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DSB Classes 7-8, February 8, 2019

- # Advanced Classification. From .R to Notebooks.

Structure of the course

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- SESSIONS 1-2 (AO): Data analytics process; from Excel to R
  - Tutorial 1: Getting comfortable with R
- SESSIONS 3-4 (AO): Time Series Models
- SESSIONS 5-6 (AO): Intro to classification, logistic regression and machine learning
- SESSIONS 7-8 (SZ): Advanced Classification; From .R to Notebooks; Dimensionality reduction
  - Tutorial 2: Midterm R help / classification
- SESSIONS 9-10 (SZ): Clustering and Segmentation
  - Tutorial 3: Q&A on R for three main modules
- SESSIONS 11-12 (SZ): The Data Science Process; Guest speaker
  - Hands-on help with projects
- SESSIONS 13-14 (AO+SZ): Project presentations

Plan for the day
Learning objectives

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- Assignment 2

- Advanced classification: metrics and methods
  - Regularization. Advanced classification methods.

- From .R scripts to Notebooks
  - New way/process for doing and communicating analytics with reproducible, publication-quality output

- (Time permitting, start..) Derived attributes and dimensionality reduction
  - Generate (a small number of) new manageable/interpretable attributes that capture most of the information in the data

Assignment 2...

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Overfitting & Regularization

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- What happened when in Assignment 2, you made a `rpart` CART tree with very small cp?
- Fundamental tradeoff of learning with data
  - Models that are too simple are not accurate on the training set, nor are they accurate on the test set
  - Models that are too complex, are accurate on the training set, but don't generalize well on the test set

Overfitting & Regularization

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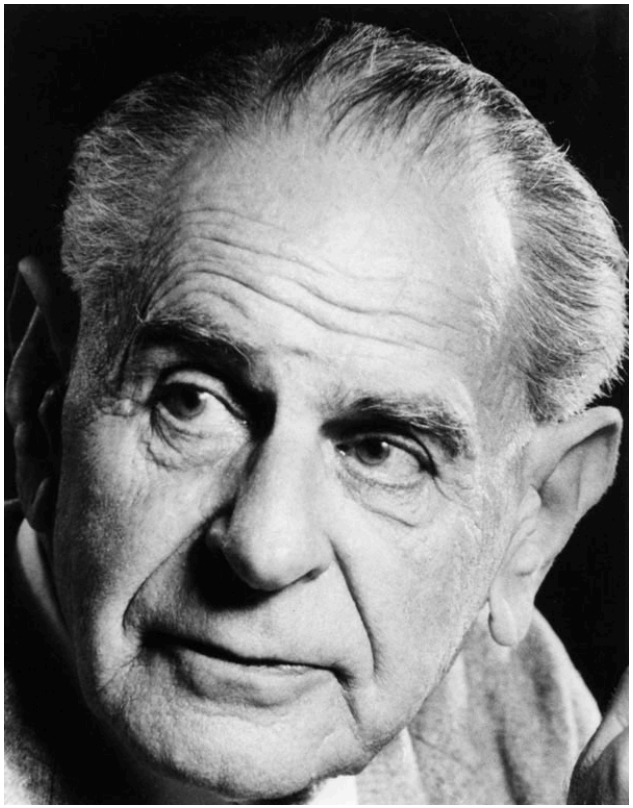
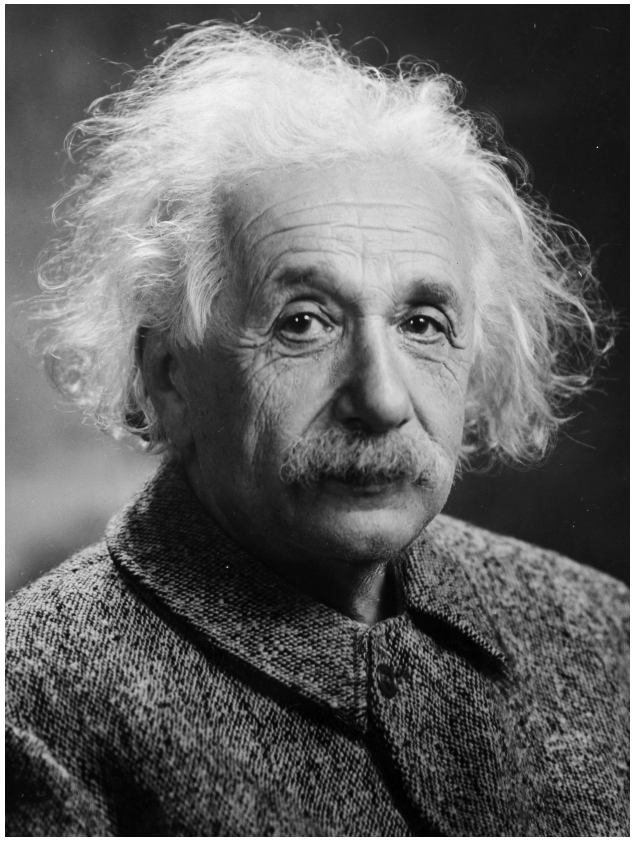


