FE8828 Programming Web Applications in Finance

Session 5 Building Financial Applications

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Section 1

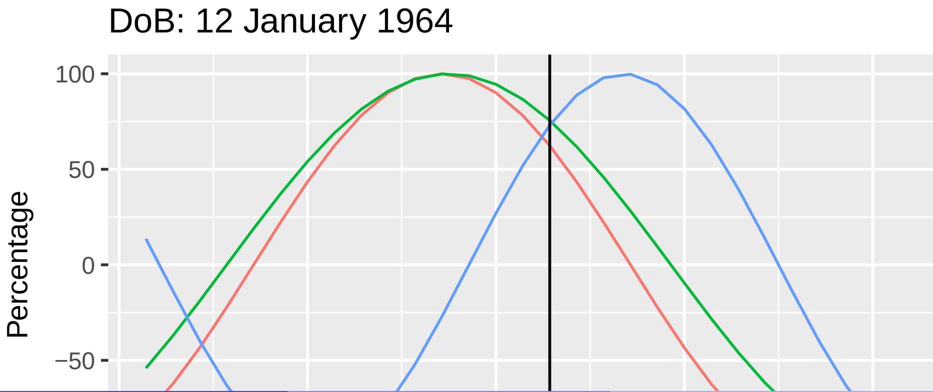
Lecture 10: Building Financial Applications

Starter

```r
# biorhythm.R

library(dplyr)
library(tidyr)
library(ggplot2)

biorhythm <- function(dob, target = Sys.Date()) {
  dob <- as.Date(dob)
  target <- as.Date(target)
  t <- round(as.numeric(difftime(target, dob)))
  days <- (t - 14) : (t + 14)
  period <- tibble(Date = seq.Date(from = target - 15, by = 1, lengt
                   Physical = sin (2 * pi * days / 23) * 100,
                   Emotional = sin (2 * pi * days / 28) * 100,
                   Intellectual = sin (2 * pi * days / 33) * 100
  period <- gather(period, key = "Biorhythm", value = "Percentage",
  ggplot(period, aes(x = Date, y = Percentage, col = Biorhythm)) +
    geom_line() +
    ggtitle(paste("DoB:", format(dob, "%d %B %Y"))) +
    geom_vline(xintercept = as.numeric(target)) +
```

Starter - Result

```r
# I took four people's birthdays. Hope they are in good mood today.
g1 <- biorhythm("1964-01-12", Sys.Date())
g2 <- biorhythm("1971-06-28", Sys.Date())
g3 <- biorhythm("1971-10-29", Sys.Date())
g4 <- biorhythm("1957-08-11", Sys.Date())
grid.arrange(g1, g2, g3, g4, ncol = 2, nrow = 2)
```



Main course

- We need following packages as a start. Use c() to install multiple packages.

```
install.packages(c("tidyquant", "Quandl", "fOptions", "fExoticOption
```

- `tidyquant` is also a collection of packages: `xts`, `quantmod`.
- Please validate option pricing code.
  - For example, I found Asian Option `TurnbullWakemanAsianApproxOption()` in `fExoticOptions` is strangely implemented. Maybe I am wrong.

tidyquant or Quandl?

Determining factors:

- `tidyquant/quantmod` can connect to various services: $_{\text{google}}$, yahoo (still active), av (AlphaAdvantage).
- Quandl only connects to Quandl
- It's subjected to where you can find the data.
  - US ETF/Stocks on Quandl is a premium service.
  - ETF in Google/AlphaAdvantage is free.

tidyquant or Quandl?

Technical details:

- quantmod returns `xts` object. Quandl returns data frame or `xts`
- xts object is can `collapse` to daily, weekly, monthly price.

Tidyquant/quantmod

```
# library(tidyquant)

# use Google
getSymbols('SPY', src = 'yahoo', adjusted = TRUE, output.size = 'ful
## [1] "SPY"
str(SPY)
## An 'xts' object on 2007-01-03/2020-09-15 containing:
##   Data: num [1:3450, 1:6] 142 141 141 141 141 ...
##  - attr(*, "dimnames")=List of 2
##   ..$ : NULL
##   ..$ : chr [1:6] "SPY.Open" "SPY.High" "SPY.Low" "SPY.Close" ...
##   Indexed by objects of class: [Date] TZ: UTC
##   xts Attributes:
## List of 2
##  $ src    : chr "yahoo"
##  $ updated: POSIXct[1:1], format: "2020-09-16 17:37:50"

# Sign up with AlphaAdvantage to get a token
# getSymbols('SPY', src = 'av', output.size = 'full', api.key = toke
# str(SPY)
```

