Chapter 11
Forecasting Demand for Services

What Is Forecasting?
- Predicting the future
  - How many people will buy Dell Dimension 8200 on December?
- Estimating/measuring the reliability of the prediction
- Forecasts are always wrong... except by accident

Learning Objectives
- Understand sources of demand variability.
- Able to pick the appropriate forecasting model.
- Exponential smoothing and moving average.
- Linear regression and time series.
- Seasonality.

How Famous People Feel About Forecasts?
"Prediction is very difficult, especially if it's about the future."
--Nils Bohr, Nobel laureate in physics.
"If you have to forecast, forecast often."
--A useful survival tactic for a consultant.
"I think there is a world market for maybe five computers."
--Thomas Watson (1874-1956), chairman of IBM, 1943.
IBM alone produces over 1 million computers per year.

We Classify Forecasting Methods Into Three Types
- Judgmental
  - Uses subjective inputs
- Time series
  - Assumes past is best predictor of future
- Associative
  - Uses explanatory variables to predict the future

Judgmental Forecasts
- Judgmental forecasts are subjective, based on
  - Executive opinions
  - Sales force composite
  - Consumer surveys
  - Outside opinion
  - Opinions of managers and staff
    - Delphi method
Time Series Forecasts

- Time series forecasts are often prepared by decomposing the data.
- **Trend**
  - Long-term movement in data
- **Seasonality**
  - Short-term regular variations in data
- **Irregular variations**
  - Caused by unusual circumstances
- **Random variations**
  - Caused by chance

Associative Forecasts

- Associative forecasts assume a correlation with predictor variables.
- **Predictor variables**
  - Used to predict values of variable interest
- **Regression**
  - Technique for fitting a line to a set
- **Least squares line**
  - Minimizes sum of squared deviations around the line

Judgmental Forecasts

- **Pros**
  - Easy to prepare
  - Can be used when no appropriate data exist for other methods
  - Relatively easy to start with new items
- **Cons**
  - Accuracy is poor
  - More often represent the forecasters' hopes rather than probable outcomes

Next, Associative Forecasts

- **Pros**
  - Some methods (e.g., Linear regression) are straightforward
  - Use causal relationships
  - Useful for sensitivity
  - Produce measures of correlation
- **Cons**
  - Data intensive
  - Computation intensive
  - Non-linear methods may not be easy
  - Linear regression may not be feasible
  - Difficult to start with new items

Lastly, Time Series Forecasts

- **Pros**
  - Methods range from easy to complex
  - Some methods are data and computation efficient
  - Does not require causal variable identification
- **Cons**
  - Some methods are data and/or computation intensive
  - Cannot incorporate causal/co-relational relationships
  - Very difficult to start with new items

Demand Patterns

- **Demand Patterns**
  - (a) Horizontal: Data cluster about a horizontal line.
Demand Patterns

(b) Trend: Data consistently increase or decrease.

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

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

(E) Seasonal multiplicative pattern

(F) Seasonal additive pattern

Linear Regression

- Regression line
  - $Y = a + bx$
  - Least-squares regression line
- Prediction
  - $r^2$
- Causation and association
Prediction
- Choose the explanatory and response variables
- Plot the data
- Look for a straight-line relationship
- Fit the data for regression line
- Substitute the value of x and calculate y

Causal Methods Linear Regression

Regression Line
- Summarizes the relationship between two variables.
- The variables must be explanatory and response variables.
- Describes how y changes as x takes different values.
- Use a regression line to predict the value of y for a given value of x.

Finding the LS Equation

\[
a = \bar{Y} - b\bar{X} \quad \quad \quad \quad b = \frac{\sum XY - n\bar{XY}}{\sum X^2 - n\bar{X}^2}
\]

Finding the LS Equation

\[
a = \bar{Y} - b\bar{X} \quad \quad \quad \quad b = \frac{1560 - 5(1.64)(171)}{14.90 - 5(1.64)^2}
\]
Finding the LS Equation

<table>
<thead>
<tr>
<th>Month</th>
<th>Sales, Y (000 units)</th>
<th>Advertising, X (000 $)</th>
<th>XY</th>
<th>X^2</th>
<th>Y^2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>264</td>
<td>2.5</td>
<td>660</td>
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<td>69,696</td>
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<tr>
<td>2</td>
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<tr>
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<td>165</td>
<td>1.4</td>
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<td>1.96</td>
<td>27,225</td>
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<td>1.00</td>
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<td>209</td>
<td>2.0</td>
<td>418.0</td>
<td>4.00</td>
<td>43,681</td>
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<tr>
<td>Total</td>
<td>855</td>
<td>8.2</td>
<td>1560.8</td>
<td>14.90</td>
<td>164,259</td>
</tr>
</tbody>
</table>

\[ \bar{Y} = 171 \quad \bar{X} = 1.64 \]

\[ a = -8.136 \quad b = 109.229 \]

\[ Y = -8.136 + 109.229(X) \]

Forecasting/prediction

\[ Y = -8.136 + 109.229(X) \]

Forecast for month 6:

Advertising expenditure = $1750

\[ Y = -8.136 + 109.229(1.75) = 183.015 \]

Prediction: More

Given the equation of the regression line

\[ Y = -8.136 + 109.229(X) \]

What is the value for the intercept?

