SESSION 1

Forecasting (1)

"I know of no way of judging the future but by the past"
Patrick Henry

"Prediction is very difficult, especially if it is about the future"
Niels Bohr

Agenda

- Forecasting - background
  - What is a forecast? Why should we forecast?
- Forecasting methods
  - Qualitative versus quantitative
  - Time series quantitative methods
- Measuring how good a forecast is

Forecasting at Walt Disney World

What needs to be forecasted?

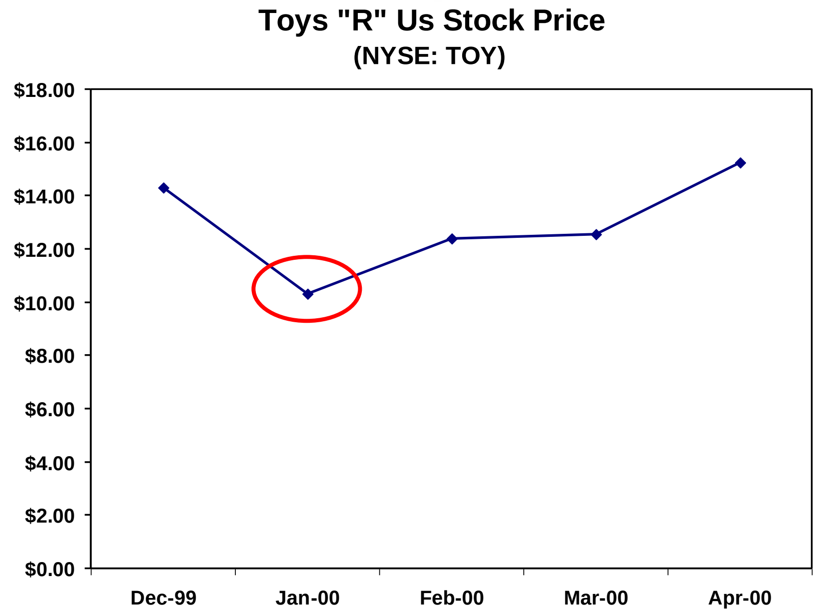
What decisions are made based on the forecasts?

Why Do We Care?

Toys “R” Us – Christmas 1999

- Could not make scheduled deliveries of its online orders before Christmas

- Example of BAD
  - Forecasting
  - Inventory planning
  - Capacity planning



Why Do We Care?

"..Apple said Monday that it sold 9 million of the two handsets [iPhone 5S and iPhone 5C] in the first three days on the market—well above what analysts had anticipated…Apple's record volume for the new iPhones compared with 5 million iPhone 5 models sold on its opening weekend a year ago. Analysts had predicted that 6 million to 7 million of this year's models would be sold in the debut weekend…Apple didn't break down its sales other than to say that demand for the iPhone 5S exceeded supply…Assessing demand for the phones is particularly difficult because more countries are involved this year:11, compared with 9 for the iPhone 5 release last year. And China, in particular, is a huge smartphone market" (Don Clark, WSJ Sept. 23, 2013)

Why Do We Care?

"Blackberry posted a $965 million quarterly loss Friday and left many questions unanswered about the smartphone maker's future…the embattled smartphone maker warned it would report a hefty operating loss, mostly due to a nearly $1 billion charge on inventory of unsold phones, and said it would lay off 4,500 employees" (Will Connors, WSJ Sept. 27, 2013)

"The new version of the 5 Series is the second vehicle launch by BMW India in as many months. It introduced the 1 Series premium hatchback in early September. The 5 Series would be assembled at BMW's factory near Chennai city where capacity is being expanded to 14,000 cars a year by the end of 2013 from 11,000 now" (Santanu Choudhury, WSJ Oct. 10, 2013)

Poor Forecasting Costs Money

- Blackberry posted a $965 million quarterly loss Friday …, mostly due to a nearly $1 billion charge on inventory of unsold phones, and said it would lay off 4,500 employees" (Will Connors, WSJ Sept. 27, 2013)
- Liz Claiborne said… earnings decline is consequence of [unanticipated] excess inventories. *WSJ 2/6/2002*
- …Ford's Big Batch Of Rare Metal [palladium] Led To $1 Billion Write-Off. *WSJ 2/6/2002*
- In June 2008, due to an industry-wide capacity constraint for compact and hybrid cars, GM estimated vehicle *shortages* cost the auto industry 40,000 sales. *WSJ 7/2/2008*

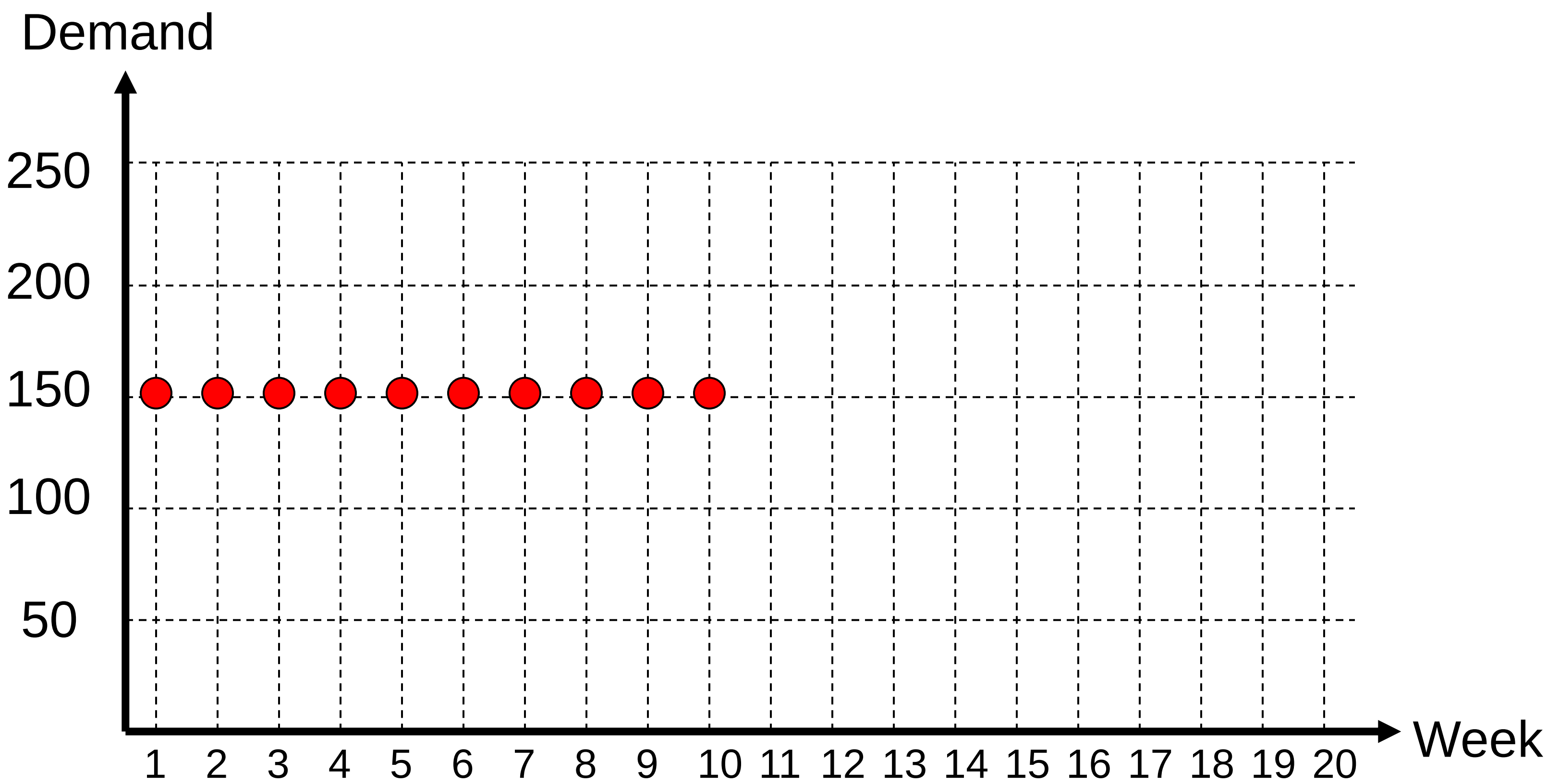
Qualitative versus Quantitative Forecasting

	Qualitative	Quantitative
Characteristic	▪ Subjective – Based on people's opinions	• Objective – Based on numeric data and equations
Strength	• Can incorporate expertise that is hard to codify	• Consistency • Can consider large amounts of data
Weakness	• Opinions can dominate/and or bias the forecast	• Must have data

Time Series Forecasts

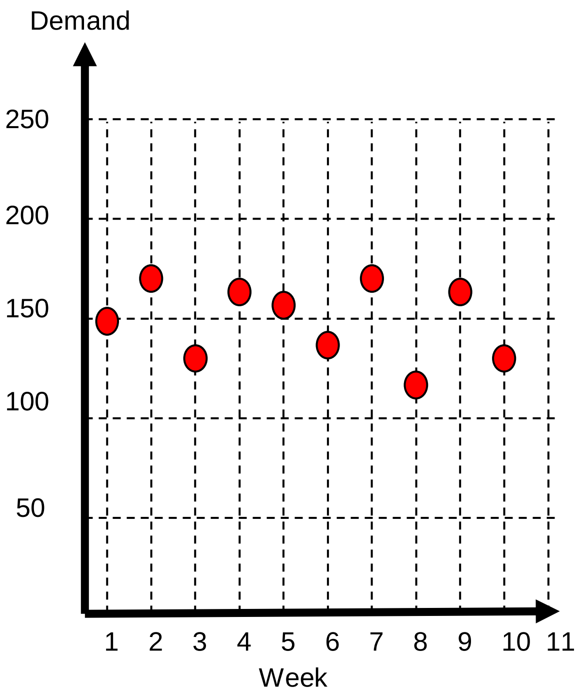
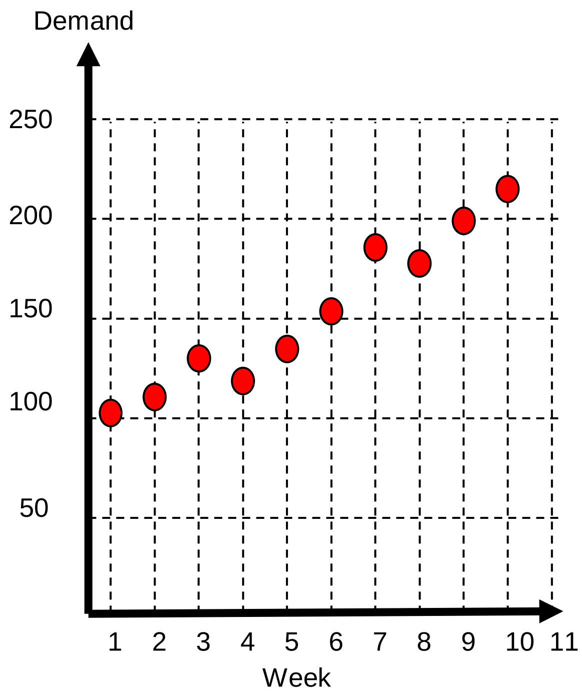
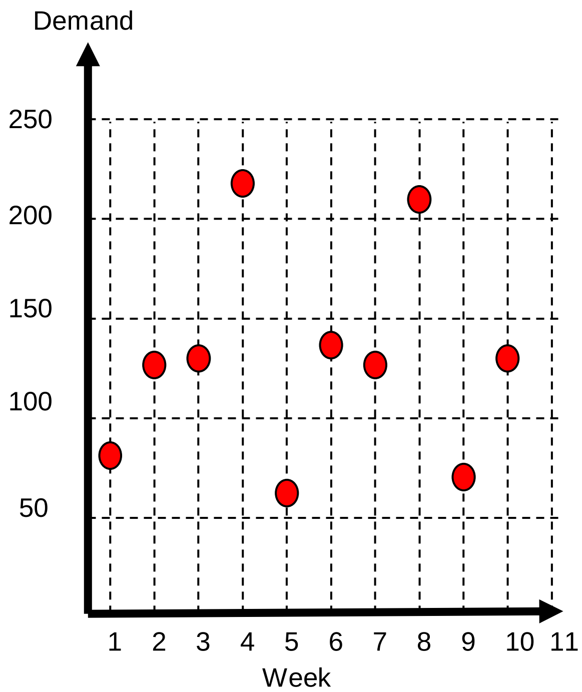
- Assumption: Past history is best predictor of the future
- Forecast based on the time series (previously observed values) of the variable to be forecasted

Forecasting Demand



What Would Be Your Forecast of Demand in Week 11 ?

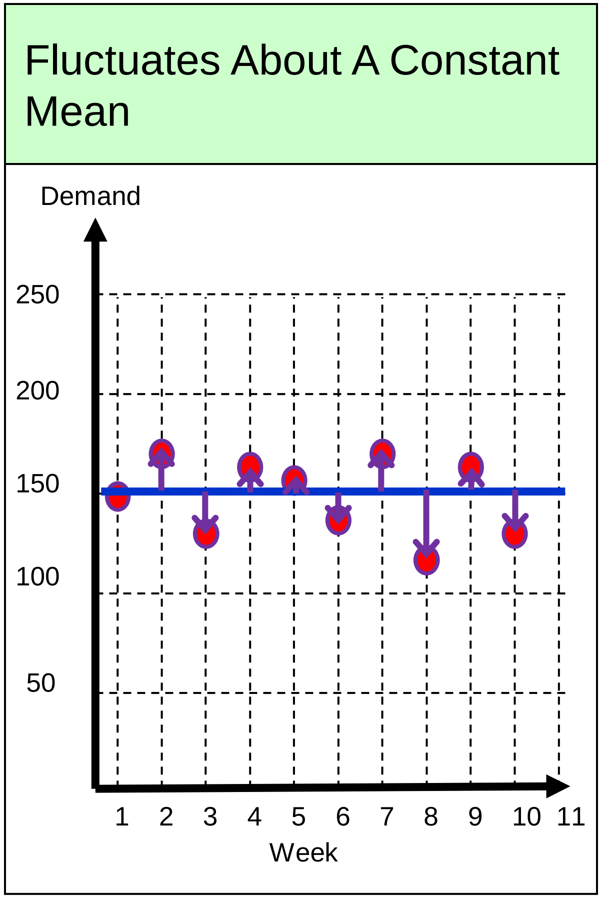
Previous Example Was Unrealistic
Demand is Almost Never Constant

1. Fluctuates About A Constant Mean	2. Fluctuates And Has Increasing (or Decreasing) Trend	3. Fluctuates And Has “Seasonal” Pattern
		

Notations

- Demand observed in period t
  - A_t
- Forecast (<u>made in period t</u>) of demand for period t+1, i.e. forecast of next period's demand
  - F_{t+1}

Today We Will Focus on Type 1 Fluctuates About a Constant Mean: Basic Time Series



Demand = Mean + Random Fluctuation

Notes:

(1) Fluctuation Can be Positive or Negative

(2) Average Fluctuation = 0

Forecast = Current Estimate of the Mean

The Challenge is to Estimate the Mean level of Demand

Motivational Example
Forecasting Demand for Polio Vaccines

- You have just joined a pediatric hospital as head of operations. You need to order polio vaccines monthly starting with February. You know that January demand was 130.

