GENERAL ASSEMBLY

DATA SCIENCE

11 WEEK PART TIME COURSE

Week 9 - Time Series
Monday 16th May 2016

AGENDA

1. Tasks from Monday
2. Time Series
3. R
4. Lab
5. Advanced Topics
6. Real World Problem
7. Review

Task List

- ☐ Read first 2 chapters of Forecasting Principles and Practice https://www.otexts.org/fpp (15 mins)
- ☐ Download and Install R (10 mins)
- ☐ Download and Install RStudio (3 mins)
- ☐ Download the forecast package in R (2 mins)

1 Getting started

2 The forecaster's toolbox

3 Judgmental forecasts

4 Simple regression

5 Multiple regression

6 Time series decomposition

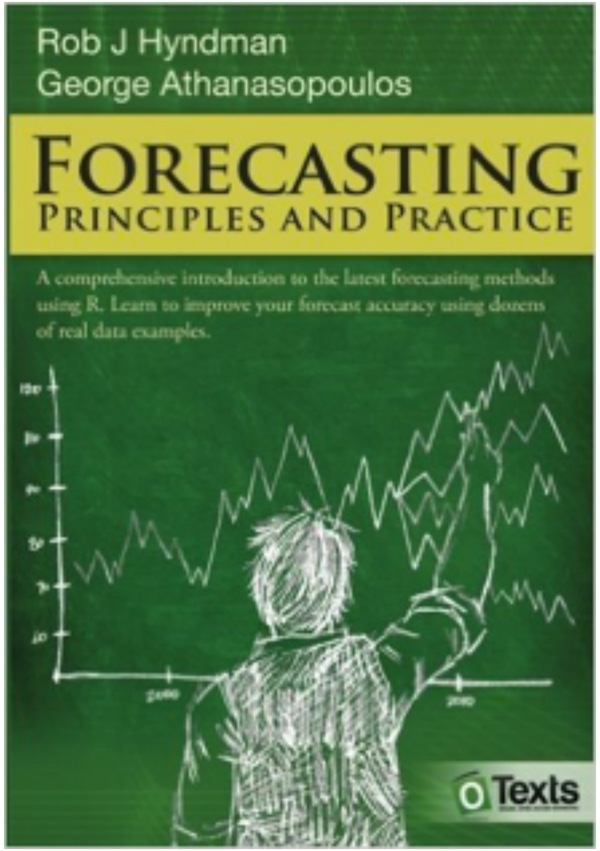
7 Exponential smoothing

8 ARIMA models

9 Advanced forecasting methods

10 Data

12 Using R



DATA SCIENCE PART TIME COURSE

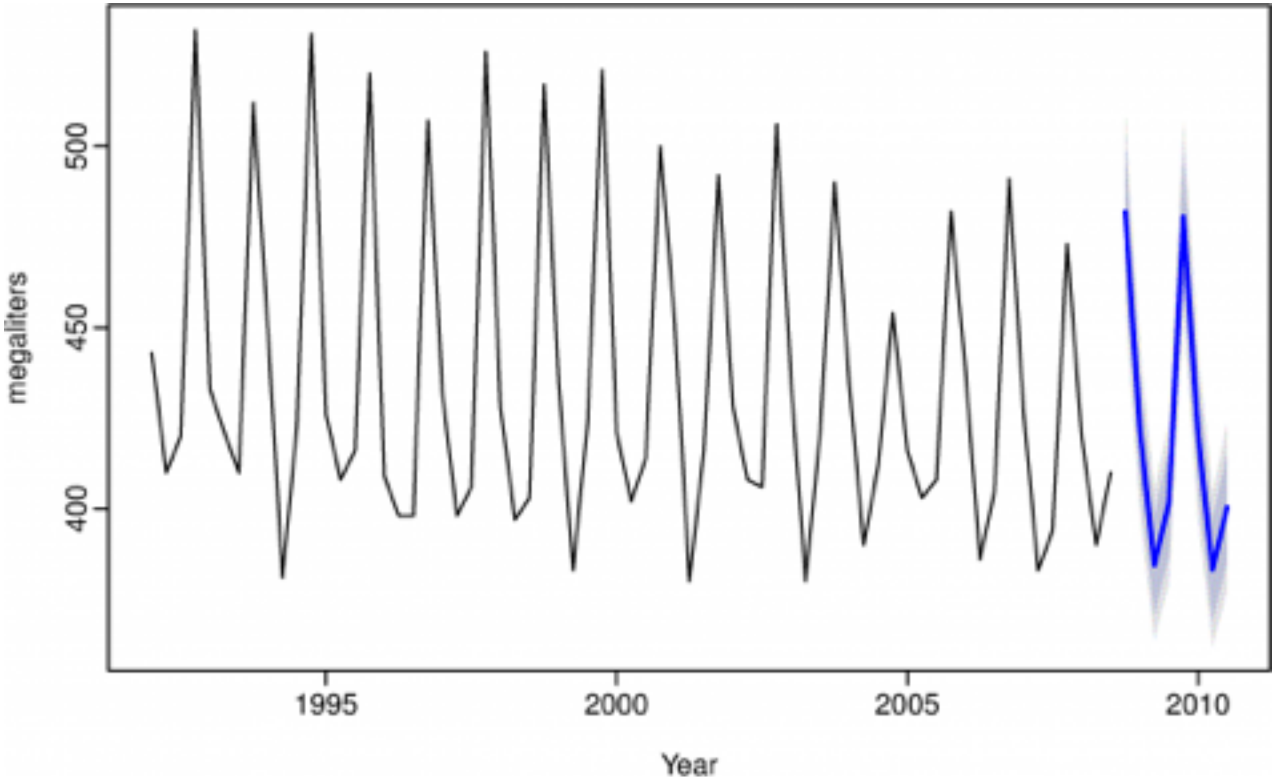
WHAT IS A TIME SERIES?

WHAT IS A TIME SERIES?

A time series is a series of data that is observed sequentially over time.

