

FORECASTS

Demand management

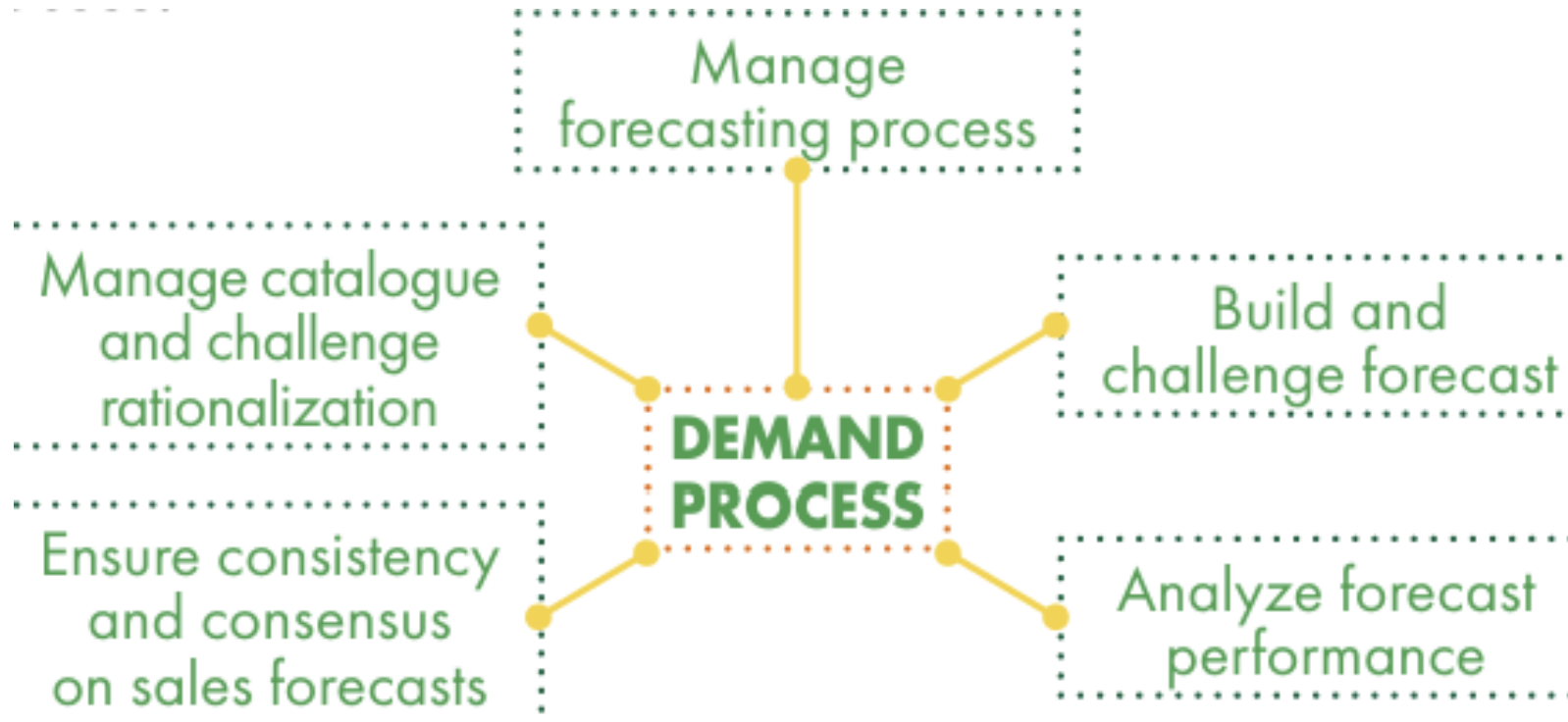
- **Forecasting**
- **Order processing**
- Forecast is usually wrong
- Do not include safety stock in forecasts
- Separating :
 - normal ; promotional ; launching
- Updating : monthly or more

Characteristics

- **Demand patterns to be identified**
- **Trend**
- **Seasonality**
- **Random variation**
- **Stable versus dynamic**
- **Dependent versus independent demand**

Cooperation

France Supply Chain



FORECASTS

Collection and preparation of data

Forecasting techniques

- Qualitative...on judgment
- Extrinsic : external factors
- Intrinsic
 - Average demand *if quite steady*
 - Moving averages *with little seasonality*
 - Exponential smoothing : *the new data can be given any weight wanted*



FORECASTS

- Seasonality
 - Index
 - Forecasts and annual demand average
 - Deseasonalized demand
 - Forecast error
 - Mean absolute deviation
 - Normal distribution
 - Production lead time / Demand lead time ratio
- 

Patterns of Demand

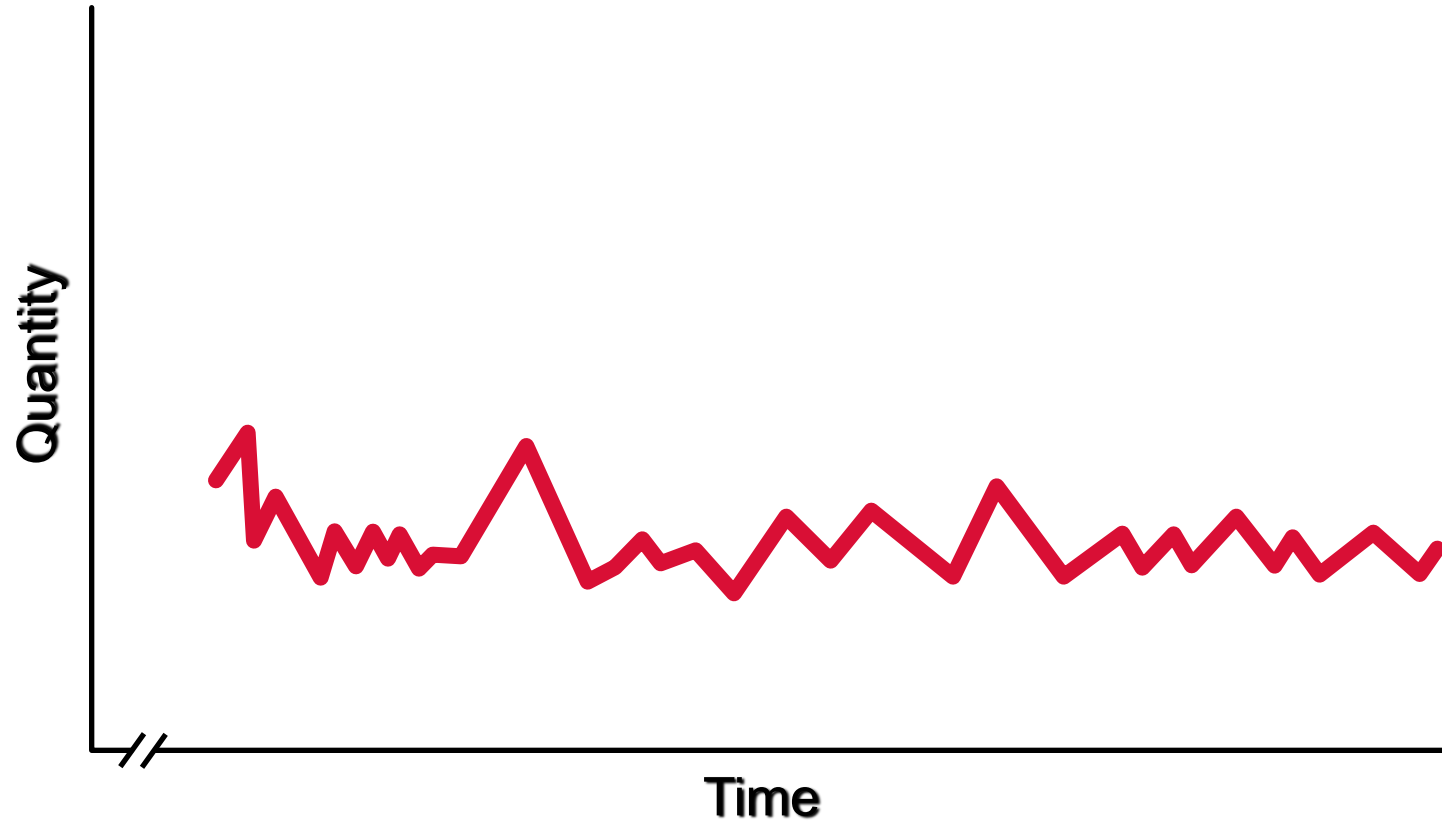
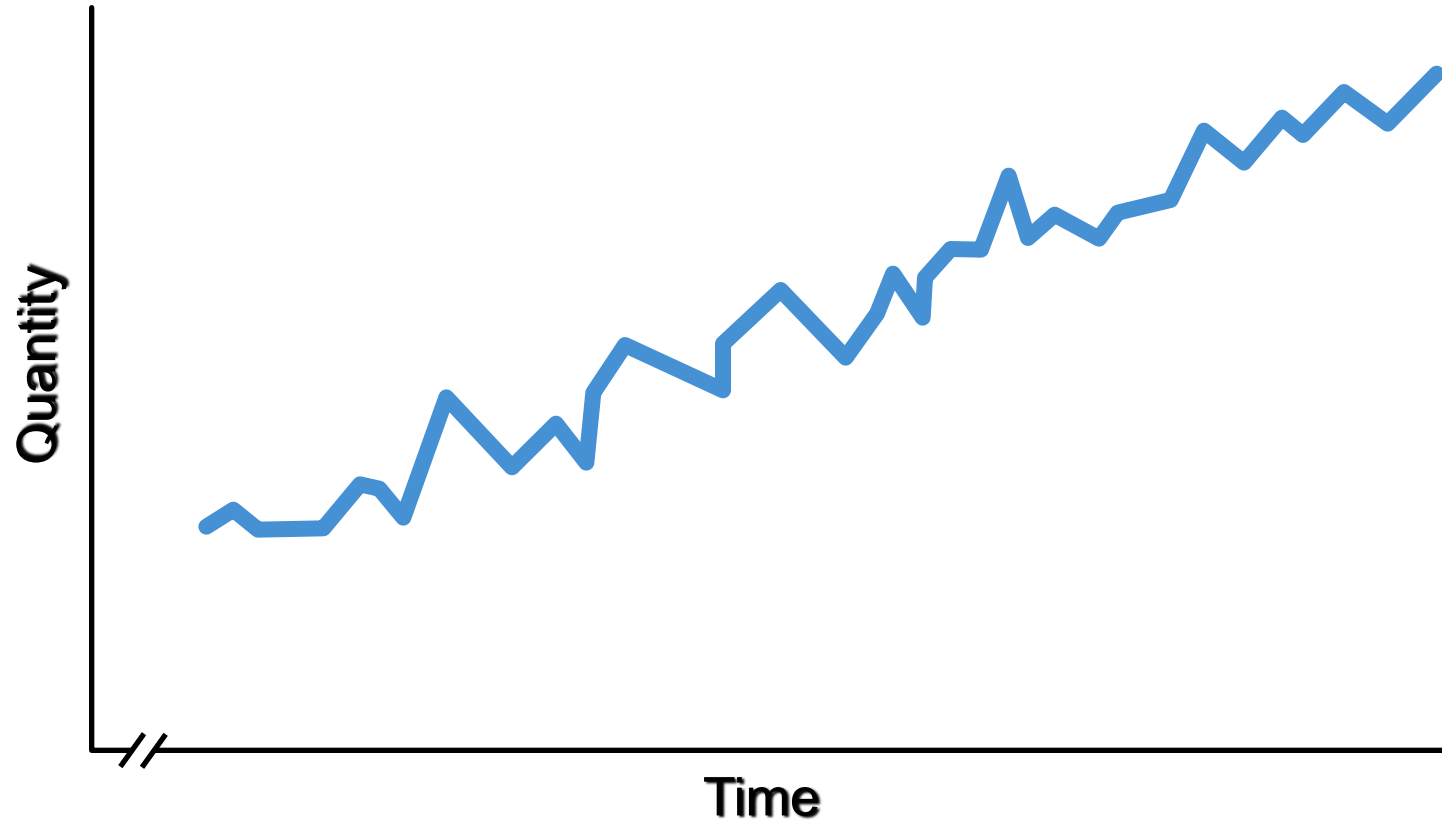


Figure 13.1

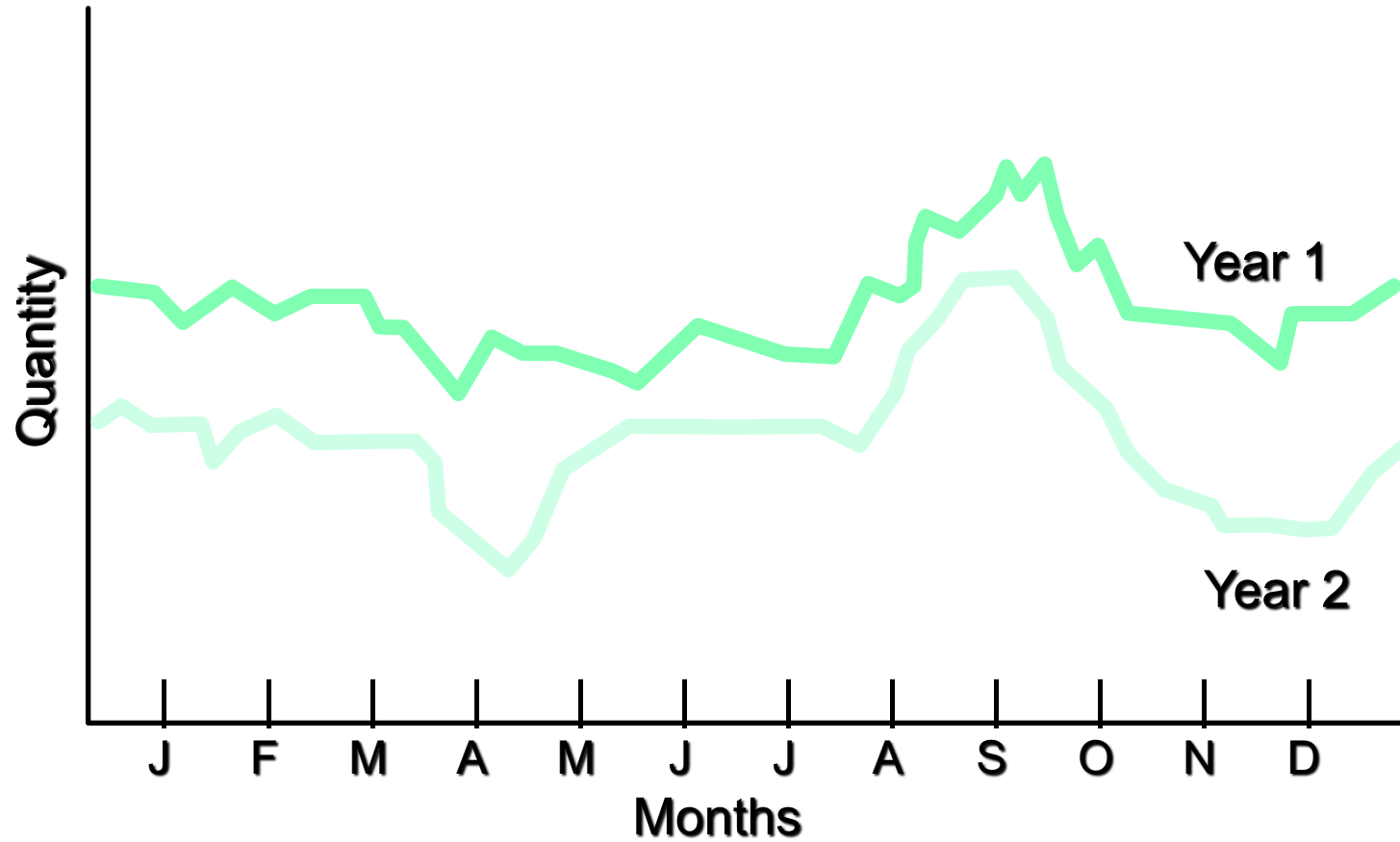
(a) Horizontal: Data cluster about a horizontal line.

