

DATA SCIENCE

10 WEEK PART TIME COURSE

Week 9 – Time Series
Monday 28th November 2016

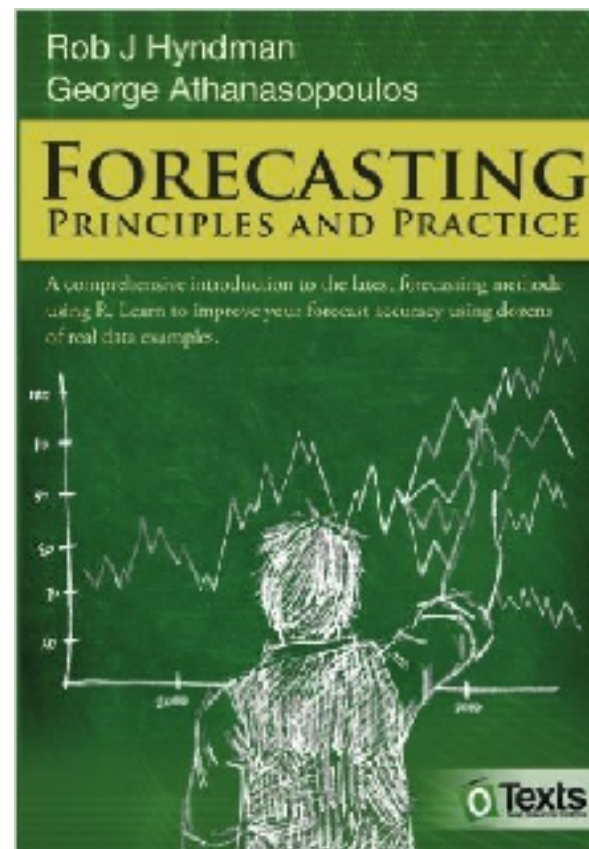
1. Time Series
2. R
3. Lab
4. Review

DATA SCIENCE - Week 8 Day 2

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?

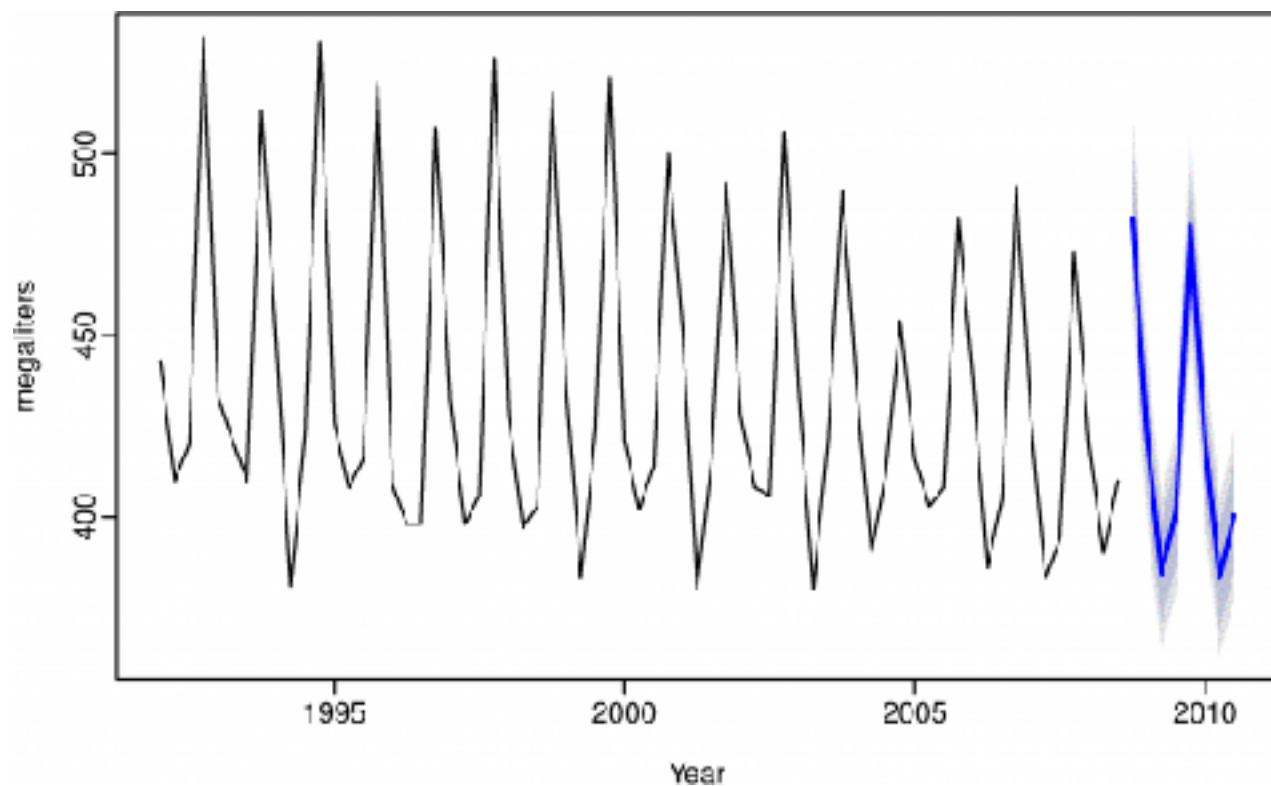
A time series is a series of data that is observed sequentially over time.

