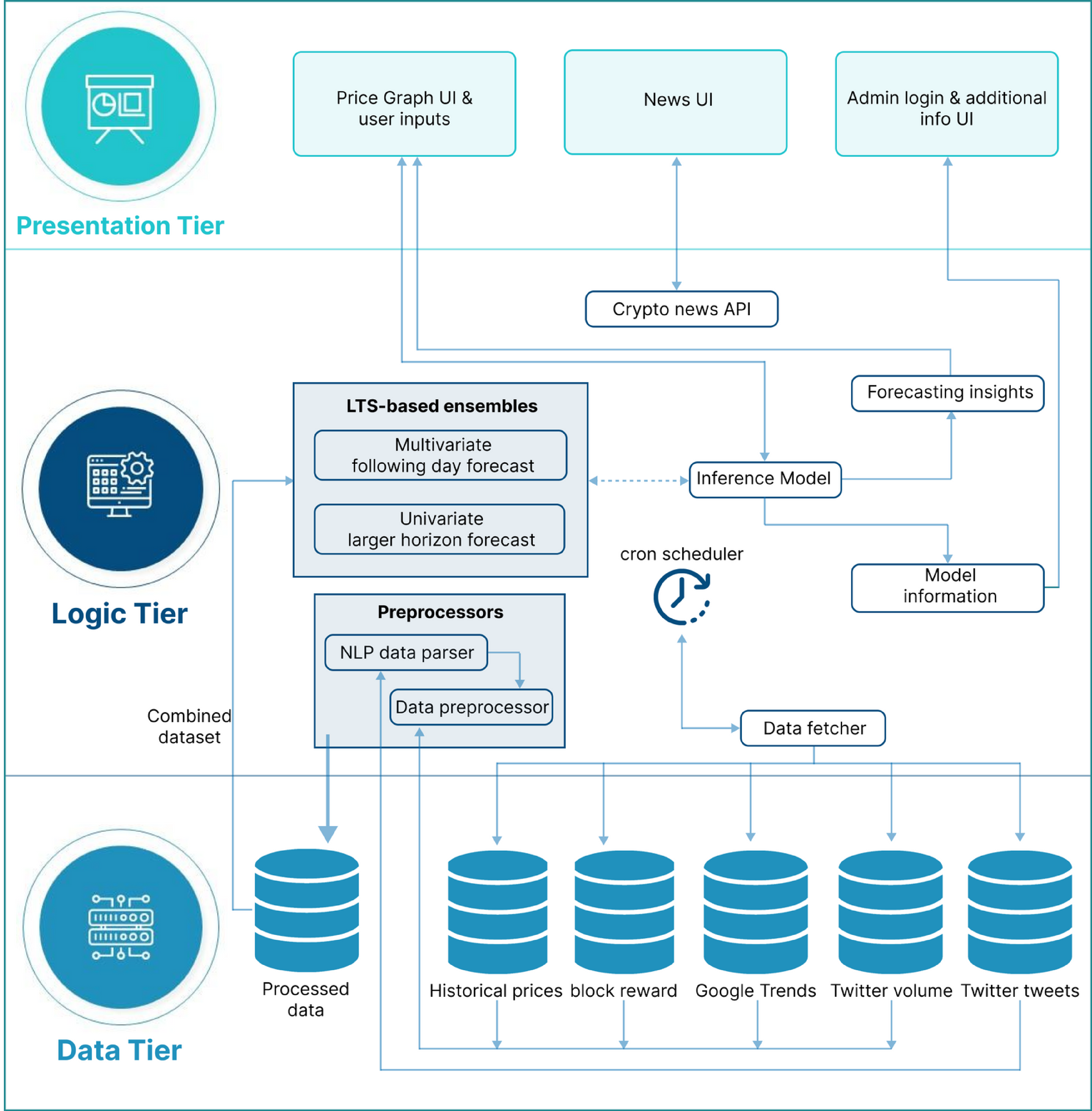
- Google Trends
- Twitter tweet volume
- Twitter thoughts/sentiments
- Block reward size

$$influencer_{sum} = \alpha \log_{10}(followers_{count} + 1) + \beta \log_{10}(lists_{count} + 1)$$

$$tweet_{sum} = \gamma \log_{10}(retweets_{count} + 1) + \delta \log_{10}(like_{count} + 1)$$

$$\boxed{weighted_{score} = \frac{tweet_{sum} + influencer_{sum}}{tweet_{sum} + influencer_{sum} + 1} * compound_{score}}$$

Proposed Architecture



Application Demo

Evaluation

	MAE	MSE	RMSE	MAPE	MASE
Traditional architectures					
Basic dense	1227	2882849	1697	3.06%	1.07
2x dense	1146	2628006	1621	2.98%	1.05
Stacked dense	1147	2604766	1613	2.88%	1.04
Conv1D	1153	2653370	1628	2.90%	1.02
LSTM	1216	283756	1683	3.07%	1.06
N-BEATS	1142	2614896	1617	2.86%	1.03
Benchmark & LTS Ensemble					
Naïve forecast	951	2021966	1421	2.56%	1.00
Ensemble	950	2013928	1419	2.56%	0.99

Future Work

- Identify and determine how other features impact the price.
- Test LTS with other SDE solvers.
- The LTS can use a hybrid SDE solver that combines the implicit and explicit Euler-Maruyama solvers.
- LTS with reverse-mode AD must be evaluated instead of the proposed BPTT approach to determine memory and time efficiency.
- Enhance the Twitter sentiment weighting formula to consider more factors.

References

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Publications

A Review on Breaking the Limits of Time Series Forecasting Algorithms

- IEEE CCWC 2023
- Extended literature review & Liquid Time-stochasticity proposal
- Accepted & Presented

Thank you!