Patterns of Demand



(b) Trend: Data consistently increase or decrease.

Patterns of Demand



(c) Seasonal: Data consistently show peaks and valleys.

FUTURE TIME HORIZON



Short-range forecast

This forecast has a time span of **up to 1 year** but is generally less than 3 months. It is used for planning purchasing, job scheduling, workforce levels, job assignments, and production levels.



Medium-range forecast

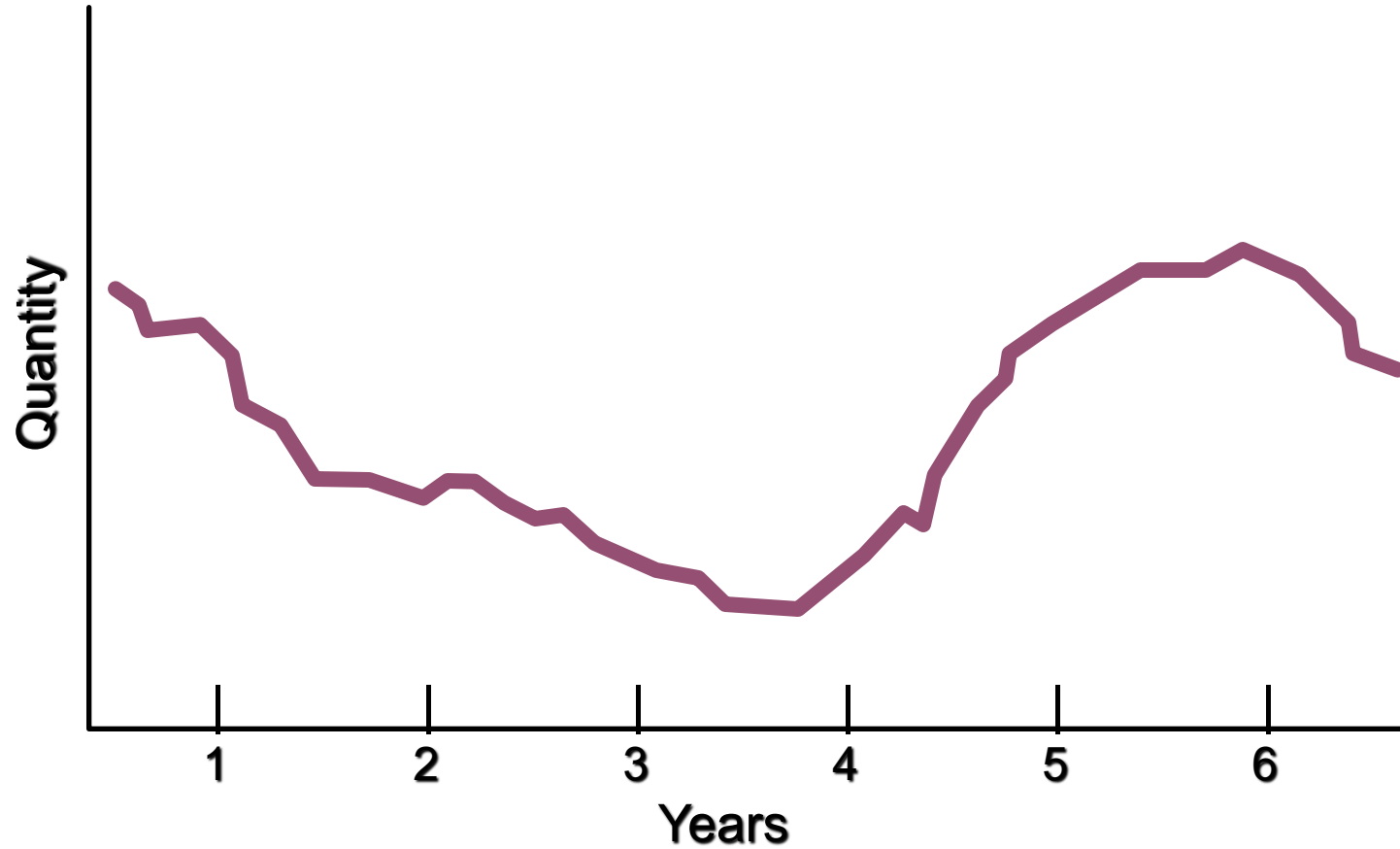
A medium-range, or intermediate, forecast generally spans from 3 months to 3 years. It is useful in sales **planning, production planning and budgeting**, cash budgeting, and analysis of various operating plans.



Long-range forecast

Generally 3 years or more in time span, long-range forecasts are used in planning for **new products, capital expenditures, facility location** or expansion, and research and development.

Patterns of Demand



(d) Cyclical: Data reveal gradual increases and decreases over extended periods.

Demand forecast application

Economic forecasts

*Planning **indicators** that are valuable in helping organizations prepare medium- to long-range forecasts.*

Technological forecasts

*Long-term forecasts concerned with the rates of **technological** progress.*

Demand forecasts

*Projections of a company's sales for each time period in the **planning horizon**.*

Connection with techniques

TABLE 13.1 DEMAND FORECAST APPLICATIONS

Application	Time Horizon		
	Short Term (0–3 months)	Medium Term (3 months– 2 years)	Long Term (more than 2 years)
Forecast quantity	Individual products or services	Total sales Groups or families of products or services	Total sales
Decision area	Inventory management Final assembly scheduling Workforce scheduling Master production scheduling	Staff planning Production planning Master production scheduling Purchasing Distribution	Facility location Capacity planning Process management
Forecasting technique	Time series Causal Judgment	Causal Judgment	Causal Judgment

Qualitative method

Jury of executive opinion

- A forecasting technique that uses the opinion of a small group of **high-level managers** to form a group estimate of demand.

Delphi method

- A forecasting technique using a group process that allows experts to make forecasts.

Sales force composite

- A forecasting technique based on salespersons' estimates of expected sales.

Market survey

- A forecasting method that solicits input from customers or potential customers regarding future purchasing plans.

FORECASTS

- **Principles**

- Forecasts are usually wrong
- Every forecast should include an estimate of error
- Forecasts are more accurate **for families or groups**
- Forecasts are more accurate for **nearer time periods**

FORECASTS

Collection and preparation of data

Forecasting techniques

- Qualitative...on judgment
- Extrinsic : external factors
- Intrinsic
 - **Average demand** if quite steady
 - **Moving averages** with little seasonality
 - **Exponential smoothing** : the new data can be given any weight wanted

Sum up



ABOUT FORECASTS
TRENDS

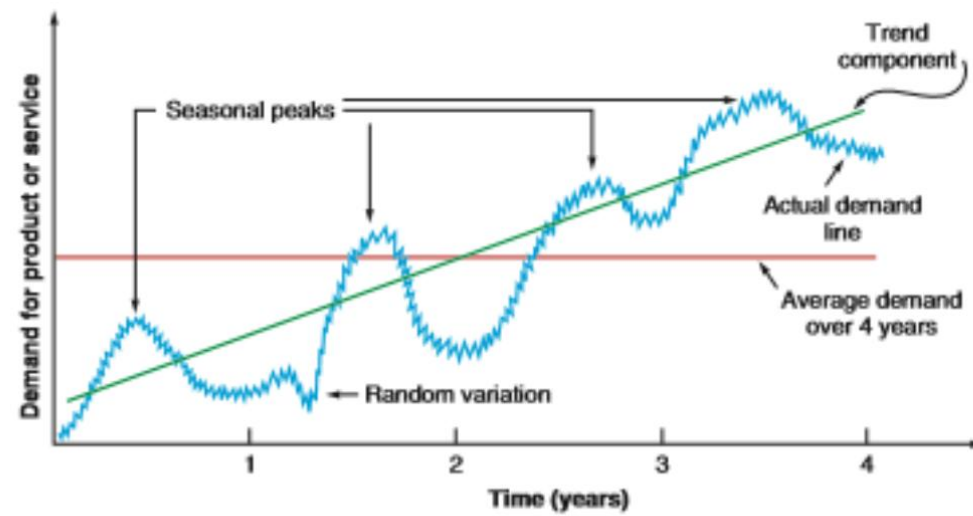


ABOUT TIME



WHAT KIND OF
MEASURES' APPROACH

Naive approach



Moving averages

Donna's Garden Supply wants a 3-month moving-average forecast, including a forecast for next January, for shed sales.

APPROACH ► Storage shed sales are shown in the middle column of the following table. A 3-month moving average appears on the right.

MONTH	ACTUAL SHED SALES	3-MONTH MOVING AVERAGE
January	10	
February	12	
March	13	
April	16	$(10 + 12 + 13)/3 = 11\frac{2}{3}$
May	19	$(12 + 13 + 16)/3 = 13\frac{2}{3}$
June	23	$(13 + 16 + 19)/3 = 16$
July	26	$(16 + 19 + 23)/3 = 19\frac{1}{3}$
August	30	$(19 + 23 + 26)/3 = 22\frac{2}{3}$
September	28	$(23 + 26 + 30)/3 = 26\frac{1}{3}$
October	18	$(26 + 30 + 28)/3 = 28$
November	16	$(30 + 28 + 18)/3 = 25\frac{1}{3}$
December	14	$(28 + 18 + 16)/3 = 20\frac{2}{3}$

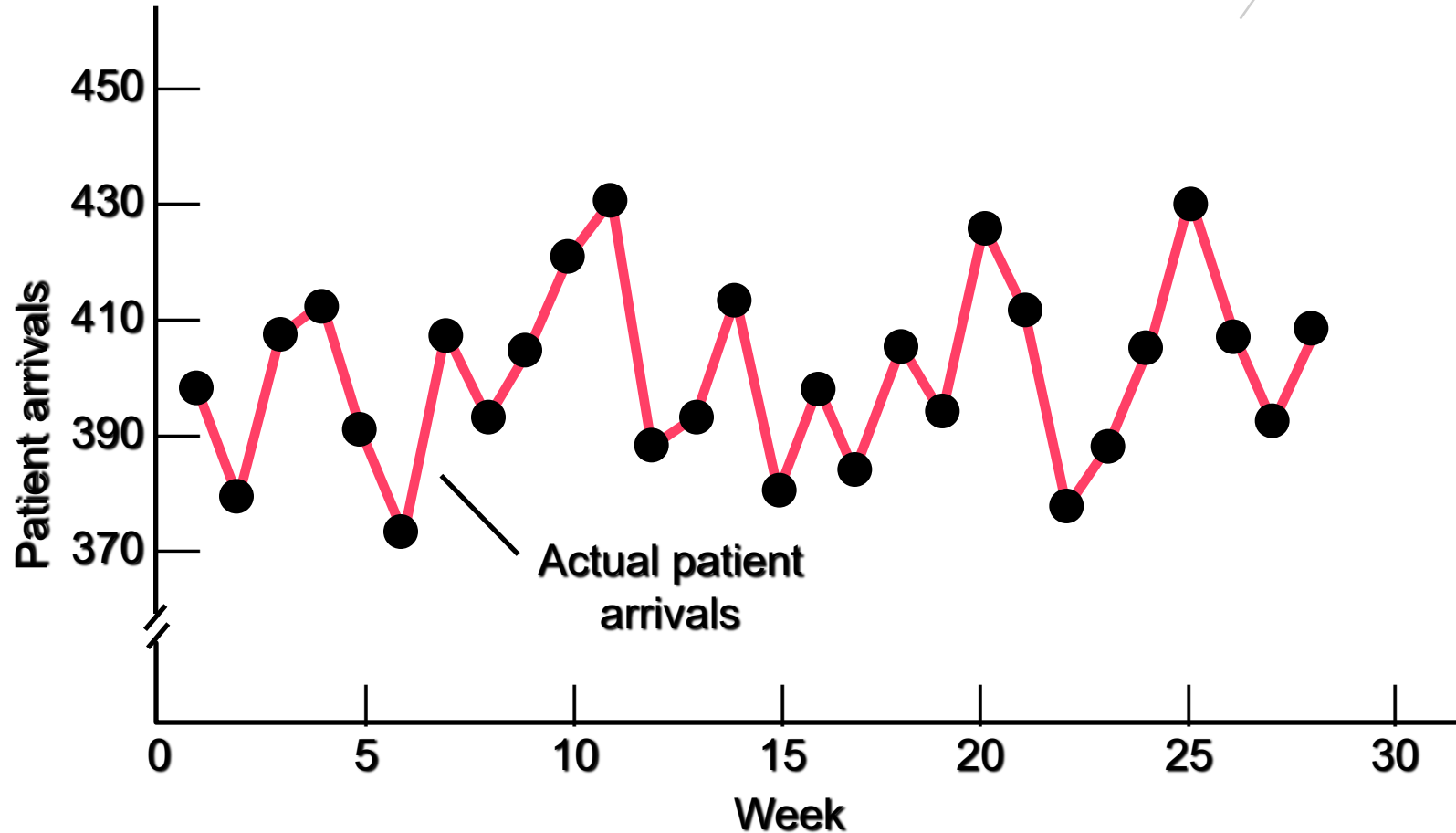
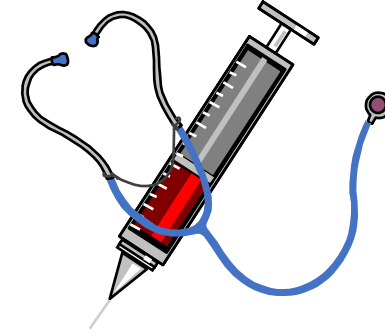
$$\text{Moving average} = \frac{\sum \text{demand in previous } n \text{ periods}}{n}$$

where n is the number of periods in the moving average—for example, 4, 5, or 6 months respectively, for a 4-, 5-, or 6-period moving average.

- A forecasting method that uses an average of the n most recent periods of data to forecast the next period.

