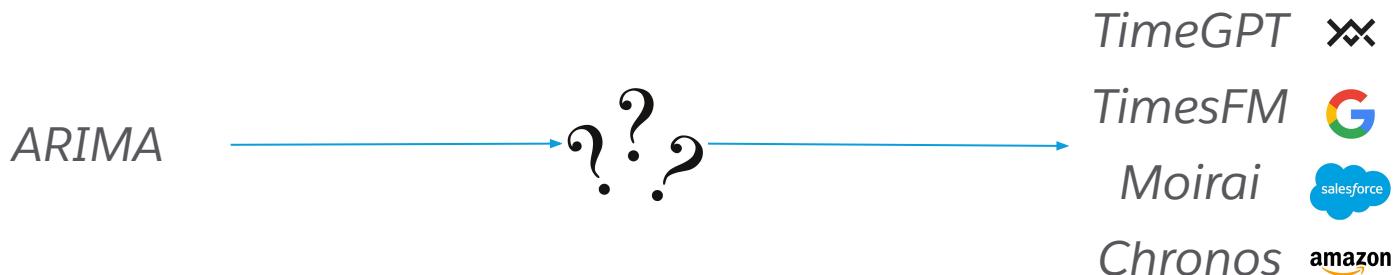


Foundational Time Series Models: the future of forecasting, or just hype?



*PyData Global, 2024
Ahad Shoaib, Salesforce*

Agenda

- ❖ Time Series Forecasting 101
- ❖ The journey from ARIMA → Foundational models
- ❖ How should you use foundational models?
 - *and how you **shouldn't***
- ❖ What's next?

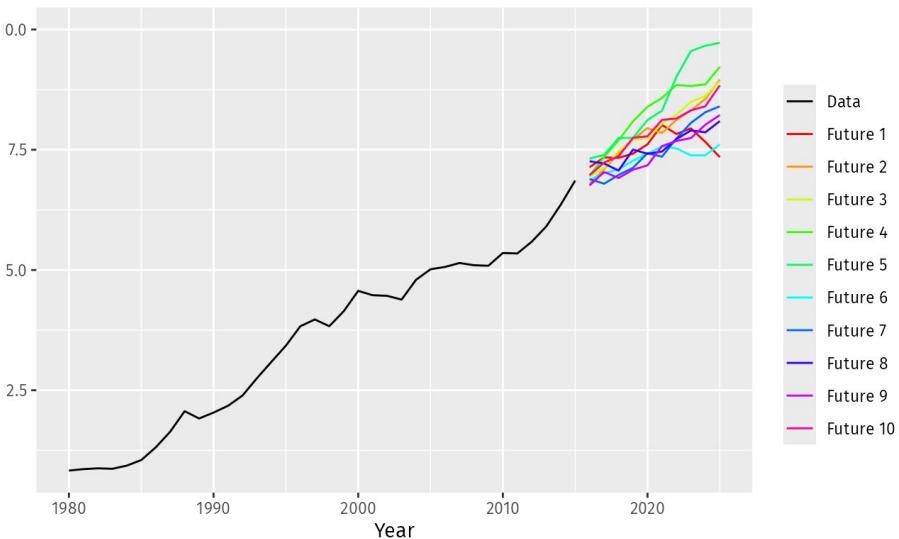
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Time Series Forecasting 101



Problem: Estimating future values using observations

generally follows the standard ML lifecycle: *data* → *fit* → *predict* → *evaluate* → *interpret*



A few use cases...

Sales Forecasting



- Retail Store Stocks (ex. Walmart)
- Finance



Infrastructure Management ★

- Capacity Planning
- Cost Optimization

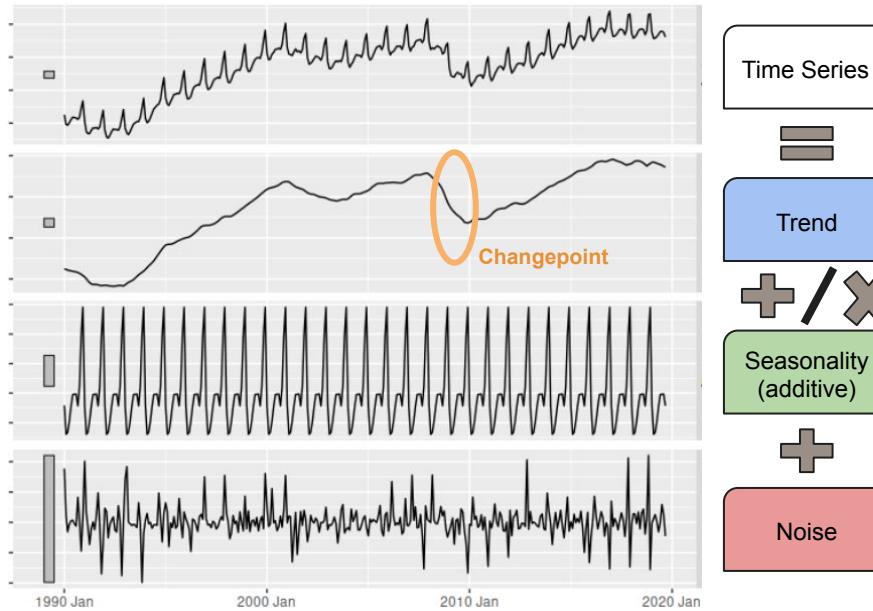


Customer Support

- Ticket Volume Prediction
- Support Call Duration Prediction



Context: Understanding the Language of Time Series



What does forecasting generally look like?

$$\text{Forecast}(t+1) = \text{Trend}(t) + \text{Seasonality}(t) + \text{Error}(t)$$

Challenge: lots of different shapes, sizes, granularities



Solution: The Forecasting Community is a bit... divided

Are Transformers Effective for Time Series Forecasting?

