

Forecasting

Supply Chain Management, Chapter 7

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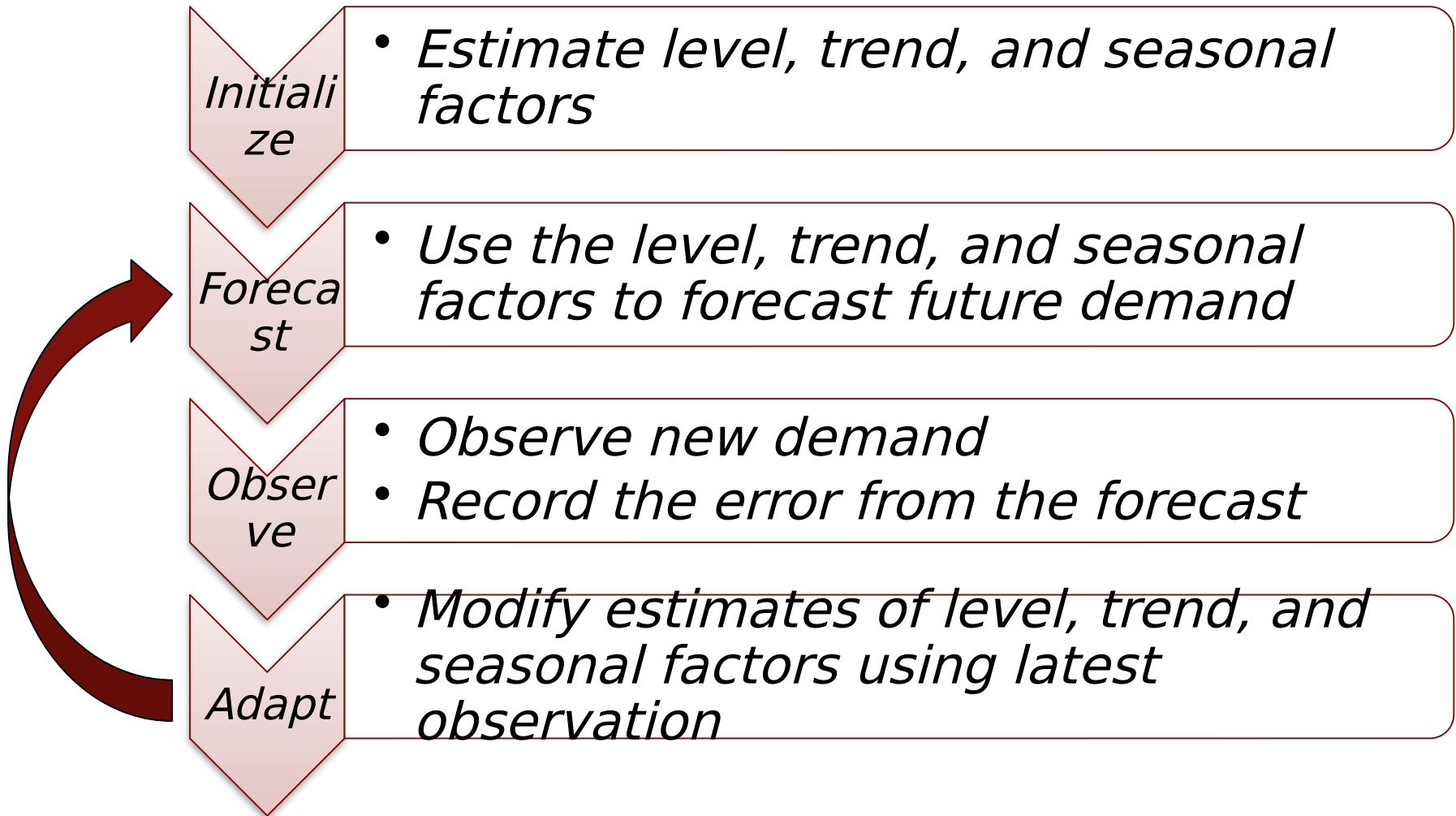
Adaptive Forecasting



