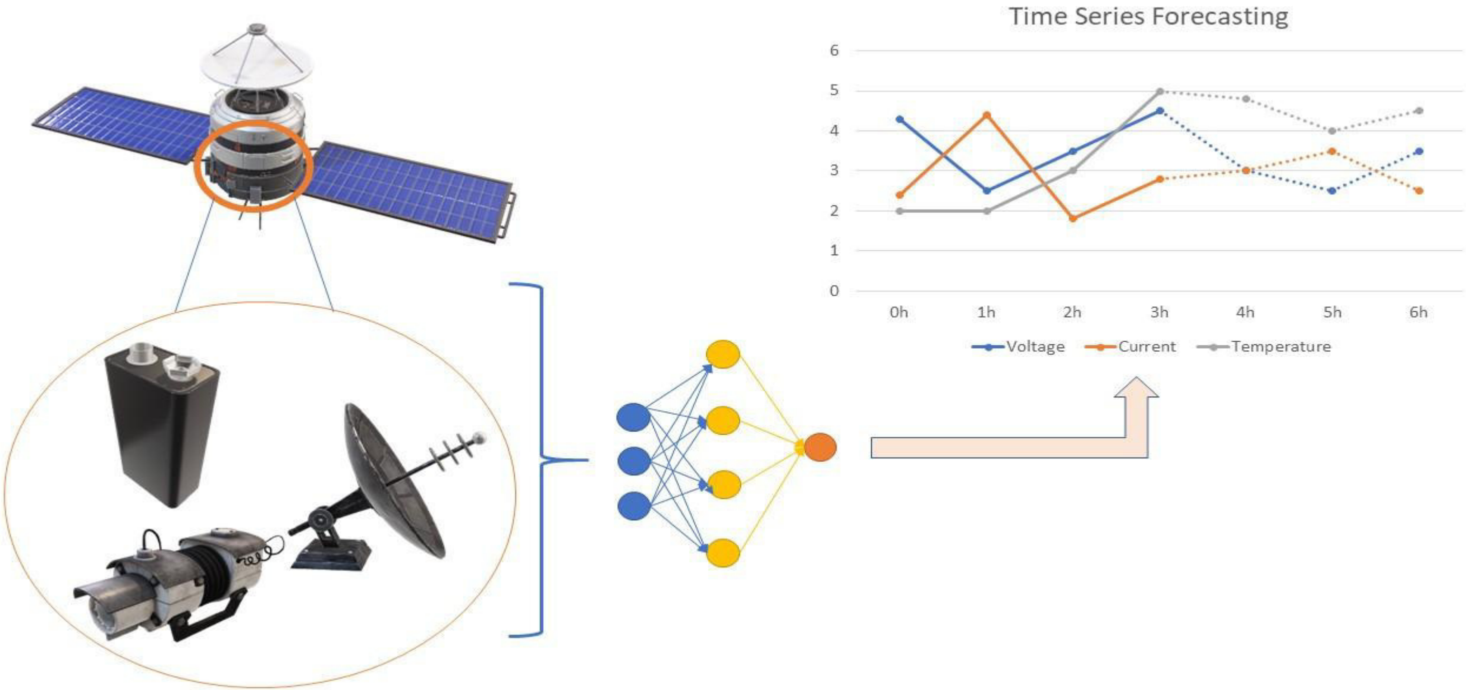
Resource Forecasting for Satellite Operations using Multivariate Time Series Data