Ailing Zeng^{1*}, Muxi Chen^{1*}, Lei Zhang², Qiang Xu¹

¹The Chinese University of Hong Kong

²International Digital Economy Academy (IDEA)



Yes, Transformers are Effective for Time Series Forecasting (+ Autoformer)

Published June 16, 2023

Update on GitHub



elisim
Eli Simhayev
guest



kashif
Kashif Rasul



nielsx
Niels Rogge

- ★ [Do We Really Need Deep Learning Models for Time Series Forecasting?](#) [Oct. 2021]
- ★ [Are Transformers Effective for Time Series Forecasting?](#) [Aug. 2022]
- ★ [Yes, Transformers are Effective for Time Series Forecasting \(+ Autoformer\)](#) [June 2023]
- ★ [Are Language Models Actually Useful for Time Series Forecasting?](#) [June 2024]
- ★ [Foundational Time Series Models: The Future, or Hype?](#) [This Talk!]

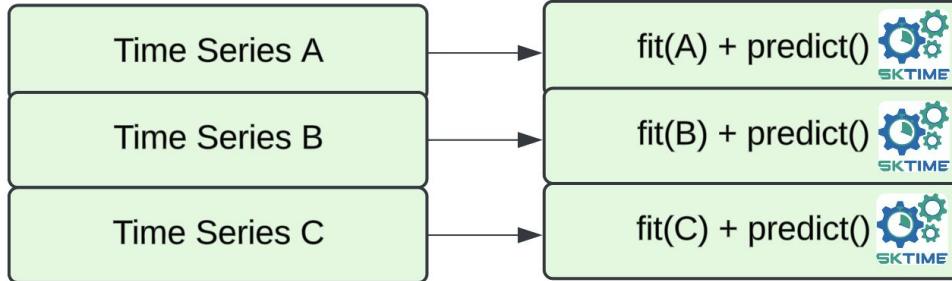
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A journey from ARIMA to foundational models

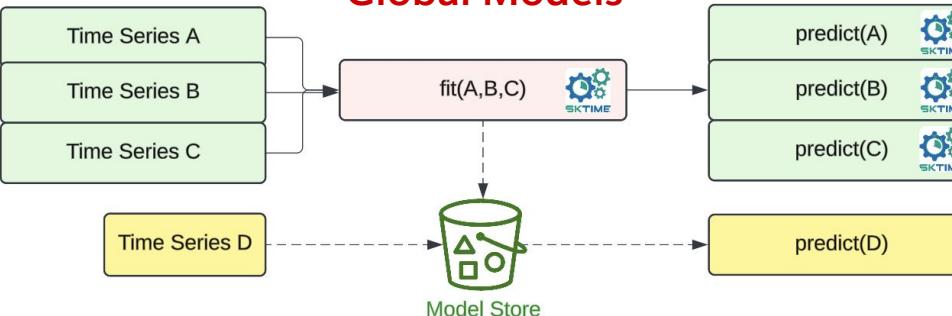


Overview: Local vs Global Forecasting Models

Local Models



Global Models



ARIMA, ETS, Prophet, ...

- Simple to build & interpret
- Easy to tweak individually with prior knowledge

But.. not always accurate @ scale

LightGBM, DeepAR, ...

- More expressive
- Accurate @ scale
 - 🏆 M5 Competition

But... require feature engineering + some ML infrastructure

Blueprint for Global Time Series Model Architecture

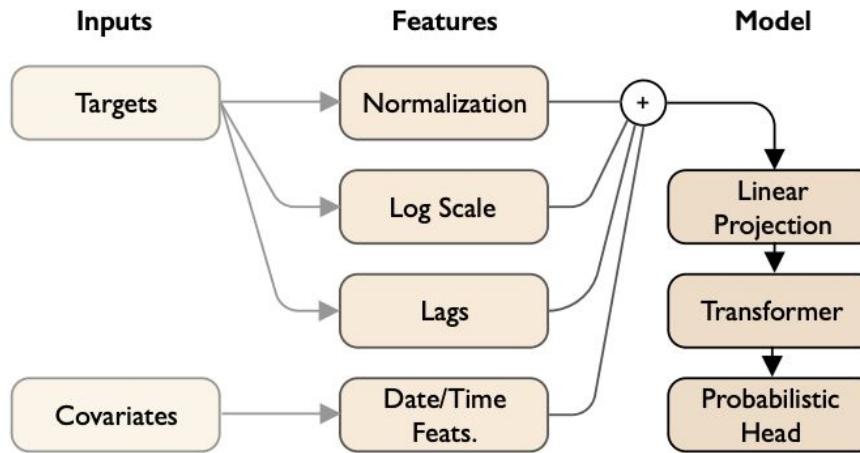


Figure 3: Data flow of a standard pipeline for probabilistic time series forecasting ([Salinas et al., 2020](#)).

<2017: Forecasting is slowly maturing, NLP enters new era

Forecasting: classical methods prevail

Latest M3 Competition:
Oct. 2000



PROPHET

Forecasting at scale.