Examples include:

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

WHAT IS A TIME SERIES?

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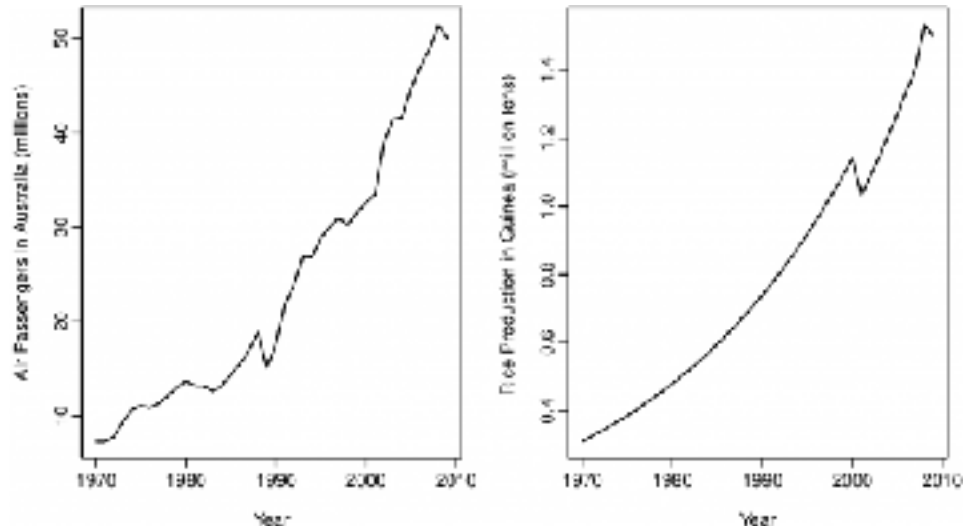
In other words, why wouldn't we just use linear regression and have the time variable as our X values?

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

WHAT MAKES A TIME SERIES DIFFERENT?

9

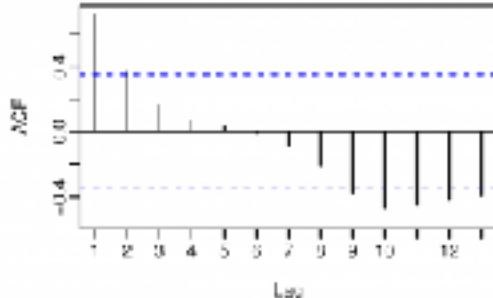
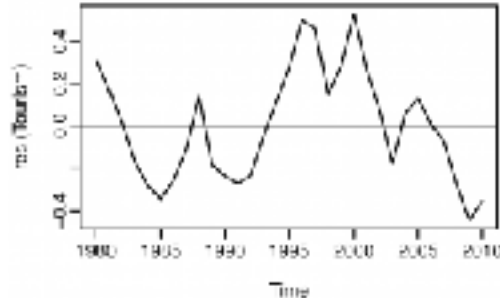
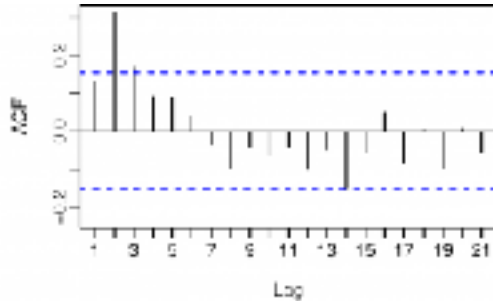
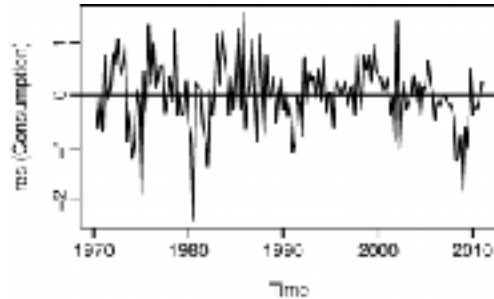
Time Series will often be ‘non-stationary’, that means that you do not have a zero mean or constant variance. This can lead to spurious regressors (factors considered influential in a model that are actually not).



WHAT MAKES A TIME SERIES DIFFERENT?

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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...



