Forecasting

BUS 735: Business Decision Making and Research

Goals and Agenda

Learning Objective	Active Learning Activity
Learn how to identify regularities in time series data	Lecture / Excel Example.
Learn popular univariate time series forecasting methods	Lecture / Excel Example.
Learn how to use regression analysis for forecasting	Lecture / Excel Example.
Practice what we learn.	In-class exercise.
More practice.	Read Chapter 15, Homework exercises.
Assess what we have learned	Quiz??

Working with Example Data

- Download data on the total number of Mining, Logging, and Construction employees (in thousands) in the La Crosse area from the Bureau of Labor Statistics website, http://www.bls.gov.
- To plot the data, we need to convert it to a single column:
  1. First generate observation numbers 1 through 273
  2. Figure out what row the observation is in: `=int((obs-1)/12)+1`
  3. Figure out what column the observation is in: `=mod((obs-1),12)+1`
  4. Pick out the right observation: `=offset([top_corner],row,col)`
- Create dates: 1990.0 through 2012.75.

Graphing Example Data

- In Excel: `Insert`, `Line`, `Line with markers`.
- Right click on data, select `Select Data`.
- Remove all the nonsense there.
- Select `Add`.
- Type "Employment" in `Series Name`. Select data for `Series Values`.
- Click `Edit` under `Horizontal Axis Values`.
- Select dates.

Time Series Characteristics

- **Trend:** gradual, long-term movement of the data in a positive or negative direction.
- **Cycle:** repetitive up-and-down movement of the data, each "cycle" need not be the same length or magnitude.
- **Seasonal pattern:** up-and-down movement of the data that can be predicted quite accurately by the time of the year.
- **Random variations:** movements in the data that are otherwise unpredictable.

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Time Series Analysis

- **Time series analysis:** use of statistical methods to uncover trend, cyclical patterns, and seasonal patterns; and using this information to forecast future outcomes for a variable.
- **Univariate time series:** using many observations of only the variable of interest to forecast that variable.
- **Multivariate time series:** using one or more related variables to help forecast variable of interest.
  - New housing sales may also help predict construction employment.
  - National price measures for costs of building materials may also help predict construction employment.
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Moving Average

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  - Often used to measure usefulness of other time series forecasts.
- **Moving average:** uses several recent values to forecast the next period's outcome.

$$MA_{t,q} = \frac{1}{q} \sum_{i=1}^{q} x_{t-i}$$

  - x_t denotes the value of the variable at time t,
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- Moving average lag length:
  - Longer lag lengths cause forecast to react more quickly/slowly to recent changes in the variable.
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- Performs (forecasting accuracy) best with data that has
  - No pronounced cyclical or seasonal variation.
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Weighted Moving Average

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$$WMA_{t,q} = \sum_{i=1}^{q} w_i x_{t-i}$$

  - w_i is the weight given to the observation that occurred i periods ago.
  - $\sum_{i=1}^{q} w_i = 1$
  - Typically, $w_i > w_{i+1}$.
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Exponential Smoothing

- **Exponential smoothing:** Averaging method using all previous data, but puts weights larger weight on the more recent observations.

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

- F_t is the forecast for period t.
- x_{t-1} is the value of the variable in the previous time period, $t-1$.
- Useful for capturing information on recent seasonal or cyclical patterns (but with a lag).
- $\alpha \in [0,1]$ is the smoothing parameter.
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Adjusted Exponential Smoothing

- **Adjusted exponential smoothing:** exponential smoothing that is adjusted to incorporate information on a *long-term trend*.

$$AF_t = F_t + T_t$$

  - AF_t is the adjusted exponential smoothing forecast.
  - F_t is the regular exponential smoothing forecast.
  - T_t is the latest estimate of the trend.
- Trend is computed by,

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

  - $\beta \in [0, 1]$ is a trend weighting parameter.
- Trend formula allows for changing trend throughout the data.

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Regression

- Regression line: equation of the line that describes the linear relationship between variable x and variable y.
- Need to assume that one variable causes another.
  - x: *independent* or *explanatory* variable.
  - y: *dependent* or *outcome* variable.
  - Variable x can influence the value for variable y, but not vice versa.

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Regression Model Example

- How does housing demand affects construction employment?
  - x_i: housing demand (independent variable, aka explanatory variable).
  - y_i: construction employment (dependent variable, aka outcome variable).
- Seasonal adjustment: how does winter season affect construction employment?
  - Dummy variable: $x_i = 1$ if winter, $x_i = 0$ otherwise).
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Seasonal Adjustment

- Previous methods capture information in recent movements, but not past seasonal fluctuations.
  - Example, we may realize that construction employment is always lowest in Jan, Feb, and March.
- **Seasonal factor:** percentage of a total year that occurs in a specific season:

$$S_k = \frac{D_k}{\sum D_k}$$

  - D_k is the sum of all values occurring in season k, for all years considered.
- Use your favorite forecasting method, forecast *years* only.
- For each season, multiply annual forecast by the seasonal factor.

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Regression Seasonal Adjustment

- Run a regression.
  - Use trend as an explanatory variable.
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