Data Analytics in Business

Operations Management

Bob Myers

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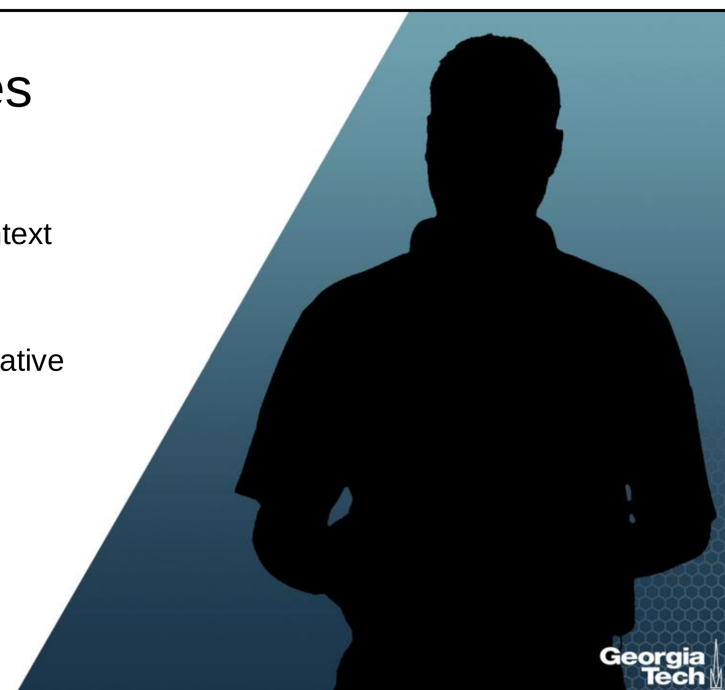
Forecasting

Learning Objectives

At the end of this lesson, you should be able to:

- Discuss forecasting in the context of operations management
- Discuss patterns of demand
- Identify qualitative and quantitative forecasting methods



What is Forecasting?

Forecasting – **prediction of future events used for planning purposes**

Used for:

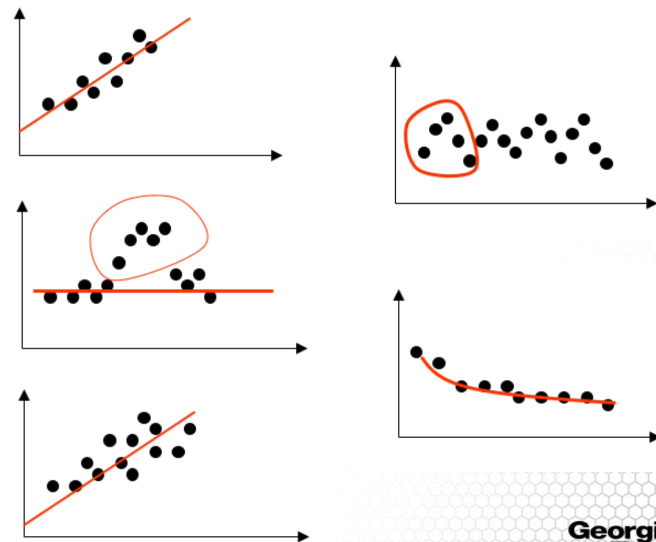
- Strategic planning (long term capacity decisions)
- Finance and Accounting (budgeting and cost control)
- Marketing (future sales trends and new product introduction)
- Production and Operations (staffing and supplier relations)

General Characteristics of Forecasts

- Forecasts are almost always wrong!
- Forecasts are more accurate from groups or families of items
- Forecasts are more accurate for shorter periods of time
- Every forecast should include an error estimate
- Forecasts are no substitute for actual demand

Patterns of Demand

- Trends
- Seasonality
- Cyclical elements
- Autocorrelation
- Random variation



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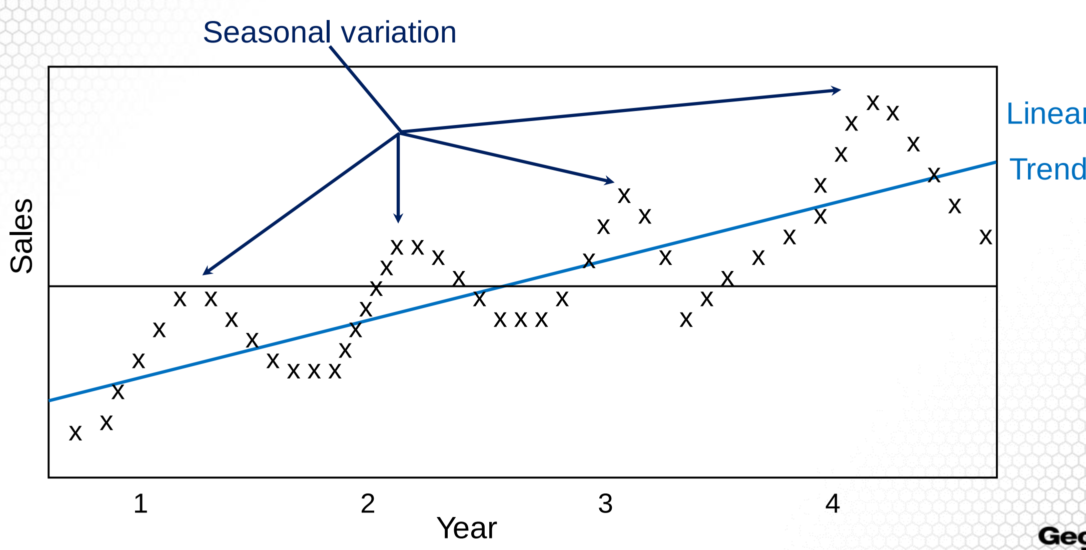
Data can Exhibit Multiple Patterns



