Time Series Analysis with R[1]

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[1]Presented at UJAT and Canberra R Users Group

Outline

Time Series Analysis with R [2]

- time series data in R
- time series decomposition, forecasting, clustering and classification
- autoregressive integrated moving average (ARIMA) model
- Dynamic Time Warping (DTW)
- Discrete Wavelet Transform (DWT)
- k-NN classification

[2] Chapter 8: Time Series Analysis and Mining, in book *R and Data Mining: Examples and Case Studies*. http://www.rdatamining.com/docs/RDataMining.pdf

R

- a free software environment for statistical computing and graphics
- runs on Windows, Linux and MacOS
- widely used in academia and research, as well as industrial applications
- 5,800+ packages (as of 13 Sept 2014)
- CRAN Task View: Time Series Analysis

  `http://cran.r-project.org/web/views/TimeSeries.html`

Time Series Data in R

- class ts
- represents data which has been sampled at equispaced points in time
- frequency=7: a weekly series
- frequency=12: a monthly series
- frequency=4: a quarterly series

Time Series Data in R

```
a <- ts(1:20, frequency = 12, start = c(2011, 3))
print(a)

##      Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
## 2011           1   2   3   4   5   6   7   8   9  10
## 2012  11  12  13  14  15  16  17  18  19  20

str(a)

##  Time-Series [1:20] from 2011 to 2013: 1 2 3 4 5 6 7 8 9 10...

attributes(a)

## $tsp
## [1] 2011 2013   12
##
## $class
## [1] "ts"
```

Outline

What is Time Series Decomposition

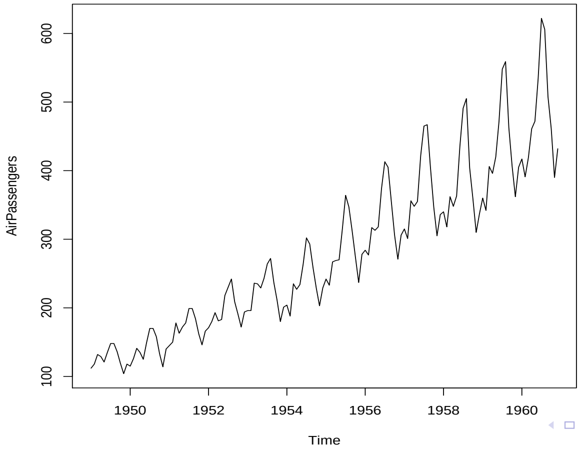
To decompose a time series into components:

- Trend component: long term trend
- Seasonal component: seasonal variation
- Cyclical component: repeated but non-periodic fluctuations
- Irregular component: the residuals

Data AirPassengers

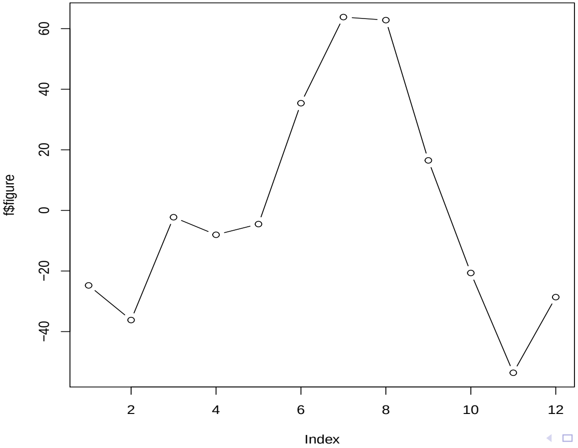
Data `AirPassengers`: monthly totals of Box Jenkins international airline passengers, 1949 to 1960. It has 144(=12×12) values.

```
plot(AirPassengers)
```