Karl Popper



Albert Einstein

GOOD THEORIES

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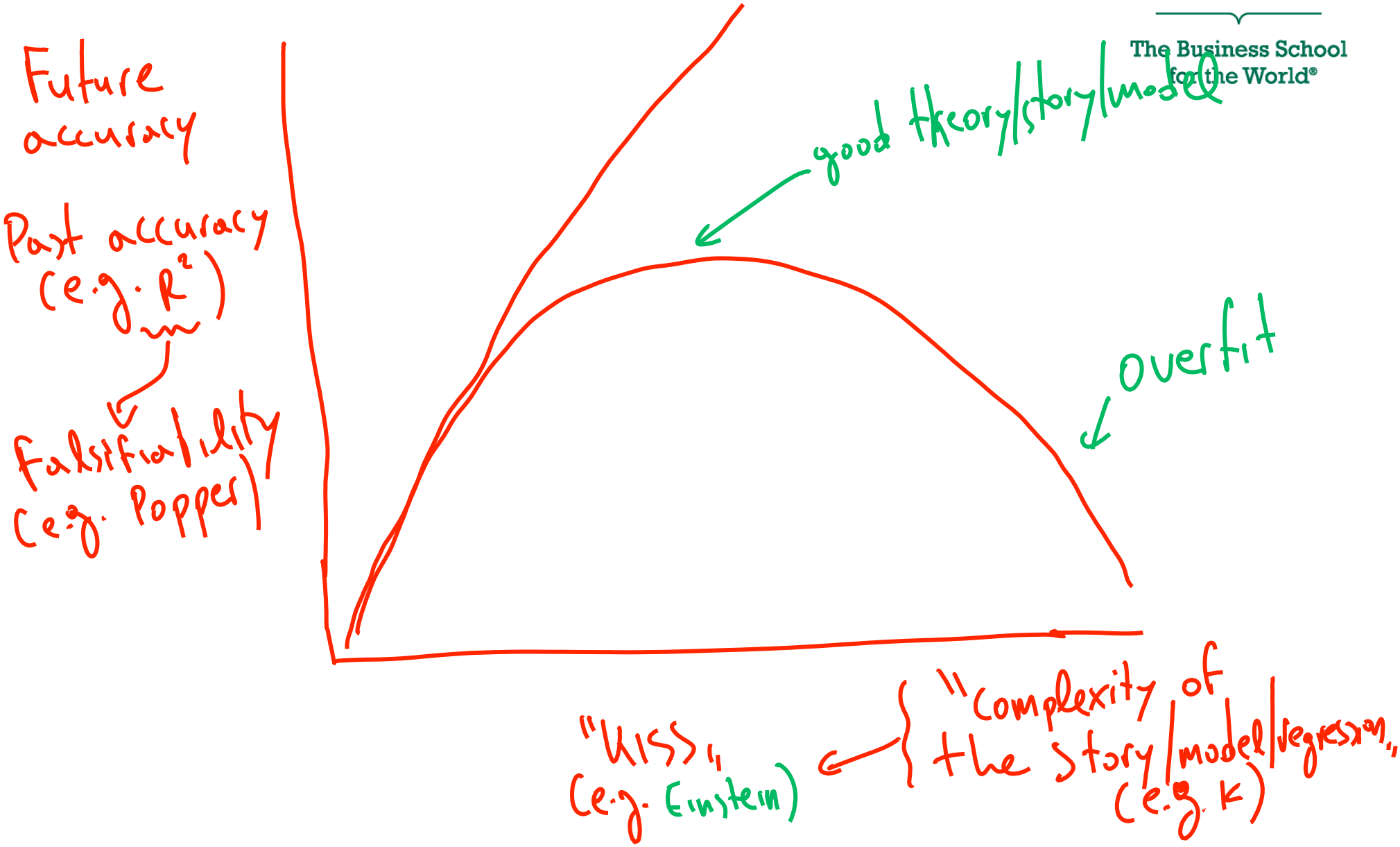

