

# The role of forecasting electricity demand in societal decarbonization

Hussain Kazmi, PhD

# Overview

- Who makes electricity demand forecasts and why?
- When (and at which aggregation levels) are the forecasts made?
- How to make electricity demand forecasts?
  - Inputs, outputs and function approximation
  - Model evaluations
  - Some lessons from recent competitions

# Why make forecasts?



Generation side



The electricity grid

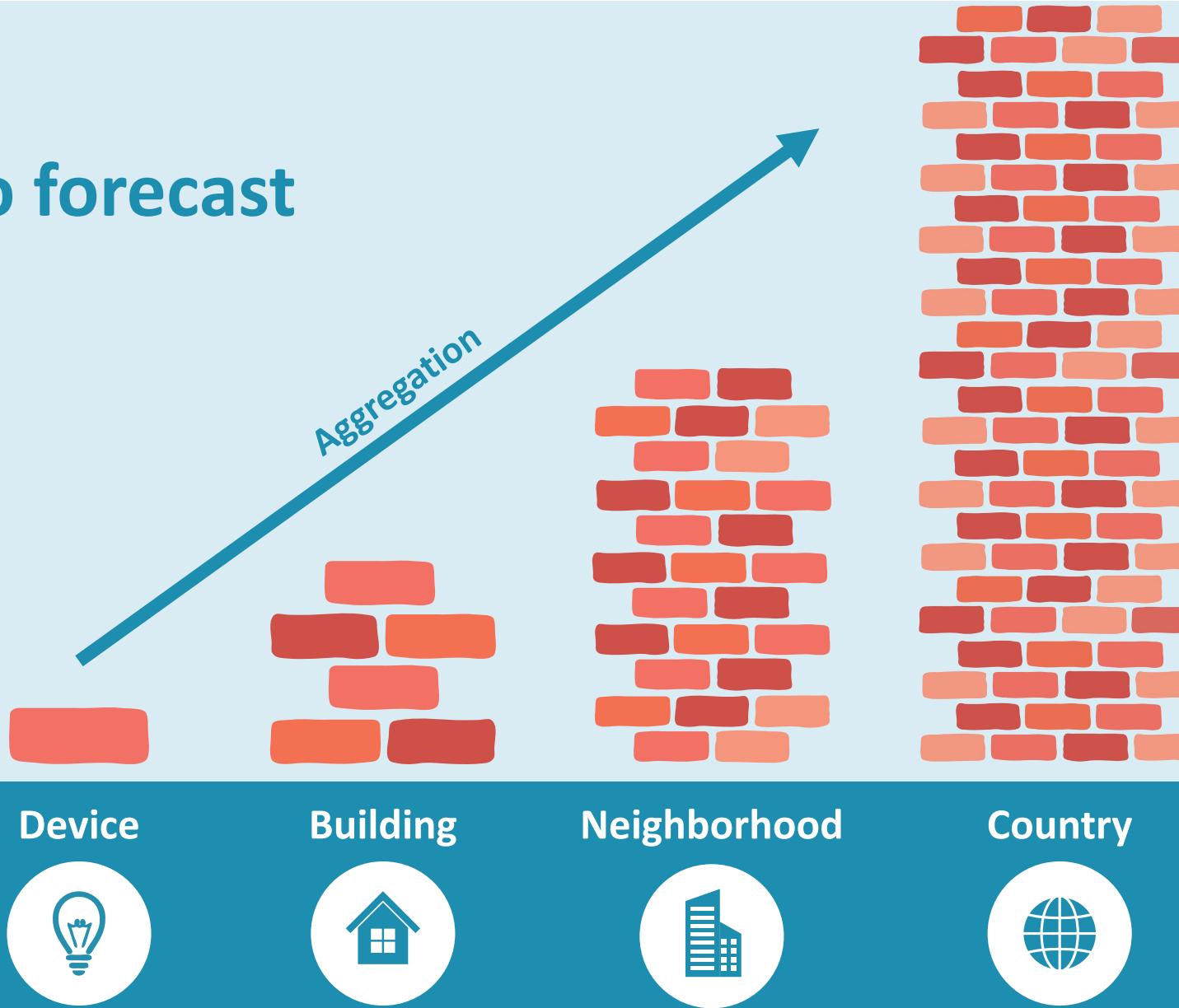


Demand side



# The energy transition

# Where to forecast





# Time resolution of datasets

# Forecasting grid load

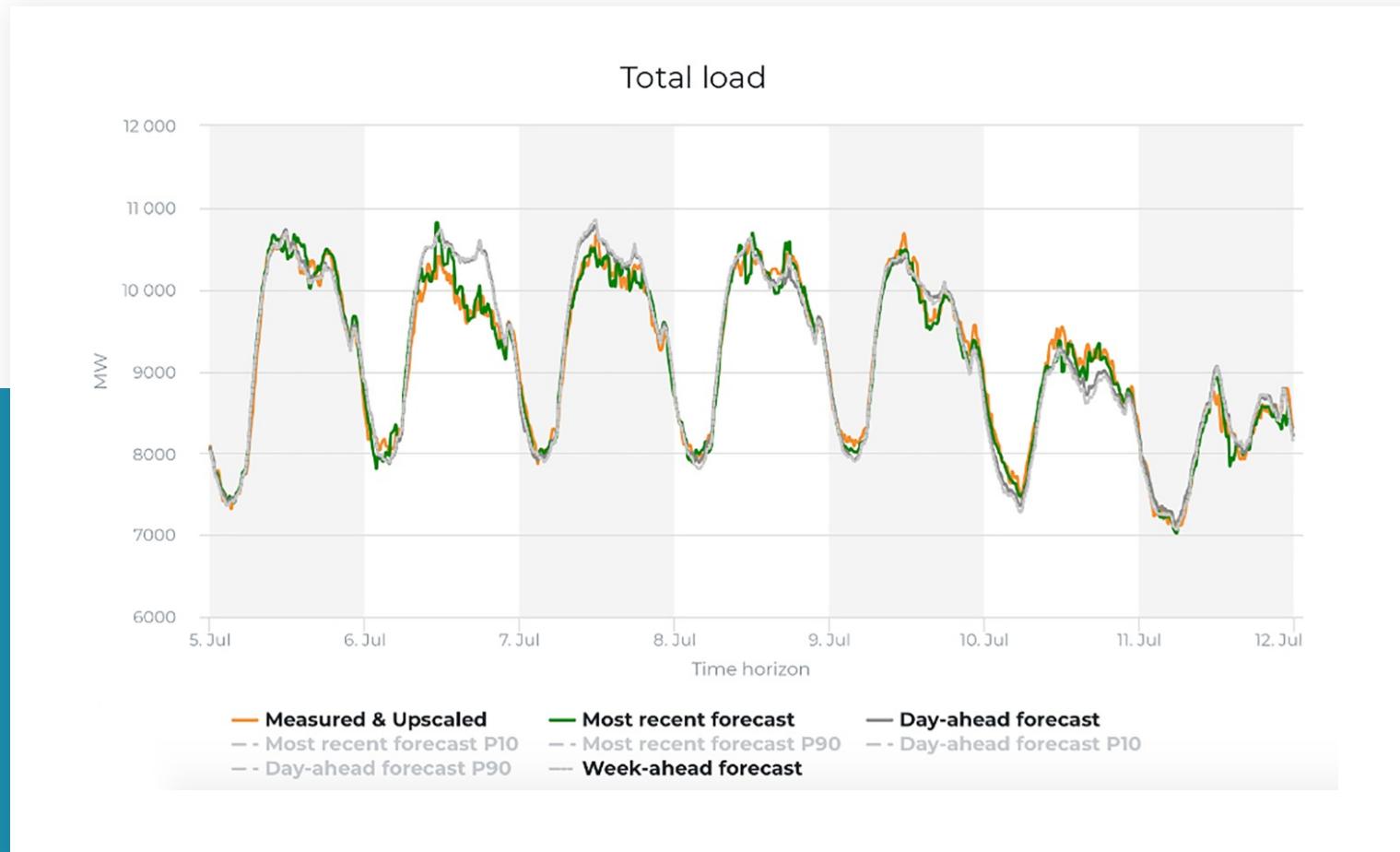
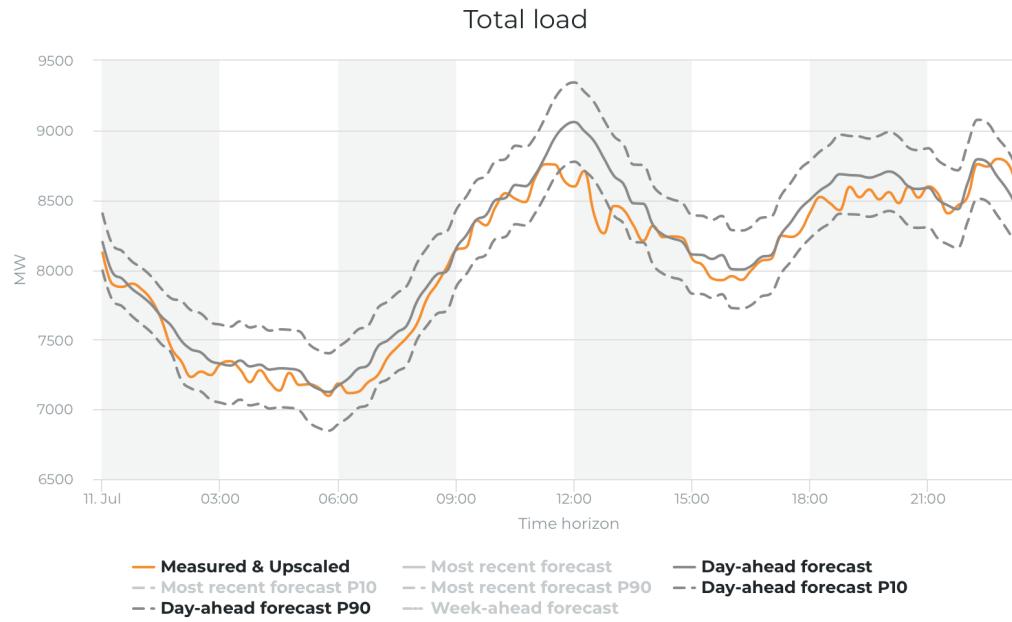


