Good morning ☺️
Notebooks and slides are in:

https://github.com/AlineQuadros/teaching_data_science

Packages we'll need:

scipy
statsmodels
prophet
pmdarima
Plotly

TIME SERIES
FOR
DATA SCIENCE

DR. ALINE QUADROS
DATA SCIENCE RETREAT

Contents

- What are time series?
- What kind of time series properties are there? *(buzz words)*
  - Trend, seasonality
  - Stationarity
  - Autocorrelation
  - Baselines
    - average, naïve, smoothing moving average
- ‘Traditional’ time series analysis:
  - Exponential smoothing (a.k.a ETS models)
  - Autoregressive models (a.k.a. AR models): ARIMA family (ARMA, ARIMA, SARIMA, SARIMAX)
- Other algorithms:
  - Prophet

Resources

- Free excellent book
  - Hyndman, R.J., & Athanasopoulos, G. (2018) *Forecasting: principles and practice*, 2nd edition, OTexts: Melbourne, Australia. www.OTexts.com/fpp2
  - *Most of the plots used in this presentation come from this book*

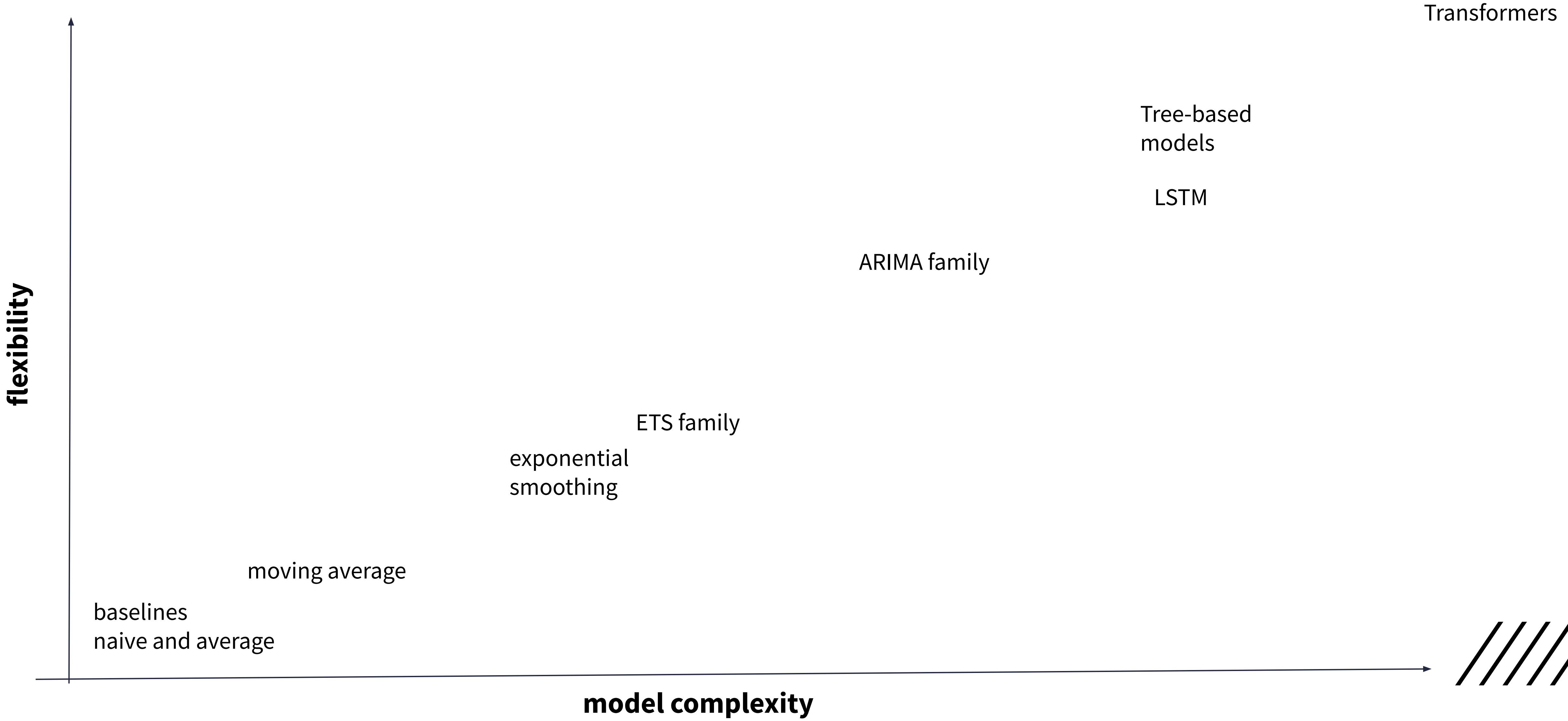
- Bastian Kubsch's repository: https://github.com/bkubsch/time_series
- Online class = https://online.stat.psu.edu/stat510/lesson/1
- Exercises: https://github.com/AlineQuadros/Timeseries_predictive_modelling

Classical
TIME SERIES
Analysis

What can we do with classical methods?

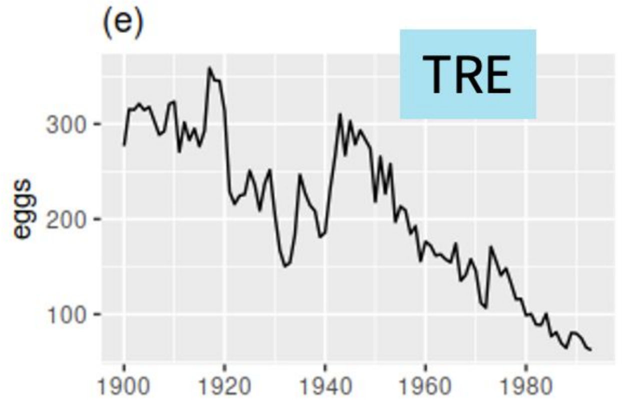
1. The task is to predict ONE time step ahead
2. Only deal with UNIVARIATE data
3. Cannot deal with nested seasonality
    a. We need to build different models for different seasonalities
4. Initially, no support for external features (but later adaptations in SARIMAX and Prophet claim to be able to handle it)
5. The interval between consecutive points is always 1
6. No handling of missing data
    a. You have to fill missing values with some interpolation of smoothing technique (like a moving average)

