UCL
SCHOOL OF
MANAGEMENT

MSIN0095: Operations Analytics

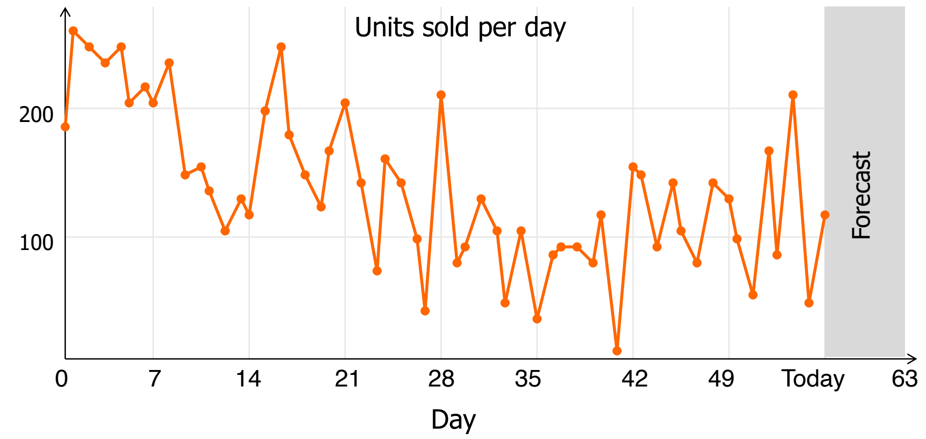
Class 1-4: Process Analysis
Class 5,7: Waiting Time Analysis
Class 6: Inventory Management – Newsvendor Model
Class 8: Inventory Management – Newsvendor, Periodic Review
Class 9: Inventory Management – EOQ
Class 10: Inventory Management – Amazon Distribution Strategy
Class 11: Supply Chain Management I: Beer Game
Class 12: Supply Chain Management II
Class 13: Supply Chain Management III: Strategic Sourcing, Sustainable Supply Chains

Class 14: Demand Forecasting

Forecasting in Operations

- It is important for firms to forecast demand to make decisions
  - Inventory planning
  - Capacity planning
  - Workforce planning
  - Marketing investments

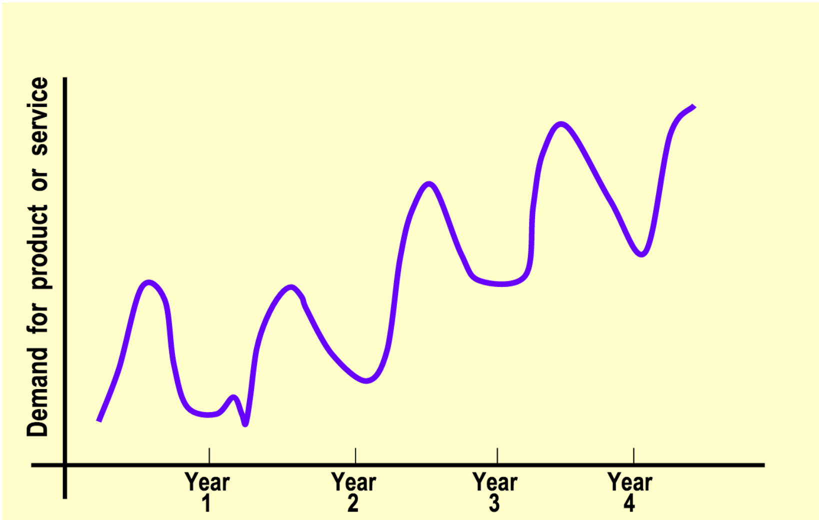
Demand Forecasting



Learning Objectives

- Time series methods
  - "Can you outpredict an OT instructor?" challenge
- Machine learning and data mining methods
- Measuring accuracy of forecasts