Month	t	Demand for Vaccine
January	1	130
February	2	
March	3	
April	4	
May	5	
June	6	
July	7	

Method 1: The Naïve Method, $F_{t+1}=A_t$
Simplest Approach to Forecasting

Forecast of Demand in Period 2

(This forecast made after seeing Demand in Period 1)

Forecast of Demand in Period 5

(This forecast made after seeing Demand in Period 4)

Period	Demand	Forecast
1	130	-
2	155	130
3	145	155
4	160	145
5	151	160
6	143	151
7		143

Method 2: The Simple Average, $F_{t+1}=(A_1+ A_2+ A_3+\ldots A_t)/t$

Period	Demand	Forecast	
1	130	-	
2	155	130.00	130/1 =130
3	145	142.50	(130+155)/2 =142.50
4	160	143.33	(130+155+145)/3 = 143.33
5	151	147.50	(130+155+145+160)/4 = 147.5
6	143	148.20	(130+155+145+160+151)/5 = 148.2
7		147.33	(130+155+145+160+151+143) / 6 = 147.33

Forecast of Demand in Period 2

(This forecast made after seeing Demand in Period 1)

Forecast of Demand in Period 5

(This forecast made after seeing Demand in Period 4)

The Moving Average Forecast
"The recent history is more relevant"

- The Simple Average forecast uses ALL THE HISTORY of demands to generate the forecast for the next period

- The (Simple) Moving Average forecast (order n) uses ONLY THE n MOST RECENT period demands to generate the forecast for the next period

Method 3: The Moving Average Forecast

$F_{t+1}=(A_{t-n+1}+\ldots A_{t-2}+A_{t-1}+A_t)/n$

Using n=3

Period	Demand	Forecast	
1	130	-	
2	155	-	Not enough history
3	145	-	Not enough history
4	160	143.33	(130+155+145)/3 = 143.33
5	151	153.33	(155+145+160)/3 = 153.33
6	143	152.00	(145+160+151)/3 = 152.00
7		151.33	(160+151+143) /3 = 151.33

Forecast of Demand in Period 2

(This forecast made after seeing Demand in Period 1)

Forecast of Demand in Period 5

(This forecast made after seeing Demand in Period 4)

The Weighted Moving Average Forecast

- The (simple) Moving Average forecast (order n) treats each of the n most recent demands EQUALLY in generating the forecast for the next period

- The Weighted Moving Average forecast (order n) weights each of the n most recent demands (possibly) DIFFERENTLY in generating the forecast for the next period

Method 4: Weighted Moving Average Forecast

$$F_{t+1}= w_{t-n+1}\ A_{t-n+1}+\ldots\ w_{t-2}\ A_{t-2}+ w_{t-1}\ A_{t-1}+w_tA_t$$

n=3:

w_t=0.5, w_{t-1}=0.3, w_{t-2}=0.2

Period	Demand	Forecast	
1	130	-	
2	155	-	Not enough history
3	145	-	Not enough history
4	160	145.00	0.2(130)+0.3(155)+0.5(145) = 145.00
5	151	154.50	0.2(155)+0.3(145)+0.5(160) = 154.50
6	143	152.50	0.2(145)+0.3(160)+0.5(151) = 152.50
7		148.80	0.2(160)+0.3(151)+0.5(143) = 148.80

Forecast of Demand in Period 2

(This forecast made after seeing Demand in Period 1)

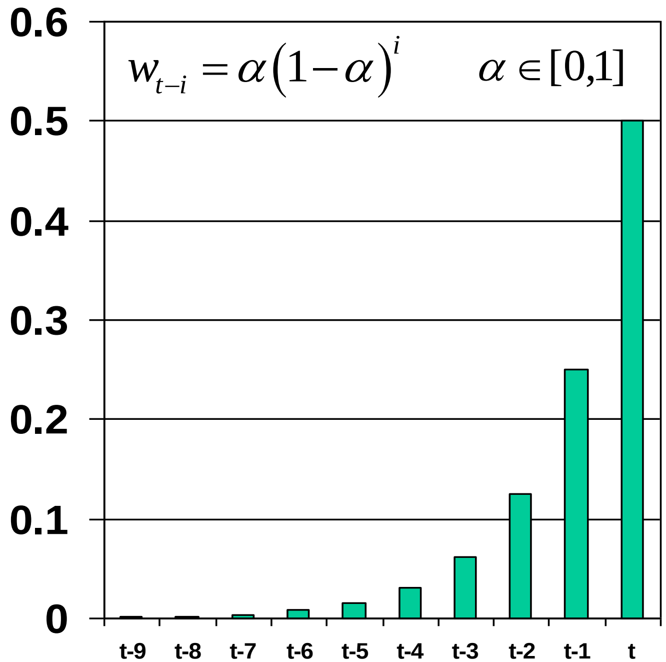
Forecast of Demand in Period 5

(This forecast made after seeing Demand in Period 4)

Method 5: Exponential Smoothing Forecast

Motivation

Consider a weighted moving average forecast with the following weights



Exponential smoothing is like a weighted average

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

Is the same as ……

$$F_{t+1} = \sum_{i=0}^{t-1} w_{t-i} A_{t-i}$$

$$w_{t-i} = \alpha(1-\alpha)^i$$

Method 5: Exponential Smoothing Forecast $F_{t+1}=\alpha A_t + (1-\alpha)F_t$

Period	Demand	Forecast
1	130	-
2		

α=.2

Forecast of Demand in Period 2

(This forecast made after seeing Demand in Period 1)

$F_2=\alpha A_1 + (1-\alpha)F_1$

$F_2=(0.2)130 + (1-0.2)F_1$

Problem!

Didn't have a forecast for period 1 so how can we start the exponential smoothing method

Options

(1) Use Naïve Forecast for Period 2 and then do exponential smoothing for periods 3,4,5,6,……

(2) Choose an initial forecast for period 1 (in some manner) and then do exponential smoothing for periods 2,3,4,5,6,……

Exponential Smoothing Forecast:
Using Naïve Method for Period 2

Period	Demand	Forecast
1	130	-
2	155	130
3	145	135.00
4	160	137.00
5	151	141.60
6	143	143.48
7		143.38

α=.2

Forecast of Demand in Period 2

(This forecast made after seeing Demand in Period 1)

Forecast of Demand in Period 5

(This forecast made after seeing Demand in Period 4)

Using Naive

0.2(155)+(1-0.2)(130) =135.00

0.2(145)+(1-0.2)(135) =137.00

0.2(160)+(1-0.2)(137) =141.60

0.2(151)+(1-0.2)(141.60) =143.48

0.2(143) + (1-0.2)(143.48) = 143.38

Exponential Smoothing Forecast:
Forecast for Period 1 Is Given

Period	Demand	Forecast
1	130	140
2	155	138
3	145	141.40
4	160	141.12
5	151	145.70
6	143	146.76
7		146.00

α=.2

Forecast of Demand in Period 2

(This forecast made after seeing Demand in Period 1)

Forecast of Demand in Period 5

(This forecast made after seeing Demand in Period 4)

0.2(130)+(1-0.2)(140)
=138.00

0.2(155)+(1-0.2)(138)
=141.40

0.2(145) + (1-0.2)(141.40)
= 141.12

0.2(160) + (1-0.2)(141.12)
= 145.70

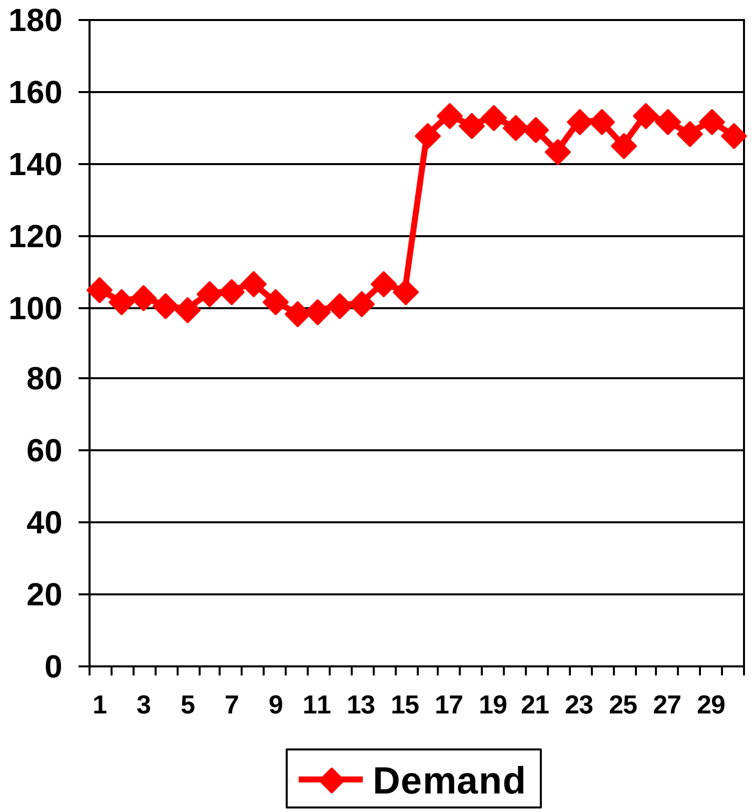
0.2(151) + (1-0.2)(145.70)
=146.76

0.2(143) + (1-0.2)(146.76)
= 146.00

Demand forecast for periods 8, 9, 10 etc.?

What If Mean Demand Level Shifts at Some Point in Time ?

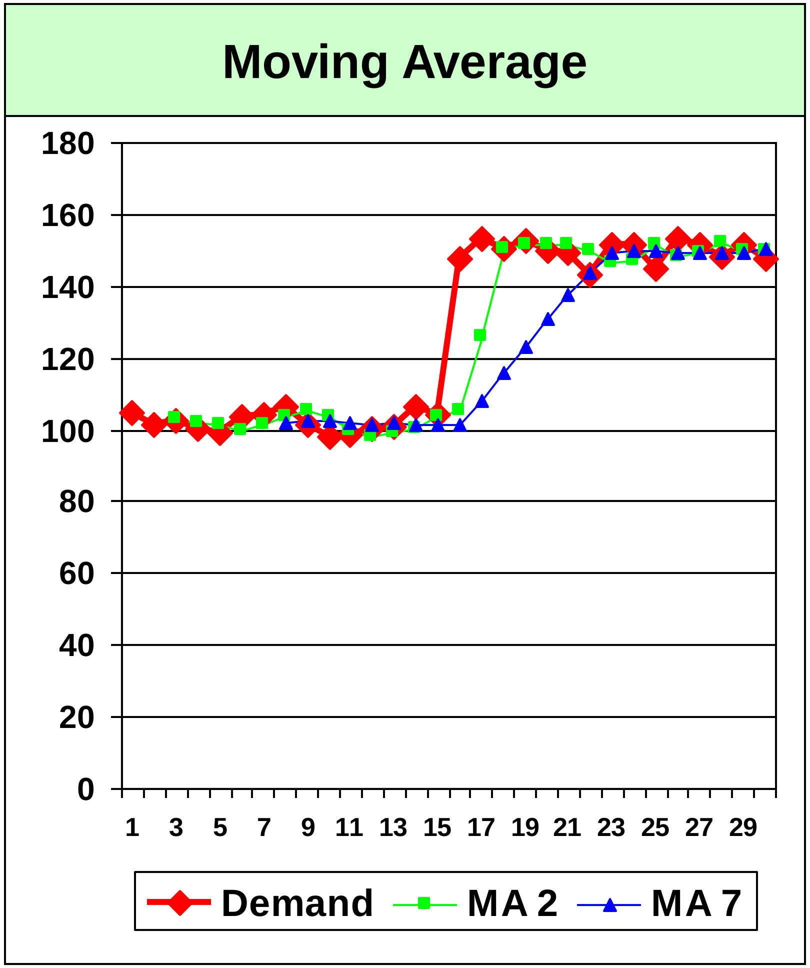
Change in Mean Demand

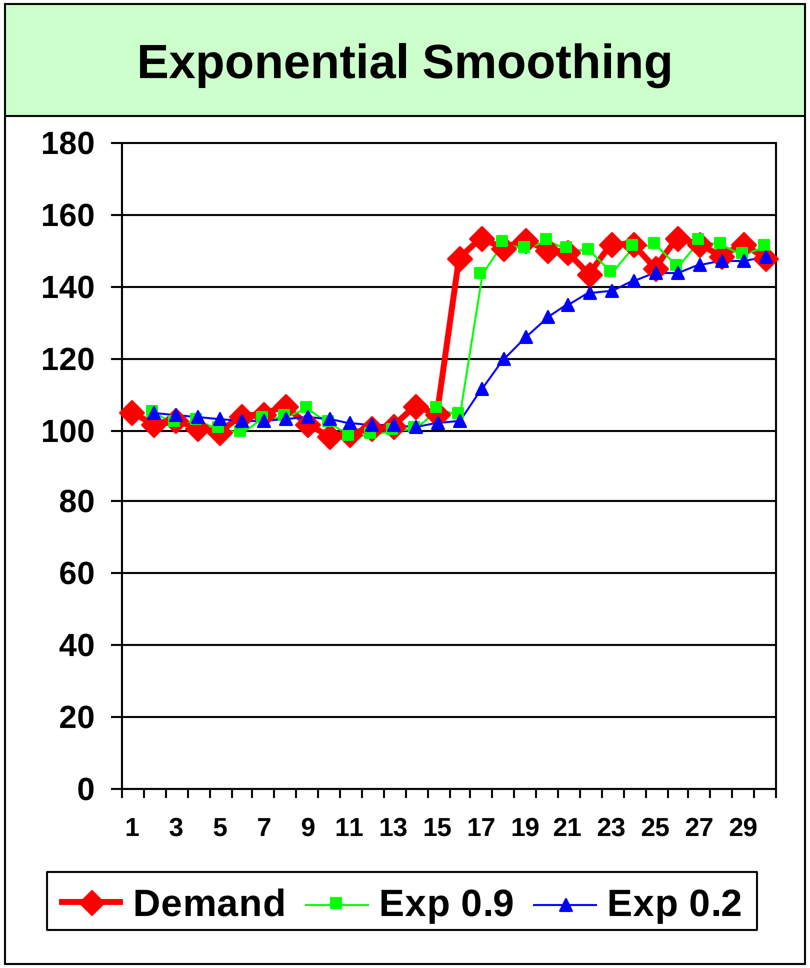


Forecast reaction?

- How will the following forecasts react
  - Moving Average
    - n=2
    - n=7
  - Exponential smoothing
    - α =0.2
    - α =0.9

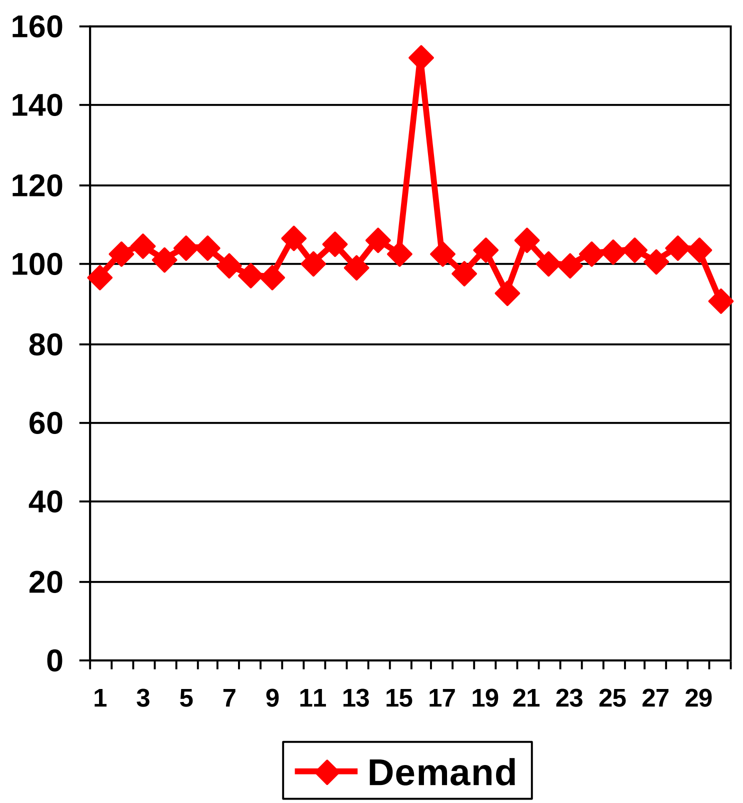
Forecast Parameter Influences *Responsiveness* to Shift in Mean





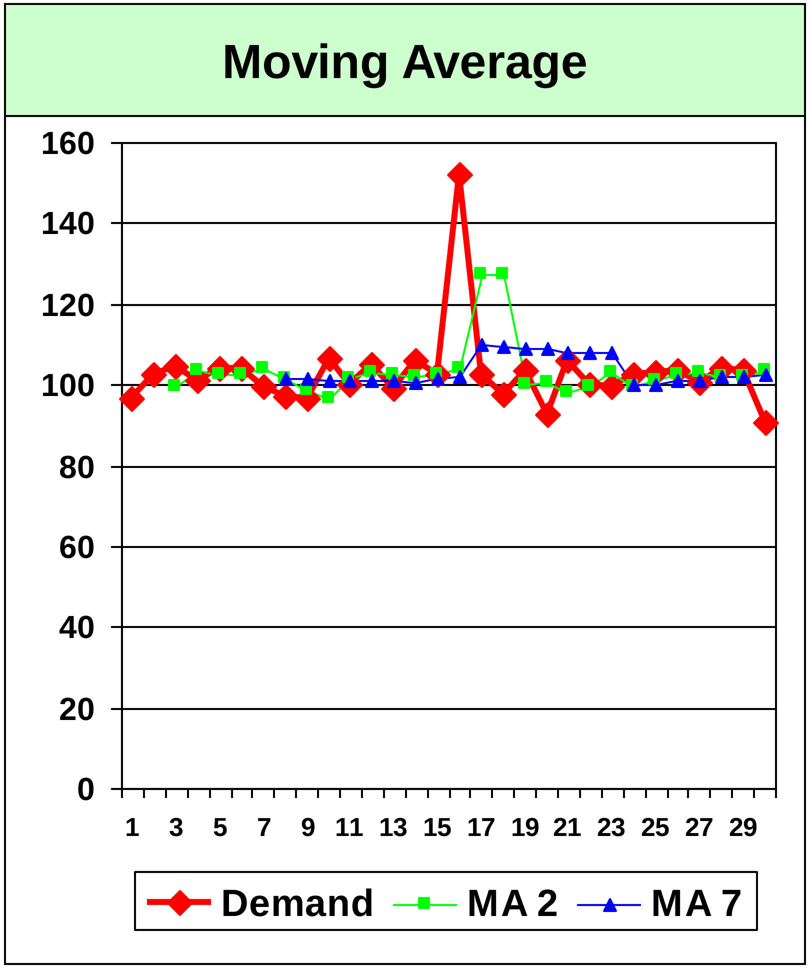
Why Not Use An Extremely Responsive Forecast?

