MachineLearnAthon - Microlecture Forecasting Methods

Recorded by Lara Kuhlmann

Learning outcomes of today

After successfully completing this micro-lecture, you are able to….

- Name, describe and differentiate between methods for time-series forecasting
- Understand how to transform a time series as input for a machine learning model

Agenda for today

- (S)ARIMA
- Preparing time series for machine learning models
- Support Vector Machine
- Support Vector Regression
- Ensemble Model
- Gradient Boosting
- LightGBM

(S)ARIMA

- One of the most widely used approaches for time series forecasting
- **AR (AutoRegressive)**: Uses the relationship between an observation and a number of lagged observations (previous values).
- **I (Integrated)**: Involves differencing the raw observations to make the time series stationary (removing trends).
- **MA (Moving Average)**: Models the relationship between an observation and a residual error from a moving average model applied to lagged observations.
- SARIMA is an extension or ARIMA including seasonality

Hyndman, R.J., & Athanasopoulos, G. (2021) *Forecasting: principles and practice*, 3rd edition
A. E. Permanasari, I. Hidayah and I. A. Bustoni, "SARIMA (Seasonal ARIMA) implementation on time series to forecast the number of Malaria incidence" (*2013)*

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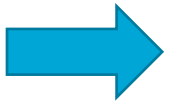
Machine Learning Methods for Time Series

- The standard time series method take only a time series as input
- For applying a machine learning algorithm, the time series needs to be transformed into a dataset with lags

t	y
2024-01-01	98
2024-02-01	103
2024-03-01	110
2024-04-01	87
2024-05-01	99
2024-06-01	93



Date	y	Lag_1	Lag_2	Lag_3
2024-01-01	98	NaN	NaN	NaN
2024-02-01	103	98	NaN	NaN
2024-03-01	110	103	98	NaN
2024-04-01	87	110	103	98
2024-05-01	99	87	110	103
2024-06-01	93	99	87	110

Support Vector Machine

- Solves binary classification problems
- Objective: find the maximum distanc between the hyperplane to classify th largest number of training points
- The data points of the hyperplane that ar closest to it are called “support vectors”

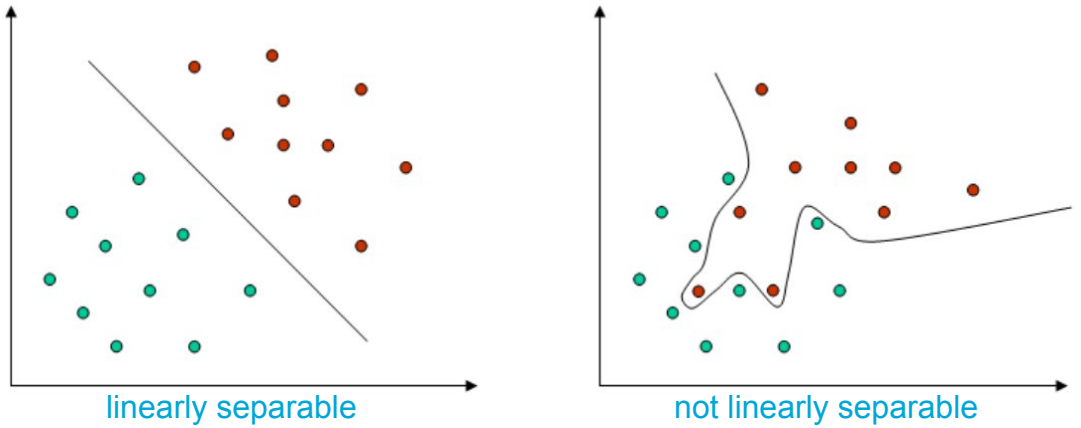


Image Source: https://de.wikipedia.org/wiki/Support_Vector_Machine

Mahdi Abolghasemi u.a. „Demand forecasting in supply chain: The impact of demand volatility in the presence of promotion“. In: Compu ters & Industrial Engineering 142 (2020)
Mariette Awad und Rahul Khanna. Efficient Learning Machines: Theories, Concepts, and Applications for Engineers and System Designers (2015)