Product demand over 4 years



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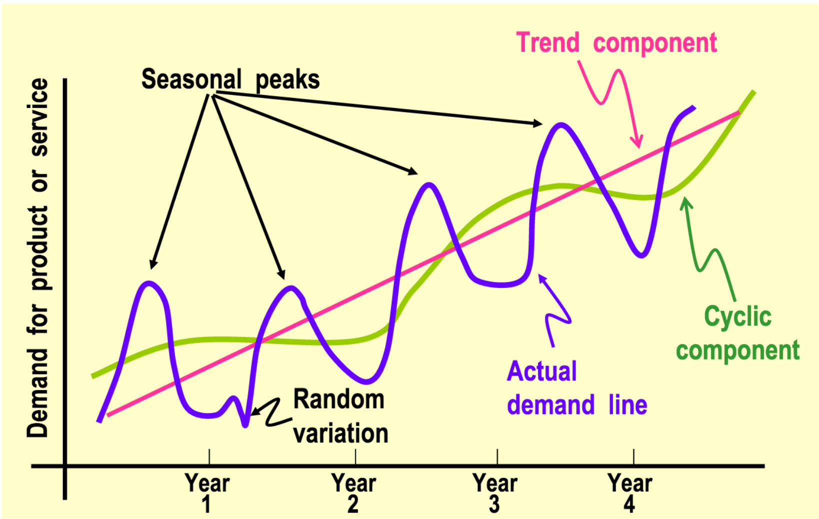
Product demand over 4 years



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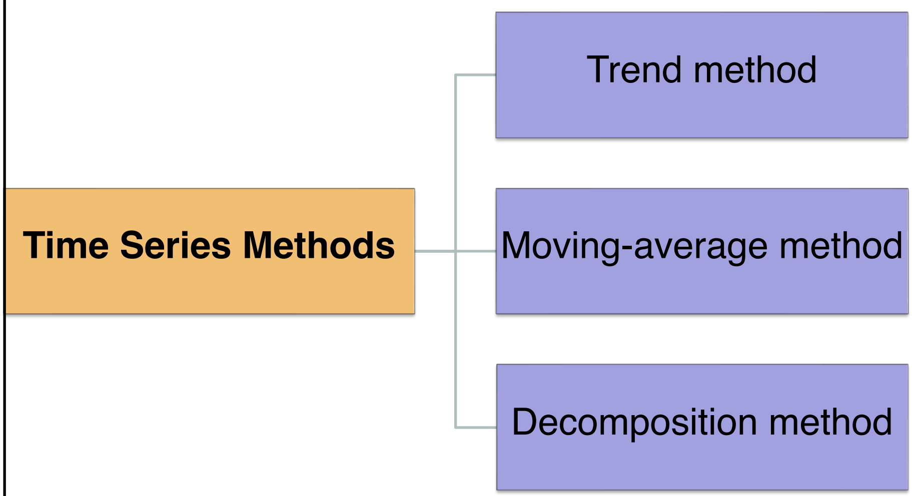
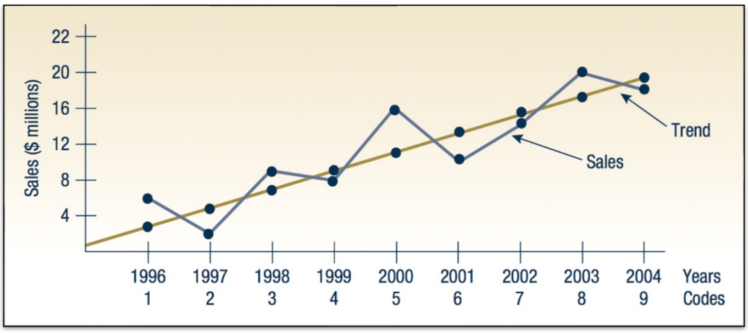
Components of a Time Series

$$\boxed{Y = f(T, C, S, R)}$$

- **Trend (T)** is a long-term upward or downward pattern
  - Due to changes in technology
- **Cyclical variation (C)** is a sizable fluctuation over 2-10 years above and below the trend
  - Due to cycles of recession, depression, and recovery
- **Seasonal variation (S)** is a recurring seasonal pattern
  - Due to weather, holidays, days of week
  - Occurs within 1 year (e.g., quarterly, monthly, weekly, etc.)
- **Random variation (R)** is erratic, unsystematic, 'residual' fluctuations
  - Due to unforeseen events like union strike, tornado



