Time-Series Forecasting

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What is time series forecasting?

- Time series forecasting is one of the most applied data science techniques in business, finance, supply chain management, production and inventory planning.
- Many prediction problems involve a time component and thus require extrapolation of time series data, or time series forecasting.
- Time series forecasting is also an important area of machine learning (ML) and can be cast as a supervised learning problem.
- ML methods such as Regression, Neural Networks, Support Vector Machines, Random Forests can be applied to it.

What is time series forecasting?

- Time series forecasting means to forecast or to predict the future value over a period of time.
- It entails developing models based on previous data and applying them to make observations and guide future strategic decisions.
- The future is forecast or estimated based on what has already happened.
- Time series adds a time order dependence between observations.

What is time series forecasting?

Time series forecasting is a technique for the prediction of events through a sequence of time. It predicts future events by analyzing the trends of the past, on the assumption that future trends will hold similar to historical trends. It is used across many fields of study in various applications including:

- Astronomy
- Business planning
- Control engineering
- Earthquake prediction
- ...

Time Series Forecasting

We talk about three models in this presentation:

- ARIMA
- Long Short-Term Memory (LSTM)
- Transformer

ARIMA

Times series methods refer to different ways to measure timed data. Common types include:

- Autoregression (AR)
- Moving Average (MA)
- Autoregressive Moving Average (ARMA)
- Autoregressive Integrated Moving Average (ARIMA)
- Seasonal Autoregressive Integrated Moving-Average (SARIMA)

ARIMA

AutoRegressive Integrated Moving Average (ARIMA) models are among the most widely used time series forecasting techniques:

- In an Autoregressive model, the forecasts correspond to a linear combination of past values of the variable.
- In a Moving Average model the forecasts correspond to a linear combination of past forecast errors.

The ARIMA models combine the above two approaches. Since they require the time series to be stationary, differencing (Integrating) the time series may be a necessary step, i.e. considering the time series of the differences instead of the original one.

ARIMA

- Autoregression is a time series model that uses observations from previous time steps as input to a regression equation to predict the value at the next time step.
- Moving-average model (MA model), also known as moving-average process, is a common approach for modeling univariate time series. The moving-average model specifies that the output variable depends linearly on the current and various past values of a stochastic (imperfectly predictable) term.

ARIMA

It has 3 hyperparameters:

- P (autoregressive lags)
- d (order of differentiation)
- Q (moving avg.)

Which respectively comes from the AR, I & MA components. The AR part is correlation between prev & current time periods. To smooth out the noise, the MA part is used. The I part binds together the AR & MA parts.

How to find value of P & Q for ARIMA ?

We need to take help of ACF(Autocorrelation Function) & PACF(Partial Autocorrelation Function) plots. ACF & PACF graphs are used to find value of P & Q for ARIMA. We need to check, for which value in x-axis, graph line drops to 0 in y-axis for 1st time.

- From PACF(at y=0), get P
- From ACF(at y=0), get Q

ARMA vs. ARIMA vs. SARIMA

ARMA (AutoRegressive Moving Average):

- Components: Combines autoregression (AR) and moving average (MA) components.
- Use Case: Suitable for stationary time series data (mean, variance, and autocorrelation structure are constant over time).
- Parameters: (p, q) where p is the order of the AR part and q is the order of the MA part.

ARMA vs. ARIMA vs. SARIMA

ARIMA (AutoRegressive Integrated Moving Average):

- Components: Adds an integration (I) component to ARMA for differencing the data to make it stationary.
- Use Case: Suitable for non-stationary time series data that can be made stationary through differencing.
- Parameters: (p, d, q) where d is the order of differencing needed to make the series stationary.

ARMA vs. ARIMA vs. SARIMA

SARIMA (Seasonal AutoRegressive Integrated Moving Average):

- Components: Extends ARIMA by including seasonal autoregressive (SAR), seasonal differencing (SI), and seasonal moving average (SMA) components.
- Use Case: Suitable for time series data with both non-stationary and seasonal patterns.
- Parameters: (p, d, q) x (P, D, Q, s) where P, D, and Q are the seasonal AR, differencing, and MA orders, and s is the length of the seasonal cycle.

ARMA vs. ARIMA vs. SARIMA

In summary:

- ARMA: Best for stationary time series.
- ARIMA: Best for non-stationary time series that can be differenced to become stationary.
- SARIMA: Best for non-stationary and seasonal time series.