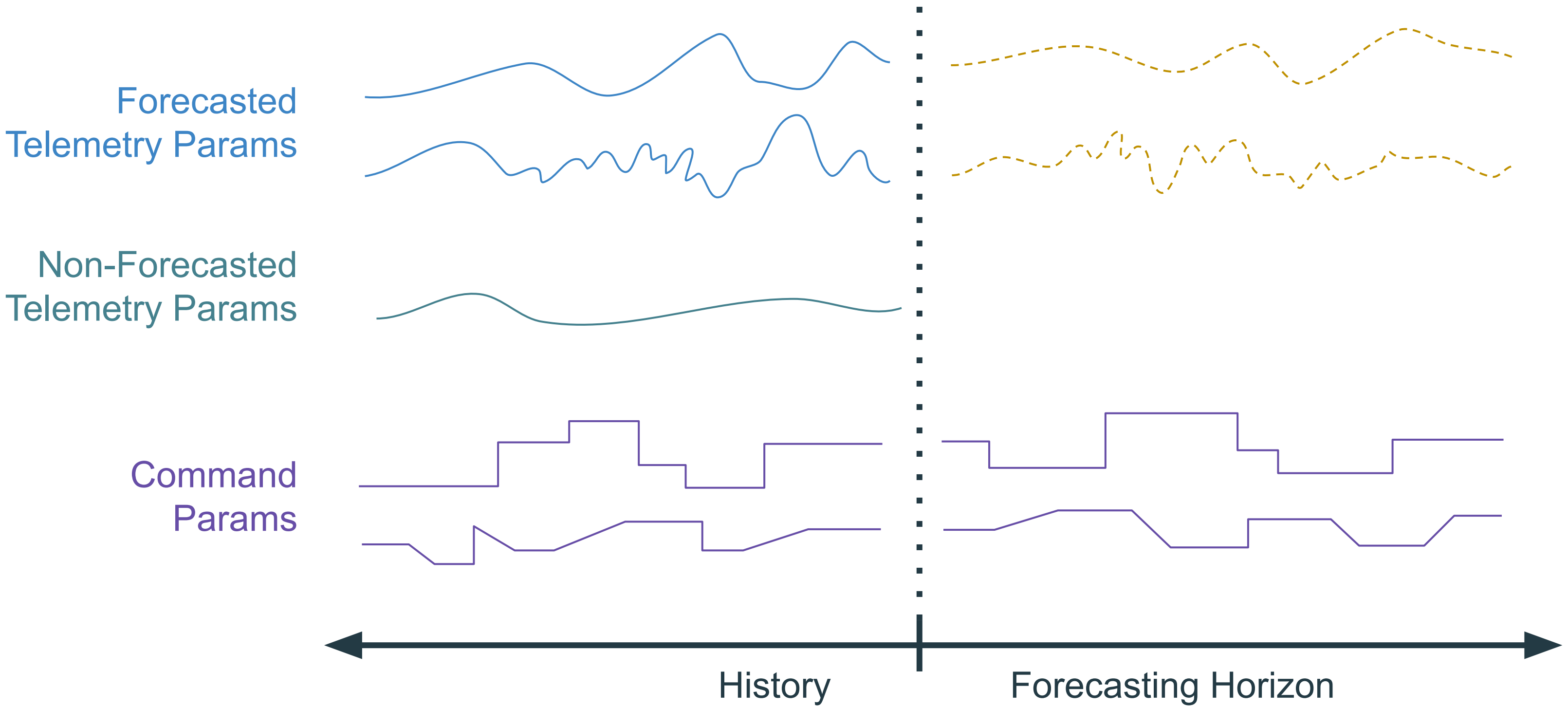
Data Innovation Lab

February 25th, 2021

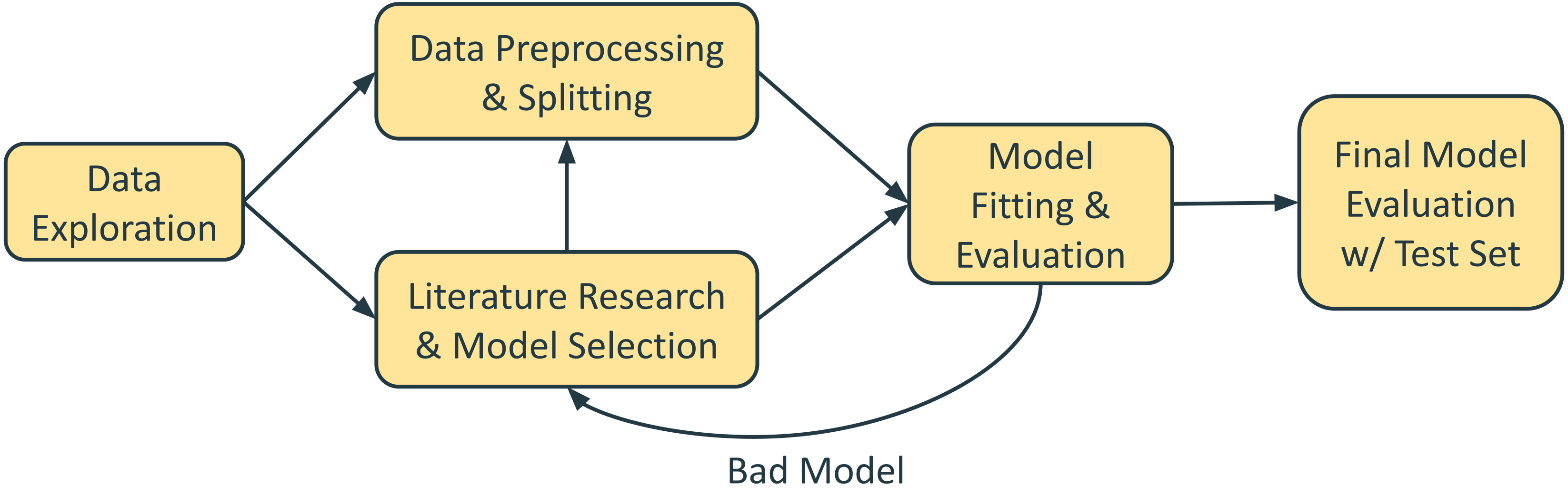
Problem Statement



Problem Statement



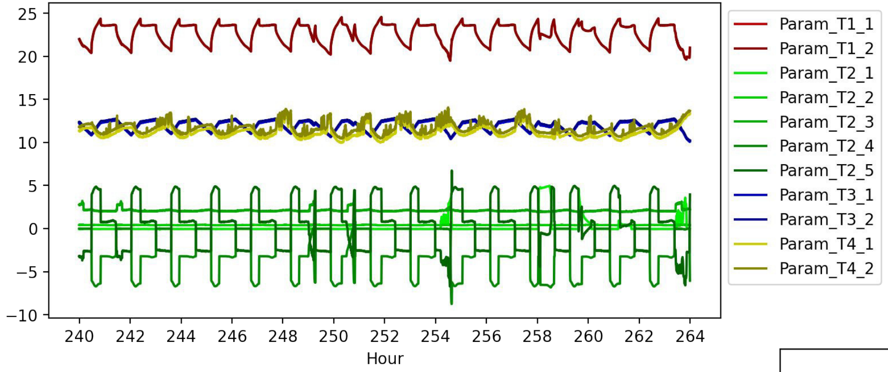
Process


Data Exploration
Data Preprocessing & Splitting
Literature Research & Model Selection
Model Fitting & Evaluation
Final Model Evaluation w/ Test Set
Bad Model

Outline

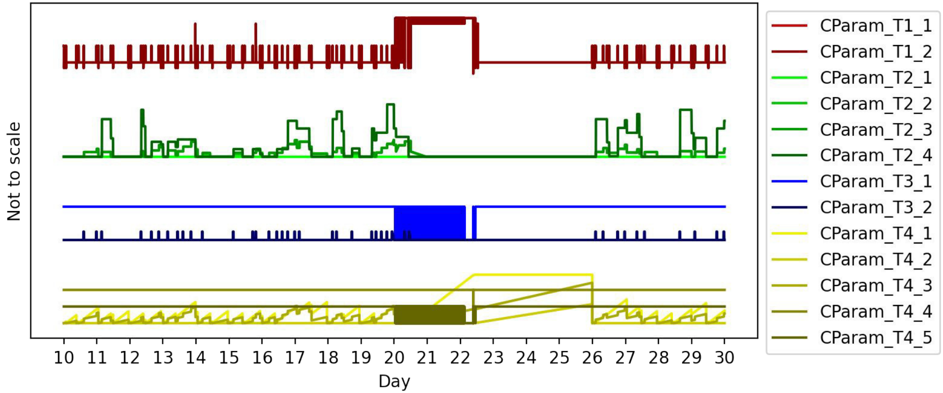
1. Problem Statement
2. Data Exploration
3. Forecasting Methods & Experiments
4. Future Research