What does the intercept mean here?

What is the value for the slope?

What does the slope mean in this example?

Understanding Prediction

Prediction works best when the model fits the data closely.

Prediction outside the range of data of available data is risky (extrapolation).

Check for outliers

What is \( r^2 \)

The square of the correlation is the fraction of the variation in the values of \( y \) that is explained by \( x \)

The variation that occurs in \( y \) can be attributed to the changing \( x \) values

\[ r^2 = \frac{\text{variation in predicted } y \text{ as } x \text{ pulls it along the line}}{\text{total variation in observed values of } y} \]

Using \( r^2 \)

Correlation tells how close the points are to the line

\( r^2 \) is the measure of how successful the regression was in explaining the response
Finding $r$ and $r^2$

Sales, $Y$  Advertising, $X$

<table>
<thead>
<tr>
<th>Month</th>
<th>(000 units)</th>
<th>(000 $)</th>
<th>$XY$</th>
<th>$X^2$</th>
<th>$Y^2$</th>
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<td>660.0</td>
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<td>2</td>
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<td>1.3</td>
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<td>1.0</td>
<td>101.0</td>
<td>1.00</td>
<td>10,201</td>
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<td>8.2</td>
<td>1560.8</td>
<td>14.90</td>
<td>164,259</td>
</tr>
</tbody>
</table>

\[ r = \frac{\sum XY - \sum X \sum Y}{\sqrt{\sum X^2 - (\sum X)^2} \sqrt{\sum Y^2 - (\sum Y)^2}} \]

$Y = 171$

\[ r^2 = 0.98 \]

$\sigma_{XY} = 15.61$

Finding $r$ and $r^2$

The Question of Causation

- A strong relationship between two variables does not always mean that changes in one variable cause changes in the other.
- The relationship between two variables is often influenced by other variables in the background.
- The best evidence for causation comes from randomized comparative experiments.

r2: Example

- Given the numerical value of the correlation for the sales/advertising data
  - $r = 0.98$
  - What percent of variation in sales is explained by how much the advertising expenditure is?

Association and Causation

- A high association can mean one of the following scenarios:
  - Causation
  - Common response
  - Confounding

Now We’re Going to Focus on Time Series Methods

- Quantitative forecasting methods
- Forecasts are not based on predictive variables
- Inherent assumption: the past is the best predictor of the future
**Time Series Forecasts**
- Time series forecasts can address all of these components
  - Trend
  - Seasonality
  - Cycles
  - Random variations

**Basic Notations**
- $D_1, D_2, D_t$: the demand of values observed during periods 1, 2, ..., t.
- $F_t$: the forecast made for period t in period t-1 before $D_t$ is observed

**Naive Forecast Method**
- What is the forecast for month 5?

<table>
<thead>
<tr>
<th>Month</th>
<th>Customer arrivals</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>800</td>
</tr>
<tr>
<td>2</td>
<td>740</td>
</tr>
<tr>
<td>3</td>
<td>810</td>
</tr>
<tr>
<td>4</td>
<td>790</td>
</tr>
</tbody>
</table>

**Simple Moving Averages**
- The procedure
  \[ F_{t+1} = \frac{D_t + D_{t-1} + ... + D_{t-n+1}}{n} \]
- $D_t$: actual demand in period t
- n: number of periods in the average

**Moving Averages**
- The main idea behind a MA is to smooth random variations
  - Uses a number of the most recent data values
  - Each data value has equal weight
Simple Moving Averages

Patient arrivals

<table>
<thead>
<tr>
<th>Week</th>
<th>Arrivals</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>400</td>
</tr>
<tr>
<td>2</td>
<td>380</td>
</tr>
<tr>
<td>3</td>
<td>411</td>
</tr>
</tbody>
</table>

\[ F_4 = \frac{411 + 380 + 400}{3} \]

Simple Moving Averages

Patient arrivals

<table>
<thead>
<tr>
<th>Week</th>
<th>Arrivals</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>400</td>
</tr>
<tr>
<td>2</td>
<td>380</td>
</tr>
<tr>
<td>3</td>
<td>411</td>
</tr>
</tbody>
</table>

\[ F_5 = \frac{415 + 411 + 380}{3} \]
Simple Moving Averages

\[ F_t = \frac{1}{n} \sum_{i=1}^{n} A_{t-i} \]