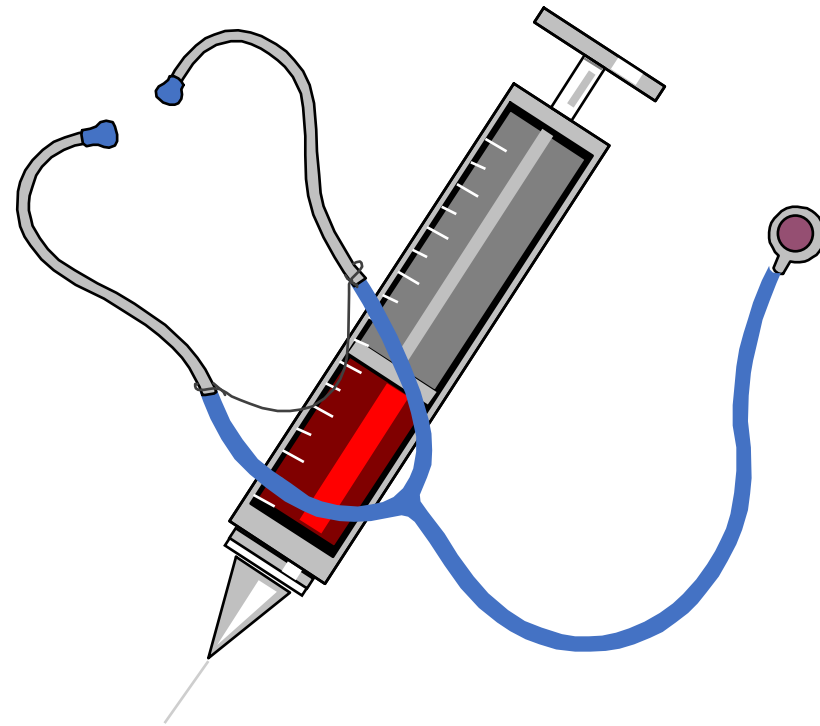
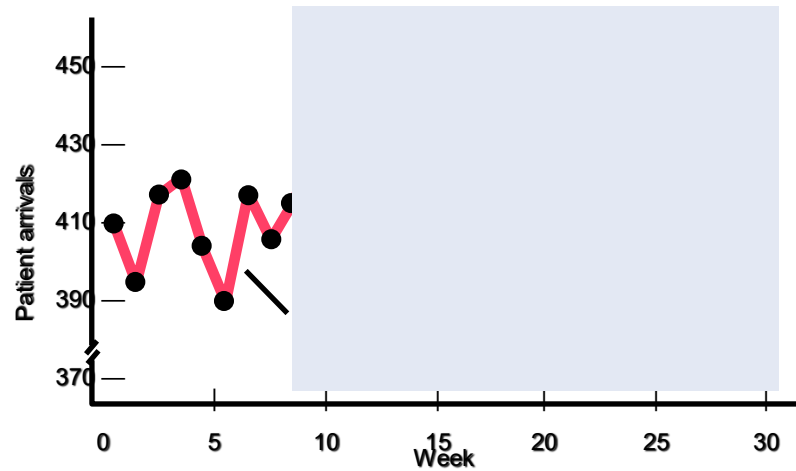
Time-Series Methods

Simple Moving Averages



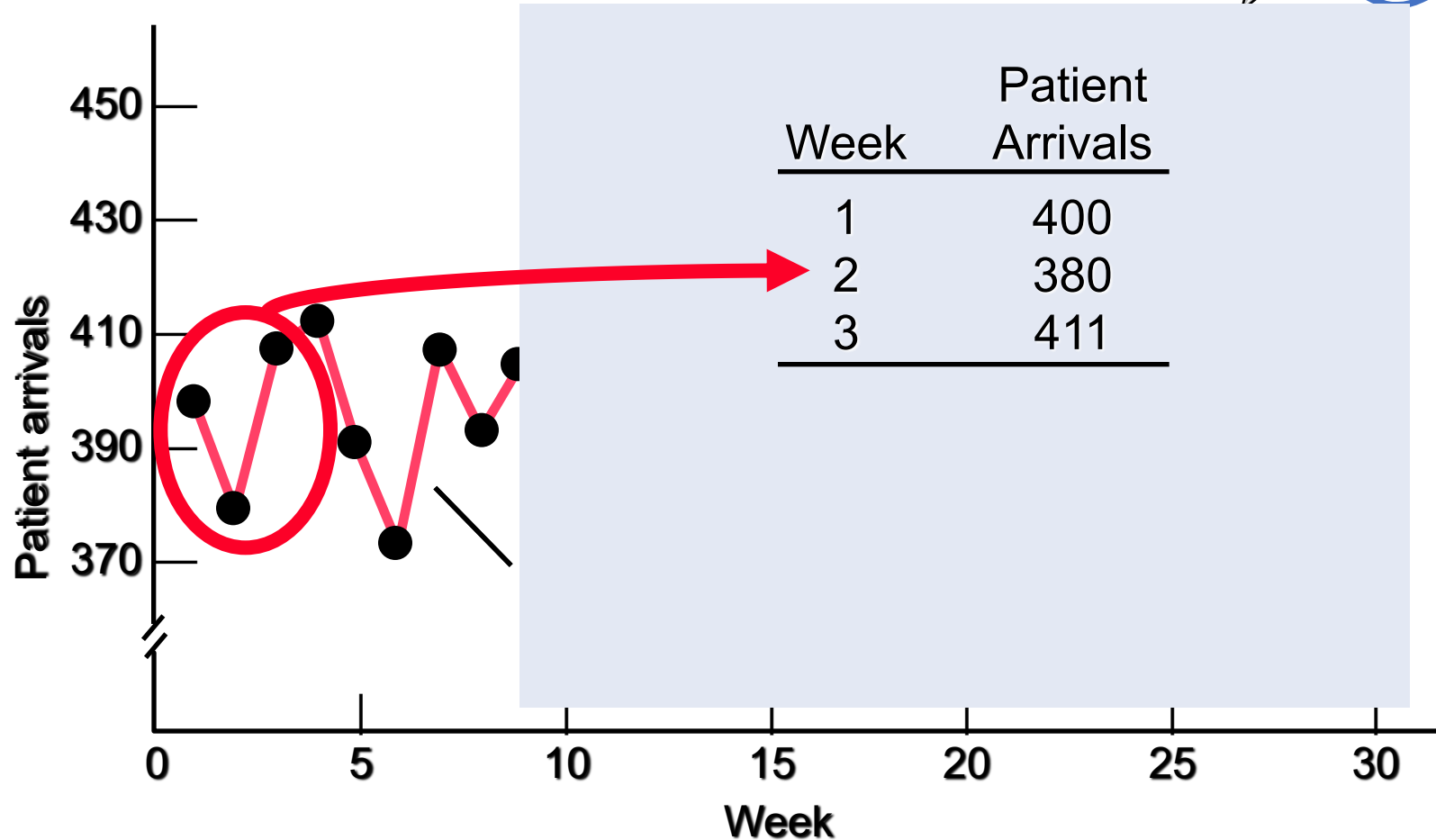
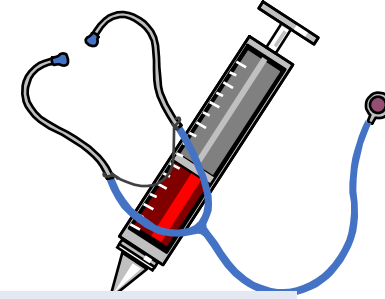
Time-Series Methods

Simple Moving Averages



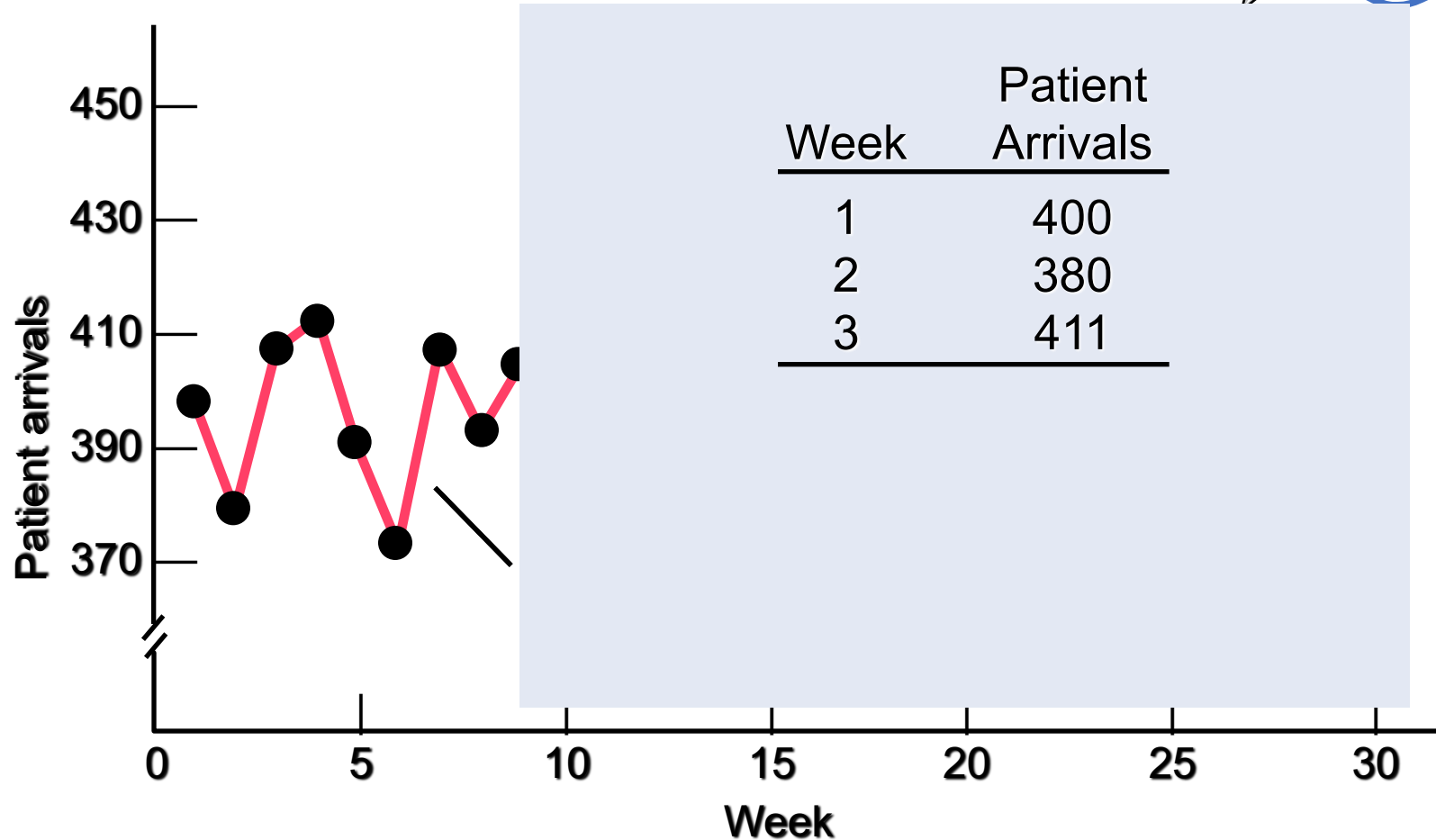
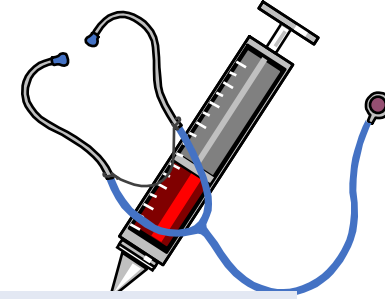
Time-Series Methods

Simple Moving Averages



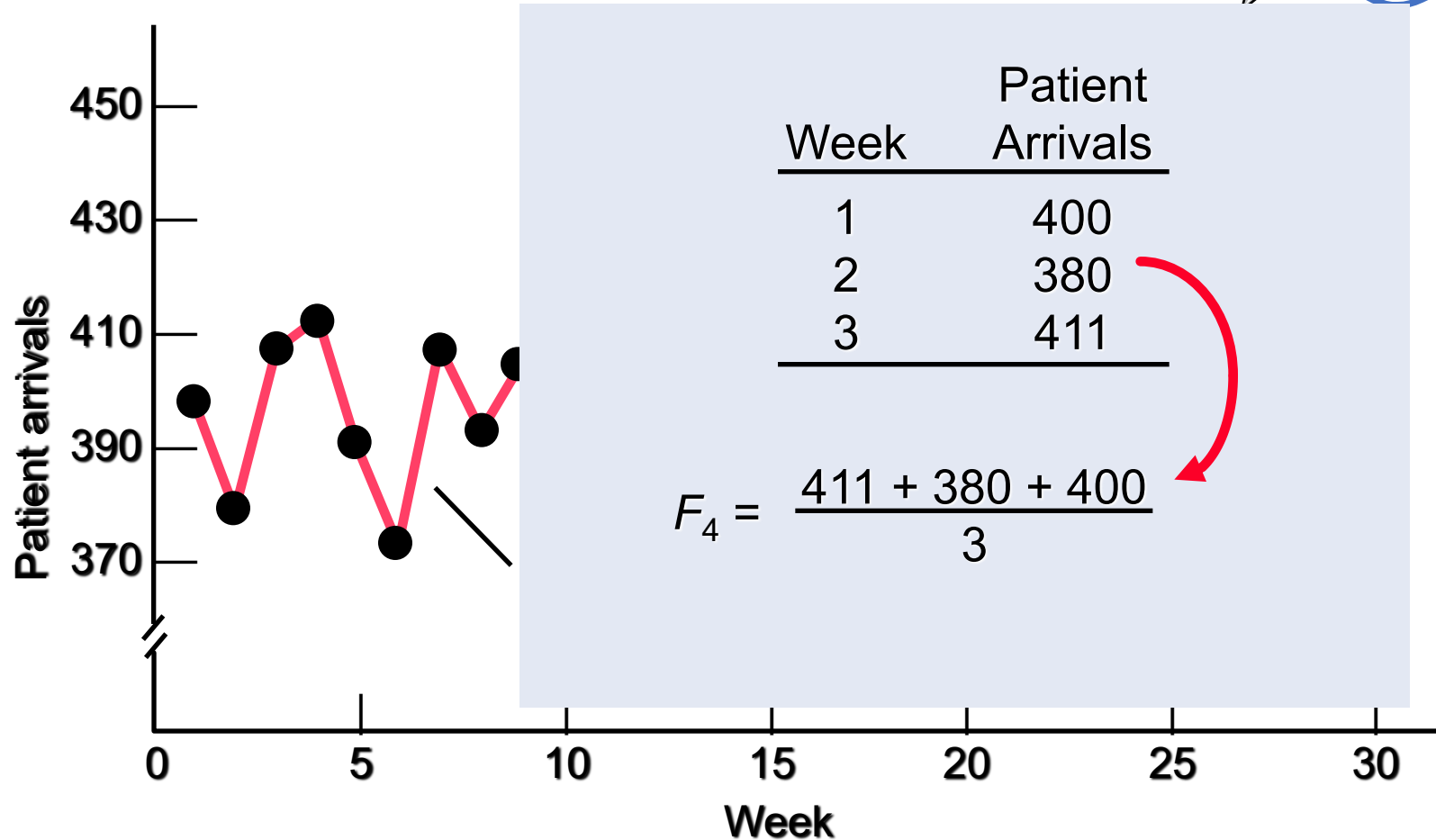
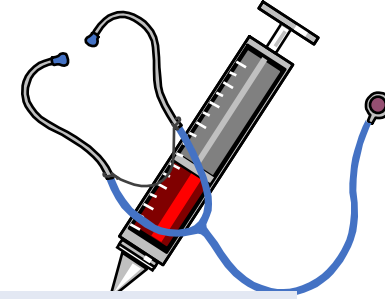
Time-Series Methods