Dataset

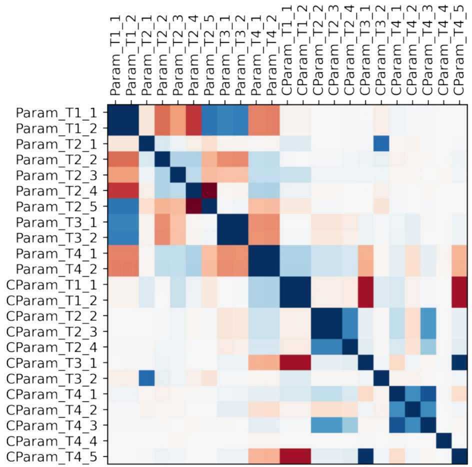


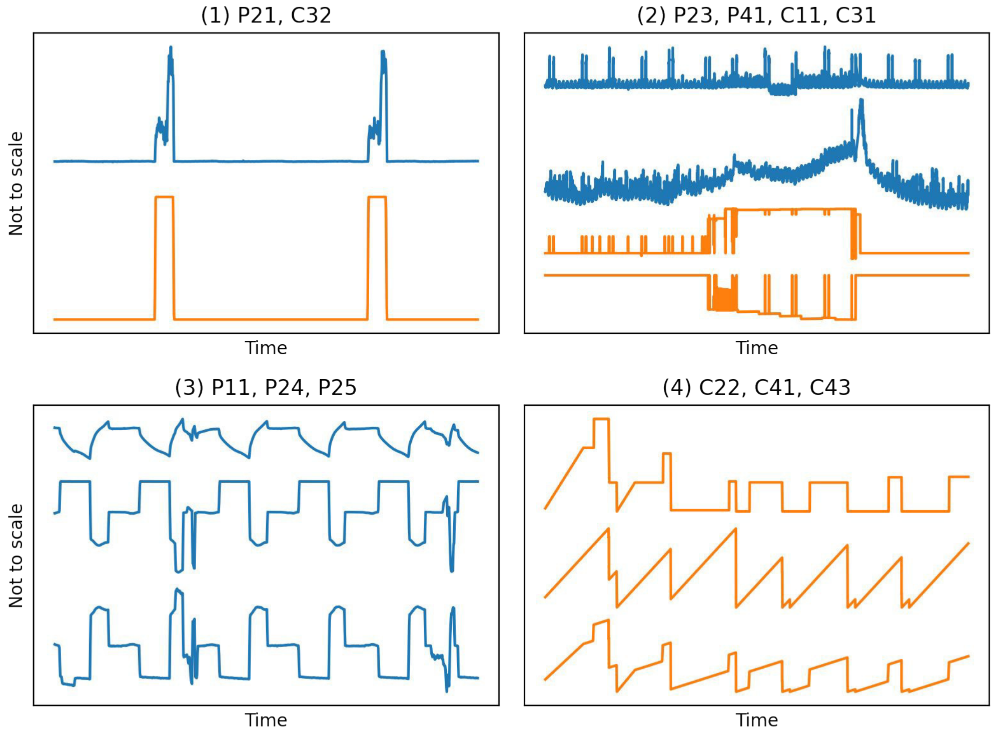
Telemetry parameters

Command parameters



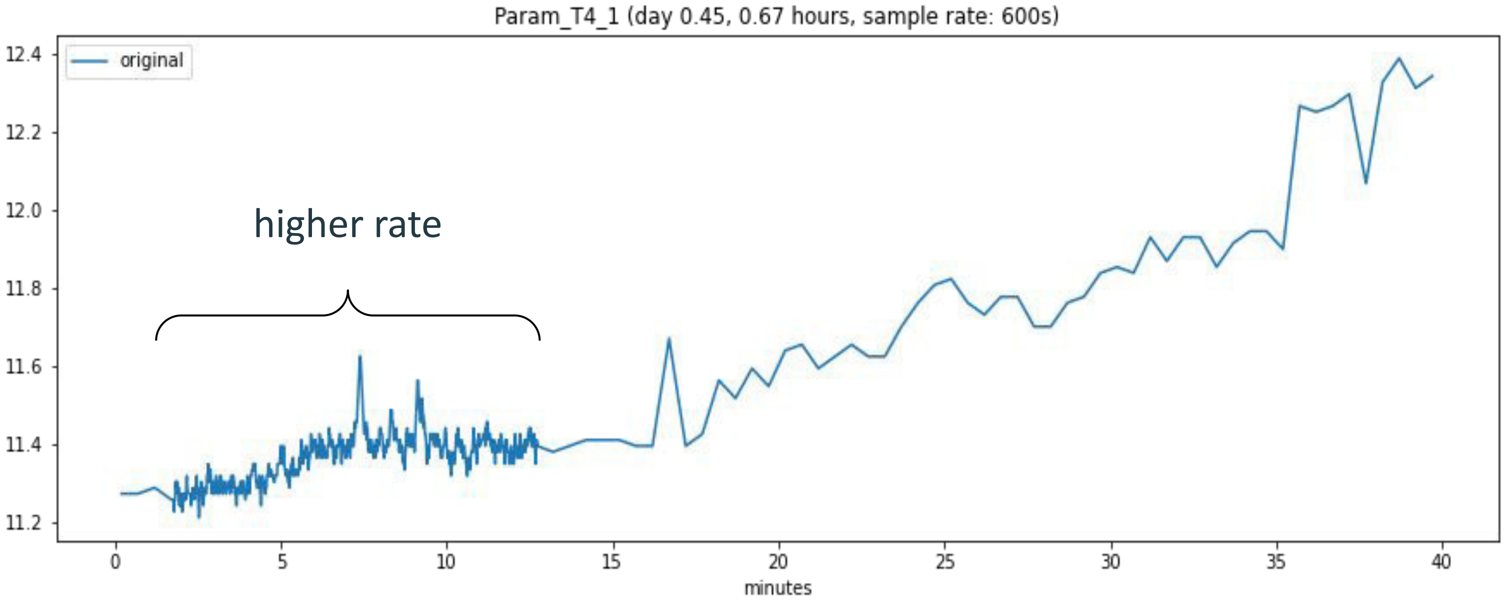
Interdependence





Data Preprocessing

Constant Rate Resampling

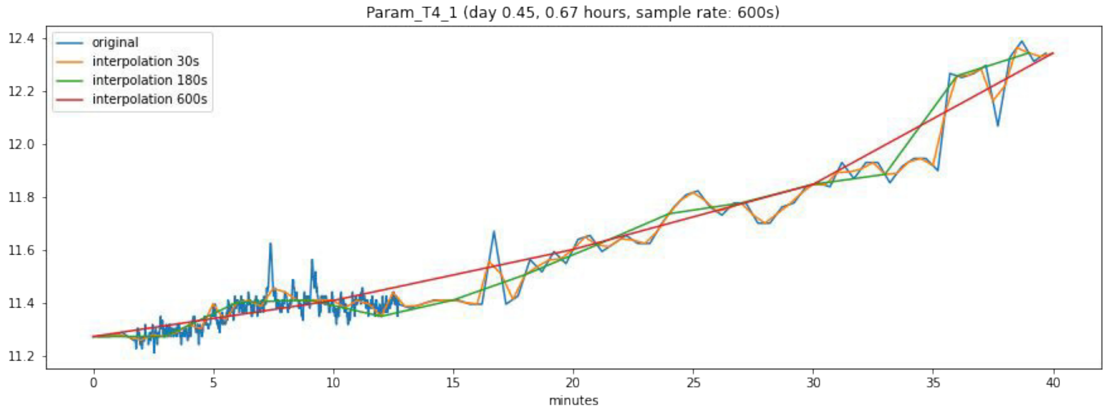


Constant Rate Resampling

Solution: Resample to constant rates

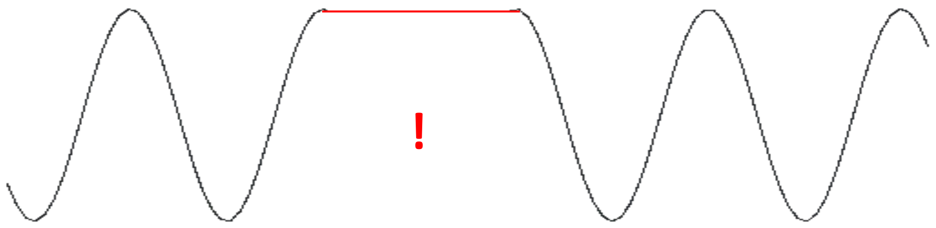
⟶ Which sampling rate? Decision: different options (30 seconds, 3 minutes, 10 minutes)

⟶ Interpolation to calculate resampled values



Gap Removal

Problem: Large gaps lead to inaccurate interpolation, which can hurt model performance



Solution: Remove time frames where one or more parameters have gaps

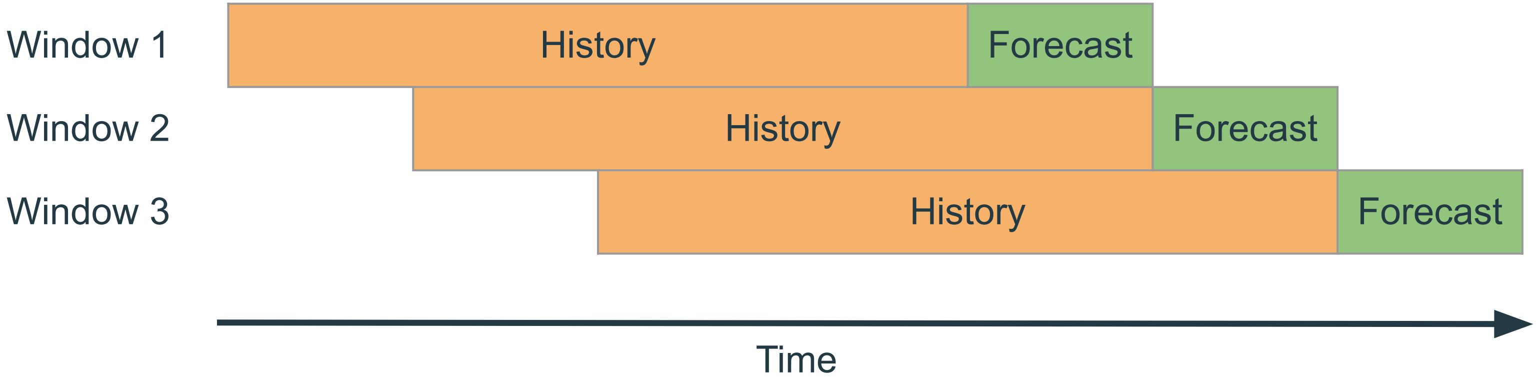
→ What counts as a gap? Decision: 3 minutes between two samples

Data Split

- first 80% for training/validation, final 20% for testing

- forecasting horizon: 3 hours
- history size: 3 & 12 hours

Split with sliding windows:



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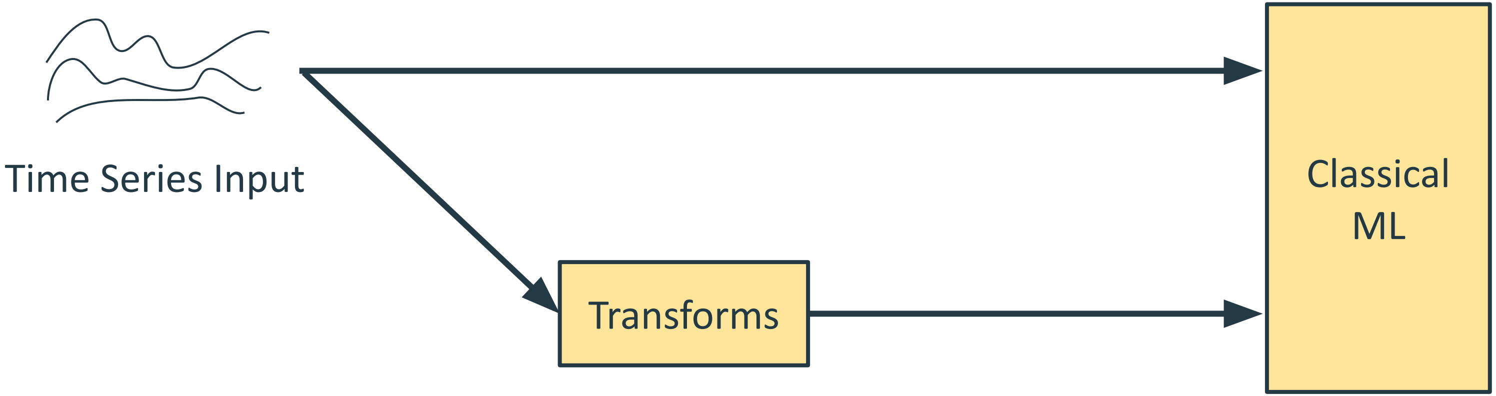
1. Problem Statement
2. Data Exploration
3. Forecasting Methods & Experiments
    a. Classical Machine Learning
    b. Classical Statistical Forecasting
    c. Hybrid Methods
    d. Deep Learning
    e. Fuzzy Time Series Forecasting
4. Future Research

	Suitability	Implemen-tation	Tuning	Performance	Training data	Comp. Complexity	Explainability
Sequence-to-sequence architectur	1	1	0	0	-1	0	-2
Stacked architecture	-1	0	0	-1	0	1	-2
Vanilla CNN - Direct Approach	0	1	0	0	-1	0	-2
Vanilla LSTM/GRU - Direct Approa	1	1	0	0	-1	0	-2
Graph Neural Networks	0	1	0	0	-1	0	-2
Temporal Fusion Transformers	2	2	0,5	1	-1	0	0
Wavelet-Arima	1	0	1	2	0	-1	1
Exponential Smoothing	1	1	1	0	1	1	1
VAR	1	1	1	-1	1	1	2
ES-RNN	0	1	1	1	-1	0	-1
GRU-ODE-Bayes	-1	1	1	1	-1		-1
Latent ODE	-1	1	1	1	-1		-1
LSTM-Arima	1	0	0	0	-1	0	-1
Wavelet-Normalizing-Flow	0	0	1	0	2		-1
Pre-built feature-based traditional	2	2	1	0	1	2	0
Feature-based NN applied directly	2	1	0		-1	0	-1
Pre-built feature-based ML model	2	1	0		1	1	0
Traditional Fuzzy Forecasting	1	2	-1	1	1	2	1
ANFIS	2	0	1	1	1	2	1

Classical Machine Learning

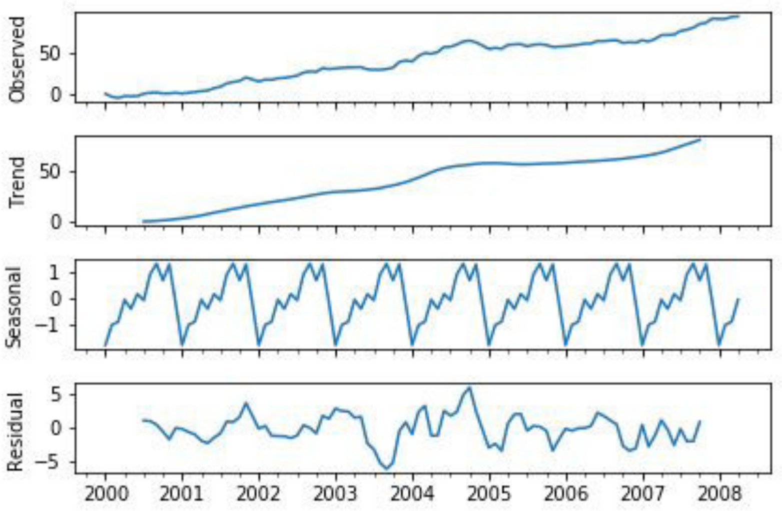
First Idea: Classical Machine Learning



Classical Statistical Forecasting

Classical Statistical Forecasting Methods

- Serves as a standard approach towards data modeling.



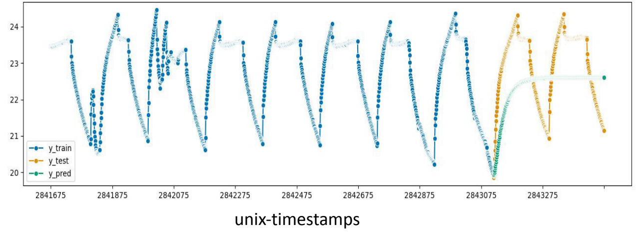
Key facts:

+ Interpretability
+ Low amount of data required

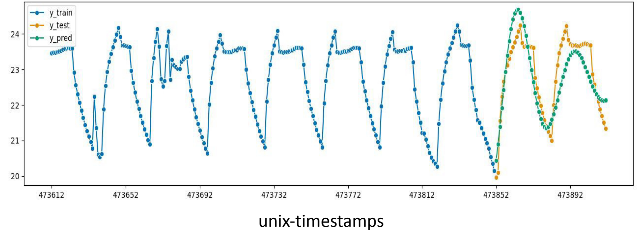
- Strict statistical assumptions
- Manually specifications, e.g., seasonality

Baseline: AutoARIMA

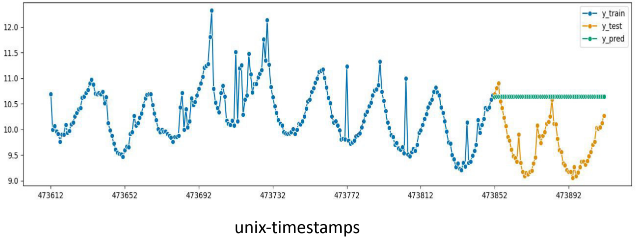
T1_1, 30s, 12hr, 3hr, window 10



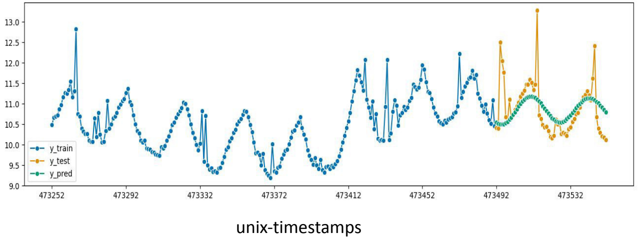
T1_1, 180s, 12hr, 3hr, window 10



T4_1, 180s, 12hr, 3hr, window 10



T4_1, 180s, 12hr, 3hr, window 4



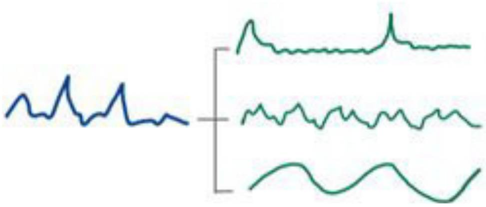
Hybrid Models

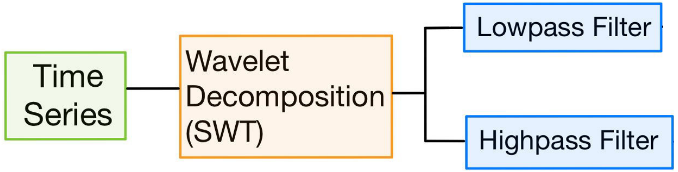
Hybrid Models Overview

- Combination of statistical methods with ANN architectures to overcome limitations of separate models
- Outperform many pure deep neural network architectures
- Pre-implemented models built to suit one/few specific datasets
  $\longrightarrow$ not applicable for our purposes
  $\longrightarrow$ create our own multi-step hybrid method