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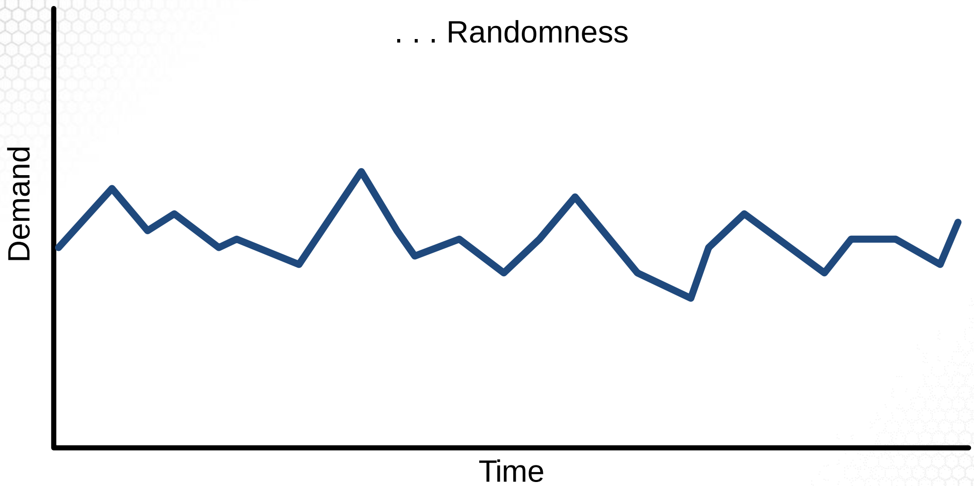
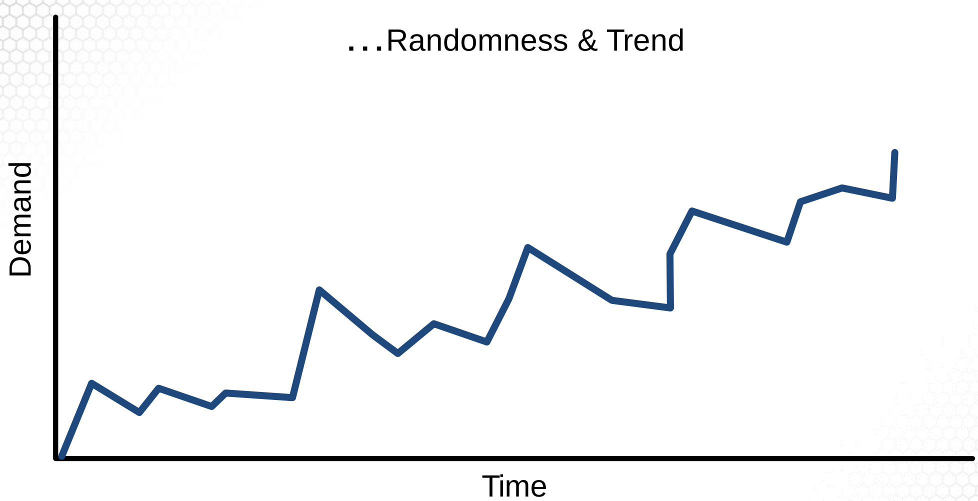
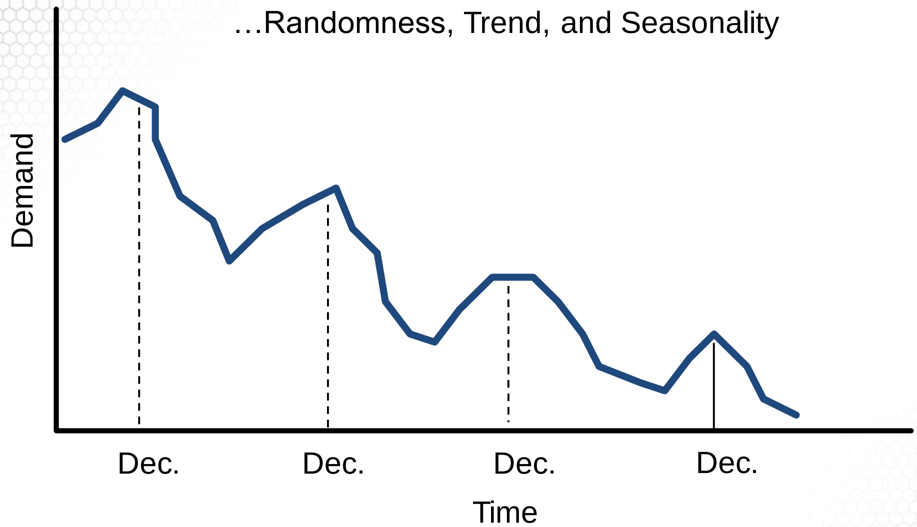
Time Series Components of Demand



Time Series with…



Time Series with…



Some Important Questions

- What is the purpose of the forecast?
- Which systems will use the forecast?
- How important is the past in predicting the future?

Answers will help determine the time horizons, techniques, and level of detail in the forecast

Type of Forecasting Methods

Qualitative

- Rely on subjective opinions from one or more experts

Quantitative

- Relay on data and analytical techniques

Quantitative Forecasting Methods

Time Series: models that predict future demand based on past history trends

Casual Relationships: models that use statistical techniques to establish relationships between various items and demand (Ex: Linear Regression)

Simulation: models that can incorporate some randomness and non-linear effects

Summary

1. Forecasting is trying to predict future events for planning purposes.
2. In Operations Management forecasting Demand is key.
3. Demand can exhibit multiple patterns
4. We will focus on Time Series techniques

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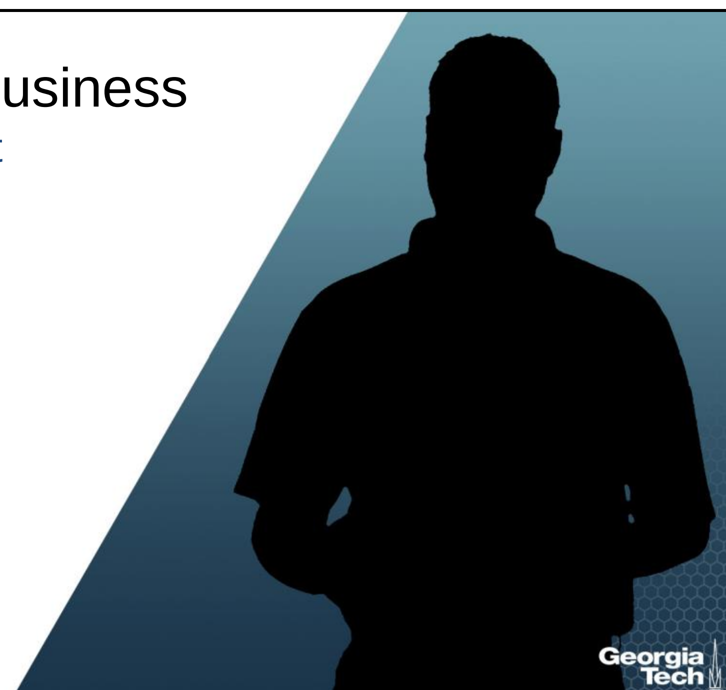
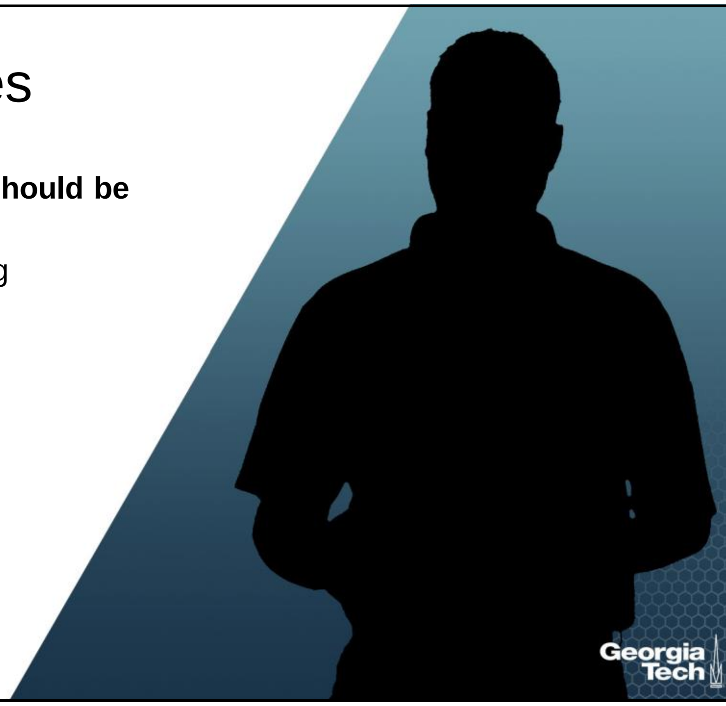
Exponential Smoothing



