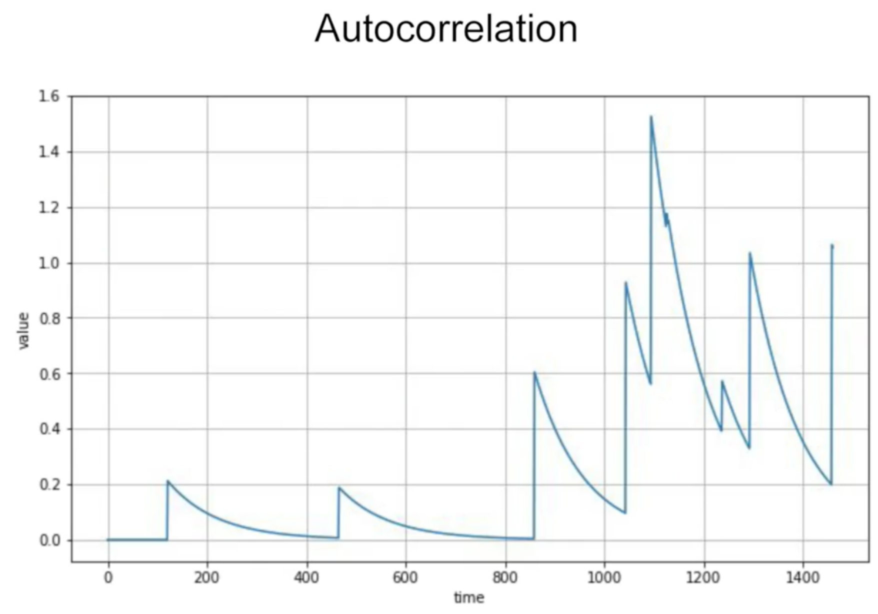
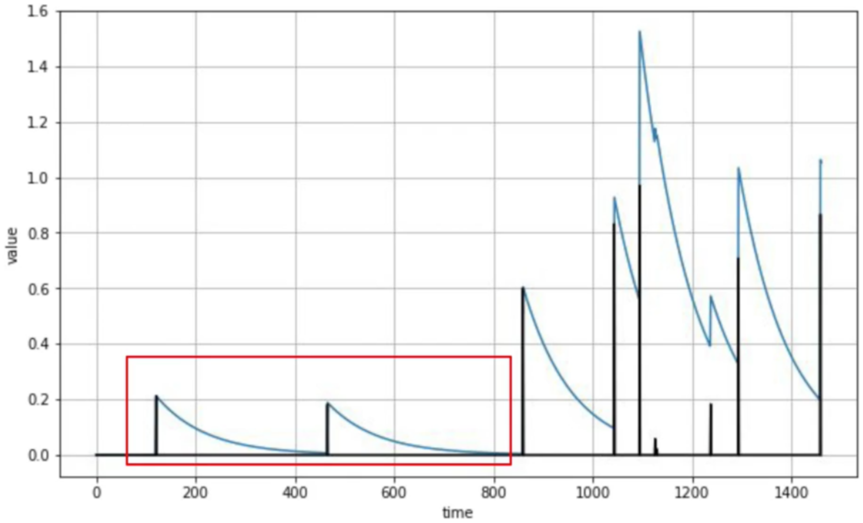
Common patterns in time series

Consider the following time series. There's no trend or seasonality, but there is a clear pattern.



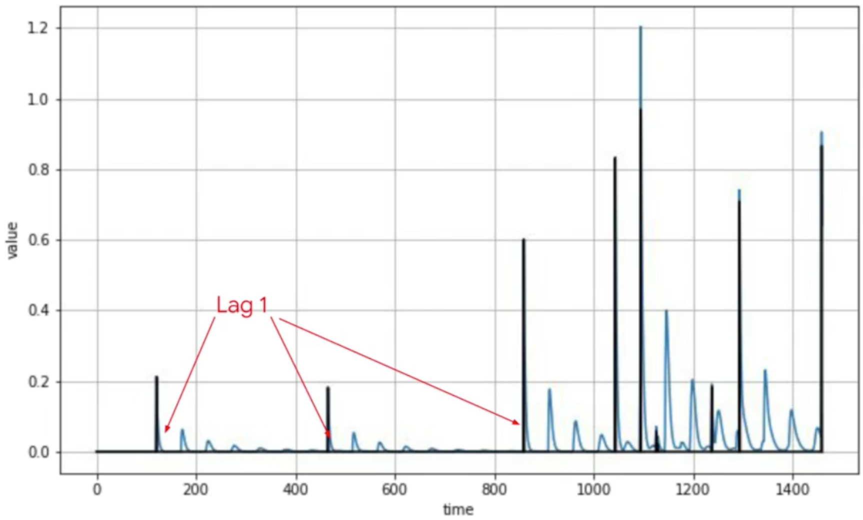
The value at every time step depends on the previous value, plus the occasional spike. The spikes (also called innovations) are random and unpredictable (cannot be predicted based on past values), but the series follows a predictable pattern between spikes. This dependence of the series on its own previous values is called autocorrelation.