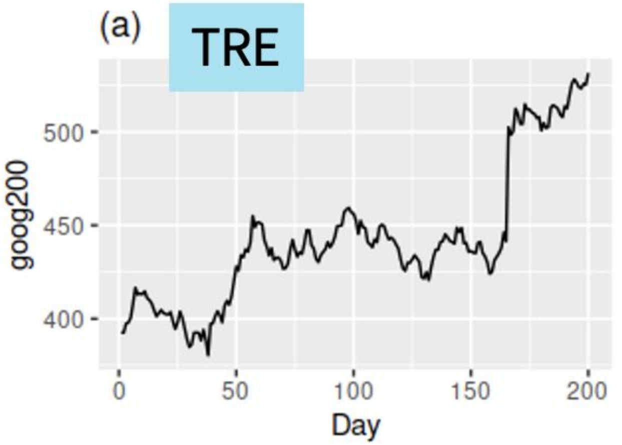
Overview of complexity/flexibility

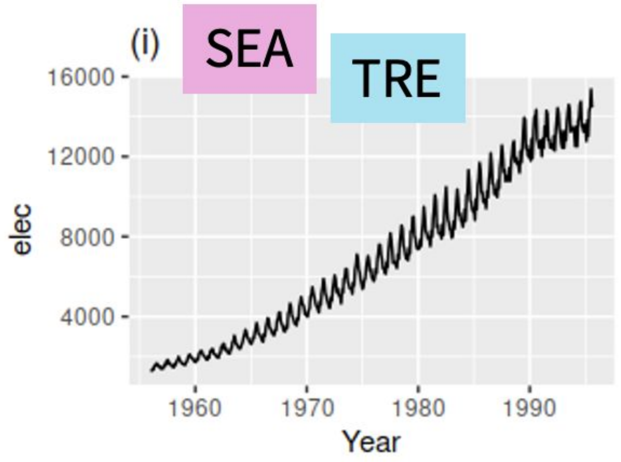


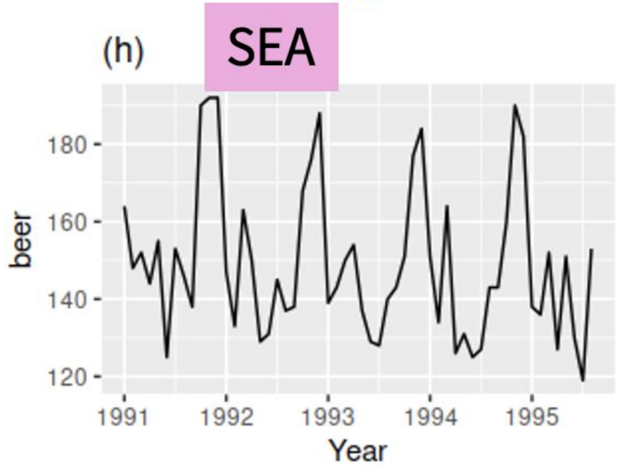
TIME SERIES PROPERTIES

Trend and seasonality







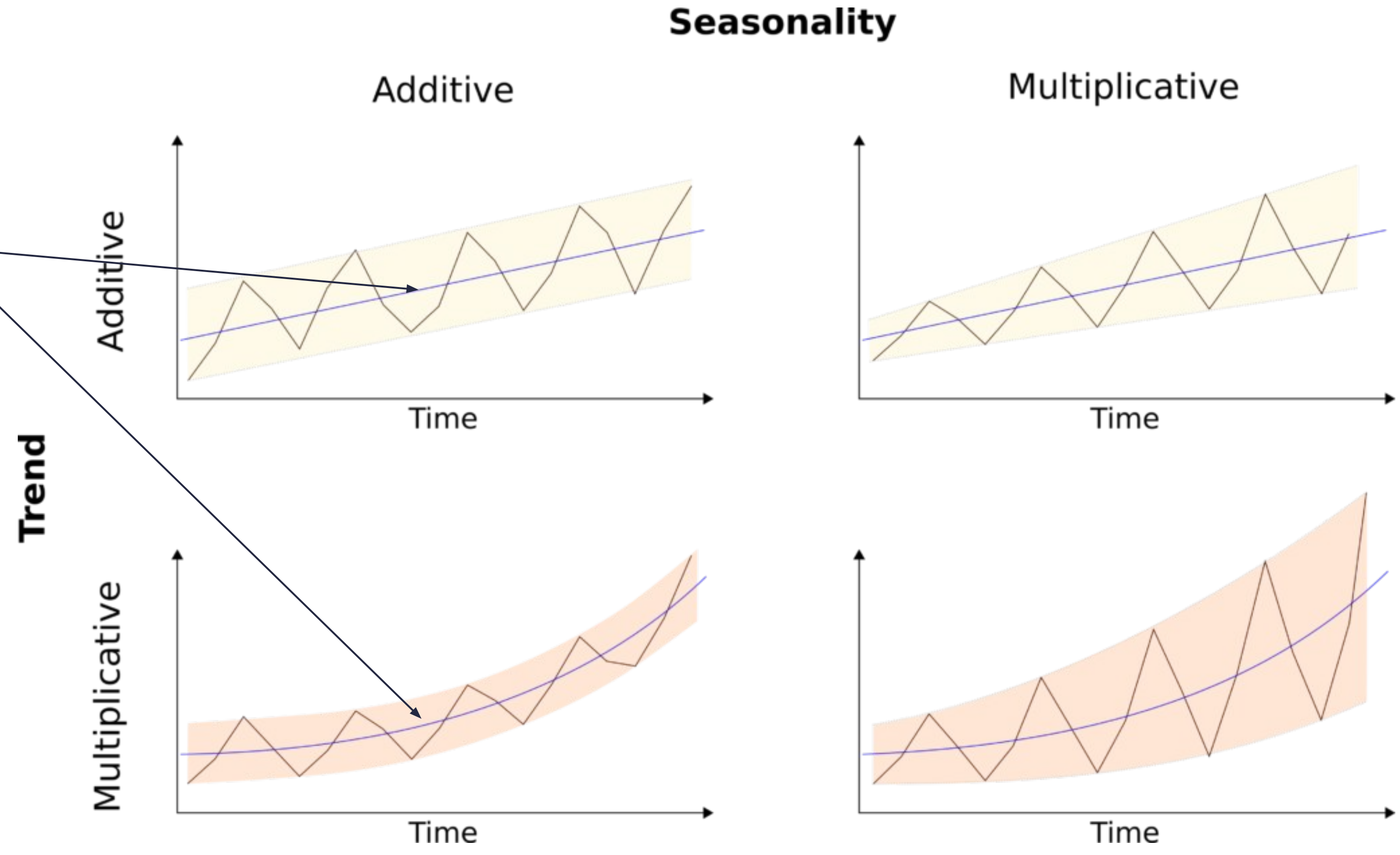


Trend: average changes over time

Seasonality: variance changes over time

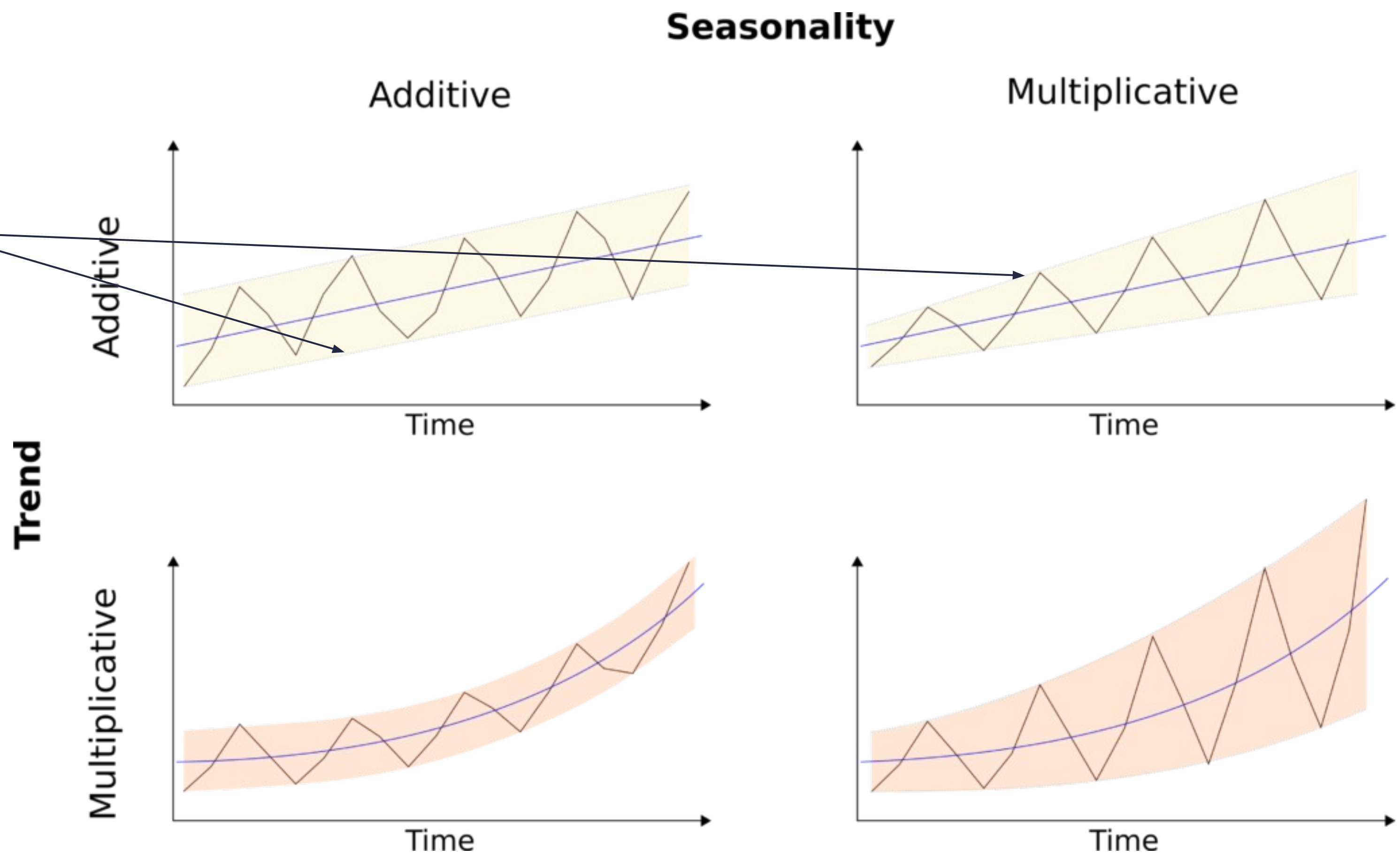
Trend and seasonality can be additive or multiplicative

