Deep Learning para series temporales

Part III

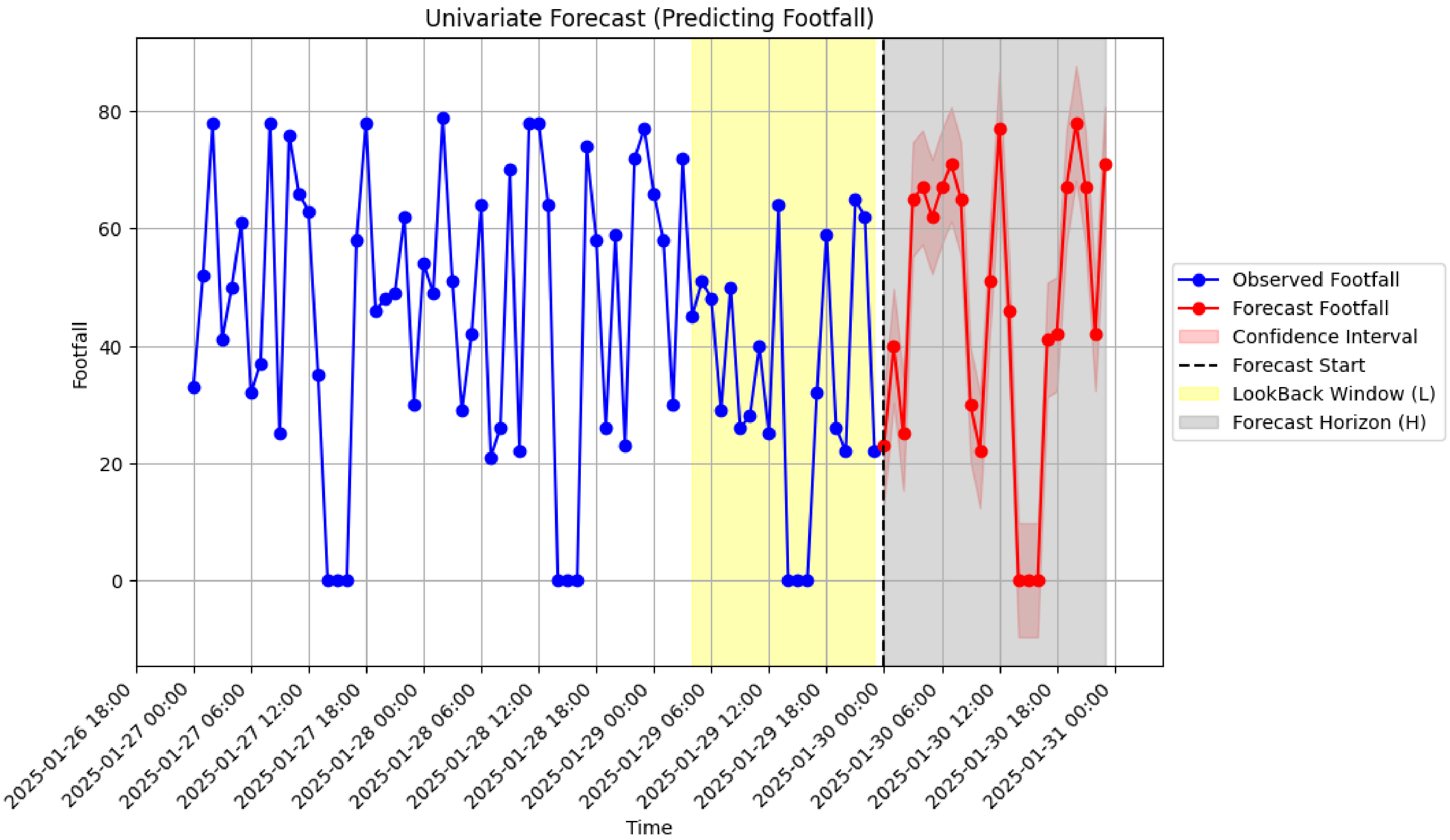
Forecasting

Contents

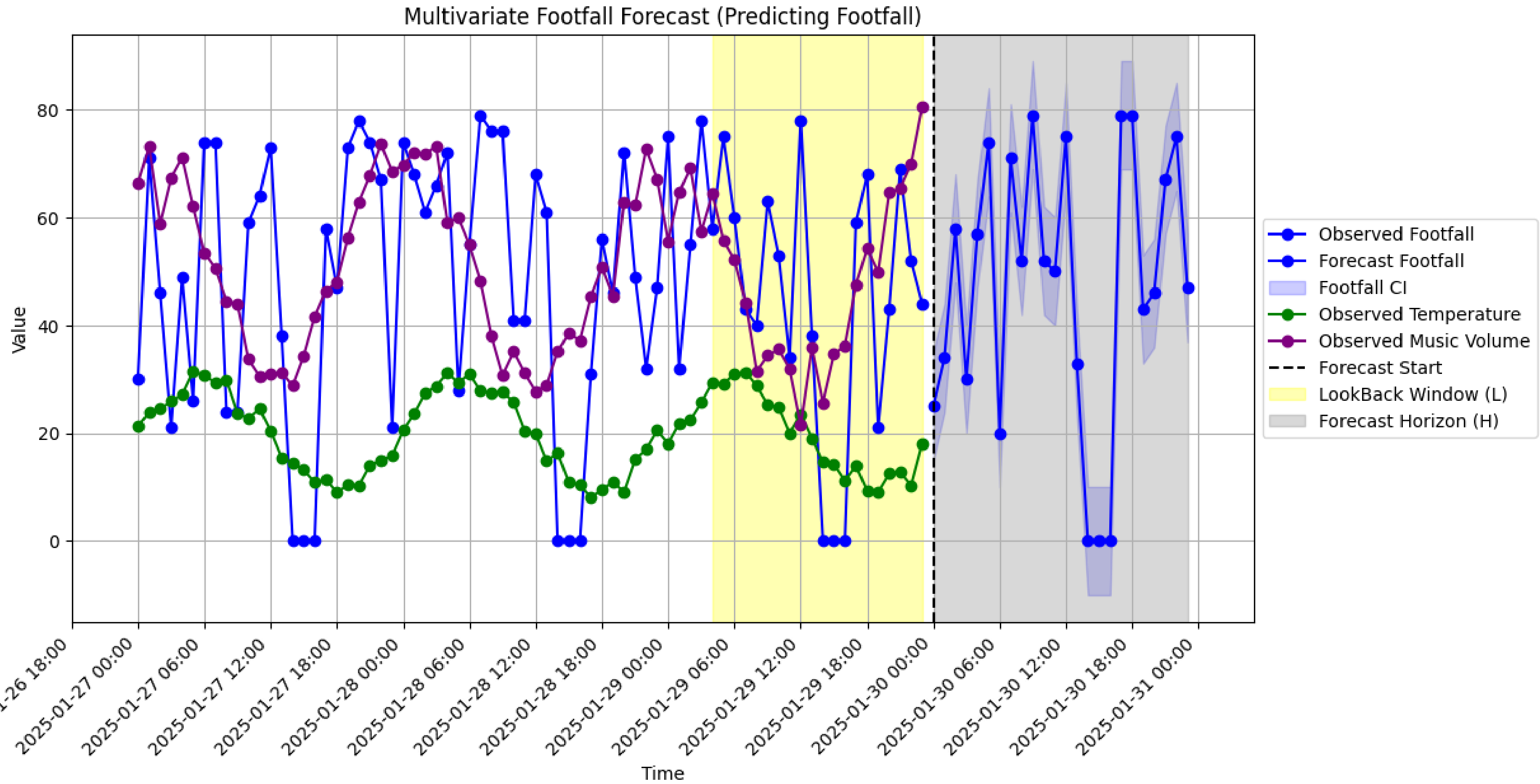
Task definition

What does forecast mean?

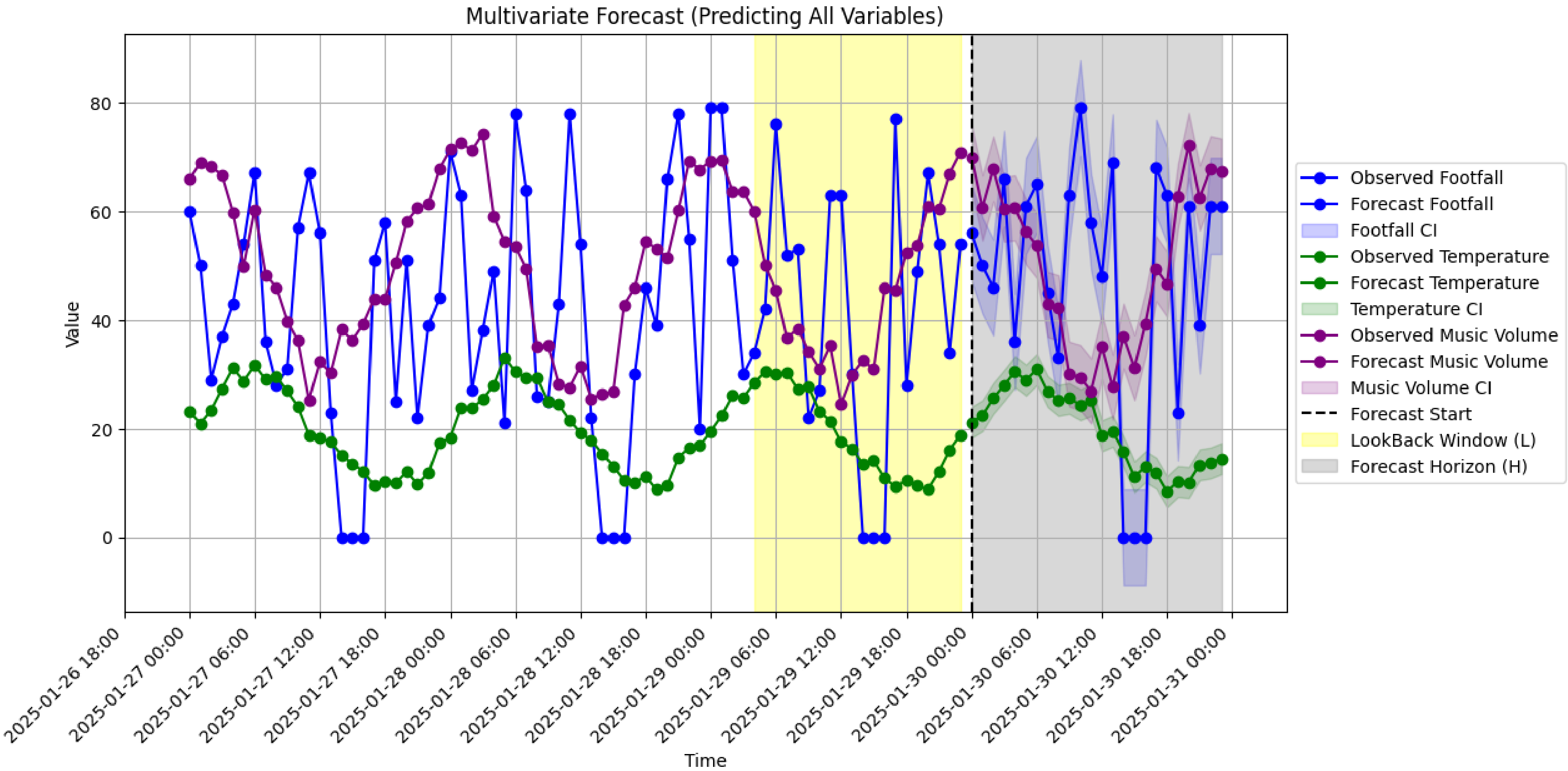
4



Univariate Forecast (Predicting Footfall)
Footfall
Time
80
60
40
20
0
2025-01-26 18:00
2025-01-27 00:00
2025-01-27 06:00
2025-01-27 12:00
2025-01-27 18:00
2025-01-28 00:00
2025-01-28 06:00
2025-01-28 12:00
2025-01-28 18:00
2025-01-29 00:00
2025-01-29 06:00
2025-01-29 12:00
2025-01-29 18:00
2025-01-30 00:00
2025-01-30 06:00
2025-01-30 12:00
2025-01-30 18:00
2025-01-31 00:00
Observed Footfall
Forecast Footfall
Confidence Interval
Forecast Start
LookBack Window (L)
Forecast Horizon (H)