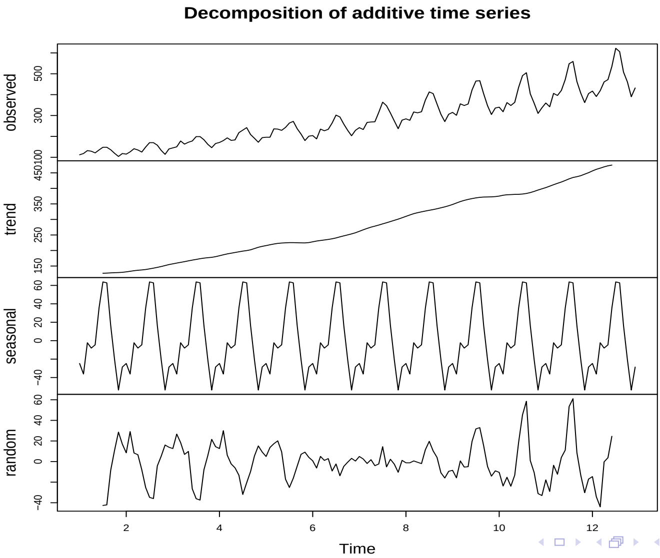
Decomposition

```
apts <- ts(AirPassengers, frequency = 12)
f <- decompose(apts)
plot(f$figure, type = "b")  # seasonal figures
```



Decomposition

```
plot(f)
```



Outline

Time Series Forecasting

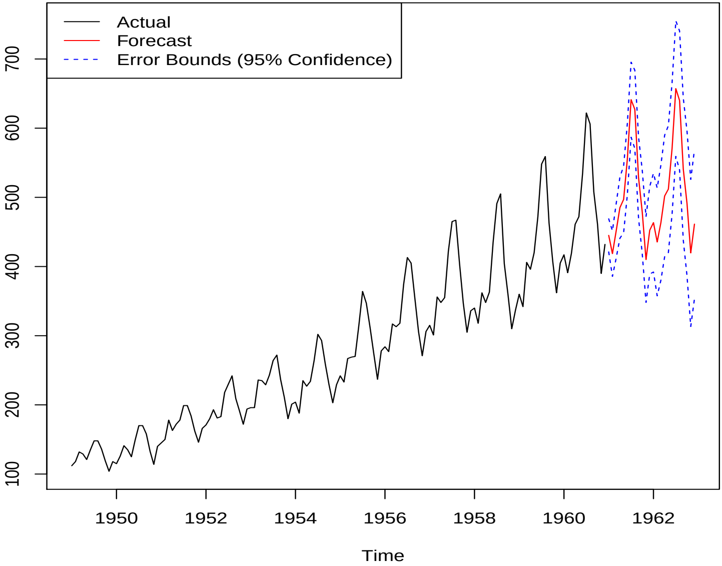
- To forecast future events based on known past data
- For example, to predict the price of a stock based on its past performance
- Popular models
  - Autoregressive moving average (ARMA)
  - Autoregressive integrated moving average (ARIMA)

Forecasting

```r
# build an ARIMA model
fit <- arima(AirPassengers, order = c(1, 0, 0), list(order = c(2,
    1, 0), period = 12))
fore <- predict(fit, n.ahead = 24)
# error bounds at 95% confidence level
U <- fore$pred + 2 * fore$se
L <- fore$pred - 2 * fore$se
```

```r
ts.plot(AirPassengers, fore$pred, U, L,
        col = c(1, 2, 4, 4), lty = c(1, 1, 2, 2))
legend("topleft", col = c(1, 2, 4), lty = c(1, 1, 2),
       c("Actual", "Forecast", "Error Bounds (95% Confidence)"))
```