Examples include:

- Weekly Rainfall
- Daily Stock price of Atlassian
- Quarterly oil import figures


megaliters
500
450
400
1995
2000
2005
2010
Year

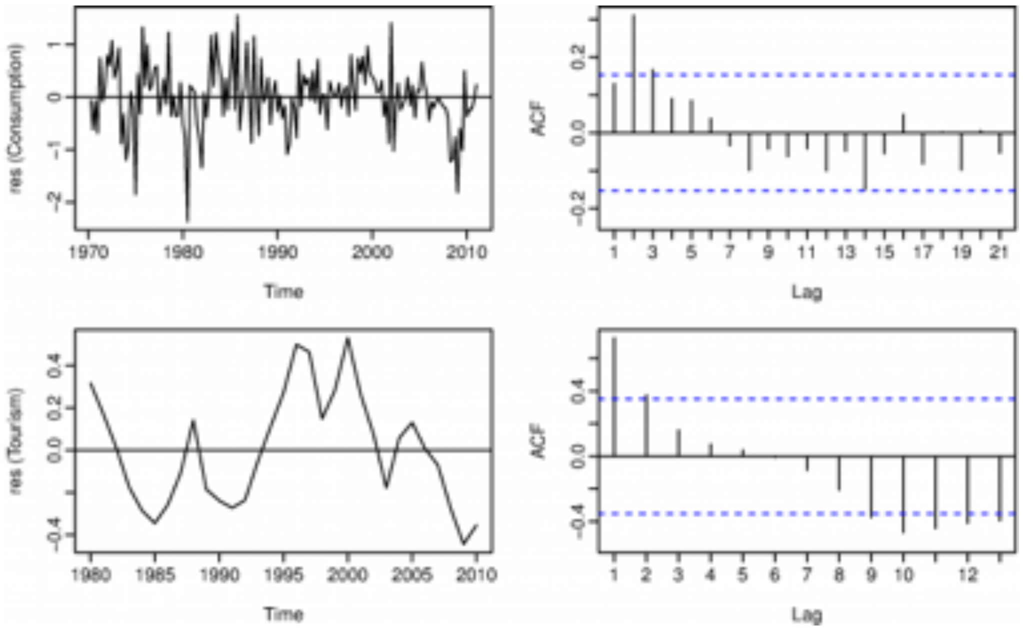
In other words, why wouldn't we just use linear regression and have the time variable as our X values?

$$y = \beta_0 + \beta_1 x + \varepsilon.$$

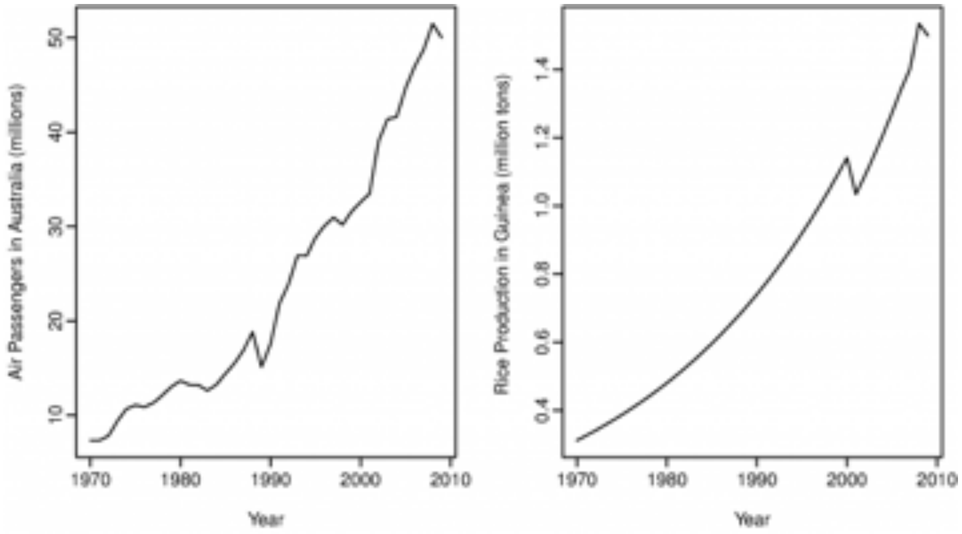
Recall some of the conditions of Linear Regression models:

- have mean zero; otherwise the forecasts will be systematically biased
- are not autocorrelated; otherwise the forecasts will be inefficient as there is more information to be exploited in the data
- are unrelated to the predictor variable; otherwise there would be more information that should be included in the systematic part of the model

With time series data it is highly likely that the value of a variable observed in the current time period will be influenced by its value in the previous period, or even the period before that, and so on…



Time Series will often be ‘non-stationary’, that means that you do not have a zero mean or constant variance. This can lead to spurious regressors (factors considered influential in a model that are actually not).