- Week 2: 380
- Week 3: 411
- Week 4: 415

Patient Arrivals

<table>
<thead>
<tr>
<th>Week</th>
<th>Patient Arrivals</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>380</td>
</tr>
<tr>
<td>3</td>
<td>411</td>
</tr>
<tr>
<td>4</td>
<td>415</td>
</tr>
</tbody>
</table>

Implications of Increasing N

\[ \text{Differences in responsiveness} \]

3-week MA forecast

6-week MA forecast

Actual patient arrivals

Simple Moving Average

Month | Customer arrivals |
-------|-------------------|
1      | 800               |
2      | 740               |
3      | 810               |
4      | 790               |

Weighted Moving Average

\[ F_{t+1} = W_0D_0 + W_1D_1 + \ldots + W_nD_n = \sum_{i=1}^{n} W_i \]

\[ \sum_{i=1}^{n} W_i = 1 \]

Assigned weights:

- \( W_0 = 0.70 \)
- \( W_{-1} = 0.20 \)
- \( W_{-2} = 0.10 \)

F4 = 0.70(411) + 0.20(380) + 0.10(400)

Weighted Moving Average

3-week MA forecast

6-week MA forecast

Actual patient arrivals
Weighted Moving Average

\[ f_{t+1} = W_0 D_t + W_1 D_{t-1} + \ldots + W_{n-1} D_{t-n+1} \]

where \( f_{t+1} \) is the forecast for period \( t+1 \)
- Let \( W_0 = 0.70, W_1 = 0.20, \) and \( W_2 = 0.10. \)
- Calculate the forecast for month 3:
  \[ f_3 = \]
- Forecast for month 5:
  \[ f_5 = \]
- If the actual demand of month 5 is 833 patients, what is the forecast for month 6?
  \[ f_6 = \]

Exponential Smoothing (ES)

Let’s review what we know about moving averages (MA & WMA)
- We need \( n \) data values for an \( n \)-period moving average
- We need \( n \) weighting factors for an \( n \)-period weighted moving average
- The responsiveness of the forecast is determined by \( n \)

Exponential Smoothing

\[ F_{t+1} = F_t + \alpha (D_t - F_t) \]
\( \alpha \) is a smoothing parameter with a value between 0 and 1
Exponential Smoothing

- Is just a weighted average between the old forecast (old ES average) and the new data value
- Efficiently incorporates more distant data values through the old forecast

\[ F_{t+1} = F_t + \alpha (D_t - F_t) \]

\[ F_3 = \frac{400 + 380}{2} \]

\[ D_3 = 411 \]

\[ F_4 = 0.10(411) + 0.90(390) \]

\[ F_4 = 392.1 \]

\[ F_5 = 394.4 \]
Exponential Smoothing

Exponential smoothing

\[ F_t = \alpha y_t + (1 - \alpha) F_{t-1} \]

where \( F_t \) = Forecast for period \( t \) + 1

- Suppose \( y_3 \) = 782 customers and \( \alpha = 0.20 \). What is forecast for month 4?
  
  \[ F_4 = \alpha y_3 + (1 - \alpha) F_3 \]

- If \( y_4 = 710 \), what is the forecast for month 5?
  
  \[ F_5 = \alpha y_4 + (1 - \alpha) F_4 \]

- Forecast for month 6

Exponential Smoothing

Advantages.
- Simplicity.
- Minimal data requirements compared to moving average.
- Inexpensive.

Disadvantages.
- Lags behind changes in underlying average.
- Does not account for any factors other than the series past performance.

Exponential Smoothing

Require only three parameters.
- Are controlled by the smoothing factor on interval \([0,1]\).
  - Values close to 0 (large \( n \)) provide very stable (unresponsive) forecasts.
  - Values close to 1 (small \( n \)) provide very aggressive (responsive) forecasts.

Moving Average and ES

We can approximate moving average with ES!

\[ \alpha = \frac{2}{n+1} \]

\[ n = \frac{2 - \alpha}{\alpha} \]
Trend-adjusted ES

Smooth estimates for the series average as well as the trend

Average: \( A_t = \alpha D_t + [1 - \alpha](A_{t-1} + T_{t-1}) \)

Average trend: \( T_t = \beta(A_t - A_{t-1}) + (1 - \beta)T_{t-1} \)

Forecast for \( p \) periods ahead: \( A_t + pT_t \)