Wavelet Hybrid Method

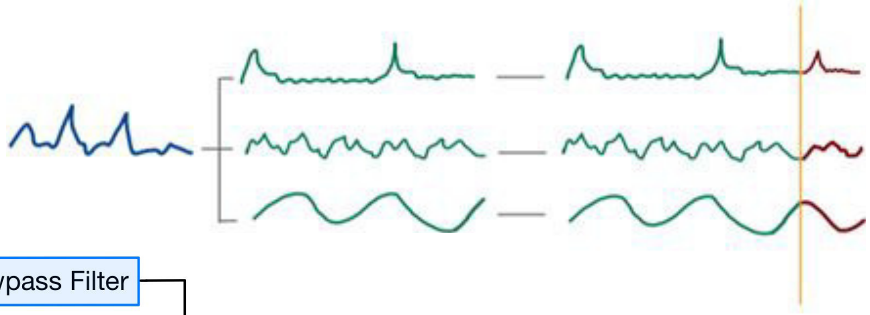
Multi-step process:

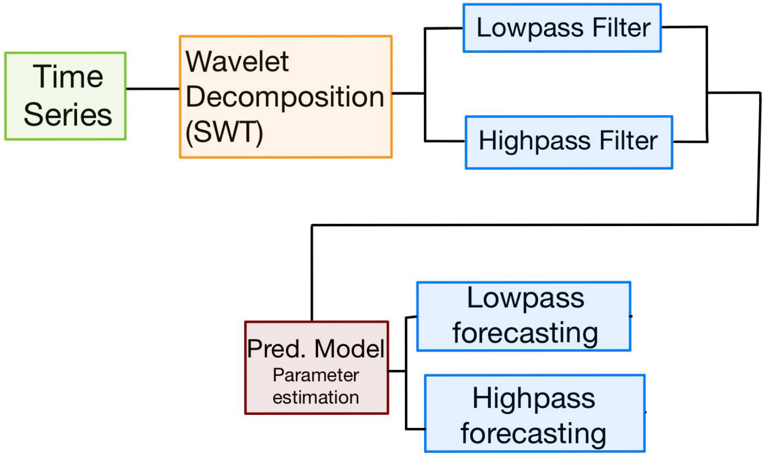




Wavelet Hybrid Method

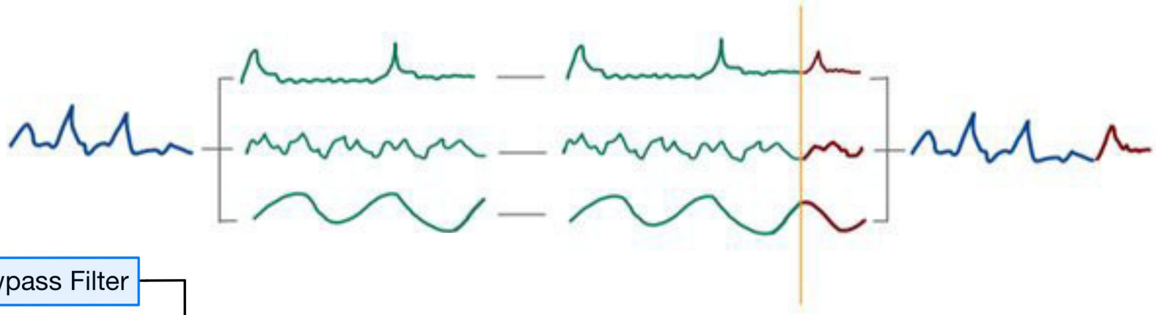
Multi-step process:

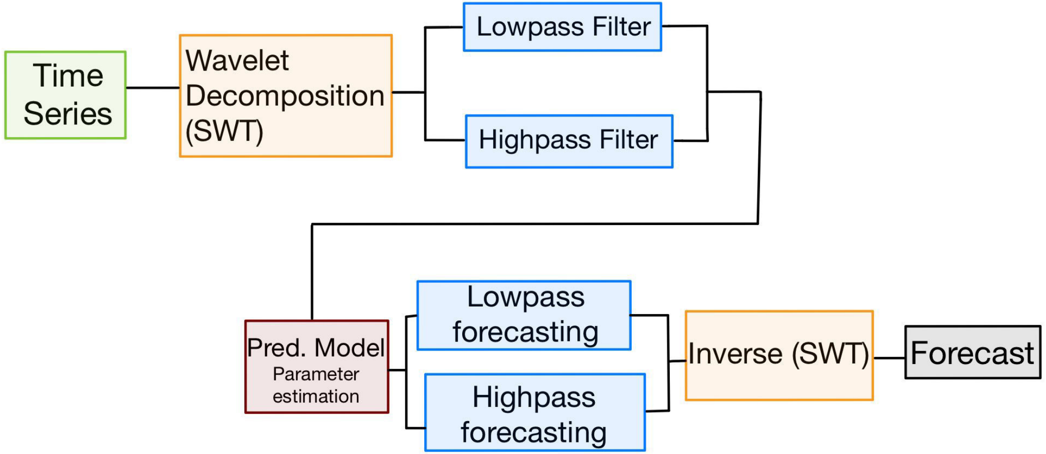




Wavelet Hybrid Method

Multi-step process:

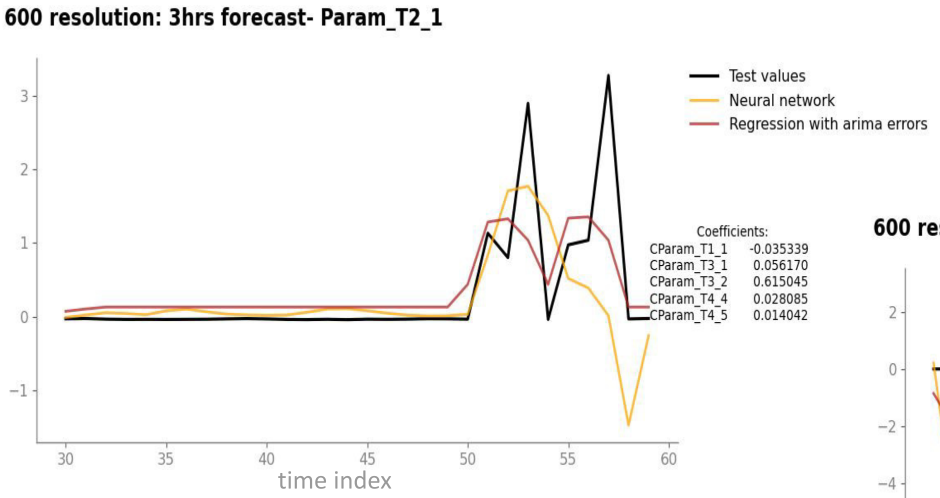


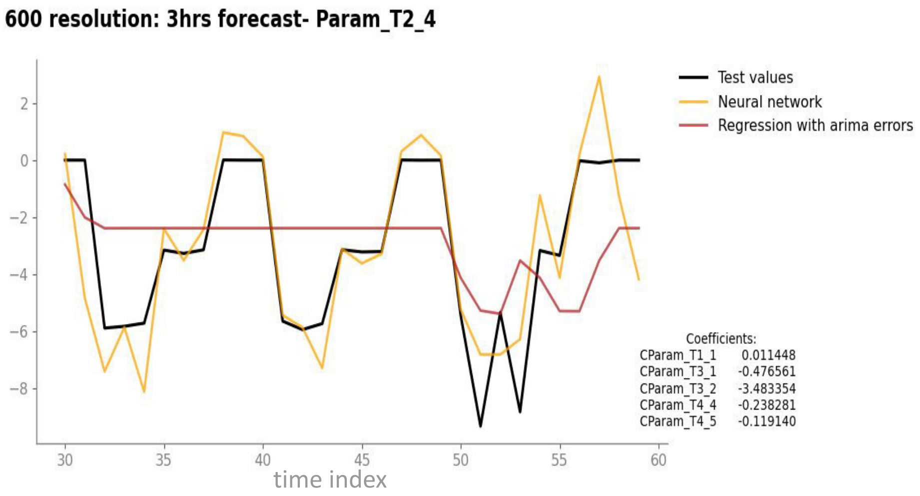


Wavelet + ARIMA & Wavelet + ANN

- First idea: Wavelets + ARIMA + Regressor to predict Wavelet coefficients
- Advanced approach: Wavelet + Multi-layer Perceptron