Trend: Look at the blue line and how it changes over time

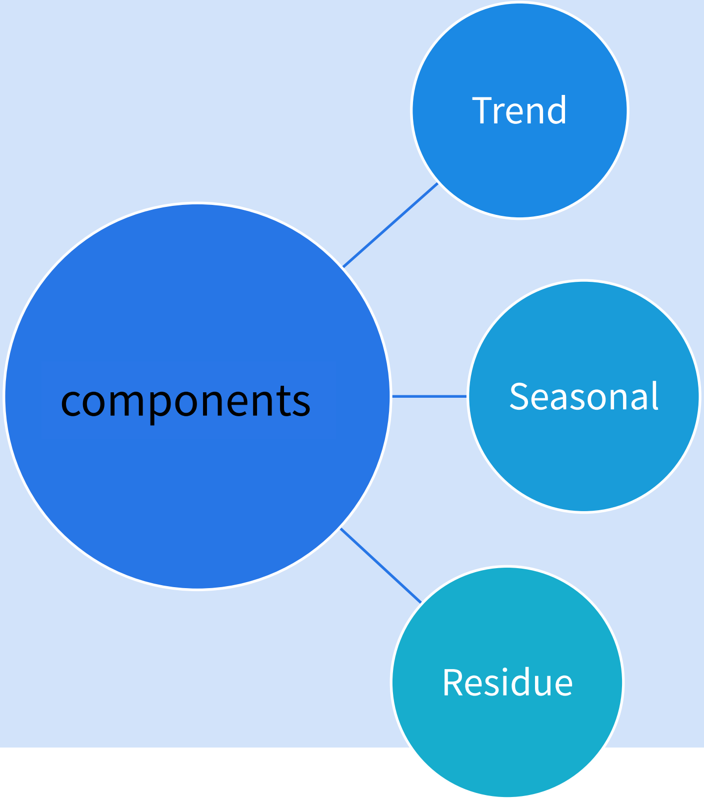


Trend and seasonality can be additive or multiplicative

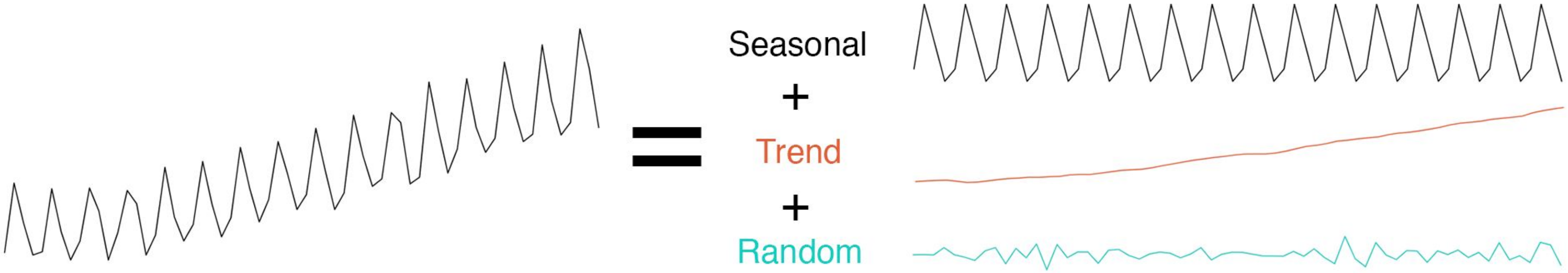
Seasonality: Look at the filled areas and how their shape changes over time



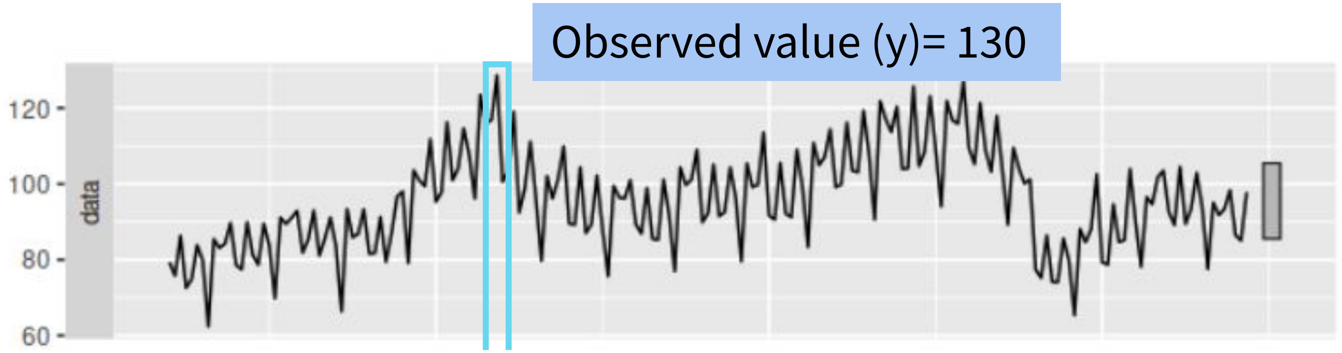
Time series decomposition



Additive = the components add to each other
Multiplicative= the effects are multiplied