There are three time series components we will use to describe a time series

- Trend
- Seasonal
- Cyclic

TIME SERIES COMPONENTS – TREND

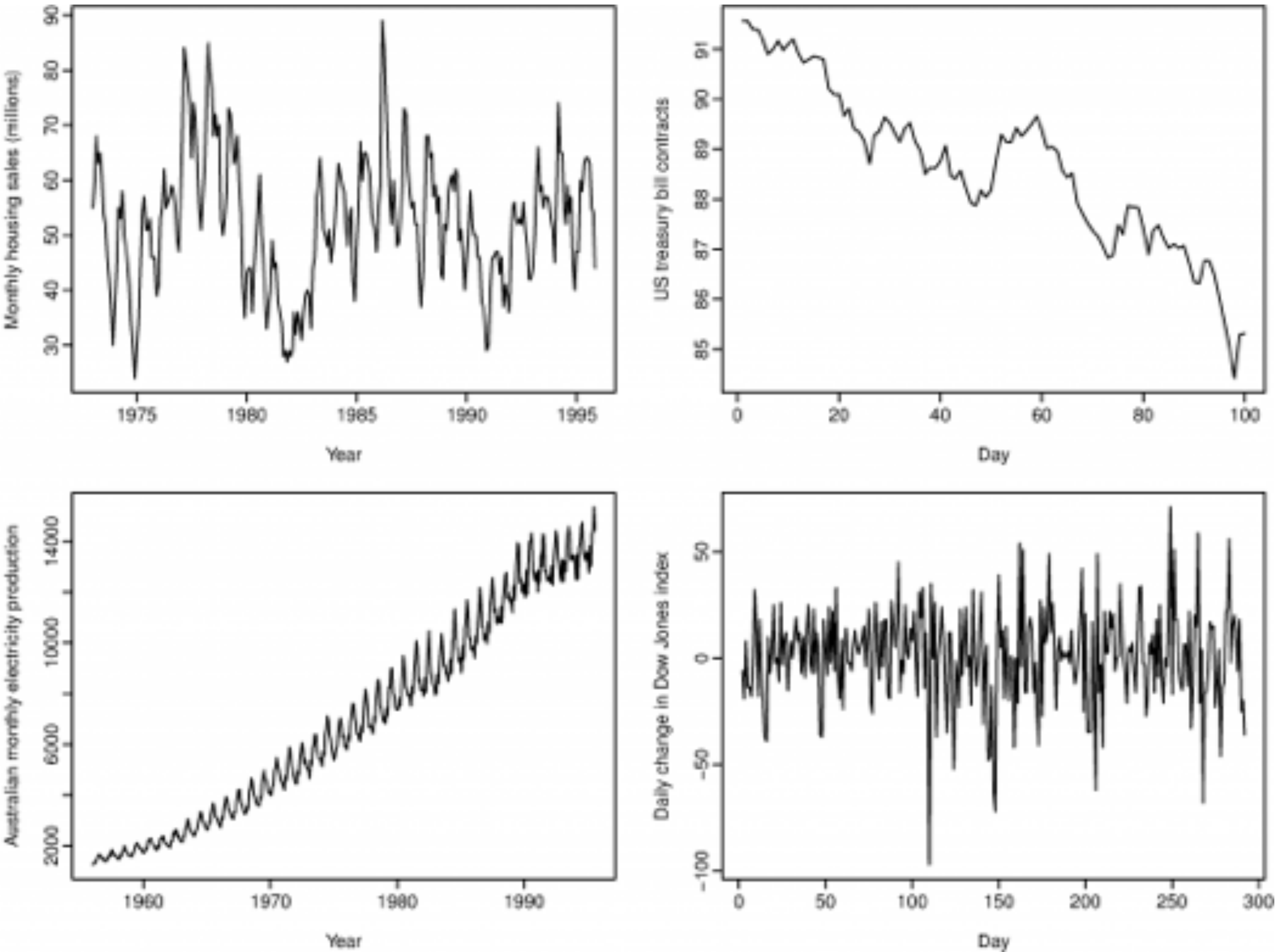
A trend exists when there is a long-term increase or decrease in the data. It does not have to be linear. Sometimes we will refer to a trend "changing direction" when it might go from an increasing trend to a decreasing trend.

TIME SERIES COMPONENTS - SEASONAL

A seasonal pattern exists when a series is influenced by seasonal factors (e.g., the quarter of the year, the month, or day of the week). Seasonality is always of a fixed and known period.

TIME SERIES COMPONENTS - CYCLIC

A cyclic pattern exists when data exhibit rises and falls that are not of fixed period. The duration of these fluctuations is usually of at least 2 years.


Monthly housing sales (millions)
Year
US treasury bill contracts
Day
Australian monthly electricity production
Year
Daily change in Dow Jones index
Day

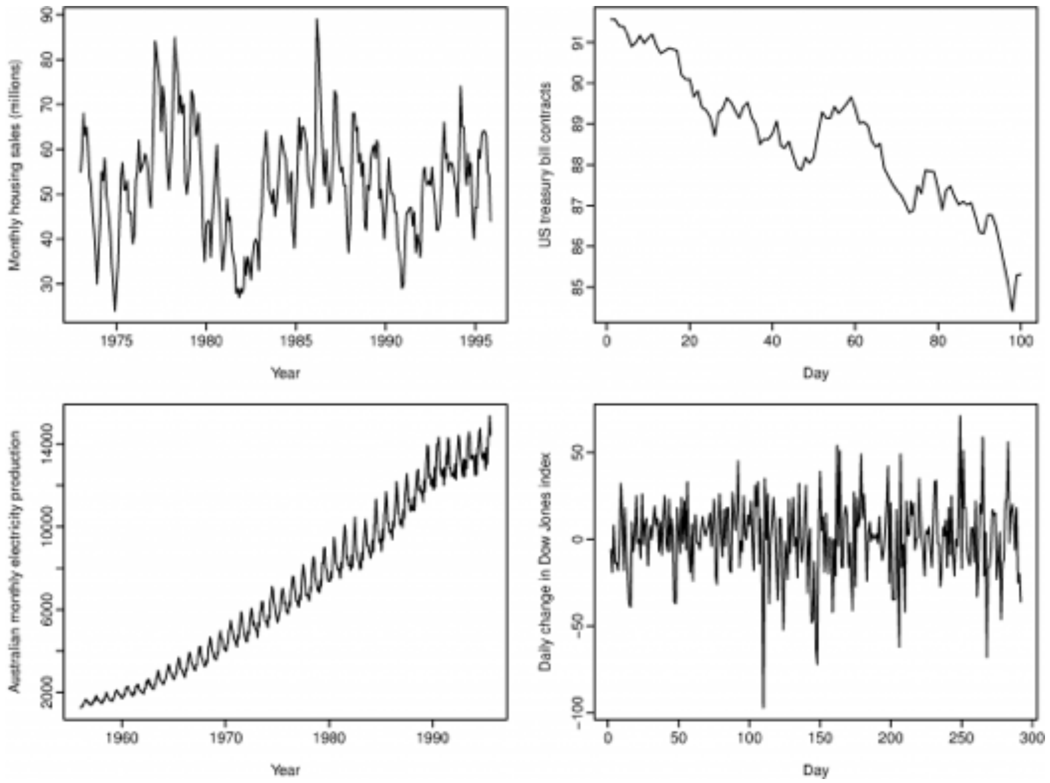
TIME SERIES COMPONENTS

Top Left: strong seasonality within each year, as well as some strong cyclic behaviour with period about 6–10 years. No Trend