Simple Moving Averages



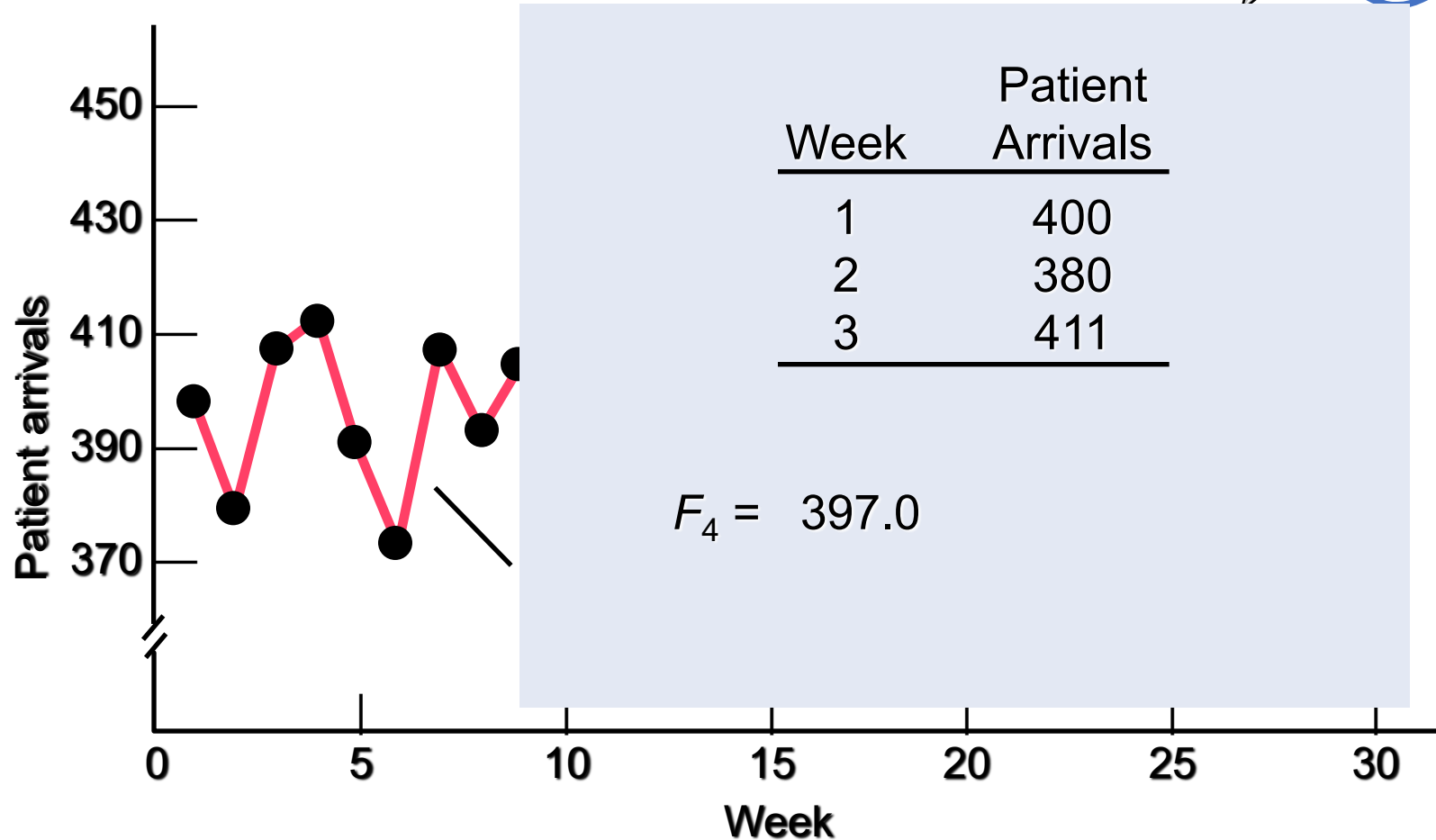
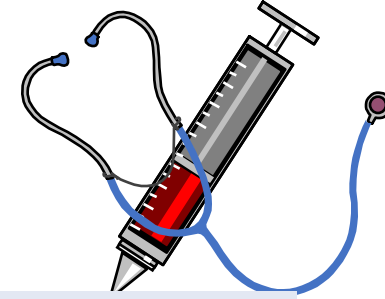
Time-Series Methods

Simple Moving Averages



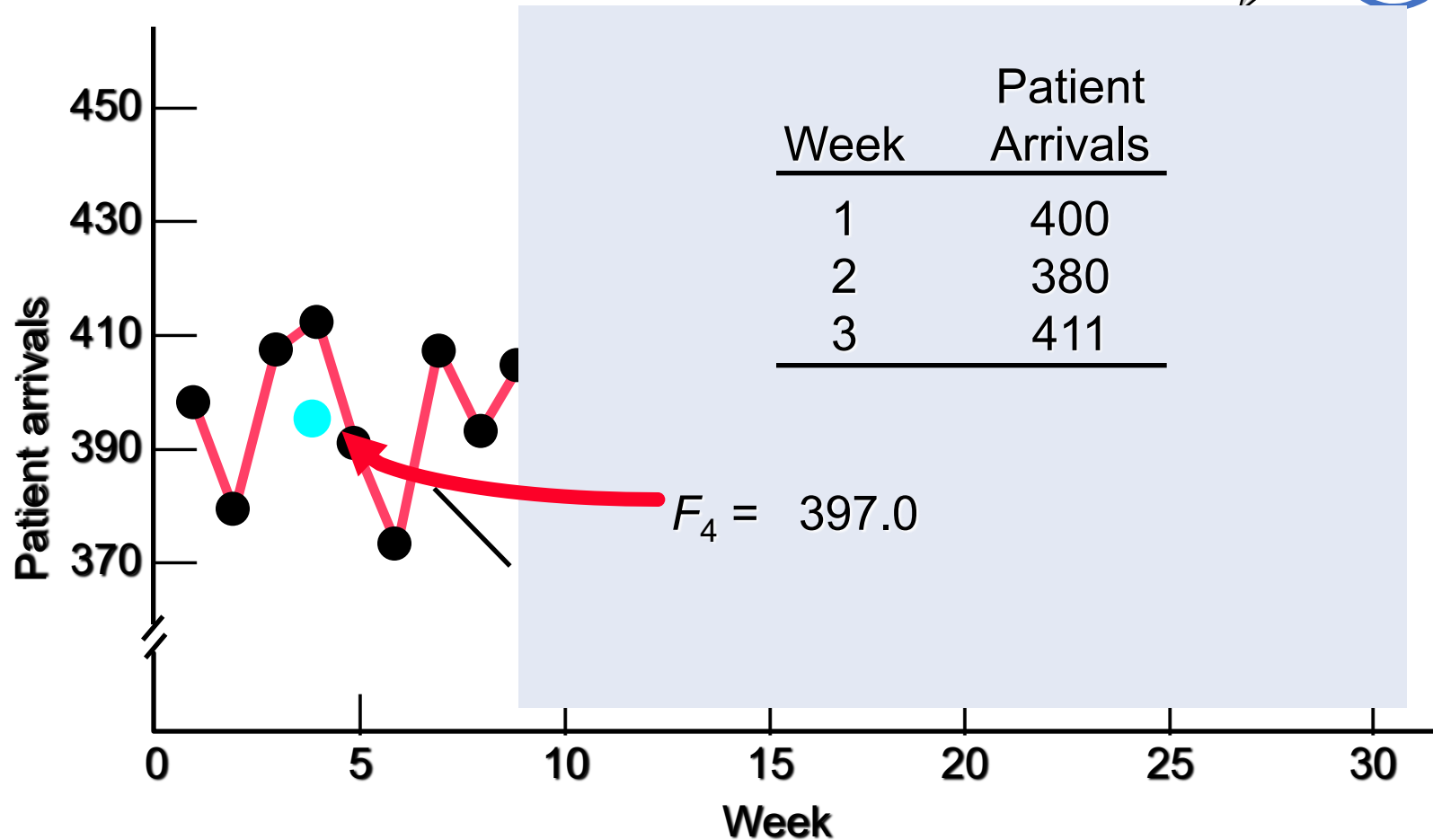
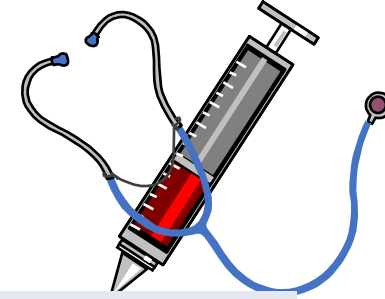
Time-Series Methods

Simple Moving Averages



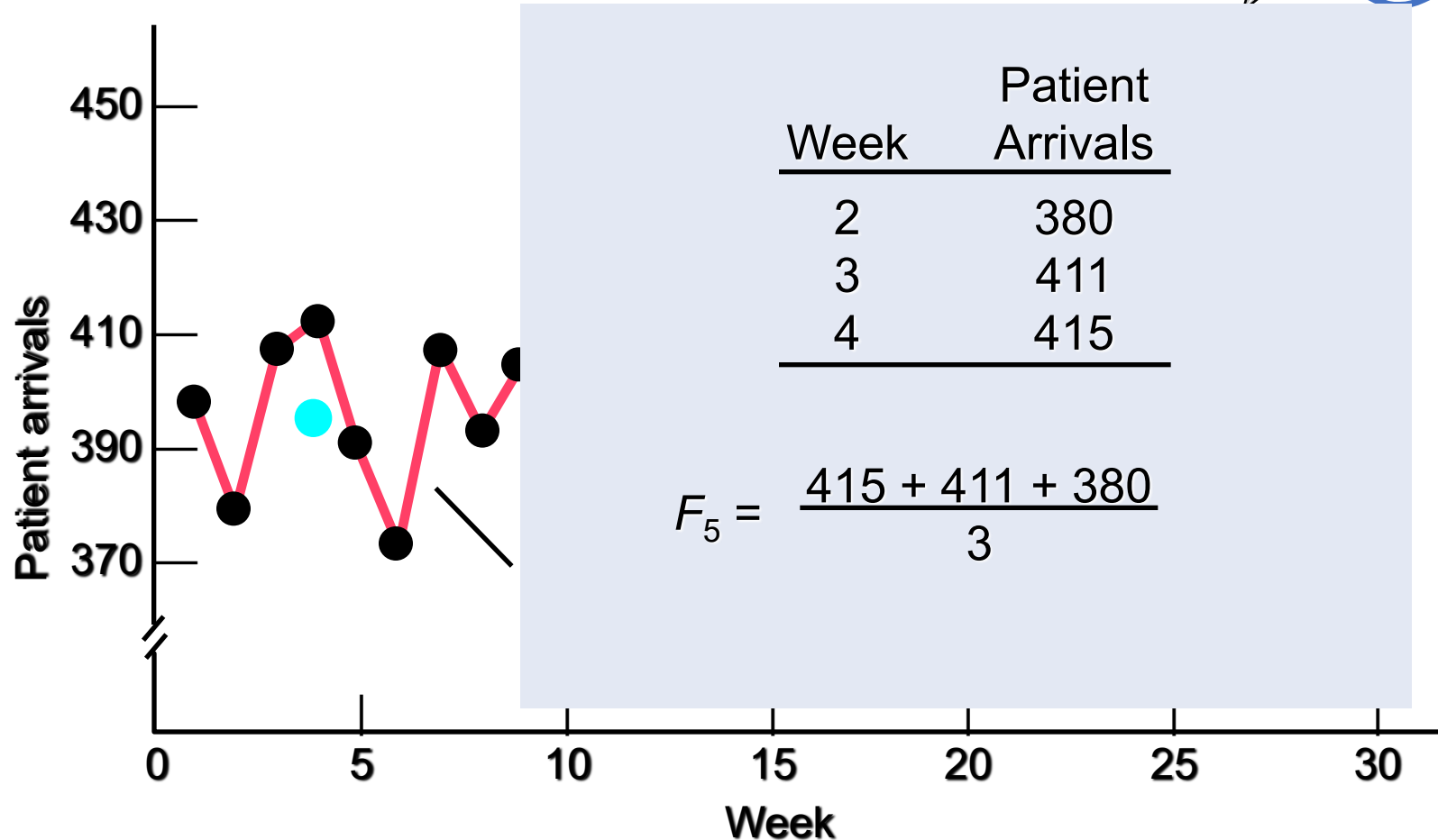
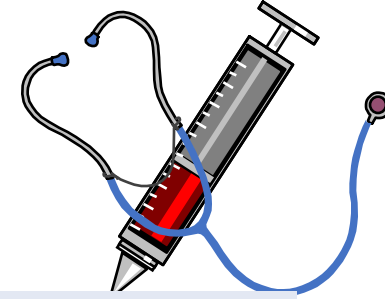
Time-Series Methods