Time series decomposition



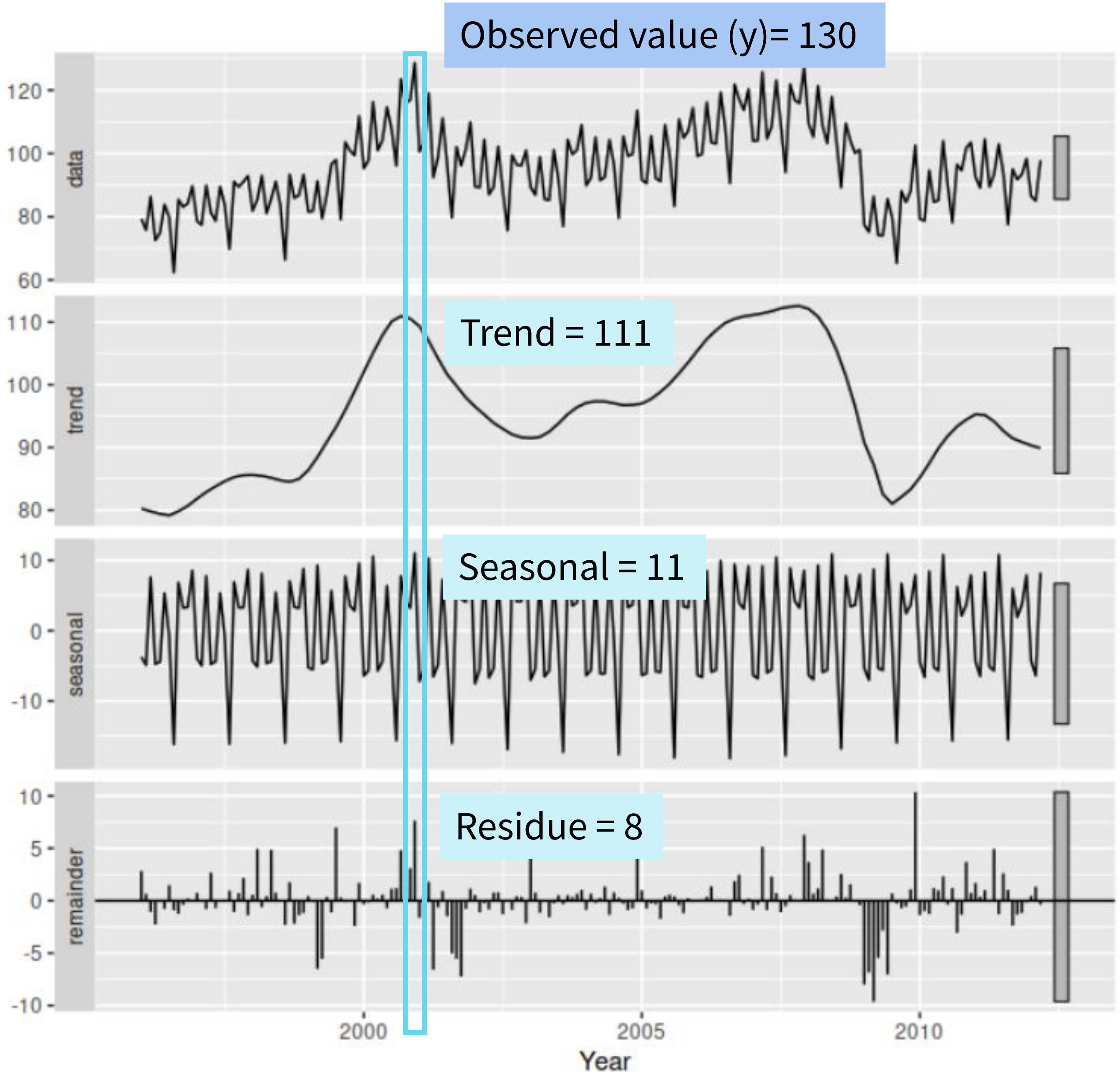
Time series decomposition

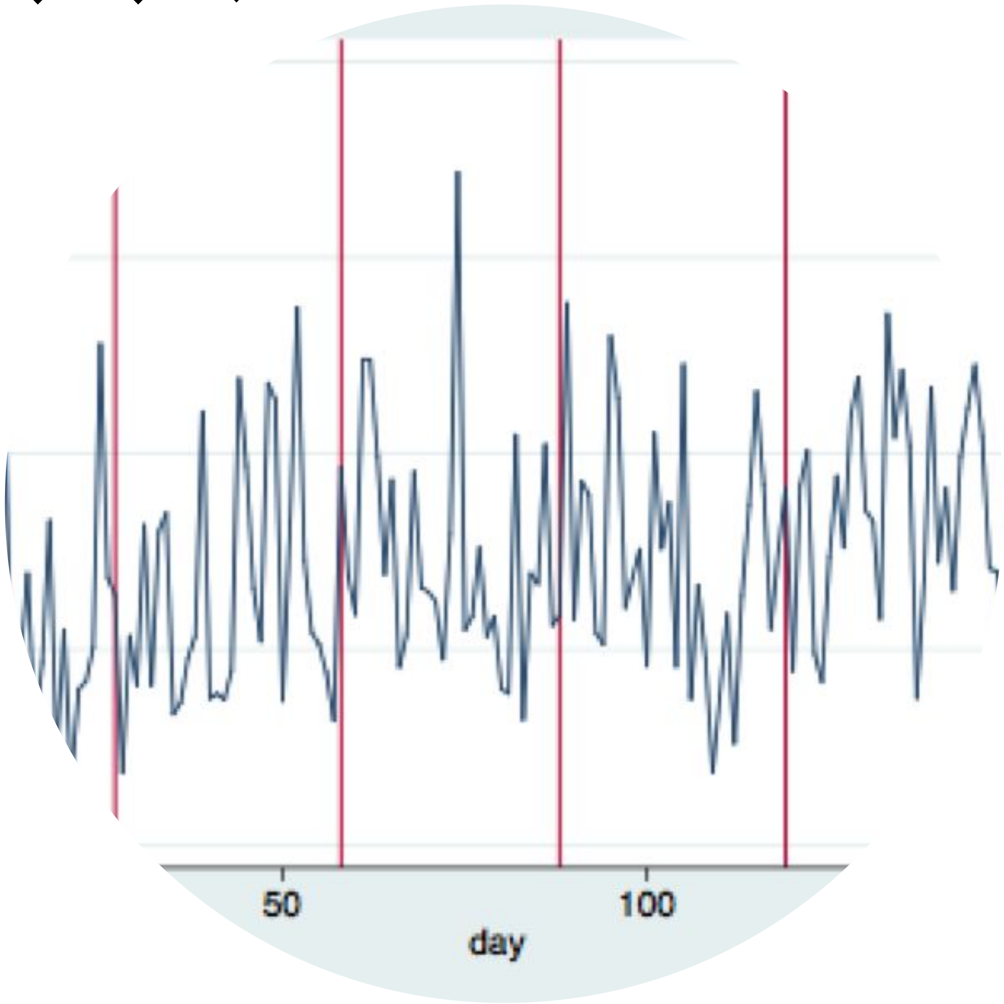
Example of additive decomposition:

Look at the value at time 2001:

The observed value (y=130) is decomposed as:

130 = 111 (trend) + 11 (seasonal) + 8 (residue)