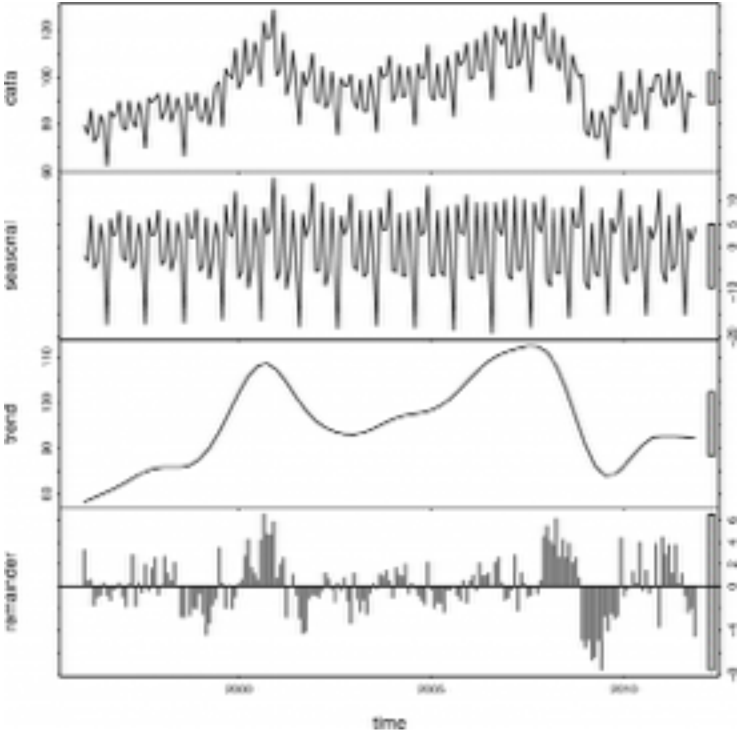
Top Right: no seasonality, but an obvious downward trend. If we had more data we may be able to observe a cycle

Bottom Left: strong increasing trend, with strong seasonality. No cycle

Bottom Right: no trend, seasonality or cyclic behaviour



Time Series Decomposition is a way to break down a time series into the Season, Trend (which includes the cycle) and Remainder.



We can consider these to be weighted averages of past observations. This means that the more recent the observation, the higher the weighting of that observation.

The Naive model is the case where the forecast is equal to the last observed value,

$$\hat{y}_{T+h|T} = y_T$$

What if we were to weight the observations to have decreasing weights as the observations got older? What would the equation look like?

$$\hat{y}_{T+1|T} = \alpha y_T + \alpha(1-\alpha) y_{T-1} + \alpha(1-\alpha)^2 y_{T-2} + \cdots$$

where $0 \leq \alpha \leq 1$ is the smoothing parameter.

The Holt-Winters method captures level, trend and seasonality.

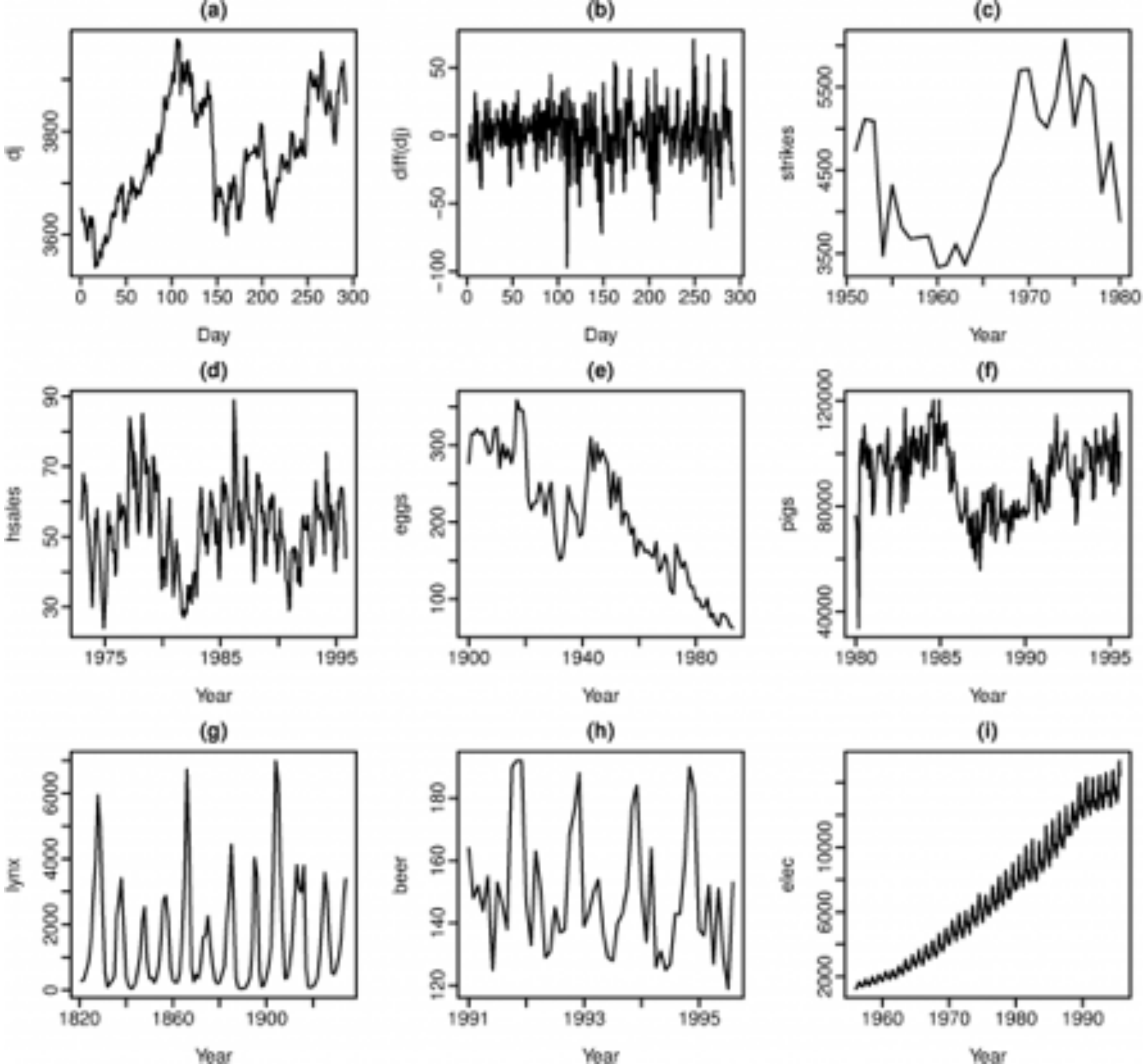
There are two variations to this method that differ in the nature of the seasonal component. The additive method is preferred when the seasonal variations are roughly constant through the series, while the multiplicative method is preferred when the seasonal variations are changing proportional to the level of the series.