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Adaptive Forecasting



Adaptive Forecasting

	Level	Trend	Seasonality
Moving Average	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Simple Exponential Smoothing	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Holt's Model	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Winter's Model	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Adaptive Forecasting: Moving Average of periods

*Initiali
ze*

- *Level = average of the demand in the last periods*

*Foreca
st*

- *Forecast for next period = level*
- *Forecast for two periods from now = level, ...*

*Obser
ve*

- *Observe the actual demand*

Adapt

- *Updated level = average of the demand in the last periods.*

Moving Average

Example 5

The following table shows the demand for penne pasta (measured in boxes) in a grocery store over the last five weeks. The grocery store uses a **four-period moving average** to forecast the future demand for pasta.

Week	Demand
1	300
2	450
3	250
4	500
5	400

- What is the forecast for week 6 demand? For week 7?
 - Initialize: Estimate the level --- $(450 + 250 + 500 + 400) / 4 = 400$
 - Current forecast for demand in week 6 = Level = 400
 - Current forecast for demand in week 7 = Level = 400

Moving Average

Example 5

It turns out that the week 6 demand was 250.

Week	Demand
1	300
2	450
3	250
4	500
5	400
6	250

- What is the forecast for week 7 demand?

Adaptive Forecasting: Simple Exponential Smoothing

*Initiali
ze*

- *Level = average of all previous demand observations*

*Foreca
st*

- *Forecast for next period = level*
- *Forecast for two periods from now = level, ...*

*Obser
ve*

- *Observe the actual demand*

Adapt

- *Updated level = observed demand previous level*

Simple Exponential Smoothing *Example 5*

The following table shows the demand for penne pasta (measured in boxes) in a grocery store over the last five weeks. The grocery store uses **exponential smoothing** to forecast the future demand.

Week	Demand
1	300
2	450
3	250
4	500
5	400

- What is the forecast for week 6 demand? For week 7?

Simple Exponential Smoothing

Example 5

It turns out that the week 6 demand was 250.

Week	Demand
1	300
2	450
3	250
4	500
5	400
6	250

- What is the forecast for week 7 demand?

Simple Exponential Smoothing

- Two extreme cases: $\alpha = 1$ and $\alpha = 0$. How do they differ in terms of weight they place on the past demand observations?
- $\alpha = 1$: updated level = D_t
- $\alpha = 0$: updated level = $L_t = L_{t-1}$
- As α increases, we are placing more weight on D_t
- What is the right value of α to use?

Adaptive Forecasting: Holt's Model

*Initiali
ze*

- *Level and trend: estimated using linear regression.*

*Foreca
st*

- *Forecast for next period = level + trend*
- *Forecast for two periods from now = level + trend, ...*