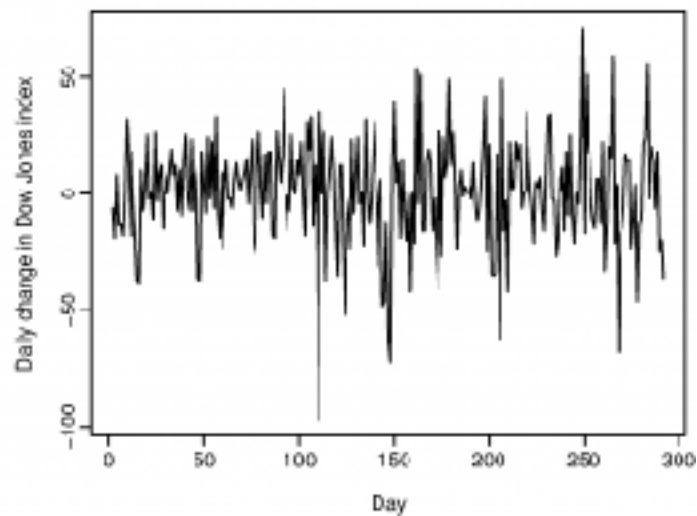
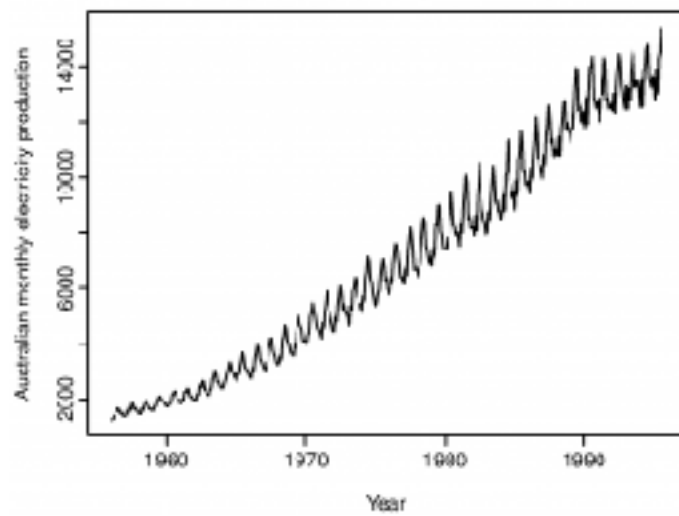
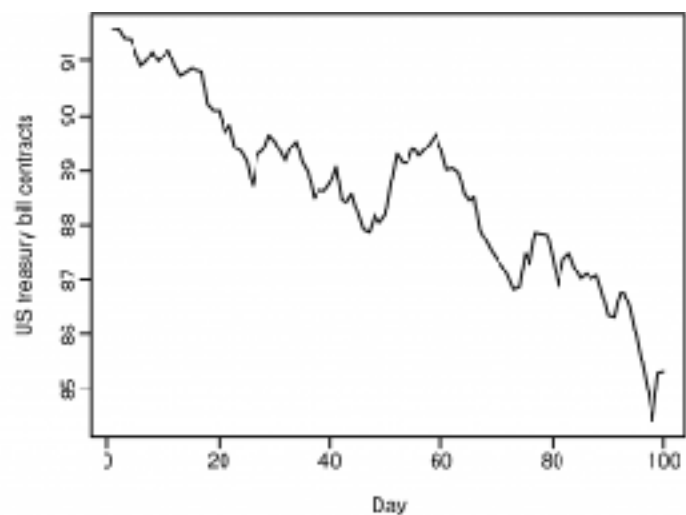
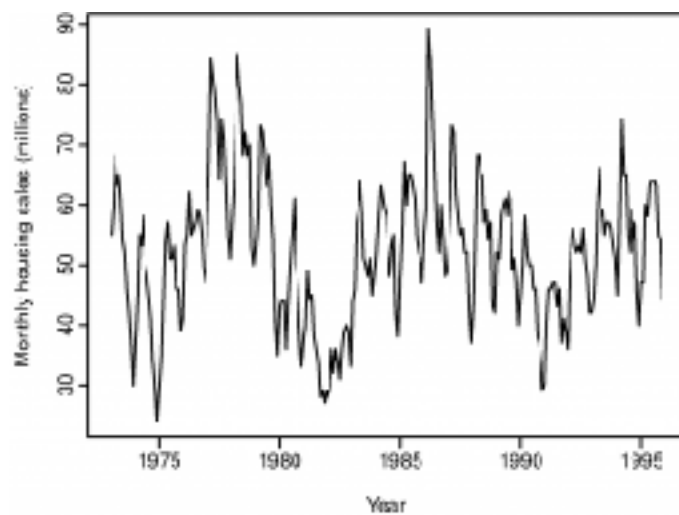
There are three time series components we will use to describe a time series

- Trend
- Seasonal
- Cyclic

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.

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.

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.



