

# This Time is Different: An Observability Perspective on Time Series Foundation Models

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#### Motivation

- Observability time series are different: Metrics are high-volume, multivariate, heavy-tailed, and nonstationary compared to standard time-series benchmarks.
- Gap in models and data: Existing TSFMs underperform on observability, and no dedicated benchmark or model existed before Toto and BOOM.

## **Toto Architecture**

• A Decoder-only transformer: Next-patch prediction for zero-shot multivariate forecasting.

Embeddings  $(M \times L/P \times D)$ 

Patches  $(M \times L/P \times P)$ 

Multivariate

time series

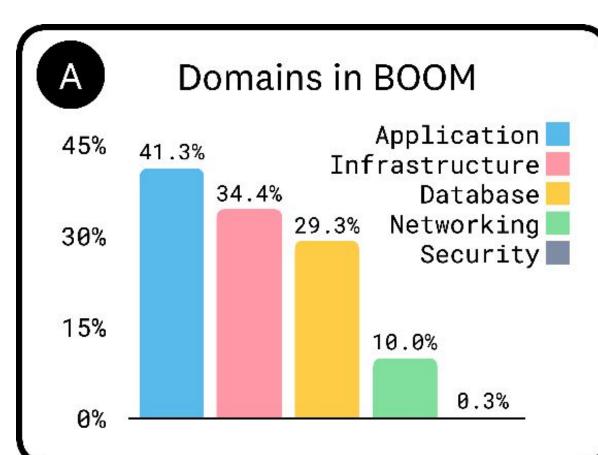
- Causal scaling: Patch-based causal instance normalization to handle strong nonstationarity.
- (B) Patch embeddings: Non-overlapping patches compress long contexts into manageable token sequences.
- C Factorized attention: Alternating time-wise and variate-wise blocks to scale to high-cardinality series.
- Student-T mixture head: Heavyto spikes and skew.
- tailed probabilistic forecasts robust

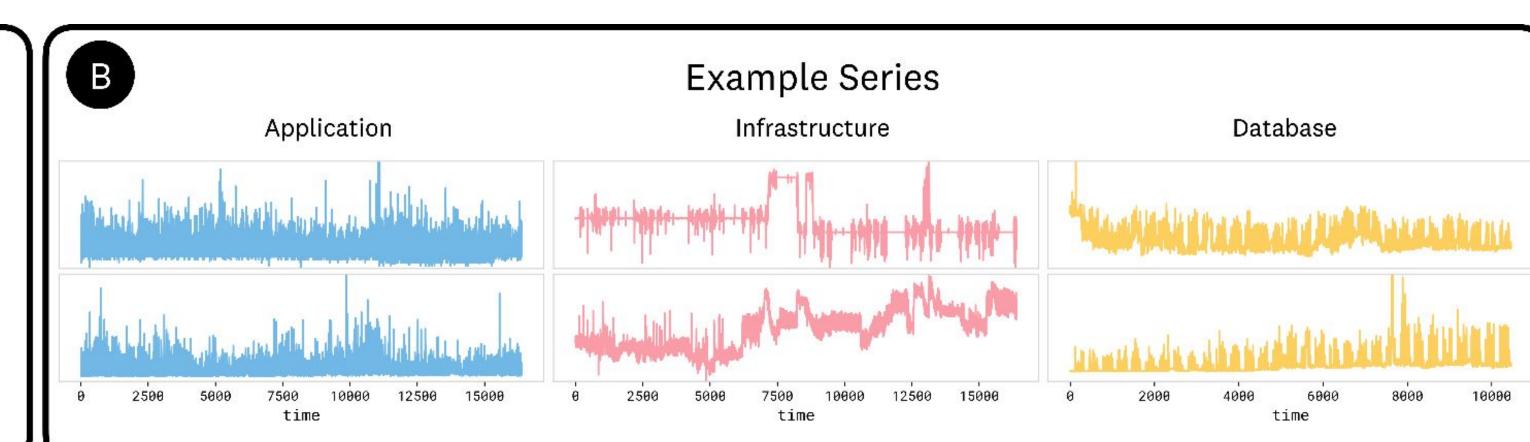


#### Contributions

- Toto: A pretrained, zero-shot time-series foundation model achieving state-of-the-art performance on BOOM, GIFT-Eval, and LSF. The first TSFM optimized for observability.
- BOOM: large observability benchmark: Massive, high-dimensional real telemetry benchmark released with Toto weights and full evaluation code.

### **BOOM Dataset**

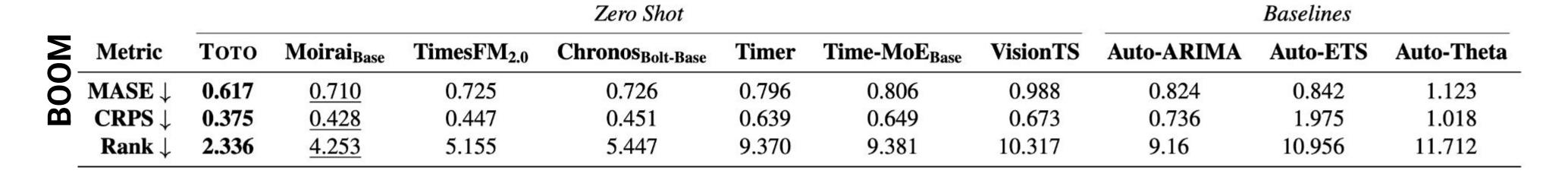




- A Real observability telemetry: 350M points across 2,807 metric queries from Datadog's internal staging environment, disjoint from Toto's pretraining data.
- Rich coverage: Application, infrastructure, database, networking, and security metrics spanning gauges, rates, counts, and distributions.
- (B) Hard, high-dimensional stats: Median ≈60 variates per series with more spikes, nonstationarity, and heavy tails than standard time-series benchmarks.