Multivariate Footfall Forecast (Predicting Footfall)
Value
80
60
40
20
0
Time
2025-01-26 18:00
2025-01-27 00:00
2025-01-27 06:00
2025-01-27 12:00
2025-01-27 18:00
2025-01-28 00:00
2025-01-28 06:00
2025-01-28 12:00
2025-01-28 18:00
2025-01-29 00:00
2025-01-29 06:00
2025-01-29 12:00
2025-01-29 18:00
2025-01-30 00:00
2025-01-30 06:00
2025-01-30 12:00
2025-01-30 18:00
2025-01-31 00:00
Observed Footfall
Forecast Footfall
Footfall CI
Observed Temperature
Observed Music Volume
Forecast Start
LookBack Window (L)
Forecast Horizon (H)



Multivariate Forecast (Predicting All Variables)
Value
80
60
40
20
0
Time
2025-01-26 18:00
2025-01-27 00:00
2025-01-27 06:00
2025-01-27 12:00
2025-01-27 18:00
2025-01-28 00:00
2025-01-28 06:00
2025-01-28 12:00
2025-01-28 18:00
2025-01-29 00:00
2025-01-29 06:00
2025-01-29 12:00
2025-01-29 18:00
2025-01-30 00:00
2025-01-30 06:00
2025-01-30 12:00
2025-01-30 18:00
2025-01-31 00:00
Observed Footfall
Forecast Footfall
Footfall CI
Observed Temperature
Forecast Temperature
Temperature CI
Observed Music Volume
Forecast Music Volume
Music Volume CI
Forecast Start
LookBack Window (L)
Forecast Horizon (H)

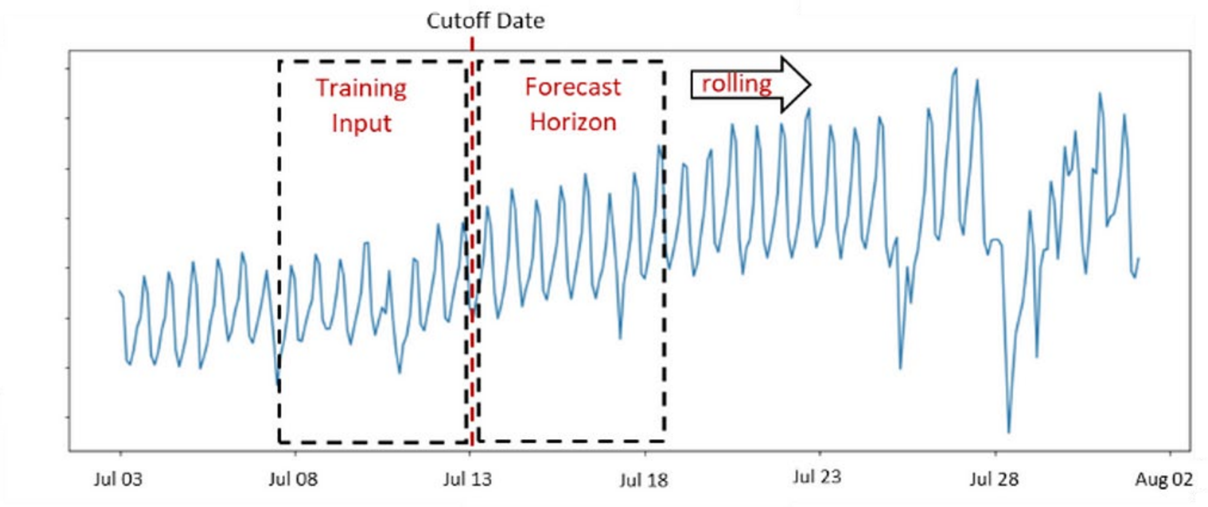
Task definition

Definition: Forecasting (informal)

Given the historical data of **d** features at the lookback (the yellow part)
we want to guess the value of **d2** variates at timestamps the horizon (the gray part)

The most similar to the real time series, the better we are doing.

Task definition | How to fill the full time series



https://medium.com/data-science-at-microsoft/time-series-forecasting-part-2-of-3-selecting-algorithms-11b6635f61bb

https://machinelearningmastery.com/lstm-model-architecture-for-rare-event-time-series-forecasting/

Task definition | How to fill the full time series

Forecast Epoch	Day										
Day 4	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11
Day 5	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11
Day 6	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11
Day 7	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11
Day 8	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11
Day 9	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11

Current Day
Lookback
Horizon Values
Unused for Step

https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2023SW003675

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Task definition

Definition: Types of time series forecasting

- **Get 1 feature -> Predict 1 feature**
  - ARIMA, Exponentials, N-BEATS
- **Get d -> predict 1**
  - ARIMAX, TimeGPT, Prophet
- **Get d -> predict d2**
  - TFT
- **Get d -> predict d**
  - VAR, PatchTST

Task definition

Definition: Long-term/short-term

The task can be further divided into

- **long-term** (large H)
- **short-term** (small H)

Some models mix both long and short term

What can we use forecasting for?

Real world applications

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Real-Word applications I/II

- Supply Chain & Inventory Management
  - Wallmart: forecasts producto demand to optimize inventory & supply chains
  - Inditex (Zara): Analyzes seasonal trends to adjust production & stock levels.
- HHRR
  - Workday: helps other enterprises to model, forecast, and budget their workforce all from the same unified data core

Real-Word applications II/II

- Mobility & Transportation
  - Uber: uses real-time ride demand forecasts for Dynamic pricing and driver allocation
  - Delta Airlines: predicts passenger volumes to optimize flight schedules and staffing.
- Agricultural Production
  - Olam International: predicts crop yields and commodity volumes for improved logistics and market planing

Model classification

Checking the options we have

Classification

- Models for stationary data
- Models for non-stationary data
- Models for confidence intervals
- Multivariate forecasting
- Adapting ML to forecasting
- Neural & DL forecasting

Models for stationary data

Existing models

Stationary data | Persistence

- Used as benchmark model
- Used for predicting
  - Future wind, solar power, photovoltaic power generation, load for households
    - Assuming clear sky. Bad due to cloud change, wind speed
  - Security returns (changes in the Price of a security –stocks, commodities- over time)

- https://www.sciencedirect.com/topics/engineering/persistence-model
- https://arxiv.org/abs/2501.05000
- https://www.researchgate.net/publication/254714552_Forecasting_Security_Returns_With_Simple_Moving_Averages

Stationary data | Persistence

Assume events repeat along time

$$\hat{f}(t+h) = f(t)$$

H=2					
0	t0	t1	t2	t3	t4
1	t0	t1	t2	t3	t4
2	t0	t1	t2	t3	T4

Stationary data | Persistence

Assume events repeat along time

$$\hat{f}(t+h) \;=\; f(t)$$

Lookback L = 2

Horizon H = 2

Current day: t + h (t2, t3, t4)