Overfitting & Regularization

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- Need to fine-tune the model so that is strikes a good balance between accuracy and simplicity
- Cross-validation does this fine-tuning
  - Break the data into training data, validation data, test data
  - Train model using training data
  - Test on validation data to fine-tune parameters, and iterate
  - "When happy," test (once) on test data to simulate how model would do in the real world

Overfitting & Regularization

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- Regularization: set of techniques to reduce overfitting
  - For logistic regression:

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} - \log likelihood(\beta, data) + \lambda \left(\frac{1-\alpha}{2} \sum_i \beta_i^2 + \alpha \sum_i |\beta_i| \right)$$

measures **fit**

controls trade off between maximizing fit and minimizing complexity

measures **complexity**

  - α= 1: penalize sum of absolute values of coefficients. Lasso regression
  - α=0: penalize sum of squares of coefficients. Ridge regression

Package: glmnet

```
cv.out <-
cv.glmnet(as.matrix(estimation_data[,independent_variables]),estimation_data[,dependent_variable],alpha=1,
                    family="binomial" )
#family= "binomial" => logistic regression
#alpha=1: Lasso
lambda <- cv.out$lambda.1se #choose value of λ
log_reg_coefficients <- as.matrix(coef(cv.out,s=lambda)) #extract the estimated coefficients
```

Overfitting & Regularization

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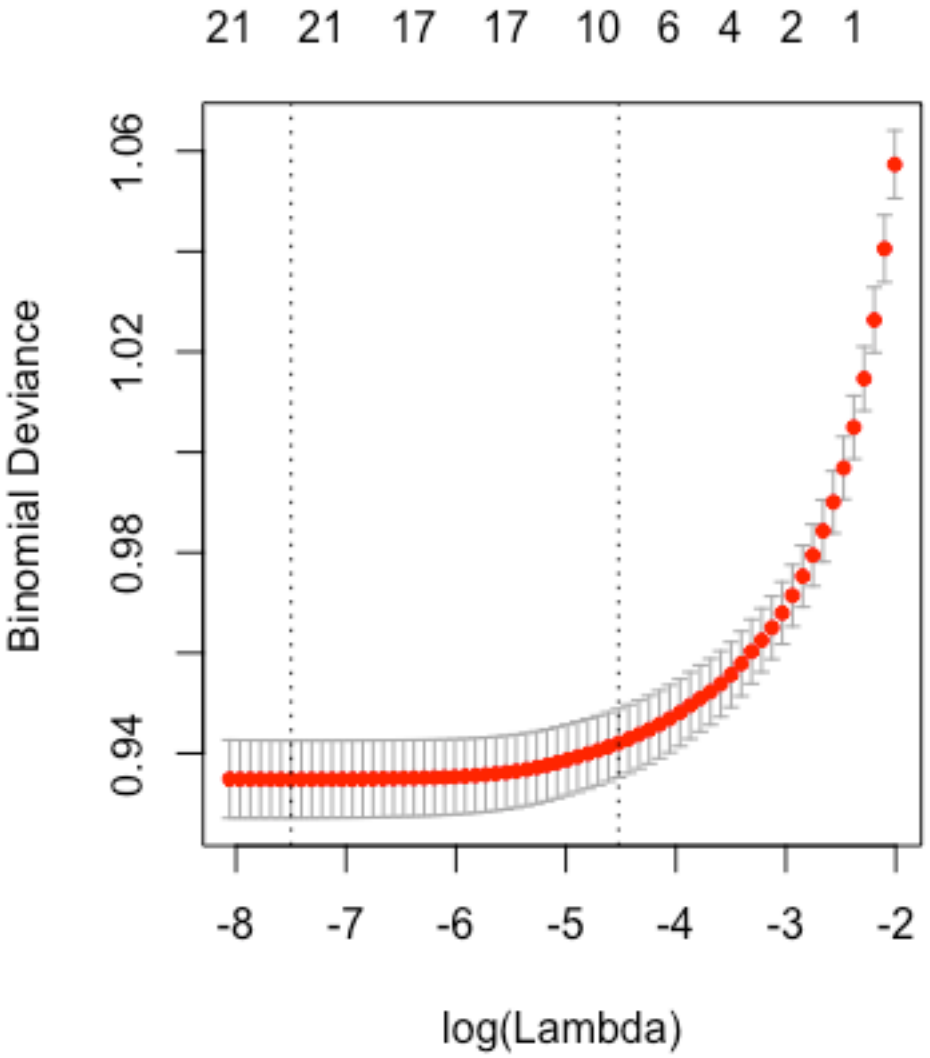
> plot(cv.out)



