

AUTOML SUMMER SCHOOL 2024, HANNOVER

Chronos

Time series forecasting in the age of pretrained models

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Agenda

PART 1

Forecasting basics

- What is forecasting?
- Traditional approaches

PART 2

Chronos

- Pretrained models
- Benchmarking

PART 3

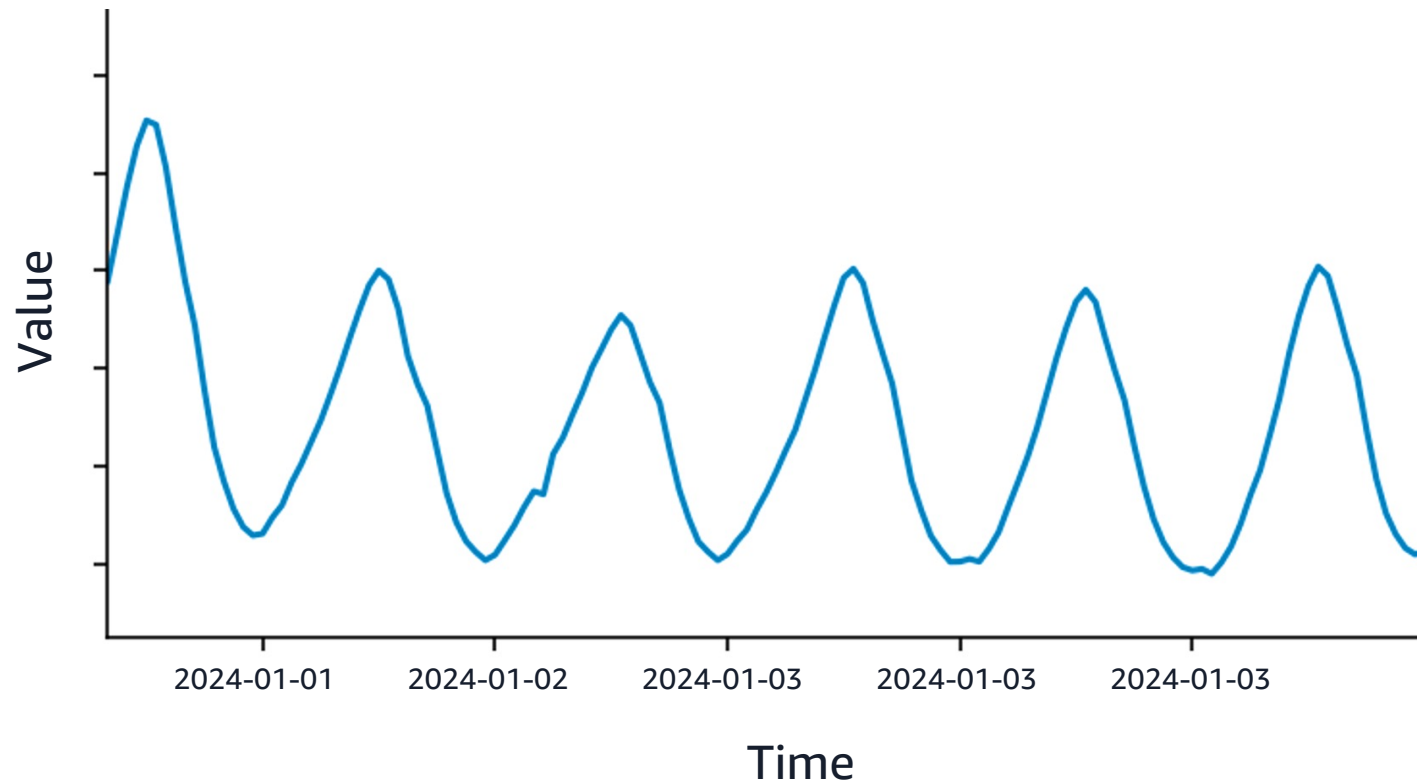
The way ahead

- Open research questions
- How does AutoML fit in?

Forecasting basics

Time series data

- Time series are **measurements** made at **regular intervals**



Energy



Finance



Retail



Traffic



Healthcare



Weather

ML tasks for time series data

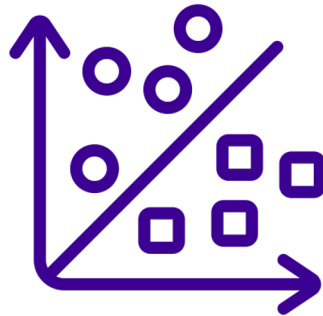


Forecasting

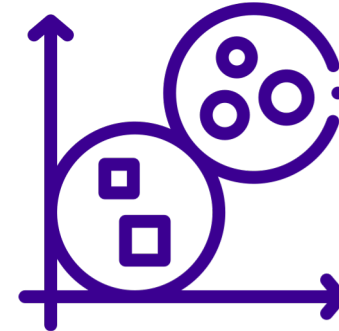
(focus of this talk)