*Obser
ve*

- *Observe the actual demand*

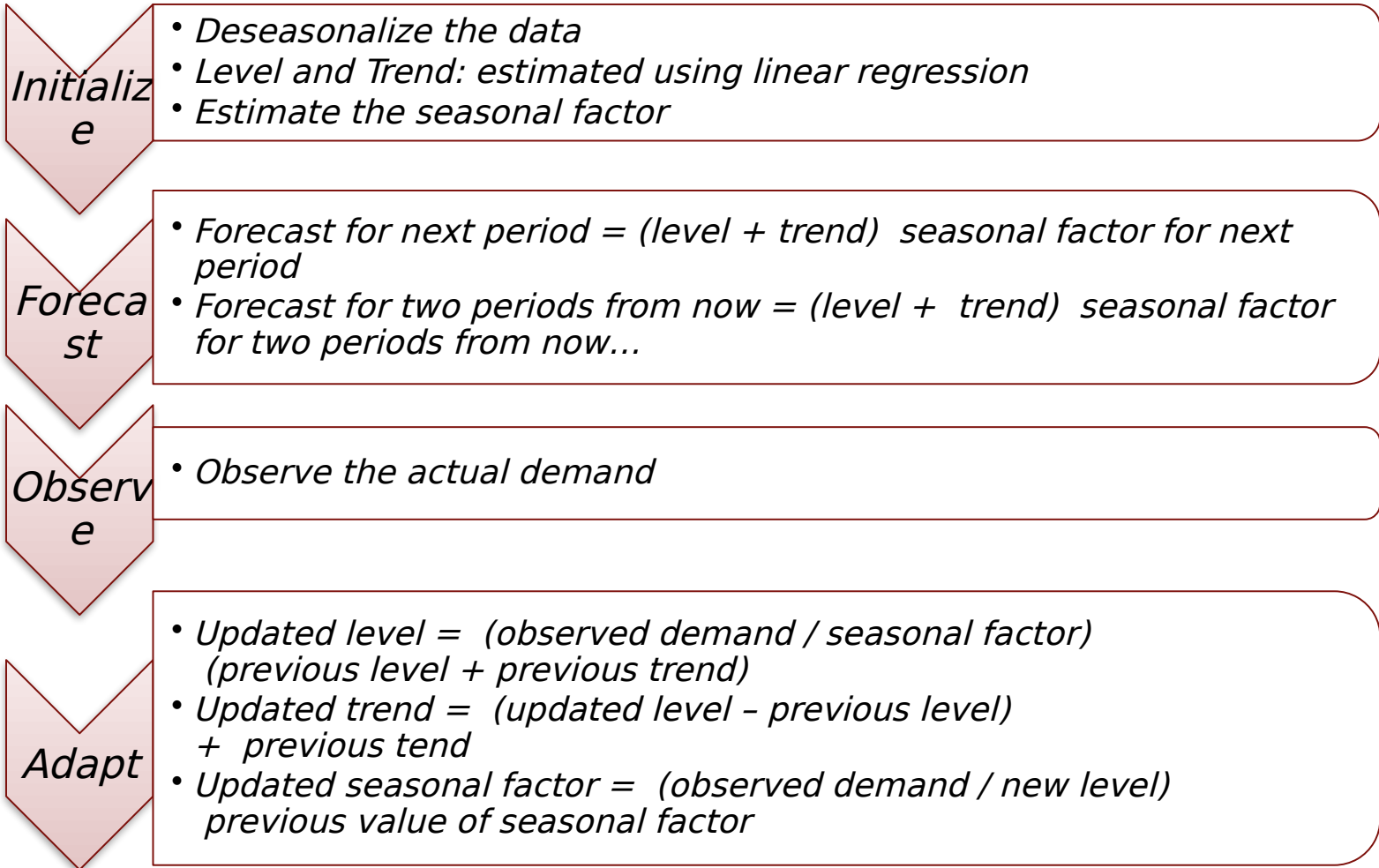
Adapt

- *Updated level = observed demand (previous level + previous trend)*
- *Updated trend = (updated level - previous level) + previous trend*

Adaptive Forecasting: Holt's Model *Example 6*

- GetSmart is a new phone that has been on the market for a few months. A retailer uses Holt's model with $\alpha = 0.1$ and $\beta = 0.2$ to forecast future demand. Suppose that the current estimates of level and trend are 173 and 71, respectively.
- What is the current forecast for next month's demand? How about the current forecast for the demand in the month after?
- Suppose next month's demand turns out to be 280. Update the level and trend estimates.
- After updating, what is the forecast for the next month's demand?

Adaptive Forecasting: Winter's Model



Adaptive Forecasting: Winter's Model *Example 7*

- JMart sells pool toys and uses Winter's method to forecast future demand (with 0.2). There are two distinct periods during the year: the high-demand period (summer) followed by the low-demand period (winter).
- Suppose that, at the end of the low-demand period, JMart's estimate for the level is 100 and its estimate for the trend is 10. Furthermore, suppose that the estimates for the seasonal factors are 1.5 and 0.5 for the high-demand and low-demand periods, respectively.
- What is the forecast for next period (summer) demand?

