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Time Series Forecasting

2.1 Machine Learning and Time Series

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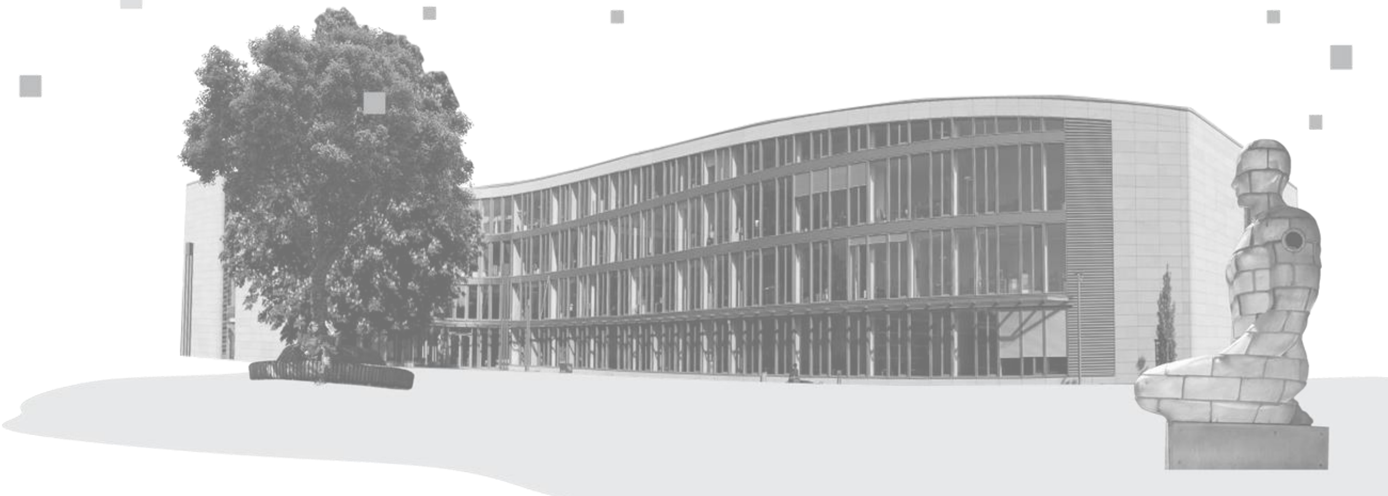

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What we‘ll cover in this video

- Why use machine learning for time series
- Why it’s not straightforward
- How to prepare time series data for ML
  - Temporal dependencies
  - Time-based features

Why Use Machine Learning for Time Series?

Flexible feature handling

Combine historical data with external factors like holidays, weather, or promotions.

Capture complex, non-linear relationships

Real-world patterns often aren’t just straight lines. ML models can learn intricate dependencies.

Scalable to many series

Easily apply the same approach across thousands of time series without building separate models for each.

Applicable to multiple related tasks

Use machine learning methods not only for forecasting but also for classification and anomaly detection.

Less reliance on domain knowledge

ML models can discover patterns automatically, even when we don’t fully understand the process.