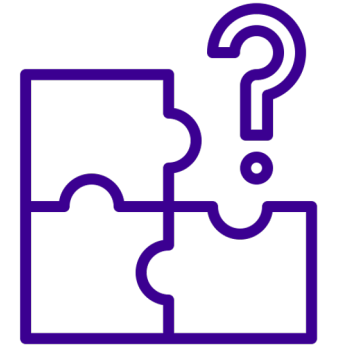
Anomaly detection



Classification



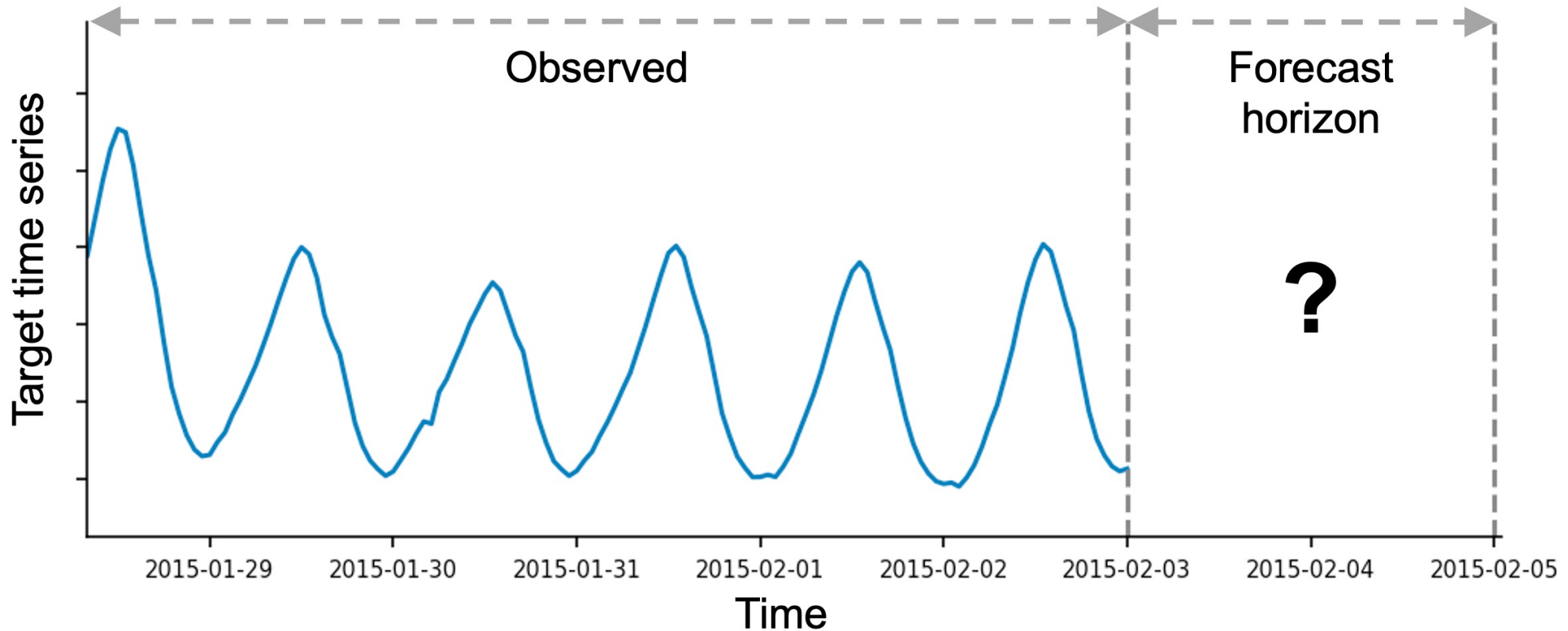
Clustering



Imputation

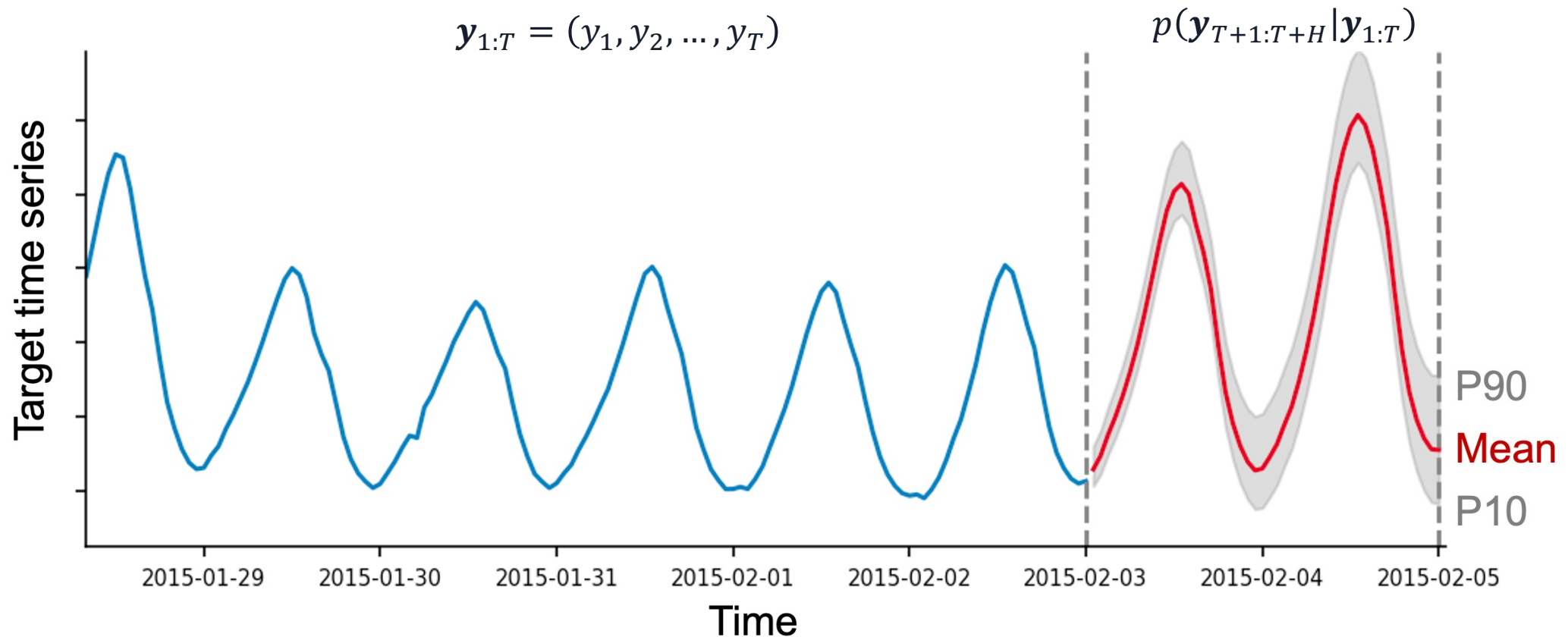
Time series forecasting

- What will happen in the future given the past?



Probabilistic forecasting

- Probabilistic forecast captures uncertainty in predictions



Local models

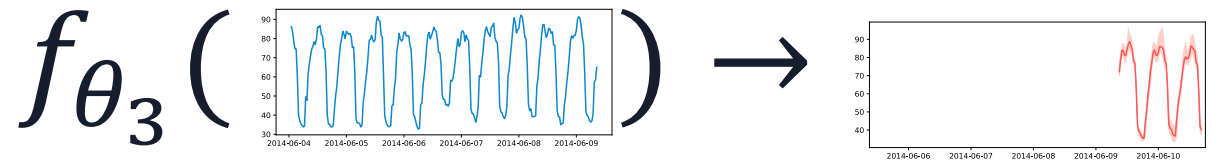
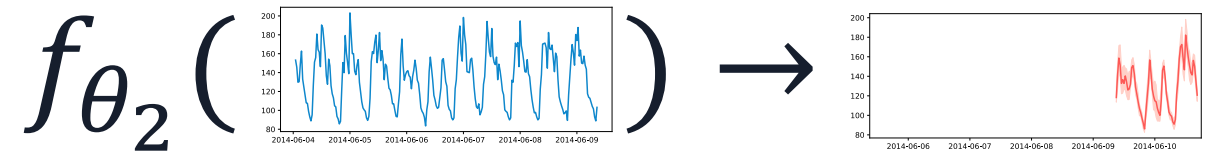
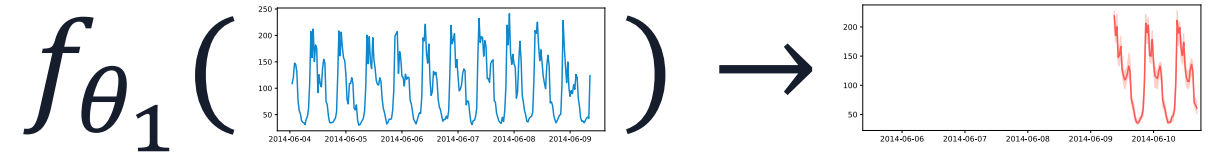
- Fit a **separate** model for each **individual** time series
- Examples: ARIMA, ETS, Theta

Strong baseline (esp. limited data)

Often interpretable

Low flexibility

Slow inference



Global models

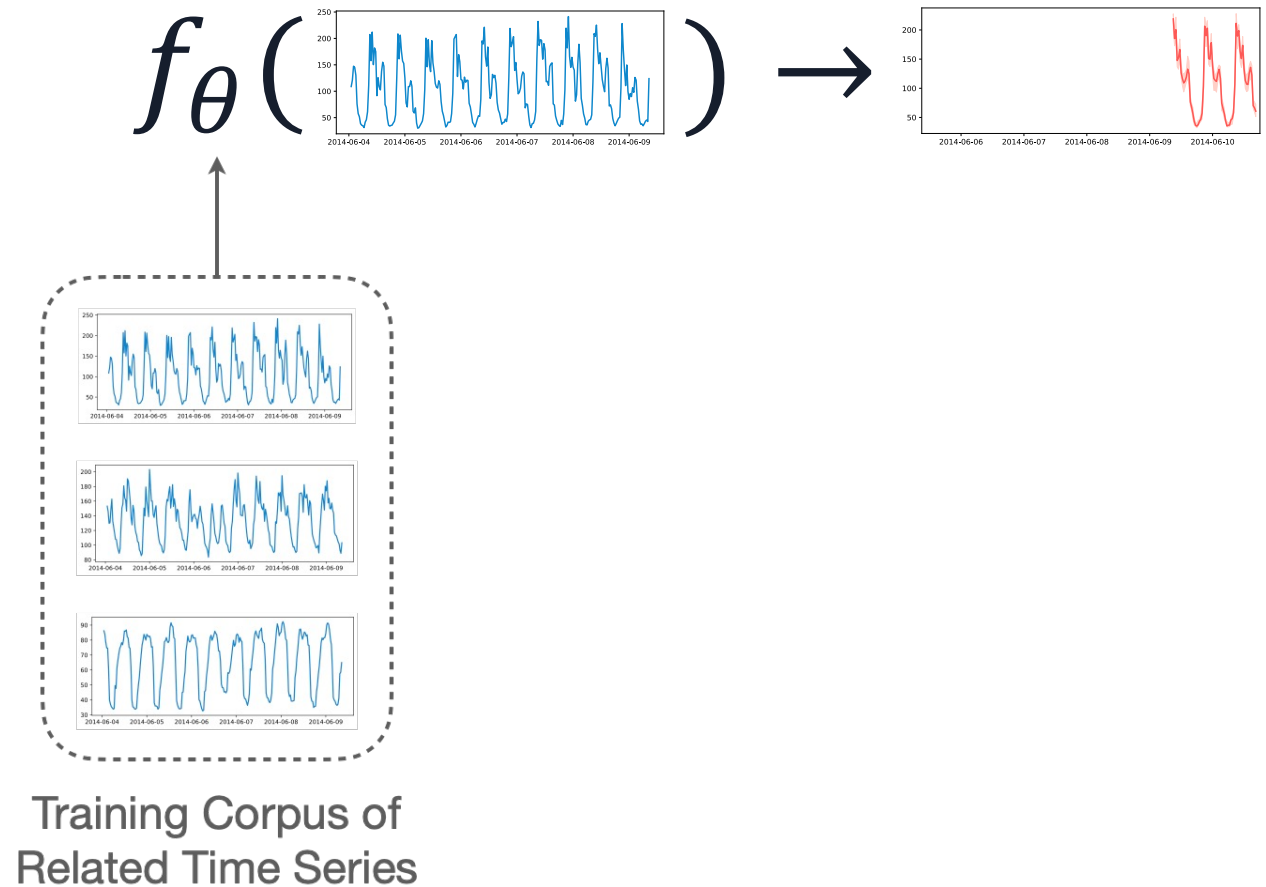
- Fit a **single** model for each **task**
- Examples: DeepAR, TFT, PatchTST