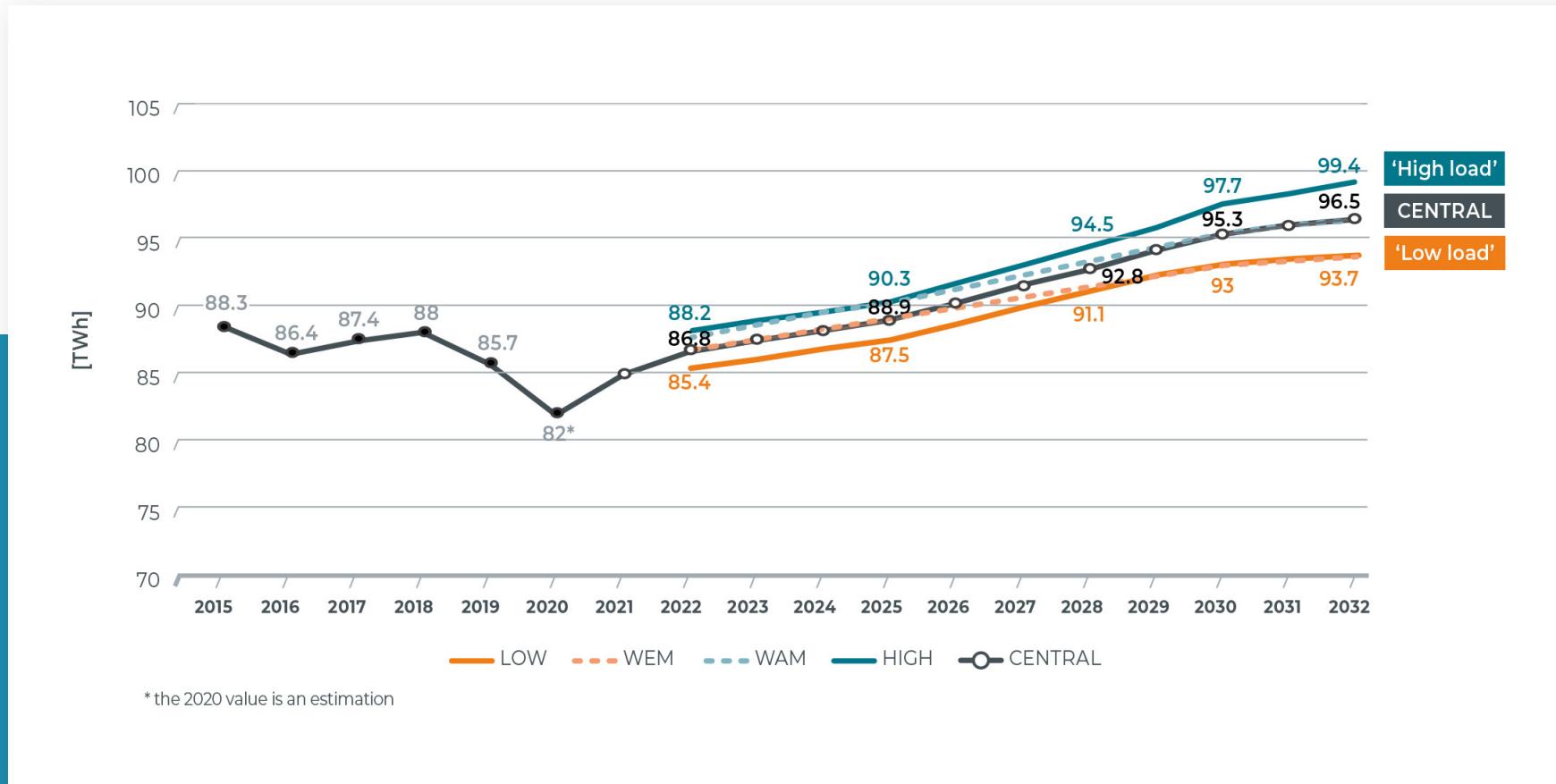
Image source: Elia

# Forecasting grid load

Image source: Elia



# Forecasting energy load

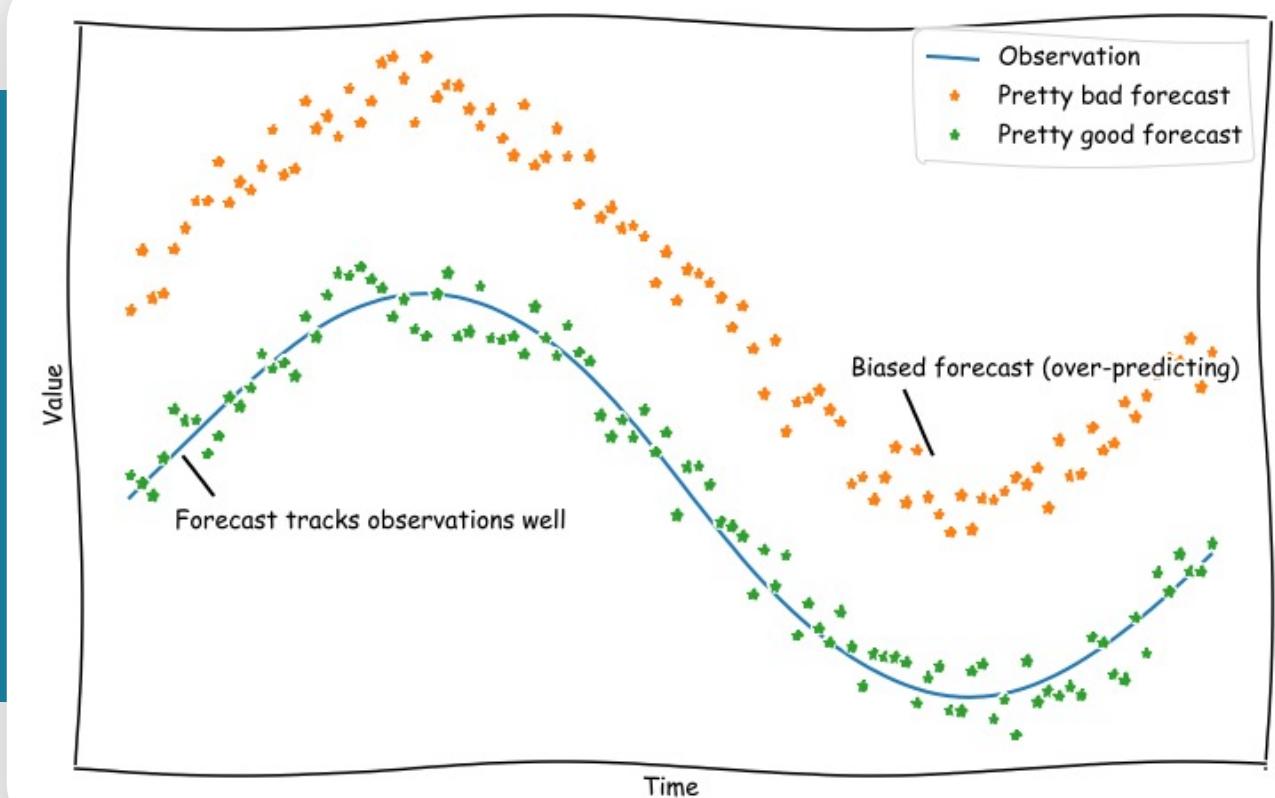


Adapted from Elia Report 2021

# What makes a good forecast?

## 1. Error metric values

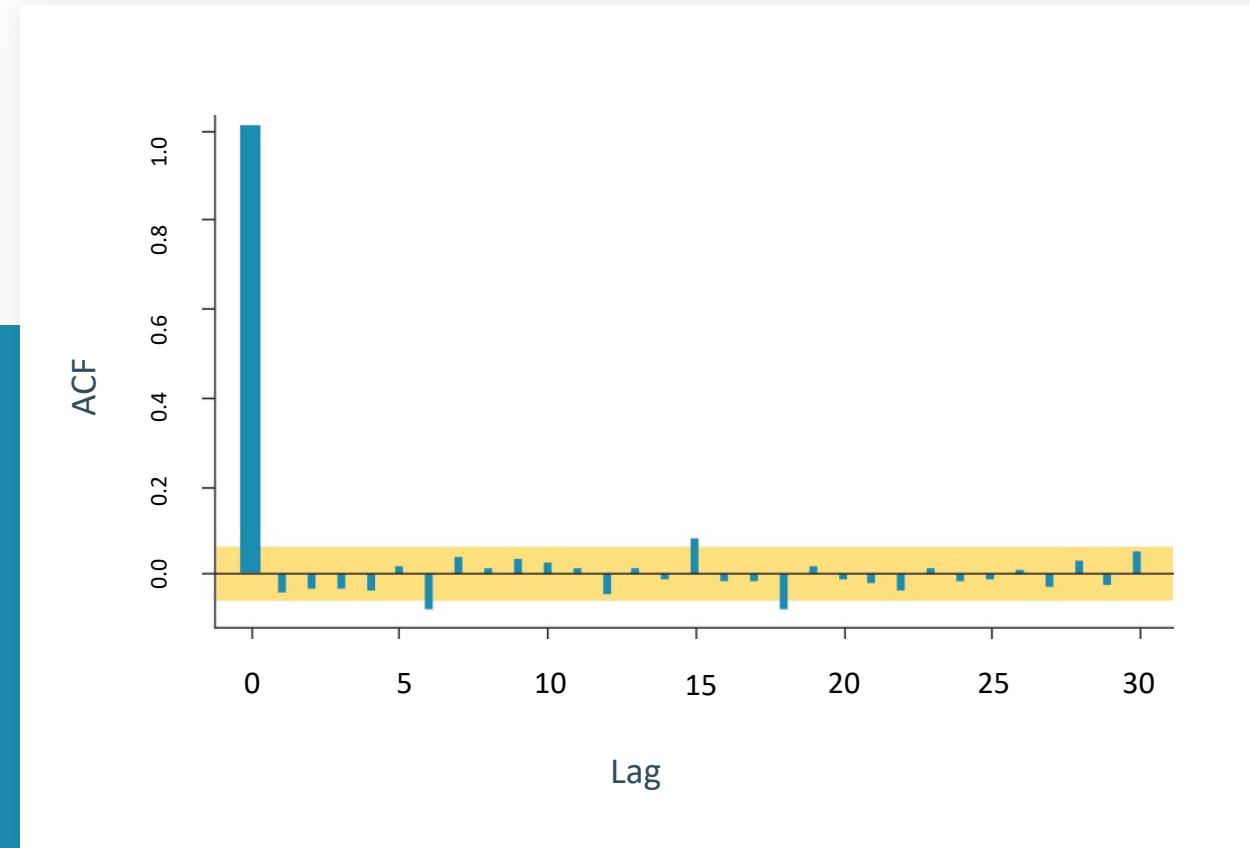
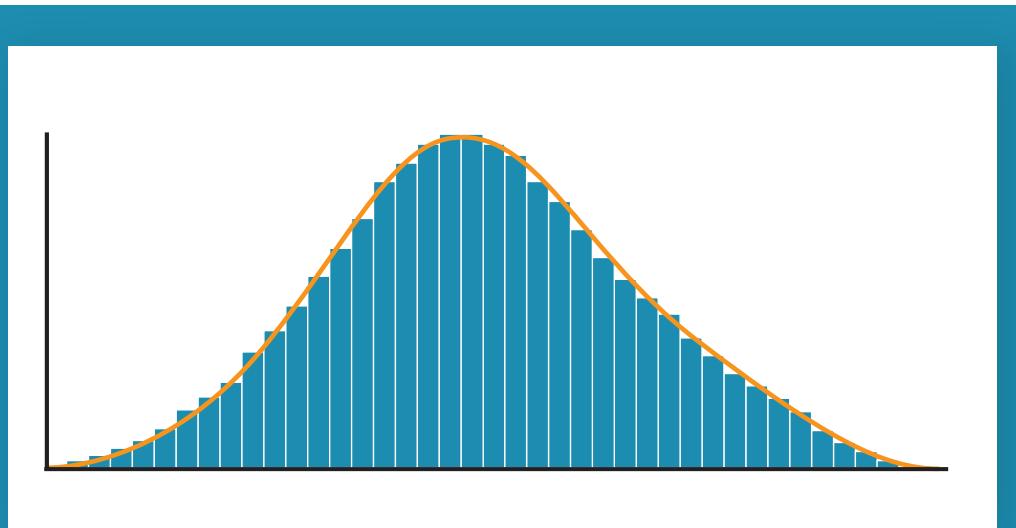
- a. Mean absolute error (MAE)