History: [t+h-L, t+h-1] | **Forecast**: [t+h, t+h+H-1]

h = 2 H = 2 L = 2 Epoch					
0	t0	t1	t2	t3	t4
1	t0	t1	t2	t3	t4
2	t0	t1	t2	t3	t4

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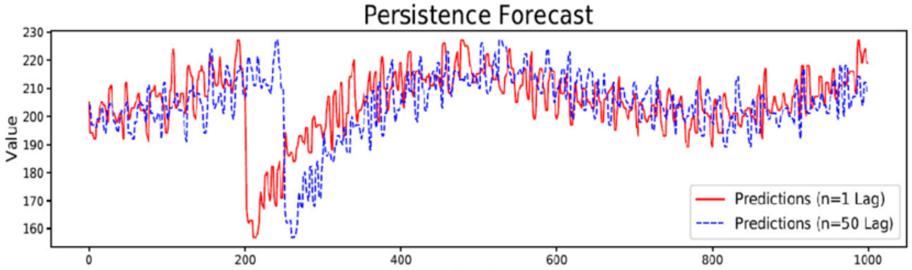
Stationary data | Persistence

Assume events repeat along time

$$\hat{f}(t+h) = f(t)$$

L = 1 H = ?



	0	1	2	3	4	5	6	7	8	9	10	11	12	13
value	10.0	12.0	9.0	10.0	15.0	13.0	18.0	18.0	20.0	NaN	NaN	NaN	NaN	NaN
predict	NaN	NaN	NaN	NaN	NaN	10.0	12.0	9.0	10.0	15.0	13.0	18.0	18.0	20.0

https://www.researchgate.net/figure/Persistence-naive-forecast-model-plot-for-50-lag-Root-Mean-Square-Error-RMSE-of_fig8_330125062

Stationary data | Persistence

Assume events repeat along time

$$\hat{f}(t+h) = f(t)$$

- Cat with refills
  - Perfect
- Cat without refills in a normal day
  - Maybe
- Cat without refills when you go out for a day for the first time
  - Good luck

Stationary data | Simple Moving Average

PROS
Simple, intuitive

CONS
Very difficult in some domains (e.g. weather)

- Further: https://otexts.com/fpp2/ses.html
- Eg.: https://academy.binance.com/en/glossary/exponential-moving-average-ema.

Stationary data | Simple Moving Average

- Traders use simple moving averages (SMAs) to chart the long-term trajectory of a stock or other security, while ignoring the noise of day-to-day price movements.
- Predict entry & exit point (any stock market)
- May be used, for example, for predicting online sales: https://www.youtube.com/watch?v=rlZTk8O6ac0

https://www.tradingview.com/chart/DOGEUSDT/nhmKCC9Q-DOGE-Easy-Trick-Targets-with-Moving-Averages/

https://www.investopedia.com/terms/s/sma.asp#:~:text=Traders%20use%20simple%20moving%20averages,over%20a%20larger%20time%20horizon.

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Stationary data | Simple Moving Average

- Assumes stationarity with very low variance over time
  - $\hat{f}(t+h) = avg(\{x_i\}_{i=t-L+1}^{t}) = \frac{x_{t-L+1}+\cdots+x_t}{L}$
  - Usually, H = 1

	0	1	2	3	4	5	6	7	8	9	10	11
prices	10.0	12.0	9.0	10.0	15.0	13.0	18.0	18.0	20.0	NaN	NaN	NaN
RollingMean_2	NaN	11.0	10.5	9.5	12.5	14.0	15.5	18.0	19.0	NaN	NaN	NaN
predict_L2_H3	NaN	NaN	NaN	NaN	11.0	10.5	9.5	12.5	14.0	11.0	13.25	12.5

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Stationary data | Simple Moving Average

PROS	CONS
Simple	Delay showing recent changes
Easy to compute and understand	Sensitive to window size
Reduces noise (smooth the function)	Outlier impact
Helps to highlight global trend	

- Further: https://otexts.com/fpp2/ses.html
- E.g.: https://academy.binance.com/en/glossary/exponential-moving-average-ema.

Stationary data | Simple Exponential Smoothing (SES)

- Used for forecasting:
  - Blood components demand
  - Spare parts inventory

- https://www.researchgate.net/profile/I-Gede-Iwan-Sudipa/publication/386424134_Performance_of_Moving_Average_and_Exponential_Smoothing_Methods_in_Forecasting_Demand_for_Blood_Components/links/6750e134f309a268c0243c91/Performance-of-Moving-Average-and-Exponential-Smoothing-Methods-in-Forecasting-Demand-for-Blood-Components.pdf
- https://eduvest.greenvest.co.id/index.php/edv/article/view/1079

Stationary data | Simple Exponential Smoothing (SES)

- Assumes stationarity with very low variance over time

$$\hat{f}(t+h) = \alpha f(t) + (1-\alpha)\hat{f}(t)$$

- Further: https://otexts.com/fpp2/ses.html
- E.g.: https://academy.binance.com/en/glossary/exponential-moving-average-ema.

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Stationary data | Simple Exponential Smoothing (SES)

PROS	CONS
Simple	Sensitive to volatility
More responsive to recent data (quickly reflect new trends or changes)	α is subjective and may affect performance and consistence
Reduced lag (reacts faster to movements => Good for short-term analysis)	Less efective for long-term analysis
Smooths out random fluctuations	

- Further: https://otexts.com/fpp2/ses.html
- Eg.: https://academy.binance.com/en/glossary/exponential-moving-average-ema.