TIME SERIES COMPONENTS

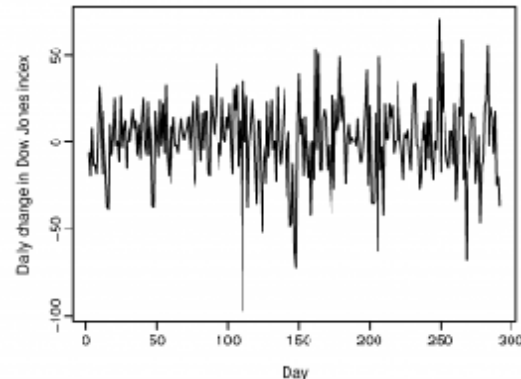
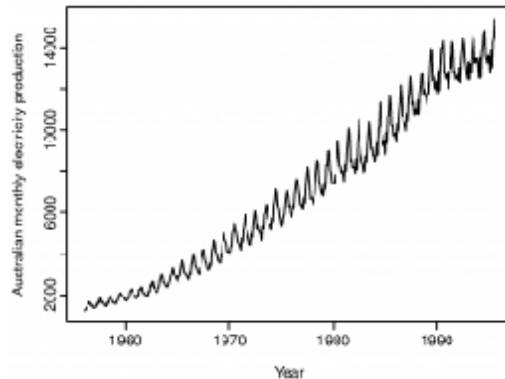
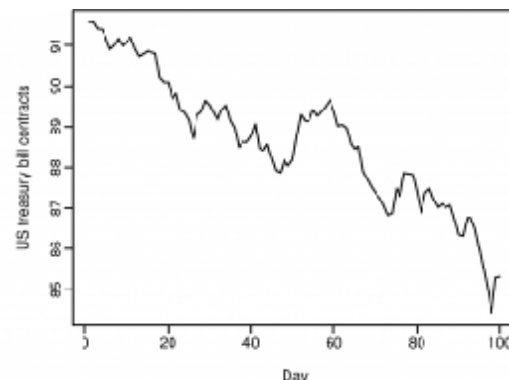
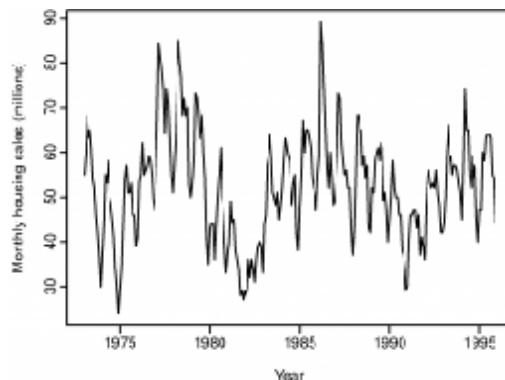
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Top Left: strong seasonality within each year, as well as some strong cyclic behaviour with period about 6–10 years. No Trend

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

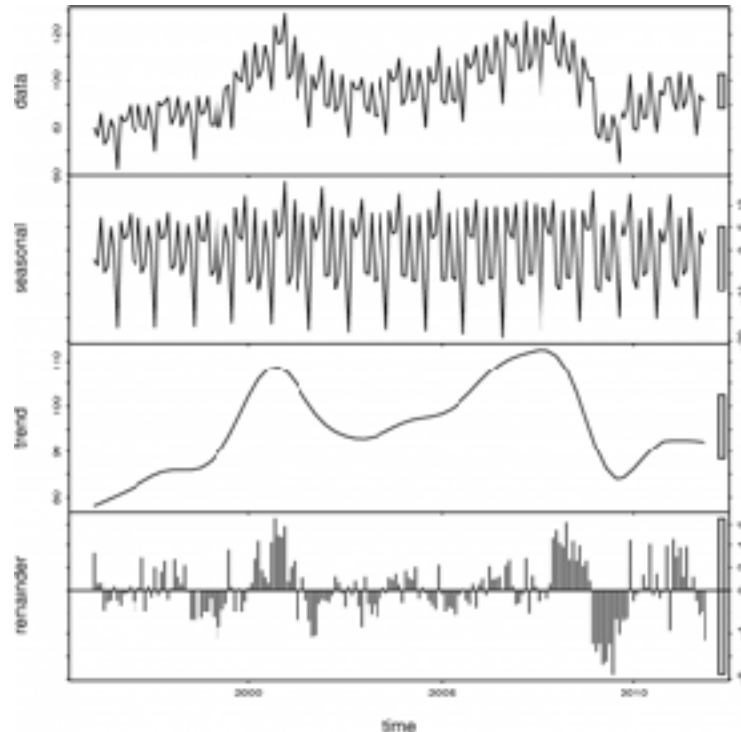
Bottom Right: no trend, seasonality or cyclic behaviour



WHAT IS A TIME SERIES DECOMPOSITION?

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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?

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

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.