- b. Mean absolute percentage error (MAPE)
- c. Relative metrics (relative MAE (rMAE), Mean absolute scaled error (MASE))
- d. Other measures ( $R^2$  score, AIC / BIC, etc.)



# What makes a good forecast?

## 2. Forecast error distribution

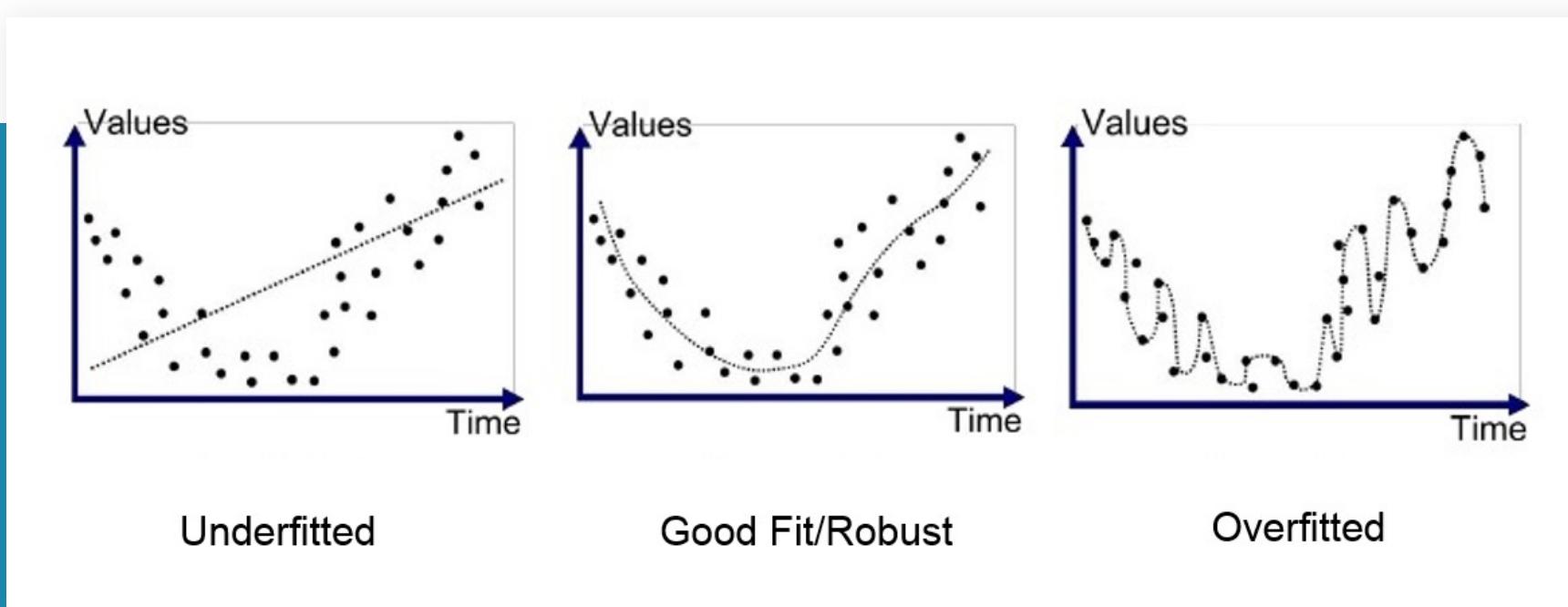
- a. Normally distributed residuals
- b. Bias-variance trade-off
- c. No autocorrelation