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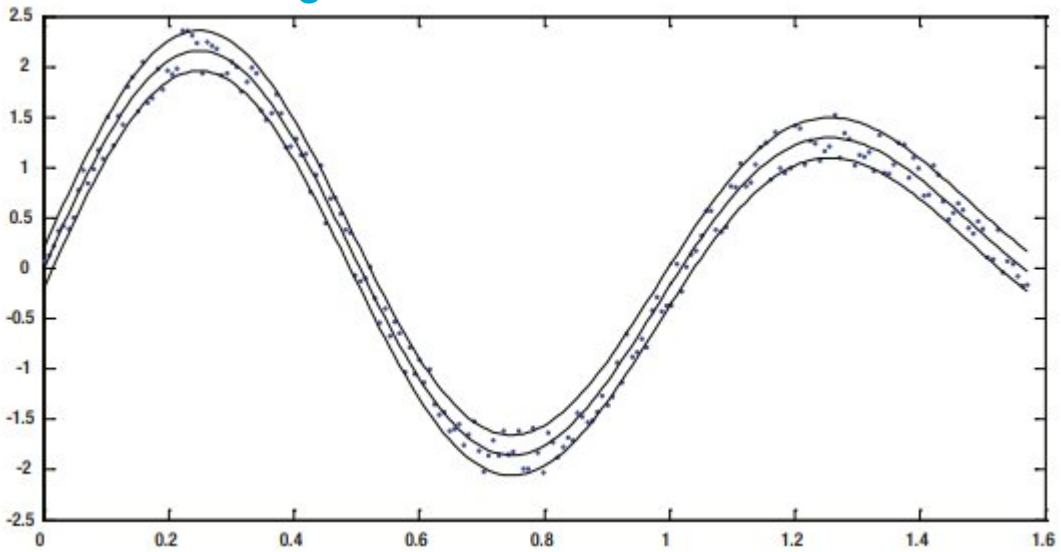
Support Vector Regression

- Support Vector Regression (SVR) is a generalization of the Support Vector Machine (SVM)
- Defined as an optimization problem and trained with a symmetric loss function
- During training, the loss function penalizes too high and too low misestimates
- The result of the optimization problem is the flattest tube, which contains the largest number of training instances

Nonlinear regression



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Ensemble Model

- Combination of several models
- Improving prediction accuracy and reducing the risk of overfitting
- Bagging: ‘Bootstrap aggregation’
  - Uses different samples to train the decision trees
  - Result is the average of all predictions
  - Advantage: outliers have less influence
  - Example method: Random Forest
- Boosting:
  - Add iteratively weak learners to the model, which focus on data that has not yet been learned well
  - Higher risk of overfitting

Carsten Lanquillon. „Grundzüge des maschinellen Lernens“ (2019)
VKishore Ayyadevara. Pro Machine Learning Algorithms: A Hands-On Approach to Implementing Algorithms in Python and R. (2018)
Joos Korstanje. Advanced Forecasting with Python. With State-of-the Art-Models Including LSTMs, Facebook’s Prophet, and Amazon’s DeepAR (2021)

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Gradient Boosting

- Ensemble method, which uses boosting
- Suitable for regression and classification problems
- Sequential approach
  - Adds decision trees that try to reduce the error of the previous one
- Combination of weak learners into a strong model
- "Gradient": Error of the created model
- Goal: Generation of a small error
- Example: XGBoost and LightGBM

VKishore Ayyadevara. Pro Machine Learning Algorithms: A Hands-On Approach to Implementing Algorithms in Python and R (2018)
Sunitha Cheriyan u.a. „Intelligent Sales Prediction Using Machine Learning Techniques“ (2018)
Arnab Mitra u.a. „A Comparative Study for Machine Learning Models in Retail Demand Forecasting“(2023)

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LightGBM

- Light Gradient Boosting Machine
- Based on Gradient Boosting
- Uses GOSS and EFB
  - Gradient-Based One-Side Sample (GOSS): Filters out data points that have already been learnt
  - Exclusive Feature Bundling (EFB): Enables fast learning

Zharfan Akbar Andriawan u.a. „Vorhersage der Stornierung von Ho telbuchungen mit CRISP-DM“ (2020)
Joos Korstanje. Advanced Forecasting with Python. With State-of-the Art-Models Including LSTMs, Facebook’s Prophet, and Amazon’s DeepAR (2021)

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Recap this lecture

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