$$\hat{y}_{t+h|t} = \ell_t + hb_t + s_{t-m+h_m^+}$$

$$\ell_t = \alpha(y_t - s_{t-m}) + (1 - \alpha)(\ell_{t-1} + b_{t-1})$$

$$b_t = \beta^*(\ell_t - \ell_{t-1}) + (1 - \beta^*)b_{t-1}$$

$$s_t = \gamma(y_t - \ell_{t-1} - b_{t-1}) + (1 - \gamma)s_{t-m},$$

$$\hat{y}_{t+h|t} = (\ell_t + hb_t)s_{t-m+h_m^+}.$$

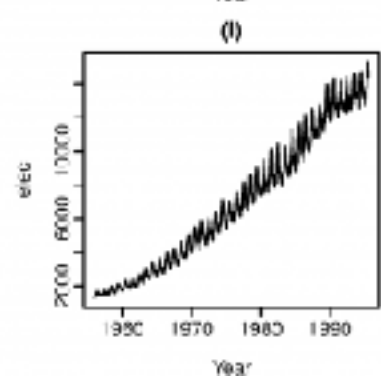
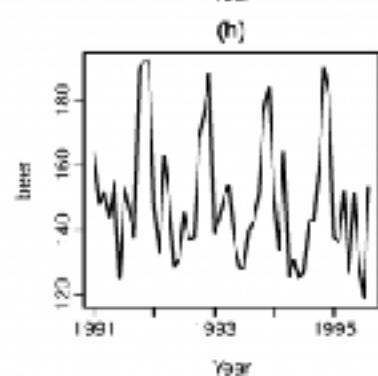
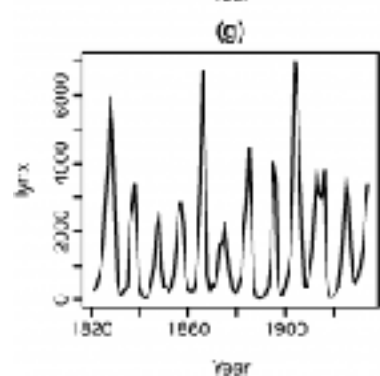
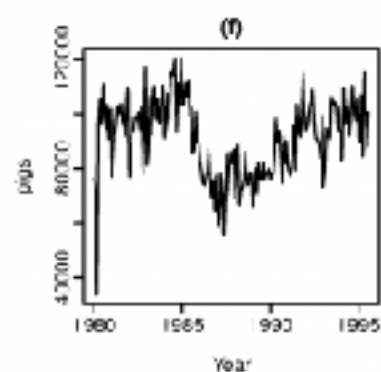
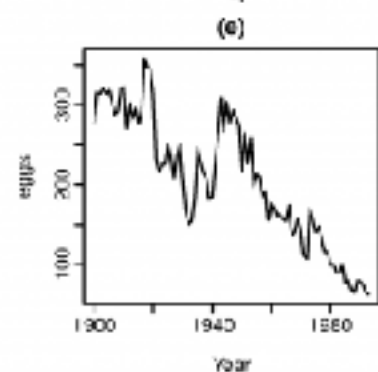
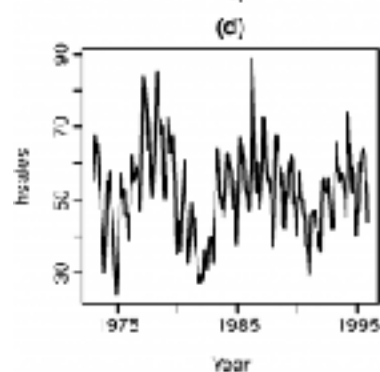
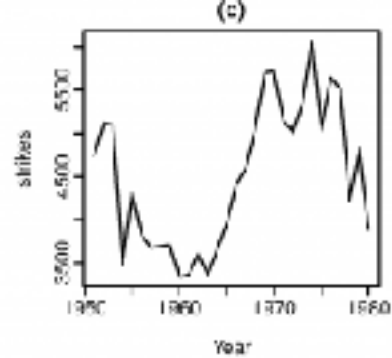
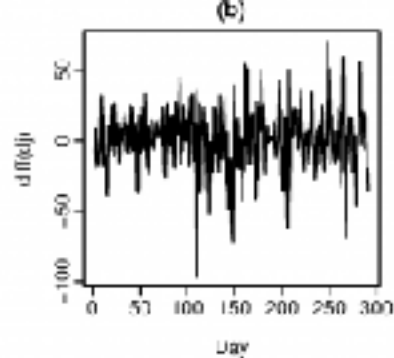
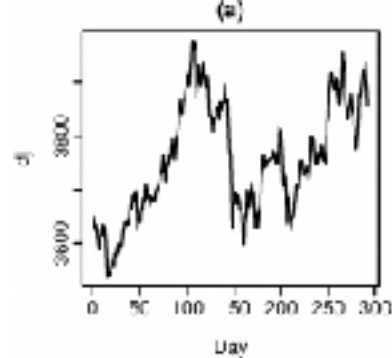
$$\ell_t = \alpha \frac{y_t}{s_{t-m}} + (1 - \alpha)(\ell_{t-1} + b_{t-1})$$

$$b_t = \beta^*(\ell_t - \ell_{t-1}) + (1 - \beta^*)b_{t-1}$$

$$s_t = \gamma \frac{y_t}{(\ell_{t-1} + b_{t-1})} + (1 - \gamma)s_{t-m}$$

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.