Learning Objectives

At the end of this lesson, you should be able to:

- Explain exponential smoothing



Time Series: Exponential Smoothing

The Prediction of the future depends mostly on the most recent observation and on the error for the latest forecast

Smoothing constant alpha α → Denotes the importance of the past error

Why Exponential Smoothing?

- Uses less storage space for data
  (although not a problem these days)
- Extremely accurate
- Easy to understand
- Little calculation complexity

Exponential Smoothing (ES)

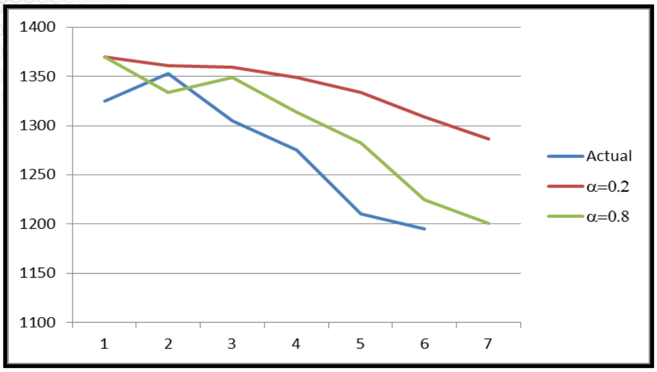
Assume that we are currently in period t. We calculated the forecast for the last period (Ft-1) and we know the actual demand last period (A_{t-1}):

$$F_{t+1} = F_t + \propto (A_{t-1} - F_{t-1})$$
$$where\ 0 \leq \propto \geq 1$$

The smoothing constant a expresses how much our forecast will react to observed differences:

- If α is **low,** there is little reaction to difference
- If α is **high,** there is a lot of reaction to differences

Plotting Exponential Smoothing Forecasts



Small α– Stable

Large α - Responsive

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Example

Week	Demand	Forecast
1	820	820
2	775	820
3	680	811
4	655	785
5	750	759
6	802	757
7	798	766
8	689	772
9	775	756
10		760

$F_2 = F_1 + \alpha(A_1 - F_1)$ =820 + 0.2(820-820)

$F_4 = F_3 + \alpha(A_3 - F_3)$ =811+ 0.2(680-811)

$F_6 = F_5 + \alpha(A_5 - F_5)$ =759+ 0.2(750-759)

$F_8 = F_7 + \alpha(A_7 - F_7)$ =766+ 0.2(798-766)

$F_{10} = F_9 + \alpha(A_9 - F_9)$ =756+ 0.2(775-756)

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How do you get started?

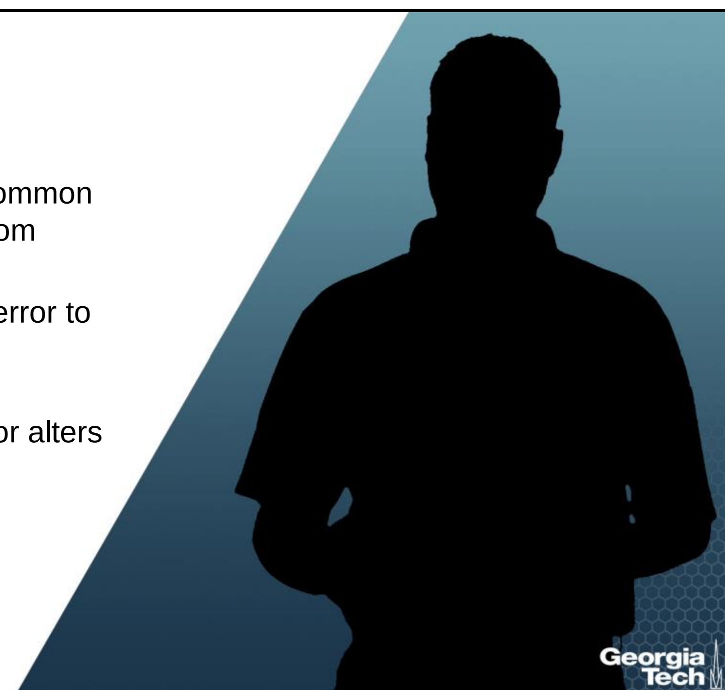
Week	Demand	Forecast
1	820	820
2	775	820
3	680	811
4	655	785
5	750	759
6	802	757
7	798	766
8	689	772
9	775	756
10		760

You must pick an initial forecast.

- Can set it equal to demand
- Can use another methods solution
- Note the initial forecast is not calculated from the exponential smoothing formula. Don't use it in evaluating the method

Summary

1. Exponential Smoothing is a common method used to forecast random behavior in demand.
2. It uses the prior forecast and error to predict the next period.
3. The smoothing constant α determines how much the error alters the next prediction (forecast).