Tidyquant/quantmod

```
# What's get returned?
head(SPY)
##            SPY.Open SPY.High SPY.Low SPY.Close SPY.Volume SPY.Adj
## 2007-01-03   142.25   142.86  140.57    141.37   94807600      10
## 2007-01-04   141.23   142.05  140.61    141.67   69620600      10
## 2007-01-05   141.33   141.40  140.38    140.54   76645300      10
## 2007-01-08   140.82   141.41  140.25    141.19   71655000      10
## 2007-01-09   141.31   141.60  140.40    141.07   75680100      10
## 2007-01-10   140.58   141.57  140.30    141.54   72428000      10
tail(SPY)
##            SPY.Open SPY.High SPY.Low SPY.Close SPY.Volume SPY.Adj
## 2020-09-08   336.71   342.64  332.88    333.21  114465300        3
## 2020-09-09   337.55   342.46  336.61    339.79   91462300        3
## 2020-09-10   341.82   342.53  332.85    333.89   90569500        3
## 2020-09-11   335.82   336.97  331.00    334.06   84680200        3
## 2020-09-14   337.49   340.38  334.22    338.46   65605700        3
## 2020-09-15   341.12   342.02  338.47    340.17   52763500        3

symbols <- c("MSFT", "AAPL")
getSymbols(symbols, src = 'yahoo', adjusted = TRUE, from = "2016-01-
```

xts object

- xts is a wide format. In contrast, ggplot/tidy uses long format.
- We have gather/spread to convert between long/wide format.
- Create xts object:
  - Put index aside, which is usually date
  - Store prices in columns.

```
library(xts)

# if df is a data frame.
# Date | V | GS
xts1 <- xts(x=df[, -1, drop = F], order.by = df[1])

# coredata: returns a matrix from xts objects
core_data <- coredata(xts2)

# index: vector of any Date, POSIXct, chron, yearmon, yearqtr, or Da
index(xts1)
```

Get data from xts object

```
# What price history is stored here.
str(SPY)
## An 'xts' object on 2007-01-03/2020-09-15 containing:
##   Data: num [1:3450, 1:6] 142 141 141 141 141 ...
##  - attr(*, "dimnames")=List of 2
##   ..$ : NULL
##   ..$ : chr [1:6] "SPY.Open" "SPY.High" "SPY.Low" "SPY.Close" ...
##   Indexed by objects of class: [Date] TZ: UTC
##   xts Attributes:
## List of 2
##  $ src    : chr "yahoo"
##  $ updated: POSIXct[1:1], format: "2020-09-16 17:37:50"
```

```
SPY2003 <- SPY["2003"]
SPY2 <- SPY["2003/2007"]
SPY3 <- SPY["2003-03-01/2007-07-01"]
SPY4 <- SPY["/2007-07-01"] # till
SPY5 <- SPY["2007-07-01/"] # from
SPY6 <- SPY["2007-07-01/", "SPY.High"]
SPY7 <- SPY["2007-07-01/", c("SPY.High", "SPY.Close")]
```

Quandl

```r
library(Quandl)
library(tidyverse)

# Sign up with Quandl to get a token
# token_qd <- "xxxx"
Quandl.api_key(token_qd)
## You don't get SPY: SPDR 500 ETF from Quandl from free service.
## rates <- Quandl(c("EOD/SPY"), start_date="2000-01-01", end_date=
## You don't get EOD US Stocks for free from Quandl from 2019
## rates <- Quandl(c("EOD/V"), start_date="2000-01-01", end_date="2
```

Quandl

```r
library(Quandl)                         # Quandl package
library(ggplot2)                        # Package for plotting
library(tidyverse)                      # Package for reshaping data

Quandl.api_key(token_qd)                          # Authenticate your token
# Build vector of currencies
rates <- Quandl(c("FRED/DEXUSAL", "FRED/DEXBZUS", "FRED/DEXUSUK", "F
                start_date="2000-01-01",
                end_date = "2018-11-28")
colnames(rates) <- c("Date", "AUD/USD", "USD/BRL", "GBP/USD", "USD/C
meltdf <- gather(rates, key = "CCY", value = "Rate", -Date)

ggplot(meltdf, aes(x = Date, y = Rate, colour = CCY, group = CCY)) +
  geom_line() +
  scale_colour_manual(values=1:22)+
  ggtitle("Major Currency Exchange Rates in USD") +
  theme_minimal()
```