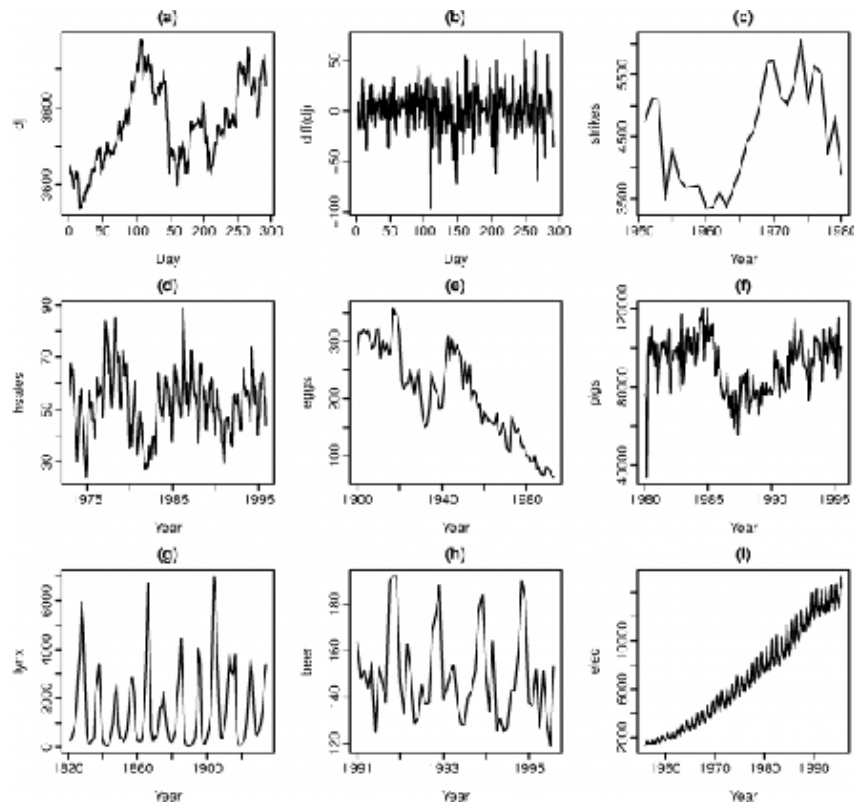


seasonality rules out series (d), (h) and (i).

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

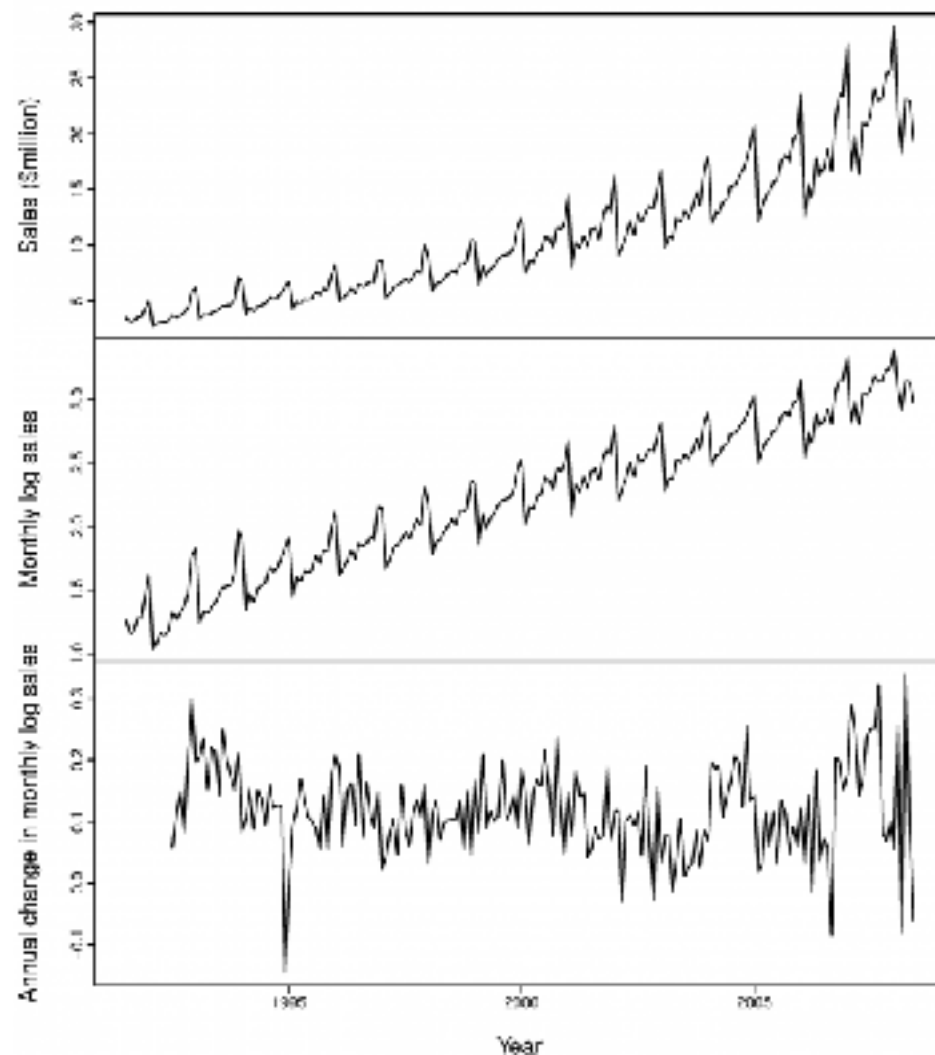


One way to make a time series stationary is to compute the differences between consecutive observations.

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



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

$$By_t = y_{t-1}$$

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

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

(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

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.