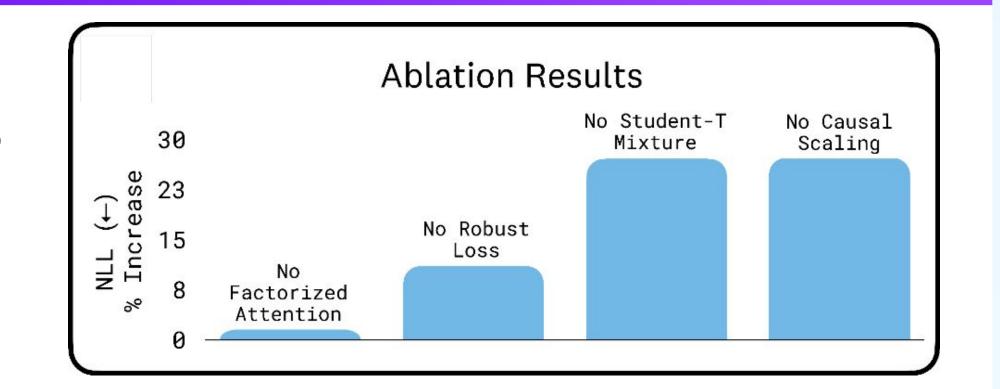
# Results

a		Zero Shot					Full Shot				Baselines		
Ž	Metric	Тото	$Moirai_{Large}$	TimesFM <sub>2.0</sub>	Chronos <sub>Bolt-Base</sub>	TabPFN-TS	TEMPO	TTM-R2	PatchTST	TFT	Auto-ARIMA	Auto-ETS	Auto-Theta
Ļ	MASE ↓	0.673	0.785	0.680	0.725	0.748	0.773	0.679	0.762	0.822	0.964	1.088	0.978
<u></u>	<b>CRPS</b> ↓	0.437	0.506	0.465	0.485	0.480	0.434	0.492	0.496	0.511	0.770	6.327	1.051
G	Rank ↓	5.495	10.330	8.412	8.309	8.402	8.897	10.103	10.268	11.629	21.608	25.134	24.134



# Ablations

 Largest performance gains come from the Student-T mixture head and causal scaling (each causing ~27% NLL degradation when removed), with variate-wise attention and the Cauchy loss term providing smaller but still measurable improvements.



Transformer Decode

Patch Embedding

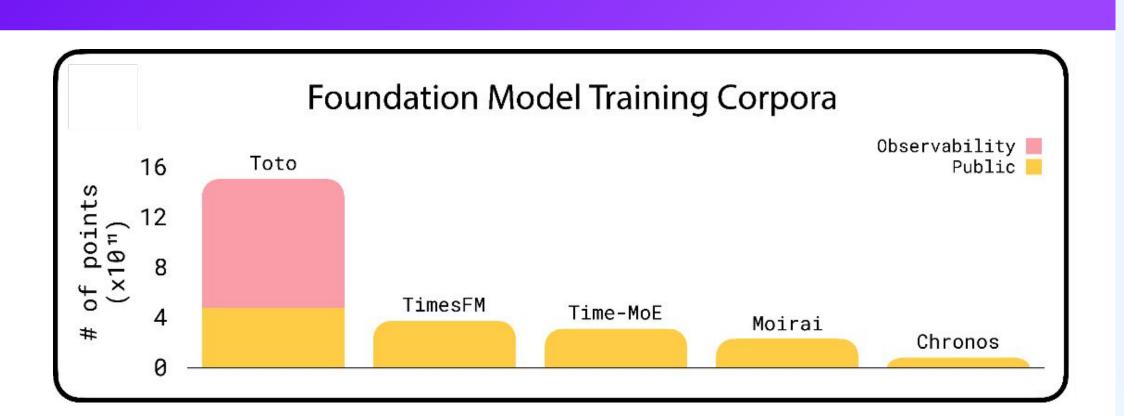
Causal Instance Norm

nputs

# **Pre-training Data**

# Total training: 2.36 trillion time points:

- 43% internal Datadog observability data
- 24% public (e.g., GIFT-Eval, Chronos)
- 33% synthetic time series
- Largest training corpus (by 4–10×)



#### Resources

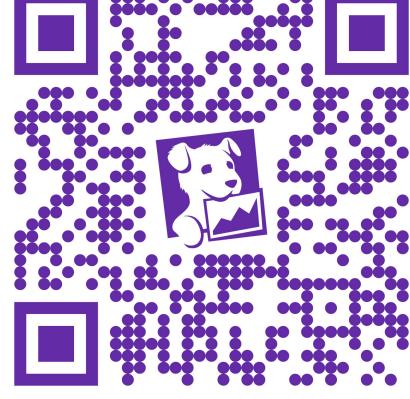


Model Card



**BOOM Dataset** 





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