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Exponential Smoothing with a Trend

Learning Objectives

At the end of this lesson, you should be able to:

- Explain exponential smoothing with a trend adjustment

Recall: Exponential Smoothing (ES)

Assume that we are currently in period t. We calculated the forecast for the last period (Ft-1) and we know the actual demand last period (A_{t-1}):

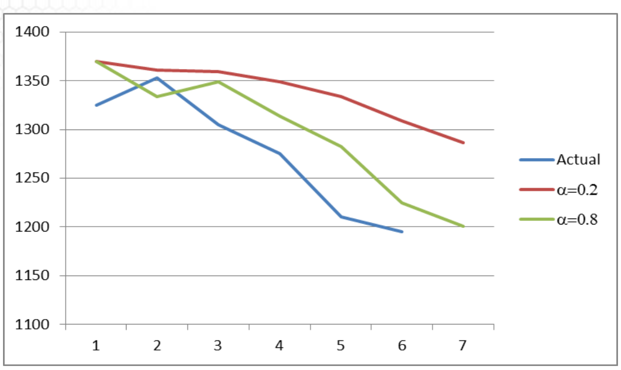
$$F_{t+1} = F_t + \propto (A_{t-1} - F_{t-1})$$
$$where\ 0 \leq \propto \geq 1$$

The smoothing constant α expresses how much our forecast will react to observed differences:

- If a is **low,** there is little reaction to difference
- If a is **high,** there is a lot of reaction to differences

What Happens if Demand is Trending?

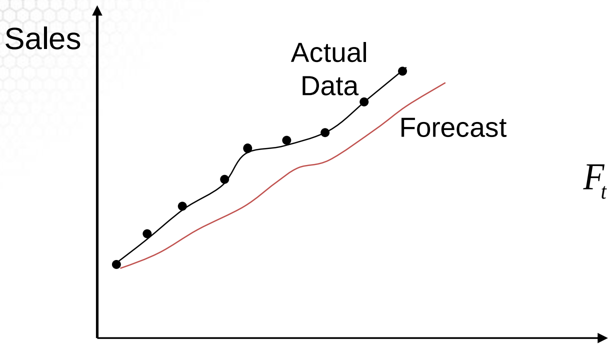
What do you think will happen to the exponential smoothing model when there is a trend in the data?



ES will lag behind trends

Exponential Smoothing With a Trend?

- How can we account for a trend in the data?



$$F_t = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$$

Forecast Including Trend

$$FIT_t = F_t + T_t$$

$$F_t = FIT_{t-1} + \alpha(A_{t-1} - FIT_{t-1})$$

$$T_t = T_{t-1} + \delta(F_t - FIT_{t-1})$$

FIT - Forecast Including Trend

δ - trend smoothing constant

The idea is that the two effects are decoupled,

(*F* is the forecast without trend and *T* is the trend component)

Example: Kroger Canned Soup Sales

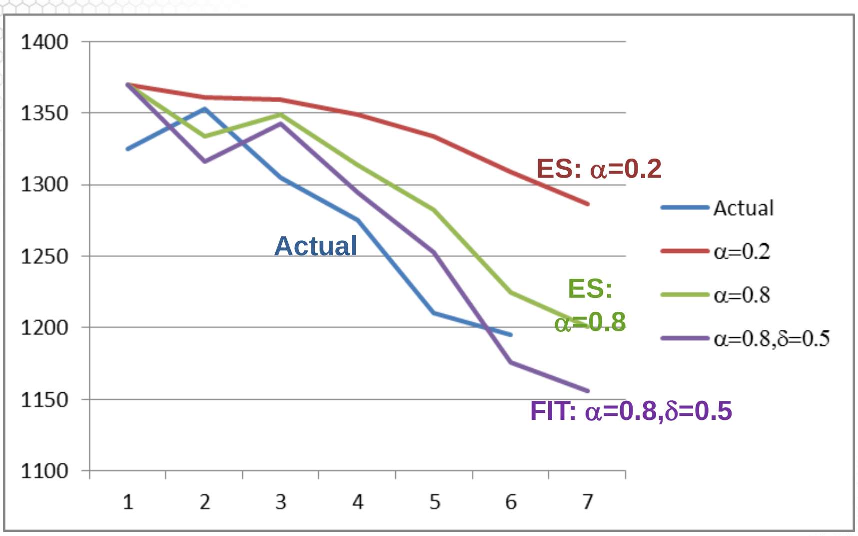
$$F_t = FIT_{t-1} + \alpha(A_{t-1} - FIT_{t-1}) \qquad T_t = T_{t-1} + \delta(F_t - FIT_{t-1})$$

Month	Actual	Forecast	Trend	FIT
Jan	1325	1370	0	1370
Feb	1353	1334	-18.0	1316
Mar	1305	1346	-3.2	1342
Apr	1275	1312	-18.2	1294
May	1210	1279	-25.9	1253
Jun	1195	1219	-43.1	1176
Jul	?	1191	-35.3	1156

$$FIT_t = F_t + T_t$$

α = 0.8, δ = 0.5

Plotting ES with and without a Trend



More on ES with and without a Trend…

- ES and FIT models require initial estimates for forecast and trend (can use prior period as baseline to start)
- Values for α and δ are found by trial and error (or using a solver to optimize).
- If initial estimates are grossly incorrect, it may take a while for the model to stabilize (higher α and δ increase convergence speed if initial estimates incorrect, but may tend to “overreact” to the noise in the data)
- ES and FIT only use the prior period’s data for estimation of the current period’s demand; this makes calculation and storage of data easy

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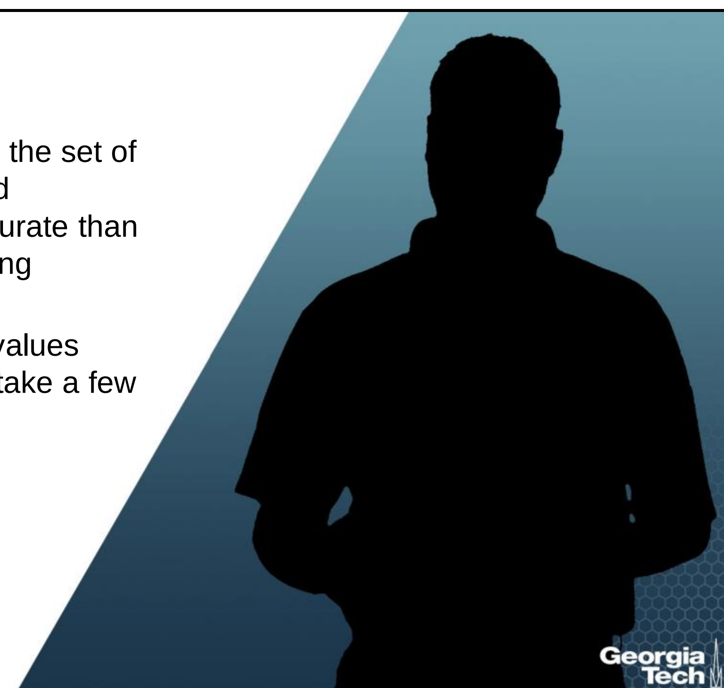
Summary

1. To account for a trend in data, the set of three Forecast Including Trend equations are much more accurate than a simple Exponential Smoothing equation.
2. The initial trend and forecast values used can cause the model to take a few periods to stabilize.