Forecasting



Outline

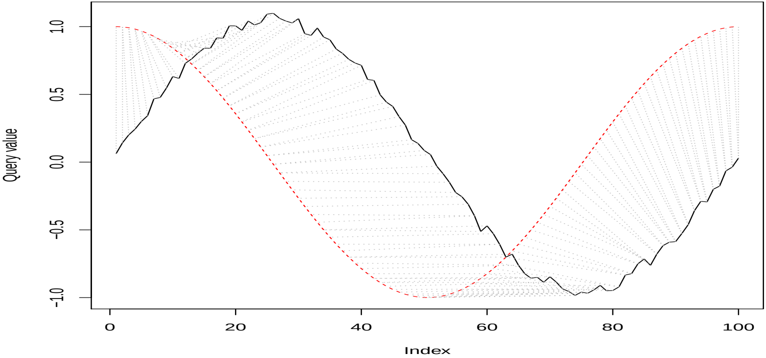
Time Series Clustering

- To partition time series data into groups based on *similarity* or *distance*, so that time series in the same cluster are similar
- Measure of distance/dissimilarity
  - Euclidean distance
  - Manhattan distance
  - Maximum norm
  - Hamming distance
  - The angle between two vectors (inner product)
  - Dynamic Time Warping (DTW) distance
  - ...

Dynamic Time Warping (DTW)

DTW finds optimal alignment between two time series.

```
library(dtw)
idx <- seq(0, 2 * pi, len = 100)
a <- sin(idx) + runif(100)/10
b <- cos(idx)
align <- dtw(a, b, step = asymmetricP1, keep = T)
dtwPlotTwoWay(align)
```



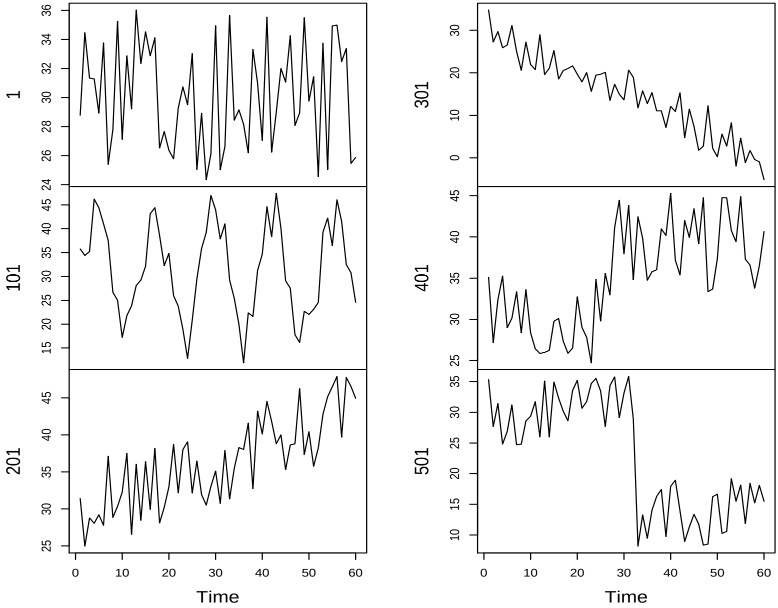
Synthetic Control Chart Time Series

- The dataset contains 600 examples of control charts synthetically generated by the process in Alcock and Manolopoulos (1999).
- Each control chart is a time series with 60 values.
- Six classes:
  - 1-100 Normal
  - 101-200 Cyclic
  - 201-300 Increasing trend
  - 301-400 Decreasing trend
  - 401-500 Upward shift
  - 501-600 Downward shift
- http://kdd.ics.uci.edu/databases/synthetic_control/synthetic_control.html

Synthetic Control Chart Time Series

```r
# read data into R sep='': the separator is white space, i.e., one
# or more spaces, tabs, newlines or carriage returns
sc <- read.table("./data/synthetic_control.data", header = F, sep = "")
# show one sample from each class
idx <- c(1, 101, 201, 301, 401, 501)
sample1 <- t(sc[idx, ])
plot.ts(sample1, main = "")
```