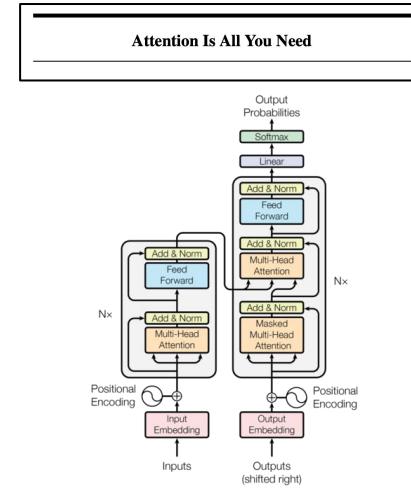


DeepAR: Probabilistic Forecasting with
Autoregressive Recurrent Networks

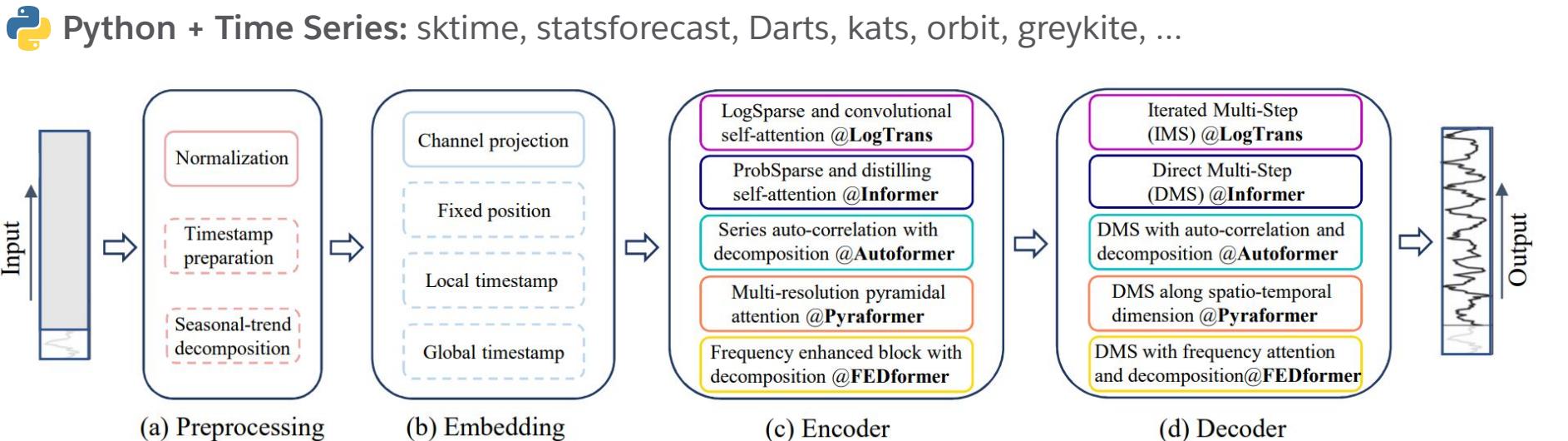
David Salinas, Valentin Flunkert, Jan Gasthaus
Amazon Research
Germany
<dsalina,flunkert,gasthaus@amazon.com>



June 2017: Transformers released!



2017-2022: Python Adoption & Transformers



DLinear/NLinear: But, a simple MLP + MovingAverage + “[RevIN](#)” beats transformers...

- ARIMA's still in the game!

Yugui Nie^{1,*}, Nam H. Nguyen^{2,*}, Phanwadee Sinthong², Jayant Kalagnanam²

¹Princeton University ²IBM Research
ynie@princeton.edu, nnguyen@us.ibm.com, Gift.Sinthong@ibm.com,
jayant@us.ibm.com

2023: PatchTST released

Intuition:

- [2020 LogSparse]: it's OK to ignore timesteps close to each other, as long as you still include a long enough context window
- **NLP**: BERT tokenizes sub-words (groups of characters) instead of characters
- **Vision**: “An Image is Worth 16x16 words”

Question: “is there a way to avoid throwing values while maintaining a long look-back window”?

- **Answer:** Patches!

Result: State of the Art →

T	model	MAPE	CRPS	Rank
◆	PatchTST	0.860	0.563	5.897
●	Moirai_large	0.856	0.585	6.072
●	Moirai_base	1.101	0.604	6.155
◆	TFT	1.116	0.596	7.031
●	Moirai_small	0.909	0.636	8.423
●	Chronos_large	0.930	0.629	8.814