Simple Moving Averages



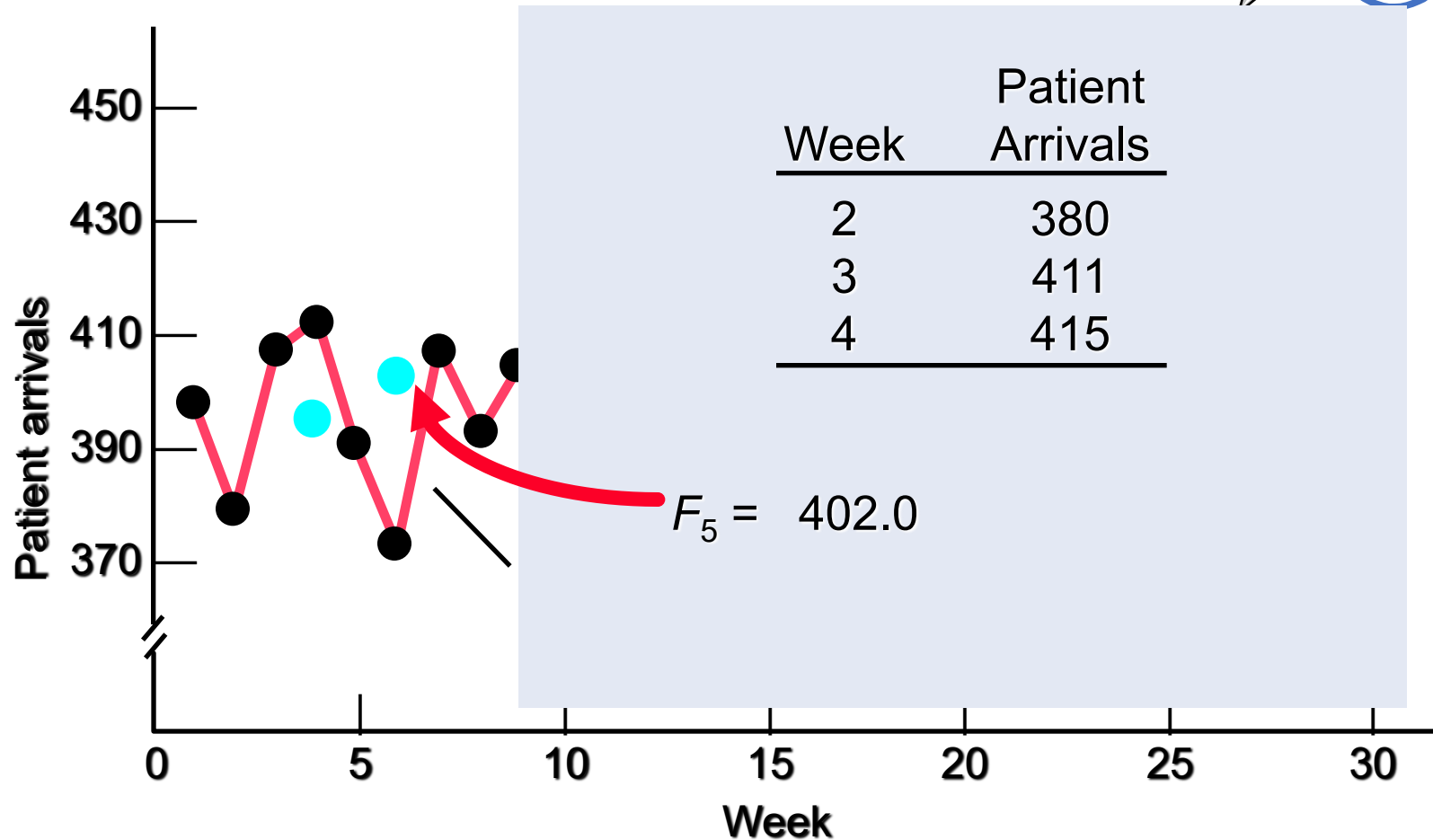
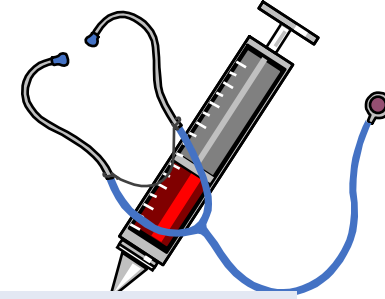
Time-Series Methods

Simple Moving Averages



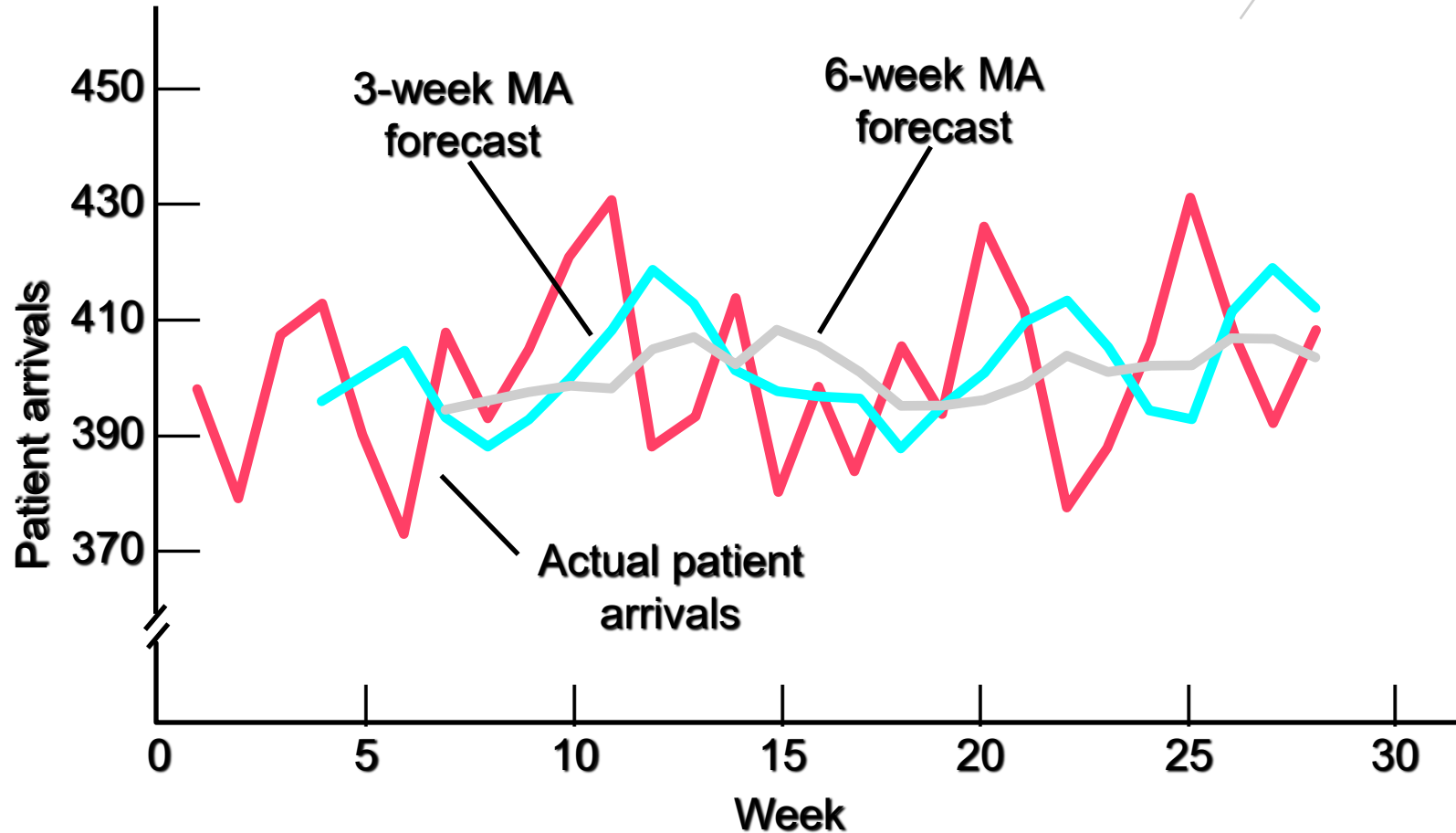
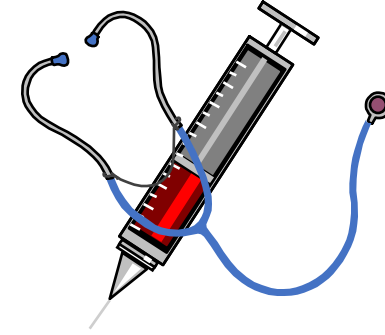
Time-Series Methods

Simple Moving Averages



Time-Series Methods

Simple Moving Averages



WEIGHTED MOVING AVERAGE

DETERMINING THE WEIGHTED MOVING AVERAGE

Donna's Garden Supply (see Example 1) wants to forecast storage shed sales by weighting the past 3 months, with more weight given to recent data to make them more significant.

APPROACH ► Assign more weight to recent data, as follows:

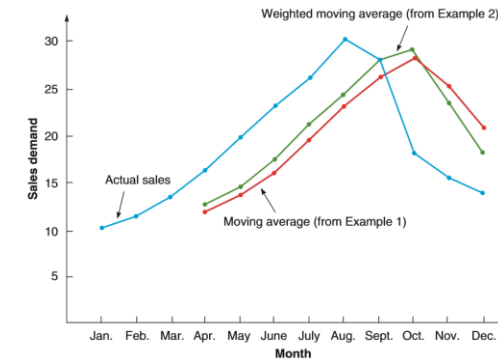
WEIGHTS APPLIED	PERIOD
3	Last month
2	Two months ago
1	Three months ago
$\frac{6}{6}$	Sum of weights
Forecast for this month =	
$3 \times \text{Sales last mo.} + 2 \times \text{Sales 2 mos. ago} + 1 \times \text{Sales 3 mos. ago}$	
Sum of the weights	

SOLUTION ► The results of this weighted-average forecast are as follows:

MONTH	ACTUAL SHED SALES	3-MONTH WEIGHTED MOVING AVERAGE
January	10	
February	12	
March	13	
April	16	$[(3 \times 13) + (2 \times 12) + (10)]/6 = 12\frac{1}{6}$
May	19	$[(3 \times 16) + (2 \times 13) + (12)]/6 = 14\frac{1}{3}$
June	23	$[(3 \times 19) + (2 \times 16) + (13)]/6 = 17$
July	26	$[(3 \times 23) + (2 \times 19) + (16)]/6 = 20\frac{1}{2}$
August	30	$[(3 \times 26) + (2 \times 23) + (19)]/6 = 23\frac{5}{6}$
September	28	$[(3 \times 30) + (2 \times 26) + (23)]/6 = 27\frac{1}{2}$
October	18	$[(3 \times 28) + (2 \times 30) + (26)]/6 = 28\frac{1}{3}$
November	16	$[(3 \times 18) + (2 \times 28) + (30)]/6 = 23\frac{1}{3}$
December	14	$[(3 \times 16) + (2 \times 18) + (28)]/6 = 18\frac{2}{3}$

Comparison

- Moving-average methods always lag behind when there is a trend present, as shown by the blue line (actual sales) for January through August.



Exponential Smoothing

Exponential Smoothing

Exponential smoothing is another weighted-moving-average forecasting method. It involves very *little* record keeping of past data and is fairly easy to use. The basic exponential smoothing formula can be shown as follows:

$$\begin{aligned} \text{New forecast} = & \text{Last period's forecast} \\ & + \alpha (\text{Last period's actual demand} - \text{Last period's forecast}) \end{aligned} \quad (4-3)$$

where α is a weight, or **smoothing constant**, chosen by the forecaster, that has a value greater than or equal to 0 and less than or equal to 1. Equation (4-3) can also be written mathematically as:

$$F_t = F_{t-1} + \alpha(A_{t-1} - F_{t-1}) \quad (4-4)$$

where

- F_t = new forecast
- F_{t-1} = previous period's forecast
- α = smoothing (or weighting) constant ($0 \leq \alpha \leq 1$)
- A_{t-1} = previous period's actual demand

Weighted exponential smoothing

It can be changed to give more weight to recent data (when Alpha is high) or more weight to past data (when Alpha is low).

WEIGHT ASSIGNED TO					
SMOOTHING CONSTANT	MOST RECENT PERIOD (α)	2ND MOST RECENT PERIOD $\alpha(1-\alpha)$	3RD MOST RECENT PERIOD $\alpha(1-\alpha)^2$	4TH MOST RECENT PERIOD $\alpha(1-\alpha)^3$	5TH MOST RECENT PERIOD $\alpha(1-\alpha)^4$
$\alpha = .1$	.1	.09	.081	.073	.066
$\alpha = .5$	.5	.25	.125	.063	.031

- Better trend identification
- Demand and forecasts are smoothed

To improve our forecast, let us illustrate a more complex exponential smoothing model, one that adjusts for trend. The idea is to compute an exponentially smoothed average of the data and then adjust for positive or negative lag in trend. The new formula is:

$$\begin{aligned} \text{Forecast including trend } (FIT_t) = & \text{Exponentially smoothed forecast average } (F_t) \\ & + \text{Exponentially smoothed trend } (T_t) \end{aligned} \quad (4-8)$$

With trend-adjusted exponential smoothing, estimates for both the average and the trend are smoothed. This procedure requires two smoothing constants: α for the average and β for the trend. We then compute the average and trend each period:

$$F_t = \alpha(\text{Actual demand last period}) + (1 - \alpha)(\text{Forecast last period} + \text{Trend estimate last period})$$

or:

$$F_t = \alpha(A_{t-1}) + (1 - \alpha)(F_{t-1} + T_{t-1}) \quad (4-9)$$

$$T_t = \beta(\text{Forecast this period} - \text{Forecast last period}) + (1 - \beta)(\text{Trend estimate last period})$$

or:

$$T_t = \beta(F_t - F_{t-1}) + (1 - \beta)T_{t-1} \quad (4-10)$$

where F_t = exponentially smoothed forecast average of the data series in period t
 T_t = exponentially smoothed trend in period t
 A_t = actual demand in period t
 α = smoothing constant for the average ($0 \leq \alpha \leq 1$)
 β = smoothing constant for the trend ($0 \leq \beta \leq 1$)

Changing trend

MONTH	ACTUAL DEMAND	FORECAST (F_t) FOR MONTHS 1-5
1	100	$F_1 = 100$ (given)
2	200	$F_2 = F_1 + \alpha(A_1 - F_1) = 100 + .4(100 - 100) = 100$
3	300	$F_3 = F_2 + \alpha(A_2 - F_2) = 100 + .4(200 - 100) = 140$
4	400	$F_4 = F_3 + \alpha(A_3 - F_3) = 140 + .4(300 - 140) = 204$
5	500	$F_5 = F_4 + \alpha(A_4 - F_4) = 204 + .4(400 - 204) = 282$

To improve our forecast, let us illustrate a more complex exponential smoothing model, one that adjusts for trend. The idea is to compute an exponentially smoothed average of the data and then adjust for positive or negative lag in trend. The new formula is:

$$\text{Forecast including trend (FIT)} = \text{Exponentially smoothed forecast average (F}_t\text{)} + \text{Exponentially smoothed trend (T}_t\text{)} \quad (4-8)$$

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or:

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where F_t = exponentially smoothed forecast average of the data series in period t