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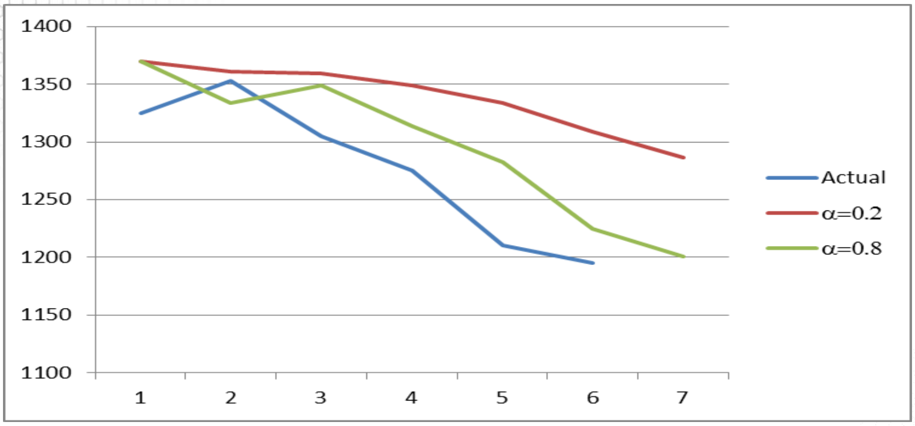
Exponential Smoothing with Seasonality

Learning Objectives

At the end of this lesson, you should be able to:

- Explain how to model seasonality with Exponential Smoothing

Plotting Exponential Smoothing Forecasts



Small α – Stable

Large α - Responsive

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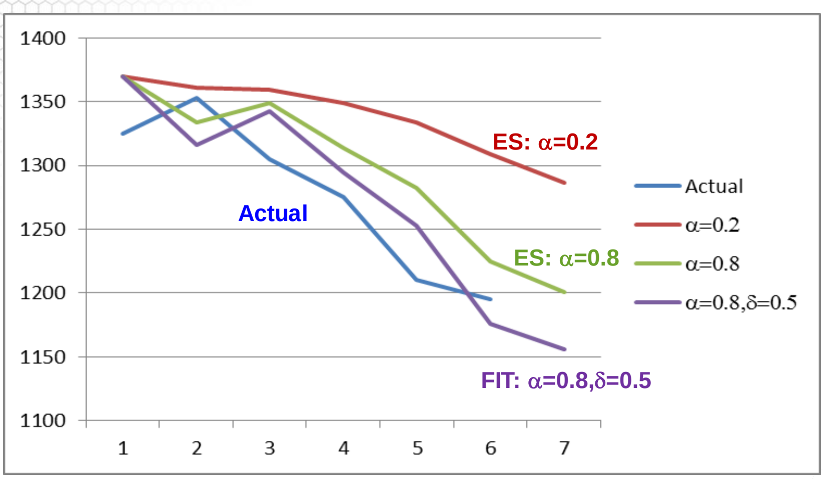
Plotting the FIT ES Forecasts



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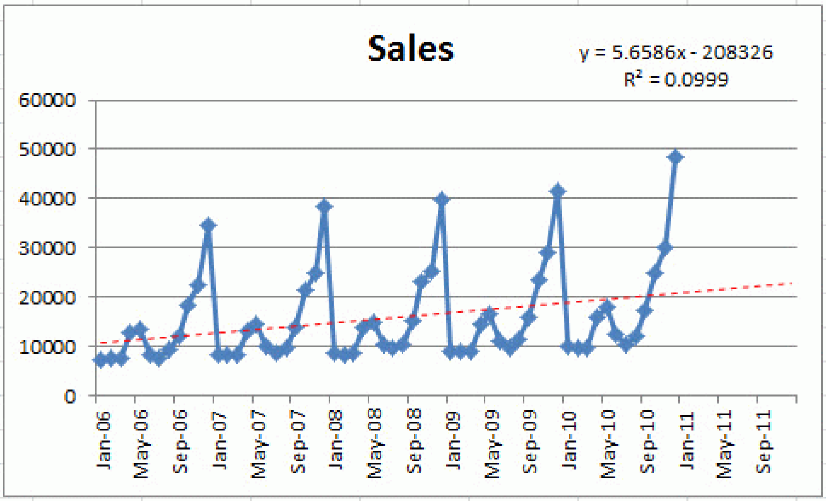
What If My Data Has Seasonality?



Seasonality Calculation

- Measures the seasonal variation in demand
- Relates the average demand in a particular period to the average demand for all periods

$$\textbf{The Seasonal Index} = \frac{\textbf{period average demand}}{\textbf{average demand for all periods}}$$

Calculation of Seasonal Index

Monthly Sales of Ice Cream

January	10		July	600
February	10		August	700
March	10		September	350
April	50		October	100
May	150		November	10
June	400		December	10

Total annual sales 2400 cases

Average monthly sales 200 cases

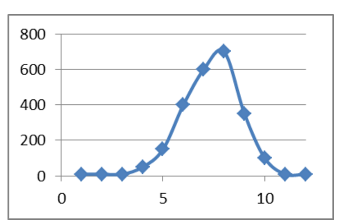
June's sales are 400 cases

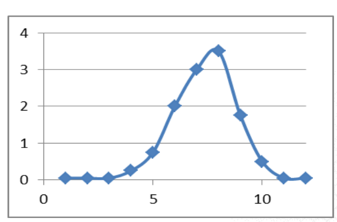
Seasonal Index for June = month's sales/avg sales = 400/200 = 2.0

Calculation of Seasonal Index

Monthly Sales of Ice Cream

		SI (calc.)	SI
Jan	10	= 10 / 200	
Feb	10	= 10 / 200	
Mar	10	= 10 / 200	
Apr	50	= 50 / 200	
May	150	= 150 / 200	
Jun	400	= 400 / 200	
Jul	600	= 600 / 200	3
Aug	700	= 700 / 200	3.5
Sep	350	= 350 / 200	1.75
Oct	100	= 100 / 200	0.5
Nov	10	= 10 / 200	0.05
Dec	10	= 10 / 200	0.05
TOTAL	2400		
AVERAGE	200		