Yugui Nie^{1*}, Nam H. Nguyen²*, Phanwadee Sinthong², Jayant Kalagnanam²

¹Princeton University ²IBM Research

ynie@princeton.edu, nnguyen@us.ibm.com, Gift.Sinthong@ibm.com, jayant@us.ibm.com

Foundational Building Block: Patching

Time Series Forecast

$t_{31}, t_{32}, \dots, t_{40}$

UNDO
Patch

Patch
 $t[1,15]$
 $t[16,30]$

Raw Time Series

t_1, t_2, \dots, t_{30}

$$\hat{x}^{(i)} \in \mathbb{R}^{1 \times 1}$$

$$z^{(i)} \in \mathbb{R}^{D \times N}$$

$$x_d^{(i)} \in \mathbb{R}^{D \times N}$$

$$x_p^{(i)} \in \mathbb{R}^{P \times N}$$

$$x^{(i)} \in \mathbb{R}^{1 \times 1}$$

Output Univariate Series

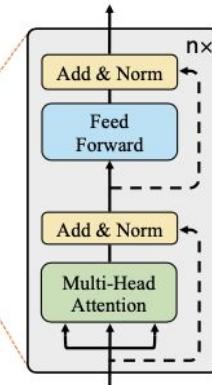
Flatten + Linear Head

Transformer Encoder

Projection + Position Embedding

Instance Norm + Patching

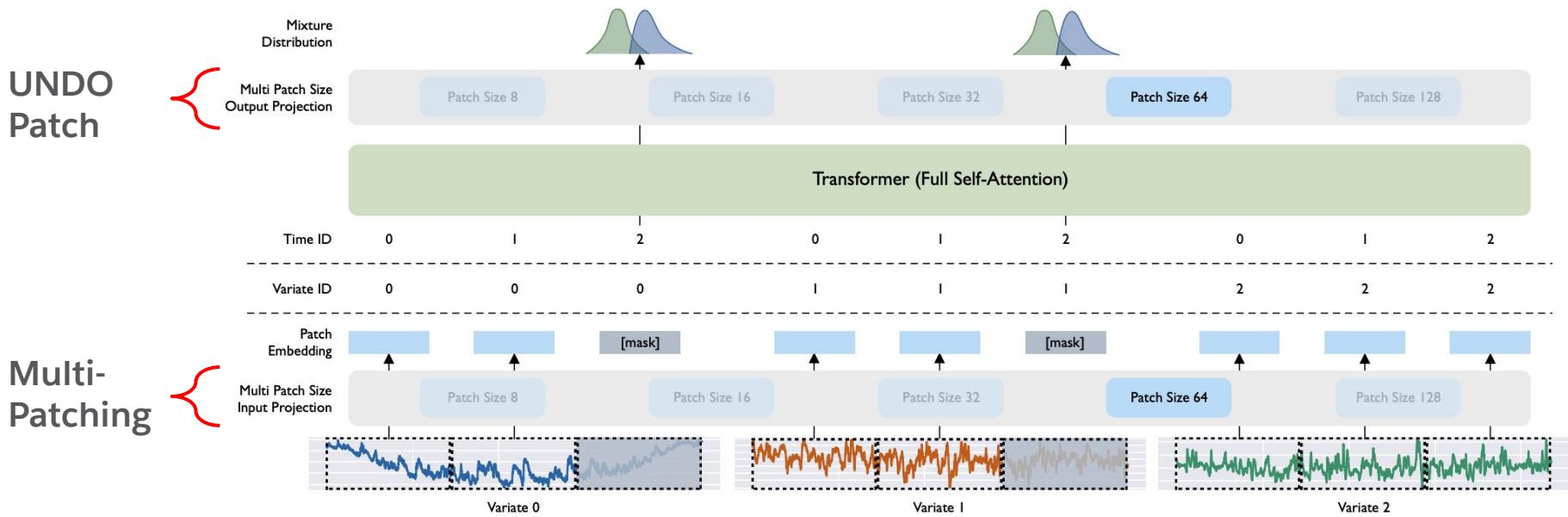
Input Univariate Series



2024: Transformer-Based Foundational Models (ex. Moirai)

Learnings from NLP*: Less inductive bias/structure + more data/compute

Architecture: [1] Transformer + [2] Patching + [3] Multi-Granularity + [4] Diverse Datasets



*great talk on the intuition behind the evolution of transformers by [Hyung Won \(Stanford CS25\)](#)