# What makes a good forecast?

## 3. Generalization

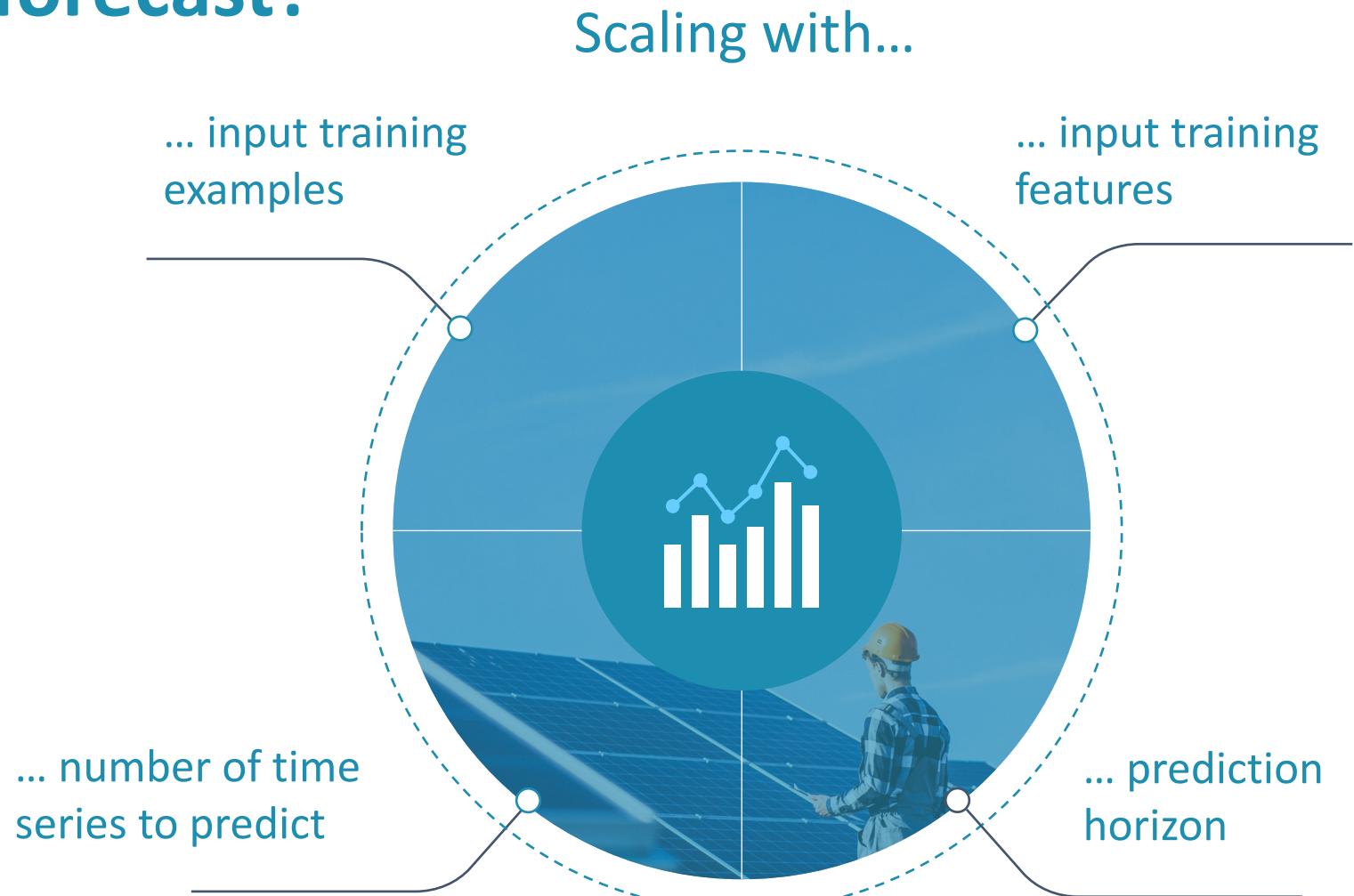
- a. Training, validation and test error
- b. Comparison with simple baselines

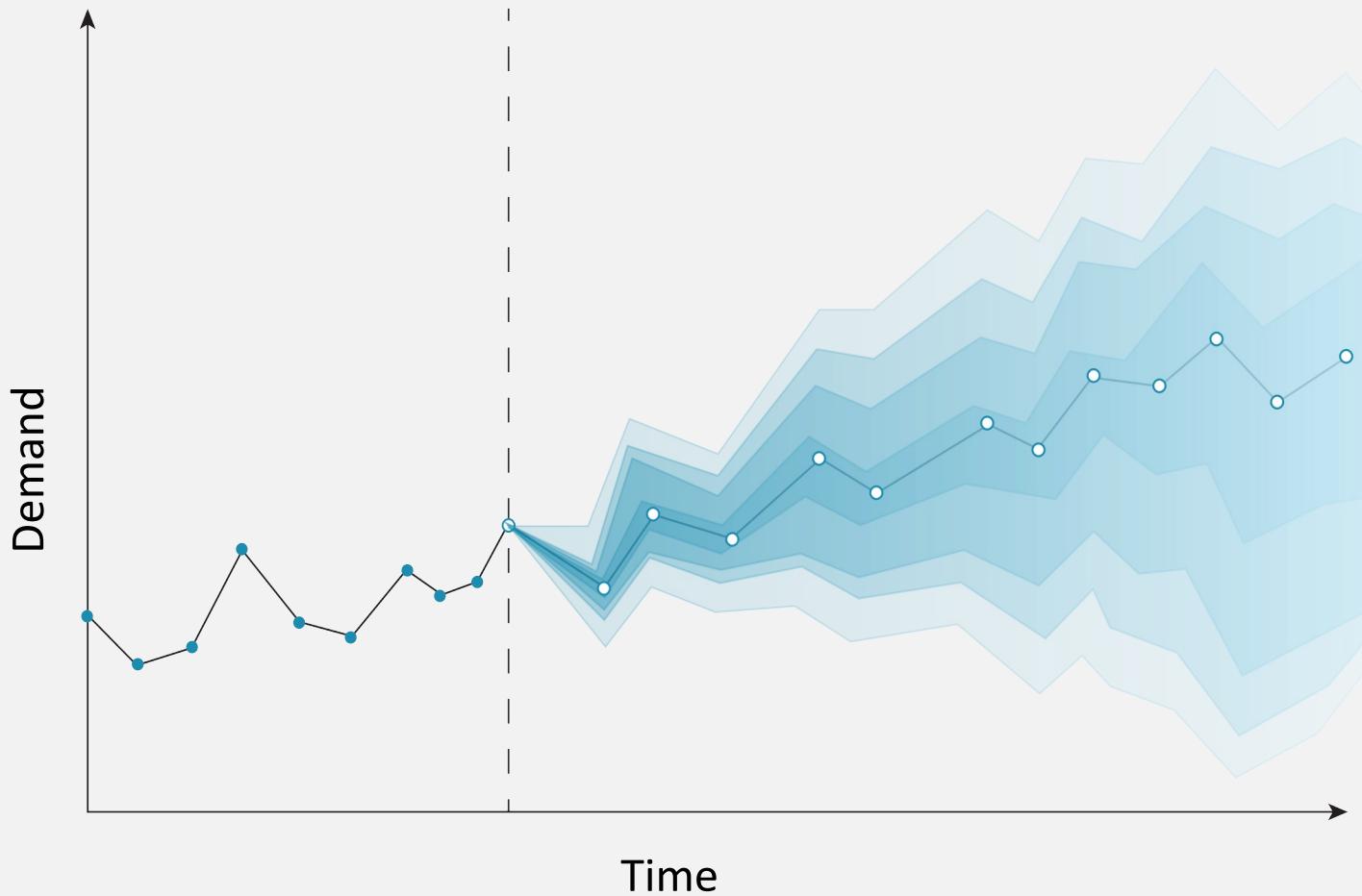


# What makes a good forecast?

## 4. Scalability and computational complexity

- a. Has low training / inference times depending on context
- b. Scales well with increasing amount of data and/or features





What makes a  
good forecast?