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Stationary data | Exponential Moving Average

https://26693533.fs1.hubspotusercontent-eu1.net/hubfs/26693533/Imported_Blog_Media/EMA_SMA.png

Stationary data I MA: Moving Average

- Inventory forecasting
- Clothing sales forecasting
- Demand forecasting
- Forecasting demand for blood components

- https://ejournal.techcart-press.com/index.php/dimis/article/view/17
- https://www.jurnal.polgan.ac.id/index.php/sinkron/article/view/13686
- https://www.sciencedirect.com/science/article/pii/S0307904X1630292X
- https://www.researchgate.net/profile/I-Gede-Iwan-Sudipa/publication/386424134_Performance_of_Moving_Average_and_Exponential_Smoothing_Methods_in_Forecasting_Demand_for_Blood_Components/links/6750e134f309a268c0243c91/Performance-of-Moving-Average-and-Exponential-Smoothing-Methods-in-Forecasting-Demand-for-Blood-Components.pdf

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Stationary data | MA: Moving Average

- *MA(order=L)* model

$$\hat{f}(t+h) = c + \epsilon_t + \sum_{i=1}^{L} \theta_i \epsilon_{t-i}$$

- c constant
- ϵ white noise
- θ weights or parameters
- Lagged errors as inputs

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Stationary data | MA: Moving Average

PROS	CONS
Models noise (smooth)	Difficult to select the parameters
Captures transitory (short-term) effects (shocks, noise)	Assumes linear relationship with past errors
Simple	

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Stationary data | AR: AutoRegression

- Lagged observation as inputs
- $\mathrm{AR(orden = p)}$

$$\hat{f}(t) = c + \sum_{i=1}^{p} \phi_i \hat{f}(t-i) + \epsilon_t$$

- c constant, ϕ_i weight or parameters, e noise/error
- https://www.geeksforgeeks.org/autoregressive-ar-model-for-time-series-forecasting/

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Stationary data | AR: AutoRegression

- Lagged observation as inputs
- $AR(orden = p)$

p = 2 H = 1 L = p					
0	t0	t1	t2	T3	t4
1	t0	t1	t2	t3	t4
2	t0	t1	t2	t3	T4

Stationary data | AR: AutoRegression

PROS
Simple: easy to understand and analyze the results
Models the noise

CONS
Only considers linear relationships with past values
Does not capture shocks – Does not directly incorporate errors or disturbances

Stationary data | ARMA: AutoRegressive Moving Average

AR: autoRegression

MA: moving average

AR + MA

- Combines the best of both
- Used for short-term load forecasting
  https://www.sciencedirect.com/science/article/pii/0378779695009771

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Stationary data | ARMA: AutoRegressive Moving Average

PROS	CONS
Integrates influence of past values and errors	Errors in parameter selection can affect accuracy
Captures complex dynamics (e.g. trend)	

Stationary data | Other examples

- Weighted Moving Average

$$\hat{f}(t+h) = \frac{2}{n(n+1)} \sum_{i=1}^{L-1} i f(t+i)$$

  - Used for product stock inventory forecasting: https://jutif.if.unsoed.ac.id/index.php/jurnal/article/view/421

Models for non-stationary data

Existing models

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Models for non-stationary data

- Based on the previous ones
- Model trend, stationarity, ...
- Predict the results using all the modelled parts, not only previous values/errors

ARIMA: AutoRegressive Integrated Moving Average

- AR: lagged observations as inputs
- I: differencing to make the time series stationary
- MA: lagged errors as inputs
- Case of use
  - Short-run forecasting of commodity prices: https://www.jstor.org/stable/3866657

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ARIMA: AutoRegressive Integrated Moving Average

- ARIMA(p,d,q)
  - $\Delta^d f(t)$ -> difference f d times
  - $\boldsymbol{\Delta^d \hat{f}(\mathrm{t}) = \mathrm{c} + \sum_{i=1}^{p} \phi_i \, \Delta^d f(t-i) + \sum_{i=1}^{q} \theta_i \, \epsilon_{t-i}}$
  - $\hat{f}(0) = f(0), \dots, \hat{f}(d-1) = f(d-1)$
  - $\hat{f}(\mathrm{t}) = \Delta^d \, \hat{f}(t) + \hat{f}(t-1)$

https://otexts.com/fpp3/MA.html

Diference: d = 1 $\Delta^d \mathrm{f}(t) = f(t+1) - f(t)$ | length decreases by 1!

ARIMA: AutoRegressive Integrated Moving Average

- AR: $\sum_{i=1}^{p} \phi_i \, \Delta^d f(t-i)$
- I: $\Delta^d f$
- MA: $\sum_{i=1}^{q} \theta_i \, \epsilon_{t-i}$

Stationary data | ARMA: AutoRegressive Moving Average

PROS
Suitable for non-stationary data as differencing removes trend and mean changes
Allows modeling evolving behaviors

CONS
Differencing may remove useful information of the original series
Parameter selection is not easy
Complex interpretation

ARIMA

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- SeasonalARIMA
  - Detects seasonal patterns
  - Check: https://www.geeksforgeeks.org/sarima-seasonal-autoregressive-integrated-moving-average/
- ARMAeXogeneous
  - More comprehensive analysis
  - Check: https://www.geeksforgeeks.org/what-is-an-arimax-model/

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ETS – Exponential Trend Seasonality models

- SES expands to ES models:
  - Holt-Linear (Double exponential smoothing) & Damped trend methods
    - adds a trend component
    - Double exponential smoothing is used for estimating rice sales
      - https://international.arimsi.or.id/index.php/IJSME/article/view/12
  - Holt-Winters' seasonal method
    - adds to Holt-Linear a seasonal component
  - And much more depending on the decomposition.
    - Check https://otexts.com/fpp2/taxonomy.html.

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ETS – Exponential Trend Seasonality models

- ES models expands to ETS models:
  - Named as…
    - Exponential-Trend-Seasonal
    - Level – Trend – Seasonal
    - State Spaced models
  - Adds prediction errors to the formulas
  - Check https://otexts.com/fpp2/ets.html

