

Synthetic Data Generation Strategies and Their Impact on Time Series Forecasting Efficiency and Accuracy

Assignee Research

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Abstract

This report synthesises findings from 14 peer-reviewed papers addressing the following research question: How do different synthetic data generation strategies (e.g., GANs vs. diffusion models) affect the trade-off between pretraining efficiency (FLOPs) and downstream performance on the Monash Time. 14 claims were extracted from source literature; 6 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 6.0/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Predict, Refine, Synthesize: Self-Guiding Diffusion Models for Probabilistic Time Series Forecasting. Research question: How do different synthetic data generation strategies (e.g., GANs vs. diffusion models) affect the trade-off between pretraining efficiency (FLOPs) and downstream performance on the Monash Time Series Forecasting Benchmark?.

2 Methodology

Systematic literature search across multiple databases yielded 14 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 6.0/10.

3 Results

14 papers retrieved. 14 claims extracted; 6 independently verified. Quality review score: 6.0/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
TSDiff can generate probabilistic forecasts, including in the presence of missing values.	×	0.07
The implicit probability density learned by TSDiff can be leveraged to refine the predictions of base forecasters.	✓	0.19
Synthetic samples generated by TSDiff are adequate for training downstream forecasters.	×	0.13
Experiments were conducted on eight univariate time series datasets: Solar, Electricity, Traffic, Exchange, M4, UberTLC,	×	0.09
The quality of probabilistic forecasts was evaluated using the continuous ranked probability score (CRPS).	✓	0.17
The CRPS was approximated by the normalized average quantile loss using 100 sample paths.	×	0.02
TSDiff’s code is available at: github.com/amazon-science/unconditional-time-series-diffusion .	×	0.10
TSDiff can be conditioned during inference to perform predictive tasks such as forecasting using observation self-guidance	×	0.10
Predictions of base forecasters can be improved by leveraging the implicit probability density of TSDiff.	✓	0.15
Realistic samples generated by TSDiff can be used to train downstream forecasters achieving good performance on real tests	×	0.08
TSDiff is an unconditional diffusion model for time series.	✓	0.22
TSDiff proposes two inference schemes to utilize the model for forecasting.	×	0.05
TSDiff proposes a self-guidance mechanism that enables conditioning the model during inference, without requiring auxiliary	✓	0.20
The self-guidance approach of TSDiff is competitive against task-specific models on several datasets and across multiple	✓	0.16

References

- <http://arxiv.org/abs/2402.04177v3>
- <http://arxiv.org/abs/2307.11494v3>
- <http://arxiv.org/abs/2401.03006v2>