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

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: $MAPE = \text{mean}(|p_i|)$

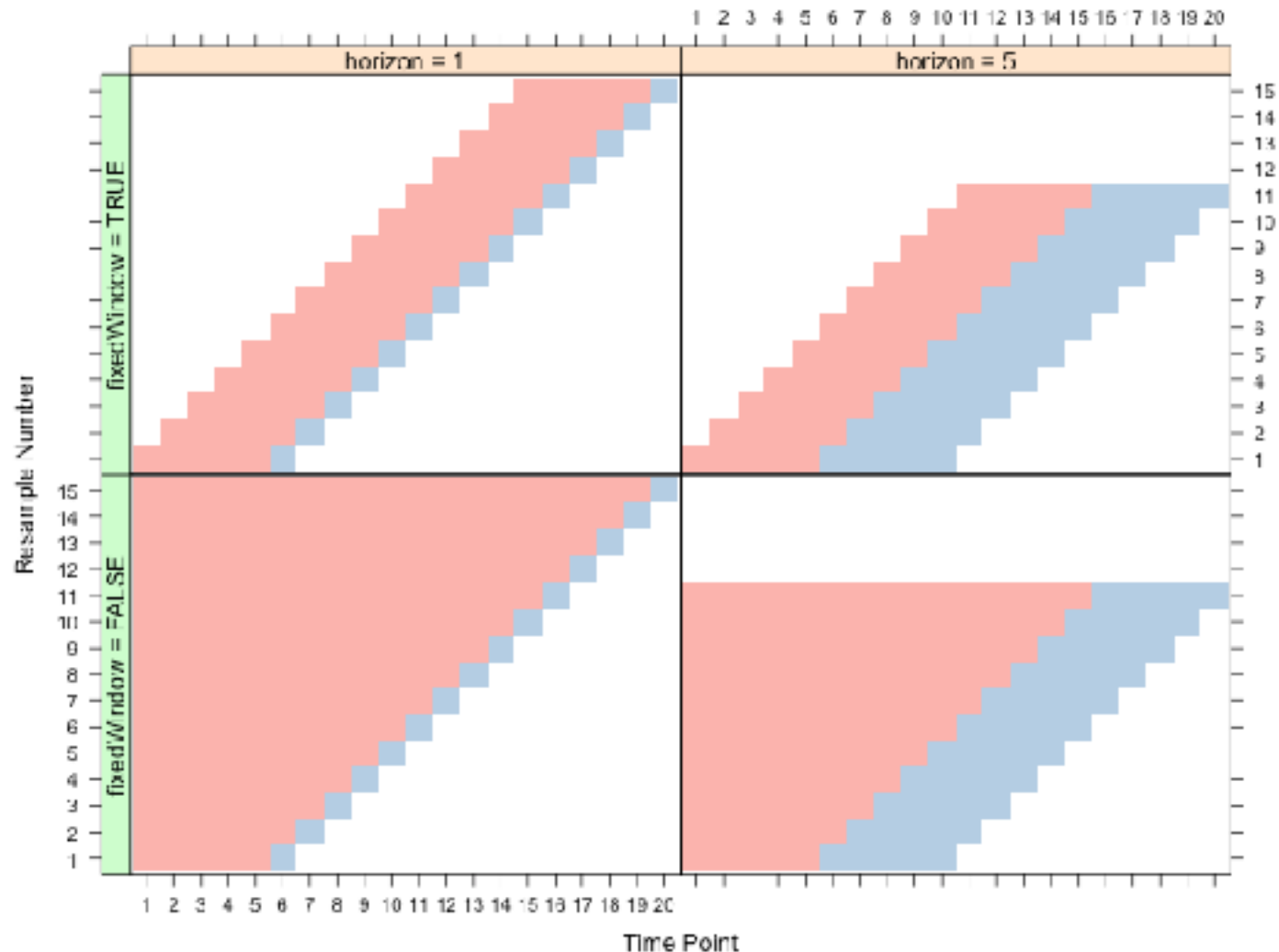
Scaled errors are an alternative to using percentage errors when comparing forecast accuracy across series on different scales. They proposed scaling the errors based on the training MAE from a simple forecast method. For a non-seasonal time series, a useful way to define a scaled error uses naïve forecasts:

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

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







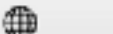

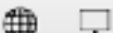

The three parameters for this type of splitting in the R Caret package are:

- `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.