$$
\begin{aligned}
\hat{y}_{t+h|t} &= \ell_t + hb_t + s_{t-m+h_m^+} \\
\ell_t &= \alpha(y_t - s_{t-m}) + (1-\alpha)(\ell_{t-1} + b_{t-1}) \\
b_t &= \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1} \\
s_t &= \gamma(y_t - \ell_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m},
\end{aligned}
$$

$$
\begin{aligned}
\hat{y}_{t+h|t} &= (\ell_t + hb_t)s_{t-m+h_m^+}. \\
\ell_t &= \alpha\frac{y_t}{s_{t-m}} + (1-\alpha)(\ell_{t-1} + b_{t-1}) \\
b_t &= \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1} \\
s_t &= \gamma\frac{y_t}{(\ell_{t-1} + b_{t-1})} + (1-\gamma)s_{t-m}
\end{aligned}
$$

A stationary time series is one whose properties do not depend on the time at which the series is observed. So time series with trends, or with seasonality, are not stationary — the trend and seasonality will affect the value of the time series at different times. On the other hand, a white noise series is stationary — it does not matter when you observe it, it should look much the same at any period of time.

In general, a stationary time series will have no predictable patterns in the long-term. Time plots will show the series to be roughly horizontal (although some cyclic behaviour is possible) with constant variance.



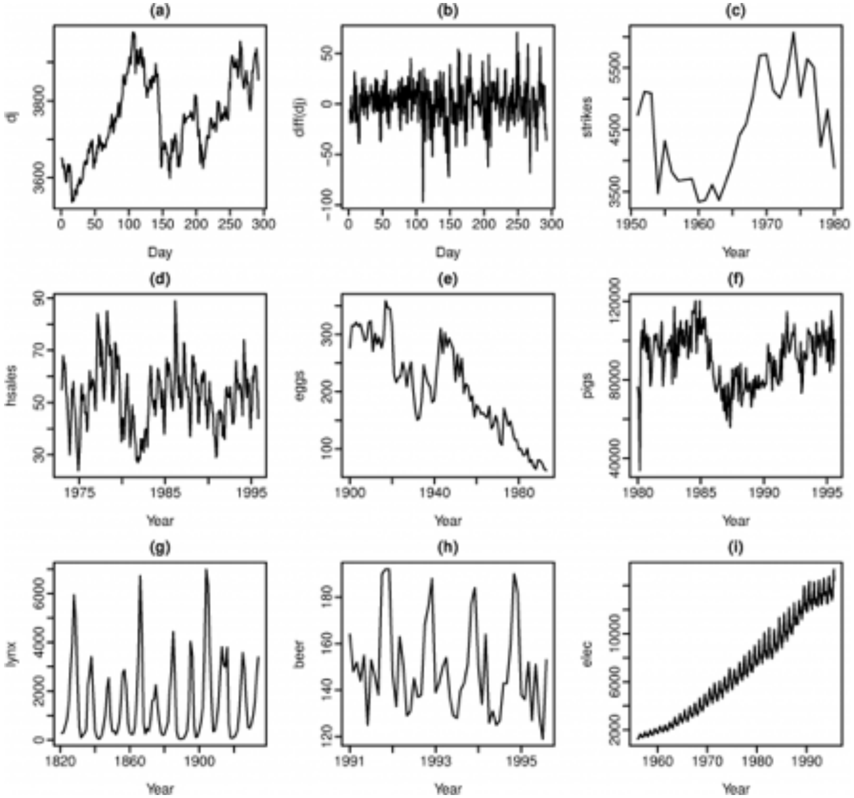
(a)
dj
3600
3800
0 50 100 150 200 250 300
Day
(b)
diff(dj)
-100
-50
0
50
0 50 100 150 200 250 300
Day
(c)
strikes
3500
4500
5500
1950 1960 1970 1980
Year
(d)
hsales
30
50
70
90
1975 1985 1995
Year
(e)
eggs
100
200
300
1900 1940 1980
Year
(f)
pigs
40000
80000
120000
1980 1985 1990 1995
Year
(g)
lynx
0
2000
4000
6000
1820 1860 1900
Year
(h)
beer
120
140
160
180
1991 1993 1995
Year
(i)
elec
2000
6000
10000
1960 1970 1980 1990
Year

seasonality rules out series (d), (h) and (i).

Trend rules out series (a), (c), (e), (f) and (i).

Increasing variance also rules out (i).