Wavelet Results

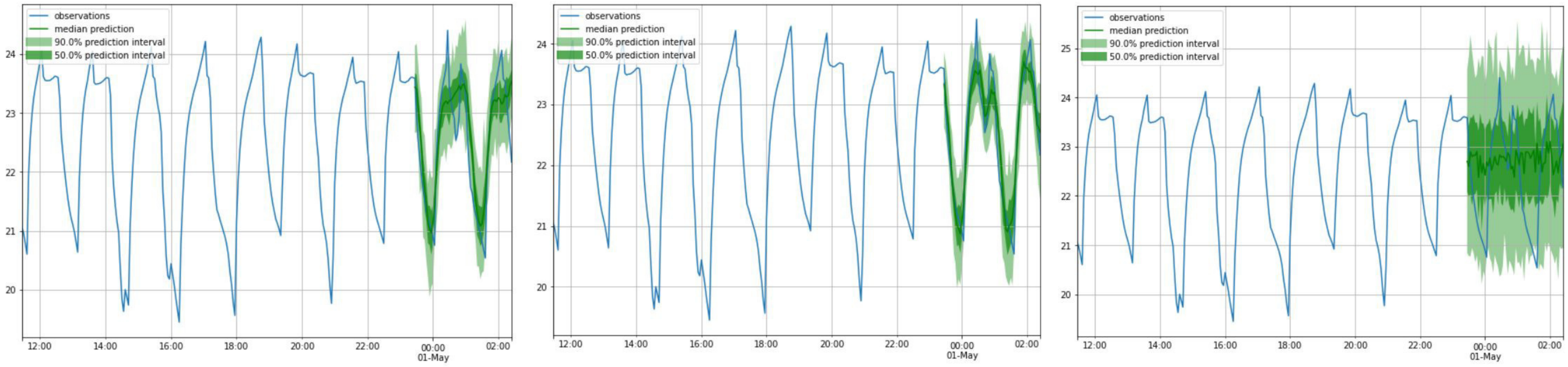




Wavelet Temporal Conditioned Norm. Flow

- Probabilistic forecasting method:
  Model learns (conditional) probability distribution of the time series
- Capable of incorporating interaction effects
- Univariate and multivariate models available

Example Forecast Normalizing Flow

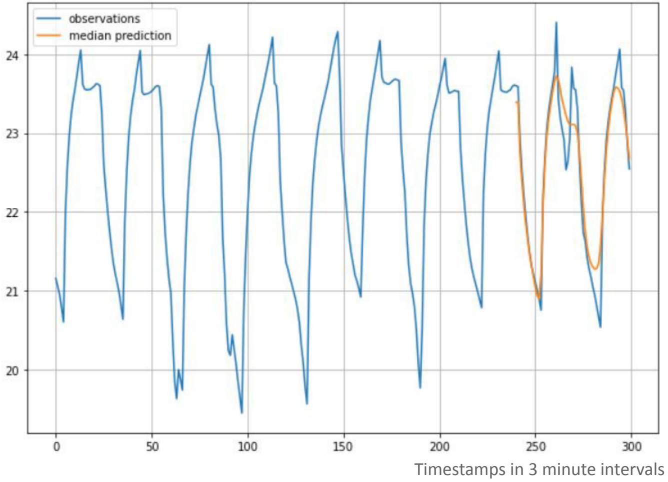


Unconditioned forecast

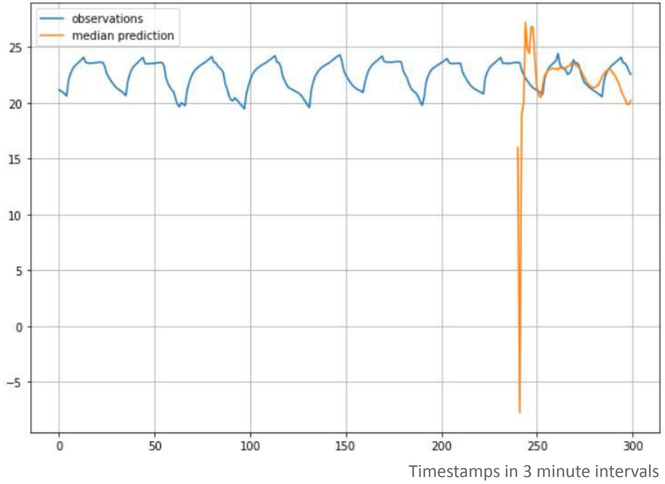
Forecast conditioned on few command parameters

Forecast conditioned on all command parameters

Results: Wavelet Normalizing Flow



Example forecast: multivariate wavelet normalizing flow

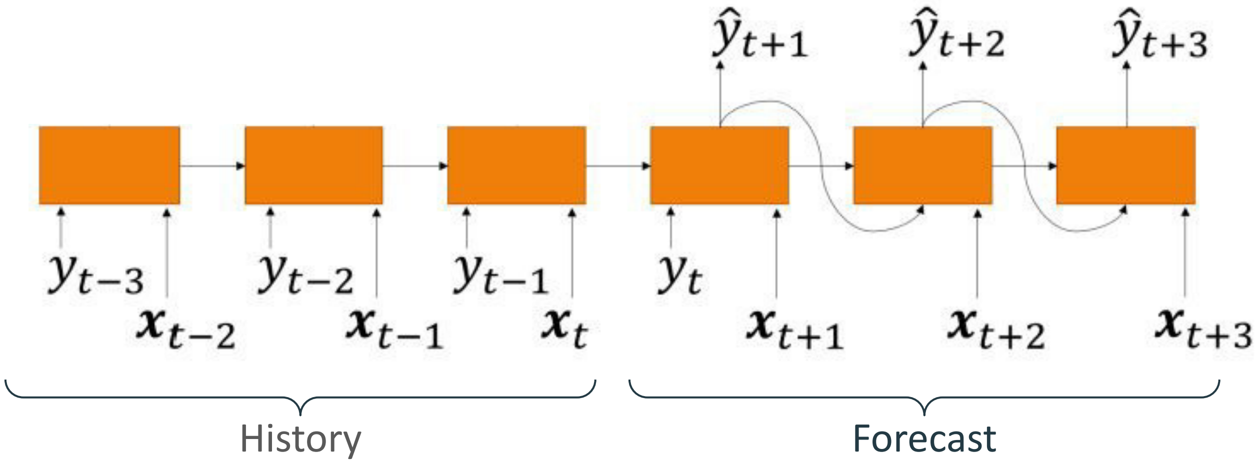


Example forecast: univariate wavelet normalizing flow

Deep Learning

Iterative Methods

"Predict one step after the other"
$\longrightarrow$ same model in each step

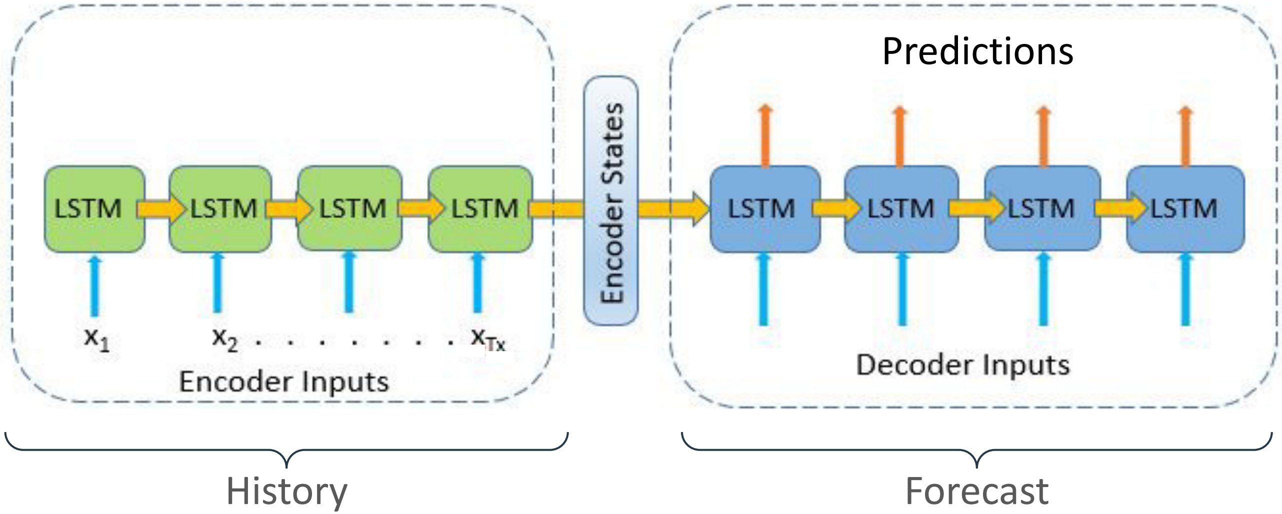


Lim et al., 2020. Time Series Forecasting With Deep Learning: A Survey.