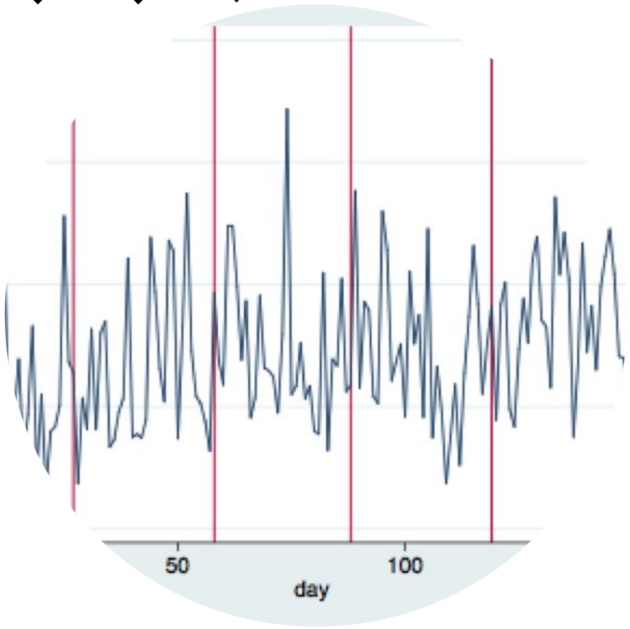




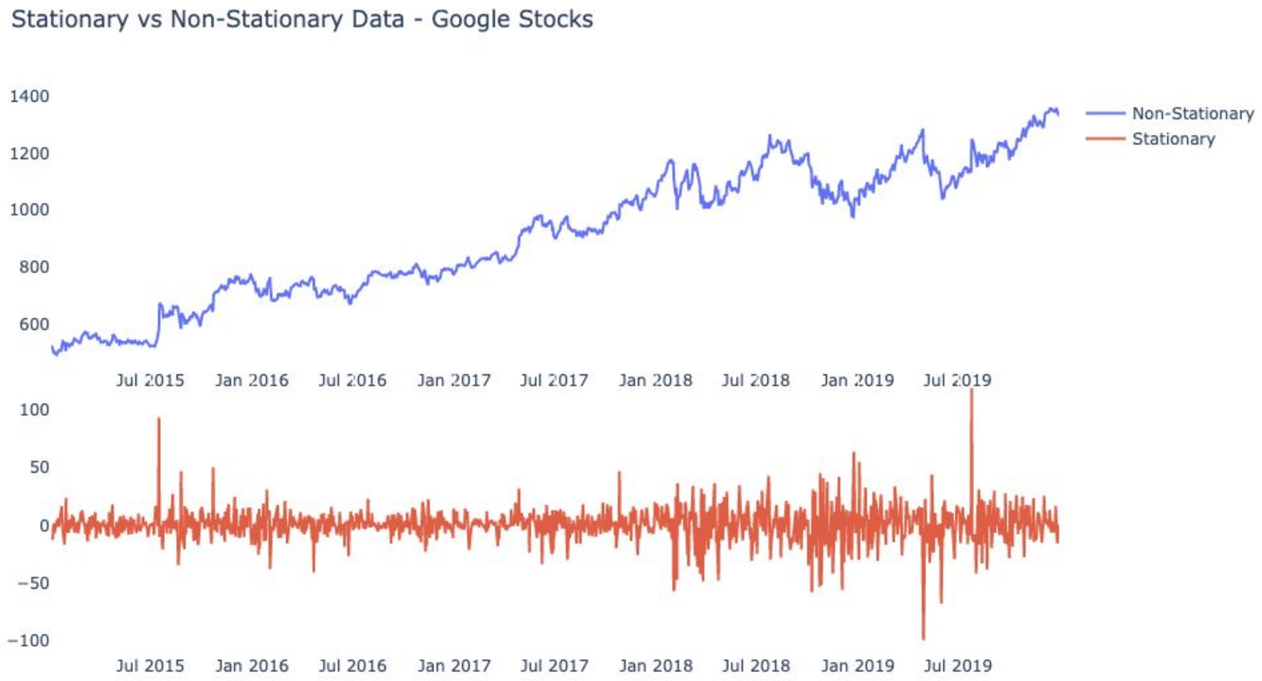
Stationarity

- Stationary data is data without trends or seasonality
- In stationary data, the mean and variance of the time series don't change over time
- **Meaning, even though the data has a time axis, its values do not depend on the time component itself**
- **How to detect non-stationarity?**
  - **Plots, ACF plots**
  - **Hypothesis tests (AD Fuller test)**

Differencing/Integrating



- How to deal with non-stationary data?
  Use the differences between observations



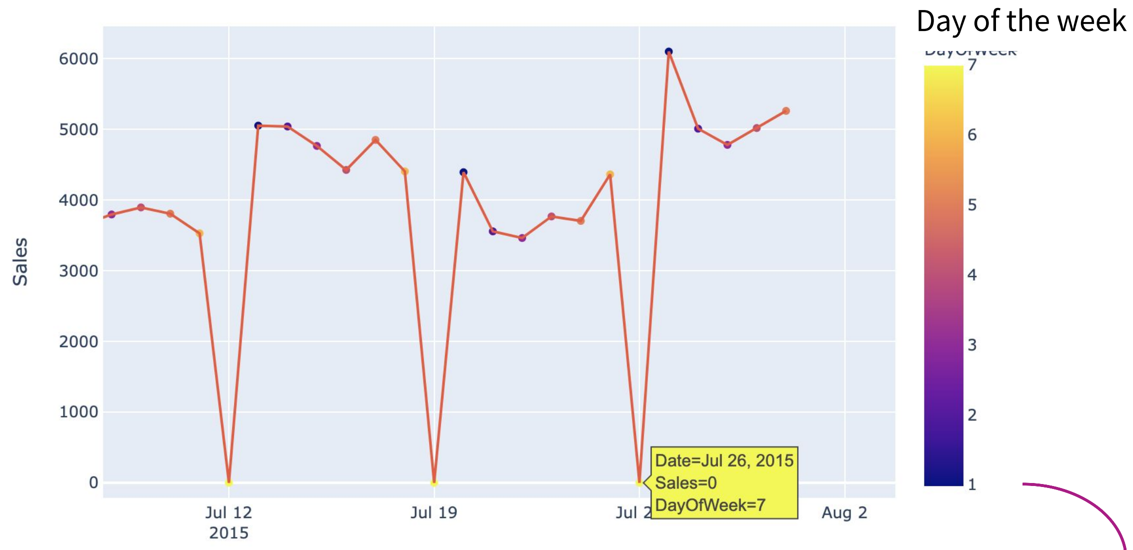
Autocorrelation

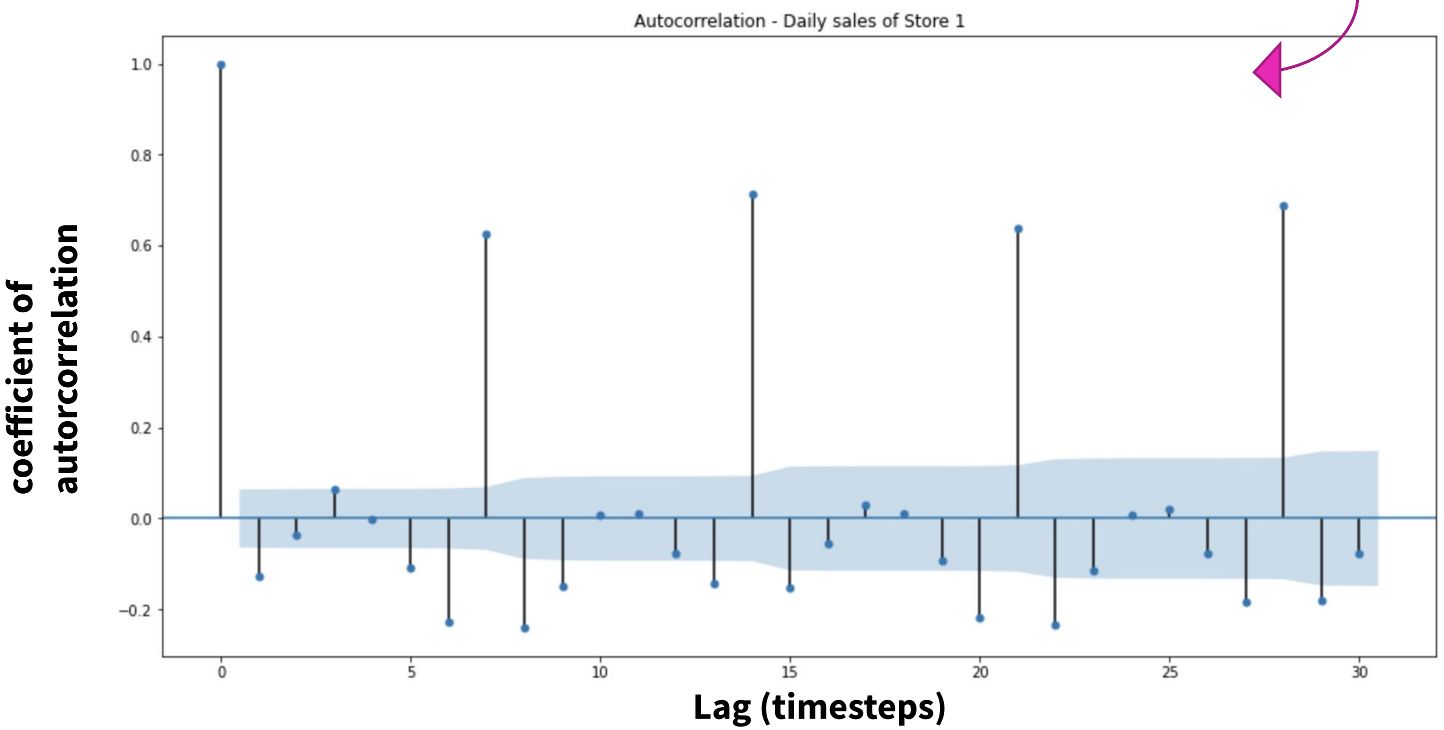
Autocorrelation = correlation with **itself** in the past

The presence of a strong, significant autocorrelation with a fixed interval is a very strong indicator of seasonality