Trend Method



- Useful when time series has a **clear linear trend** with **little variation** around trend line

$$\boxed{Y_t = a + b\,t}$$

Moving average method

- Moving average
  - The average of ***n* most recent data**

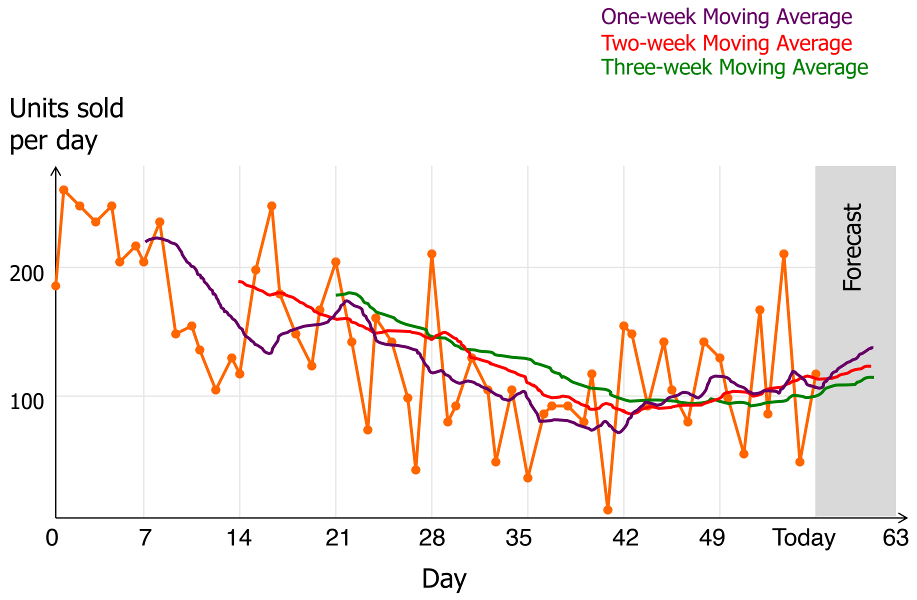
Month	Sales	Two-month Moving Total	Two-month Moving Average
Jan	1,325		
Feb	1,353		
Mar	1,305	2,678	1,339
Apr	1,275	2,658	1,329
May	1,210	2,580	1,290
Jun	1,195	2,485	1,242.5
Jul	?	2,405	1,202.5

Window size = 2 months

Moving average method

Month	Sales	Three-month Moving Total	Three-month Moving Average
Jan	1,325		
Feb	1,353		
Mar	1,305		
Apr	1,275	3,983	1,327.7
May	1,210	3,933	1,311
Jun	1,195	3,970	1,263.3
Jul	?	3,680	1,226.7

Window size = 3 months



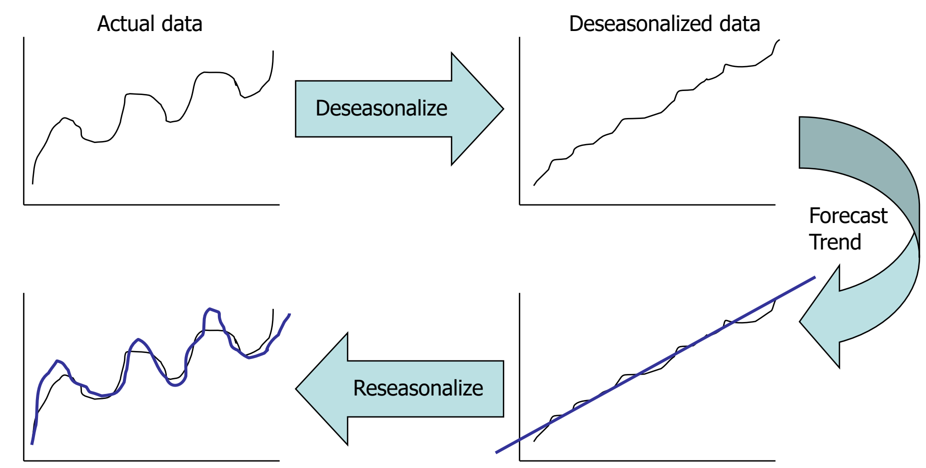
Moving average Method

- Choosing the window size
  - Large n → smoother, but less responsive to data
  - Small *n* → more responsive, but less stable
- When to use moving averages?
  - Moving average method smoothens short-term fluctuations in the time-series.
  - Useful if data has fairly linear trend or cyclical (long-term) pattern

Decomposition Method

- When is it used?
  - If there are short-term seasonal patterns (e.g. weekly, monthly, or quarterly) and long-term trends.
- How it works?
  - Deseasonalizing: Remove short-term fluctuation to forecast long-term effects (trend, cycle)
  - Reseasonalizing: Adjust forecast with seasonal effect

Decomposition method



Step 1: Estimating the seasonal pattern

- Seasonal fluctuations can be expressed as **seasonal indexes**.