High flexibility

Fast inference

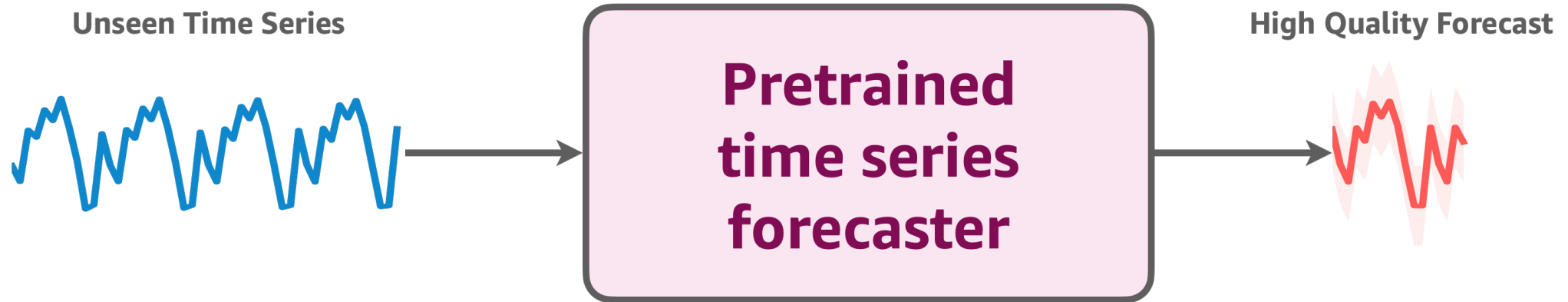
Slow training

Data hungry



Pretrained models

- Can we develop a single model that both
 - requires no dataset-specific training and
 - performs well on new time series tasks?



LLM-based forecasting models

Text-based prompting

Fine-tuning of pretrained LLMs

Context: From August 16, 2019, Friday to August 30, 2019, Friday, the average temperature of region 110 was 78, 81, 83, 84, 84, 82, 83, 78, 77, 77, 74, 77, 78, 73, 76 degree on each day.

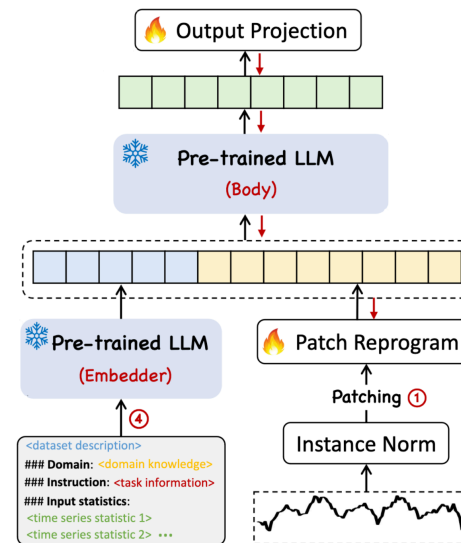
Question: What is the temperature going to be on August 31, 2019, Saturday?

Answer: The temperature will be 78 degree.

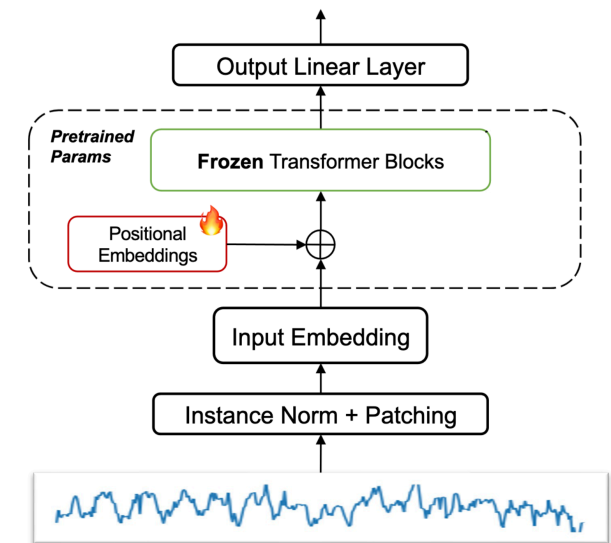
PromptCast

0.123, 1.23, 12.3, 123.0 → " 1 2 , 1 2 3 , 1 2 3 0 , 1 2 3 0 0 "

LLMTime



TimeLLM



GPT4TS

Extremely slow & expensive inference

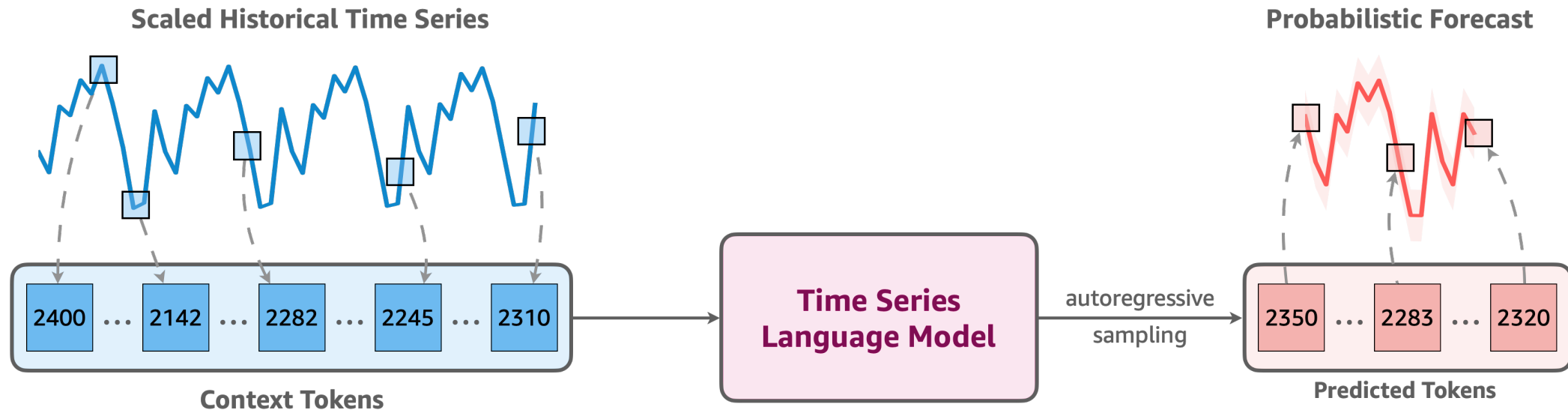
✗ Require task-specific prompt engineering & fine-tuning

Chronos



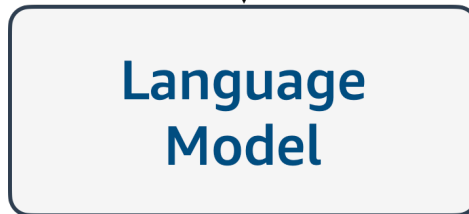
Introducing Chronos

- Main idea: Adapt LLM architectures for time series forecasting



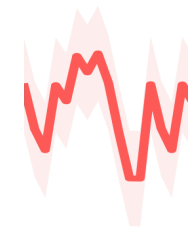
Language modeling and forecasting

*“Three Rings for the Elven-kings under the sky,
Seven for the Dwarf-lords in their halls of stone,
Nine for Mortal Men doomed to die,
One for the Dark Lord on his dark throne
In the Land of Mordor where the Shadows lie.”*



*“One Ring to rule them all, One Ring to find them,
One Ring to bring them all and in the darkness bind them
In the Land of Mordor where the Shadows lie.”*

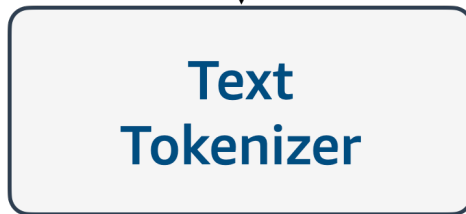
Predict the next sequence of words (tokens)



Predict future values conditioned on the past

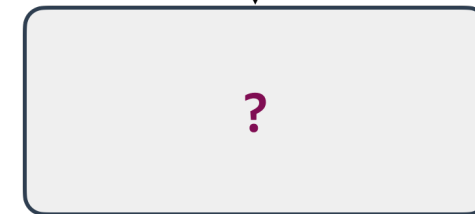
Time series tokenization

*“Three Rings for the Elven-kings under the sky,
Seven for the Dwarf-lords in their halls of stone,
Nine for Mortal Men doomed to die,
One for the Dark Lord on his dark throne
In the Land of Mordor where the Shadows lie.”*



“ Three ” “ Ring ” “ s ” “ for ” “ the ” “ El ” “ ven ” “ - ” “ king ” “ s ” ...