Example:
Rossman's stores are closed on sundays, and sales pick up on mondays

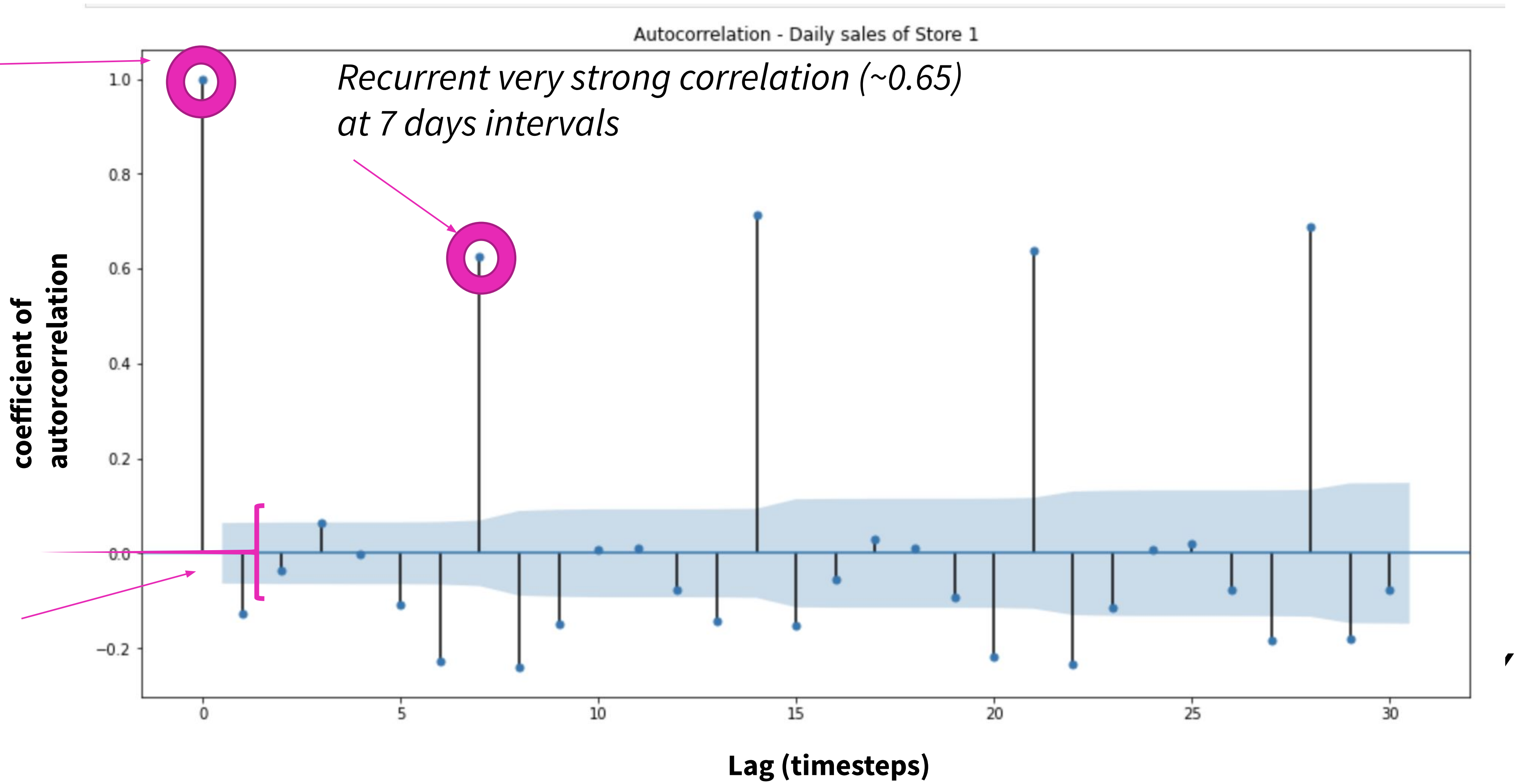
Rossman Dataset – Daily sales of store 1





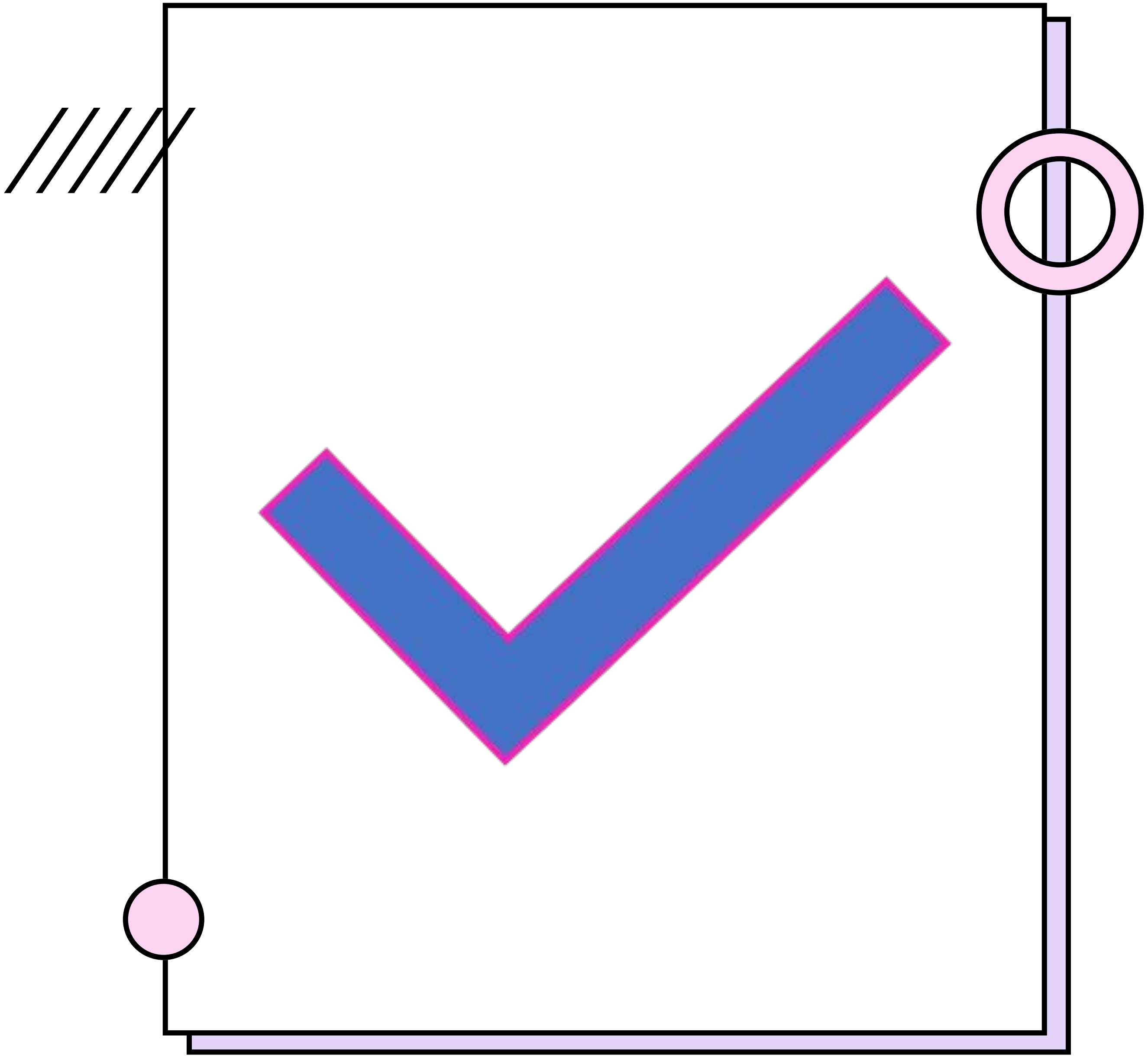
How to interpret the autocorrelation plot

Correlation with itself at the present moment is always 1, or 100%



The shaded area indicates the 95% confidence intervals.
The null hypothesis is that autocorrelation=0

BASELINES



Simplest possible forecast (baselines)