Seasonal Series Indexing Sample Data

Month	Year 1	Year 2	Year 3	Total	Seasonal Index
Jan	10	12	11		
Feb	13	13	11		
Mar	33	38	29	100	
Apr	45	54	47	146	1.46
May	53	56	55	164	1.64
Jun	57	56	55	168	1.68
Jul	33	27	34	94	0.94
Aug	20	18	19	57	0.57
Sep	19	22	20	61	0.61
Oct	18	18	15	51	0.51
Nov	46	50	55	141	1.41
Dec	48	53	47	148	1.48
Total	395	417	388	1200	12.00

$$(SI) = \frac{\text{Monthly Total (MT)}}{\text{Average Month (AM)}}$$

Where:

$$AM = \frac{1200}{12} = 100$$

$$SI_{JAN} = \frac{33}{100} = .33$$

Calculate ES with Seasonal Forecast

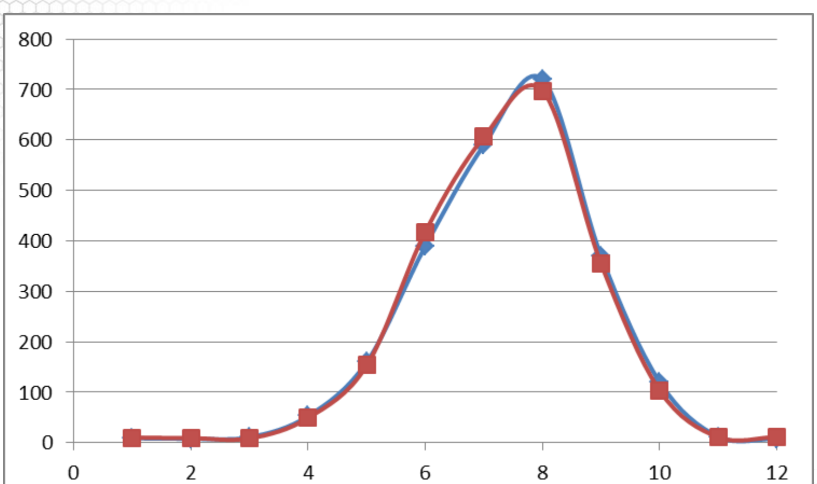
1. Inputs: Realized seasonal demand in the previous period ($\sim A_t$), seasonal forecast for the previous period ($\sim F_t$), and smoothing constant α
2. De-seasonalize demand and forecasts to obtain A_t and F_t
   - $A_t = \sim A_t / SI_t$ and $F_t = \sim F_t / SI_t$
3. Use the exponential smoothing formula to obtain the de-seasonalized forecast F_{t+1}
   - $F_{t+1} = \alpha A_t + (1 - \alpha) F_t$
4. Re-seasonalize the forecast to obtain $\sim F_{t+1.}$
   - $\sim F_{t+1} = F_{t+1} \times SI_{t+1}$

Example: ES with Seasonality

		$\alpha = 0.5$			
				De-Seasonalized	De-Seasonalized
	Actual	Forecast	SI	Actual	Forecast
Jan	9	10	0.05		
Feb			0.05		
Mar			0.05		
Apr			0.25		
May			0.75		
Jun			2	195.0	209.0
Jul	590	606.1	3	196.7	202.0
Aug	720	697.7	3.5	205.7	199.3
Sep	370	354.4	1.75	211.4	202.5
Oct	120	103.5	0.5	240.0	207.0
Nov	12	11.2	0.05	240.0	223.5
Dec	8	11.6	0.05	160.0	231.7

1. De-seasonalize Actual and Forecast at time t (demand / SI)
2. Apply ES calculation: $F_{t+1} = F_t + a (A_t – F_t)$
3. Re-seasonalize Forecast for t+1 (F_{t+1} x SI)

Example: ES With Seasonality



Summary

1. This method can capture more than one seasonal pattern.
2. This method can be combined with FIT to capture demand that has random behavior with a trend and seasonality.

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Error Methods

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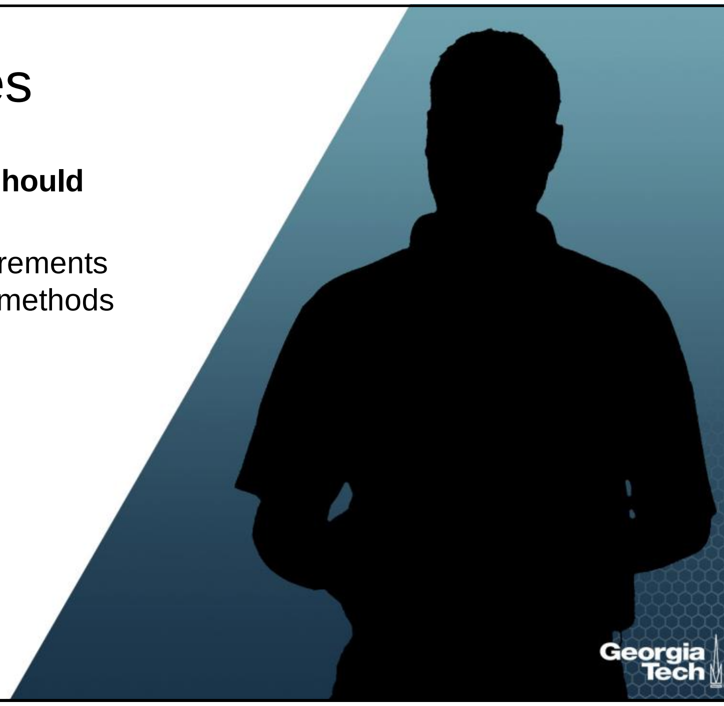
Learning Objectives



At the end of this lesson, you should be able to:

- Discuss different Error measurements used to evaluate Forecasting methods

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How can we Compare Different Models?

We need a metric that provides estimation of accuracy

Forecast error = the difference between the actual and forecasted value (also known as residual)

Errors can be:

1. Biased (consistent)
2. Random

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Measures of Forecast Accuracy

Error = Actual demand - Forecast

or

$$e_t = A_t - F_t$$

- e_t can be positive of negative
- Positive e_t means that the forecast was too low
- Negative e_t means that the forecast was too high

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Measures of Forecast Error

RSFE – Running Sum of Forecast Error

$$\text{RSFE}=\sum (A_i - F_i) = \sum e_i$$

MFE – Mean Forecast Error (Bias)

$$\text{MFE}= \frac{\sum (A_i - F_i)}{n} = \frac{\text{RSFE}}{n}$$

MAD – Mean Absolute Deviation

$$\text{MAD} = \frac{\sum |A_i - F_i|}{n}$$

TS – Tracking Signal

$$\text{TS} = \frac{\text{RSFE}}{\text{MAD}}$$

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Measuring Accuracy: MFE

- MFE = Mean Forecast Error; also called Bias
  - Average error in the observation

$$\text{MFE} = \frac{\sum_{i=1}^{n}(A_t - F_t)}{n} = \frac{\sum_{i=1}^{n} e_t}{n} = \frac{RSFE}{n}$$

  - A more positive or negative MFE implies worse performance, the forecast on average is biased from the actual demand