5. Uncertainty  
estimates?

# Establishing a baseline





# Defining a persistence baseline model

# Defining an auto-ml baseline model



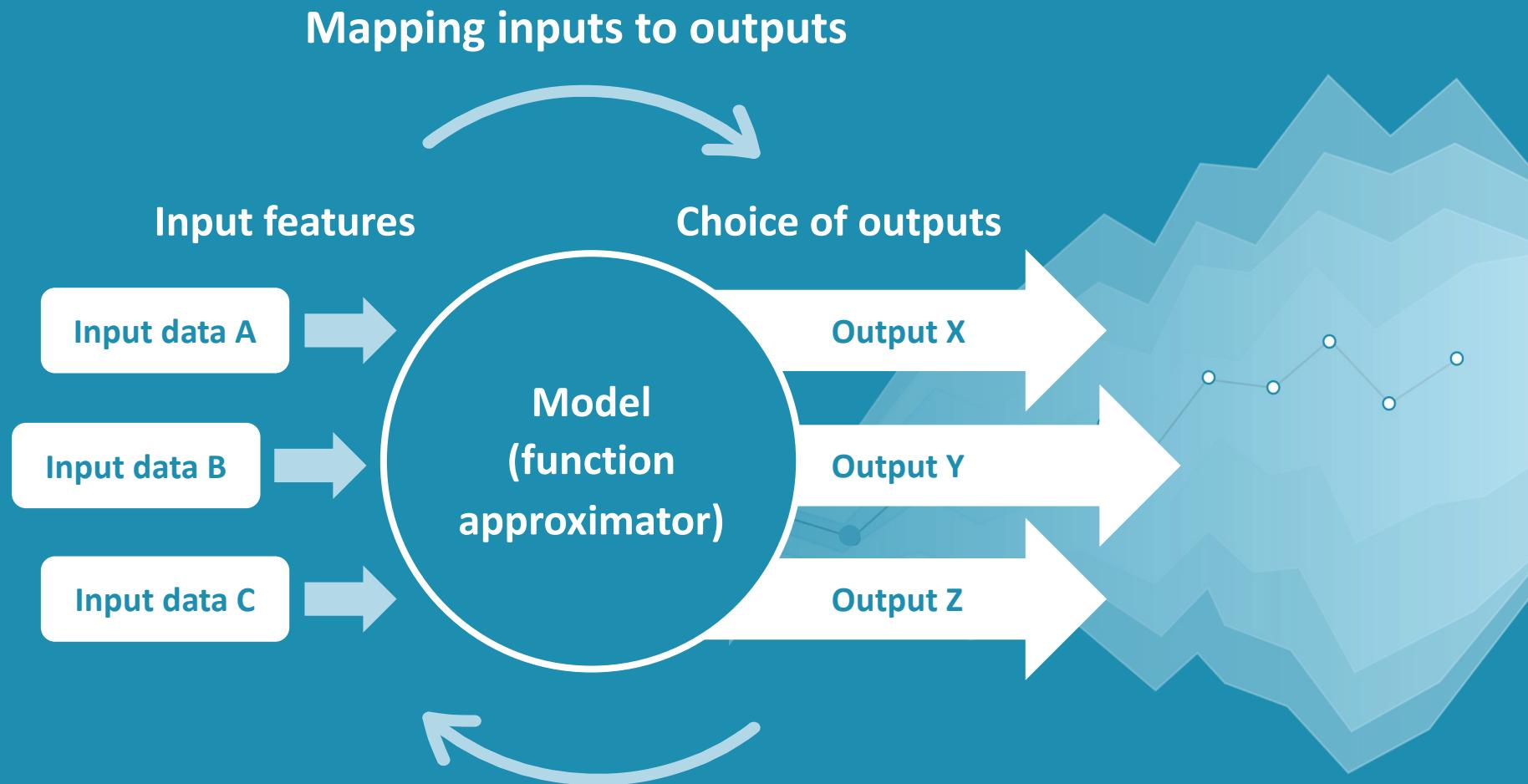


# How to build a forecast model

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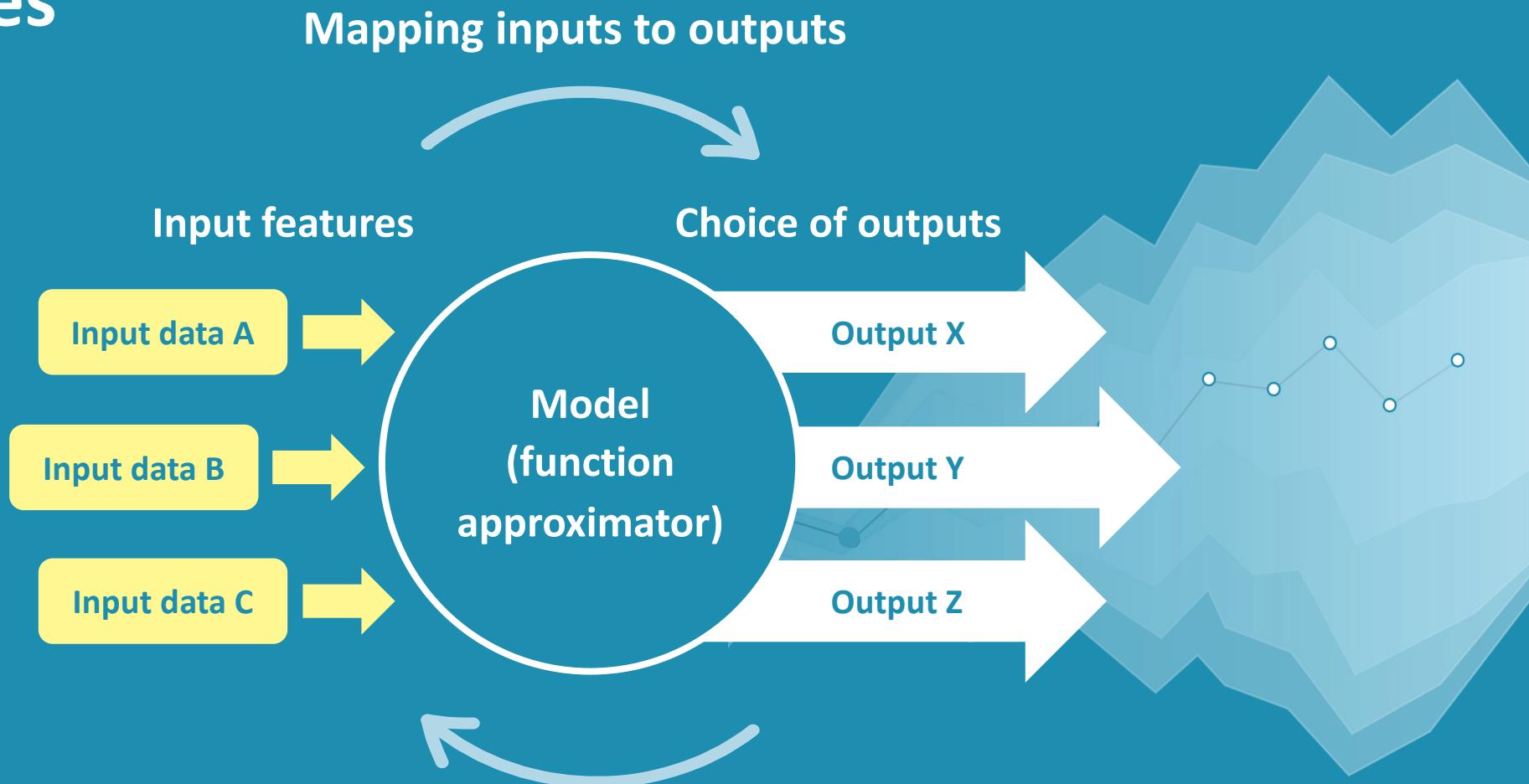
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# Building a forecast model