The Recipe for Foundational Time Series Models in 2024

Big Data



Transformers

+ patching

OR

LLMs

Wikipedia +
Synthetic Data



LOTSA: Curated
Datasets



Time Series Pile



TimeGPT*
*closed source

TimesFM

Moirai

MOMENT

Tiny Time Mixers*
*based on TSMixer backbone

Lag-Llama

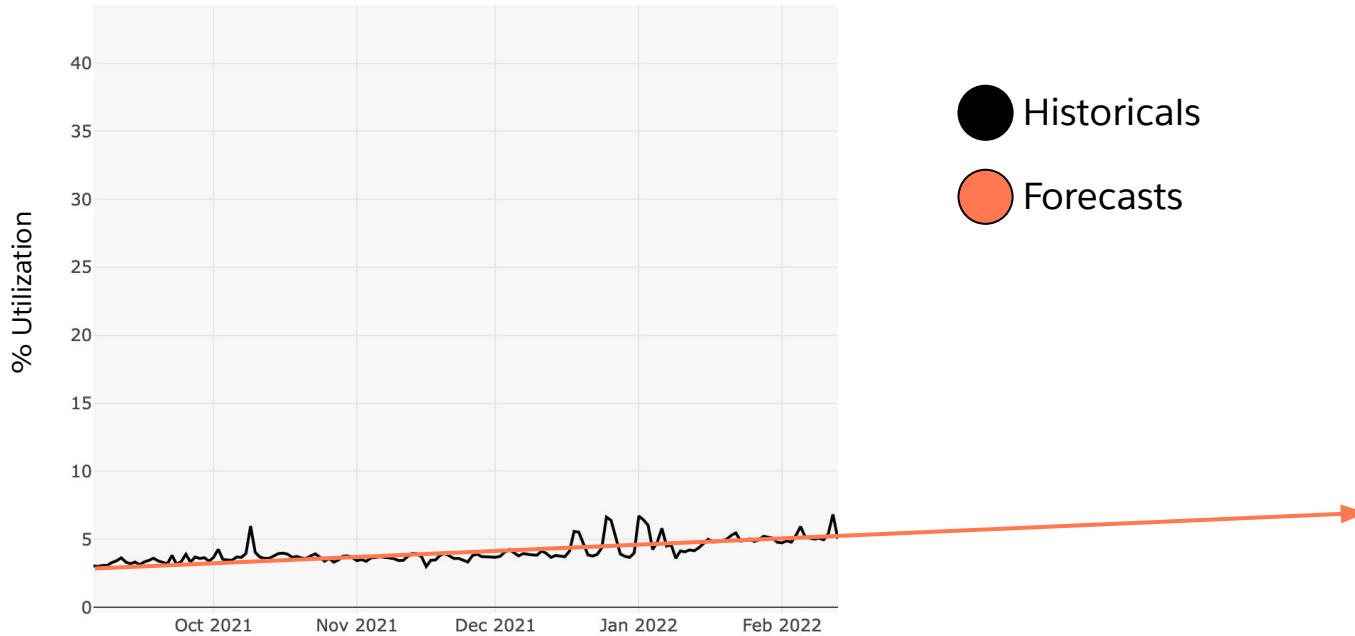
Chronos

GPT4TS

So, how should you use foundational time series models?



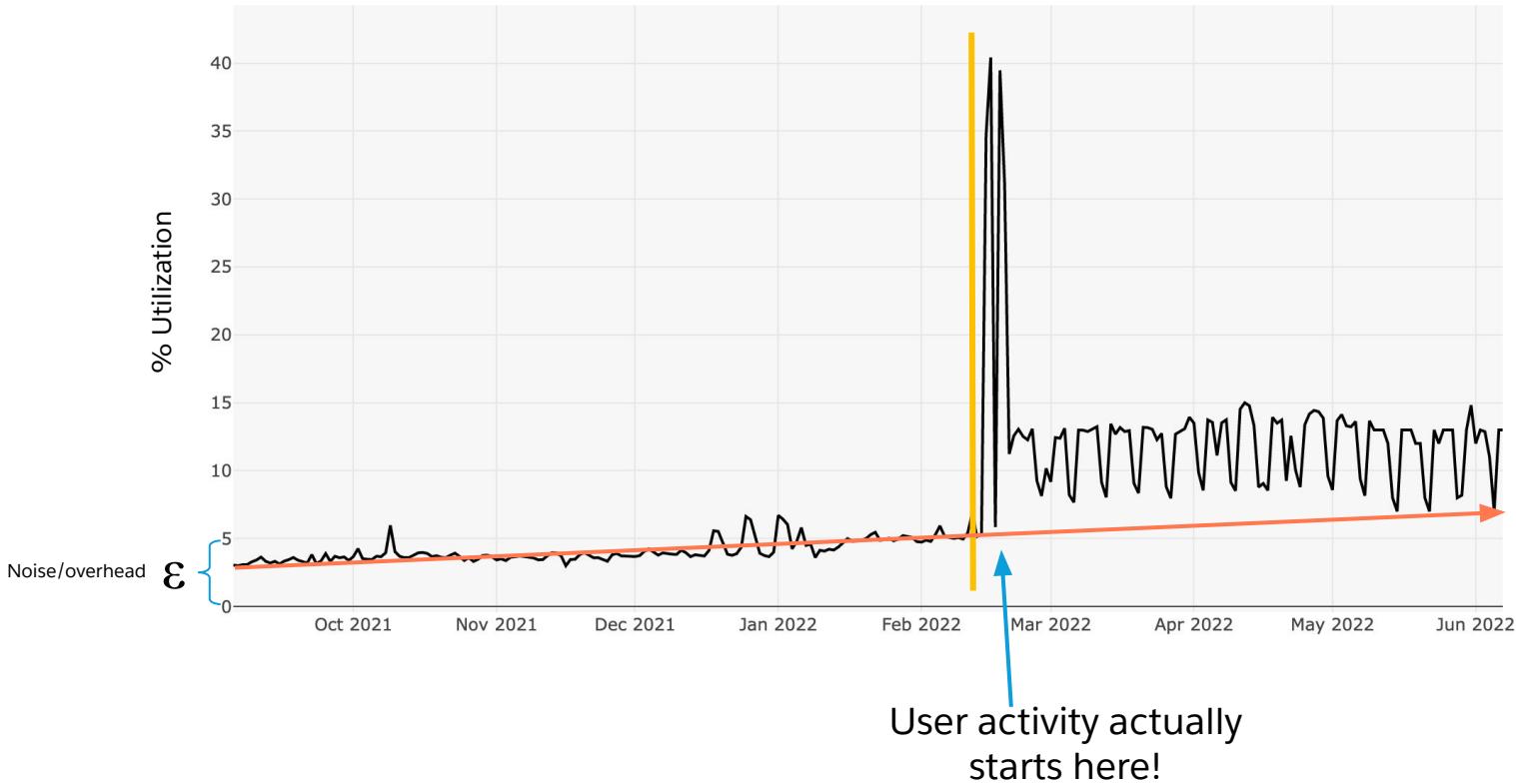
Wow! Can foundational models really predict the future?