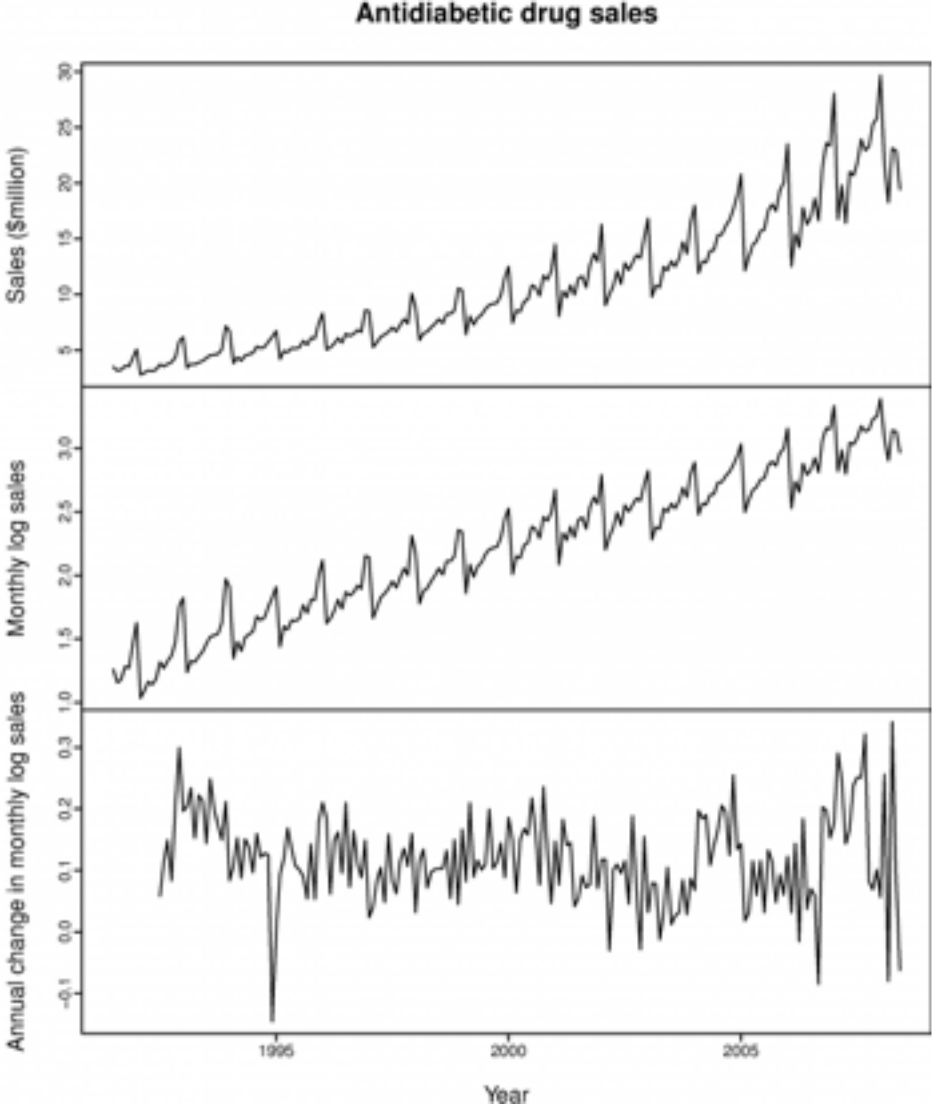
That leaves only (b) and (g) as stationary series. At first glance, the strong cycles in series (g) might appear to make it non-stationary. But these cycles are aperiodic



One way to make a time series stationary is to compute the differences between consecutive observations.

Differencing can help stabilize the mean of a time series by removing changes in the level of a time series, and so eliminating trend and seasonality.

A seasonal difference is the difference between an observation and the corresponding observation from the previous year



Antidiabetic drug sales
Sales ($million)
Monthly log sales
Annual change in monthly log sales
Year
1995
2000
2005

The backward shift operator BB is a useful notational device when working with time series lags:

$By_t = y_{t-1}$

Two applications of BB to y_t shifts the data back two periods:

$B(By_t) = B^2 y_t = y_{t-2}$

(This is also known as a Lag operator)

In an autoregression model, we forecast the variable of interest using a linear combination of past values of the variable. The term autoregression indicates that it is a regression of the variable against itself.

This is like a multiple regression but with lagged values of y_t as predictors. We refer to this as an AR(p) model

ARIMA MODELS - MOVING AVERAGE (MA)

Rather than use past values of the forecast variable in a regression, a moving average model uses past forecast errors in a regression-like model.

We refer to this as an MA(q) model

If we combine differencing with autoregression and a moving average model, we obtain a non-seasonal ARIMA model. ARIMA is an acronym for AutoRegressive Integrated Moving Average model ("integration" in this context is the reverse of differencing).

We call this an ARIMA(p,d,q) model, where

p= order of the autoregressive part;

d= degree of first differencing involved;

q= order of the moving average part.

The forecast error is simply $e_i=y_i-\hat{y}_i$, which is on the same scale as the data. Accuracy measures that are based on e_i are therefore scale-dependent and cannot be used to make comparisons between series that are on different scales.

$$\text{Mean absolute error: MAE} = \text{mean}(|e_i|),$$

$$\text{Root mean squared error: RMSE} = \sqrt{\text{mean}(e_i^2)}.$$

The percentage error is given by $p_i = 100e_i/y_i$. Percentage errors have the advantage of being scale-independent, and so are frequently used to compare forecast performance between different data sets.