Seasonal Indexes for Department Store Sales

January	87.0	July	86.0
February	83.2	August	99.7
March	100.5	September	101.4
April	106.5	October	105.8
May	101.6	November	111.9
June	89.6	December	126.8

July sales are 14% below an average month

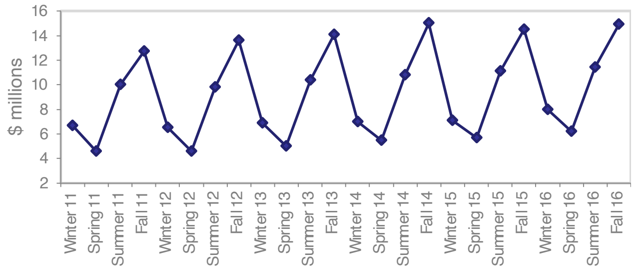
Nov sales are 12% above an average month

*Index 100 = Sales of an average month

Computing the seasonal indexes

Quarterly Sales of Toys International ($ millions)

Year	Winter	Spring	Summer	Fall
2011	6.7	4.6	10.0	12.7
2012	6.5	4.6	9.8	13.6
2013	6.9	5.0	10.4	14.1
2014	7.0	5.5	10.8	15.0
2015	7.1	5.7	11.1	14.5
2016	8.0	6.2	11.4	14.9

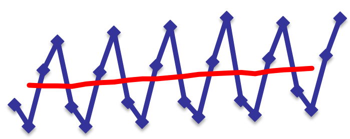


Computing the seasonal indexes

Remove short-term fluctuations by computing the **centered moving averages (CMA)**

Year	Season	Sales	Centered Moving Average
2011	Winter	6.7	
2011	Spring	4.6	
2011	Summer	10	8.5
2011	Fall	12.7	8.45
2012	Winter	6.5	8.45
2012	Spring	4.6	8.4 8.625
2012	Summer	9.8	8.725
2012	Fall	13.6	8.825
2013	Winter	6.9	8.975
2013	Spring	5	9.1
2013	Summer	10.4	9.125
2013	Fall	14.1	9.25
2014	Winter	7	9.35
2014	Spring	5.5	9.575
2014	Summer	10.8	9.6
2014	Fall	15	9.65

- Choose window size as a multiple of the number of periods ("seasons") before pattern repeats. E.g., 4 quarters or 8 quarters
- "Place" the average roughly in the center of the interval used



Sales = Trend,Cyc,Seas,Random
CMA = Trend,Cycle

Computing the seasonal indexes

Determine the effect of season in each period by computing the **specific seasonal index (SSI)**.

Year	Season	Sales	Centered Moving Average	Specific Seasonal Index
2011	Winter	6.7		
2011	Spring	4.6	8.5	
2011	Summer	10	8.45	10/8.45*100=118.3
2011	Fall	12.7	8.45	150.3
2012	Winter	6.5	8.4	77.4
2012	Spring	4.6	8.625	53.3
2012	Summer	9.8	8.725	112.3
2012	Fall	13.6	8.825	154.1
2013	Winter	6.9	8.975	76.9
2013	Spring	5	9.1	54.9
2013	Summer	10.4	9.125	114.0
2013	Fall	14.1	9.25	152.4
2014	Winter	7	9.35	74.9
2014	Spring	5.5	9.575	57.4
2014	Summer	10.8	9.6	112.5
2014	Fall	15	9.65	155.4

Sales = Trend, Cycle, Seasonality, Random

CMA = Trend, Cycle

SSI = Seasonality, Random

Computing the seasonal indexes

Find the average effect of a season by computing the **typical seasonal index (SI)** = the average SSI of periods in the same season

Year	Winter	Spring	Summer	Fall
2011		54.1	118.3	150.3
2012	77.4	53.3	112.3	154.1
2013	76.9	54.9	114.0	152.4
2014	74.9	57.4	112.5	155.4
2015	73.0	59.4	113.0	145.7
2016	79.8	61.2		
Mean	**76.4**	**56.7**	**114.0**	**151.6**

Sales = Trend, Cycle, Seasonal, Random
CMA = Trend, Cycle
Specific Seas. Ind. = Seasonal, Random
Typical Seasonal Ind = Seasonal

Step 2: Deseasonalization

Use seasonal indexes to remove the seasonal effect on sales.