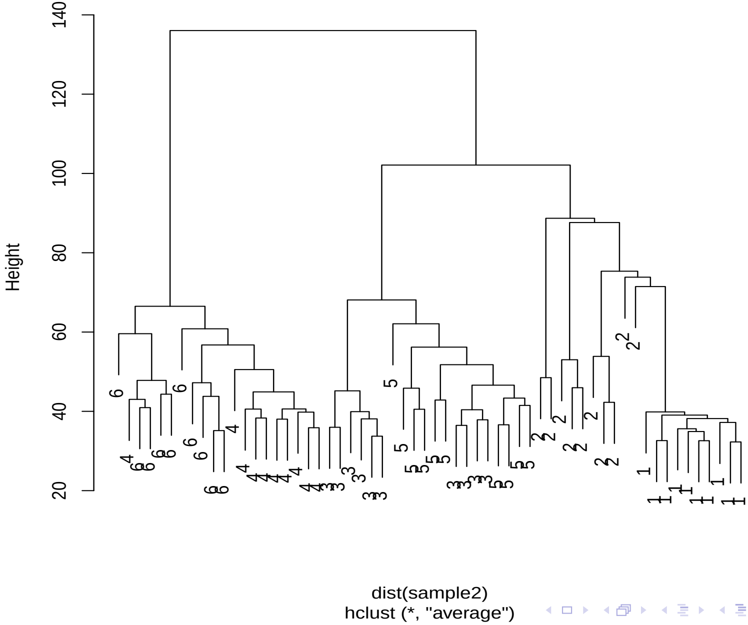
Six Classes



Hierarchical Clustering with Euclidean distance

```r
# sample n cases from every class
n <- 10
s <- sample(1:100, n)
idx <- c(s, 100 + s, 200 + s, 300 + s, 400 + s, 500 + s)
sample2 <- sc[idx, ]
observedLabels <- rep(1:6, each = n)
# hierarchical clustering with Euclidean distance
hc <- hclust(dist(sample2), method = "ave")
plot(hc, labels = observedLabels, main = "")
```

Hierarchical Clustering with Euclidean distance



Hierarchical Clustering with Euclidean distance

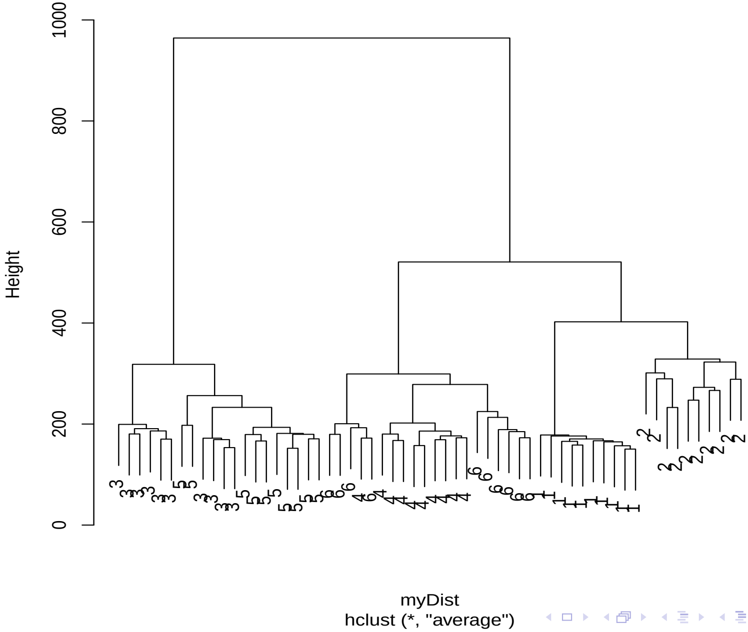
```
# cut tree to get 8 clusters
memb <- cutree(hc, k = 8)
table(observedLabels, memb)

##                memb
## observedLabels  1  2  3  4  5  6  7  8
##              1 10  0  0  0  0  0  0  0
##              2  0  3  1  1  3  2  0  0
##              3  0  0  0  0  0  0 10  0
##              4  0  0  0  0  0  0  0 10
##              5  0  0  0  0  0  0 10  0
##              6  0  0  0  0  0  0  0 10
```