Major Currency Exchange Rates in USD

Quandl and forecast

```
cat(htmltools::includeText("example/52-quandl-forecast.R"))
```

Section 2

dygraph

dygraph

dygraph for xts https://rstudio.github.io/dygraphs/shiny.html

```
dygraphOutput("dygraph")

dygraph(oil_combined_xts, main = "Oil Prices: Historical and Forecas
  # Add the actual series
  dySeries("Actual", label = "Actual") %>%
  # Add the three forecasted series
  dySeries(c("Lo_95", "Forecast", "Hi_95"))
```

Section 3

Quandl/Shiny/dygraph

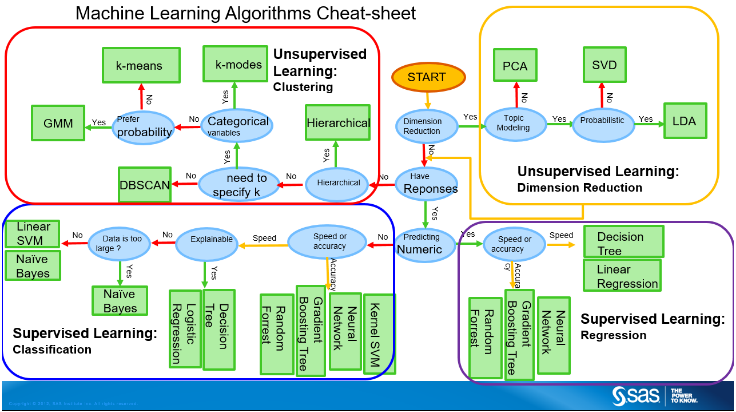
Quandl/Shiny/dygraph

```r
# shiny-51-quandl.R
cat(htmltools::includeText("example/51-quandl.R"))
```

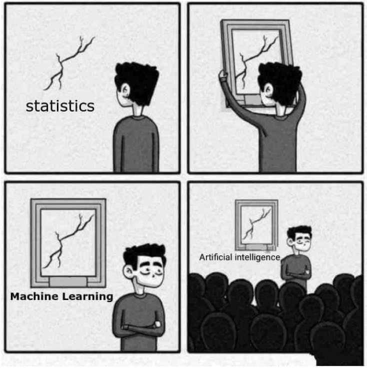
Section 4

Lecture 11: Building Predictive Model

Machine Learning



Statistics and Machine Learning



Statistics and Machine Learning

- Statistics is a age-old year subject, with many developed theory.
- Machine learning is an algorithm that can learn from data without relying on rules-based.
- ML uses many statistical theories in application.
- ML emphasizes optimization and performance (accuracy) over inference (conclusion based on reasons and evidence) which is what statistics is concerned about.

  | ML professional: “The model is 85% accurate in predicting Y, given a, b and c.”
  | Statistician: “The model is 85% accurate in predicting Y, given a, b and c; and I am 90% certain that you will obtain the same result.”

Supervised v.s. Unsupervised

- Supervised learning: It is based on example input-output pairs. It infers a function from labeled training data consisting of a set of training examples
- Unsupervised learning: It is a type of self-organized learning that helps find previously unknown patterns in data set without pre-existing labels. It is also known as self-organization and allows modeling probability densities of given inputs.
- Reinforcement learning: . . .

Machine Learning

- Regression
- Classification
- Ensemble
  - hetreogenous ensembles
  - homogenous ensembles
  - metalmodelling
- Neutral network
  - Deep learning: multiple hidden layers.

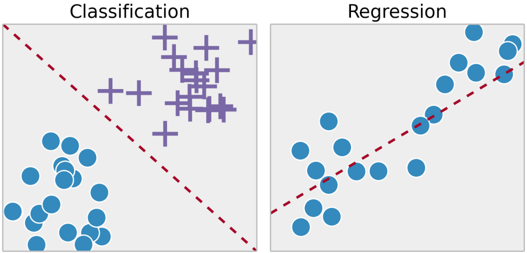
Model Error

model error = variance + bias + noise

- variance-bias trade-off: increase variance and more bias

Regression and Classification

Regression and classification are two main categories of machine learning algorithms under supervised learning.