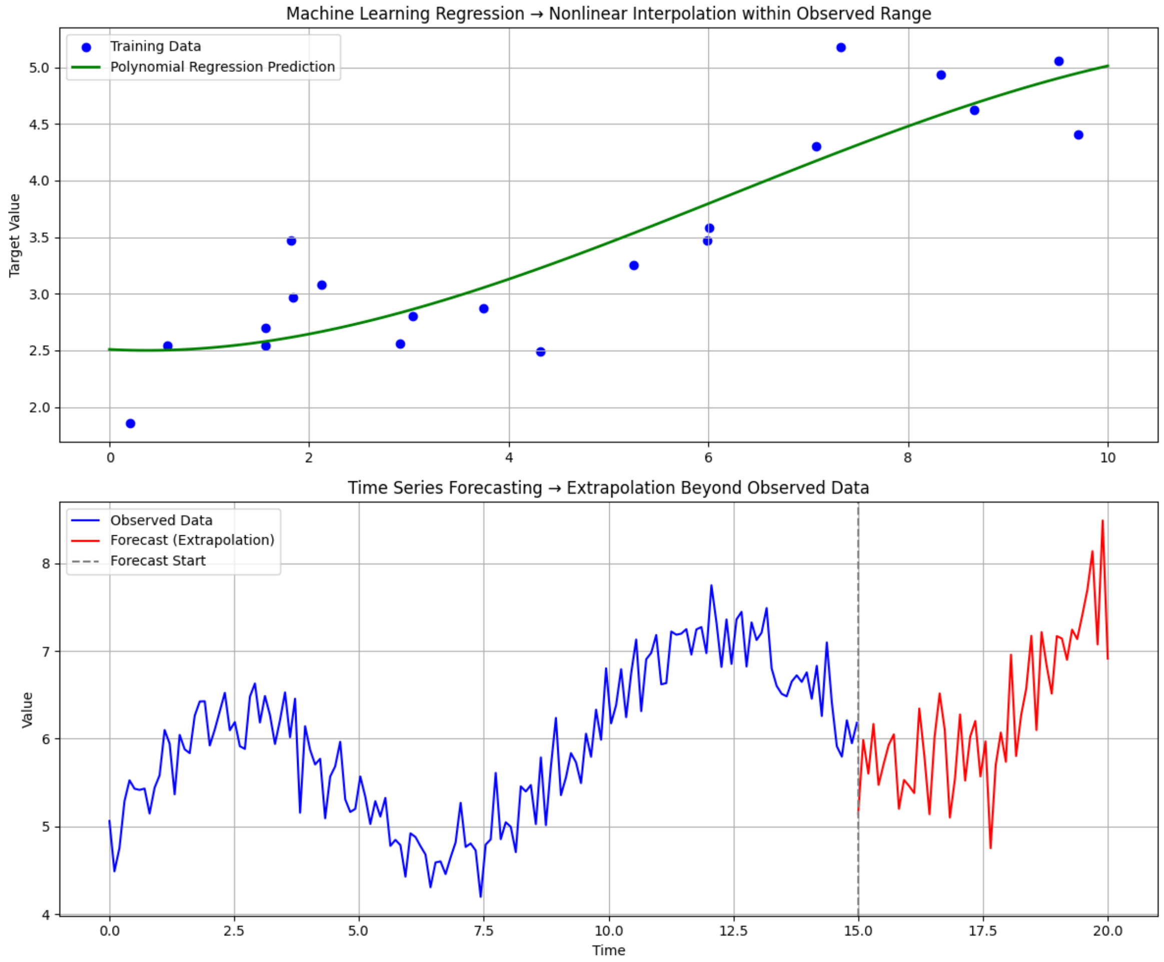
Adaptability to changing patterns

Can adjust to evolving data and concept drift by retraining or online learning.

Temporal Dependencies

In standard machine learning regression, the goal is often interpolation within an i.i.d. dataset. Time series forecasting requires extrapolation into the future, accounting for temporal structure and evolving patterns.

- **Temporal dependence**: Consecutive observations are correlated, violating the independence assumption of many ML algorithms.
- **Non-stationarity**: Trends, seasonality, and structural changes cause the statistical properties of the series to vary over time.
- **Sequential structure**: The chronological order of the data is essential, and random shuffling removes the temporal context necessary for forecasting.
- **Risk of information leakage:** Using future observations or features derived from them during training leads to overly optimistic performance estimates.



Temporal Dependencies

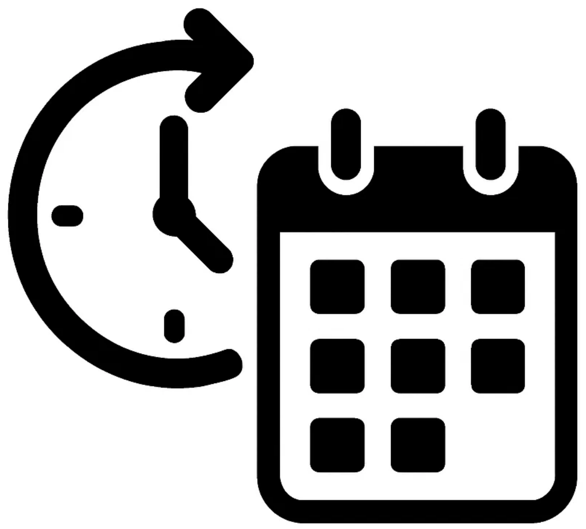
Past values and patterns influencing current observations, forming the backbone of time series dynamics.

- **Lags:** Using previous time points as predictors.
- **Seasonal lags:** Values from the same point in previous seasonal cycles.
- **Rolling window aggregations:** Summaries of recent history to smooth noise and detect trends.
- **Seasonal rolling windows:** Aggregations aligned with seasonal cycles to capture recurring patterns.
- **Exponentially weighted moving averages**: Weighting recent observations more heavily for adaptability.
- **Autoregressive terms**: Linear dependence on past values used in classic time series models.

Time-based Features

They provide essential context about calendar patterns, trends, and special events that raw historical values alone can’t fully capture.

- **Calendar features**: Day of week, month, quarter, weekends, holidays, business hours.
- **Elapsed time features**: Time since start, time since last event, or other relevant milestones.
- **Fourier terms**: Mathematical functions to model complex and multiple seasonal cycles smoothly.
- **Lagged event indicators**: Flags for recent events that might affect the series suddenly.
- **Trend indicators**: Time-based variables capturing gradual changes over time.
- **Special events calendars**: Regional holidays, cultural events, and other impactful dates.



What we‛ve learnt

- Machine learning can help with time series forecasting but they represent distinct approaches.
- This difference means we need to carefully design features that capture the time-related structure inherent in time series data.
- Temporal dependencies like lags, rolling windows, and moving averages help represent how past observations influence the present.
- Time-based features—calendar information, elapsed time, and Fourier terms, provide crucial context about seasonality, trends, and special events.