Hierarchical Clustering with DTW Distance

```
myDist <- dist(sample2, method = "DTW")
hc <- hclust(myDist, method = "average")
plot(hc, labels = observedLabels, main = "")
# cut tree to get 8 clusters
memb <- cutree(hc, k = 8)
table(observedLabels, memb)
```

```
##                memb
## observedLabels  1  2  3  4  5  6  7  8
##              1 10  0  0  0  0  0  0  0
##              2  0  4  3  2  1  0  0  0
##              3  0  0  0  0  0  6  4  0
##              4  0  0  0  0  0  0  0 10
##              5  0  0  0  0  0  0 10  0
##              6  0  0  0  0  0  0  0 10
```

Hierarchical Clustering with DTW Distance



Outline

Time Series Classification

Time Series Classification

- To build a classification model based on labelled time series
- and then use the model to predict the lable of unlabelled time series

Feature Extraction

- Singular Value Decomposition (SVD)
- Discrete Fourier Transform (DFT)
- Discrete Wavelet Transform (DWT)
- Piecewise Aggregate Approximation (PAA)
- Perpetually Important Points (PIP)
- Piecewise Linear Representation
- Symbolic Representation

Decision Tree (ctree)

ctree from package party

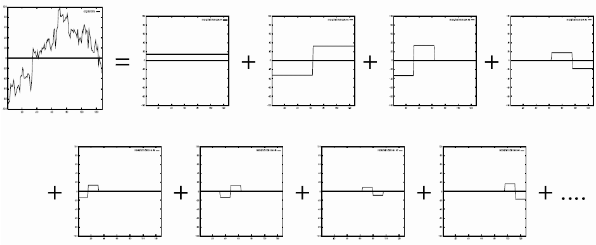
```
classId <- rep(as.character(1:6), each = 100)
newSc <- data.frame(cbind(classId, sc))
library(party)
ct <- ctree(classId ~ ., data = newSc,
            controls = ctree_control(minsplit = 20,
                                     minbucket = 5, maxdepth = 5))
```

Decision Tree

```
pClassId <- predict(ct)
table(classId, pClassId)

##        pClassId
## classId   1   2   3   4   5   6
##       1 100   0   0   0   0   0
##       2   1  97   2   0   0   0
##       3   0   0  99   0   1   0
##       4   0   0   0 100   0   0
##       5   4   0   8   0  88   0
##       6   0   3   0  90   0   7

# accuracy
(sum(classId == pClassId))/nrow(sc)

## [1] 0.8183
```

DWT (Discrete Wavelet Transform)

- Wavelet transform provides a multi-resolution representation using wavelets.
- Haar Wavelet Transform – the simplest DWT
  http://dmr.ath.cx/gfx/haar/



- DFT (Discrete Fourier Transform): another popular feature extraction technique

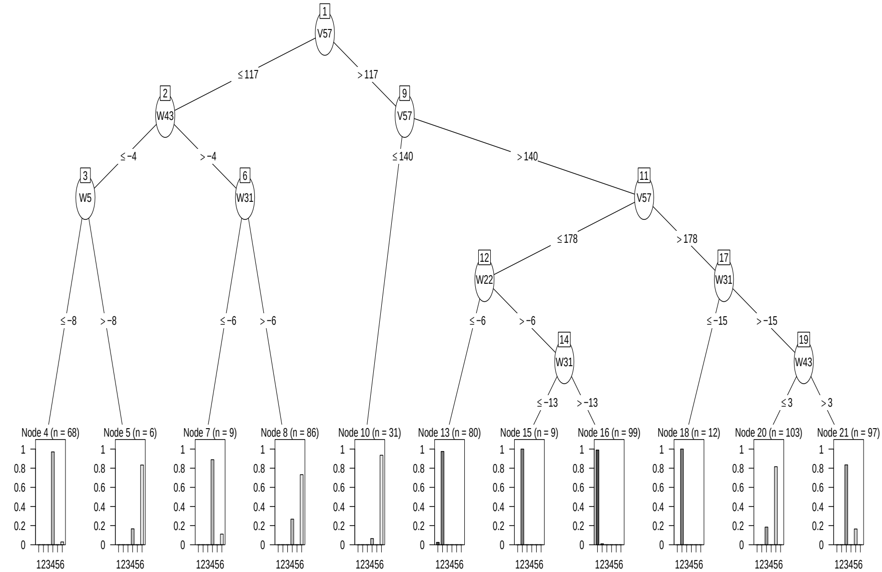
DWT (Discrete Wavelet Transform)

```r
# extract DWT (with Haar filter) coefficients
library(wavelets)
wtData <- NULL
for (i in 1:nrow(sc)) {
    a <- t(sc[i, ])
    wt <- dwt(a, filter = "haar", boundary = "periodic")
    wtData <- rbind(wtData, unlist(c(wt@W, wt@V[[wt@level]])))
}
wtData <- as.data.frame(wtData)
wtSc <- data.frame(cbind(classId, wtData))
```