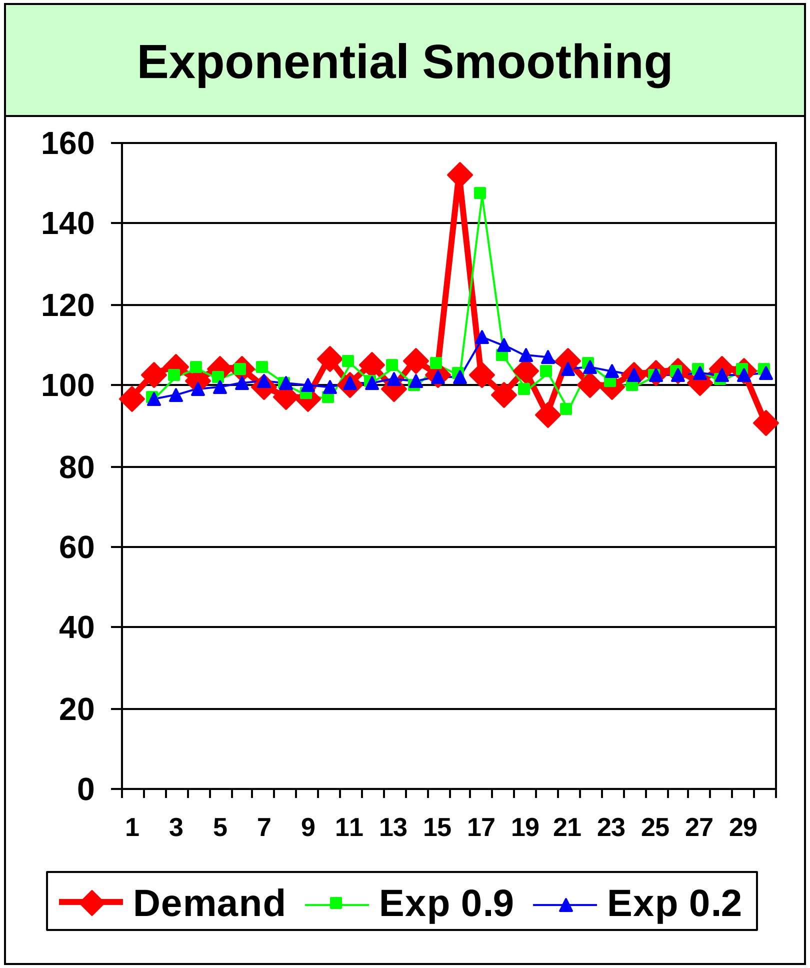
No Change in Mean Demand	Forecast reaction?



- How will the following forecasts react
  - Moving Average
    - n=2
    - n=7
  - Exponential smoothing
    - α=0.9
    - α=0.2

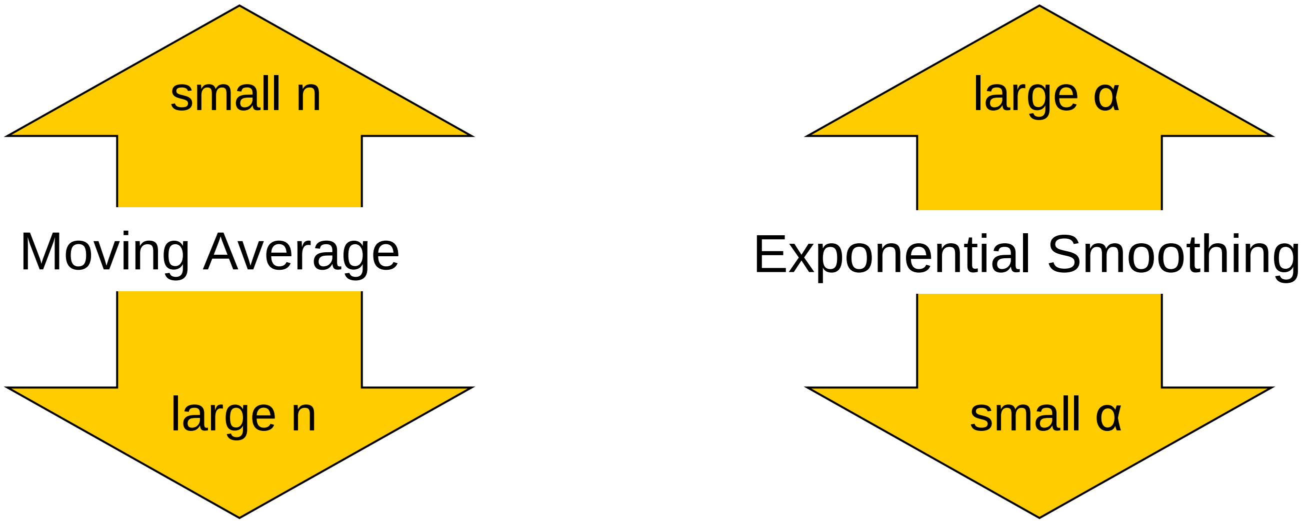
Forecast Parameter Influences *Stability* to Random Fluctuations





Responsiveness vs. Stability: Trade-off

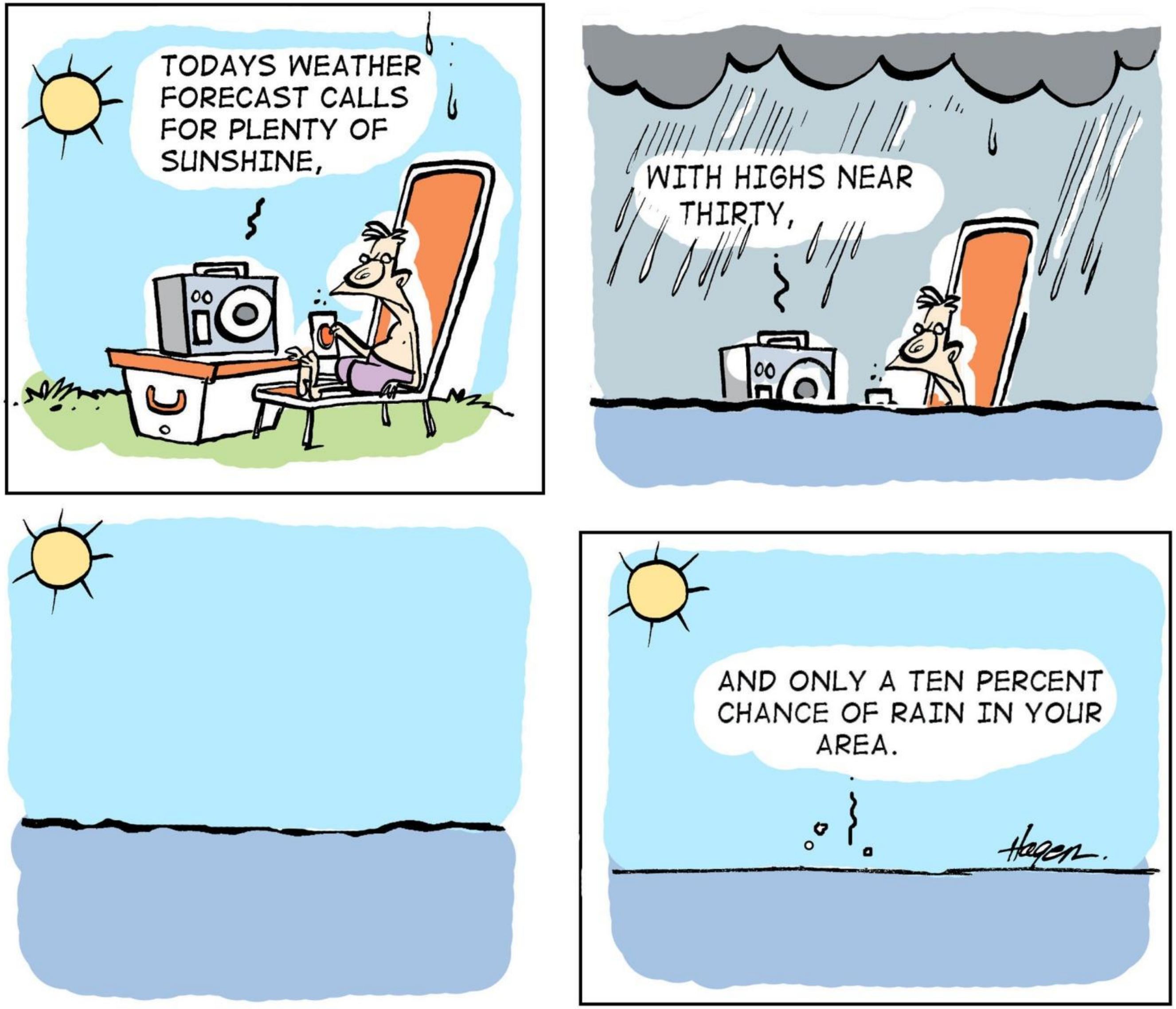
Responsiveness: Ability of forecast to respond quickly to a true change in mean level demand



Stability: Ability of forecast to ignore random variations

Summary of Basic Time Series Methods

Technique	Decision	Implicit assumption
• Simple Average	• None	• All periods are equally informative.
• Simple Moving Average	• Length (*n*)	• Only last *n* periods are important (equally).
• Weighted Moving Average	• Length (*n*) and weights	• Not all recent periods equally important.
• Exponential Smoothing	• Smoothing constant, alpha (α)	• Importance of data declines smoothly (in an exponential fashion)


TODAYS WEATHER FORECAST CALLS FOR PLENTY OF SUNSHINE,
WITH HIGHS NEAR THIRTY,
AND ONLY A TEN PERCENT CHANCE OF RAIN IN YOUR AREA.
Hagen.

Measuring Forecast Errors

- All measures start with per period forecast error
- Forecast Error_t = Demand_t – Forecast_t
- $e_t = A_t – F_t$

Measuring Forecast Errors:

Mean Forecast Error (MFE)

Period	Demand	Forecast	Error
1	130	-	-
2	155	130.00	25.00
3	145	155.00	-10.00
4	160	145.00	15.00
5	151	160.00	-9.00
6	143	151.00	-8.00
		Mean Forecast Error =	2.60

(25+(-10)+15+(-9)+(-8))/5

= 2.60

Measuring Forecast Errors:

Mean Absolute Deviation (MAD)

Period	Demand	Forecast	Error	Absolute Error
1	130	-	-	-
2	155	130.00	25.00	25.00
3	145	155.00	-10.00	10.00
4	160	145.00	15.00	15.00
5	151	160.00	-9.00	9.00
6	143	151.00	-8.00	8.00
			MAD =	13.40

Absolute Deviation = $|Error|$

Measuring Forecast Errors:

Mean Squared Error (MSE)

Period	Demand	Forecast	Error	Squared Error
1	130	-	-	-
2	155	130.00	25.00	625.00
3	145	155.00	-10.00	100.00
4	160	145.00	15.00	225.00
5	151	160.00	-9.00	81.00
6	143	151.00	-8.00	64.00
			MSE =	219.00

MAD vs. MSE

- MSE penalizes large errors while MAD treats all errors equally.

- If a manager prefers a forecasting method that generates **small frequent** forecasting errors over than one that generates **large infrequent** errors (obviously, everyone likes small and infrequent errors and no one likes large and frequent errors), which approach should he use to measure forecasting errors? MAD or MSE?

Measuring Forecast Errors:

Mean Absolute Percentage Error (MAPE)

Period	Demand	Forecast	Error	% Error	Abs % Error
1	130	-	-	-	-
2	155	130.00	25.00	=25/155=16.13%	16.13%
3	145	155.00	-10.00	=-10/145=-6.90%	6.9%
4	160	145.00	15.00	=15/160=9.38%	9.38%
5	151	160.00	-9.00	=-9/151=-5.96%	5.96%
6	143	151.00	-8.00	=-8/143=-5.59%	5.59%
				MAPE	8.79%

Absolute Percentage Error = $\left|\frac{Error}{Demand}\right| \times 100\%$

Summary

- Poor forecasting costs money!!!
- Time Series Methods
  - Naïve
  - Simple Average
  - Simple Moving Average
  - Weighted Moving Average
  - (Simple) Exponential Smoothing
- Responsiveness vs. Stability trade-off
- Measures of Forecast Errors
  - MFE
  - MAD
  - MSE
  - MAPE

“How close to the truth to you want to come, sir?”

SESSION 2

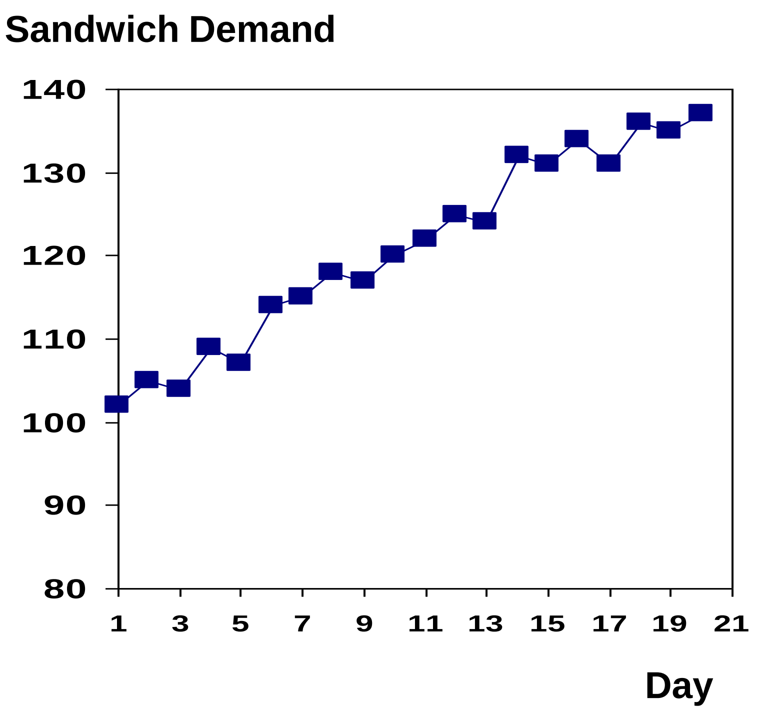
Forecasting (2)

Agenda

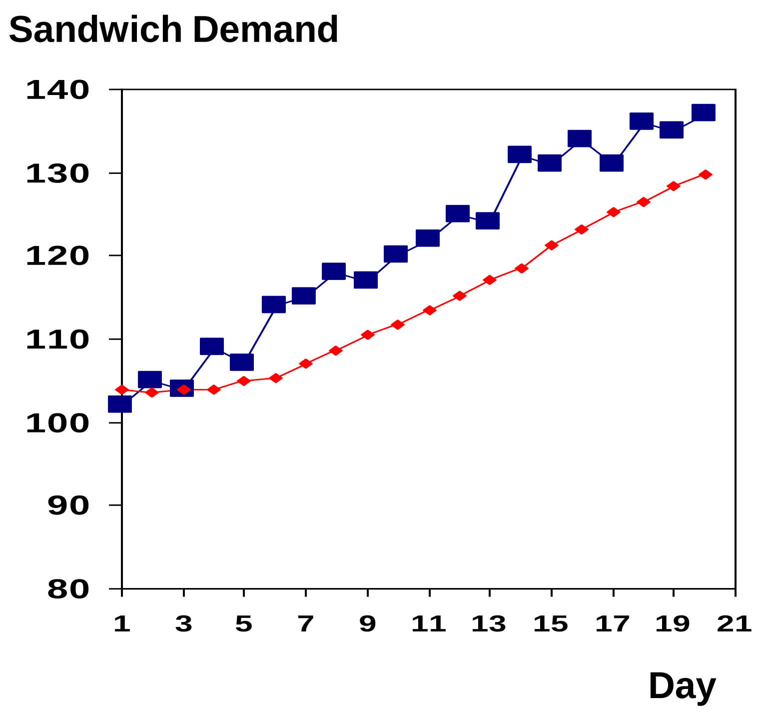
- Advanced Time Series Forecasting
  - Trends
  - Seasonality
- Causal Relationship Forecasting
  - Regression
- Some Forecasting Insights

Time Series With Trends

Consider the following time series of sandwich demand



What would happen if we used the techniques from the last session ?