- λ that minimizes mean cross-validated error:

> log(cv.out$lambda.min)

[1] -7.498859

- Largest λ s.t. error is within 1 standard error of the minimum:

> log(cv.out$lambda.1se)

[1] -4.52178

Emphasizes simplicity (even) more

Back to Assignment 2...
Time to make decisions

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Important classification metric: Profit Curve

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- Measure business profit if we only select the top cases in terms of the probability of "response"
- For this, we need to define values and costs of correct classifications and misclassifications

	Predicted: default	Predicted: no default
Actual: default	$0	-$5000
Actual: no default	$0	$1500

Profit = # of 1's correctly predicted * value of capturing a 1
+# of 0's correctly predicted * value of capturing a 0
+# of 1's incorrectly predicted as 0 * cost of missing a 1
+# of 0's incorrectly predicted as 1 * cost of missing a 0

Important classification metric: Profit Curve

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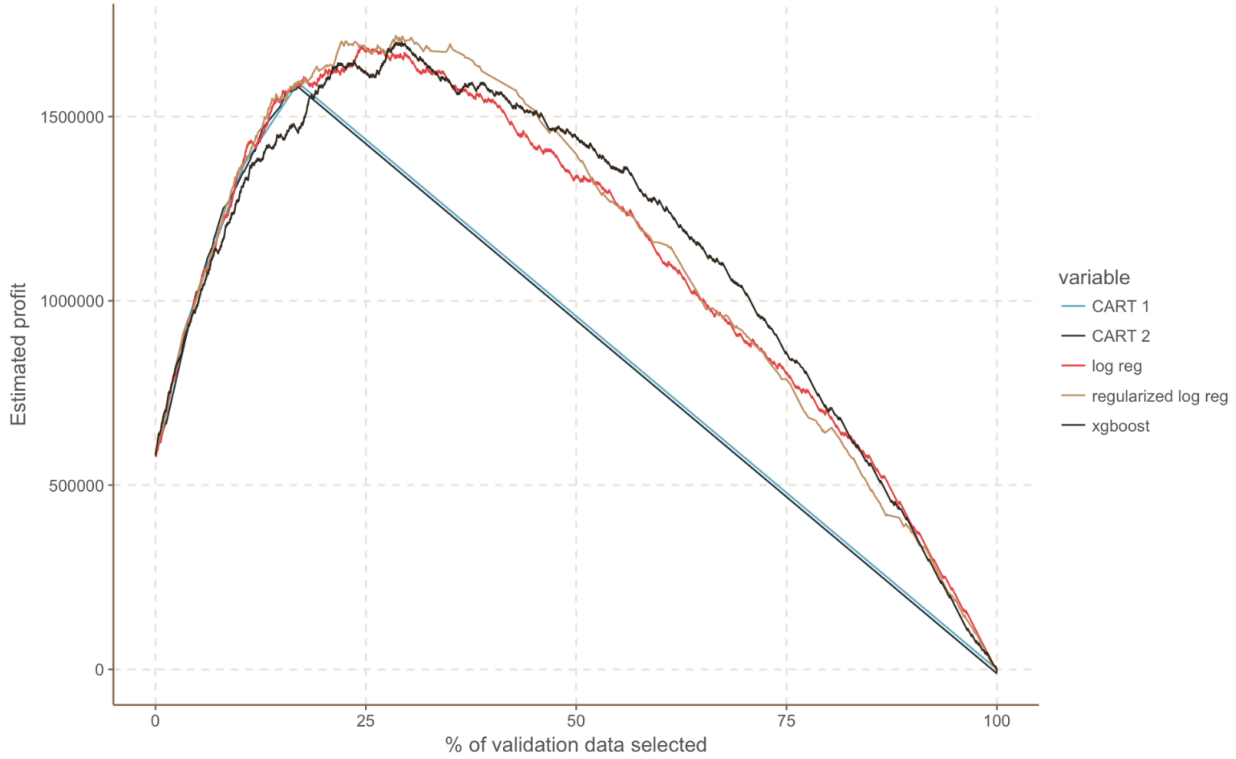
- Given a classifier, rank instances in the test data from highest predicted probability of belonging to class 1 (= default) to lowest
- Can put the cutoff for giving vs. not giving credit at any rank
- As I move the cutoff, calculate the corresponding profit…



Back to Assignment 2... Feature engineering?