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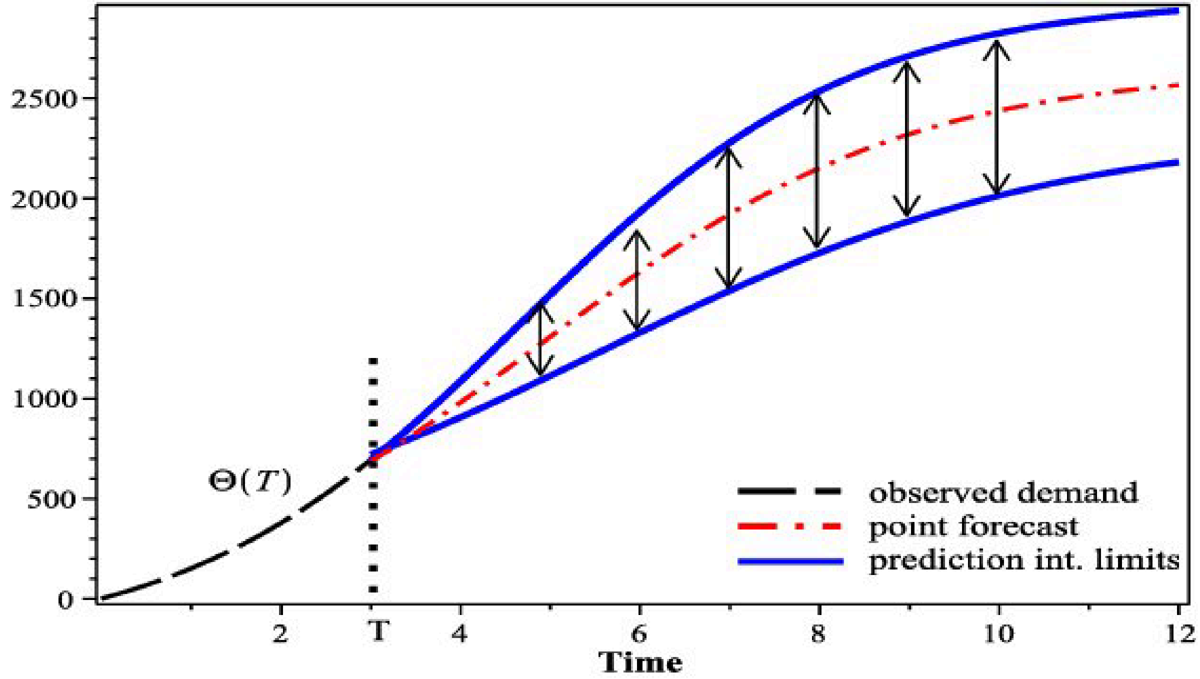
ETS – Exponential Trend Seasonality models

- ETS expands to ETSX? Yes!
  - And make them more accurate
  - Some old trials:
    - The neutral Interest Rate And The Stance Of **Monetary Policy In Brazil**
    - Demand forecasting in **supply chain**: The impact of demand volatility in the presence of promotion
  - Research paper with generic explanation (p. 15)
    - Analysis of the impact of policy measures on **parking behavior** using interpretable time series models

Models based on confidence intervals

Existing models

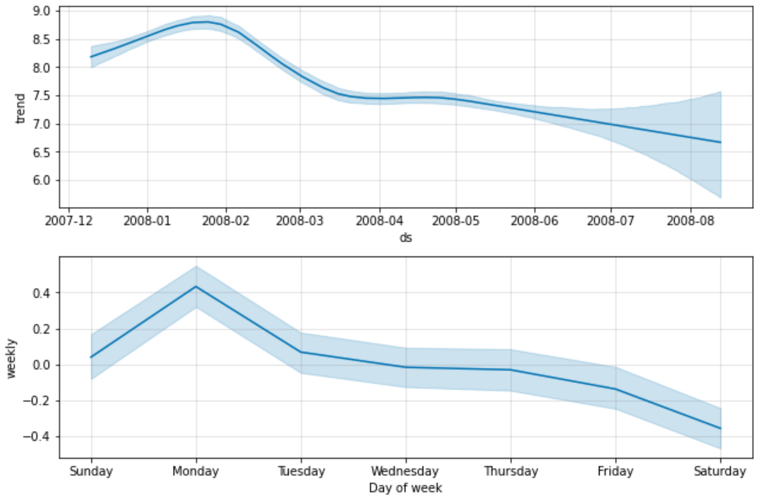
Confidence Interval



https://www.researchgate.net/publication/228456351_Extending_Bass_for_Improved_New_Product_Forecasting/figures?lo=1

Confidence Interval | Prophet

- Robust forecasting model
- Developed by Meta
- Computes the confidence
- Good at modeling holidays



- https://facebook.github.io/prophet/docs/uncertainty_intervals.html
- https://www.linkedin.com/advice/1/how-does-prophet-handle-seasonality-holidays-better

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Confidence Interval | Are they used?

- Probabilistic load **forecasting** for integrated energy systems based on quantile regression patch time series Transformer
- **Forecasting** coastal stability: Digital shoreline analysis system and machine learning techniques in evaluating Impacts of cyclones
- A Time Series Approach to **Forecasting** Financial Indicators in the Wholesale and Retail Trade
- Assessing the efficacy of machine learning algorithms in weather **forecasting**: A comparative study of Erode weather data from local weather station
- Long-Term Product **Forecasting** in Pharmaceuticals.

Other

Existing models

Other | Multivariate forecasting
Vector Autoregression

- VAR is a stochastic process to fit a model.
- It models the time series using matrices to define equations $\hat{F}(t) = C + AF(t-1)Err(t)$

Other | Machine Learning

- Any ML may be used to model a time series using

$$\hat{f}(t+H) = \ model\big(f(t) + .. + f(t-L)\big)$$

- Usually, they lack on detect temporal dependencies
- Are language **models** actually useful for time series **forecasting**?

Other | Neural & Deep |

- LTSMs: long-term short-term
  - Recurrent Neural Networks
  - Capture temporal relations on data
  - Fail to capture trends

Other | Neural & Deep IV

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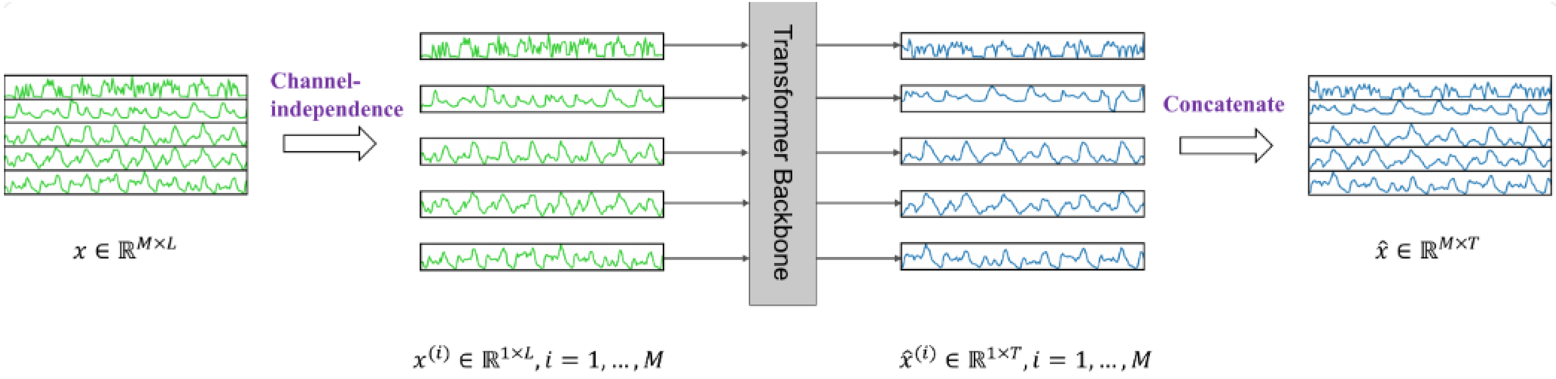
- **Transformers**