Need to Account for the Trend: Double Exponential Smoothing

Step	Equation
• Forecast of level	$S_t = \alpha A_t + (1-\alpha)(S_{t-1} + T_{t-1})$
• Forecast of trend	$T_t = \beta(S_t - S_{t-1}) + (1-\beta)T_{t-1}$
• Forecast of next period	$FIT_{t+1} = S_t + T_t$

Double Exponential Smoothing
Assume S1 and T1 Are Given

α=.3, β=.4

t = 3

Period	Demand	S_t $S_t = \alpha A_t + (1-\alpha)(S_{t-1}+T_{t-1})$	T_t $T_t = \beta(S_t - S_{t-1}) + (1-\beta)T_{t-1}$	Forecast $FIT_{t+1} = S_t + T_t$
1	102	100.00	1.00	-
2	105	0.3(105)+(1-0.3)(101.00)=102.2 102.20	0.4(102.2-100.0)+(1-0.4)(1.00)=1.48 1.48	100.00+1.00=101.00 101.00
3	104	0.3(104)+(1-0.3)(103.68)=103.78 103.78	0.4(103.78-102.2)+(1-0.4)(1. 48)=1.52 1.52	102.20+1.48=103.68 103.68
4	109	0.3(109)+(1-0.3)(105.30)=106.41 106.41	0.4(106.41-103.78)+(1-0.4)(1.52)=1.96 1.96	103.78+1.52=105.30 105.30
5	107	0.3(107)+(1-0.3)(108.37)=107.96 107.96	0.4(107.96-106.41)+(1-0.4)(1.96)=1.80 1.80	106.41+1.96=108.37 108.37
6	114			107.96+1.80=109.76 109.76
7				

Double Exponential Smoothing
Assume S1 and T1 Are Given

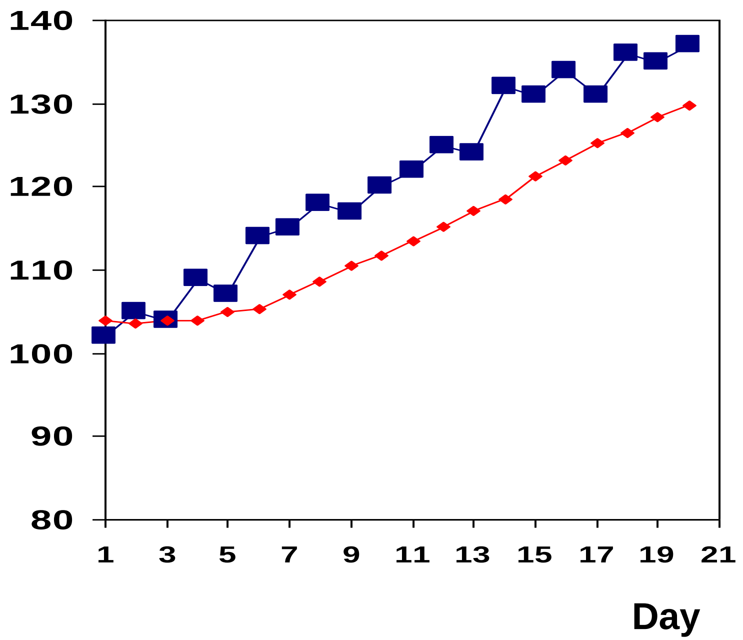
α=.3, β=.4

Period	Demand	S_t $S_t = \alpha A_t + (1-\alpha)(S_{t-1} + T_{t-1})$	T_t $T_t = \beta(S_t - S_{t-1}) + (1-\beta)T_{t-1}$	Forecast $FIT_{t+1} = S_t + T_t$
1	102	100.00	1.00	-
2	105	0.3(105)+(1-0.3)(101.00)=102.2 102.20	0.4(102.2-100.0)+(1-0.4)(1.00)=1.48 1.48	100.00+1.00=101.00 101.00
3	104	0.3(104)+(1-0.3)(103.68)=103.78 103.78	0.4(103.78-102.2)+(1-0.4)(1. 48)=1.52 1.52	102.20+1.48=103.68 103.68
4	109	0.3(109)+(1-0.3)(105.30)=106.41 106.41	0.4(106.41-103.78)+(1-0.4)(1.52)=1.96 1.96	103.78+1.52=105.30 105.30
5	107	0.3(107)+(1-0.3)(108.37)=107.96 107.96	0.4(107.96-106.41)+(1-0.4)(1.96)=1.80 1.80	106.41+1.96=108.37 108.37
6	114	0.3(114)+(1-0.3)(109.76)=111.03 111.03	0.4(111.03-107.96)+(1-0.4)(1.80)=2.31 2.31	107.96+1.80=109.76 109.76
7				111.03+2.31=113.34 113.34

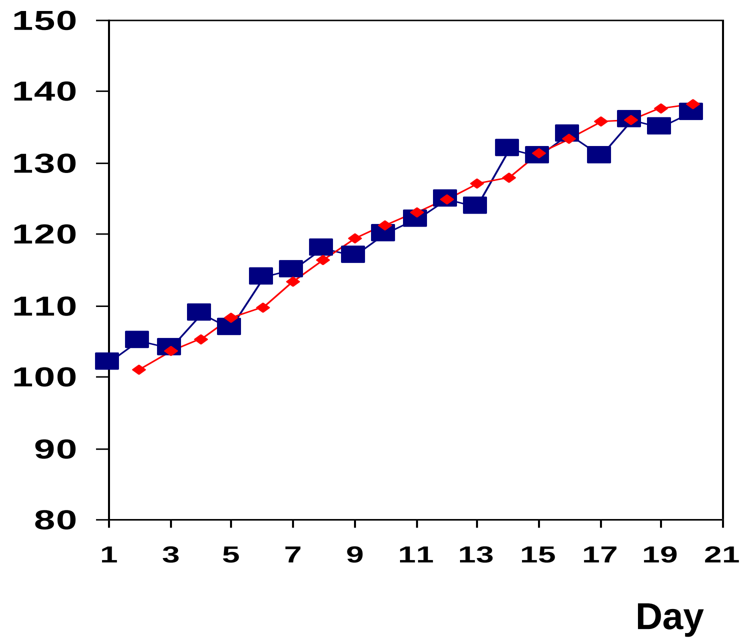
Time Series With Trends

Simple Exponential Smoothing	Double Exponential Smoothing

Sandwich Demand



Sandwich Demand



Causal Forecasting (Regression)

- Assumption: Variable we want to forecast is related to other variables in the environment.

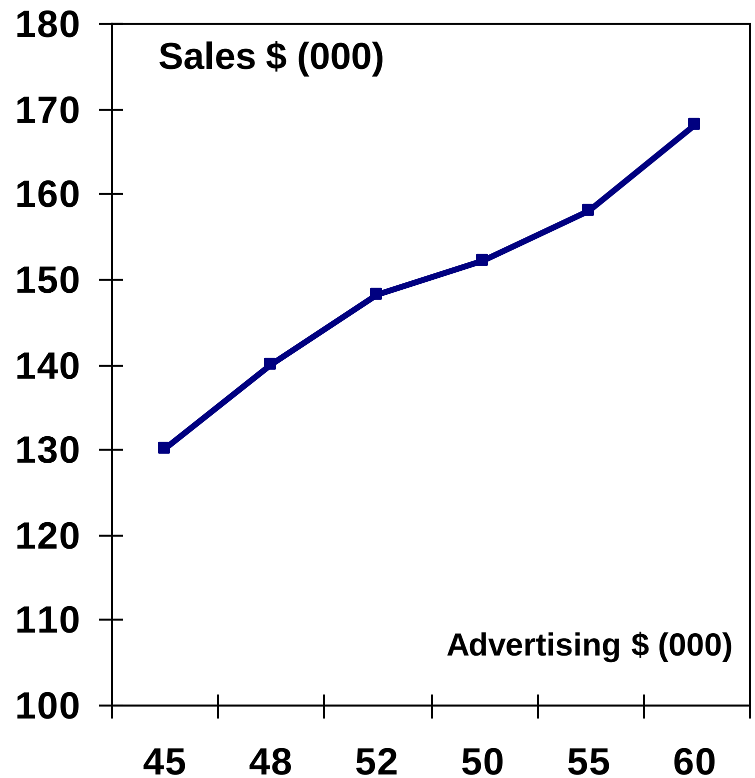
Dependent variable **Independent variable(s)**

- In this course we consider models with a single independent variable

Causal Forecasting

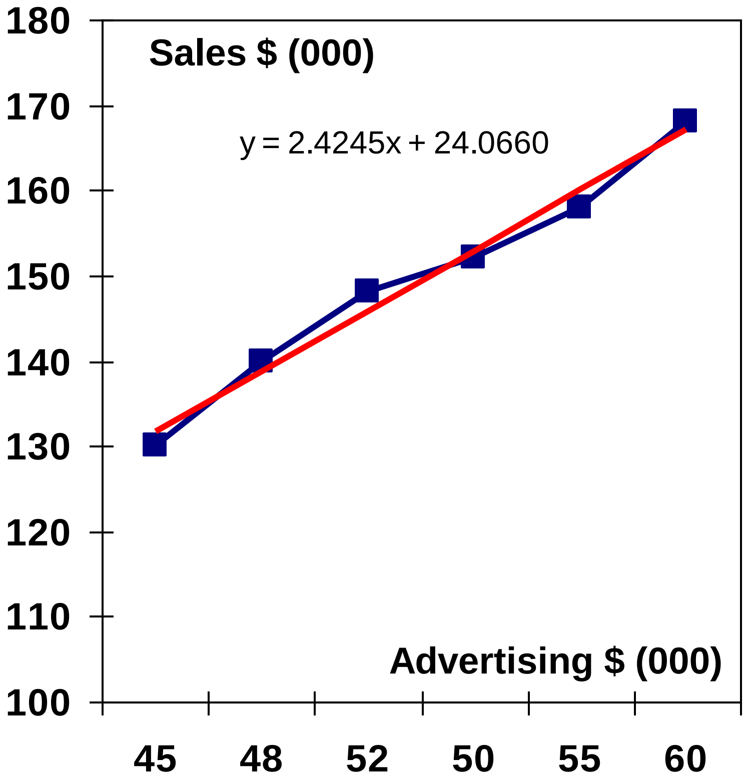
Variable Y depends on Variable X	The relationship might be linear

- Number of people at the beach depends on the temperature
- Gasoline price in US depends on world oil production
- Sales depends on advertising
- Others ?



Given X (ind. var), You Can Predict Y (dep. var)

Use Linear Regression Technique



Equations

$$Y = a + bX$$

Where …

$$b = \frac{\sum XY - n\overline{X}\,\overline{Y}}{\sum X^2 - n\overline{X}^2}$$

$$a = \overline{Y} - b\overline{X}$$

Linear Regression from Excel

Use the “SLOPE” and “INTERCEPT” functions in Excel, Or

Use *Data Analysis* in Excel

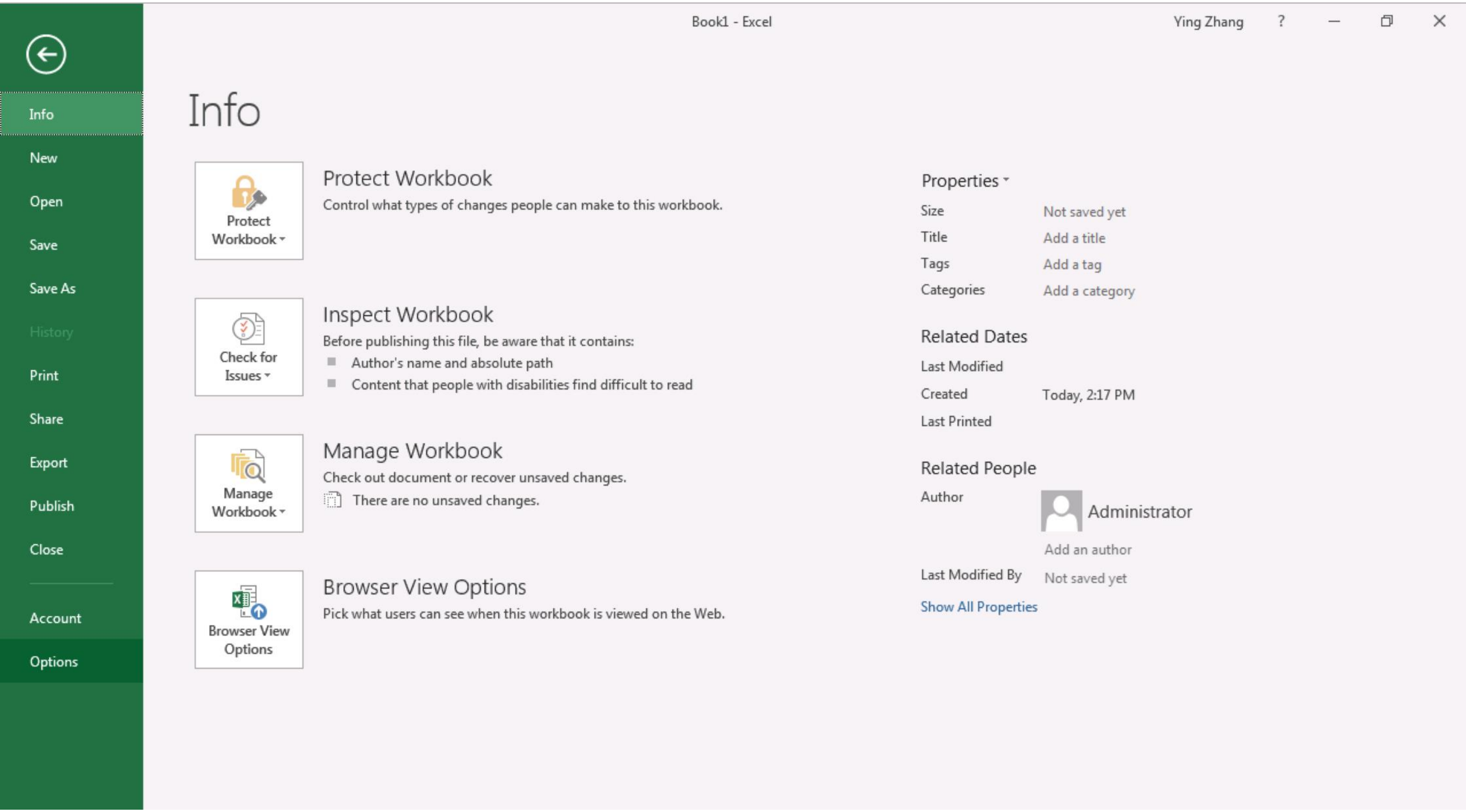
Regression Statistics	
Multiple R	0.9644
R Square	0.9300
Adjusted R Square	0.9125
Standard Error	3.9537
Observations	6.0000

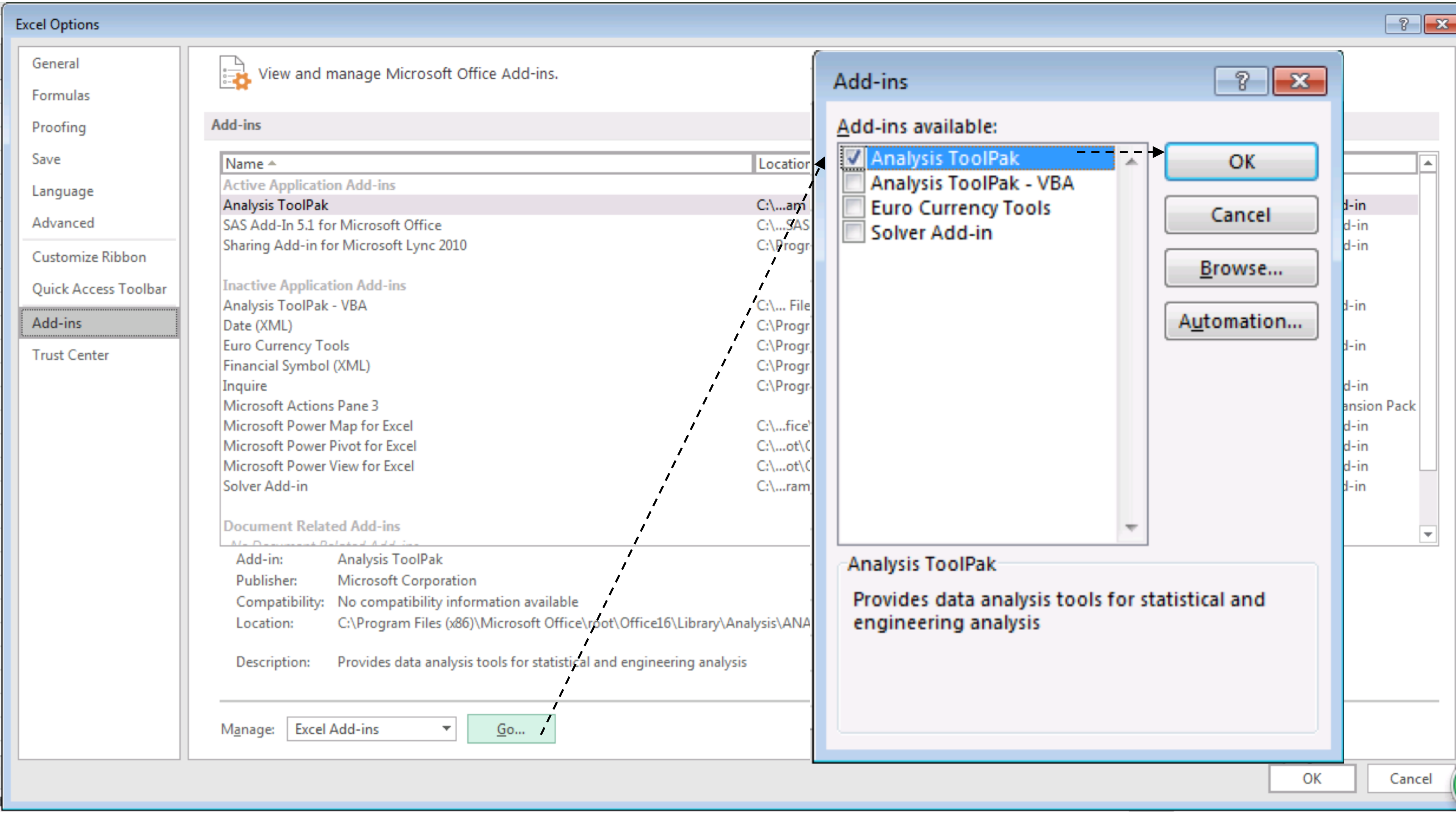
ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1.0000	830.8050	830.8050	53.1475	0.0019
Residual	4.0000	62.5283	15.6321		
Total	5.0000	893.3333			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	24.0660	17.2585	1.3944	0.2356	-23.8514	71.9834
Adverstising	2.4245	0.3326	7.2902	0.0019	1.5012	3.3479

Data Analysis Package in Excel (Windows)