Direct Methods

“Predict all steps at once”

⟶ Sequence-to-Sequence (Encoder-Decoder) architecture



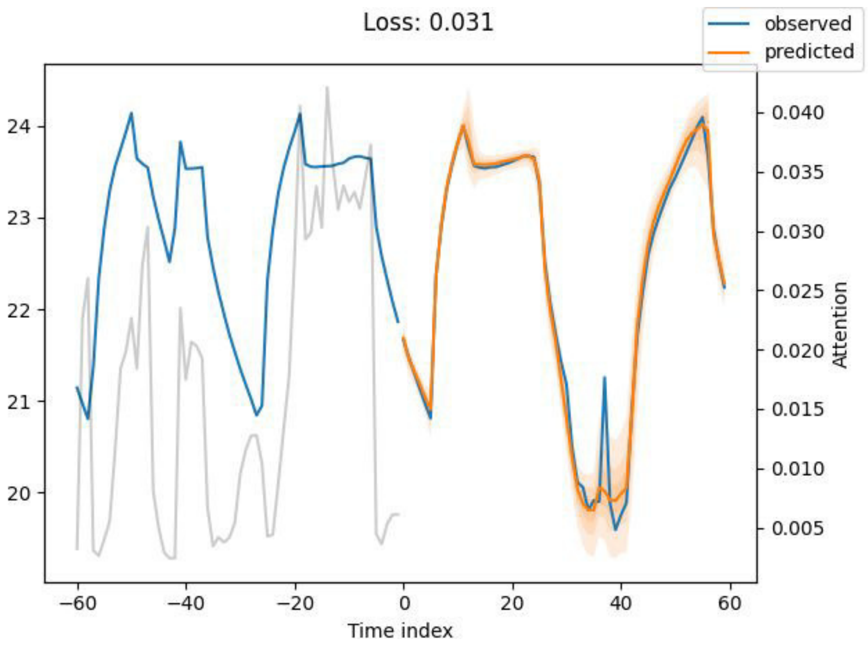
Direct Methods – Extensions

Additional concepts that have been used in time series forecasting:

- Attention mechanisms
- Quantile forecasts
- Graph Neural Networks

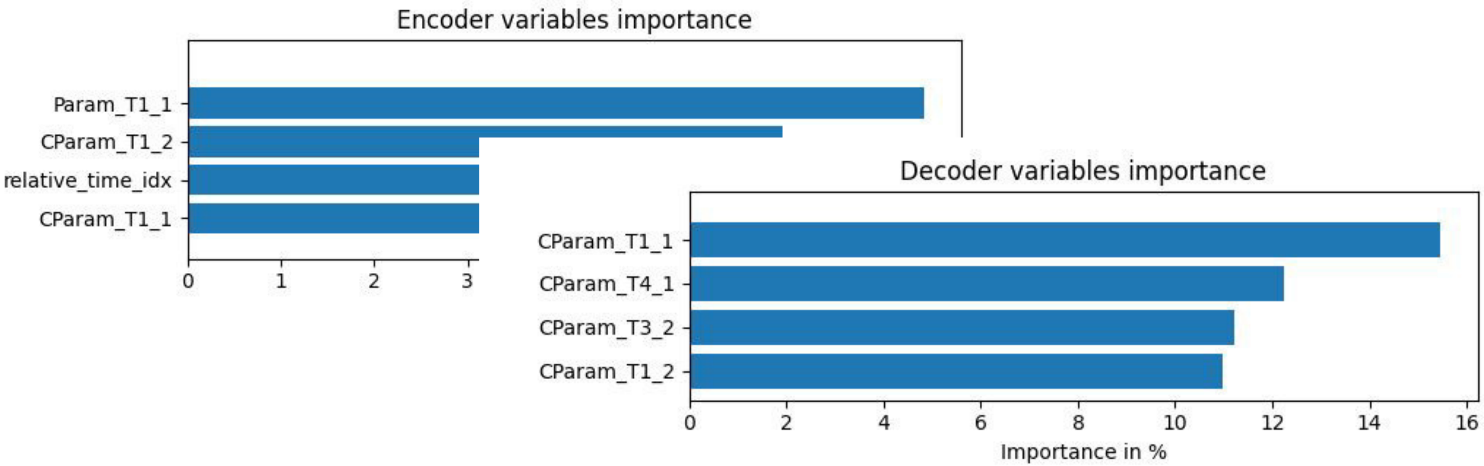
→ Method of choice: Temporal Fusion Transformer (TFT)

TFT: Forecast



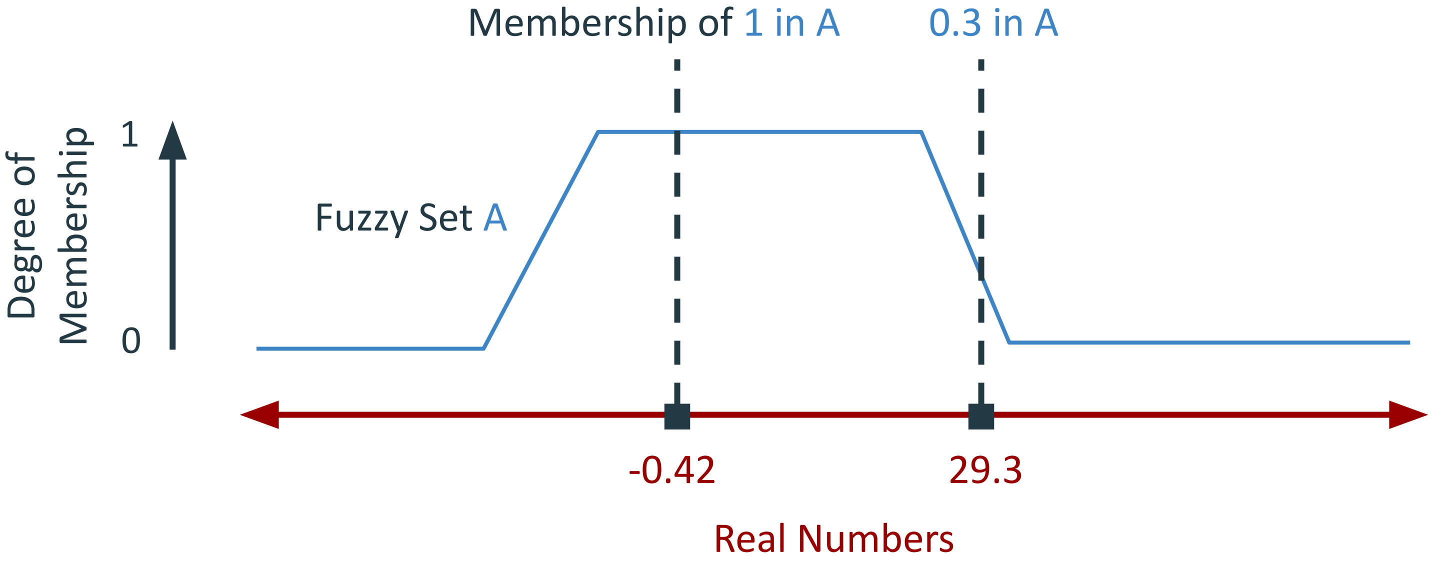
TFT: Explainability

Explainability feature: How important was each parameter?