(a) PatchTST Model Overview

- https://arxiv.org/abs/2211.14730

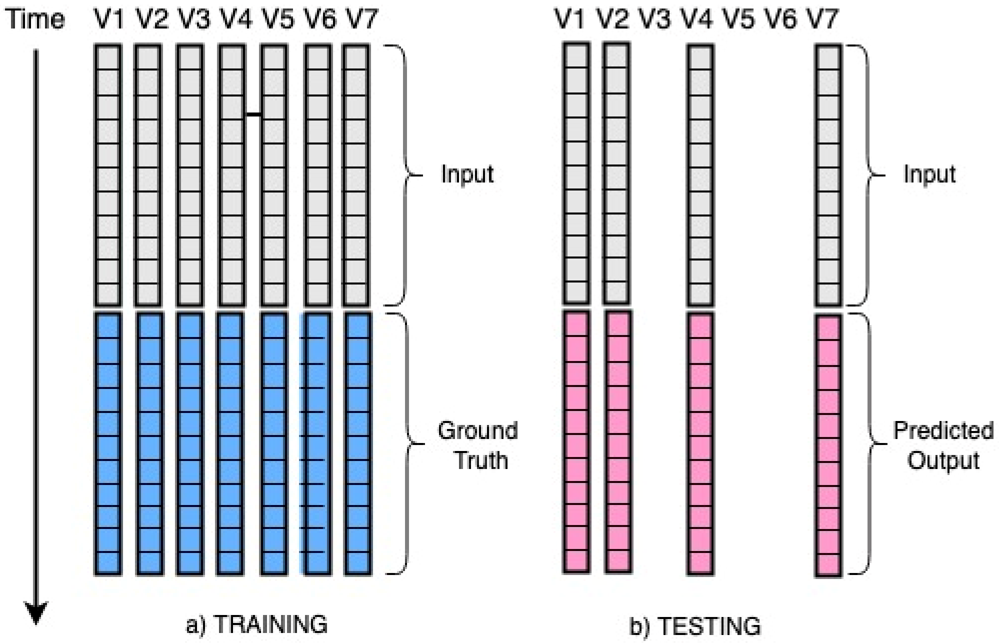
Other | Neural & Deep IV

- **Transformers**
  - Are they useful for time series?
    - [2023] Are you sure Transformers are good?
      - Temporal loss correlation
      - Are Transformers Effective for Time Series Forecasting?
    - [2023] Autoformer | Yes! They are useful: https://huggingface.co/blog/autoformer
    - [2025] People are using it: A systematic review for transformer-based long-term series forecasting

Other | Neural & Deep IV

- **Informer**
  - Insights: https://huggingface.co/blog/informer
  - Research paper: https://arxiv.org/abs/2012.07436
- **Other:**
  - CT-PatchTST: https://arxiv.org/abs/2501.08620
  - PathFormer: https://arxiv.org/abs/2402.05956
  - Timexer: https://arxiv.org/abs/2402.19072
  - QR-PatchTST: https://www.sciencedirect.com/science/article/pii/S2352484724007777

Other | Multi-Variate Time Series Forecasting on Variable Subsets



- What if when I am inferring I don't have all the variates?

Other | Feature engineering

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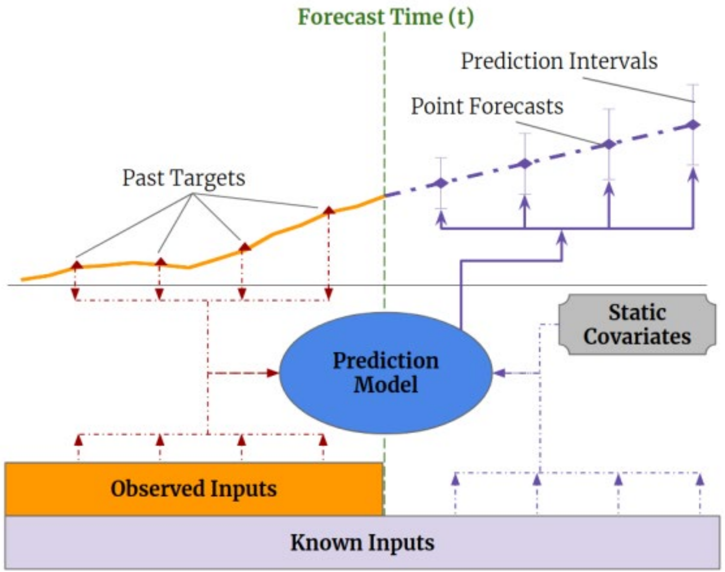

- … We like exogeneous variates ☺
- TFT: https://arxiv.org/pdf/1912.09363

... What about Transfer Learning?

... Is it possible in time series?

?

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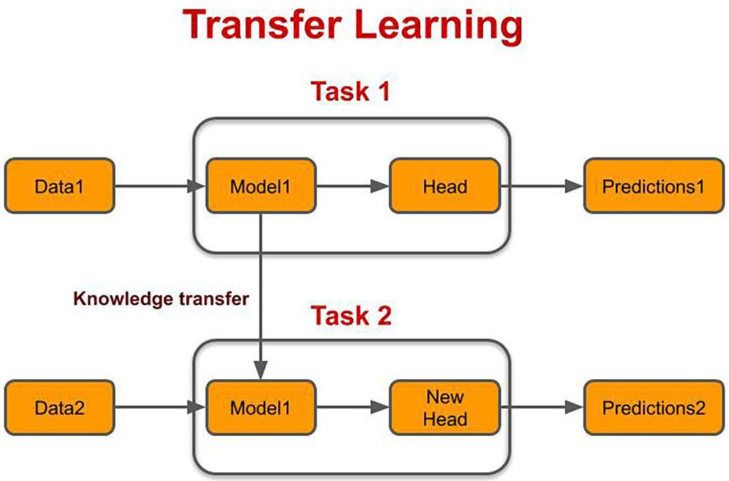
Other | Transfer Learning

- Using learned knowledge to boost performance on a related task.