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Analysis ToolPak - VBA
Date (XML)
Euro Currency Tools
Financial Symbol (XML)
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Microsoft Power Pivot for Excel
Microsoft Power View for Excel
Solver Add-in
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Add-in: Analysis ToolPak
Publisher: Microsoft Corporation
Compatibility: No compatibility information available
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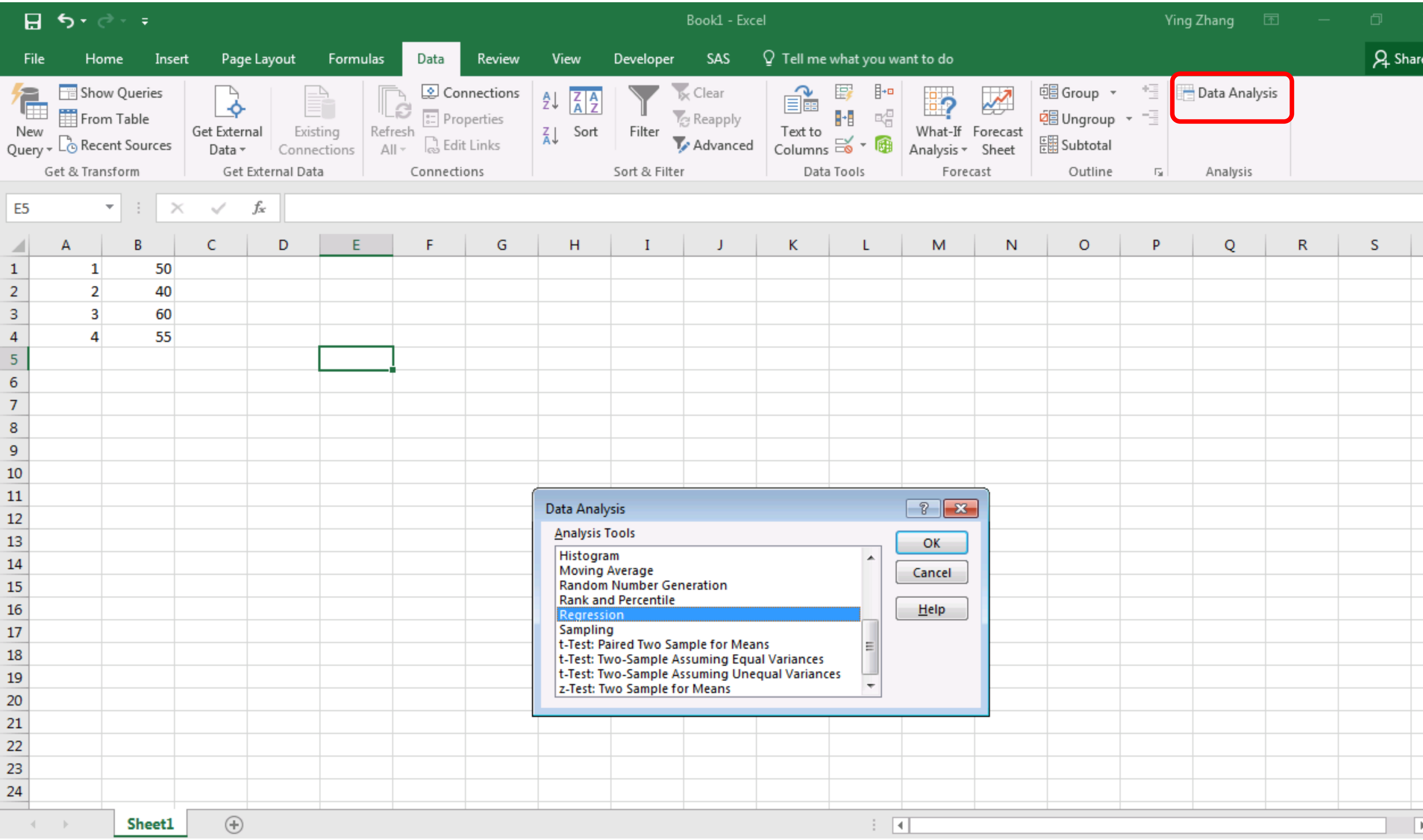
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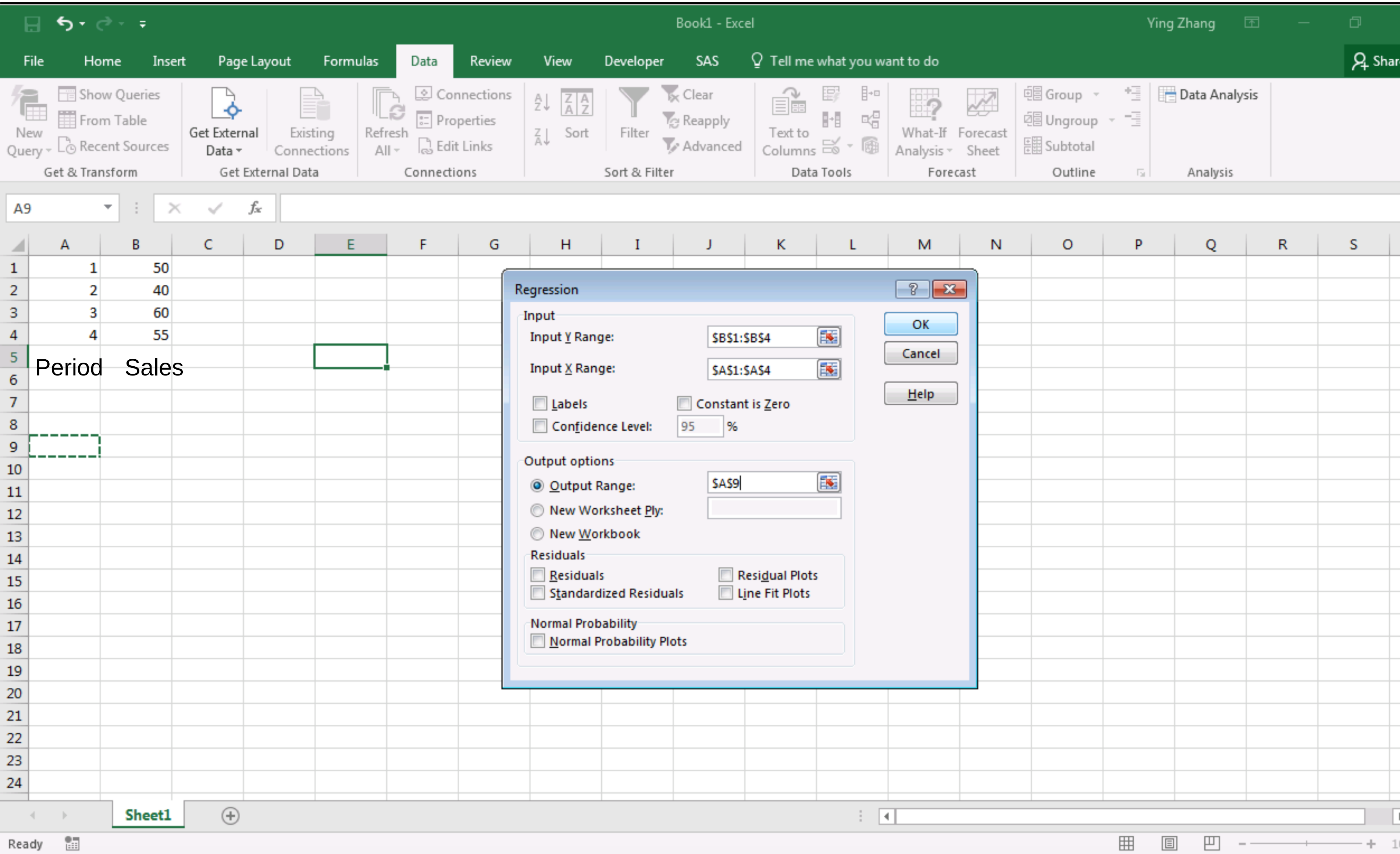
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Line Fit Plots
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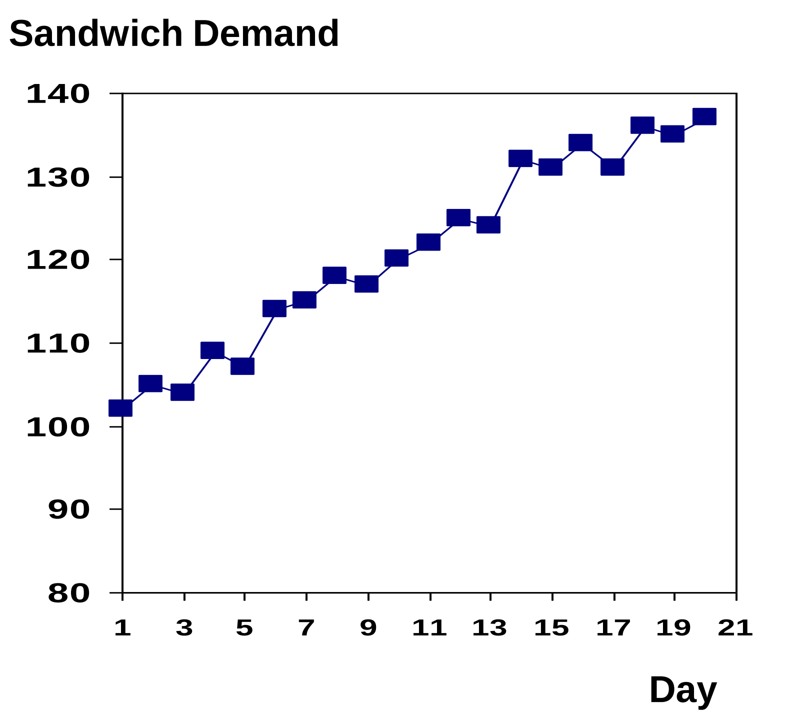
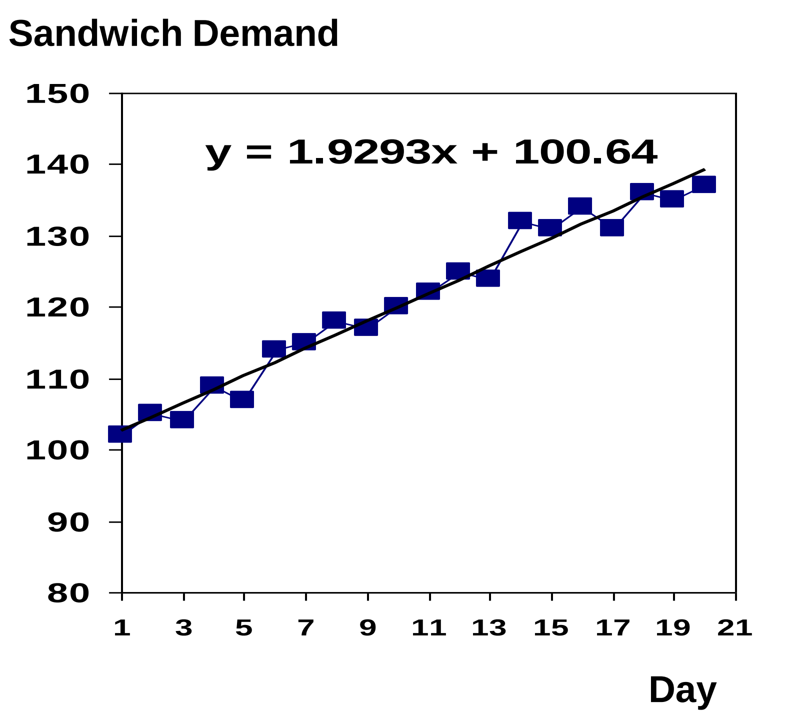
Ready

Using Regression for Time Series with Trends

Look at the following time series



Can use the time period as the independent variable, X

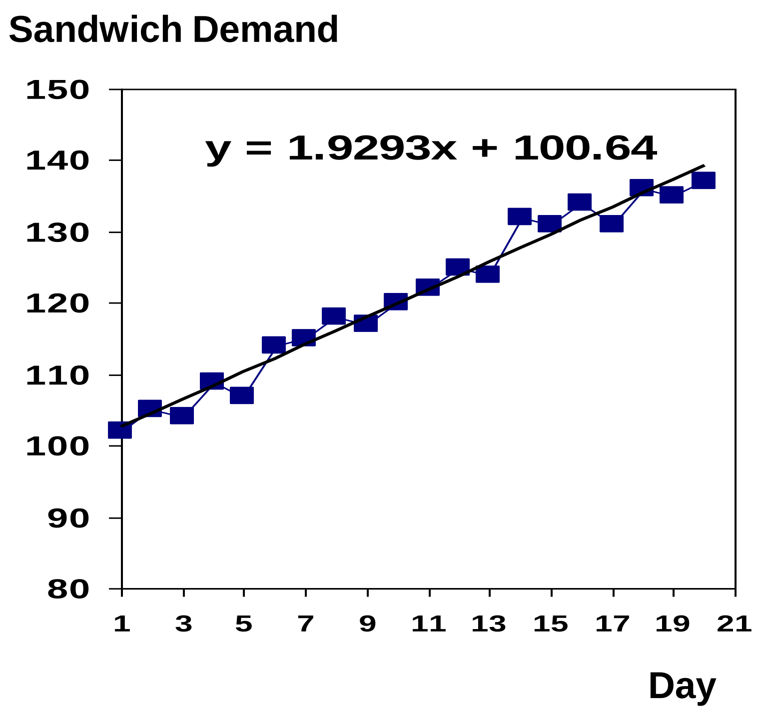


Using Regression for Time Series with Trends

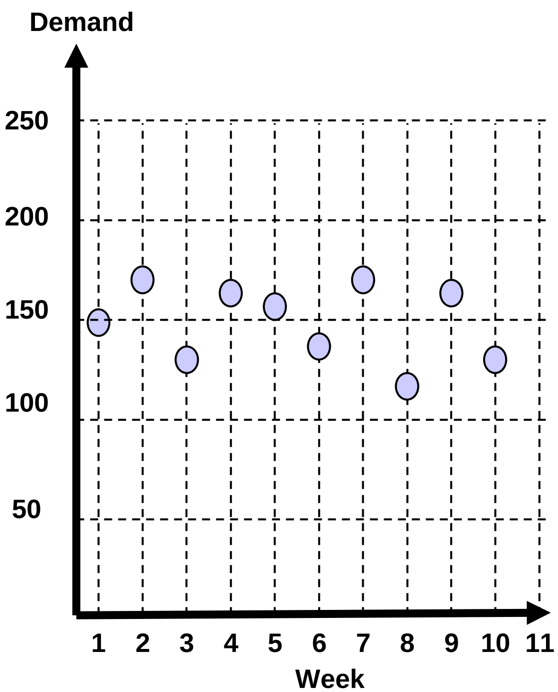
- According to this forecasting model, the sandwich demand for period 21 would be

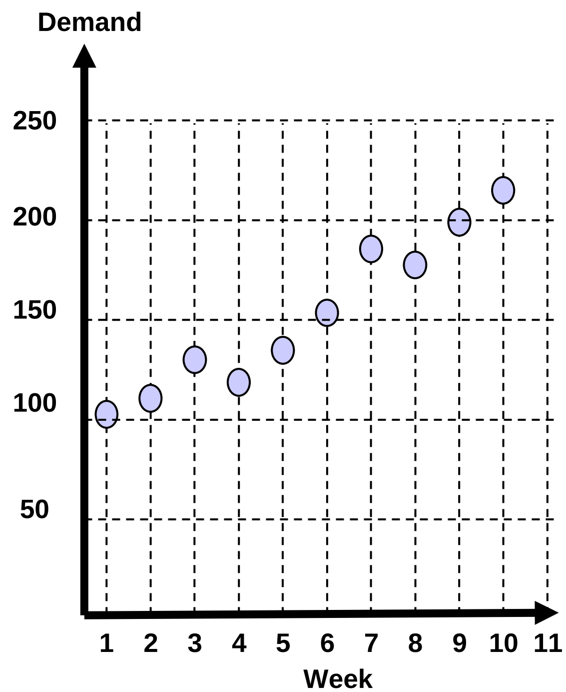
F_{21} = 100.64+1.9293*21
= 141.1553

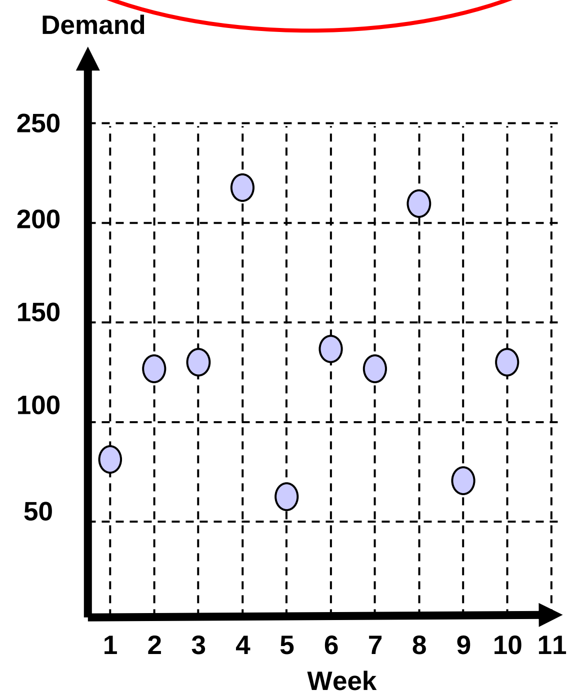
Can use the regression line to forecast demand in future



1. Fluctuates About A Constant Mean	2. Fluctuates And Has Increasing (or Decreasing) Trend	3. Fluctuates And Has “Seasonal” Pattern





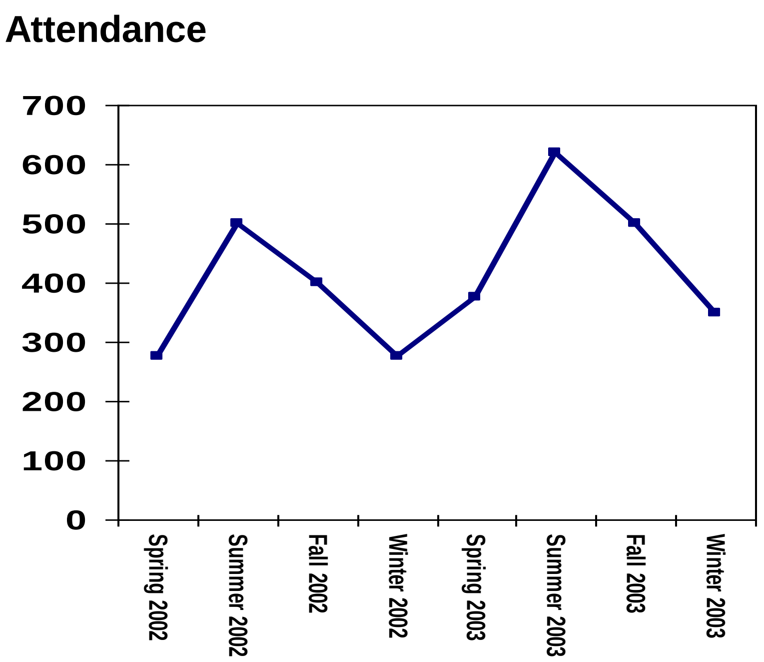


- Simple Average
- Simple Moving Average
- Weighted Moving Average
- Exponential Smoothing

- Double Exponential Smoothing
- Linear Regression

Time Series With Repeated Patterns

Consider the following time series of amusement park attendance



Where else might you find seasonality ?