# 1. Input features for a forecast model

## a. Feature selection



# Building a forecast model

1. Input features for a forecast model
- b. Sliding and expanding windows

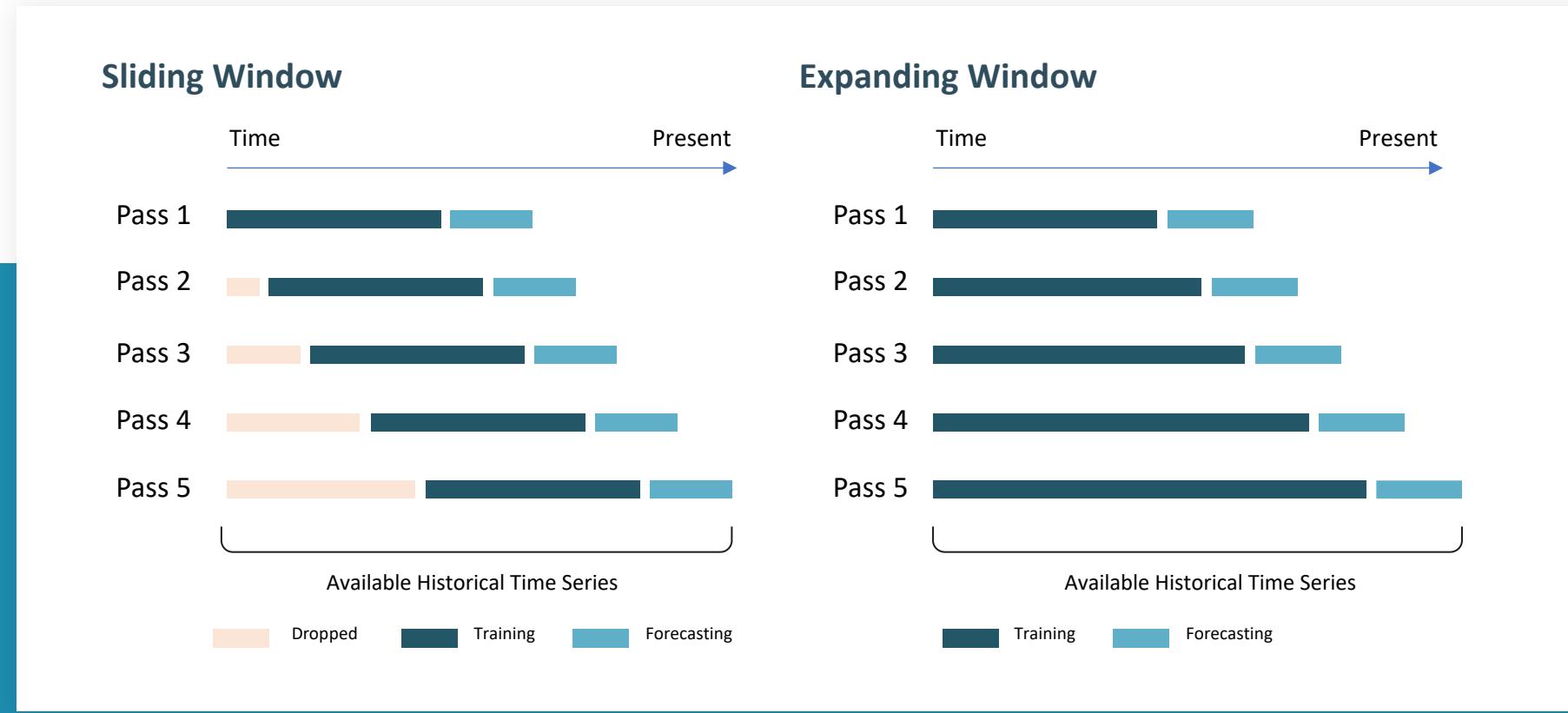


Image adapted from Uber



# Building a forecast model

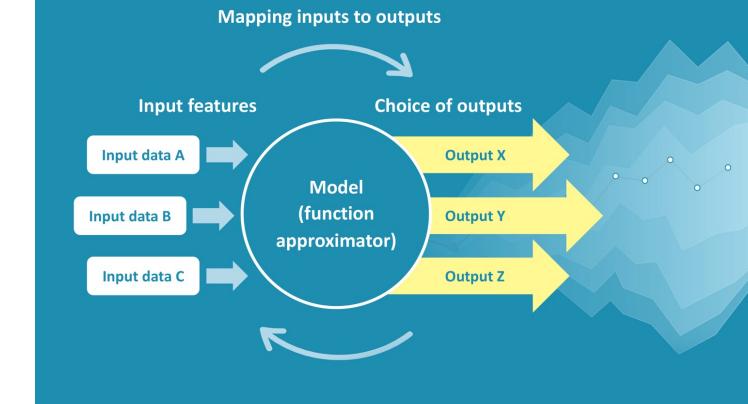
1. Input features for a forecast model
- c. Feature transformations

# Building a forecast model

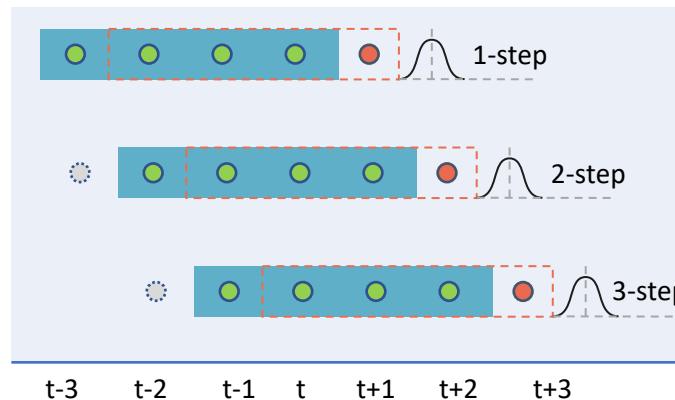
## 2. Choice of outputs

- a. Point and interval forecasts
- b. Recursive, direct & multi-step forecasts

### Building a forecast model



(a) Recursive MS



(b) Direct MS

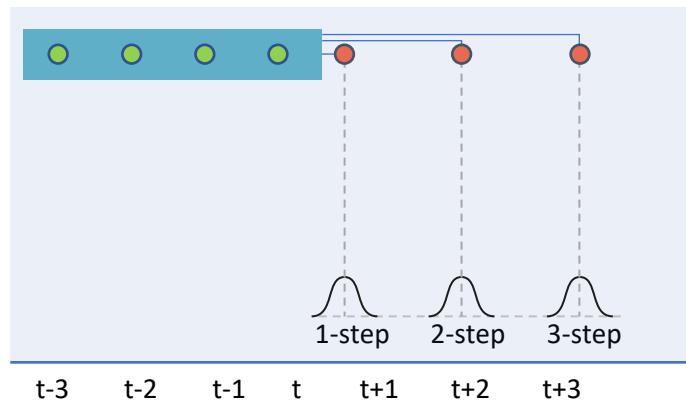
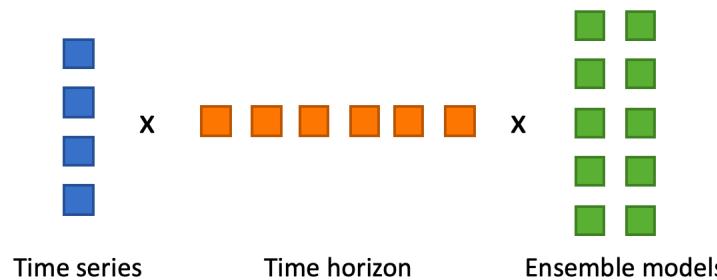