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Feature Engineering

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Your data may have more information than what is contained in your existing variables

- Spend lots of time thinking of ways to combine your variables into new ones!
- "Engineering" good features may be more important than using a better method
- Requires contextual knowledge of the business
  - Can not be outsourced

Feature Engineering

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Example for credit card default case (Code in ClassificationProcessCreditCardMoreMethods.Rmd):

```
tmpx = t(apply(ProjectData[,7:12], 1,
                        function(r) matrix(c(sum(r==-2), sum(r==-1), sum(r==0),sum(r > 0)), nrow=1)))
                        #apply: apply the function to an array of values
                        # argument "1": apply the function over rows
                        # Summarize the PAY variables for each customer with a vector of how
                        many -2s, -1's, 0's, >0's
ProjectData = cbind(ProjectData[,2:5], #cbind: combine a set of columns
                          tmpx,
                          apply(ProjectData[,13:18], 1, function(r) median(r[!is.na(r)])),
                        # Replace the BILL_AMT variable for each customer with their median
                          apply(ProjectData[,19:24]/ProjectData[,13:18], 1, function(r)
                                    ifelse(sum(!is.na(r) & !is.infinite(r)), mean(r[!is.na(r) & !is.infinite(r)]),0)),
                        # Replace the PAY_AMT variable for each customer with the  mean of the ratio of
                        paid over consumed
                           ProjectData[,25])


dependent_variable = 11
independent_variables = c(1:10) # use all the new attributes
```

Back to Assignment 2...

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Sensitivity and Specificity

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		True condition	
	Total population	Condition positive	Condition negative
Predicted condition	Predicted condition positive	**True positive**, Power	**False positive**, Type I error
	Predicted condition negative	**False negative**, Type II error	**True negative**
		True positive rate (TPR), Recall, Sensitivity, probability of detection = $\frac{\Sigma \text{ True positive}}{\Sigma \text{ Condition positive}}$	False positive rate (FPR), Fall-out, probability of false alarm = $\frac{\Sigma \text{ False positive}}{\Sigma \text{ Condition negative}}$
		False negative rate (FNR), Miss rate = $\frac{\Sigma \text{ False negative}}{\Sigma \text{ Condition positive}}$	Specificity (SPC), Selectivity, True negative rate (TNR) = $\frac{\Sigma \text{ True negative}}{\Sigma \text{ Condition negative}}$

Source: Wikipedia

Tree Ensemble Methods

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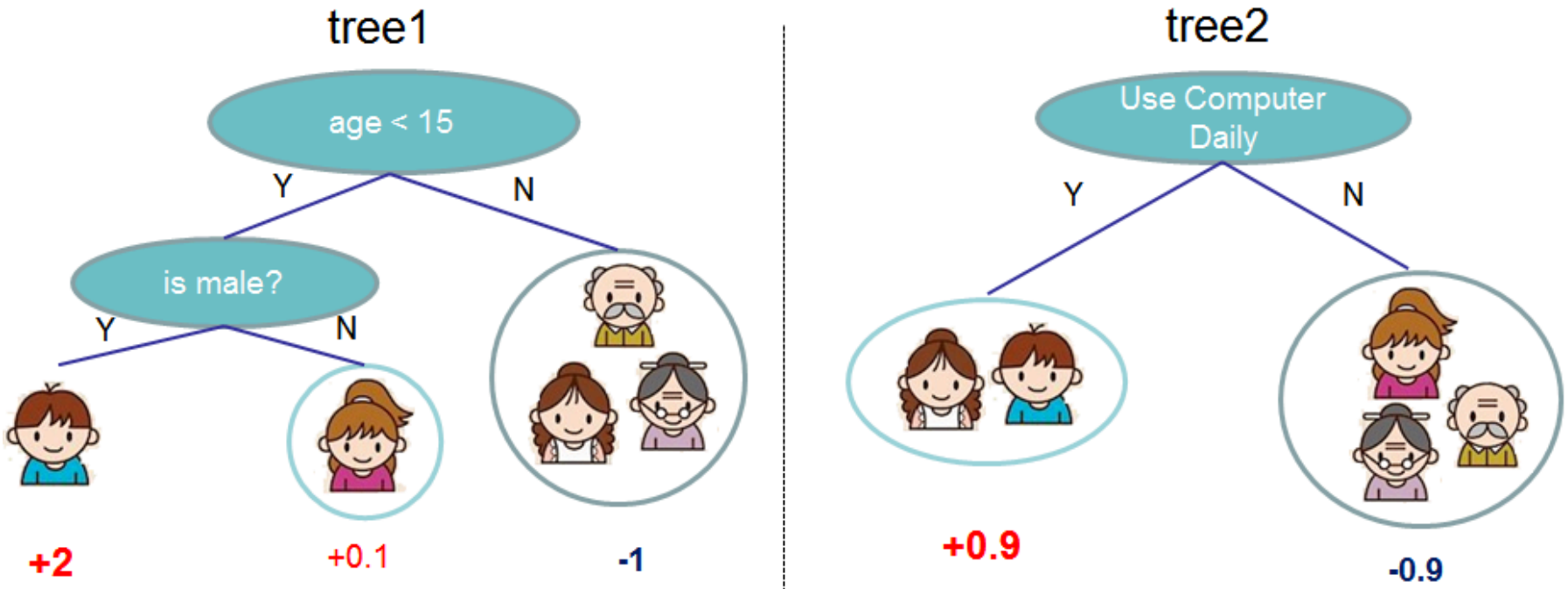
- Main idea: put a set of CARTs together, output a combination (e.g., mode, mean) of the respective outputs the CARTs