<table>
<thead>
<tr>
<th>Week</th>
<th>Arrivals</th>
<th>Smoothed Average</th>
<th>Trend Average</th>
<th>Forecast</th>
<th>Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>28</td>
<td>28.00</td>
<td>3.00</td>
<td>0.00</td>
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<tr>
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<td>31.00</td>
<td>-4.00</td>
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<td>7</td>
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<td>75</td>
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<td>2.28</td>
<td>64.22</td>
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</table>

SUMMARY

Average demand: 49.80
Mean square error: 76.13
Mean absolute deviation: 7.35
Forecast for week 16: 66.66
Forecast for week 17: 70.95
Forecast for week 18: 73.24
Trend-adjusted ES

The forecaster for Canine Gourmet dog breath fresheners estimated (in March) the series average to be 300,000 cases sold per month and the trend to be +8,000 per month. The actual sales for April were 330,000 cases. What are the forecasts for May and July, assuming alpha 0.2 and beta 0.1?

\[ A_m = 300,000 \text{ cases} \quad T_m = +8,000 \text{ cases} \]
\[ D_m = 330,000 \text{ cases} \quad \alpha = 0.2 \quad \beta = 0.1 \]

What are the forecasts for May and July?

\[ A_m = 0.2(330) + 0.8(300 + 8) = 312.4 \]
\[ T_m = 0.1(312.4 - 300.6) + 0.9(8) = 8.44 \]

Forecast for May: \[ 312.4 + (8.44) = 320.84 \text{, or 320,840 cases} \]

Forecast for July: \[ 312.4 + (8.44) = 317.72 \text{, or 317,720 cases} \]

Seasonal Patterns

(a) Multiplicative pattern

(b) Additive pattern

Seasonal Influences

Multiplicative seasonal method

Step 1: Calculate the average demand per period for each year of past data.

Step 2: Divide the actual demand for each period by the average demand per period to get a seasonal factor. Repeat for each year of data.

Step 3: Calculate the average seasonal factor for each period.

Step 4: To get a forecast for a given period in a future year, multiply the seasonal factor by the estimated average demand per period in that year.

<table>
<thead>
<tr>
<th>Quarter</th>
<th>Year 1</th>
<th>Year 2</th>
<th>Year 3</th>
<th>Year 4</th>
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<td><strong>1800</strong></td>
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<td>250</td>
<td>300</td>
<td>450</td>
<td>550</td>
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Seasonal Patterns

<table>
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<tr>
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<th>Index</th>
<th>Demand</th>
<th>Index</th>
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<td>1.24</td>
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<td>200</td>
<td>0.80</td>
<td>216</td>
<td>0.72</td>
<td>0.76</td>
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<tr>
<td>Avg.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.94</td>
</tr>
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Forecast Error

Forecast error is the difference between the actual demand and forecast.

\[ E_t = D_t - F_t \]

Cumulative sum of forecast errors (CFE).

- Useful for bias measurement.
- Used in tracking signals.

Average forecast error equals CFE divided by the number of data points.

Mean absolute deviation (MAD).

- Measures dispersion of forecast errors
- Easier for managers to understand than standard deviation

Standard deviation (\( \sigma \)).

- Measures dispersion of forecast errors
- Want to have small values of \( \sigma \)
- MAD = 0.8 \( \sigma \)
- \( \sigma = 1.25 \times \text{MAD} \)

Mean squared error (MSE).

- Measures dispersion of forecast errors.
- Places greater weight than MAD on large errors.

Mean absolute percent error (MAPE).

- Relates forecast error to level of demand
- Puts the size of a forecast error in proper perspective

Forecast Error Table

<table>
<thead>
<tr>
<th>Month</th>
<th>Demand</th>
<th>Forecast</th>
<th>Error</th>
<th>Squared Error</th>
<th>Absolute Error</th>
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</thead>
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<td>1600</td>
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<td>275</td>
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<td>Total</td>
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<td>-15</td>
<td>5275</td>
<td>195</td>
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### Forecast Error

<table>
<thead>
<tr>
<th>Measures of Error</th>
<th>Error</th>
<th>Absolute Error</th>
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<tr>
<td>CFE = –15</td>
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<tr>
<td>( \bar{E} = \frac{-15}{8} ) = –1.875</td>
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<tr>
<td>MSE = ( \frac{5275}{8} ) = 659.4</td>
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<tr>
<td>( \sigma = 27.4 )</td>
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<tr>
<td>MAD = 195</td>
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<tr>
<td>8 ( \sigma = 27.4 )</td>
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<tr>
<td>MAPE = ( \frac{81.3%}{8} ) = 10.2%</td>
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</tbody>
</table>

### Criteria for Selecting Time Series Methods

#### Statistical criteria
- Minimize bias.
- Minimize MAD or MSE.
- Meet managerial expectations of changes.
- Minimize the forecast error last period.
- Use a holdout set (data from more recent periods) as a final test, after constructing model from data from earlier periods.