T_t = exponentially smoothed trend in period t

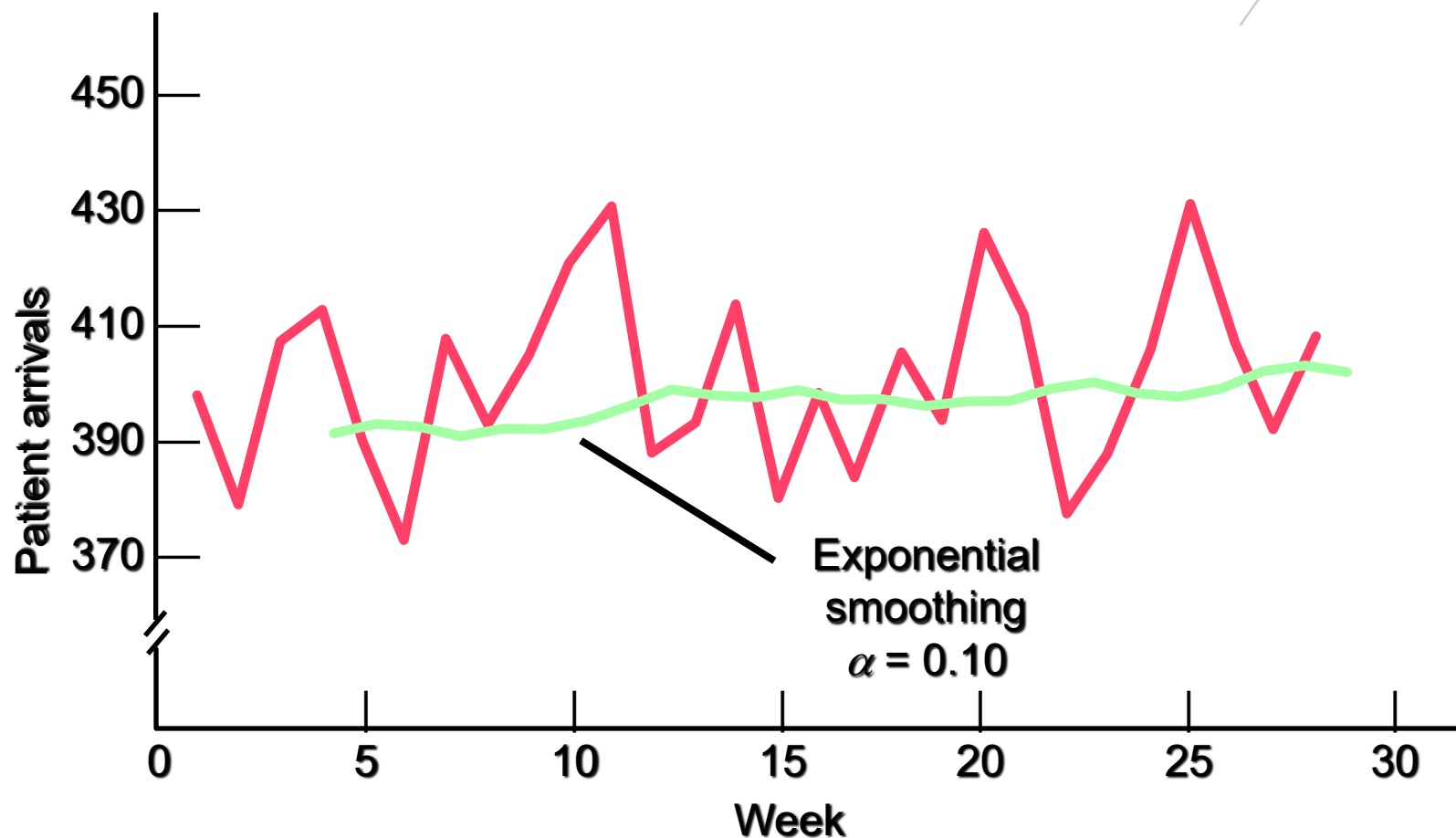
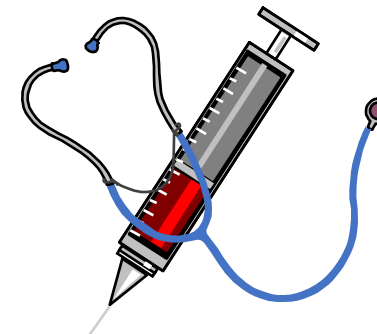
A_t = actual demand in period t

α = smoothing constant for the average ($0 \leq \alpha \leq 1$)

β = smoothing constant for the trend ($0 \leq \beta \leq 1$)

Time-Series Methods

Exponential Smoothing



Exponential Smoothing with Trend Adjustment Example

MONTH (t)	ACTUAL DEMAND (A_t)	MONTH (t)	ACTUAL DEMAND (A_t)
1	12	6	21
2	17	7	31
3	20	8	28
4	19	9	36
5	24	10	?

$$\alpha = .2$$

$$\beta = .4$$

Exponential Smoothing with Trend Adjustment Example (1 of 5)

Table 4.2 Forecast with $\alpha = .2$ and $\beta = .4$

MONTH	ACTUAL DEMAND	SMOOTHED FORECAST AVERAGE, F_t	SMOOTHED TREND, T_t	FORECAST INCLUDING TREND, FIT_t
1	12	11	2	13.00
2	17	12.80		
3	20			
4	19			
5	24			
6	21			
7	31			
8	28			
9	36			
10	—			

Step 1: Average for Month 2

$$F_2 = \alpha A_1 + (1 - \alpha)(F_1 + T_1)$$

$$F_2 = (.2)(12) + (1 - .2)(11 + 2)$$

$$= 2.4 + (.8)(13) = 2.4 + 10.4$$

$$= 12.8 \text{ units}$$

Exponential Smoothing with Trend Adjustment Example (2 of 5)

Table 4.2 Forecast with $\alpha = .2$ and $\beta = .4$

MONTH	ACTUAL DEMAND	SMOOTHED FORECAST AVERAGE, F_t	SMOOTHED TREND, T_t	FORECAST INCLUDING TREND, FIT_t
1	12	11	2	13.00
2	17	12.80	1.92	
3	20			
4	19			
5	24			
6	21			
7	31			
8	28			
9	36			
10	—			

Step 2: Trend for Month 2

$$T_2 = \beta(F_2 - F_1) + (1 - \beta)T_1$$
$$T_2 = (.4)(12.8 - 11) + (1 - .4)(2)$$
$$= .72 + 1.2 = 1.92 \text{ units}$$

Exponential Smoothing with Trend Adjustment Example (3 of 5)

Table 4.2 Forecast with $\alpha = .2$ and $\beta = .4$

MONTH	ACTUAL DEMAND	SMOOTHED FORECAST AVERAGE, F_t	SMOOTHED TREND, T_t	FORECAST INCLUDING TREND, FIT_t
1	12	11	2	13.00
2	17	12.80	1.92	14.72
3	20			
4	19			
5	24			
6	21			
7	31			
8	28			
9	36			
10	—			

Step 3: Calculate FIT for Month 2

$$FIT_2 = F_2 + T_2$$
$$FIT_2 = 12.8 + 1.92$$
$$= 14.72 \text{ units}$$

Exponential Smoothing with Trend Adjustment Example (4 of 5)

Table 4.2 Forecast with $\alpha = .2$ and $\beta = .4$

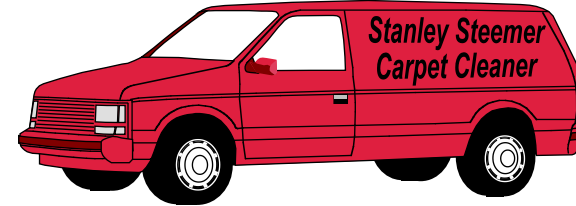
MONTH	ACTUAL DEMAND	SMOOTHED FORECAST AVERAGE, F_t	SMOOTHED TREND, T_t	FORECAST INCLUDING TREND, FIT_t
1	12	11	2	13.00
2	17	12.80	1.92	14.72
3	20	15.18	2.10	17.28
4	19	17.82	2.32	20.14
5	24	19.91	2.23	22.14
6	21	22.51	2.38	24.89
7	31	24.11	2.07	26.18
8	28	27.14	2.45	29.59
9	36	29.28	2.32	31.60
10		32.48	2.68	35.16

Seasonal indices

1. Find the *average historical demand each season* (or month in this case) by summing the demand for that month in each year and dividing by the number of years of data available. For example, if, in January, we have seen sales of 8, 6, and 10 over the past 3 years, average January demand equals $(8 + 6 + 10)/3 = 8$ units.
2. Compute the *average demand over all months* by dividing the total average annual demand by the number of seasons. For example, if the total average demand for a year is 120 units and there are 12 seasons (each month), the average monthly demand is $120/12 = 10$ units.
3. Compute a *seasonal index* for each season by dividing that *month's* historical average demand (from Step 1) by the average demand over all months (from Step 2). For example, if the average historical January demand over the past 3 years is 8 units and the average demand over all months is 10 units, the seasonal index for January is $8/10 = .80$. Likewise, a seasonal index of 1.20 for February would mean that February's demand is 20% larger than the average demand over all months.
4. Estimate next year's total annual demand.
5. Divide this estimate of total annual demand by the number of seasons, then multiply it by the seasonal index for each month. This provides the *seasonal forecast*.

Time-Series Methods

Seasonal Influences

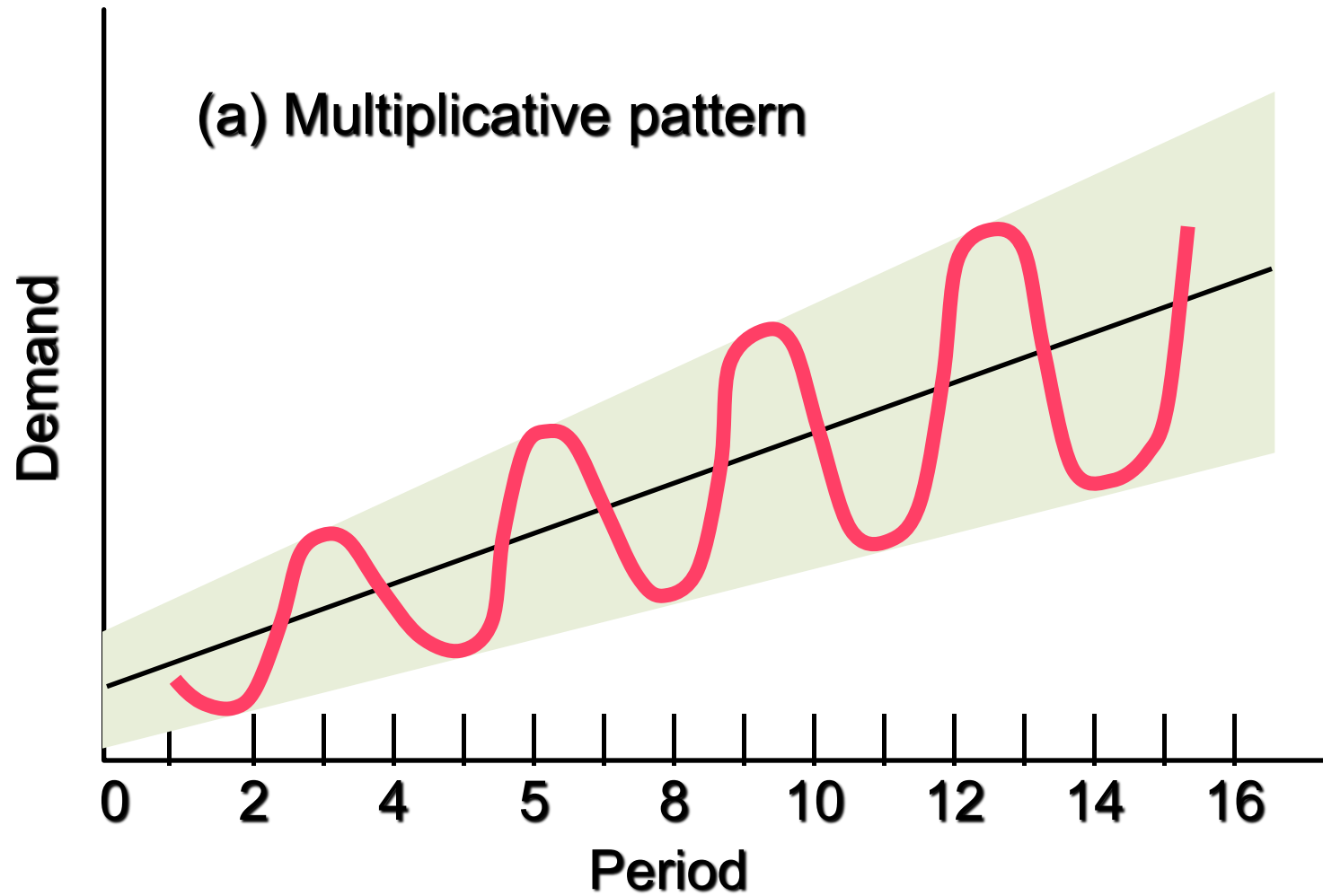


Quarter	Year 1	Year 2	Year 3	Year 4
1	45	70	100	100
2	335	370	585	725
3	520	590	830	1160
4	100	170	285	215
Total	1000	1200	1800	2200

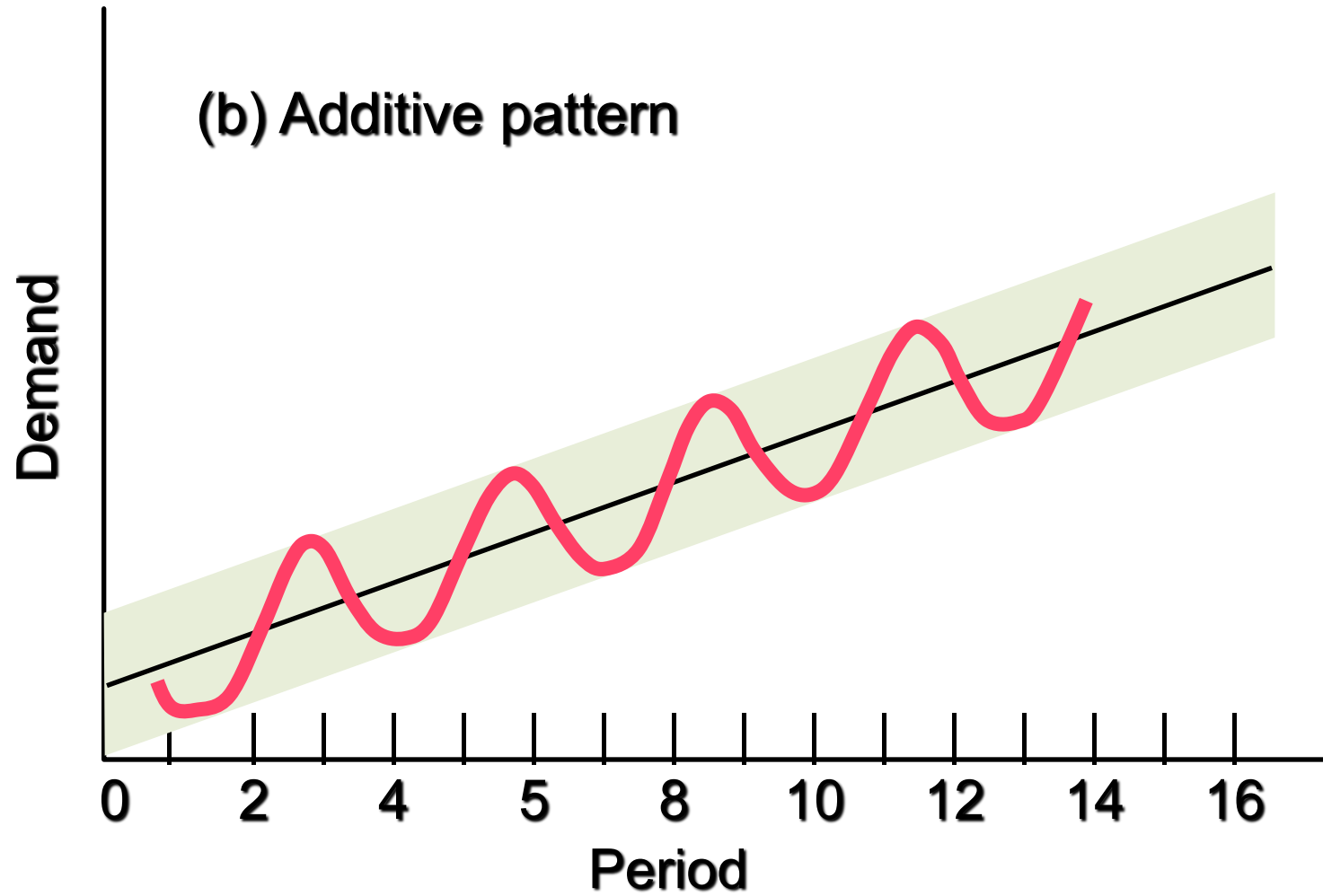
Seasonal variations

Regular upward or downward movements in a time series that tie to recurring events.