Mean absolute percentage error: $\text{MAPE} = \text{mean}(|p_i|)$

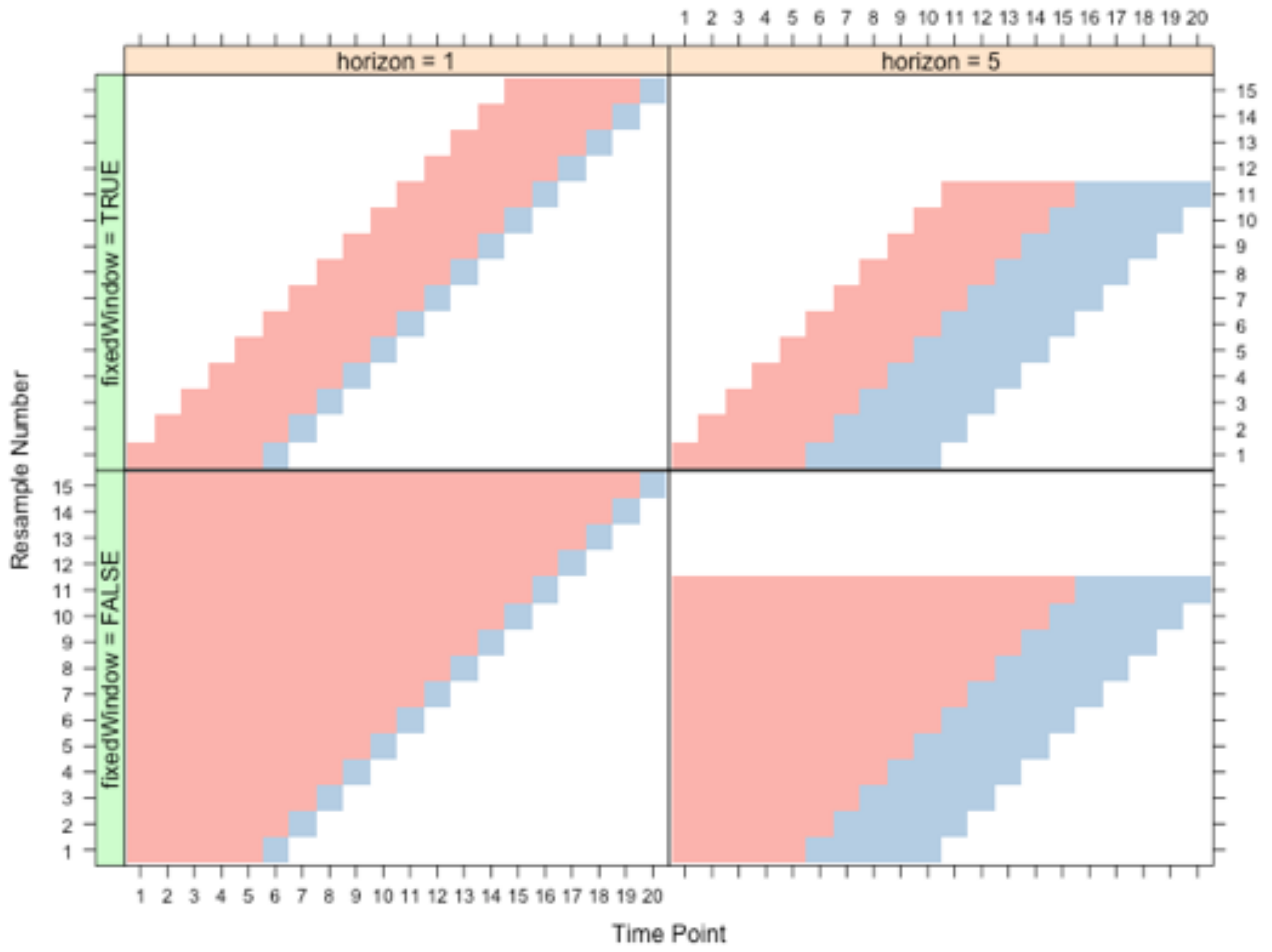
Scaled errors are an alternative to using percentage errors when comparing forecast accuracy across series on different scales. They proposed scaling the errors based on the training MAE from a simple forecast method. For a non-seasonal time series, a useful way to define a scaled error uses naïve forecasts:

$$q_j = \frac{e_j}{\frac{1}{T-1}\sum_{t=2}^{T}|y_t - y_{t-1}|}.$$

A scaled error is less than one if it arises from a better forecast than the average naïve forecast computed on the training data.

The three parameters for this type of splitting in the R Caret package are:

- initialWindow: the initial number of consecutive values in each training set sample
- horizon: The number of consecutive values in test set sample
- fixedWindow: A logical: if FALSE, the training set always start at the first sample and the training set size will vary over data splits.



horizon = 1
horizon = 5
fixedWindow = TRUE
fixedWindow = FALSE
Resample Number
Time Point