*there is usually a 0-5%~ constant utilization overhead

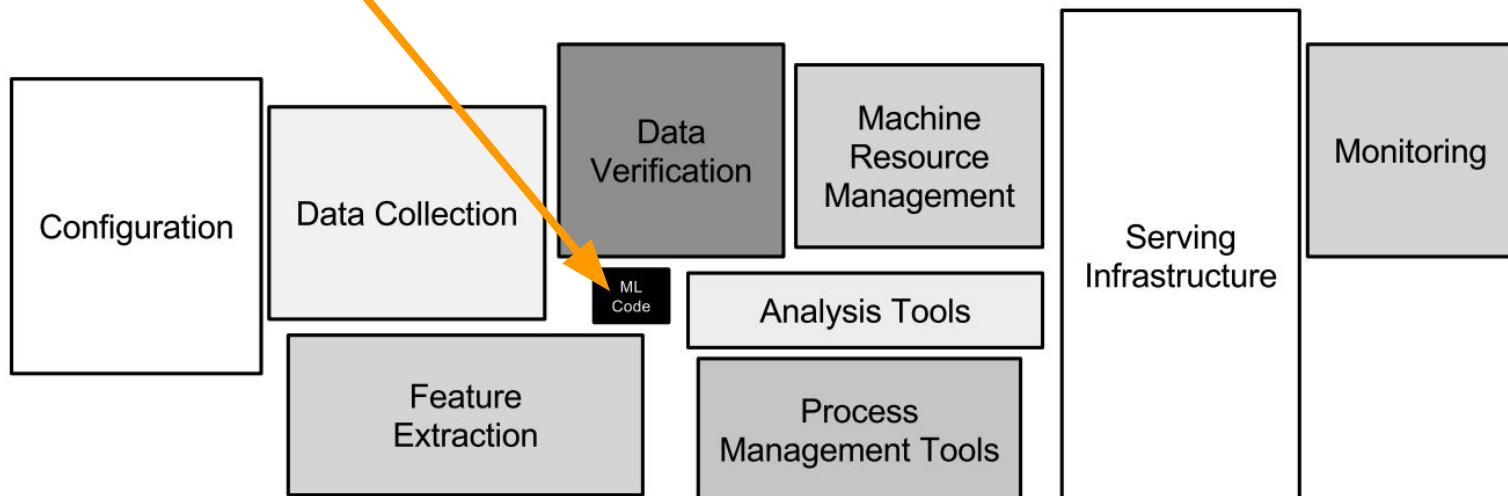
No, you still need data + some external knowledge

Solution ideas: (1) use “similar” time series, (2) dynamic hierarchies, (3) human-based drivers



Ok, but can I just replace my Forecasting team & ML Platform with these models? Not yet!

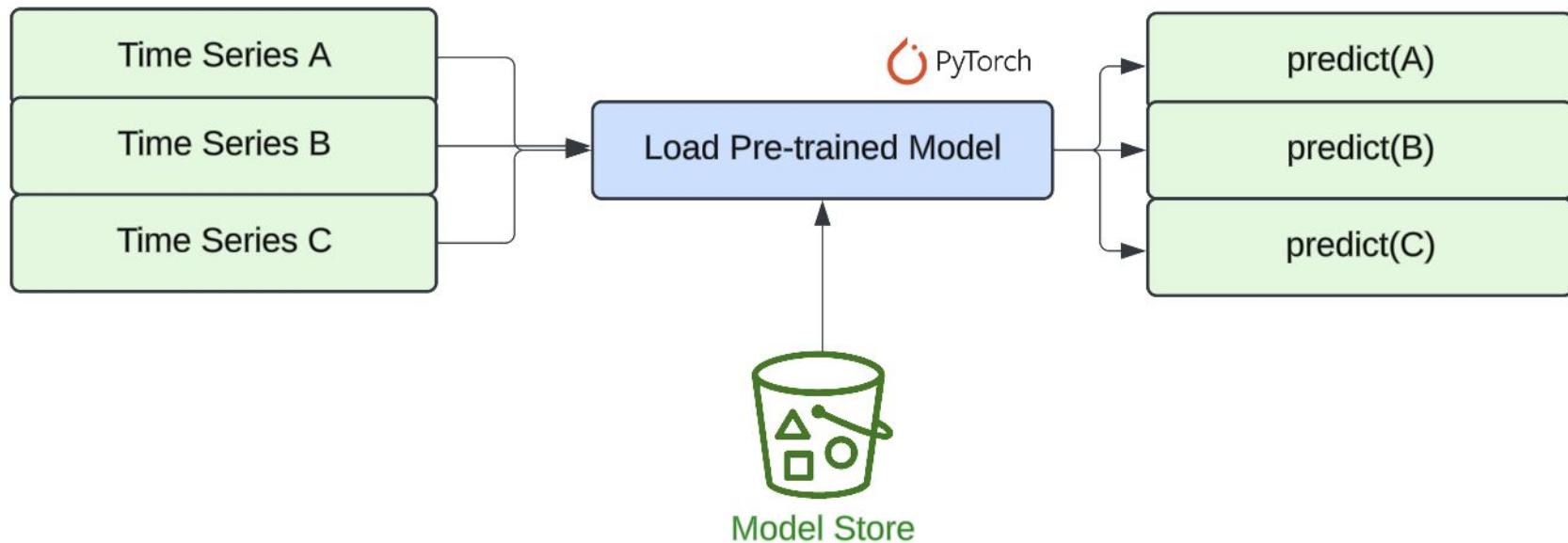
Foundational Time Series Models



Interested in ML platforms? Here's a blog on how [we built our Forecasting Platform](#)

What does this mean for me, as a forecaster?

- It's still a ML model, but without training – data in, forecasts out!
- TLDR: Higher accuracy out of the box, less training/tuning effort, better “cold start”



When should I train my own foundational model?