Image adapted from: IEEE

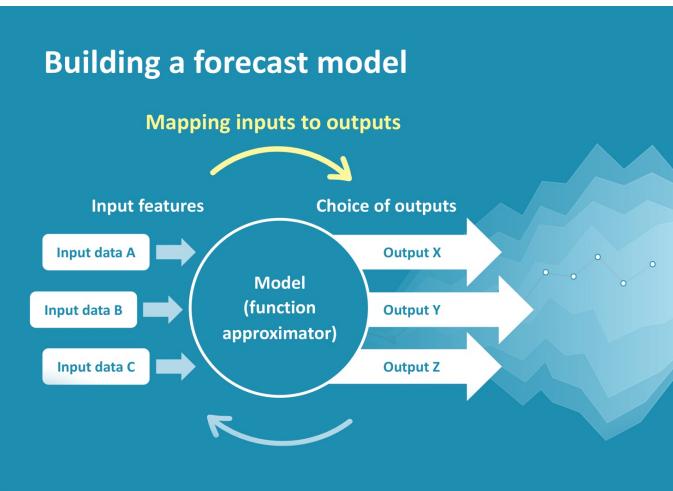
# Building a forecast model

## 3. Mapping inputs to outputs

### a. Choice of function approximator



| Model type                               | Number of models                              |
|--|---|
| Recursive, global model (no ensembling)  | $1 \times 1 \times 1 = 1$                     |
| Recursive, local model (no ensembling)   | $4 \times 1 \times 1 = 4$                     |
| Direct, global model (no ensembling)     | $1 \times 6 \times 1 = 6$                     |
| <b>Recursive, global, ensemble model</b> | <b><math>1 \times 1 \times 10 = 10</math></b> |
| Direct, local model (no ensembling)      | $4 \times 6 \times 1 = 24$                    |
| Recursive, local, ensemble model         | $4 \times 1 \times 10 = 40$                   |
| Direct, global, ensemble model           | $1 \times 6 \times 10 = 60$                   |
| Direct, local, ensemble model            | $4 \times 6 \times 10 = 240$                  |



# Building a forecast model

3. Mapping inputs to outputs
- b. Generalization via regularization

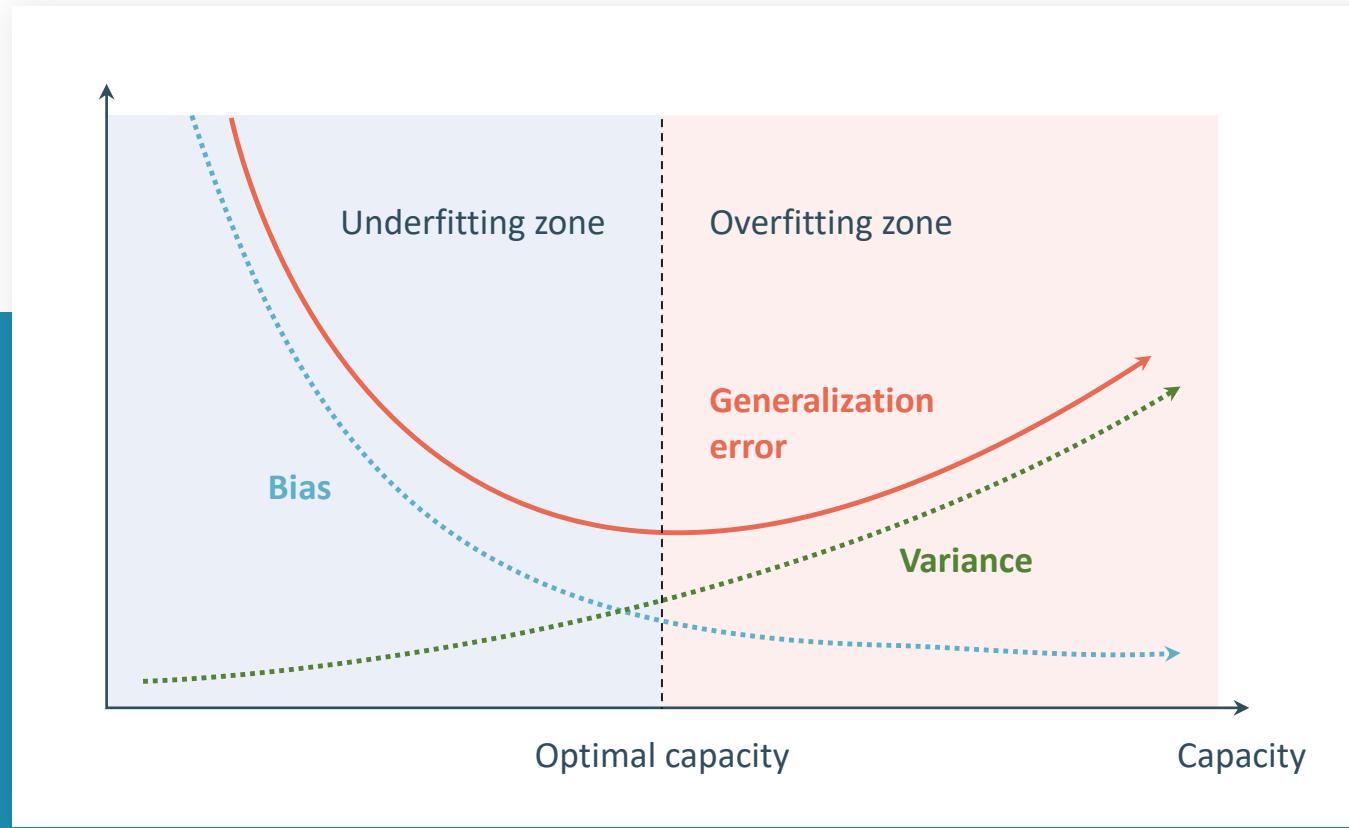


Image adapted  
from: Deepai



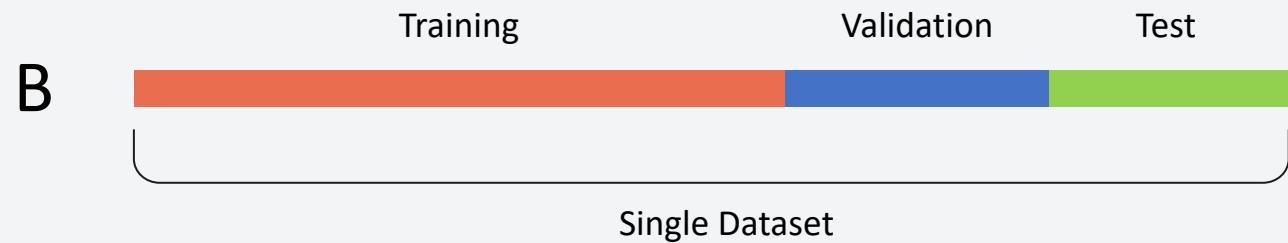
# Model comparisons

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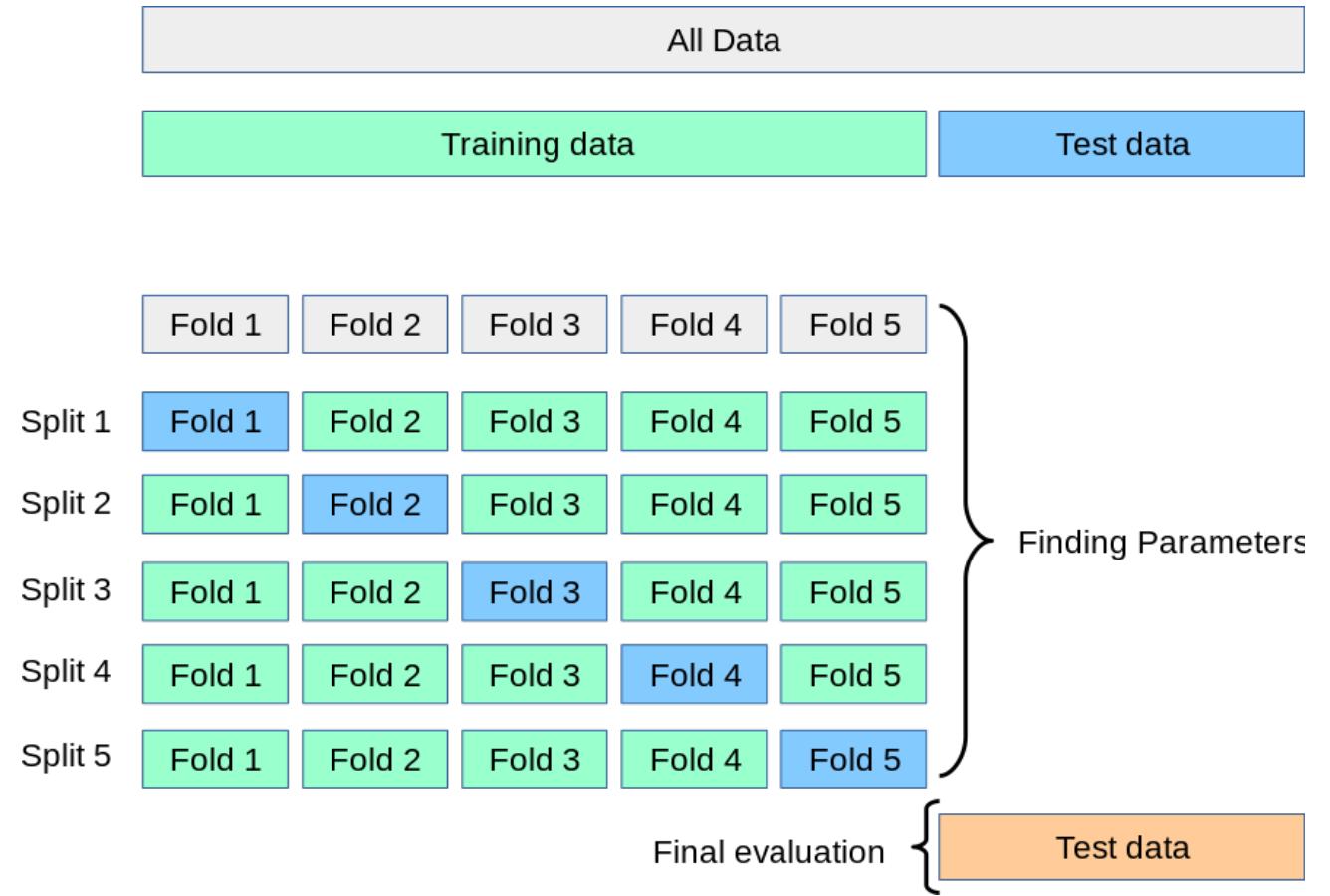
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# Data splits

