Summary/Review

Stationarity

Stationarity impacts our ability to model and forecast

- A **stationary** series has the same mean and variance over time
- **Non-stationary** series are much harder to model

Common approach:

- Identify sources of non-stationarity
- Transform series to make it stationary
- Build models with stationary series

The **Augmented Dickey-Fuller (ADF) test** specifically tests for stationarity.

- It is a hypothesis test: the test returns a p-value, and we generally say the series is non-stationary if the p-value is less than 0.05.
- It is a less appropriate test to use with small datasets, or data with heteroscedasticity (different variance across observations) present.
- It is best to pair ADF with other techniques such as: run-sequence plots, summary statistics, or histograms.

Common Transformations for Time Series include:
Transformations allow us to generate stationary inputs required by most models.
There are several ways to transform nonstationary time series data:

- Remove trend (constant mean)
- Remove heteroscedasticity with log (constant variance)
- Remove autocorrelation with differencing (exploit constant structure)
- Remove seasonality (no periodic component)
- Multiple transformations are often required.

Time Series Smoothing

Smoothing is a process that often improves our ability to forecast series by reducing the impact of noise.
There are many ways to smooth data. Some examples:

- Simple average smoothing
- Equally weighted moving average
- Exponentially weighted moving average

This are some suggestions for selecting a Smoothing Technique. If your data:

– lack a trend

- Then use Single Exponential Smoothing

– have trend but no seasonality

- Then use Double Exponential Smoothing

– have trend and seasonality

- Then use Triple Exponential Smoothing