Simplest representation of trend, seasonality and autocorrelation

In practice, they will be used as a reference to compare our candidate models

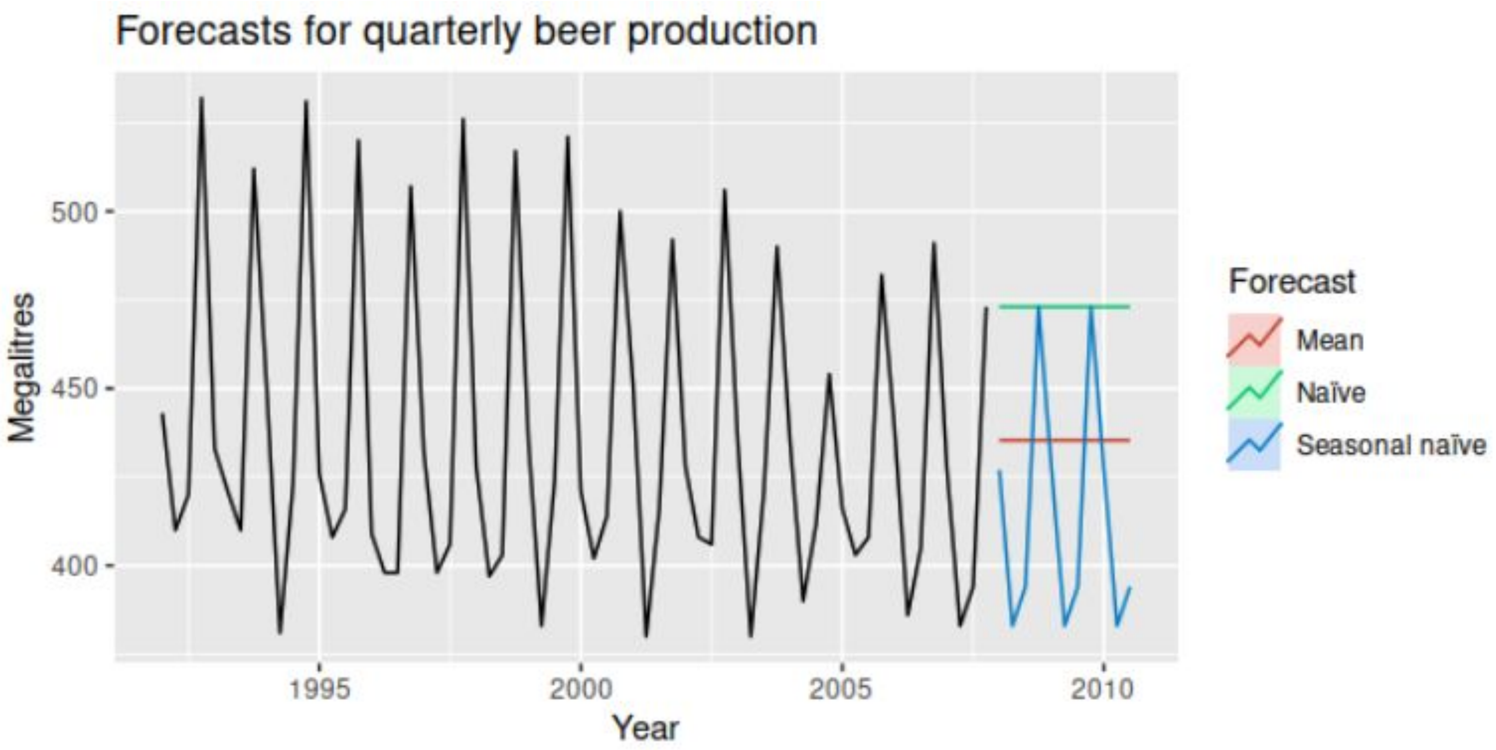


Figure 3.1: Forecasts of Australian quarterly beer production.

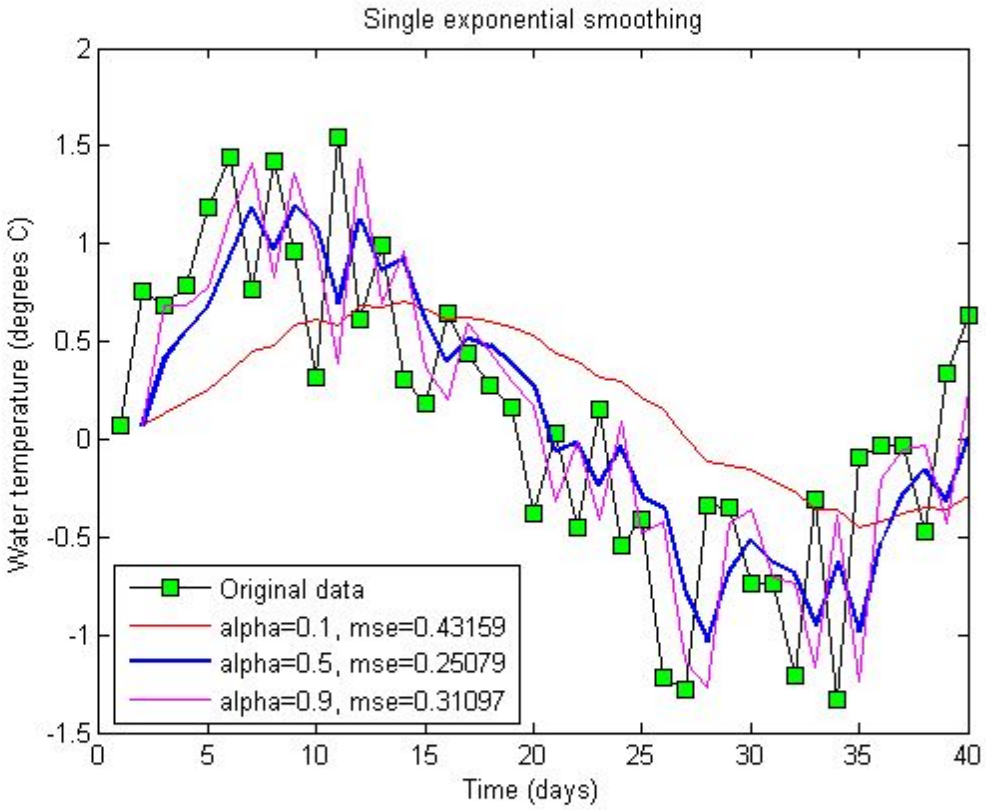
EXPONENTIAL SMOOTHING

Exponential Smoothing

Exponential smoothing methods are weighted averages of past observations

The weights decrease exponentially as the observations get older

The degree of decrease is given by parameter alpha.



Exponential Smoothing

The way the weights are distributed along time is determined by the smoothing parameter alpha (α)

Small α	Shifts weight toward the past
Large α	Shifts the weights toward the most recent observation
If α =1?	Same as naive forecast

Alpha

How the weights are distributed along time is determined by the smoothing parameter alpha (α)

	$\alpha = 0.2$	$\alpha = 0.4$	$\alpha = 0.6$	$\alpha = 0.8$
y_T	0.2000	0.4000	0.6000	0.8000
y_{T-1}	0.1600	0.2400	0.2400	0.1600
y_{T-2}	0.1280	0.1440	0.0960	0.0320
y_{T-3}	0.1024	0.0864	0.0384	0.0064
y_{T-4}	0.0819	0.0518	0.0154	0.0013
y_{T-5}	0.0655	0.0311	0.0061	0.0003

Methods

- Simple Exponential Smoothing
  - For time series without a clear trend or seasonality, i. e. for stationary data
- Holt-Winter's family of methods
  - Can be applied in time series with trend and/or seasonality
  - Trend and seasonality can be additive or multiplicative:
    - Additive: magnitude does not change over time
    - Multiplicative: magnitude of trend or length of cycle (seasonality) changes over time
    - How to check? Plotting the data

Time series scenarios (and appropriate models)

		SEASONALITY		
		None	Constant (Additive)	Increasing (Multiplicative)
TREND	None	(N,N) **Simple exponential smoothing** ***(uses just alpha)***	(N, A)	(N, M)
	Linear (Additive)	(A, N) **Holt's linear method**	(A, A) **Additive Holt-Winter's**	(A, M) **Multiplicative Holt-Winter's**
	Exponential (Additive damped)	(Ad, N) **Additive damped trend method**	(Ad, A)	(Ad, M) **Holt-Winter's damped**

AUTO REGRESSIVE MODELS

Autoregressive models

- Classic and robust methods. Can be applied in many different situations
- Univariate
- ARIMA = Autoregressive Integrated Moving Average
- ARIMA models describe the autocorrelation in the data
- Can deal with non-stationarity: trend and seasonality (SARIMA)

The notation **(p, q, d)**

AR I MA

AUTOREGRESSIVE component
a.k.a. **p**

Linear combination of past values; Regression against itself

DIFFERENCING component
a.k.a. **d**

Helps to stabilise the mean, reducing trend and seasonality

MOVING AVERAGE component
a.k.a. **q**

Weighted moving average of past errors

VARIATIONS:

NON-SEASONAL ARIMA
ARIMA(p, d, q)

SEASONAL ARIMA
ARIMA (p, d, q) (P, D, Q)m

SARIMAX
+ features

m = the width of the seasonality,

Understanding (p, d, q) and m

- p = is the AR term. Is the number of lags of Y to use as predictors
- q = is the MA term. Is the number of lags to use to get the forecast errors
- d determines how many periods to lag before calculating the differences
  - For an Array[10, 4, 2, 9, 34] => d =1 results in [-6, -2, 7, 25]
  - If the data is already stationary, d = 0
- The m indicates the number of observations per seasonal cycle, will be used in SARIMA and SARIMAX.