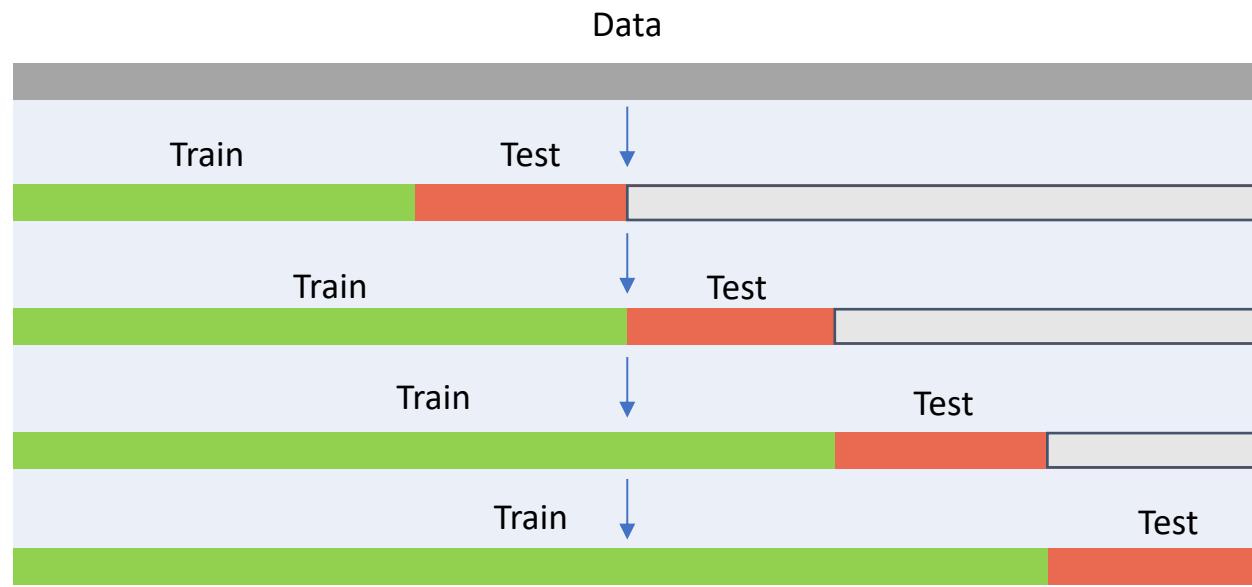


# From splitting data to cross-validation

Image source: Scikit-learn



# Cross-validation in time series





# Some lessons from recent competitions

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# The Great energy predictor III challenge



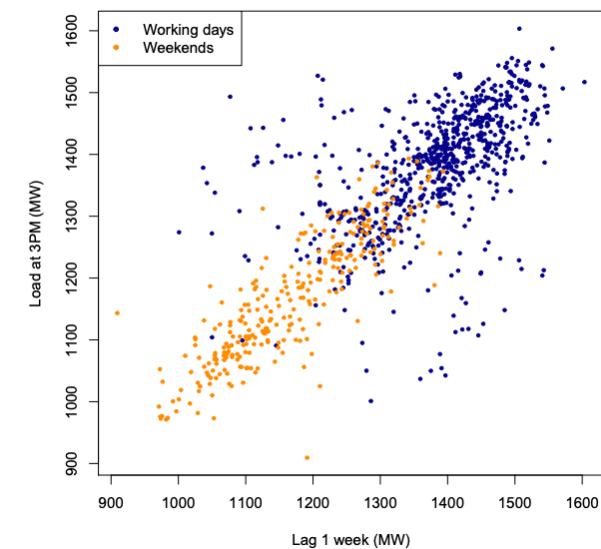
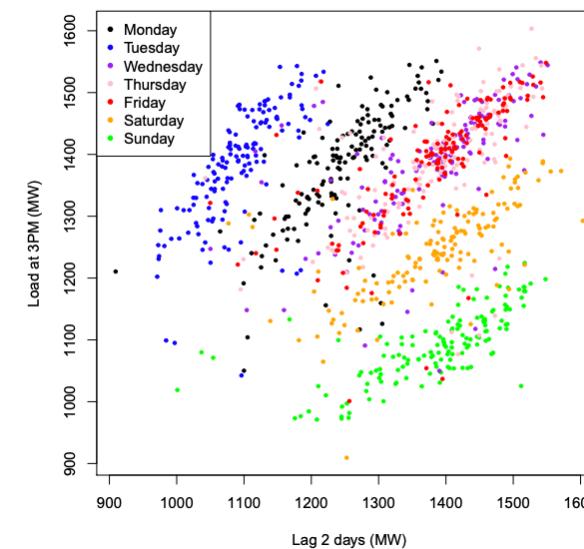
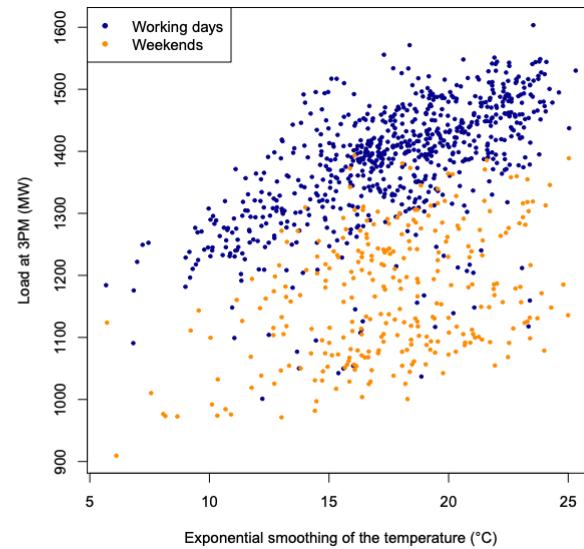
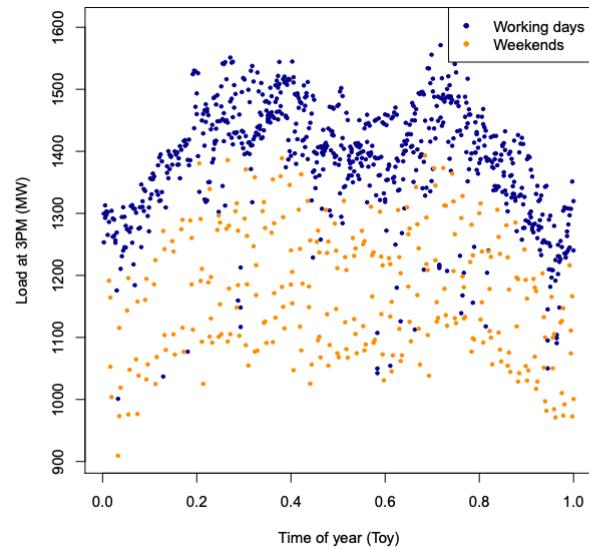
- Preprocessing and data transformations are a critical step
- Gradient boosted models are extremely effective, while out-of-the-box deep learning models tend to underperform

# The post-Covid-19 electricity forecasting challenge



- Ensembles increase forecasting accuracy(although they increase complexity)
- Modelling holidays (and special events) well is extremely important
- More generally, understanding concept or data drift is critical

# The post-Covid-19 electricity forecasting challenge





Onwards to the demo