Year	Season	Sales	Seasonal Index	Deseasonalized Sales
2011	Winter	6.7	76.4	6.7/76.4*100=8.8
2011	Spring	4.6	56.7	4.6/56.7*100=8.1
2011	Summer	10	114.0	8.8
2011	Fall	12.7	151.6	8.4
2012	Winter	6.5	76.4	8.5
2012	Spring	4.6	56.7	8.1
2012	Summer	9.8	114.0	8.6
2012	Fall	13.6	151.6	9.0
2013	Winter	6.9	76.4	9.0
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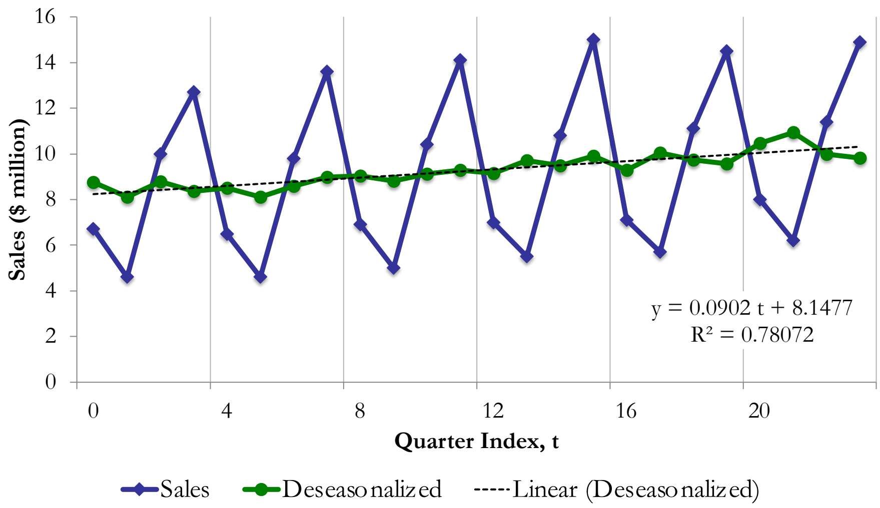
2013	Summer	10.4	114.0	9.1
2013	Fall	14.1	151.6	9.3
2014	Winter	7	76.4	9.2
2014	Spring	5.5	56.7	9.7
2014	Summer	10.8	114.0	9.5
2014	Fall	15	151.6	9.9

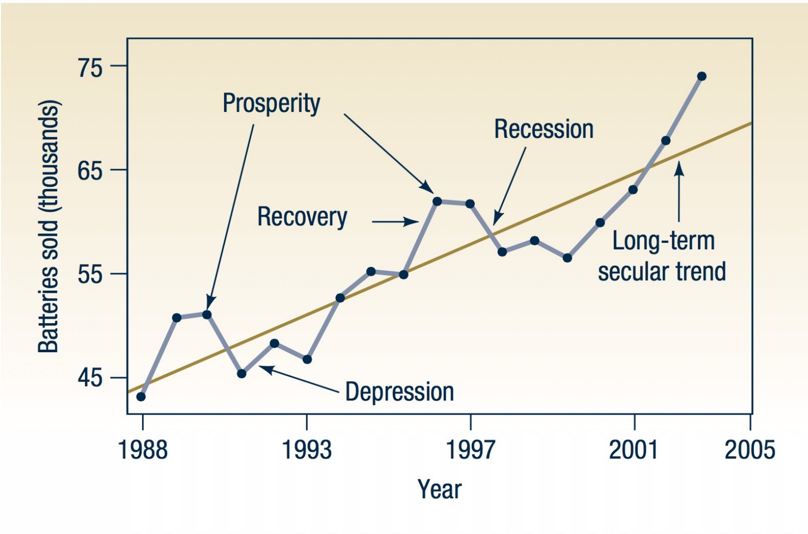
Deseaonalized Sales = Trend, Cycle, Random