Regression

We can use many linear regression methods.

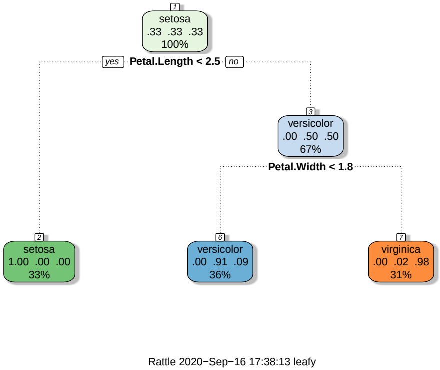
```
p1 <- ggplot(iris, aes(x = Sepal.Length, y = Petal.Width, color = Sp
  geom_smooth(method = "lm") +
  geom_point() +
  labs(title = "Petal.Width ~ Sepal.Length")

p2 <- ggplot(iris, aes(x = Petal.Length, y = Petal.Width, color = Sp
  geom_smooth(method = "lm") +
  geom_point() +
  labs(title = "Petal.Width ~ Petal.Length")

p3 <- ggplot(iris, aes(x = Sepal.Length, y = Sepal.Width, color = Sp
  geom_smooth(method = "lm") +
  geom_point() +
  labs(title = "Sepal.Width ~ Sepal.Length")

p4 <- ggplot(iris, aes(x = Petal.Length, y = Sepal.Width, color = Sp
  geom_smooth(method = "lm") +
  geom_point() +
  labs(title = "Sepal.Width ~ Petal.Length")
```

Regression

```
## `geom_smooth()` using formula 'y ~ x'
## `geom_smooth()` using formula 'y ~ x'
## `geom_smooth()` using formula 'y ~ x'
## `geom_smooth()` using formula 'y ~ x'
```

Classification

Decision Tree




```
predictions <- predict(iris_rp, iris, type = "class")
which(iris$Species != predictions)
## [1]  71 107 120 130 134 135
# caret::confusionMatrix(predictions, iris$Species)
```

Ensemble

- Bagging: reducing bias and keep variance in control
- AdaBoost: wrong result will get more weight
- GradientBoost: reduce on residue
- Random forest: random selection of features and component tree to be flexible, no pruning.
  - "bumping" is to use the most effective tree "dtree" will use it.
- Stacking/Subsemble/SuperLearner

Confusion Matrix

- Shows how model performs

```
Actual Target |          0         |  1  |
Model Output  |                    |     |
          0   |         90         | 10  |
          1   |         10         | 90  |
```

Machine Learning workflow

1. Setting
2. Exploratory Data Analysis
3. Feature Engineering
4. Data Preparation
5. Modelling
6. Conclusion

Machine Learning

- Data preparation:

Split into different groups. For simple data, we may split using 75/25 or 80/20. For complex data, we need to ensure selected 75 has coverage for different kinds, to avoid bias. For example, we are to predict a infrequent event (occuring 20%), shall our selected sample contain 20% or 50% or 75%?

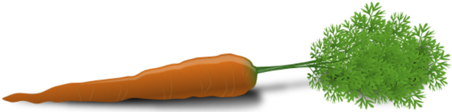
- Modeling:

Choose a few models and tune the hyperparametes. Tuning of hyperparameters is model-specific. You shall learn it in-depth with each model.

Measure the performacne and optimize it. Confusion matrix, AUC/ROC, model-specific output...

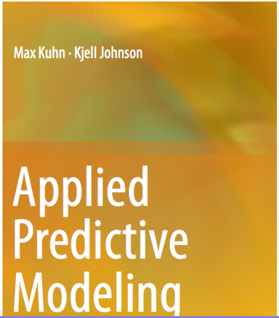
Caret Package

Caret is short for _C_lassification _A_nd _RE_gression _T_raining.



Main author is Max Kuhn. He has a book “Applied Predictive Modeling”, By Max Kuhn and Kjell Johnson.

Max is now in RStudio, working on *parsnip* in tidymodel.