Does someone like computer games?



f( ) = 2 + 0.9= 2.9 f( )= -1 - 0.9 = -1.9

Source: http://xgboost.readthedocs.io/en/latest/model.html#

Tree Ensemble Methods

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Both **random forests** and **boosted trees** generate multiple random samples from the training set (with replacement), and train a different CART for each sample of the data. This is called bagging.

- Random Forests
  - The samples are completely random. No adaptiveness.
  - Use fully grown CARTs (each with low bias, high variance). Reduce variance by bagging together many uncorrelated trees.
  - Final prediction is the simple average

- Boosted trees
  - Based on small trees: weak learners with high bias, low variance
  - But adaptive: instances modeled poorly by the overall system before, have larger probability of being picked now → higher weight
  - Final prediction is a weighted average

Tree Ensemble Methods

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- Random Forests

Package: `randomForest`

```
model_forest <- randomForest(x=estimation_data[,independent_variables],
                             y=estimation_data[,dependent_variable],
                             importance=TRUE, proximity=TRUE, type="classification")
```

- Boosted trees

Package: `xgboost`

```
model_xgboost <- xgboost(data = as.matrix(estimation_data[,independent_variables]),
                         label = estimation_data[,dependent_variable],
                         eta = 0.3, max_depth = 10, nrounds=10, objective = "binary:logistic",
verbose = 0)
#objective= "binary:logistic" => logistic regression for classification
#eta: step size of each boosting step. max.depth: maximum depth of tree.
#nrounds: the max number of iterations
```

How to then retrieve predicted probabilities (and therefore also classes)?

```
validation_Probability_class1<-
        predict(model,newdata=as.matrix(validation_data[,independent_variables]),
                type=  "prob" )
```