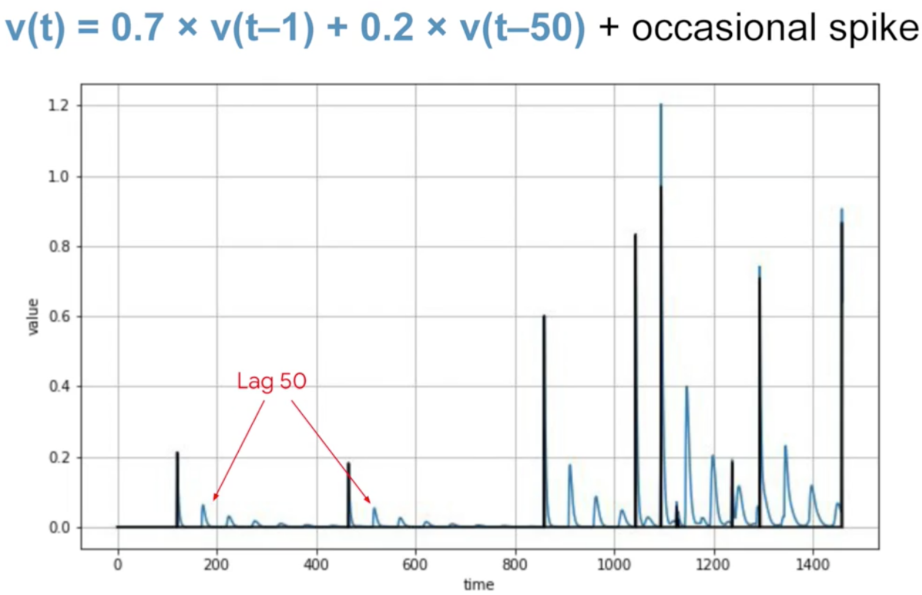
v(t) = 0.99 × v(t–1) + occasional spike



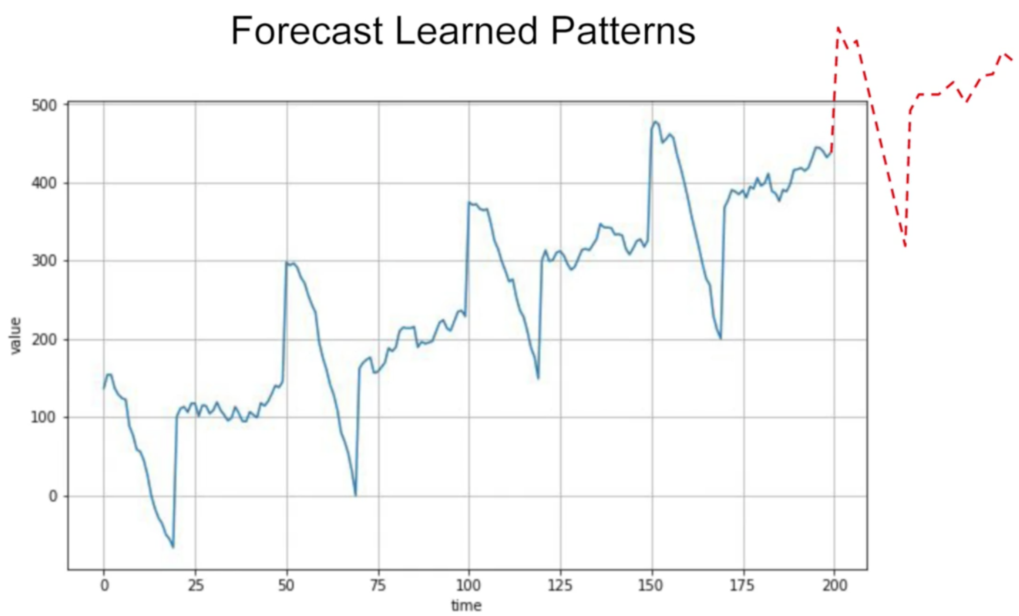
The following series is an example with multiple autocorrelations. Lag 1 gives the steep decay immediately after the impulse, whereas lag 50 gives the small bumps between impulses.

v(t) = 0.7 × v(t–1) + 0.2 × v(t–50) + occasional spike

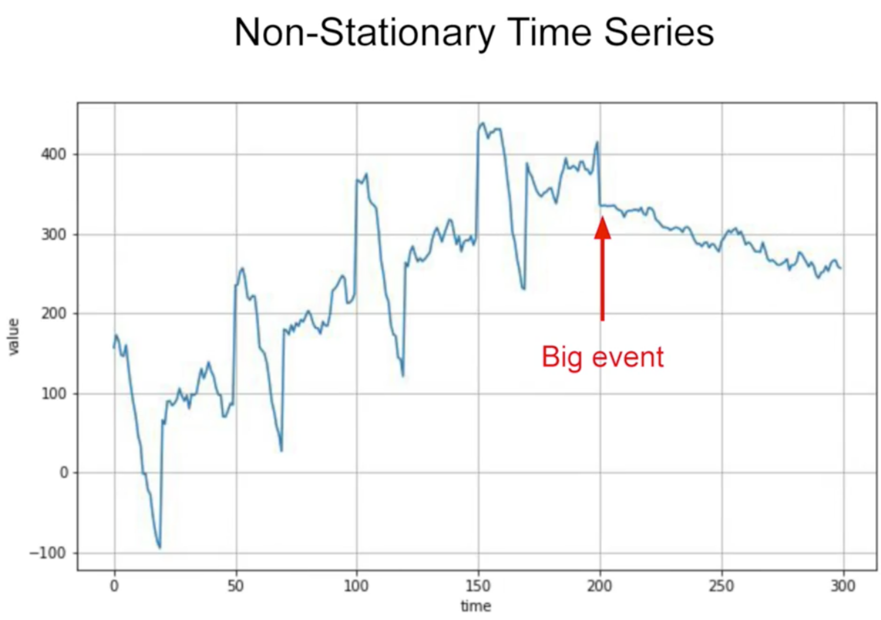




Real life signals consist of a mix of trend, seasonality, autocorrelation and noise. Our objective is to create models that make predictions about the future based on this data. Note that this assumes that patterns prevalent in the past will continue in the future.



Such series are called stationary time series, since their properties remain consistent over time. However, sometimes a big event may cause a change in the established pattern - for example, a stock market crash causing prices to drop. Such series are non-stationary.



In such situations, we can train our model on a subset of the series for better performance.