Caret Package

Links to 200 over (238 as of this version)
https://topepo.github.io/caret/available-models.html

```
## [1] "ada,  AdaBag,  AdaBoost.M1,  adaboost,  amdai,  ANFIS,  avNN
```

Project Iris

Use the petal/sepal width/length to determine which species it is.

```
library(caret)

set.seed(123)
trainIndex <- createDataPartition(iris$Species, p = .8,
 list = FALSE,
 times = 1)

train <- iris[ trainIndex,]
test  <- iris[-trainIndex,]

train_x <- select(train, -Species)
train_y <- train$Species

test_x <- select(test, -Species)
test_y <- test$Species

# Cross validation
fitControl <- trainControl(
 method = "repeatedcv",
```

Project Bank

We previous whether our telemarketing is successful.

The output is binary - classification for binary output is very common.

For model simplicity, we use logistic regression. For logistic regression, we need to use one-hot encoding.

One-hot Encoding is implemented with dummy variables in R.

If one column contains more-than-one value, e.g. "admin", "engineer", "manager", we replace it with 2 = 3 - 1 columns

```
| job      |        | job_admin | job_engineer |
| admin    |   ==>  |     1     |      0       |
| engineer |        |     0     |      1       |
| manager  |        |     0     |      0       |
```

Project Bank - Load

```
bank <- read.csv("https://goo.gl/PBQnBt", sep = ";")
# We only work on following fields.
bank_fit <- bank %>% select(y,
                loan,
                default,
                housing,
                poutcome,
                job,
                marital) %>%
  mutate_if(is.factor, as.character) %>%
  mutate(y = ifelse(y == "yes", "y", "n"))

str(bank_fit)
```

Project Bank - Dummy Variables

```
# create dummy variables
dummies <- dummyVars("y ~ loan + default + housing + poutcome + job
                     data = bank_fit, fullRank = TRUE)
# generate data frame of dummy variables
bank_new <- data.frame(predict(dummies, newdata = bank_fit))
# add back y variable to data
bank_new <- bind_cols(bank_fit["y"], bank_new) %>% mutate(y = factor

summary(bank_new)
```

Project Bank - Train/Test Data

```
# library(caret)
set.seed(1234)
trainIndex <- createDataPartition(bank_new$y, p = .8,
 list = FALSE,
 times = 1)

bank_train <- bank_new[ trainIndex,]
bank_test  <- bank_new[-trainIndex,]

featurePlot(x = bank_new[-1],
            y = bank_new$y,
            plot = "box",
            strip=strip.custom(par.strip.text=list(cex=.7)),
            scales = list(x = list(relation="free"),
                          y = list(relation="free")))
```

Project Bank - Feature Plot

```r
featurePlot(x = bank_new[-1],
            y = bank_new$y,
            plot = "density",
            strip=strip.custom(par.strip.text=list(cex=.7)),
            scales = list(x = list(relation="free"),
                          y = list(relation="free")))
```

Project Bank - Train

```r
train_control <- trainControl(
    method = 'repeatedcv',                           # k-fold cross validati
    number = 5,                              # number of folds
    savePredictions = 'final',               # saves predictions for optimal
    classProbs = TRUE,                          # should class probabilities
)

if (FALSE) {
  # Running time is too long. Skip running.
  adaboost_fit <- train(y ~ .,
                         data = bank_train,
                        method='adaboost',
                        tuneLength=2,
                        trControl = train_control)
  adaboost_fit

  predictions <- predict(adaboost_fit, newdata = bank_train)
  confusionMatrix(predictions, bank_train$y)

  predictions <- predict(adaboost_fit, bank_test)
```

Project Bank - Train with Decision Tree

```r
# Recursive Partitioning and Regression Trees
rpart_fit <- train(y ~ .,
                   data = bank_train,
                   method="rpart",
                   trControl = train_control)
predictions <- predict(rpart_fit, bank_train)
confusionMatrix(predictions, bank_train$y)

predictions <- predict(rpart_fit, bank_test)
confusionMatrix(predictions, bank_test$y)
```

```r
rattle::ggVarImp(rpart_fit$finalModel, log=TRUE)
rattle::fancyRpartPlot(rpart_fit$finalModel)
```

Project Bank - Model comparison

```r
models_compare <- resamples(list(RP = rpart_fit, GLM = log_fit))

# Summary of the models performances
summary(models_compare)
```

Section 5

Project Australia Weather

Project Australia Weather

- A complete project with some feature engineering.

https://www.dropbox.com/s/p73mdxcrx05mbwb/aus_weather_predict.Rmd?dl=1