Seasonal Patterns



Seasonal Patterns



Seasonal Index Example (1 of 6)

DEMAND						
MONTH	YEAR 1	YEAR 2	YEAR 3	AVERAGE PERIOD DEMAND	AVERAGE MONTHLY DEMAND	SEASONAL INDEX
Jan	80	85	105	90		
Feb	70	85	85	80		
Mar	80	93	82	85		
Apr	90	95	115	100		
May	113	125	131	123		
June	110	115	120	115		
July	100	102	113	105		
Aug	88	102	110	100		
Sept	85	90	95	90		
Oct	77	78	85	80		
Nov	75	82	83	80		
Dec	82	78	80	80		
Total average annual demand =				1,128		

Seasonal Index Example (2 of 6)

DEMAND						
MONTH	YEAR 1	YEAR 2	YEAR 3	AVERAGE PERIOD DEMAND	AVERAGE MONTHLY DEMAND	SEASONAL INDEX
Jan	80	85	105	90	94	
Feb	70	85	85	80	94	
Mar				5	94	
Apr				0	94	
May				3	94	
June				5	94	
July	100	102	115	105	94	
Aug	88	102	110	100	94	
Sept	85	90	95	90	94	
Oct	77	78	85	80	94	
Nov	75	82	83	80	94	
Dec	82	78	80	80	94	
Total average annual demand =				1,128		

$$\text{Average monthly demand} = \frac{1,128}{12 \text{ months}} = 94$$

Seasonal Index Example (3 of 6)

DEMAND						
MONTH	YEAR 1	YEAR 2	YEAR 3	AVERAGE PERIOD DEMAND	AVERAGE MONTHLY DEMAND	SEASONAL INDEX
Jan	80	85	105	90	94	.957 (= 90/94)
Feb	70	85	85	80	94	
Mar	80	93	82	85	94	
Apr	90	95	115	100	94	
$\text{Seasonal index} = \frac{\text{Average monthly demand for past 3 years}}{\text{Average monthly demand}}$						
Sept	85	90	95	90	94	
Oct	77	78	85	80	94	
Nov	75	82	83	80	94	
Dec	82	78	80	80	94	
Total average annual demand =				1,128		

Seasonal Index Example (4 of 6)

DEMAND						
MONTH	YEAR 1	YEAR 2	YEAR 3	AVERAGE PERIOD DEMAND	AVERAGE MONTHLY DEMAND	SEASONAL INDEX
Jan	80	85	105	90	94	.957 (= 90/94)
Feb	70	85	85	80	94	.851 (= 80/94)
Mar	80	93	82	85	94	.904 (= 85/94)
Apr	90	95	115	100	94	1.064 (= 100/94)
May	113	125	131	123	94	1.309 (= 123/94)
June	110	115	120	115	94	1.223 (= 115/94)
July	100	102	113	105	94	1.117 (= 105/94)
Aug	88	102	110	100	94	1.064 (= 100/94)
Sept	85	90	95	90	94	.957 (= 90/94)
Oct	77	78	85	80	94	.851 (= 80/94)
Nov	75	82	83	80	94	.851 (= 80/94)
Dec	82	78	80	80	94	.851 (= 80/94)
Total average annual demand =				1,128		

Seasonal Index Example (5 of 6)

Seasonal forecast for Year 4

MONTH	DEMAND	MONTH	DEMAND
Jan	$\frac{1,200}{12} \times .957 = 96$	July	$\frac{1,200}{12} \times 1.117 = 112$
Feb	$\frac{1,200}{12} \times .851 = 85$	Aug	$\frac{1,200}{12} \times 1.064 = 106$
Mar	$\frac{1,200}{12} \times .904 = 90$	Sept	$\frac{1,200}{12} \times .957 = 96$
Apr	$\frac{1,200}{12} \times 1.064 = 106$	Oct	$\frac{1,200}{12} \times .851 = 85$
May	$\frac{1,200}{12} \times 1.309 = 131$	Nov	$\frac{1,200}{12} \times .851 = 85$
June	$\frac{1,200}{12} \times 1.223 = 122$	Dec	$\frac{1,200}{12} \times .851 = 85$

USING REGRESSION ANALYSIS FOR FORECASTING

- We can use the same mathematical model that we employed in the least-squares method of trend projection to perform a linear-regression analysis.
- The dependent variables that we want to forecast will still be y . But now the independent variable, x , need no longer be time.
- We use the equation: $y = a + bx$
where y = value of the dependent variable (in our example, sales) a =
y-axis intercept b = slope of the
regression line x = independent
variable

We now deal with the same mathematical model that we saw earlier, the least-squares method. But we use any potential “cause-and-effect”

Trend projections

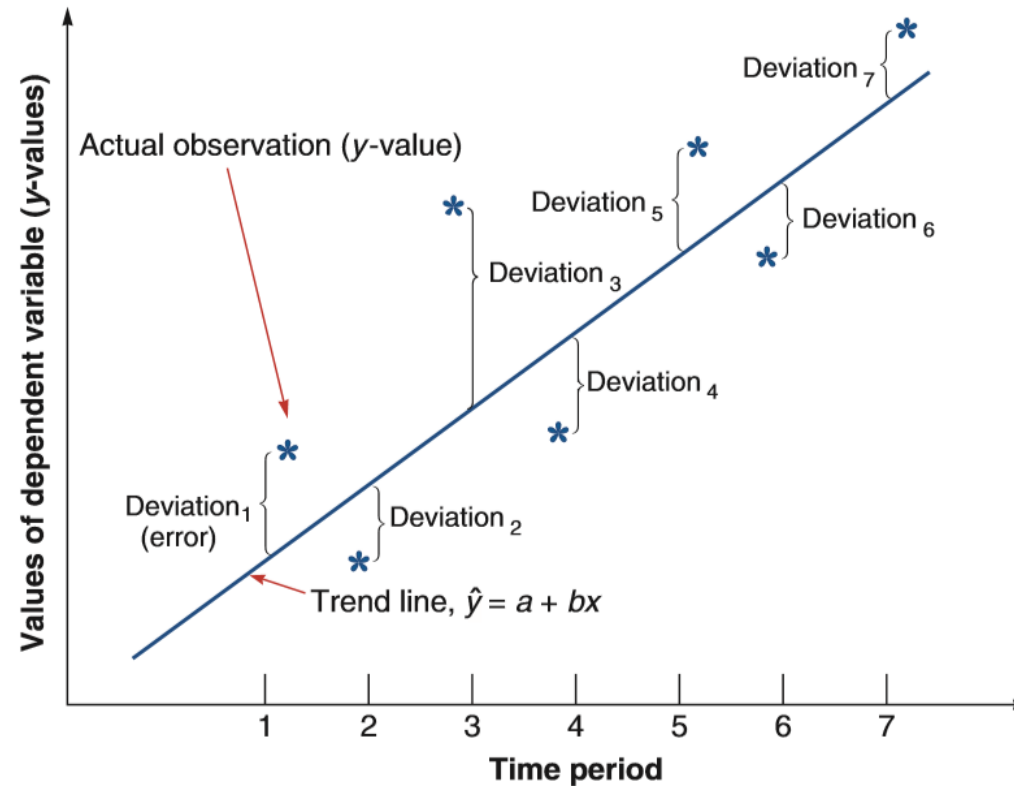
And a is = (average y) – b (average x)

$$\hat{y} = a + bx$$

$$b = \frac{\sum xy - n\bar{x}\bar{y}}{\sum x^2 - n\bar{x}^2}$$

Figure 4.4

The Least-Squares Method for Finding the Best-Fitting Straight Line, Where the Asterisks Are the Locations of the Seven Actual Observations or Data Points



Least Squares Example

YEAR	ELECTRICAL POWER DEMAND	YEAR	ELECTRICAL POWER DEMAND
1	74	5	105
2	79	6	142
3	80	7	122
4	90		

Least Squares Example

YEAR (x)	ELECTRICAL POWER DEMAND (y)	x^2	xy
1	74	1	74
2	79	4	158
3	80	9	240
4	90	16	360
5	105	25	525
6	142	36	852
7	122	49	854
$\Sigma x = 28$	$\Sigma y = 692$	$\Sigma x^2 = 140$	$\Sigma xy = 3,063$

$$\bar{x} = \frac{\sum x}{n} = \frac{28}{7} = 4 \quad \bar{y} = \frac{\sum y}{n} = \frac{692}{7} = 98.86$$

Least Squares Example

$$b = \frac{\sum xy - n\bar{x}\bar{y}}{\sum x^2 - n\bar{x}^2} = \frac{3,063 - (7)(4)(98.86)}{140 - (7)(4^2)} = \frac{295}{28} = 10.54$$

$$a = \bar{y} - b\bar{x} = 98.86 - 10.54(4) = 56.70$$

$$\text{Thus, } \hat{y} = 56.70 + 10.54x$$

$\Sigma x = 28$

$\Sigma y = 692$

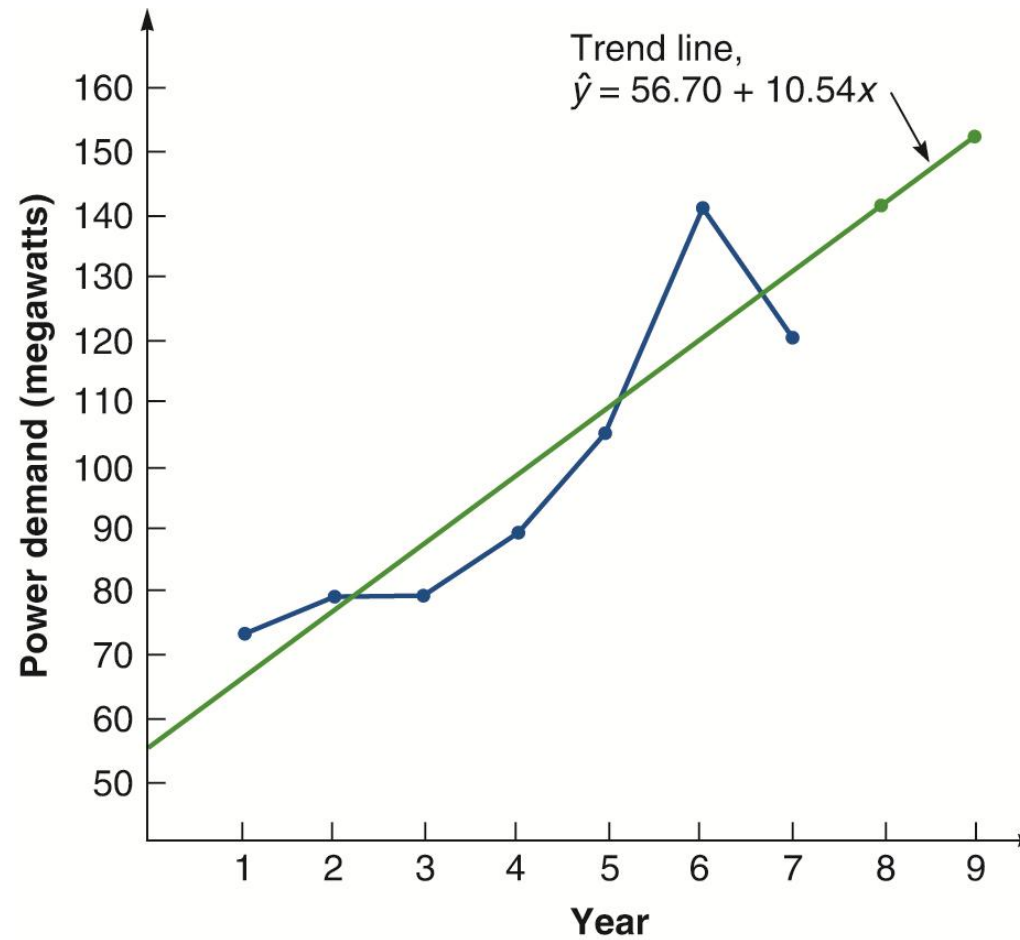
$\Sigma x^2 = 140$

$\Sigma xy = 3,063$

Demand in year 8 = $56.70 + 10.54(8)$
= 141.02, or 141 megawatts

Least Squares Example

Figure 4.5



Least Squares Requirements

We always plot the data to insure a linear relationship

We do not predict time periods far beyond the database

Deviations around the least squares line are assumed to be random

Forecast errors

$$\begin{aligned}\text{Tracking signal} &= \frac{\text{Cumulative error}}{\text{MAD}} \\ &= \frac{\sum(\text{Actual demand in period } i - \text{Forecast demand in period } i)}{\text{MAD}}\end{aligned}$$

where

$$\text{MAD} = \frac{\sum |\text{Actual} - \text{Forecast}|}{n}$$

Monitoring and controlling forecast

- ▶ Using a tracking signal is a good way to make sure the forecasting system is continuing to do a good job
- ▶ even negative or positive

Choosing a Method

Forecast Error

MEASURE	MEANING	EQUATION
Mean absolute deviation (MAD)	How much the forecast missed the target	$\text{MAD} = \frac{\sum \text{Actual} - \text{Forecast} }{n}$
Mean squared error (MSE)	The square of how much the forecast missed the target	$\text{MSE} = \frac{\sum (\text{Forecast errors})^2}{n}$
Mean absolute percent error (MAPE)	The average percent error	$\text{MAPE} = \frac{\sum_{i=1}^n 100 \text{Actual}_i - \text{Forecast}_i / \text{Actual}_i}{n}$

FORECAST ERRORS MAD

$$\begin{aligned}\text{Forecast error} &= \text{Actual demand} - \text{Forecast value} \\ &= A_t - F_t\end{aligned}$$

Several measures are used in practice to calculate the overall forecast error. These measures can be used to compare different forecasting models, as well as to monitor forecasts to ensure they are performing well. Three of the most popular measures are mean absolute deviation (MAD), mean squared error (MSE), and mean absolute percent error (MAPE). We now describe and give an example of each.

Mean Absolute Deviation The first measure of the overall forecast error for a model is the [mean absolute deviation \(MAD\)](#). This value is computed by taking the sum of the absolute values of the individual forecast errors (deviations) and dividing by the number of periods of data (n):

$$\text{MAD} = \frac{\sum |\text{Actual} - \text{Forecast}|}{n} \quad (4-5)$$

MAPE

DETERMINING THE MEAN ABSOLUTE PERCENT ERROR (MAPE)

The Port of Baltimore wants to now calculate the MAPE when $\alpha = .10$.

APPROACH ► Equation (4-7) is applied to the forecast data computed in Example 4.

SOLUTION ►

QUARTER	ACTUAL TONNAGE UNLOADED	FORECAST FOR $\alpha = .10$	ABSOLUTE PERCENT ERROR 100 (ERROR/ACTUAL)
1	180	175.00	$100(5/180) = 2.78\%$
2	168	175.50	$100(7.5/168) = 4.46\%$
3	159	174.75	$100(15.75/159) = 9.90\%$
4	175	173.18	$100(1.82/175) = 1.05\%$
5	190	173.36	$100(16.64/190) = 8.76\%$
6	205	175.02	$100(29.98/205) = 14.62\%$
7	180	178.02	$100(1.98/180) = 1.10\%$
8	182	178.22	$100(3.78/182) = 2.08\%$
			Sum of % errors = 44.75%

$$\text{MAPE} = \frac{\sum \text{absolute percent error}}{n} = \frac{44.75\%}{8} = 5.59\%$$

INSIGHT ► MAPE expresses the error as a percent of the actual values, undistorted by a single large value.