Support Vector Machines

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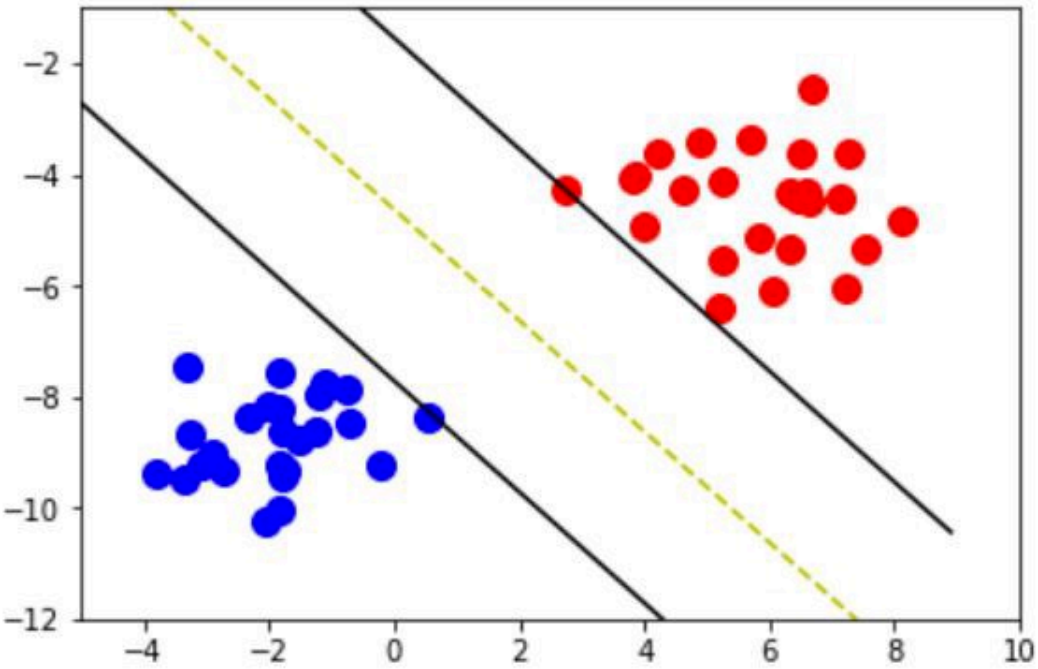
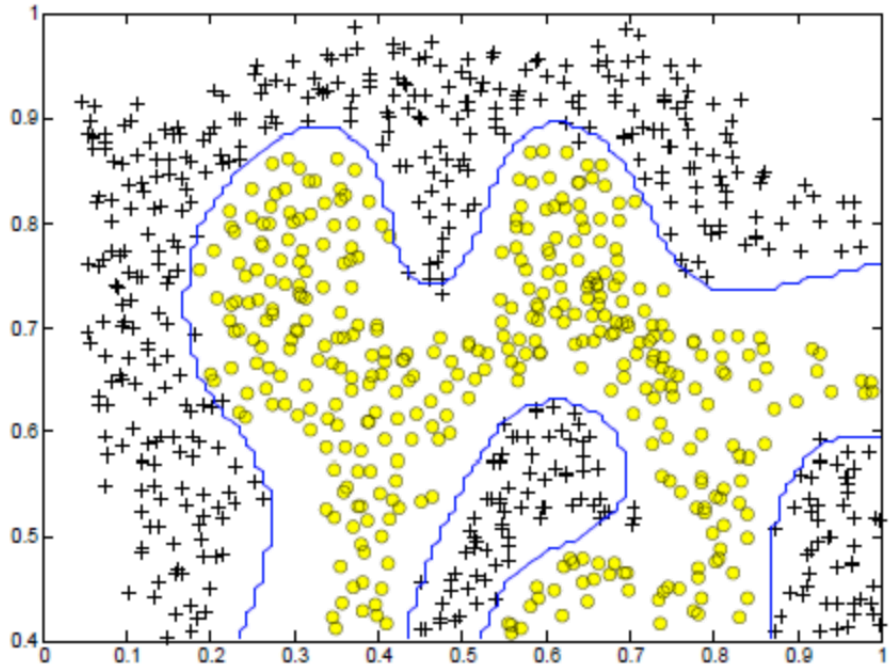
- Main idea
  - Training: Divide parameter space in two regions using maximum-margin hyperplanes, based on training set.
  - Decision: read the label of the region where the new instance falls



Linear kernel



Radial basis (Gaussian) kernel

Package: `e1071`

```
Model_svm <- svm(Retained.in.2012.~., data=training)
#Can choose the kernel, and parameters such as the kernel parameter, the cost of constraint violations, etc. Default is radial kernel.
```

(A) Process for Classification

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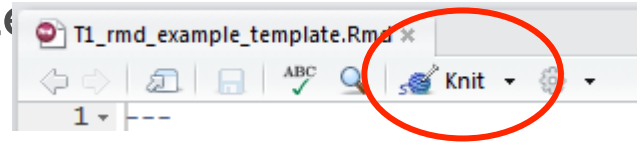
1. Split the data
2. Set up the dependent variable
3. Simple Analysis
4. Classification and Interpretation
5. Validation accuracy
   - Use various classification metrics you know
6. Test accuracy

From R to Notebooks

- You traditional approach for "using" analytics has been two-step:
  - "do" analytics (e.g., plot a graph in Excel)
  - "communicate" analytics (e.g., copy-paste the graph into a PowerPoint presentation / Word file report, etc.)

- With coding (and R) there is a better way: "notebooks"
  - "knit" the R markdown (*.Rmd) file



  - This will create a *.html report (a webpage) with the analysis outputs, graphs, text. Can also create a PDF report
  - Main advantage of this approach: ALL IN ONE PLACE
    - When the new data is available (e.g., next quarter's sales numbers come in), creating an updated report will take you… 1 click
  - Along with sharing tools (GitHub): reusable, replicable, easy to share, all-in-one-place way of doing and communicating analytics with publication-quality output

Summary of Sessions 7-8

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- Advanced classification:
  - Regularization, profit curve, more methods (regularized regression, XGBoost, SVM), a process for classification
- Feature engineering
- From R scripts to Notebooks
  - New way/process for doing and communicating analytics with reproducible, publication-quality output
- (If time allows, start..) Derived attributes and dimensionality reduction
  - A process for dimensionality reduction using Principal Component Analysis
  - Then continue analysis on the new attributes