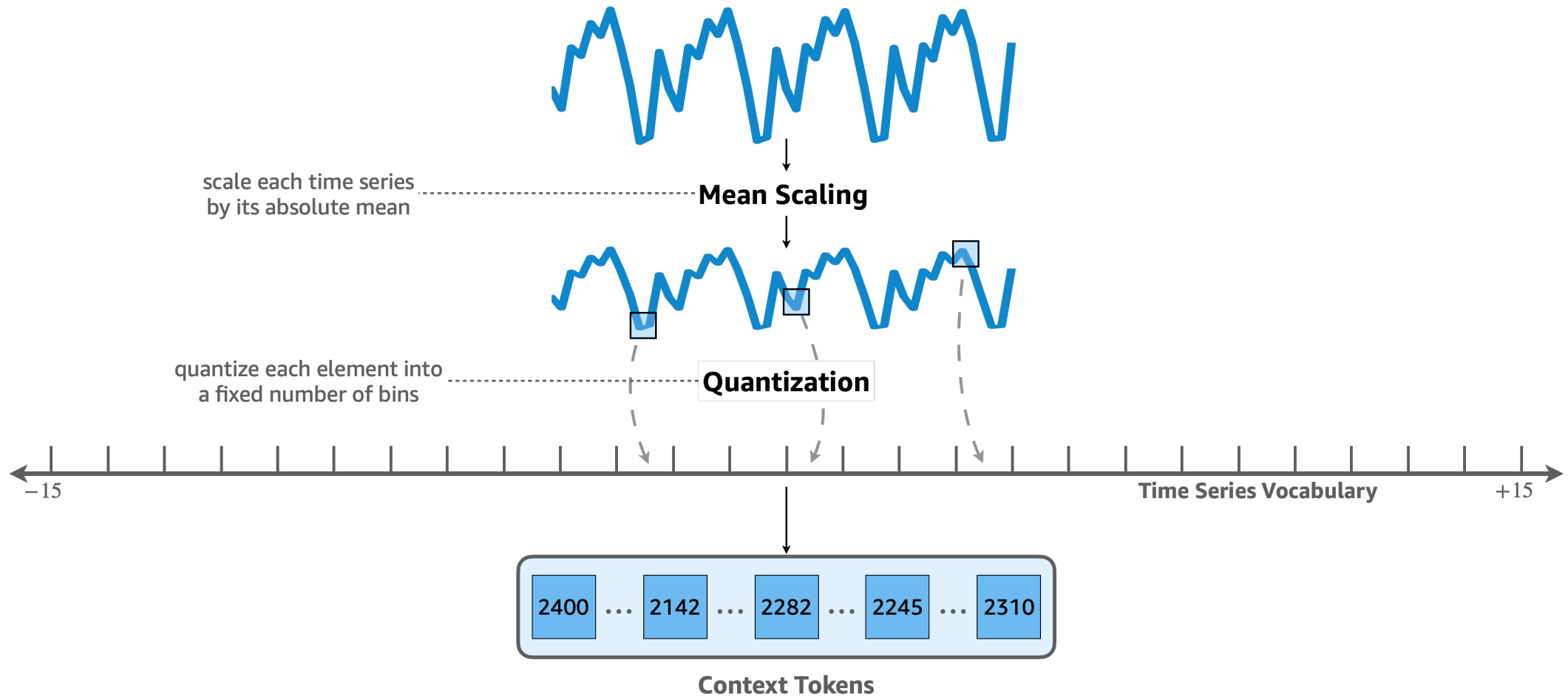
Text language models have a discrete vocabulary



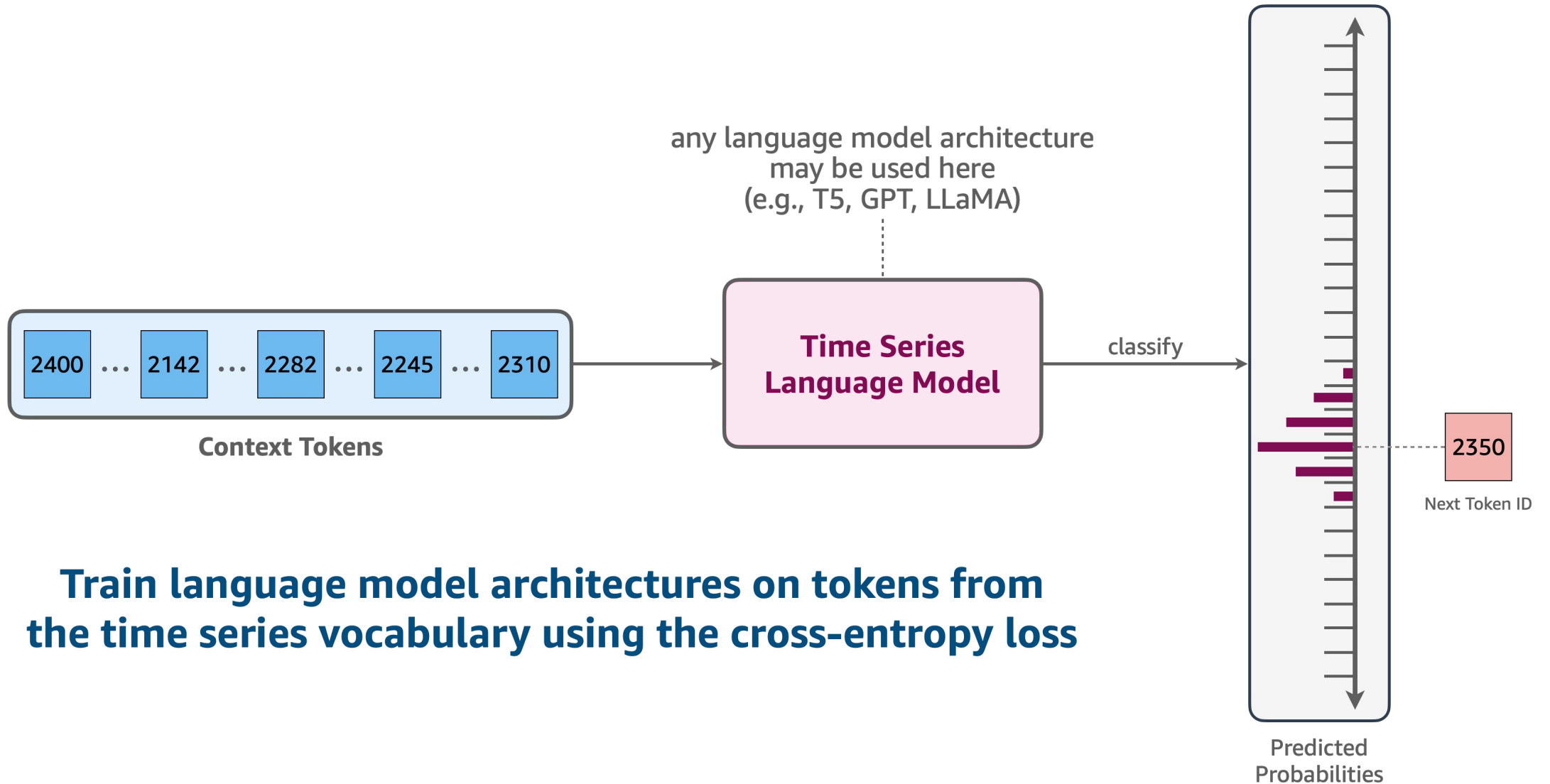
?