Poor backtesting results? Have lots of time series? Tired of feature engineering?

(Moirai) LOTSA Training Dataset Distribution

Table 2. Key statistics of LOTSA by domain.									
	Energy	Transport	Climate	CloudOps	Web	Sales	Nature	Econ/Fin	Healthcare
# Datasets	30	23	6	3	3	6	5	23	6
# Obs.	16,358,600,896	4,900,453,419	4,188,011,890	1,518,268,292	428,082,373	197,984,339	28,547,647	24,919,596	1,594,281
%	59.17%	17.73%	15.15%	5.49%	1.55%	0.72%	0.09%	0.10%	0.01%

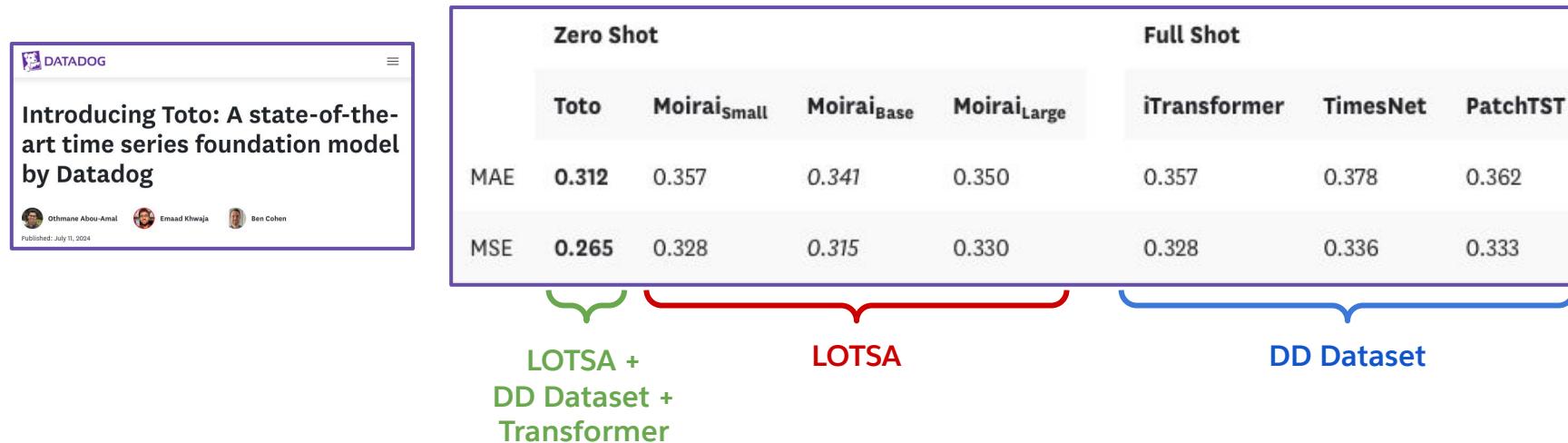
*Forecasting cloud infrastructure?
Consider adding more specialized data!*

Table 3. Key statistics of LOTSA by frequency.

	Yearly	Quarterly	Monthly	Weekly	Daily	(Multi) Hourly	(Multi) Minute-level	(Multi) Second-level
# Datasets	4	5	10	7	21	31	25	2
# Obs.	873,297	2,312,027	11,040,648	18,481,871	709,017,118	19,875,993,973	7,013,949,430	14,794,369
%	0.003%	0.008%	0.040%	0.067%	2.565%	71.893%	25.370%	0.054%

Case Study: Toto = LOTSA (27B) + CloudOps Data (750B)

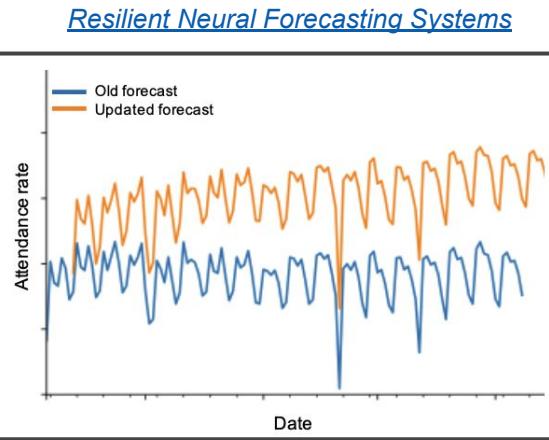
- Fine-tuning/re-training with a larger set of domain specific dataset
 - Better than (1) Zero-shot or (2) Domain-specific model



- We've found similar improvements from our own infrastructure usage data

Model stability: critical for automated forecasting

- Training instability observed in large global models – critical for automated re-training
 - Generally not as important for “pre-trained” models, but...



- Inference stability
 - Anomaly Detection as preprocessing → greatly improved uncertainty intervals
 - “# samples” generated in Forecasting == “Temperature” in LLMs

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What's next?