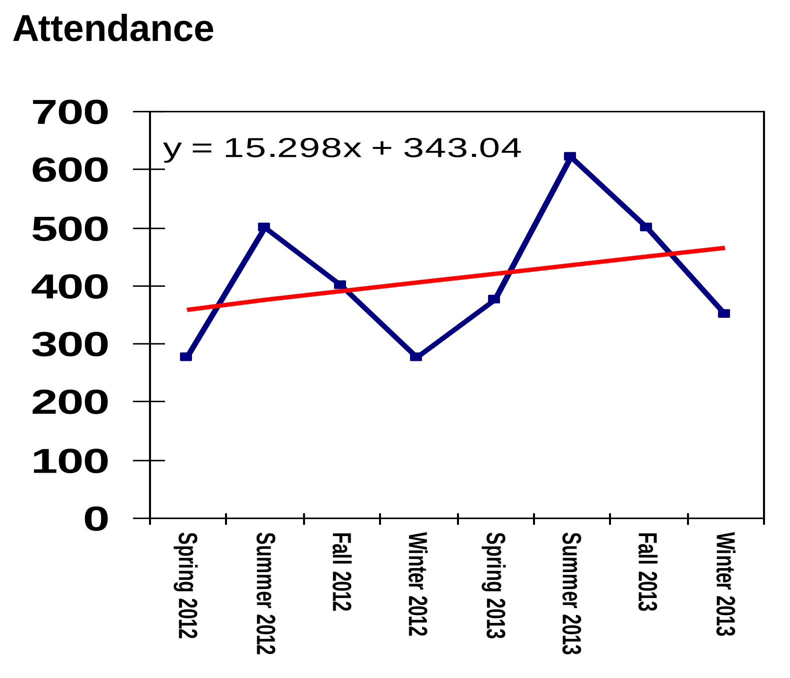
- Umbrellas
- Coats
- Swimsuits
- Halloween Costumes
- Gift Wrap
- Ice Cream
- PS4/Wii/XBOX
- Fireworks

Forecasting with Seasonality (I)

How to forecast the attendance for year 2014?

- **One approach – linear regression with seasonal index**

1. Perform a linear regression



Note: **In this example there is an increasing trend as well as seasonality**

Forecasting approach:

Account for trend using Regression

Calculate seasonal index

Use both trend and seasonal component to make the forecast

Forecasting with Seasonality (II)

2. Compare actual and regression forecast to get seasonal indices

Regression forecast

	Time Period	Actual, A_t	Forecast, F_t	Actual/ Forecast
Spring 2012	1	275	358.33	0.77
Summer 2012	2	500	373.63	1.34
Fall 2012	3	400	388.93	1.03
Winter 2012	4	275	404.23	0.68
Spring 2013	5	375	419.52	0.89
Summer 2013	6	620	434.82	1.43
Fall 2013	7	500	**450.12**	**1.11**
Winter 2013	8	350	**465.42**	**0.75**

E.g. F_6=15.298(6)+343.04=434.82

y = 15.298*x + 343.04

- Seasonal Index (SI) for each season =

$$\frac{\text{Actual Demand}}{\text{ForecastDemand}}$$

- SI > 1 means that demand was more than forecast (“in” season)
- SI < 1 means that demand was less than forecast (“out of” season)

Forecasting with Seasonality (II)

2. Compare actual and regression forecast to get seasonal indices

Regression forecast

	Time Period	Actual, A_t	Forecast, F_t	Actual/ Forecast
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Winter 2013	8	350	**465.42**	**0.75**

E.g. F_6=15.298(6)+343.04=434.82

3. Get the average index for each season

	2012	2013	Average
Spring	0.77	0.89	0.831
Summer	**1.34**	1.43	1.382
Fall	**1.03**	**1.11**	**1.070**
Winter	0.68	**0.75**	**0.716**

E.g. Average index for Spring season = (0.77+0.89)/2=0.831

y = 15.298*x + 343.04

Forecasting with Seasonality (III)

4. Get regression forecasts for future periods (ignoring seasonality)

	Time Period	Regression Forecast
Spring 2014	9	480.71
Summer 2014	10	496.01
Fall 2014	11	511.31
Winter 2014	12	526.61

E.g. RF_{11}=15.298(11)+343.04

=511.31

5. Apply average seasonal indices to regression forecasts

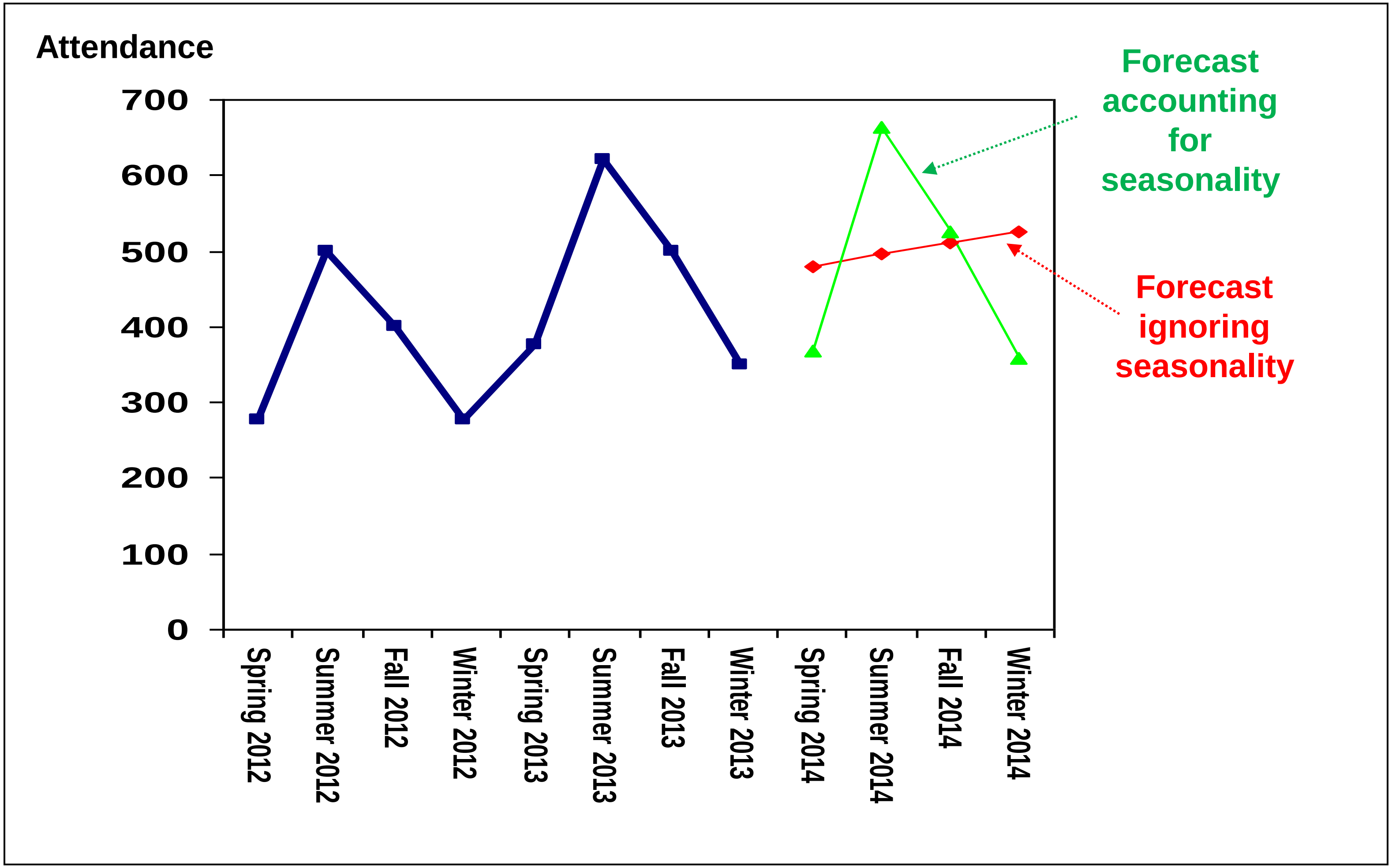
	Time Period	Regression Forecast	Seasonal Index	Final Forecast
Spring 2014	9	480.71	0.831	**399.31**
Summer 2014	10	496.01	1.382	**685.51**
Fall 2014	11	511.31	1.070	546.92
Winter 2014	12	526.61	0.716	377.14

E.g. $F_{\text{winter 2014}}$= 526.61*0.716

Regression forecast

Average Seasonal Index for Winter

Let’s Look at The Forecasts

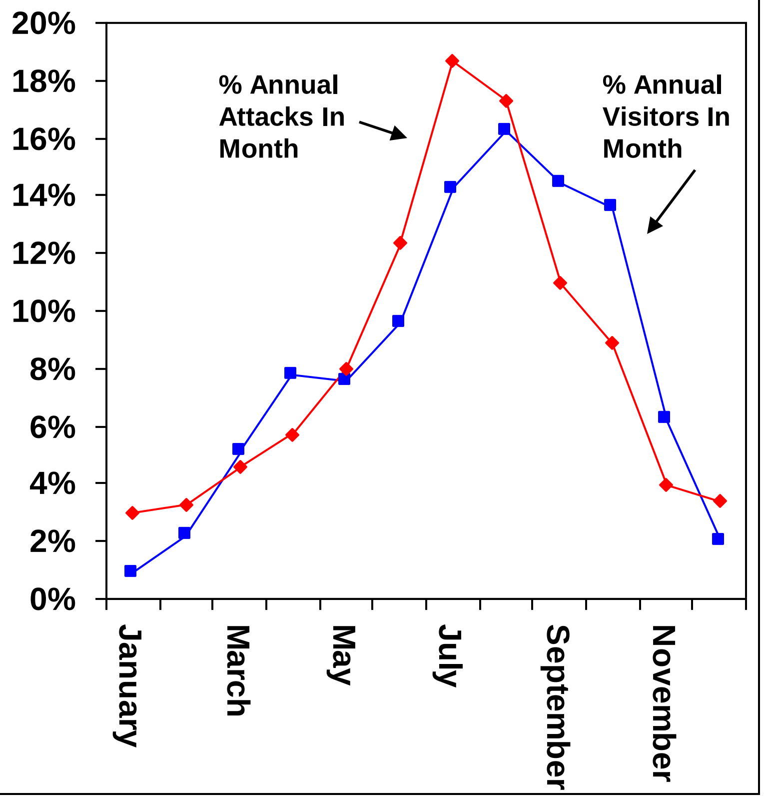


Be Careful With the Words "Season" and "Year"

Forecast quantity	"Season"	"Year"
• McDonalds drive thru customers	Hour	Day
• Newspaper Sales	Day	Week
• Hotel visitors	Month	Year

Be Very Careful With Correlation

Both shark attacks and visitors to Cape Cod vary with the time of year



Correlation may not equal causality

- Number of visitors to Cape Cod does not depend on the number of shark attacks in Florida
- But they both depend on the time of year
- This is an example of common response – a frequent reason people misattribute correlation to be a causal relationship

Some Forecasting Insights

#1. Forecasting Demand for Families of Products is Easier than Forecasting Demand for Members

- Example:
  - Family: Top 5 flavors for Ben&Jerry’s, Members: Different flavors
  - Say Ben&Jerry’s sells 100 lbs of each flavor each week

	Forecasts							Absolute Percentage Errors					
Week	Cherry Garcia	Ch. Chip Cookie Dough	Ch. Fudge Brownie	Chunky Monkey	NY Super Fudge	Total		Cherry Garcia	Ch. Chip Cookie Dough	Ch. Fudge Brownie	Chunky Monkey	NY Super Fudge	Total
1	102	101	102	107	106	518		2	1	2	7	6	3.60
2	88	87	95	108	110	488		12	13	5	8	10	2.40
3	108	106	105	85	99	503		8	6	5	15	1	0.60
4	95	107	101	109	104	516		5	7	1	9	4	3.20
5	97	93	105	101	101	497		3	7	5	1	1	0.60
6	101	109	113	108	88	519		1	9	13	6	12	3.80
7	99	105	107	106	93	510		1	5	7	6	3	2.00
8	102	96	86	103	108	496		2	4	14	3	8	0.80
9	101	105	108	92	103	509		1	5	8	8	3	1.80
10	92	101	96	102	98	488		8	1	4	2	2	2.40
11	104	102	102	92	102	502		4	2	2	8	2	0.40
12	95	115	97	98	115	520		5	15	3	2	15	4.00
13	108	108	99	103	108	526		8	8	1	3	8	4.00
14	102	99	110	116	130	557		2	1	10	16	39	5.20
15	99	95	87	106	97	484		1	5	13	6	3	11.40
16	103	102	90	108	107	510		3	2	10	8	7	3.20
								4.125	**5.6875**	**6.4375**	**6.75**	**7.75**	**3.088**

Why is MAPE lower for the overall family than for individual flavors?

Some Forecasting Insights

#2. Forecasting Demand for a Month is More Accurate than Forecasting Demand for a Week

• Forecasting weekly demand for the Top 5 ice cream flavors

Week	Forecast	Absolute % error
1	518	3.60
2	488	2.40
3	503	0.60
4	516	3.20
5	497	0.60
6	519	3.80
7	510	2.00
8	496	0.80
9	509	1.80
10	488	2.40
11	502	0.40
12	520	4.00
13	526	4.00
14	557	5.20
15	484	11.4
16	510	3.2
	MAPE	**3.0875**

• Forecasting monthly demand for the Top 5 ice cream flavors

Weeks	Forecast	Absolute % error
1--4	2025	1.23
5--8	2022	1.10
9--12	2019	0.97
13--16	2076	3.82
	MAPE	1.78

Why is MAPE lower for the monthly forecasts than for weekly forecasts?

Some Forecasting Insights

#3. The further into the future you want to forecast demand the less accurate you are likely to be

- The forecast for demand for ice cream in October 2024 will be more accurate than the forecast for demand in October 2025
  - Why?

Some Forecasting Insights

#4. Danger of using Sales As Estimate of Demand

- Is the number of pounds of Cherry Garcia flavor sold at a particular store necessarily a good estimate of demand for Cherry Garcia at that store?
- Why or why not?

Some Forecasting Insights

#5. Beware of using Sales Targets as Forecasts

- Forecasts are often generated in different parts of the company and for different reasons
- Sales sometimes generate forecasts that are used as targets or goals
- Dangerous to use a sales target as a forecast
  - Why?