Adaptive Forecasting: Winter's Model *Example 7*

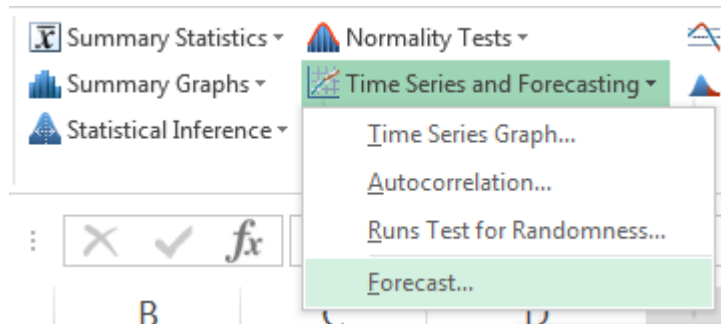
- Suppose the summer demand turns out to be 150. Update the estimates of level, trend, and seasonal factors.
- After updating, what is the forecast for the demand in the next period (winter)? How about the forecast for next summer?

Using StatTools to automate adaptive forecasting

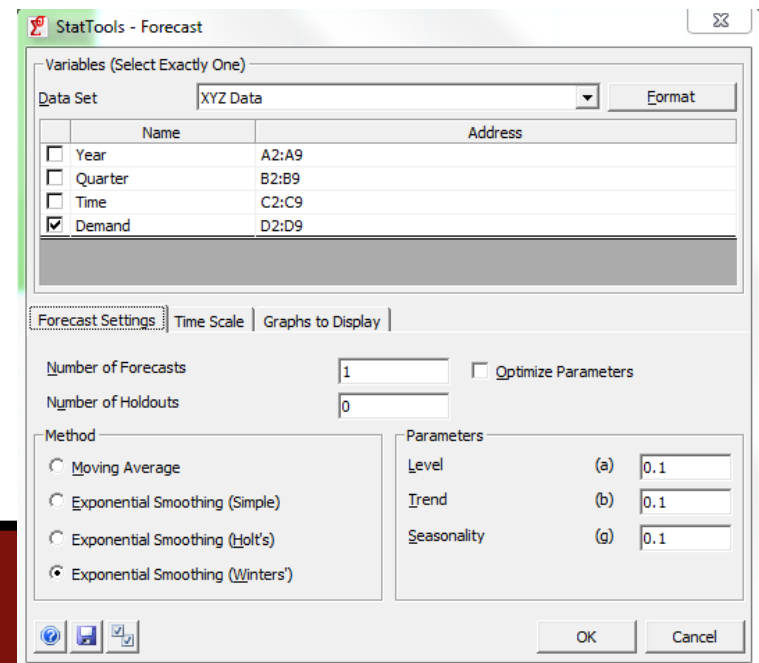
- **Warning:** StatTools calculates the **initial estimate of trend** in adaptive forecasts slightly different from the textbook. Otherwise, everything is the same.
- **Note:** for Winter's method, StatTools requires data for *more than double the number of seasons*. Example: if there are 4 seasons, StatTools requires more than 8 data points.

Using StatTools to automate adaptive forecasting

- Use the “Forecast” tool

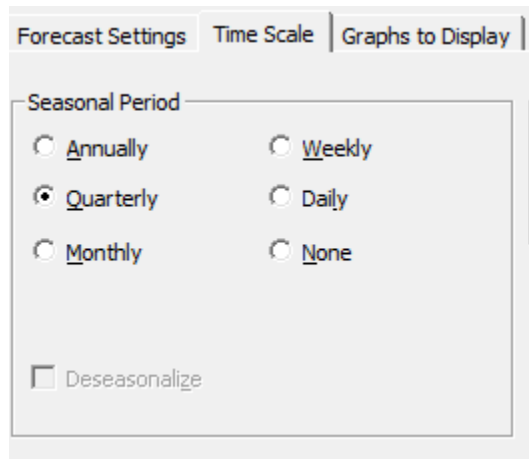


- Select variables and forecasting method



Using StatTools to automate adaptive forecasting

- Select type of seasonality (if applicable). StatTools may try to do this for you but always check.