Time series are real-valued signals

Time series tokenization

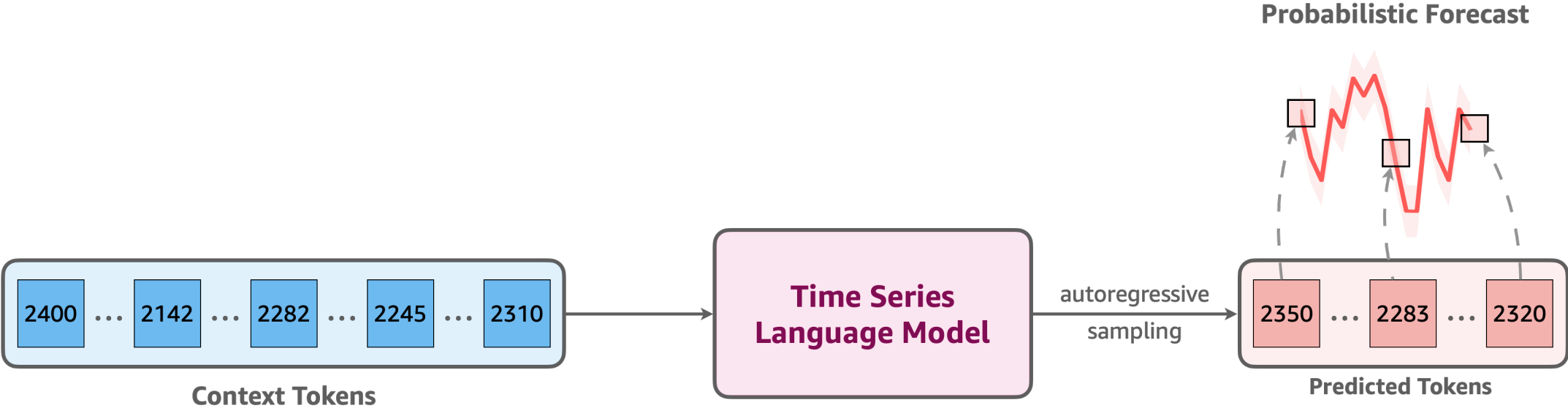


Regression via classification



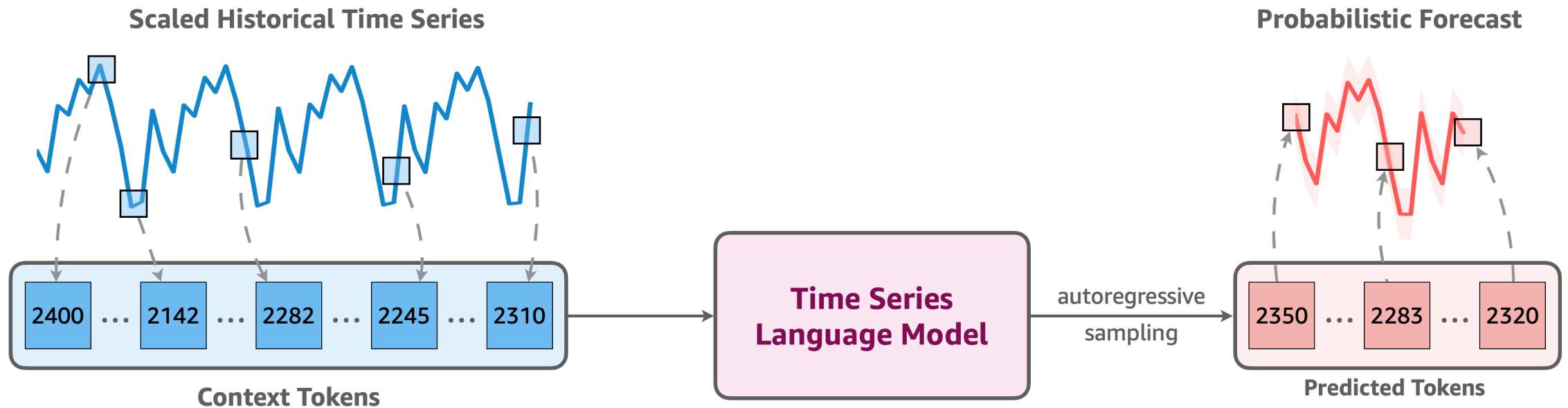
Train language model architectures on tokens from the time series vocabulary using the cross-entropy loss

Sampling



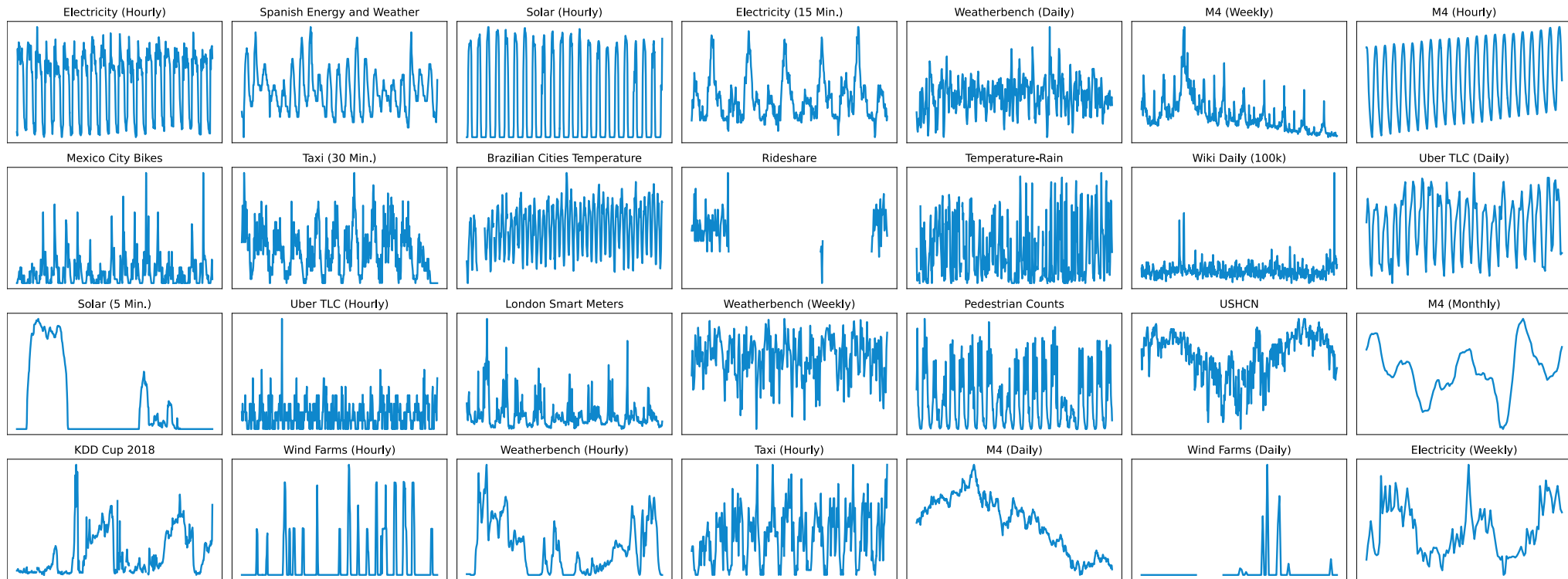
The complete Chronos framework

- Requires no changes to the language model architecture & training procedure
- Probabilistic by design



Training datasets

- 28 datasets from various domains and frequencies
- 890K time series with 84B observations



TSMixup: Data augmentation for time series

Improve pattern diversity by mixing time series from different datasets

- Sample $K \sim \{1, 2, 3\}$ time series

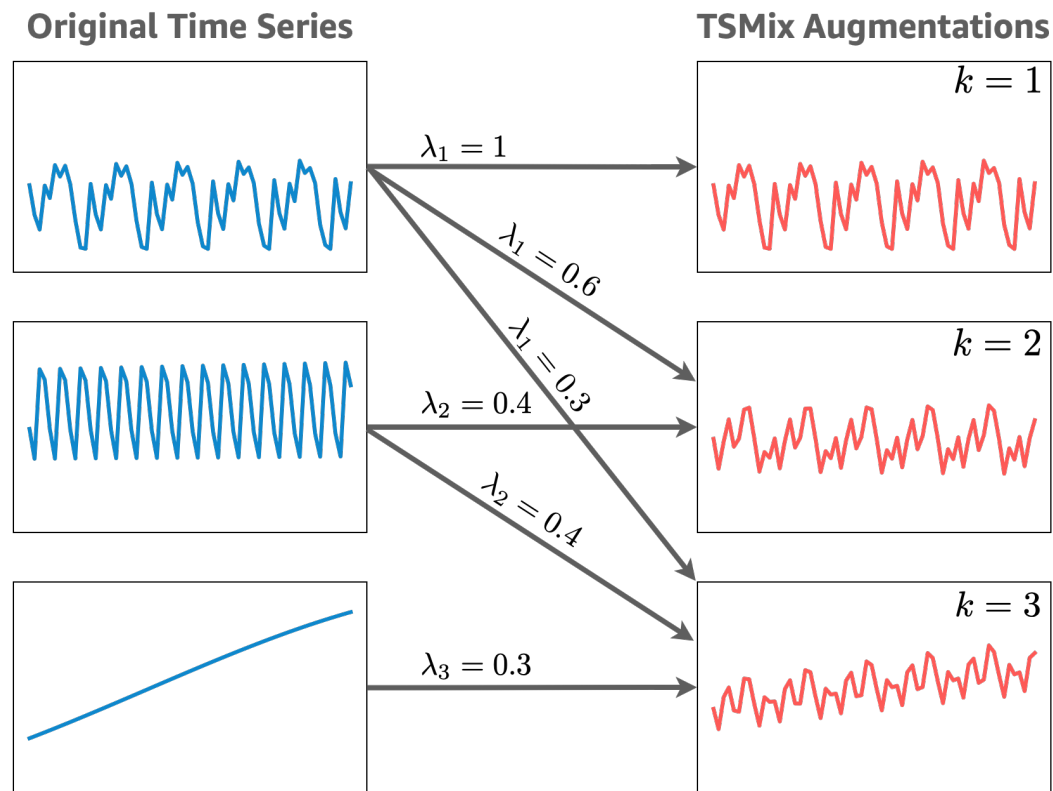
$$y_1, \dots, y_K \sim \mathcal{D}_{\text{train}}$$