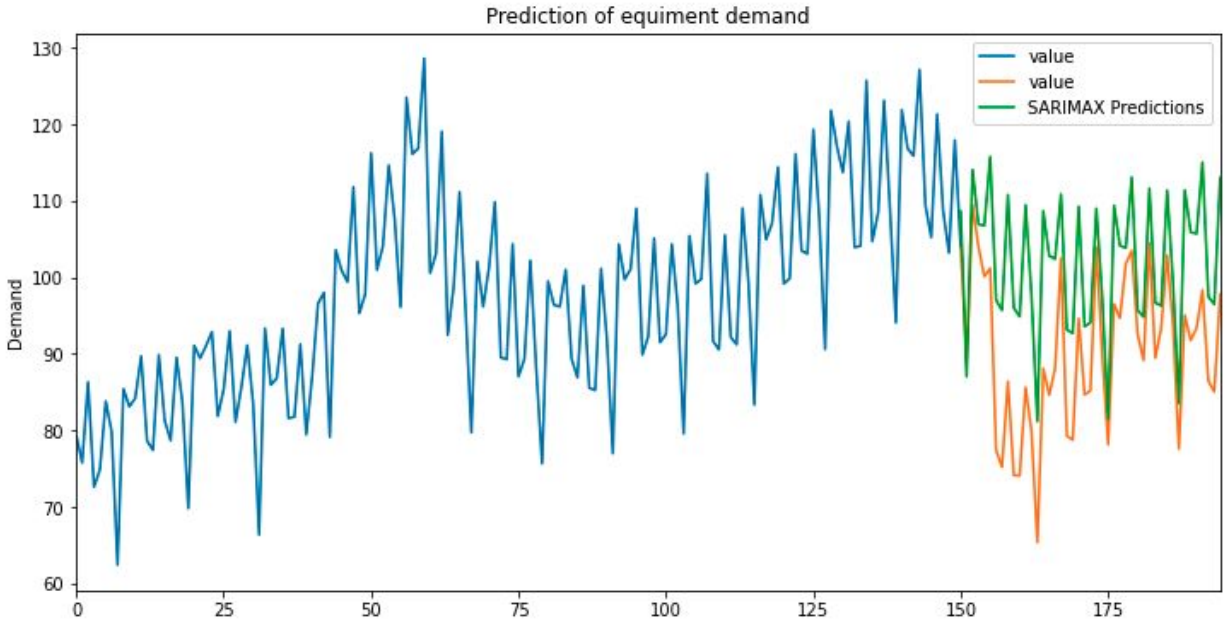
ARMA

Family of models

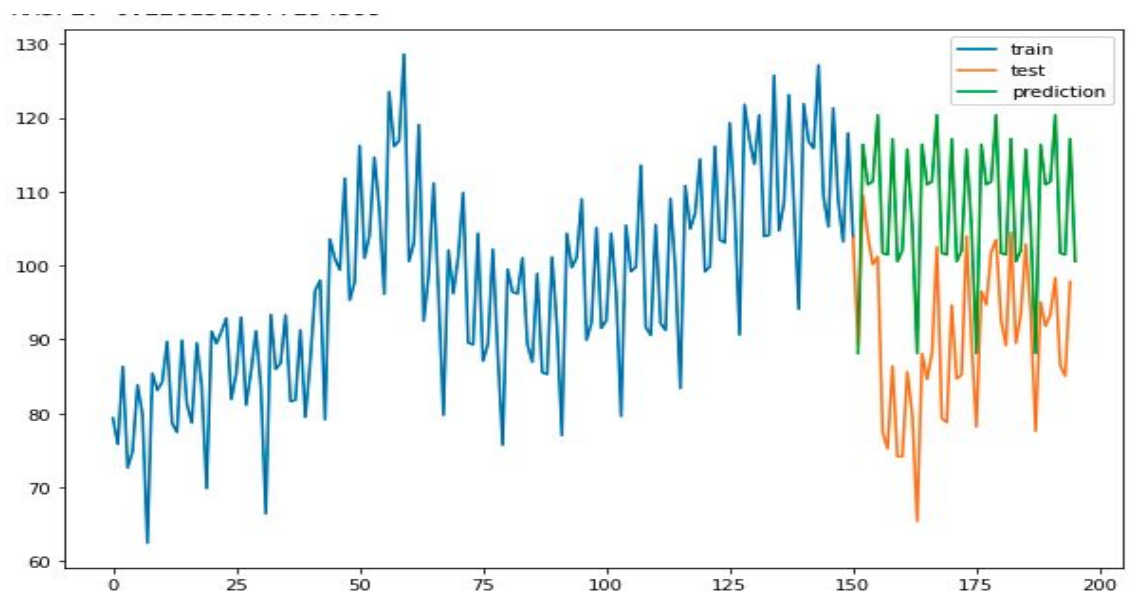
ARMA	Only handles stationary data
ARIMA	Can handle trends by applying differentiation
SARIMA	Can handle trends and seasonality
SARIMAx	Can handle trends + seasonality + regressors

Fitting with Exp. smoothing vs. SARIMA

BEST MODEL with Exponential smoothing



BEST MODEL with SARIMA



WHAT’S NEXT?

ML MODELS/Deep learning for time series

OVERVIEW OF TIMESERIES METHODS

Components	**Only univariate** (i. e., one time series at time)	**Univariate + regressors** (other related timeseries)	**Multivariate** (i. e., multiple time series for multiple features)
Stationary	ARMA Exponential smoothing (ES) (classical)	SARIMAX Prophet LSTM	Tree algorithms RNN
Trend	ARIMA Exp. Smoothing Holz-winter	SARIMAX Prophet LSTM	RNN
Seasonality	SARIMA Exp. Smoothing Holz-winter	SARIMAX Prophet LSTM	Tree algorithms RNN
Trend+seasonality	SARIMA Exp. Smoothing Holz-winter	SARIMAX Prophet LSTM	RNN
Complex seasonality	TBATS	LSTM Prophet	Tree algorithms RNN

ML-based time series forecasting

- Tree models (Random forests, boosted trees)
- Prophet (can handle combinations of seasonality (e.g. weekday + yearly))

Deep learning:

- LSTMs and RNN (next classes)
- AWS SAGEMAKER DEEPAR
  - Based on RNN
  - https://docs.aws.amazon.com/sagemaker/latest/dg/deepar.html

Temporal fusion Transformers (you can apply almost all you'll learn about language models to time series forecasting)

ML and TIME SERIES basics

- Always create a baseline model (naïve, average, moving average) to have a clearer understanding of how well your candidate models are performing
  - They should at least be better than the average

- Use as validation and test sets a period as long as the one you are being asked to predict:
  - Example: If you need to predict sales of next 3 months, use the last 3 months of data as test set, and the 3 months before that for cross-validation (for gridsearch, for example)

Forecast with Prophet

Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects. It works best with time series that have strong seasonal effects and several seasons of historical data. Prophet is robust to missing data and shifts in the trend, and typically handles outliers well.

Note: Prophet is optimized for business data, i. e., timeseries on calendar dates. Can account for holidays *out-of-the-box*

https://facebook.github.io/prophet/
Based on this publication: https://peerj.com/preprints/3190/ (super recommended reading)