The screenshot shows the 'Forecast Settings' tab of a dialog box. It has three tabs: 'Forecast Settings', 'Time Scale', and 'Graphs to Display'. The 'Seasonal Period' section contains six radio button options: 'Annually', 'Quarterly' (which is selected), 'Monthly', 'Weekly', 'Daily', and 'None'. Below these options is a checkbox labeled 'Deseasonalize' which is currently unchecked.

Measures of Forecast Error

- Why measure error?
 - Determine accuracy of forecast.
 - Formulate contingency plans.
- Let \hat{D}_t be the forecast in time t .
- Let D_t be the observed demand in time t .
- The forecast error e_t is given by $e_t = D_t - \hat{D}_t$.

Measures of Forecast Error

- Mean Squared Error (MSE)
- Mean Absolute Deviation (MAD)
- Mean Absolute Percentage Error (MAPE)

MSE vs MAD

Example MSE vs MAD

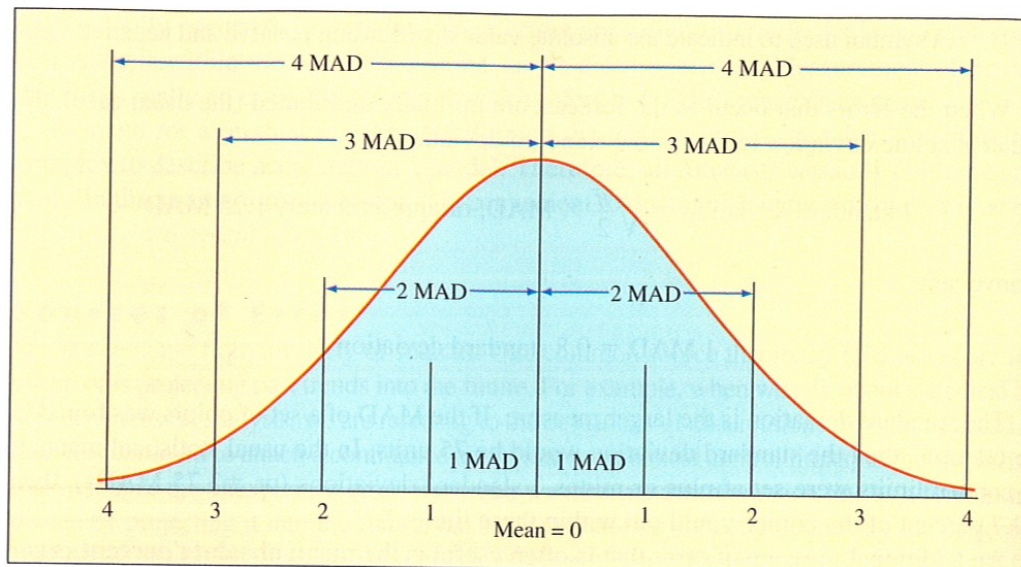
- Suppose you have the following demand and two different forecasts. Calculate the MSE and MAD for each. Which forecast is better? Why?

Time	Demand	Forecast 1	Forecast 2
1	27	37	47
2	63	53	63
3	25	15	25
4	26	36	46

Measures of Forecast Error

- Mean Absolute Deviation (MAD)

Can be used to approximate the amount of variability in the data. Typically, the standard deviation of demand is about $1.25 \times \text{MAD}$



Measures of Forecast Error

- Bias
 - What if bias is positive [negative] most of the time?
 - Systematically overestimating [underestimating] the demand.
- Tracking Signal (TS) in period
- Rule of thumb: TS should be between and .

Measures of Forecast Error

- Tracking signal is commonly plotted over time to see if there are changes in the underlying level of demand.