- Sample weights

$$\lambda_1, \dots, \lambda_K \sim \text{Dirichlet}(\alpha)$$

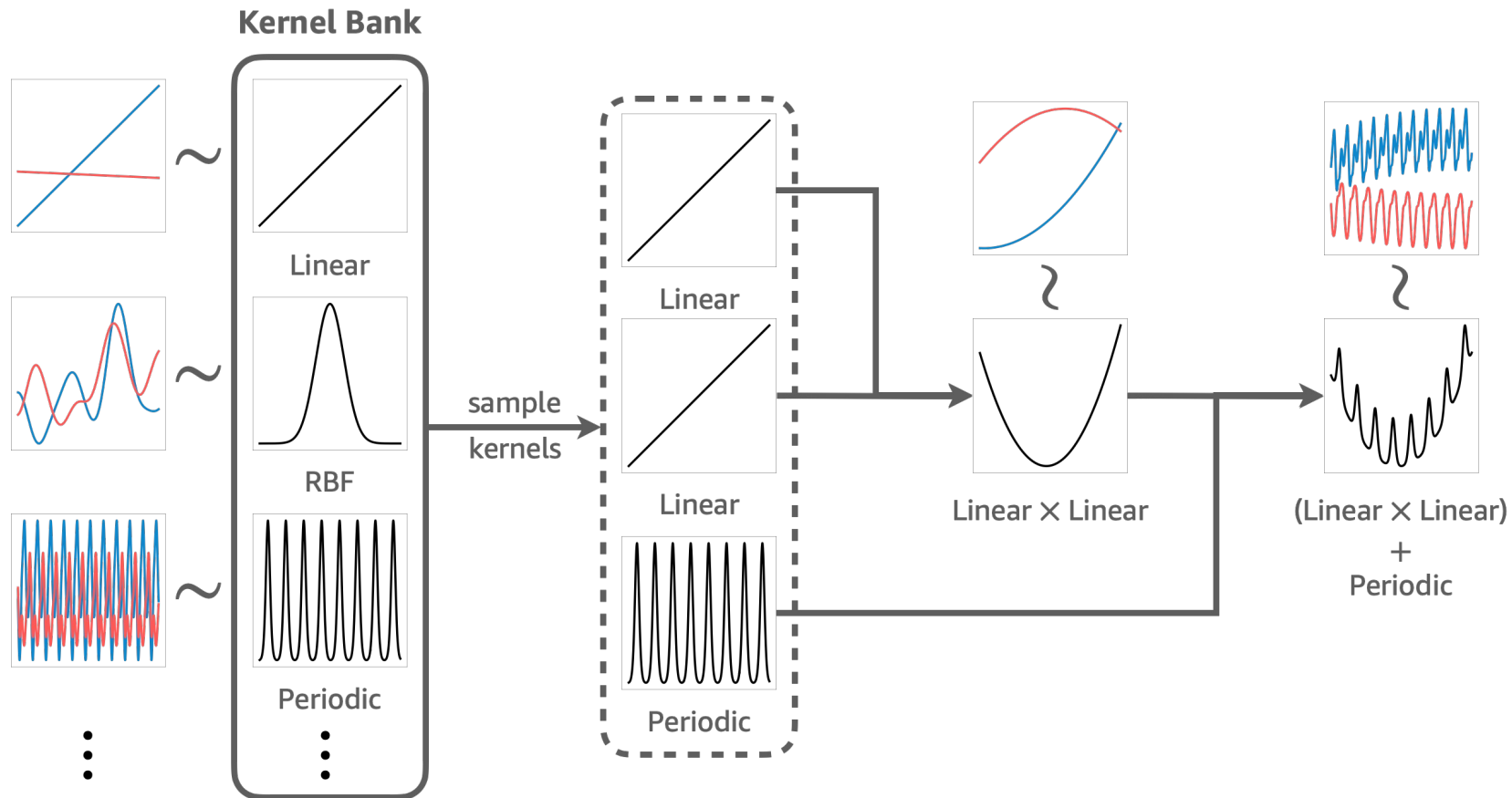
- Combine time series

$$y = \sum_{k=1}^K \lambda_k y_k$$



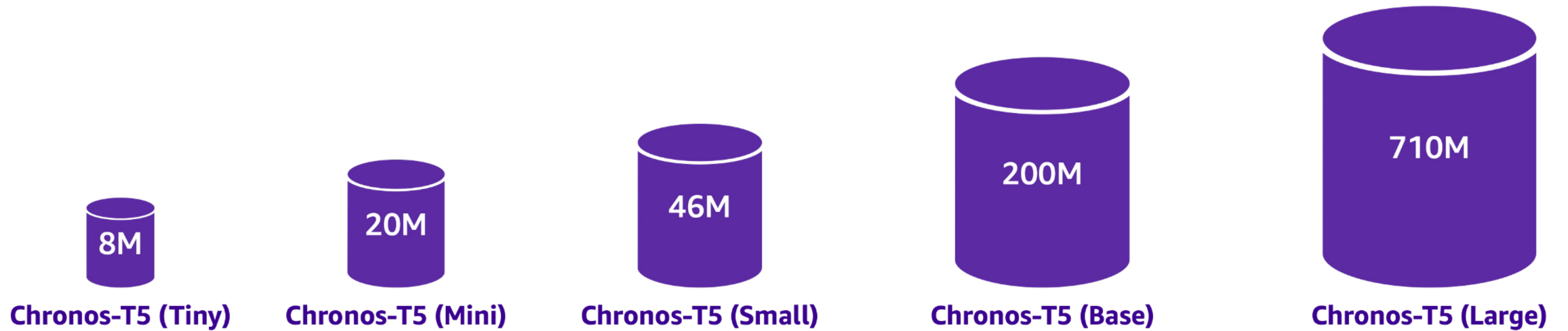
KernelSynth: Synthetic data generation

- Supplement real data with synthetic time series from Gaussian processes

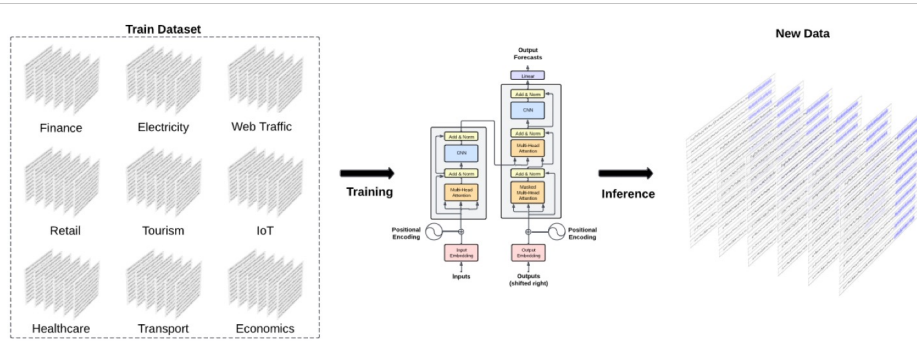


Chronos variants

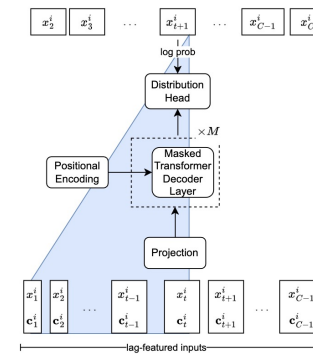
Based on the T5 encoder-decoder architecture



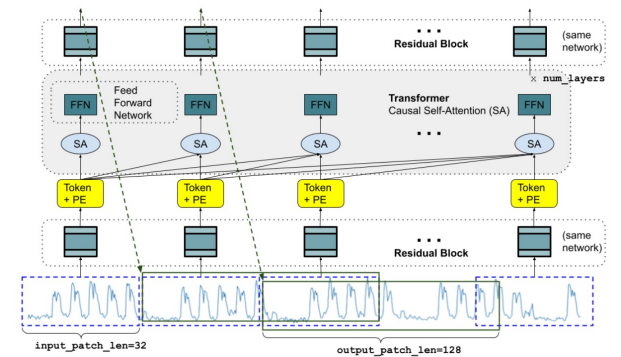
Other pretrained time series models



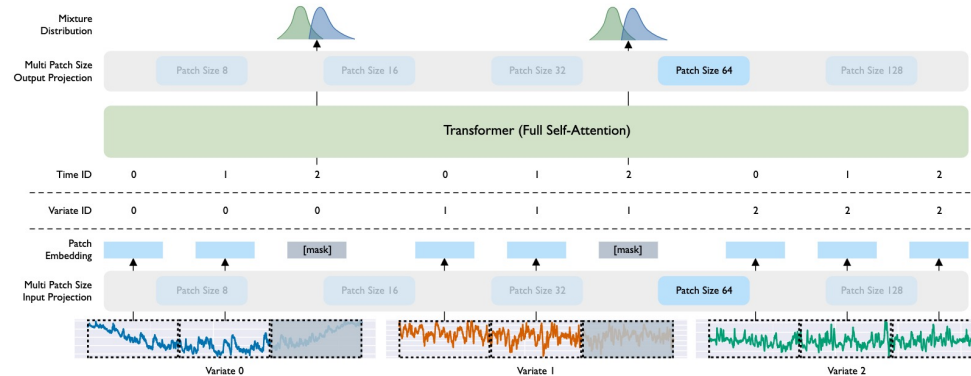
TimeGPT (Nixtla)