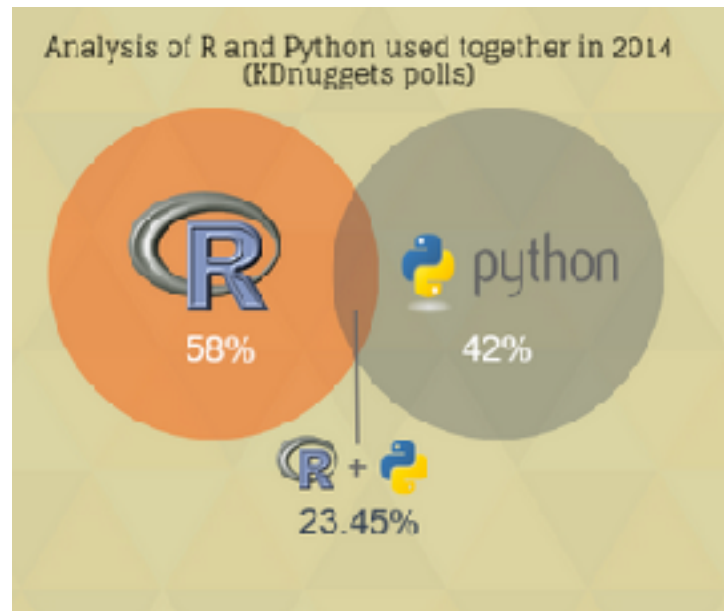


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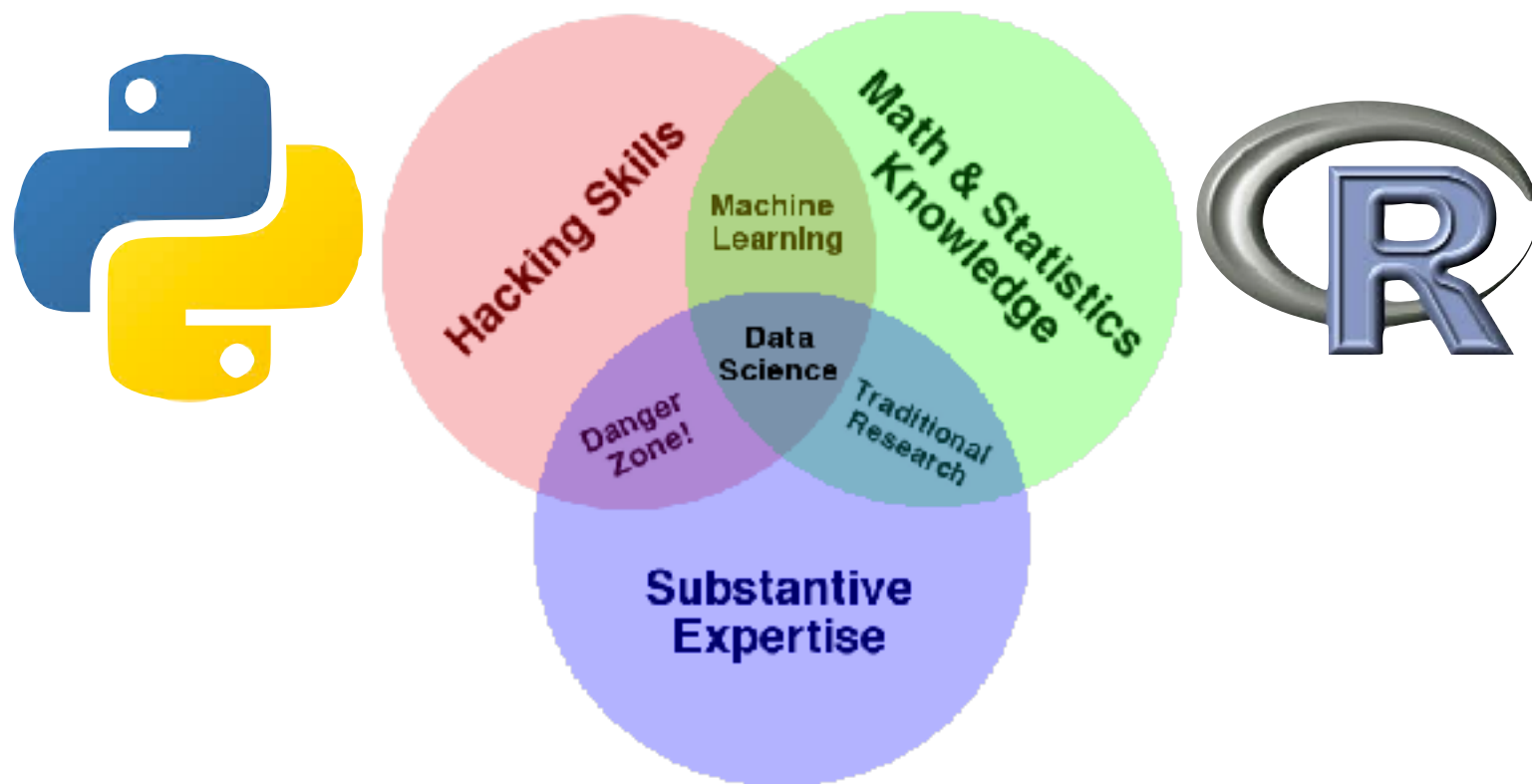


Language Rank	Types	Spectrum Ranking
1. Java		100.0
2. C		99.9
3. C++		99.4
4. Python		96.5
5. C#		91.3
6. R		84.8
7. PHP		84.5
8. JavaScript		83.0
9. Ruby		76.2
10. Matlab		72.4

IEEE Spectrum Survey 2015



DataCamp Infographic 2015



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

DATA SCIENCE PART TIME COURSE

LAB

1. re-name your labs with lab_name.<yourname>.ipynb (to prevent a conflict)
2. cd <path to the root of your SYD_DAT_6 local repo>
3. commit your changes ahead of sync
 - git status
 - git add .
 - git commit -m "descriptive label for the commit"
 - git status
4. download new material from official course repo (upstream) and merge it
 - git checkout master (ensures you are in the master branch)
 - git fetch upstream
 - git merge upstream/master



DATA SCIENCE

HOMEWORK

Homework

- **Homework 3 – Due Monday 28th of November**