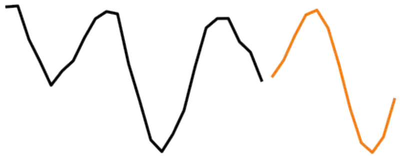
Fuzzy Time Series Forecasting

Fuzzy Sets

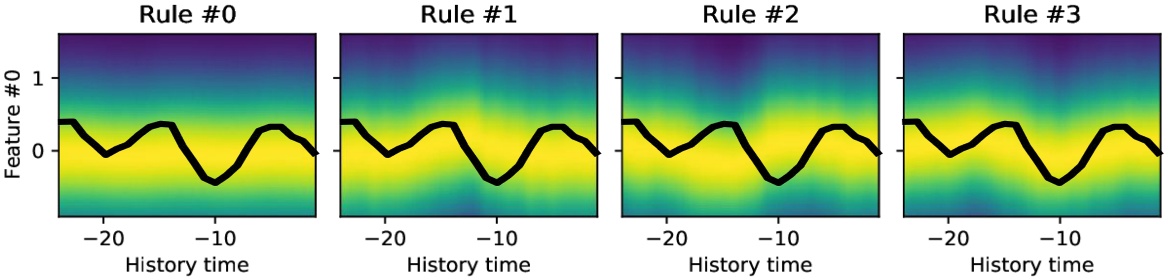


Membership of 1 in A
0.3 in A
Degree of Membership
1
0
Fuzzy Set A
-0.42
29.3
Real Numbers

1.Ord. Sugeno Fuzzy TS Forecast.



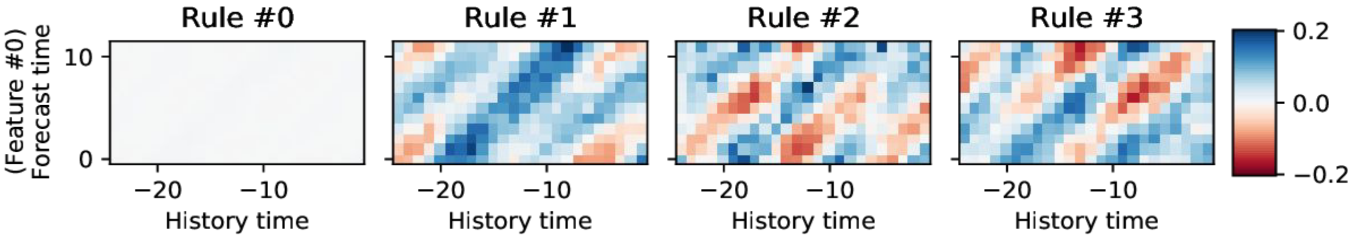
Fuzzy Sets



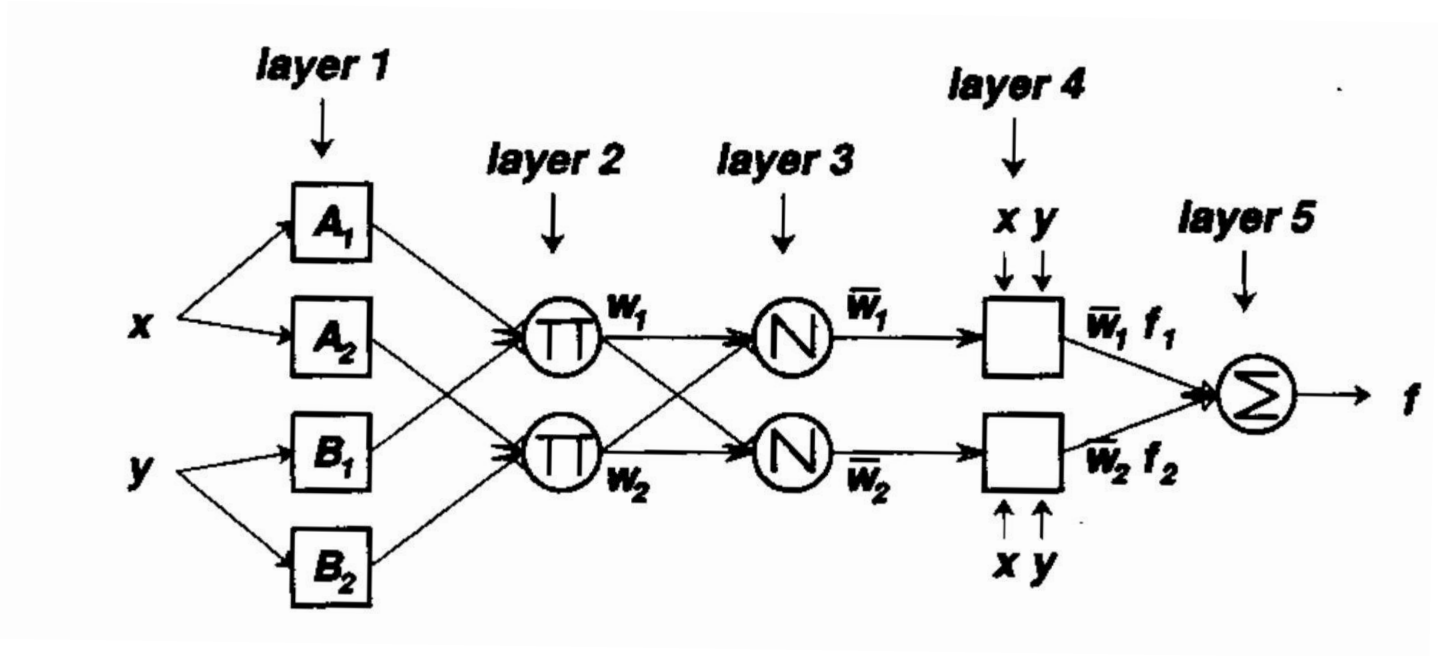
Normalized Memberships

0.1	0.2	0.1	0.6

Linear Regression Weights

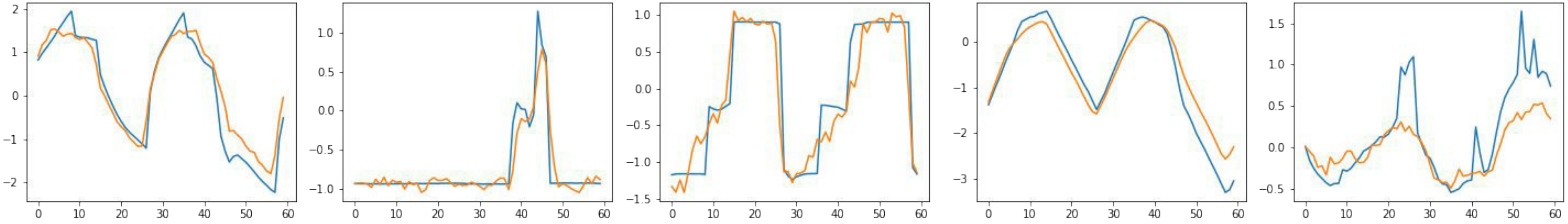


Fuzzy meets Neural Networks: ANFIS



Jang, 1993. ANFIS: Adaptive-Network-Based Fuzzy Inference System.

Sample Forecasts



Model Comparison

Model Comparison

Sampling			ARIMA	Wav-ARIMA	TFT	ANFIS
3h	3h	30s	5.644	0.726	0.117	**0.101**
		180s	0.839	0.681	**0.067**	0.097
		600s	0.557	0.760	**0.091**	0.114
12h	3h	30s	0.799	0.662	**0.123**	-
		180s	0.517	0.685	**0.084**	-
		600s	0.475	0.509	**0.095**	-

Evaluation metric: MSE on normalized data

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Future Research

1) Temporal Fusion Transformer:
   Optimize hyperparameters

2) Wavelet-ARIMA / Wavelet-ANN:
   Try combining the wavelet transform with a more complex neural network architecture

3) Wavelet-Normalizing-Flow:
   Explore direct performance of the temporal conditioned normalizing flow on the parameters

4) ANFIS:
   Investigate effect of amount of rules on accuracy & try to make the model more scalable