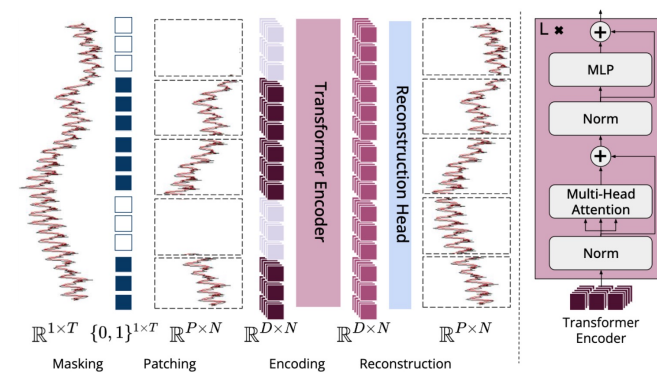
LagLlama



TimesFM (Google)



Moirai (Salesforce)



MOMENT (CMU)

Baseline models

Pretrained models

Single pretrained model used across all tasks

- LLMTime
- ForecastPFN
- LagLlama
- Moirai
- TimesFM

Task-specific models

Separate model trained / fine-tuned for each task

- PatchTST
- DeepAR
- WaveNet
- TFT
- DLinear
- NBEATS
- NHiTS
- GPT4TS

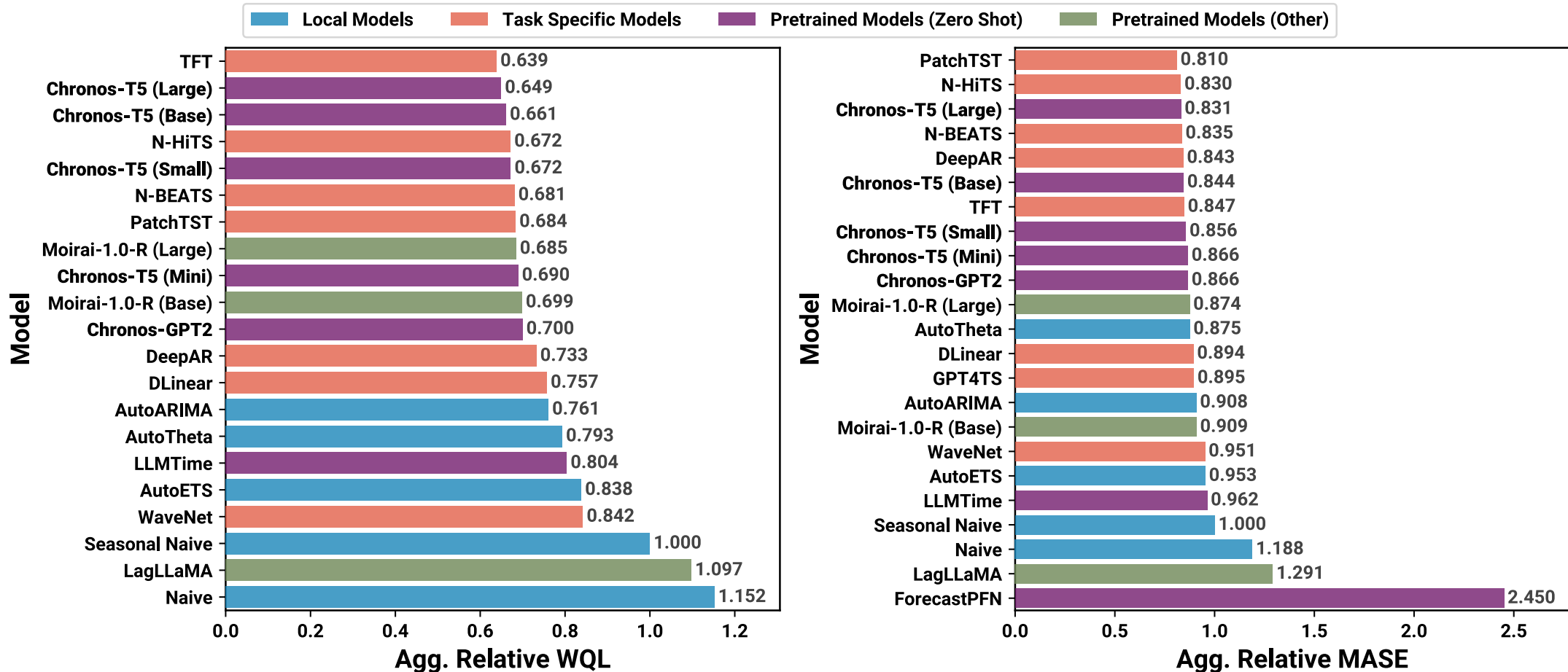
Local models

Separate model trained for each time series




- Naive
- SeasonalNaive
- AutoETS
- AutoARIMA
- AutoTheta

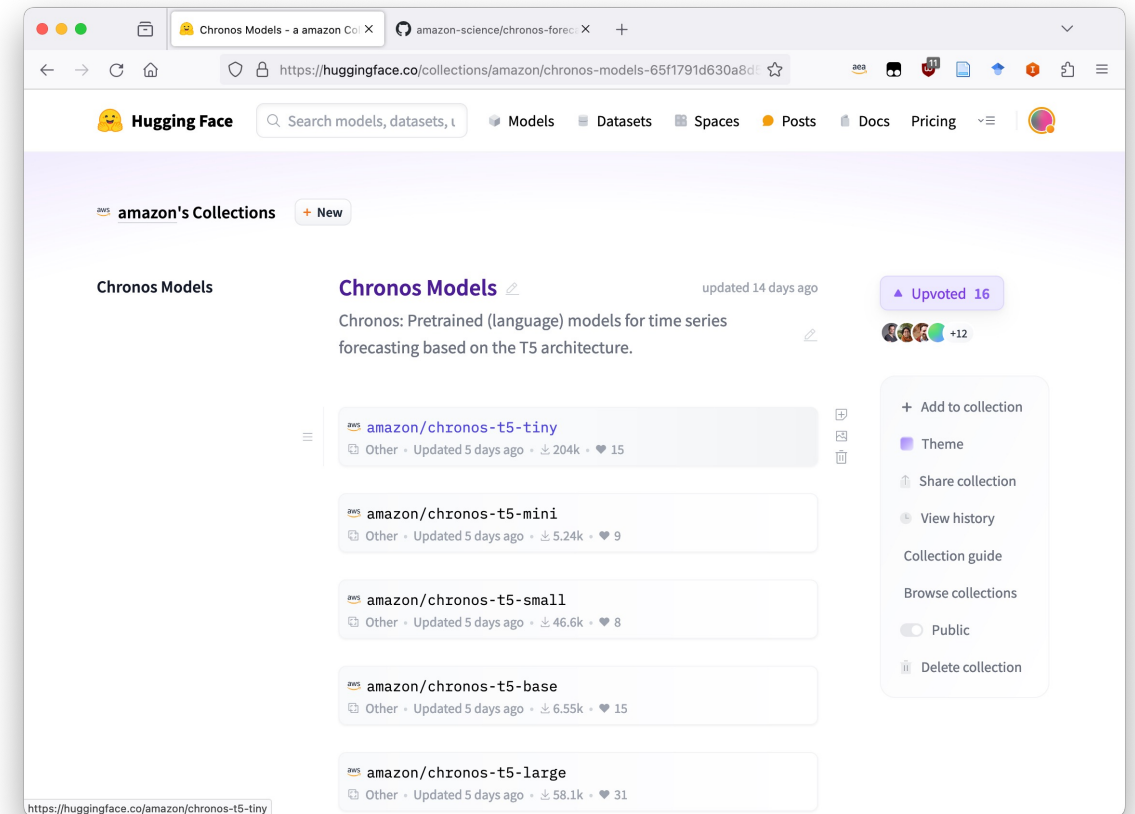
Benchmarking Chronos

- Zero-shot probabilistic & point forecasting performance on 29 datasets



Try out Chronos

- Training, inference & evaluation code available on GitHub 
- Model weights & training data available on Hugging Face 
- Run Chronos with 1 line of code using AutoGluon 



Downloaded 60M+ times on Hugging Face 

The way ahead

Is forecasting now “solved”?

- A powerful recipe



- Can we now just follow the NLP playbook to “solve” forecasting?
 - More data
 - Bigger models
 - ⇒ One model to rule them all?

Why AutoML is the future of forecasting

- Pretrained forecasting models are fast & cheap (by LLM standards)
- Many ways to **improve a single model!**
 - Preprocessing, fine-tuning, calibration, conformal prediction, ...
- Many ways to **combine models!**
 - Ensembling, stacking, boosting, ...

Pretrained models in the AutoML toolbox

Preprocessing

Preprocessing can improve accuracy

- Scaling
- Box-Cox transform
- Outlier removal
- ...