Next…

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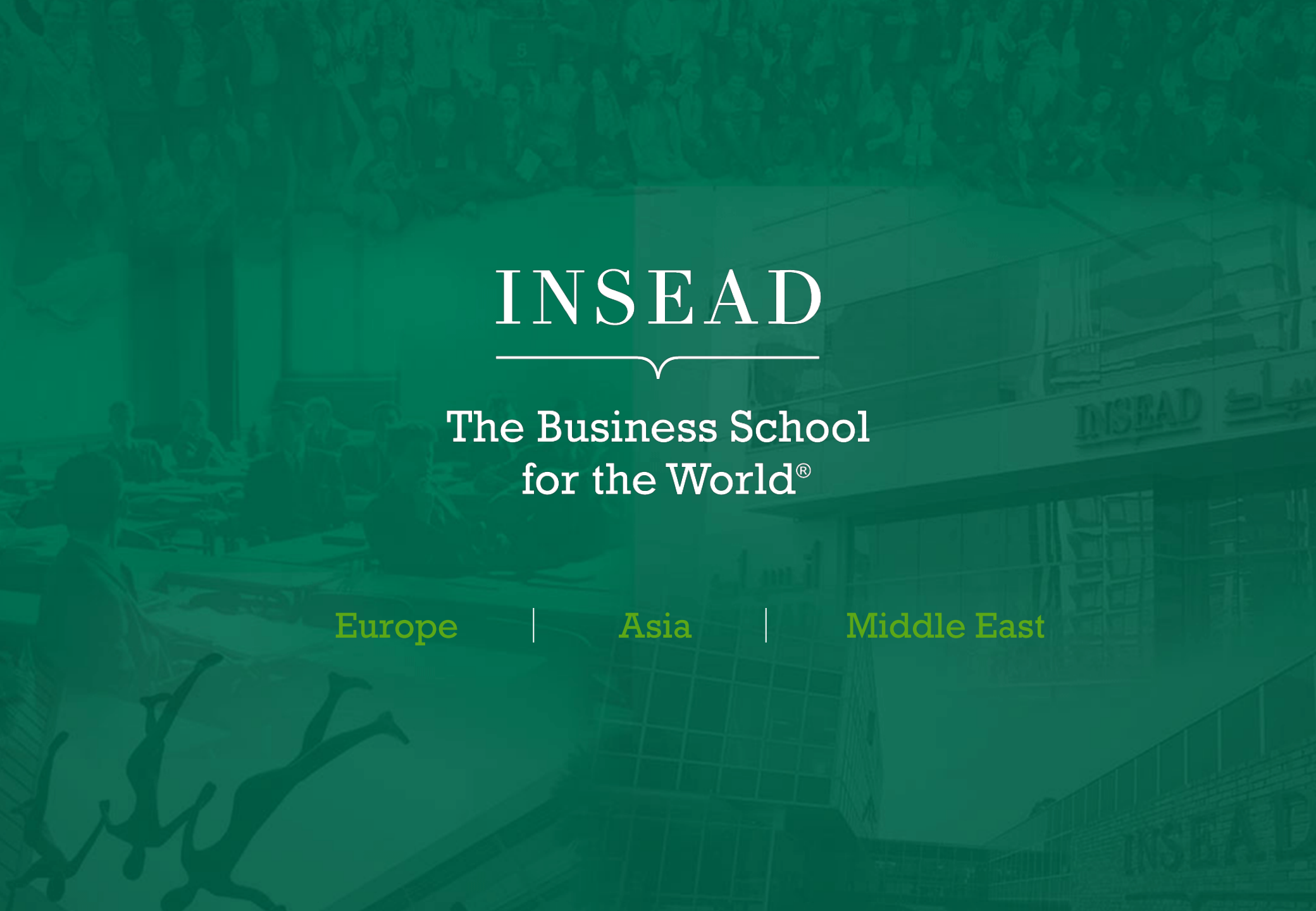
- Tutorial 2: [Sat, Feb 9]
  - Set up with Github repo and knitting, Classification review, Feature engineering

- Sessions 9-10: [Tue, Feb 12]
  - Dimensionality Reduction/Cluster Analysis and Segmentation
  - Please come to class having set up and knitted MarketSegmentationProcessInClass.Rmd
  - BOR – work on the market segmentation process for the Boats (A) case

- Assignment 3 (due Feb 15):
  - Complete the market segmentation process for the Boats (A) case

- Proposal for final project (due Feb 16)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