Step 3: Forecast trends or cycles on deseasonalized data



*Assign a quarter index to each period

Types of Cyclical Patterns



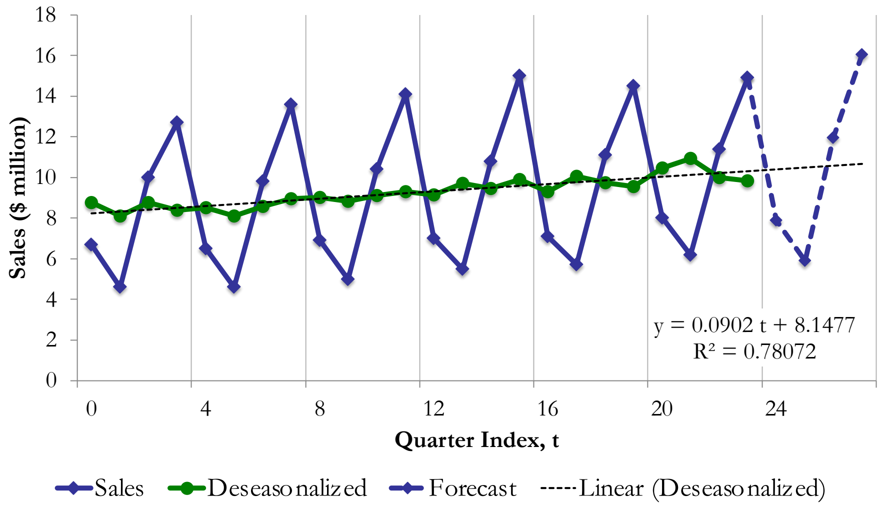
Step 4: Reseasonalization

- Trend/cycle forecast and seasonal indexes can be combined to yield seasonally adjusted forecasts.
- **Example:** Provide a demand forecast for Toys Incorporated 2017 Quarterly Sales.

Quarter	Quarter index, t	Trend	Seasonal Index	Reseasonalized Data
Winter 2017	24	.0902*24+8.15 =10.3	76.4	10.3*76.4/100 =7.9
Spring 2017	25	10.4	56.7	5.9
Summer 2017	26	10.5	114	12.0
Fall 2017	27	10.6	151.6	16.0

*Winter 2011 quarter index = 0

Decomposition method



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Machine learning and data mining

- Demand can be affected by many things
  - Price or promotions
  - Weather patterns
  - Holidays (e.g. Thanksgiving, Christmas)
  - Social network

- Machine learning can tease out relationships between demand and multiple factors
  - Basic: Multiple Linear Regression
  - Supervised Learning
  - Unsupervised Learning

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Learning Objectives

- Time series methods
  - “Can you outpredict a TO instructor?” challenge
- Machine learning and data mining methods
- **Measuring accuracy of forecasts**

A forecast is always wrong. But how wrong?

We need a metric that provides estimation of accuracy. All are functions of forecast error:

$$E_t = A_t - F_t$$

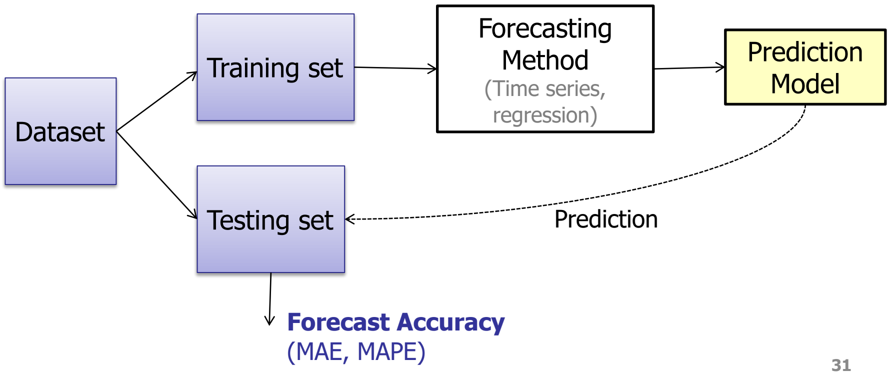
Actual value Forecast value

Common metrics:

1. Mean Absolute Error (MAE) = $\frac{\sum_{t=1}^{T} |E_t|}{T}$
2. Mean Absolute Percentage Error (MAPE) = $\frac{\sum_{t=1}^{T} |E_t|/A_t}{T}$
3. Mean Percentage Error (MPE) = $\frac{\sum_{t=1}^{T} E_t/A_t}{T}$

Comparing forecasting models

- An important purpose for demand forecasting models is their use in making predictions.
- We test the predictive power of a model on a test set or "out-of-sample" set.



Summary

- Demand forecasting is important for making good decisions
- Time series forecasts detect short-term and long-term patterns
- Machine learning is becoming popular due to its ability to detect complex relationships from many factors