Continuing Research @ Time Series Forecasting

Mostly advancements from October 2024+

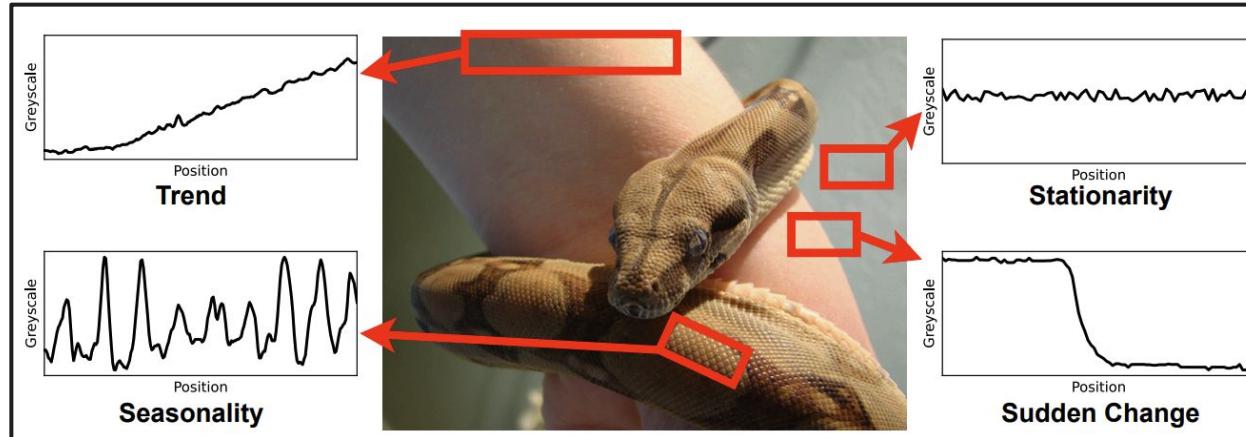


1. More open source datasets

- [Time Series Pile](#)
- [GIFT-Eval](#)
- [Time-300B](#)

2. Better models

- MoE-based ([Time-MoE](#), [Moirai-MoE](#))
- Mamba-based ([CMMamba](#), [Foundational](#))
- Vision-based ([VisionTS](#))



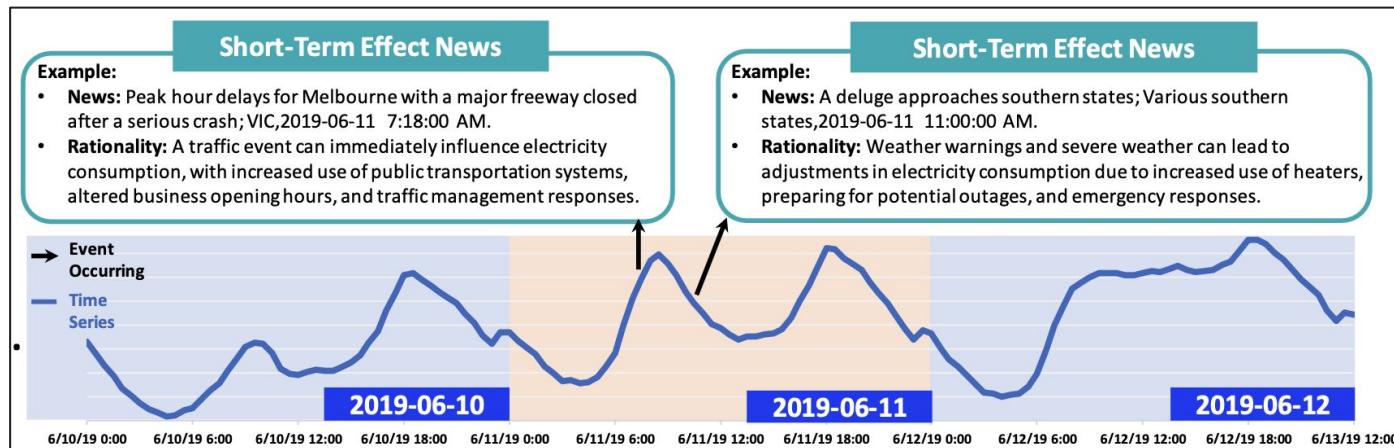
[VisionTS: Visual Masked Autoencoders Are Free-Lunch Zero-Shot Time Series Forecasters](#)

Multimodal Explainability: Time Series + Language



3. Time Series Understanding

- **Applications:** hierarchical time series correlations, root cause analysis (changepoints)
- LLMs + News Data [1][2]
- General Reasoning [3][4]



(Xinlei Wang et al.) From News to Forecast: Integrating Event Analysis in LLM-Based Time Series Forecasting with Reflection

Foundational Time Series Models

the
future?

hype?

Foundational Time Series Models

the
future!



hype!

salesforce

Thank you





Interested in chatting about time series? Reach out on [LinkedIn](#)!

Useful Links

- **Models:**
 - Moirai + Moirai-MoE: <https://github.com/SalesforceAIResearch/uni2ts>
 - Time-MoE: <https://github.com/Time-MoE/Time-MoE>
 - TimesFM: <https://github.com/google-research/timesfm>
 - Chronos: <https://github.com/amazon-science/chronos-forecasting>
 - Moment: <https://github.com/moment-timeseries-foundation-model/moment>
 - TimeGPT API: https://docs.nixtla.io/docs/getting-started-timegpt_quickstart
- **Datasets**
 - LOTSA: https://huggingface.co/datasets/Salesforce/lotsa_data
 - Time Series Pile: <https://huggingface.co/datasets/AutonLab/Timeseries-PILE>
 - Time-300B: <https://huggingface.co/datasets/Maple728/Time-300B>
 - GIFT-Eval: <https://huggingface.co/datasets/Salesforce/GiftEval>
- **Model Leaderboards:**
 - <https://huggingface.co/spaces/Salesforce/GIFT-Eval>
 - <https://github.com/thuml/Time-Series-Library>