Decision Tree with DWT

```
ct <- ctree(classId ~ ., data = wtSc,
            controls = ctree_control(minsplit=20, minbucket=5,
                                     maxdepth=5))
pClassId <- predict(ct)
table(classId, pClassId)

##         pClassId
## classId  1  2  3  4  5  6
##       1 98  2  0  0  0  0
##       2  1 99  0  0  0  0
##       3  0  0 81  0 19  0
##       4  0  0  0 74  0 26
##       5  0  0 16  0 84  0
##       6  0  0  0  3  0 97

(sum(classId==pClassId)) / nrow(wtSc)

## [1] 0.8883
```

```r
plot(ct, ip_args = list(pval = F), ep_args = list(digits = 0))
```



k-NN Classification

- find the k nearest neighbours of a new instance
- label it by majority voting
- needs an efficient indexing structure for large datasets

```
k <- 20
newTS <- sc[501, ] + runif(100) * 15
distances <- dist(newTS, sc, method = "DTW")
s <- sort(as.vector(distances), index.return = TRUE)
# class IDs of k nearest neighbours
table(classId[s$ix[1:k]])
```

```
##
##  4  6
##  3 17
```

k-NN Classification

- find the k nearest neighbours of a new instance
- label it by majority voting
- needs an efficient indexing structure for large datasets

```
k <- 20
newTS <- sc[501, ] + runif(100) * 15
distances <- dist(newTS, sc, method = "DTW")
s <- sort(as.vector(distances), index.return = TRUE)
# class IDs of k nearest neighbours
table(classId[s$ix[1:k]])

##
##  4  6
##  3 17
```

Results of majority voting: class 6

The TSclust Package

- TSclust: a package for time seriesclustering [3]
- measures of dissimilarity between time series to perform time series clustering.
- metrics based on raw data, on generating models and on the forecast behavior
- time series clustering algorithms and cluster evaluation metrics

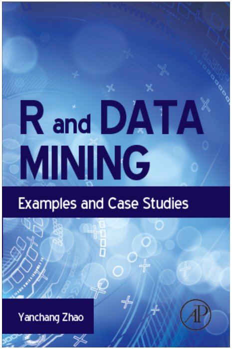
[3] http://cran.r-project.org/web/packages/TSclust/

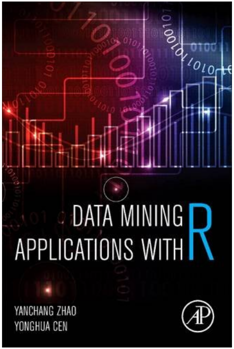
Outline

Online Resources

- Chapter 8: Time Series Analysis and Mining, in book *R and Data Mining: Examples and Case Studies*
  http://www.rdatamining.com/docs/RDataMining.pdf
- R Reference Card for Data Mining
  http://www.rdatamining.com/docs/R-refcard-data-mining.pdf
- Free online courses and documents
  http://www.rdatamining.com/resources/
- RDataMining Group on LinkedIn (7,000+ members)
  http://group.rdatamining.com
- RDataMining on Twitter (1,700+ followers)
  @RDataMining

The End





Thanks!

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