- https://www.topbots.com/transfer-learning-in-nlp/

Other | Transfer Learning

- Pushing the Limits of Pre-training for Time Series Forecasting in the CloudOps Domain

lightweight models outperform expressive Transformer-based architectures and data scale is not a limiting factor. Secondly, unlike image and text data which naturally share semantic information across datasets and domains, time series data may not enjoy such properties of transferability as the semantics of time series data may be unique to their dataset or domain. As such, it is still unclear how time series models can benefit from pre-training and transfer learning.

Other | Transfer Learning

- [Transfer larning for time series classification]

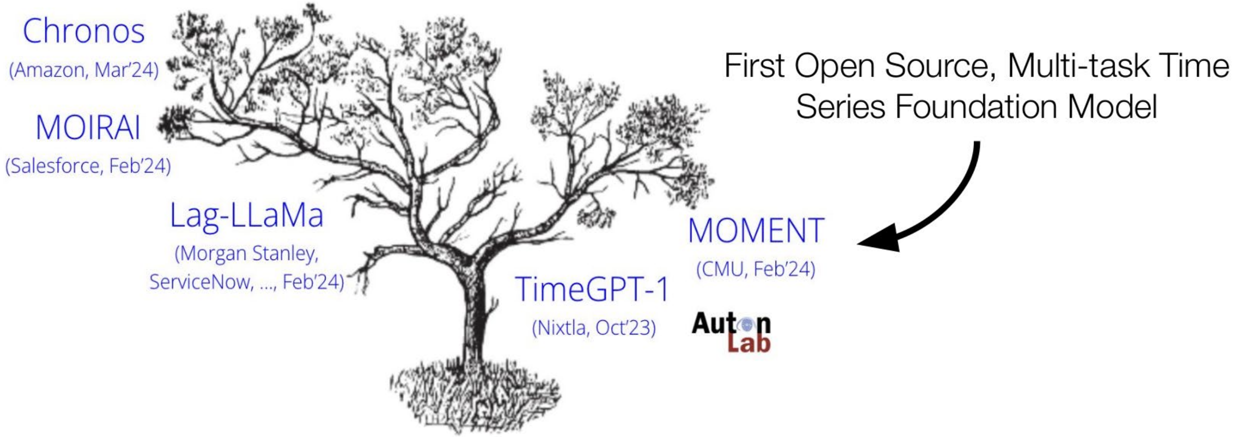
Our results should motivate the big data practitioners to no longer train models from scratch when classifying time series, but instead to fine-tune pre-trained models. Especially because CNNs, if designed properly, can be adapted across different time series datasets with varying length.

Other | Transfer Learning

- Mixed contrastive **transfer learning** for few-shot workload **prediction** in the cloud
- A prospective real-time transfer learning approach to estimate influenza hospitalizations with limited data

Other | Foundational models

Time Series Foundation Models



Most influential foundational models published, ordered from bottom top in chronological order and with the AutonLab branch to the right.

- Video: https://www.youtube.com/watch?v=D87XbbdB11M
- Slides: https://conference.mlinpl.org/docs/srw_talk_3.pdf

Miscellaneous

Auxiliar material

Further reading

- TimeGPT: https://docs.nixtla.io/docs/getting-started-about_timegpt
- Moirai: https://github.com/SalesforceAIResearch/uni2ts/tree/main
- Moment: https://github.com/moment-timeseries-foundation-model/moment/tree/fb620934ef6b67f878bc21b8640b22d117dbffa6
- Moving average (MA)/exponential smoothing (ETS) forecasting examples: https://people.brunel.ac.uk/~mastjjb/jeb/or/formore.html
- Holt-winters: https://ichi.pro/es/una-introduccion-completa-a-la-prediccion-de-holt-winters-213408615547110

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Further reading

- Research paper (Multi-Variate Time Series Forecasting on Variable Subsets): https://arxiv.org/abs/2206.12626.
- Prophet docs: https://h1ros.github.io/posts/prophet-101-a-time-series-forecasting-module/
- Prophet example: https://h1ros.github.io/posts/prophet-101-a-time-series-forecasting-module/
- Prophet example with multiple regressors: https://www.kaggle.com/code/pythonafroz/fb-prophet-with-multiple-regressors

Further reading

- Research paper TFT (Temporal Fusion Transformers for Interpretable Multi-horizon Time Series Forecasting): https://arxiv.org/pdf/1912.09363.
- Research paper (Short-Term Forecasting of Off-Street Parking Occupancy): https://www.researchgate.net/publication/354324012_Short-Term_Forecasting_of_Off-Street_Parking_Occupancy/download?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6Il9kaXJlY3QiLCJwYWdlIjoiX2RpcmVjdCJ9fQ.
- Research paper (Forecasting electric vehicle sales with arima and exponential smoothing method: The case of india): https://idp.springer.com/authorize/casa?redirect_uri=https://link.springer.com/article/10.1007/s40890-024-00216-y&casa_token=f1vkGCcAengAAAAA:rRQYouO_sfH1kf0t5DeJ6wf7es5hu0ROiKlzGjjELPp_66W5mraLoACghxdf-FIferWFVKgmykn8NHaLew

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Further reading

- Research paper (A Novel Theoretical Framework for Exponential Smoothing): https://arxiv.org/abs/2403.04345.
- Research paper (Analysis of the impact of policy measures on parking behavior using interpretable time series models): https://www.jtlu.org/index.php/jtlu/article/view/2455.
- Research paper (N-BEATS: Neural basis expansion analysis for interpretable time series forecasting): https://arxiv.org/abs/1905.10437.
- Example using transfer learning for time series forecasting: https://github.com/Nixtla/transfer-learning-time-series

Google Collab

03_forecasting.ipynb

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Summary

Summary of the lesson

Máster Deep Learning

What this we just learned?

- What is forecasting
- Classical & Deep Learning models for forecasting
- Models classification

Google Collab

03_forecasting_exercises.ipynb

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What is the next step?

- Supervised learning:
  - Classification
    - Can we automatically assign labels to different time series?
  - Clustering
    - Can we automatically assign labels to subsequences of the time series?
  - …

To be continued...

Questions? mi.santamaria@upm.es

Deep Learning para series temporales

Part II

Preprocessing and Analysis