Model portfolio

Collection of (small) pre-trained models

- Chronos
- TimesFM
- MOIRAI
- ...

Adaptation

Adapt pretrained models to the task at hand

- Fine-tuning
- Calibration
- Conformal prediction
- ...

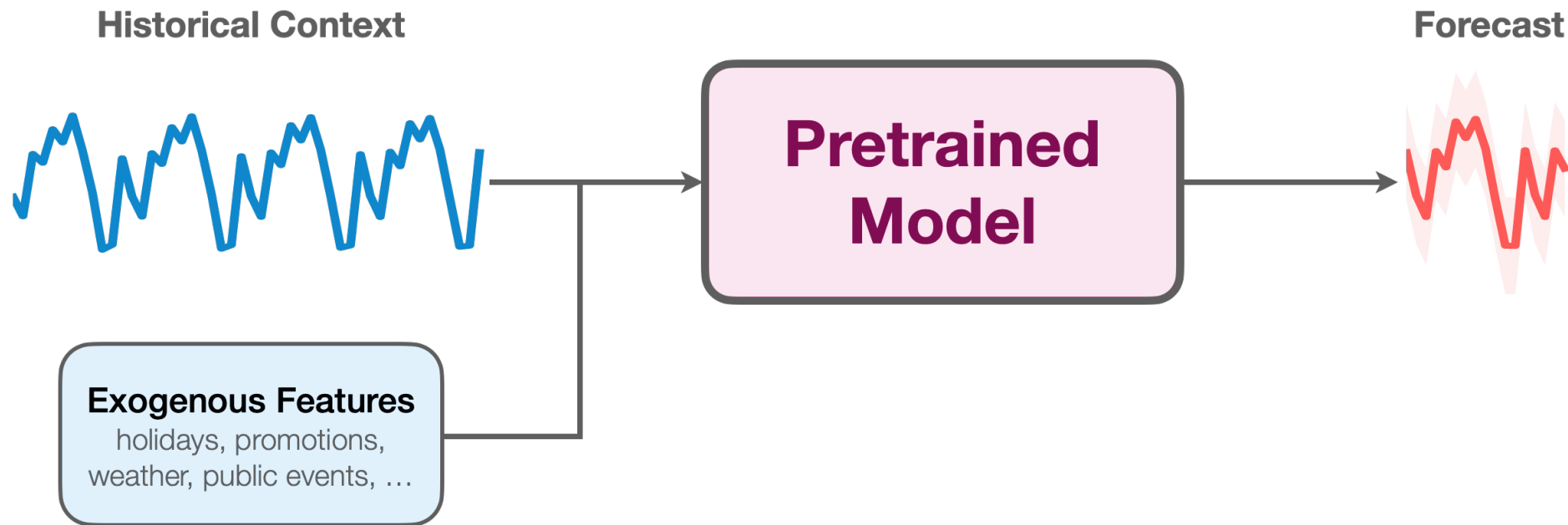
Ensembling

Combine several models into an ensemble

- Boosting
- Stacking
- Linear ensembles
- ...

Beyond univariate forecasting

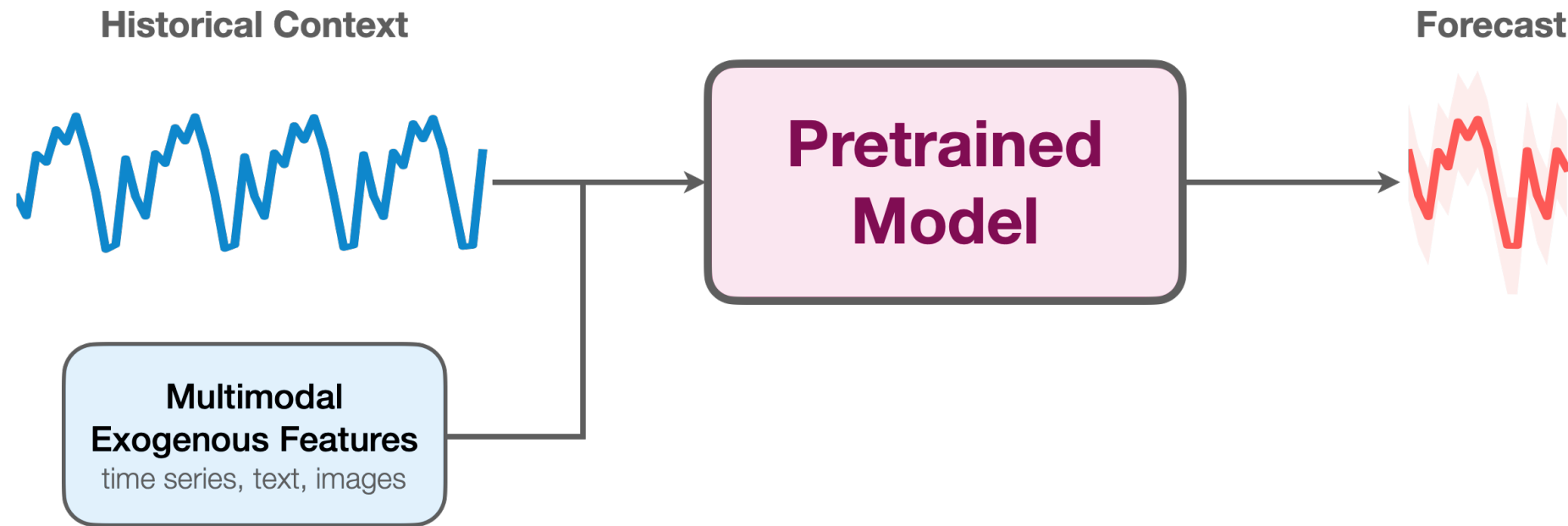
- **Covariates** may provide important exogenous information



- Challenge: Number and type of covariates are not known a priori

Multimodal forecasting

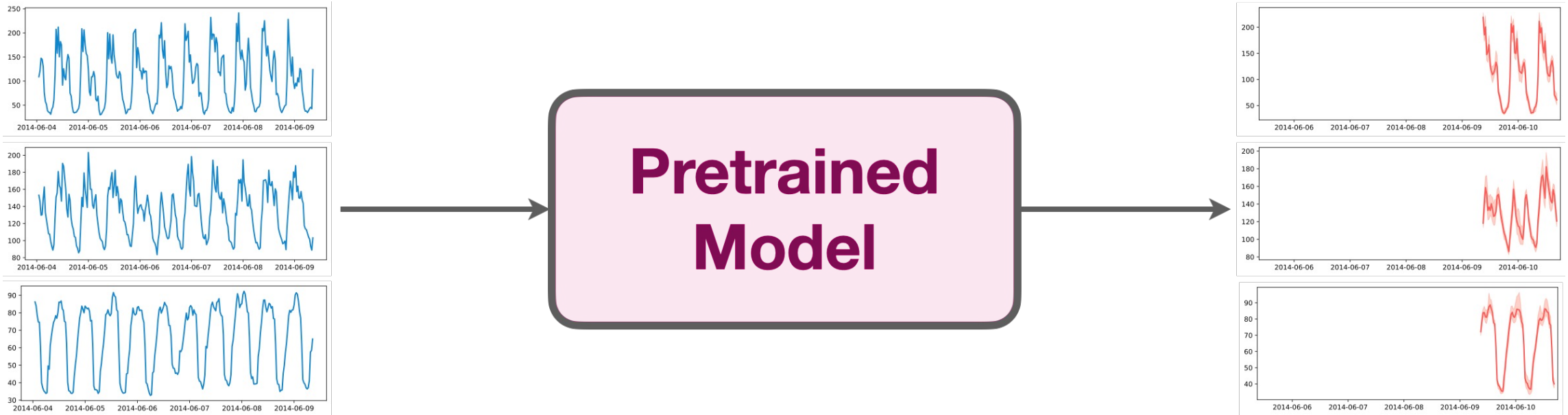
- Other **modalities** (e.g., text and images) can be relevant for the forecast



- Challenge: Public multimodal time series datasets are extremely scarce

Multivariate forecasting

- Joint modeling of **multi-dimensional** time series



- Challenge: Number of dimensions and their interactions not known a priori

Data & benchmarks

- High-quality datasets are essential for continued progress
- Many important questions on the data side
 - How to quantify the quality and diversity of time series data?
 - Is synthetic data all you need?
 - How to correctly benchmark time series models?

Chronos team



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Xiyuan
Zhang



Pedro Mercado
Lopez



Huibin
Shen



Syama
Rangapuram



Sebastian
Arango



Shubham
Kapoor



Jasper
Zschienger



Danielle
Robinson



Andrew
Wilson



Kari
Torkkola



Michael
Mahoney



Michael
Bohlke-Schneider



Bernie
Wang

Summary

- Pretrained models can make accurate **zero-shot** forecasts
- **Chronos** turns forecasting into **next-token prediction** via scaling & quantization
- Lots of exciting **open research questions** in this space
... and AutoML is likely the answer to some of them!