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Measuring Accuracy: MAD

- MAD = Mean Absolute Deviation
  - Average absolute error in the observation

$$\text{MAD} = \frac{\sum_{i=1}^{n}|A_t - F_t|}{n} = \frac{\sum_{i=1}^{n}|e_t|}{n}$$

  - Higher MAD implies worse performance

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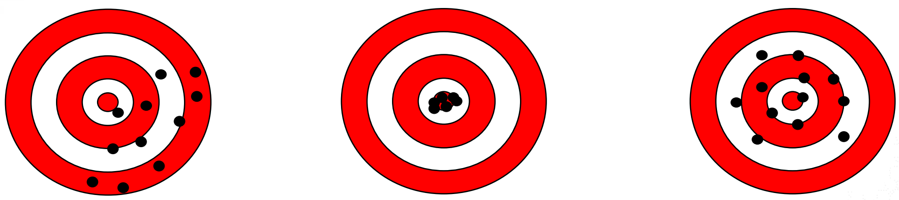
Dartboard Analogy to MFE and MAD

- MFE is a measure of the overall average accuracy of the forecast (lower MFE is better)
- MAD is a measure of the overall variability of the error terms (lower MAD is better)



Large MFE
Large MAD

Small MFE
Small MAD

Small MFE
Large MAD

MFE and MAD (by the numbers)

RSFE =

Bias = MFE =

Mean Absolute Deviation (MAD) =

PD	F = Forecast	A= Actual Sales	E= Error (Sales Forecast)	Absolute Error
1	1,000	1,200		
2	1,000	1,000		
3	1,000	800		
4	1,000	900		
5	1,000	1,400	400	400
6	1,000	1,200	200	200
7	1,000	1,100	100	100
8	1,000	700	-300	300
9	1,000	1,000	0	0
10	1,000	900	-100	100
	10,000	10,200		

Measuring Accuracy: Tracking Signal

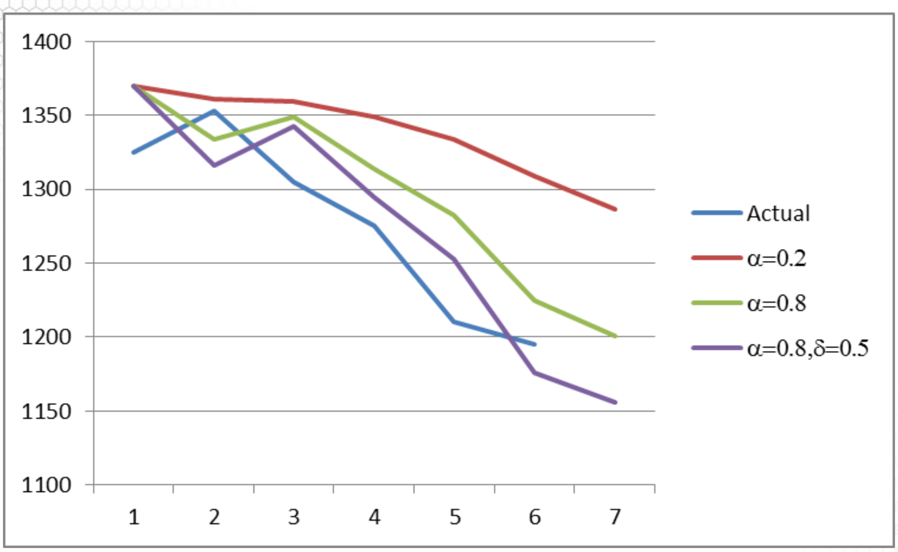
TS = Tracking Signal

- Measure of how often our estimations have been above or below the actual value. It is used to decide when to re-evaluate the model

$$TS = \frac{RSFE}{MAD}$$

- Positive tracking signal – most of the time, the actual values are above the forecasted values
- Negative tracking signal – most of the time, the actual values are below the forecasted values
- If TS **<** -4 or TS **>** 4, ***investigate!*** (|TS| **>**4)

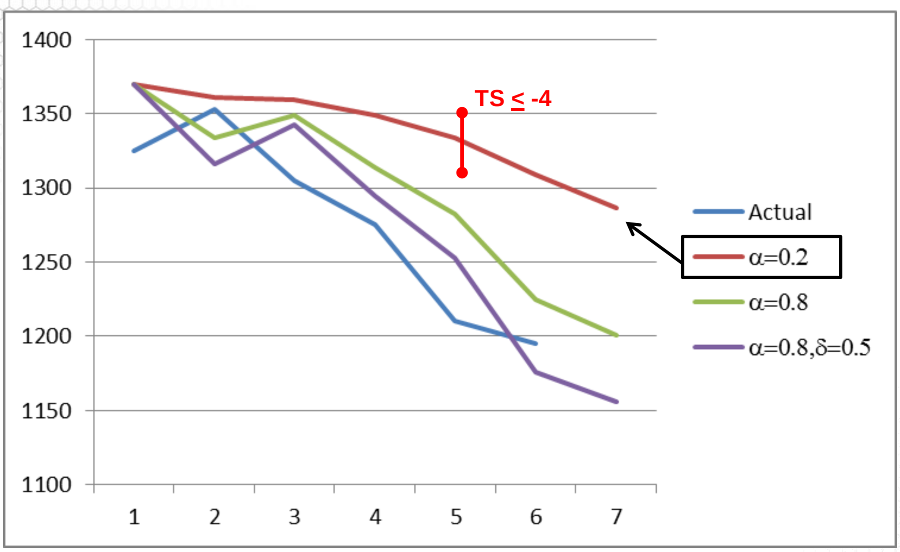
Let's Compare Accuracy Measures



MAD and TS for ES with α = 0.2

Month	Actual	ES: α=0.2	error	RSFE	MFE	Abs error	MAD	TS
Jan	1325	1370						
Feb	1353	1361						
Mar	1305	1359						
Apr	1275	1349						
May	1210	1334						
Jun	1195	1309						