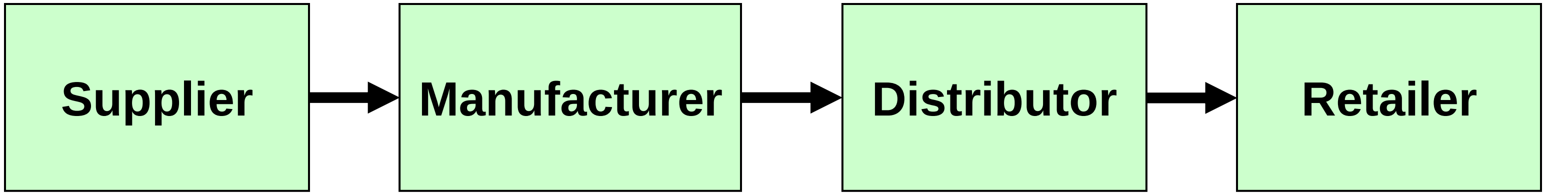
SESSION 3

Supply Chain Management

Agenda

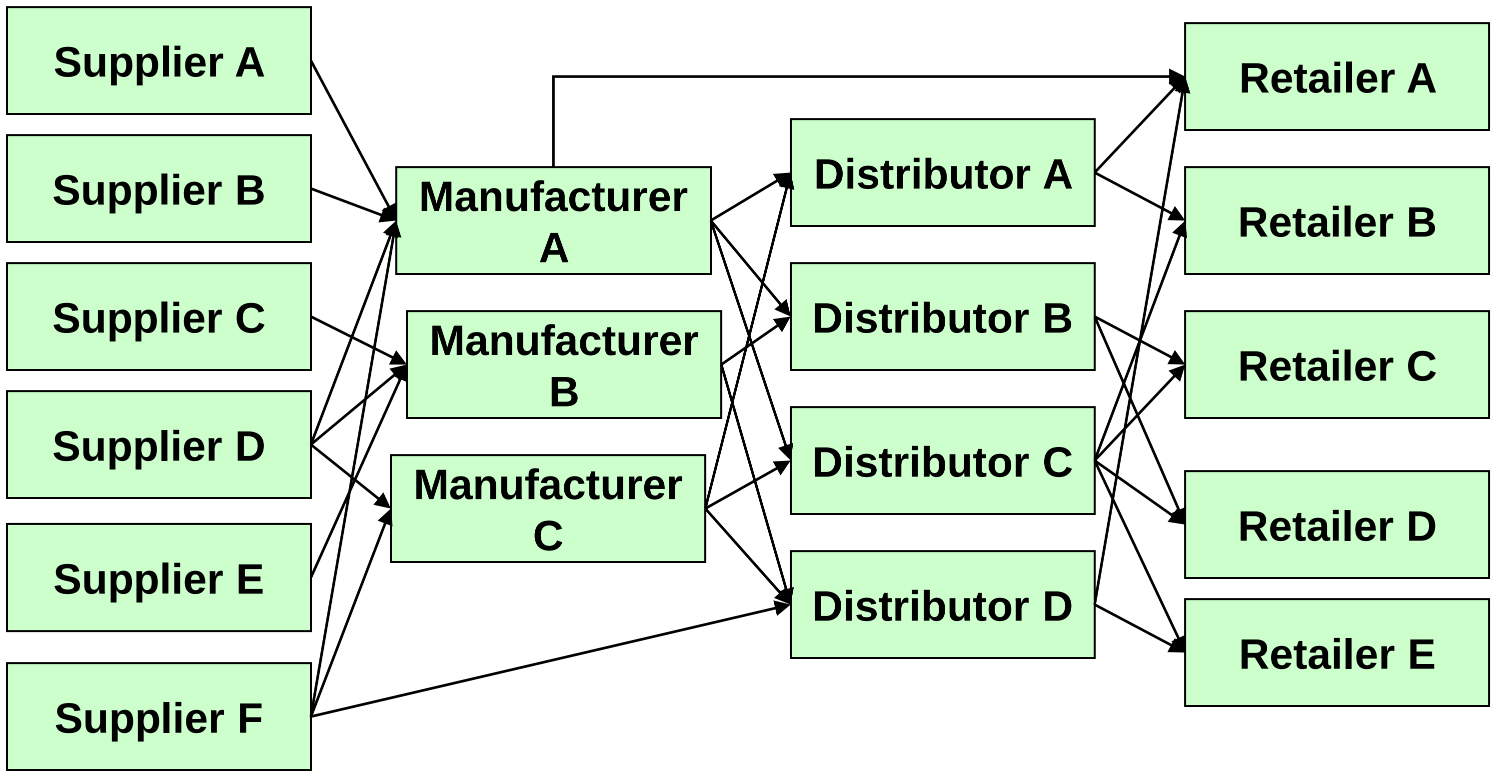
- Introduction to Supply Chain Management
- Drivers and solutions to the bullwhip effect
- Risk pooling in supply chains
    - Demand pooling
    - Common component (Postponement)
    - Inventory centralization by local pooling

Supply Chain Management
A Simple View



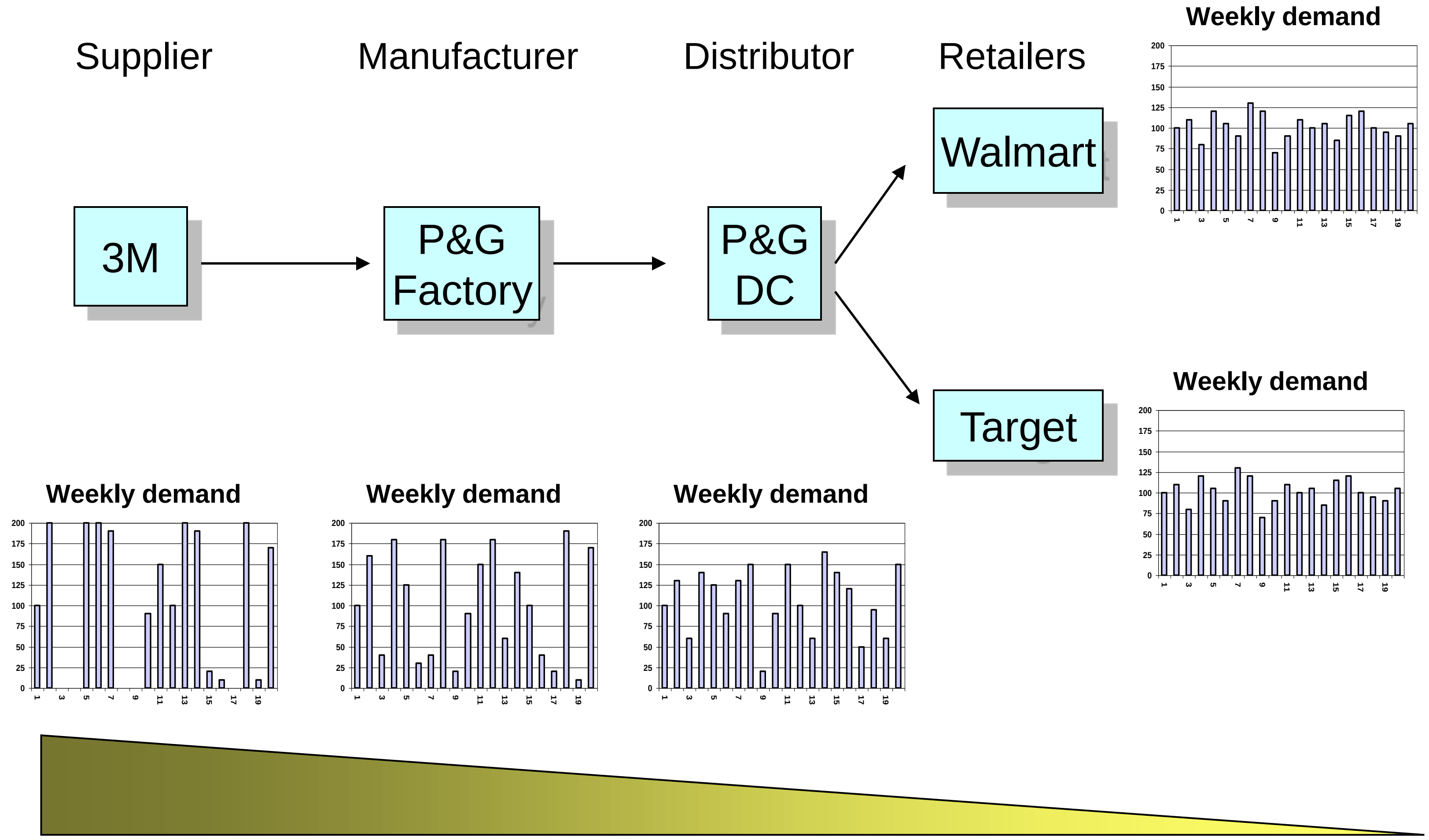
- Many different companies are involved in the process of fulfilling customer demand.
- Not all supply chains have all these players, e.g. Dell has cut out the distributor and the retailer and sells directly to the customer. In some supply chains, the manufacturer sells directly to the retailer

Supply Chain Management
A More Realistic View



Supply Chains are complex networks of company relationships, with product, money and information flowing between the companies. Normally products flow from left to right and money flows from right to left, but not always (think of Kodak single use cameras or when you return products – the product flows back in the supply chain).

So What’s This I Hear About Bullwhips and Supply Chains



Demand volatility can be amplified as you go back in the supply chain

Variability amplification!!

1. Bullwhip effect: volatility of demand, orders, and inventories in the supply chain tends to amplify as one moves upstream.
2. The more tiers in the supply chain, the more variability amplification. What does this say for secondary level suppliers?
3. Variability -- Who cares?
   - Variability drives up costs due to excess inventory and underutilized resources

Potential Causes of the Bull Whip Effect (1)

Order Batching

- Imagine that the distribution center (DC) sees a demand of 100+/-30 each day but has to order in sizes of 1000 from the factory (due to order batching policies such as EOQ)
  - Factory will see demand of 1000 followed by lots of zero demand days

Potential Causes of the Bull Whip Effect (2)

Allocation/Shortage Gaming

- The distribution center (DC) places Wal-Mart and Target on allocation due to product shortage
  - Each retailer will only get 75% of their order size
- Wal-Mart and Target artificially inflate their order size
  - They order more than the real customer demand as they know they won't get their whole order

Potential Causes of the Bull Whip Effect (3)

Price Speculation and Stockpiling

- P&G announces that wholesale prices are going to increase two months from now
  - Wal-Mart and Target order more now than current customer demand so they can fulfill demand later with the lower-price products

Potential Causes of the Bull Whip Effect (4)

Demand Forecast Updates Not Shared

- Wal-Mart forecasts an average increase of 20 units per day in demand.
  - It increases its initial order size on the DC by more than 20 (say increases by 30) as it also needs to build up its safety stock
- The DC sees an increase of 30 and thinks customer demand is increasing by 30 units per day
  - It increases its initial order size on the factory by more than 30

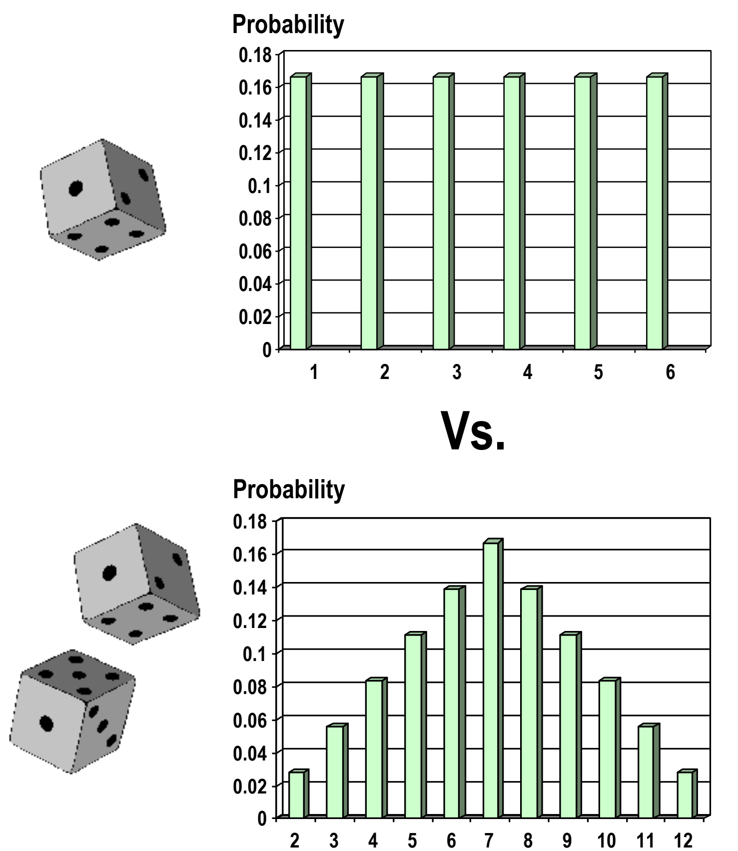
Hence all the talk about Collaborative Planning, Forecasting and Replenishment

Mitigating the Bullwhip Effect

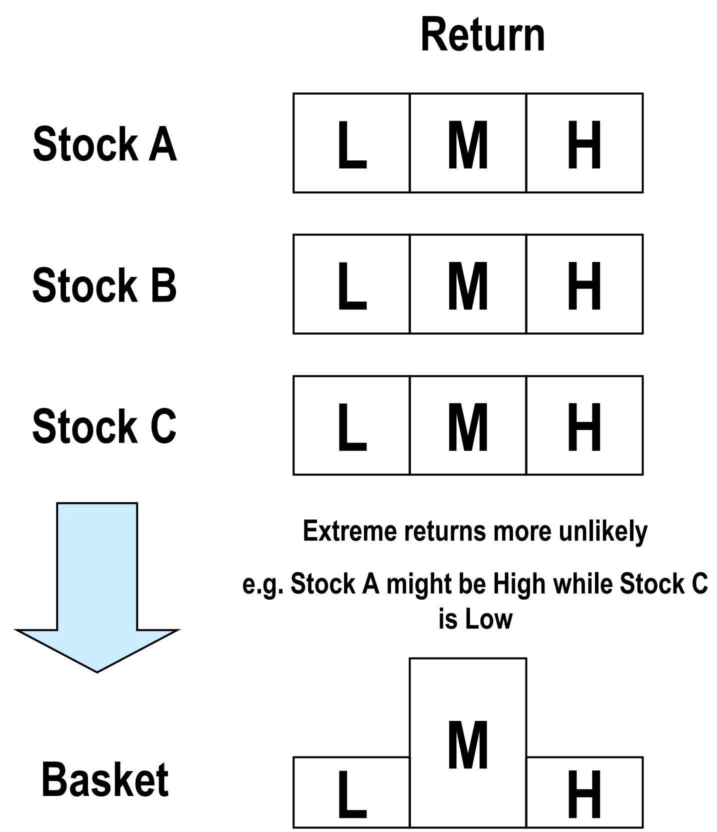
1. Better information visibility and tracking of inventory,
2. Better sharing of demand and inventory information: Collaborative Planning and Forecasting Replenishment (CPFR)
3. Allocation based on past sales instead of current orders when shortage occurs
4. Reducing lead times: Less safety stock needed
5. Suppliers located close by
6. Everyday low prices

What is statistical (risk) pooling?

Extreme Outcomes Less Likely with Two Die



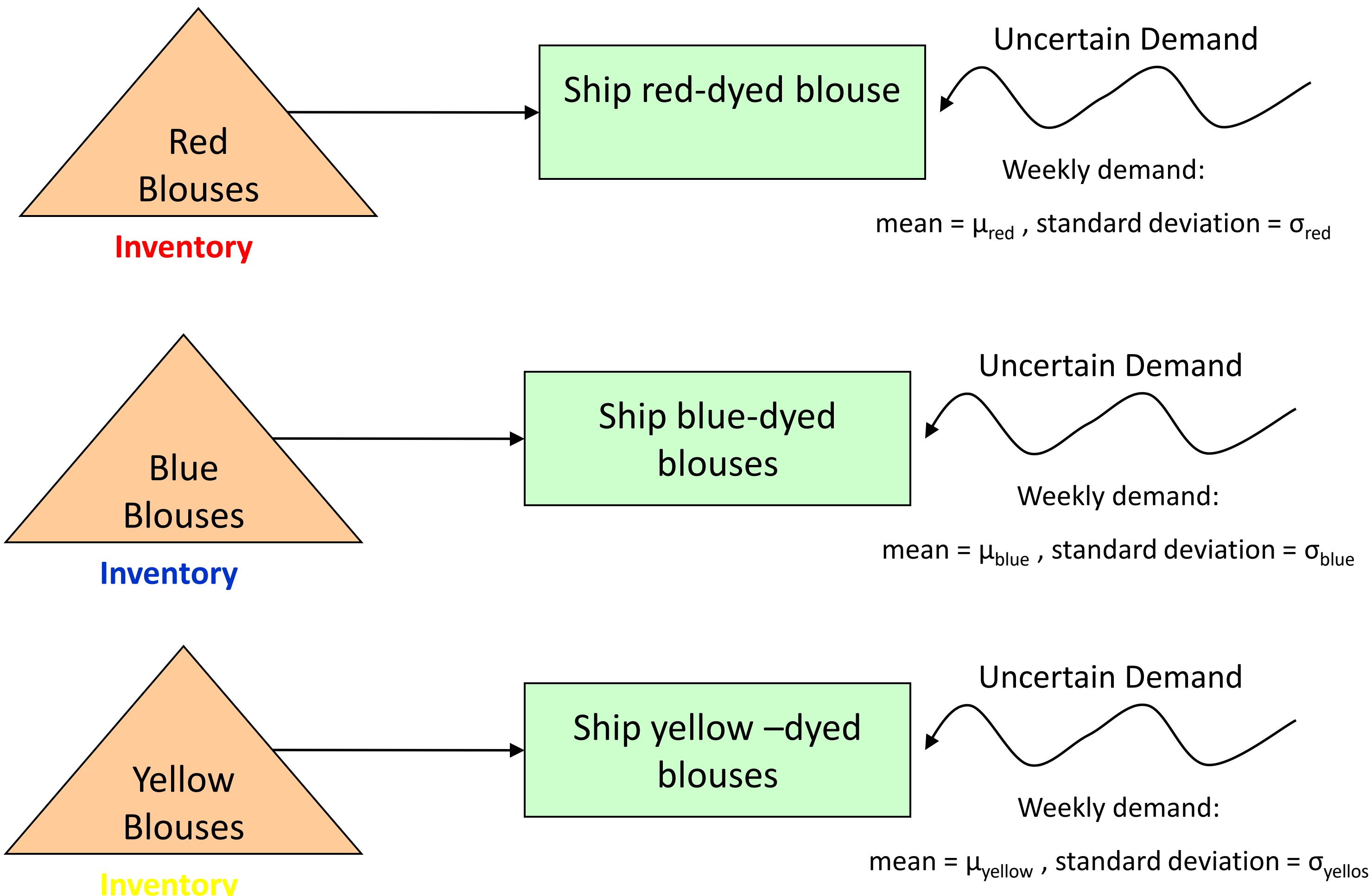
Statistical Pooling Concept Applied to an Investment Portfolio



Risk Pooling Applications in Supply Chains

- Demand pooling
  - E-commerce channel aggregates customer orders from various markets
- Component commonality
  - Share common components in multiple products
- Location pooling (inventory centralization)
  - Use central warehouses or large regional warehouses to serve multiple markets

Consider an apparel company producing blouses in different colors



How much safety stock in blouses do we need?