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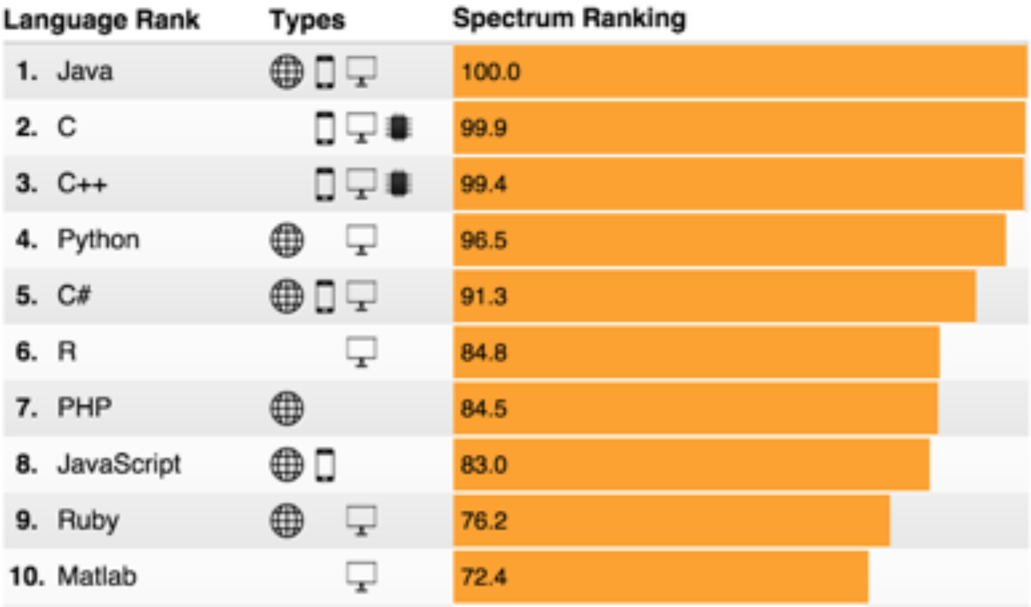
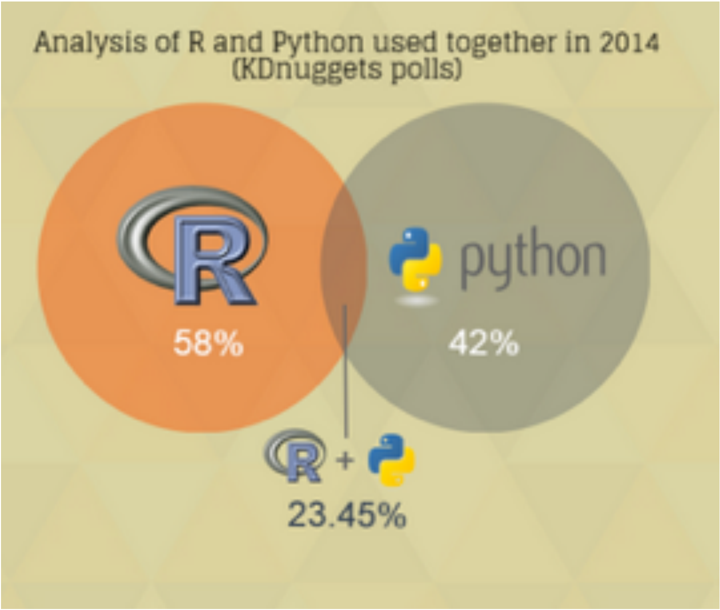
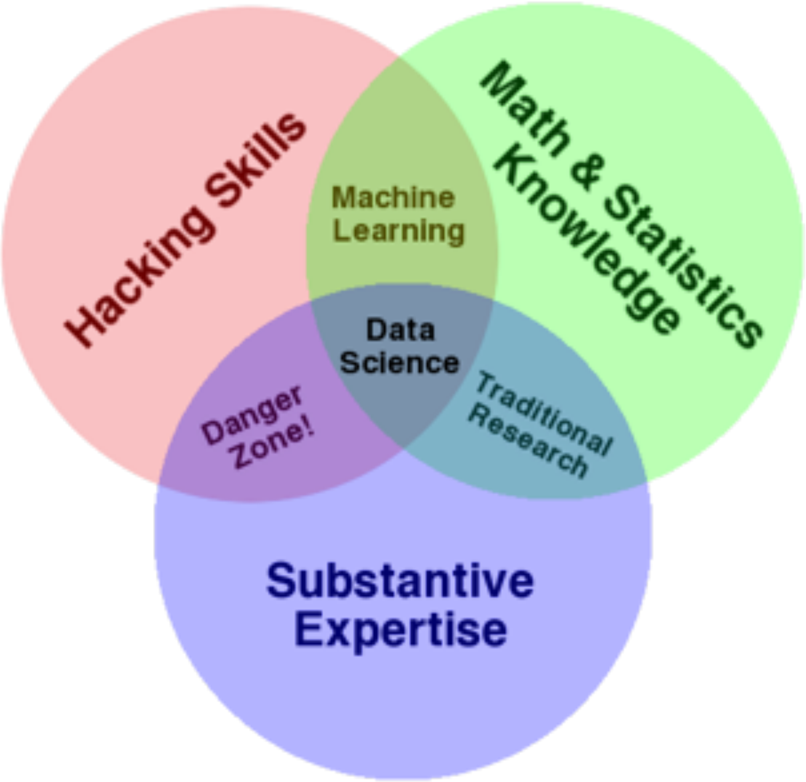
PYTHON & R



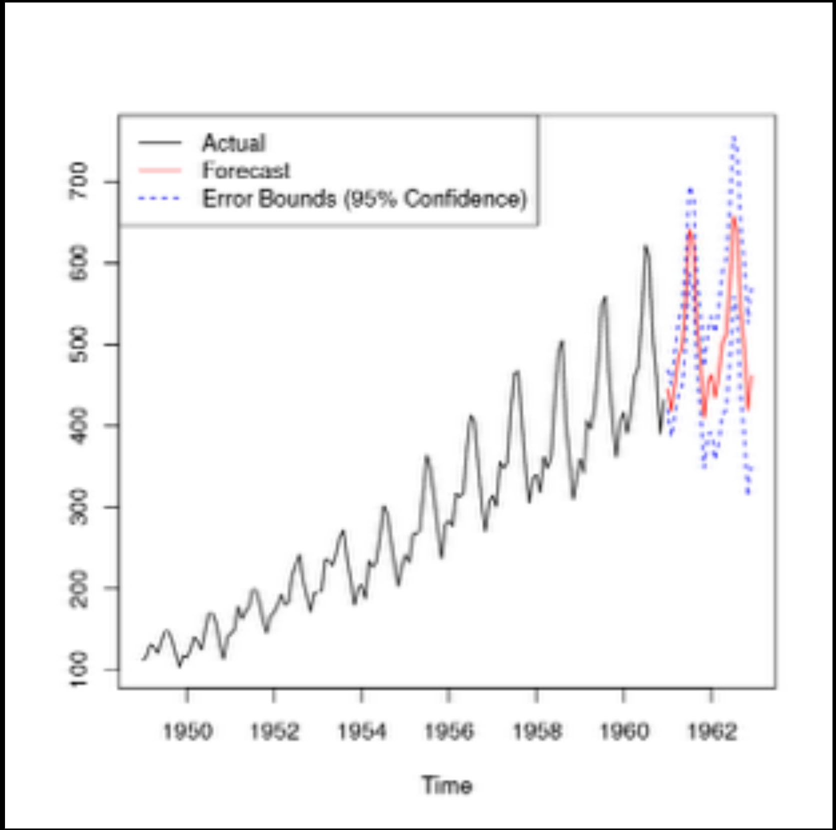
IEEE Spectrum Survey 2015



DataCamp Infographic 2015


Hacking Skills
Math & Statistics Knowledge
Machine Learning
Data Science
Danger Zone!
Traditional Research
Substantive Expertise

LAB


Actual
Forecast
Error Bounds (95% Confidence)
700
600
500
400
300
200
100
1950
1952
1954
1956
1958
1960
1962
Time

ADVANCED TOPICS

1. Recurrent Neural Networks (RNNs)
2. Clustering Time Series
3. Hierarchical Time Series
4. Bayesian Structural Time Series
5. Causal Impact
6. Outlier Analysis

DISCUSSION TIME

- Talk through a real problem
- Review
- Questions
- Task List

REAL PROBLEMS

DATA SCIENCE – Week 8 Day 2