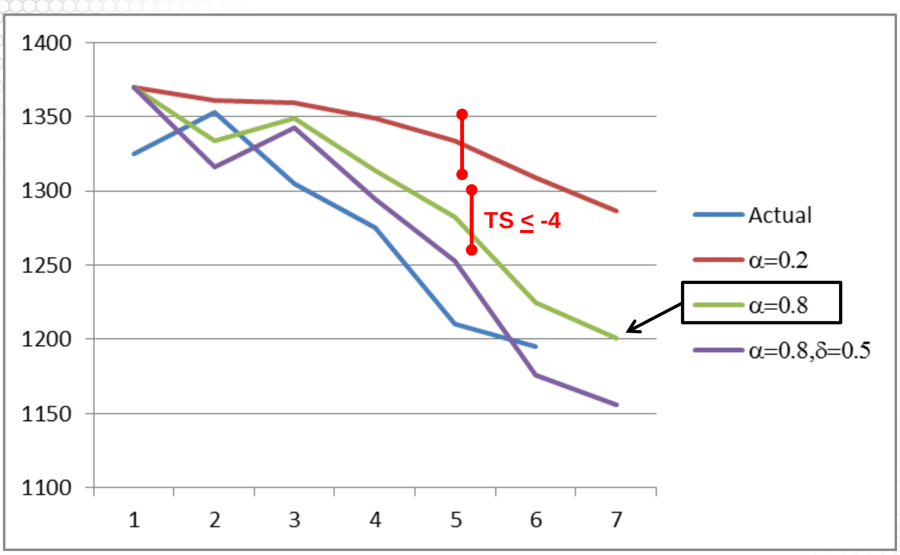
Compare Accuracy Measures



MAD and TS for ES with α = 0.8

Month	Actual	ES: α=0.8	error	RSFE	MFE	Abs error	MAD	TS
Jan	1325	1370						
Feb	1353	1334						
Mar	1305	1349						
Apr	1275	1314						
May	1210	1283						
Jun	1195	1225						

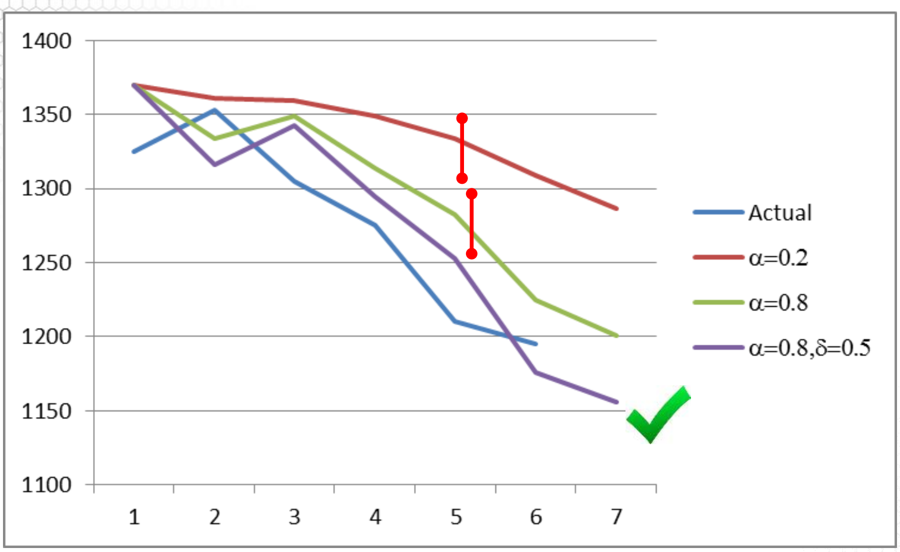
Let’s Compare Accuracy Measures



MAD and TS for FIT with α = 0.8 and δ = 0.5

Month	Actual	FIT: a=0.8,d=0.5	error	RSFE	MFE	Abs error	MAD	TS
Jan	1325	1370						
Feb	1353	1316						
Mar	1305	1342						
Apr	1275	1294						
May	1210	1253						
Jun	1195	1176						

Let's Compare Accuracy Measures



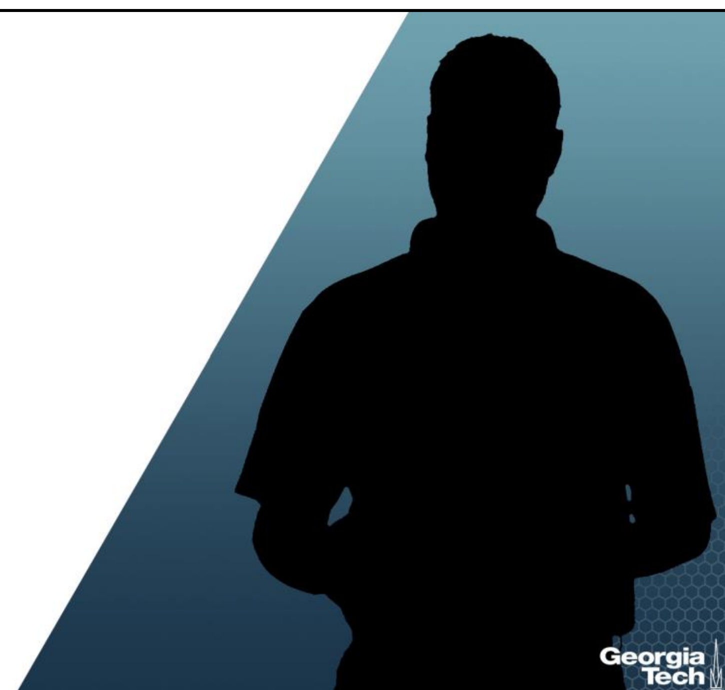
Comparing the Models

	MFE	MAD	TS
ES: a=0.2	-69.8	69.8	-6.0
ES: a=0.8	-35.3	41.7	-5.1
FIT: a=0.8,d=0.5	-14.7	33.3	-2.6

- The tracking signals for both ES models are below -4, thus indicating that these models are not fitting the data well
- The FIT model yields the smallest MFE, MAD, and TS; this is the only model with an acceptable tracking signal

Summary

1. Error measurements are needed to evaluate different forecast models
2. The tracking signal is useful to alert us to changes in patterns of demand



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Forecasting Recap

Learning Objectives

- Discuss and recap lessons from this week
- Assess tie back to analytics

Which Forecasting Method Should You Use

- Gather historical data of what you want to forecast
- Divide the data into initiation and evaluation sets
- Use the first data set to develop the models
- Use the second data set to evaluate the models
- Compare the MADs and MFEs of each model, keeping an eye on the tracking signals
- Incorporate seasonality and trending aspects into the model if the data displays those characteristics

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Recap

- Forecasting is based on the assumption that the past predicts the future.
- Components of demand include the average, trends, seasonal elements, cyclical elements, random variation, and autocorrelation.
- Qualitative forecasting is used when hard data is unavailable.
- Exponential Smoothing uses the most recent data and forecast error.
- Forecast Including Trend (FIT) extends Exponential Smoothing to applications with a clear trend.
- Seasonality can be incorporated into forecasting models

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Recap

- Forecast error is the difference between the actual and forecasted values
- Mean Forecast Error (Bias) is as measure of the overall average of the forecast to actual demand
- Mean Absolute Deviation is a measure of variation in the error between the forecast and actual demand
- Tracking Signals tell whether a forecast is above or below actual and by how much

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