COMPARING

QUARTER	ACTUAL TONNAGE UNLOADED	FORECAST WITH $\alpha = .10$	ABSOLUTE DEVIATION FOR $\alpha = .10$	FORECAST WITH $\alpha = .50$	ABSOLUTE DEVIATION FOR $\alpha = .50$
1	180	175	5.00	175	5.00
2	168	175.50	7.50	177.50	9.50
3	159	174.75	15.75	172.75	13.75
4	175	173.18	1.82	165.88	9.12
5	190	173.36	16.64	170.44	19.56
6	205	175.02	29.98	180.22	24.78
7	180	178.02	1.98	192.61	12.61
8	182	178.22	<u>3.78</u>	186.30	<u>4.30</u>
Sum of absolute deviations:			82.45		98.62
MAD = $\frac{\sum \text{Deviations} }{n}$			10.31		12.33

Monitoring and Controlling Forecasts

Tracking Signal

- Measures **how well the forecast is predicting actual values**
- Ratio of cumulative forecast errors to mean absolute deviation (MAD)
 - Good tracking signal has low values
 - If forecasts are continually high or low, the forecast has a bias error

Monitoring and Controlling Forecasts (2 of 2)

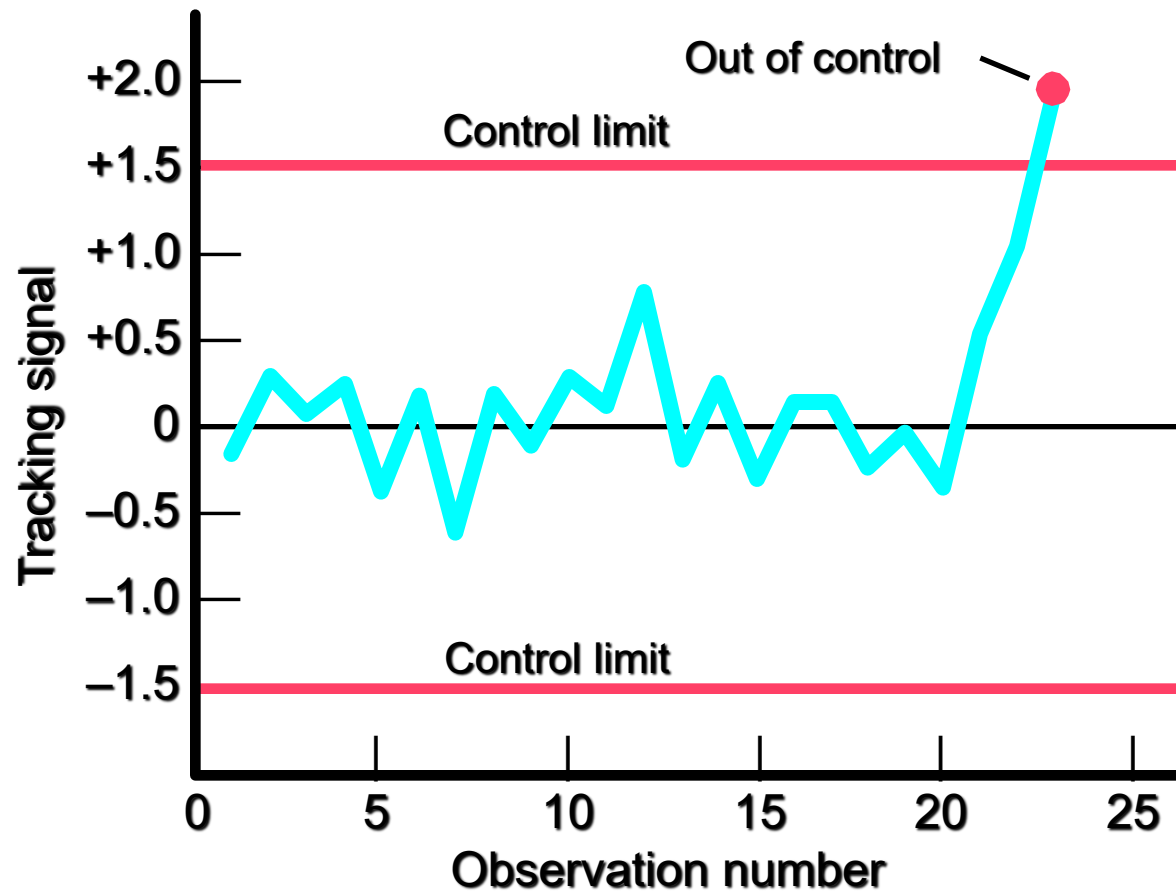
$$\text{Tracking signal} = \frac{\text{Cumulative error}}{\text{MAD}}$$

$$= \frac{\sum (\text{Actual demand in period } i - \text{Forecast demand in period } i)}{\frac{\sum |\text{Actual} - \text{Forecast}|}{n}}$$

Choosing a Method

Tracking Signals

$$\text{Tracking signal} = \frac{\text{CFE}}{\text{MAD}}$$



Application

COMPUTING THE TRACKING SIGNAL AT CARLSON'S BAKERY

Carlson's Bakery wants to evaluate performance of its croissant forecast.

APPROACH ► Develop a tracking signal for the forecast, and see if it stays within acceptable limits, which we define as ± 4 MADs.

SOLUTION ► Using the forecast and demand data for the past 6 quarters for croissant sales, we develop a tracking signal in the following table:

QUARTER	ACTUAL DEMAND	FORECAST DEMAND	ERROR	CUMULATIVE ERROR	ABSOLUTE FORECAST ERROR	CUMULATIVE ABSOLUTE FORECAST ERROR	MAD	TRACKING SIGNAL (CUMULATIVE ERROR/MAD)
1	90	100	-10	-10	10	10	10.0	-10/10 = -1
2	95	100	-5	-15	5	15	7.5	-15/7.5 = -2
3	115	100	+15	0	15	30	10.0	0/10 = 0
4	100	110	-10	-10	10	40	10.0	-10/10 = -1
5	125	110	+15	+5	15	55	11.0	+5/11 = +0.5
6	140	110	+30	+35	30	85	14.2	+35/14.2 = +2.5

$$\text{At the end of quarter 6, MAD} = \frac{\sum |\text{Forecast errors}|}{n} = \frac{85}{6} = 14.2$$

$$\text{and Tracking signal} = \frac{\text{Cumulative error}}{\text{MAD}} = \frac{35}{14.2} = 2.5 \text{ MADs}$$

Forecasting in the service sector

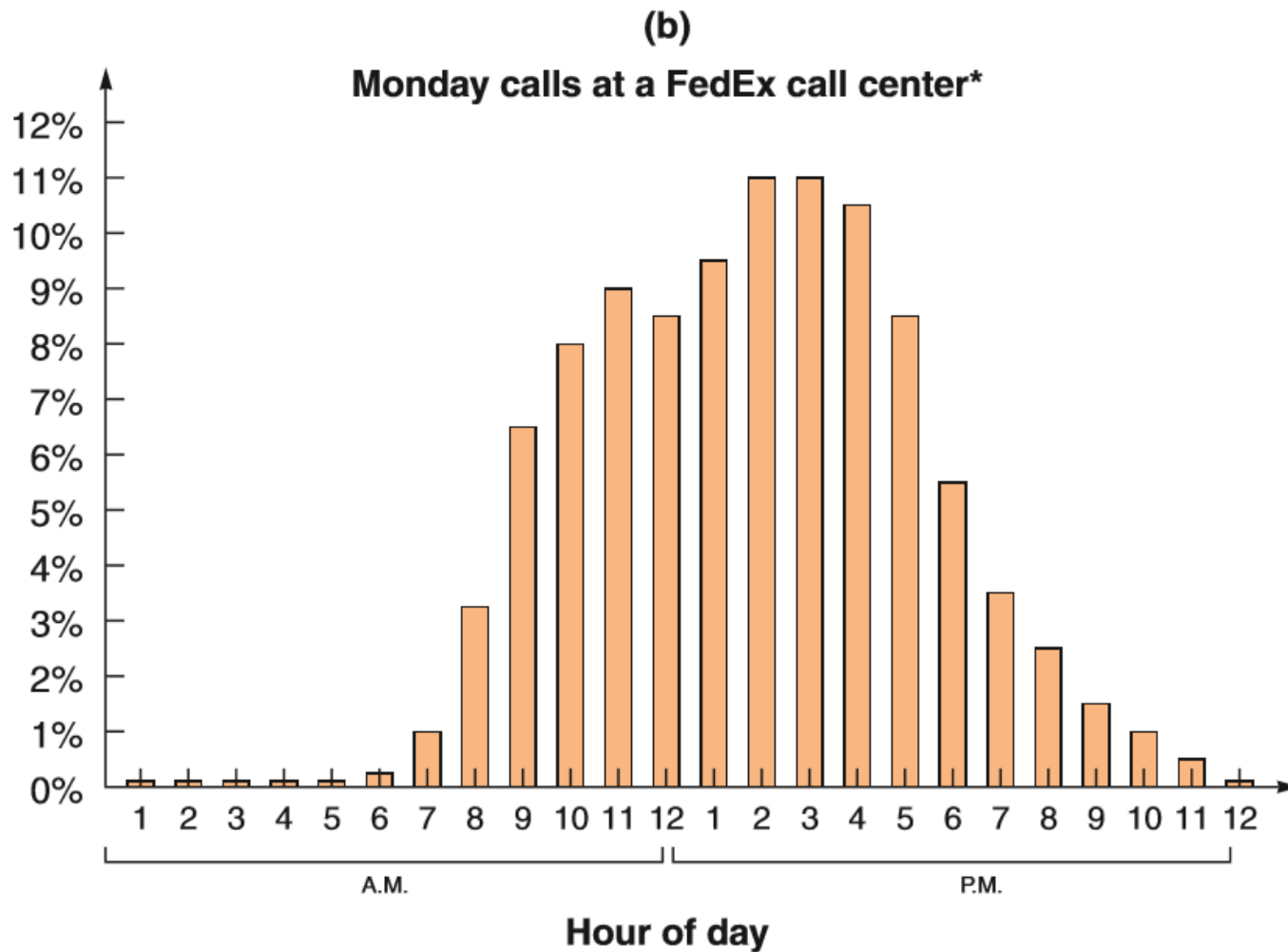
Forecasting at McDonald's, FedEx, and Walmart is as important and complex as it is for manufacturers such as Toyota and Dell.

Specialty retail facilities, such as flower shops, may have other unusual demand patterns, and those patterns will differ depending on the holiday

Fast-food restaurants are well aware not only of weekly, daily, and hourly but even 15-minute variations in demands that influence sales. Therefore, detailed forecasts of demand are needed

Services again

- Taco Bell now use point-of-sale computers that track sales every quarter hour. Taco Bell found that a 6-week moving average was the forecasting technique that minimized its mean squared error (MSE) of these quarter-hour forecasts.
- Projections of customer transactions. These in turn are used by store managers to schedule staff, who begin in 15-minute increments, not 1-hour blocks as in other industries. The forecasting model has been so successful that Taco Bell has increased customer service while documenting more than \$50 million in labor cost savings in 4 years of use.



TEST

1- Forecasting time horizons include :

- a) long range.
- b) medium range.**
- c) short range.
- d) all of the above.

2- Average demand for iPods in the Rome, Italy, Apple store is 800 units per month. The May monthly index is 1.25. What is the seasonally adjusted sales forecast for May?

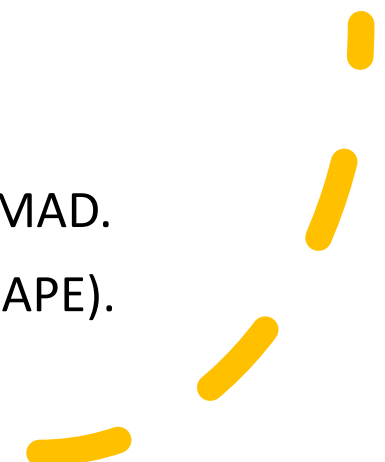
- a) 640 units
- b) 798.75 units**
- c) 800 units
- d) 1,000 units
- e) cannot be calculated with the information given

To
continue

3- Qualitative methods of forecasting include:

- a) sales force composite.
- b) jury of executive opinion.**
- c) consumer market survey.
- d) exponential smoothing.
- e) all except d

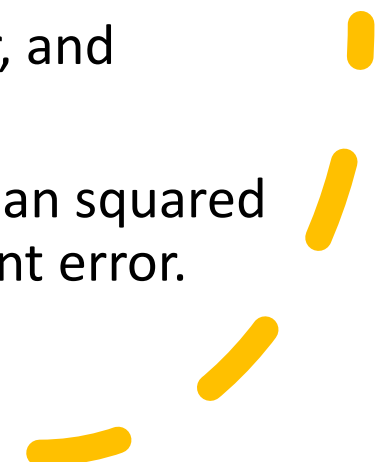
4- The tracking signal is the:

- a) standard error of the estimate.**
 - b) cumulative error.
 - c) mean absolute deviation (MAD).
 - d) ratio of the cumulative error to MAD.
 - e) mean absolute percent error (MAPE).
- 

Self test

5-The difference between a *moving-average* model and an *exponential smoothing* model is that

6-Three popular measures of forecast accuracy are:

- a) total error, average error, and mean error.
 - b) average error, median error, and maximum error.
 - c) median error, minimum error, and maximum absolute error.
 - d) mean absolute deviation, mean squared error, and mean absolute percent error.
- 

Exercise

The following data come from regression line projections:

PERIOD	FORECAST VALUES	ACTUAL VALUES
1	410	406
2	419	423
3	428	423
4	435	440

Compute the MAD and MSE.

Another

Room registrations in the Toronto Towers Plaza Hotel have been recorded for the past 9 years. To project future occupancy, management would like to determine the mathematical trend of guest registration. This estimate will help the hotel determine whether future expansion will be needed. Given the following time-series data, develop a regression equation relating registrations to time (e.g., a trend equation). Then forecast year 11 registrations. Room registrations are in the thousands:

Year 1: 17	Year 2: 16	Year 3: 16	Year 4: 21	Year 5: 20
Year 6: 20	Year 7: 23	Year 8: 25	Year 9: 24	

Seasonal

Quarterly demand for Ford F150 pickups at a New York auto dealer is forecast with the equation:

$$\hat{y} = 10 + 3x$$

where x = quarters, and:

Quarter I of year 1 = 0

Quarter II of year 1 = 1

Quarter III of year 1 = 2

Quarter IV of year 1 = 3

Quarter I of year 2 = 4

and so on

and:

$\hat{y}$ = quarterly demand

The demand for trucks is seasonal, and the indices for Quarters I, II, III, and IV are 0.80, 1.00, 1.30, and 0.90, respectively. Forecast demand for each quarter of year 3. Then, seasonalize each forecast to adjust for quarterly variations.