- The lead time for each shipment is L weeks (no matter what color of blouse).
- Let's say we need enough inventory of each blouse color to provide a service level of p%.

$$\text{Safety stock of Red blouses} = z_p \sigma_{red} \sqrt{L}$$

$$\text{Safety stock of Blue blouses} = z_p \sigma_{blue} \sqrt{L}$$

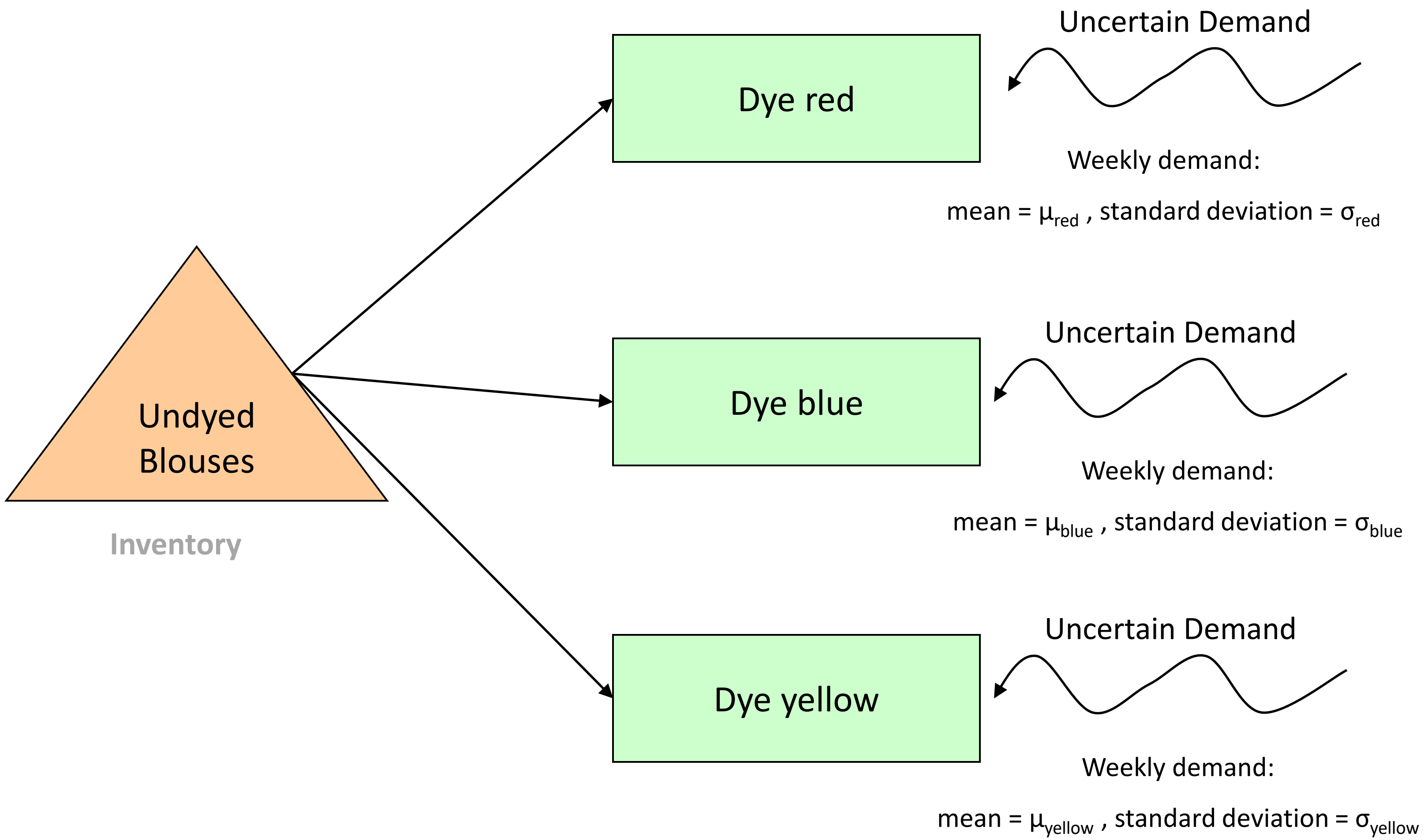
$$\text{Safety stock of Yellow blouses} = z_p \sigma_{yellow} \sqrt{L}$$

If we want a 90% service level ($z_{.90}$ = 1.28) and the *weekly* standard deviation for red blouses is 50, blue blouses is 75, and yellow = 35, how much total safety stock must be held? Assume the lead time is 2 weeks.

$$SS_{red} = 1.28 * 50 * \sqrt{2} = 91, SS_{blue} = 1.28 * 75 * \sqrt{2} = 136$$

$$SS_{yellow} = 1.28 * 35 * \sqrt{2} = 63, Total = 91 + 136 + 63 = 290$$

What if the company postponed the dyeing of blouses?



Safety stock of the undyed blouses = ?

- Again assume
  - The lead time is L weeks.
  - Let's say the blouse inventories need to provide a service level of p%.
- What is the mean demand that is placed on the undyed blouses?
  - Mean demand for undyed blouses = red demand + blue demand + yellow demand
- What is the variance of demand that is placed on the undyed blouse inventory?
  - Variance of demand for undyed blouses[1] = Variance of red demand + Variance of blue demand + Variance of yellow demand, $\sigma^2_{Unidyed} = \sigma^2_{red} + \sigma^2_{blue} + \sigma^2_{yellow}$
- What is the standard deviation of demand of undyed blouse?
  - Standard deviation for undyed blouse supply, $\sqrt{\sigma^2{}_{Undyed}} = \sqrt{\sigma^2{}_{red} + \sigma^2{}_{blue} + \sigma^2{}_{yellow}}$

$$\text{Safety stock of undyed blouse inventory} = z_p \sigma_{undyed} \sqrt{L} = z_p \left(\sqrt{\sigma^2_{red} + \sigma^2_{blue} + \sigma^2_{yellow}} \right) \sqrt{L}$$

Suppose all blouses remain undyed until the last minute, what is the amount of safety stock of undyed blouses that would be needed? Lead time = 2 weeks

$$SS_{undyed} = 1.28 * \sqrt{50^2 + 75^2 + 35^2} * \sqrt{2} = 175$$

What is the relative difference in safety stock between the two strategies ?

- Dye early, separate color inventories

$$\text{Safety Stock} = z_p(\sigma_{red} + \sigma_{blue} + \sigma_{yellow})\sqrt{L}$$

- Undyed blouse inventory:

$$\text{Safety Stock} = z_p\left(\sqrt{\sigma_{red}^2 + \sigma_{blue}^2 + \sigma_{yellow}^2}\right)\sqrt{L}$$

Difference in Safety Stock $= z_p\sqrt{L}\left(\sigma_{red} + \sigma_{blue} + \sigma_{yellow} - \sqrt{\sigma_{red}^2 + \sigma_{blue}^2 + \sigma_{yellow}^2}\right)$

Note: Differentiated safety stock = 290. Undyed safety stock = 175.

We can save inventory (safety stock = 125 units) by keeping the blouses undyed and waiting until the last minute to dye them the required color. Also, we may have better forecasts of demand if we wait to dye the blouses at the last minute.

- aggregate demand forecast more accuracy
- individual forecast closer to demand realization

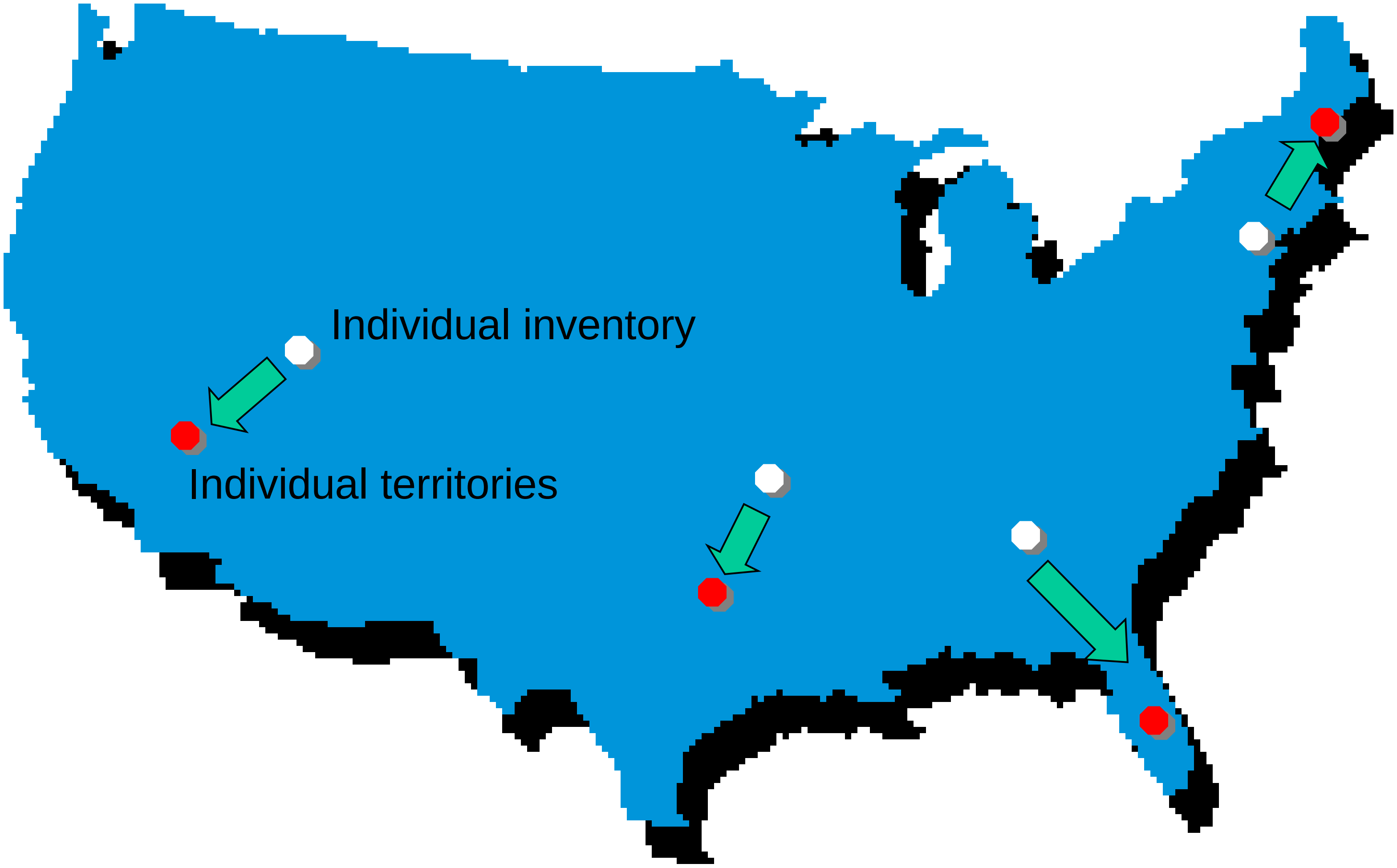
Postponement is an Ideal Strategy If …

- Forecasts in the aggregate are more accurate than individual forecasts
- Color variety can be added quickly based on new market information
- Dyeing is a quick step which can be postponed until the blouse is nearly completed. Buttons and fixtures not affected.
- Demand for products is independent

Possible downsides of using a common component

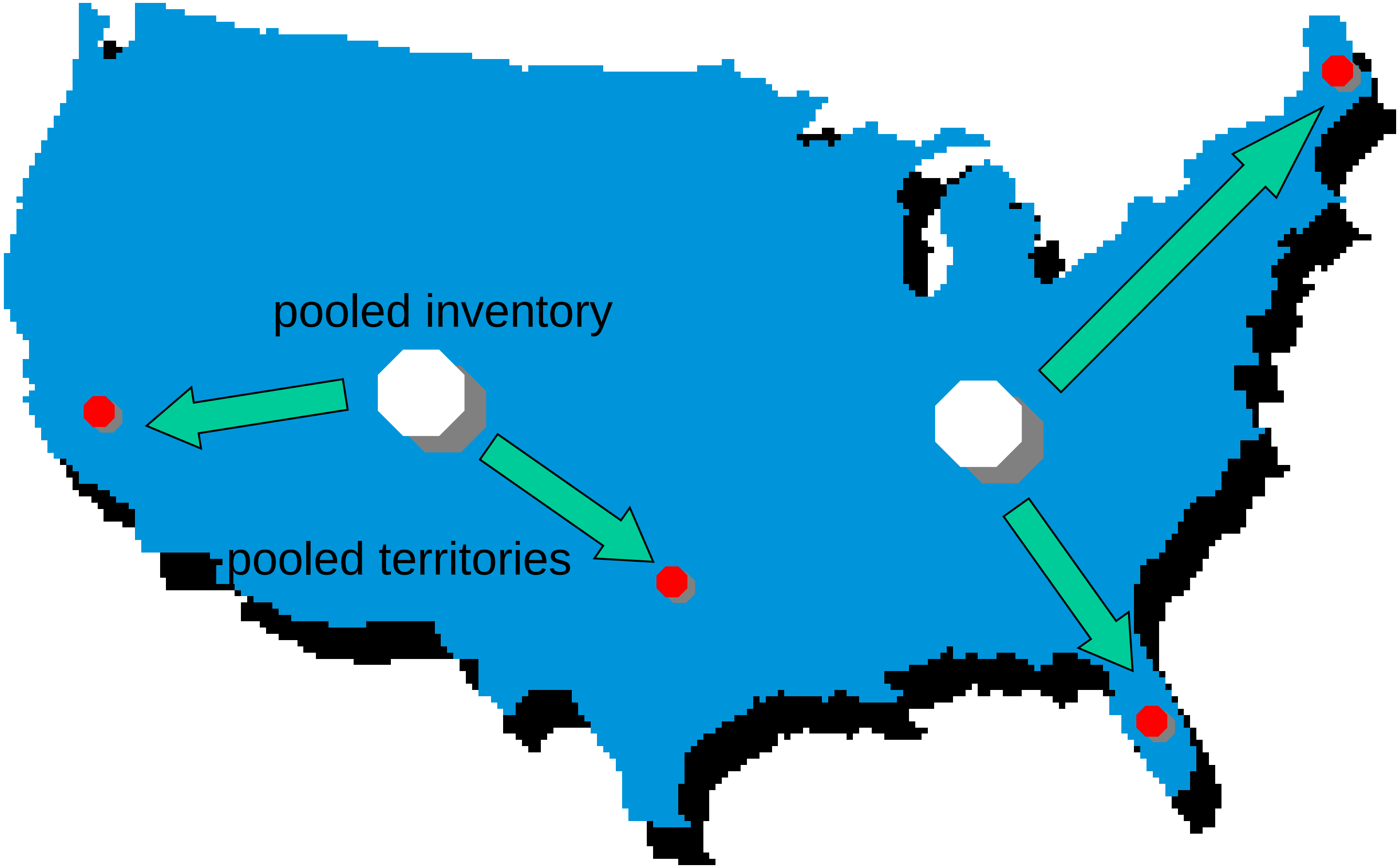
- The common component may cost more money to produce/procure
  - Would need to check if the annual inventory savings are larger than the increase in annual procurement cost.
- The common component may not achieve the same functionality.
- Impact on brand value
  - How happy are you if you spend money on a Lexus and find that it has the same components as a Toyota Camry?

Location Pooling (I)



Location Pooling (II)

Location Pooling – strategy of combining the inventory from multiple territories/locations into a single location



What are advantages/disadvantages of location pooling?

- Advantages
  - Same service level with less inventory OR
  - Better service level with same amount of inventory
  - Consolidate fixed costs of inventory management systems and handling: Economies of scale.

- Disadvantages
  - Longer transit times
  - Higher transportation costs
  - Local tastes may dictate locally-customized products and make local pooling ineffective