MSE vs MAD

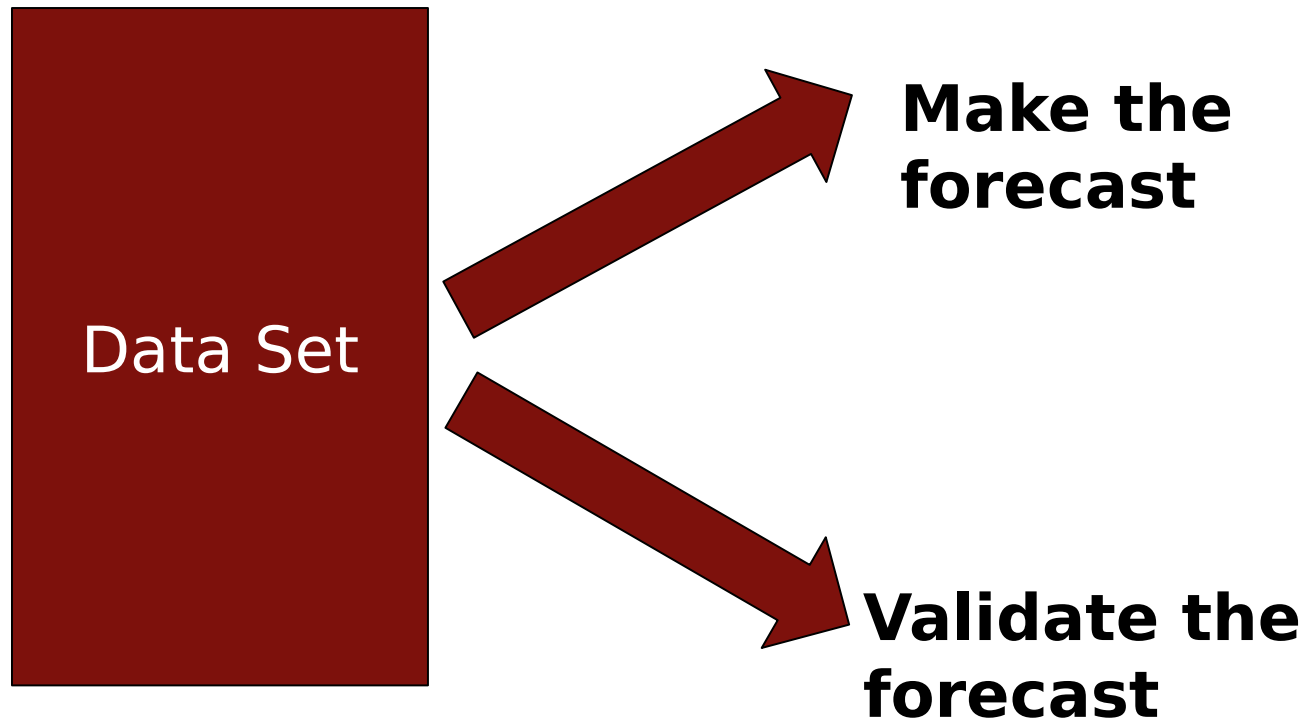
*Example MSE vs
MAD*

- Calculate the bias and tracking signal for each period t

Time	Demand	Forecast 1	Forecast 2
1	27	37	47
2	63	53	63
3	25	15	25
4	26	36	46

Validating a Forecasting Method

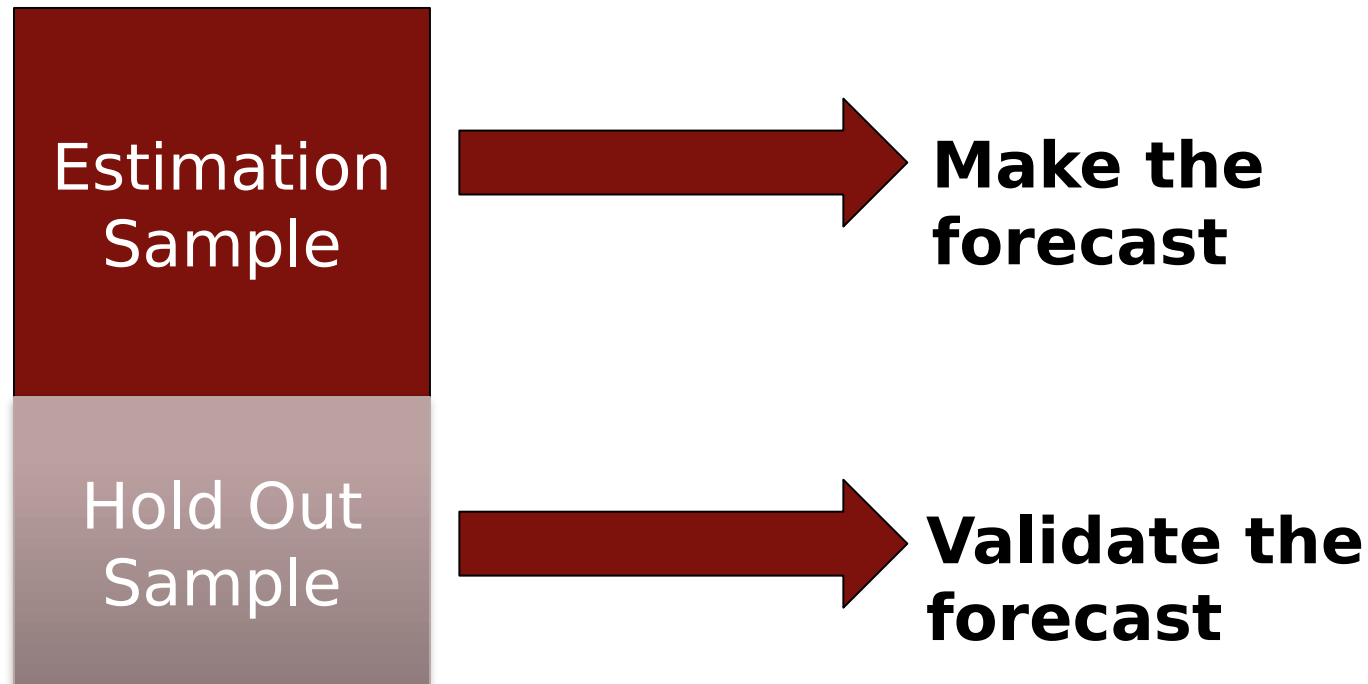
- Book's method:



Risk: overfitting, i.e., the forecast looks good because you are validating against the same data used to create it.

Validating a Forecasting Method

- Our preferred method: Hold-out sample



Benefit: model does not “see” the hold-out sample, so it cannot be overfitting.

Validating a Forecasting Method

- Book's method checks whether a forecast model is **descriptive**:
does the model fit well with the existing data?
- Hold out method checks whether a forecast model is **predictive**:
*can the model be used to predict (i.e., **forecast**) the future?*

Using a Hold Out Sample

- Use only first **part** of the data (training set) to construct the forecast.
- Use the last part of the data (hold out sample or validation set) to update and compute error terms. The part of the data we don't use to construct the forecast is "held out" for validation.
- How do we choose the size of the hold out sample?
 - When the estimation sample is larger,
 - When the hold out sample is larger,
- Rules of thumb:
 - Use **at least half** the data to estimate.
 - If the data has seasonality, make sure hold out sample has **at least one observation from each season.**

Using StatTools to validate a forecast

- Forecast tool:
 - Holdout size = number of **observations** you want to hold out.
 - StatTools calculates error separately for training set and hold out.
- **Note:** StatTools calculates
 - The MAD (called Mean Abs Err).
 - The *square root* of the MSE (called Root Mean Sq Err). You need to square this to get the MSE.
 - The MAPE (called Mean Abs Per% Err).
- StatTools also calculates the raw error for each forecast, so you can easily calculate Bias and TS.

Choosing the smoothing constant

- The smoothing constant(s) can be chosen to minimize MSE, MAPE, MAD.
 - In the absence of a preference, minimize MSE.
 - Rule of thumb: smoothing constants of >0.2 should only be used for a short period of time.
- In StatTools, choose “Optimize Parameters” to select smoothing constants that minimize MSE.
- **Note:** the forecast page in StatTools is “live”, so you can change the smoothing constants and watch it update.

Conclusions

- Many companies offer sophisticated forecasting software, often under the name “demand planning.”
- Things to be careful about:
 - Apply human intelligence.
 - Collaborate with supply chain partners.
 - Garbage in, garbage out.
 - Distinguish between sales versus demand.