Machine Learning for Business

Module 10: Random forest

Day 5, 13.00 – 16.00

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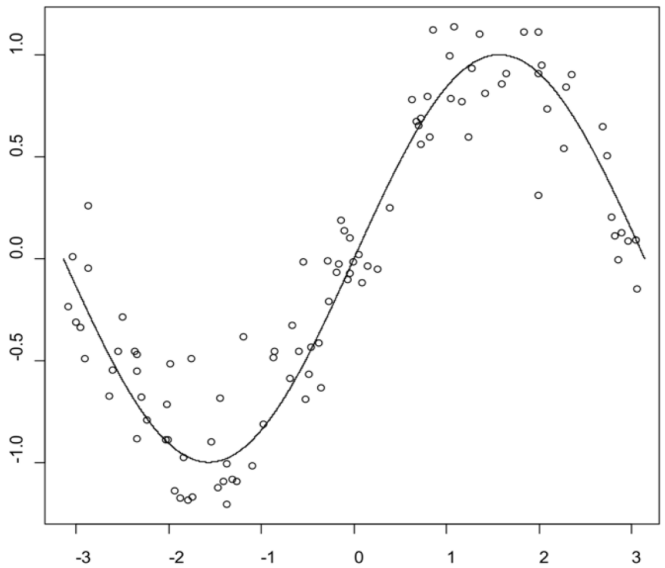
BIG DATA EXPERIENCE CENTER

Data and underlying function



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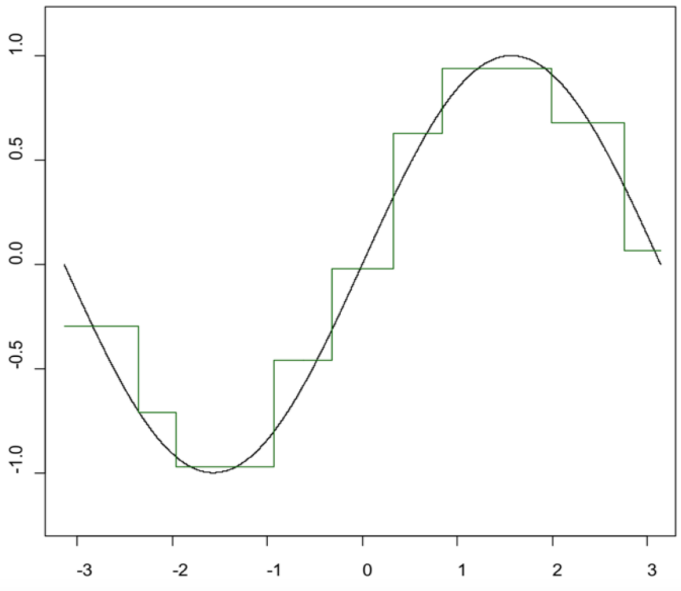
Single regression tree



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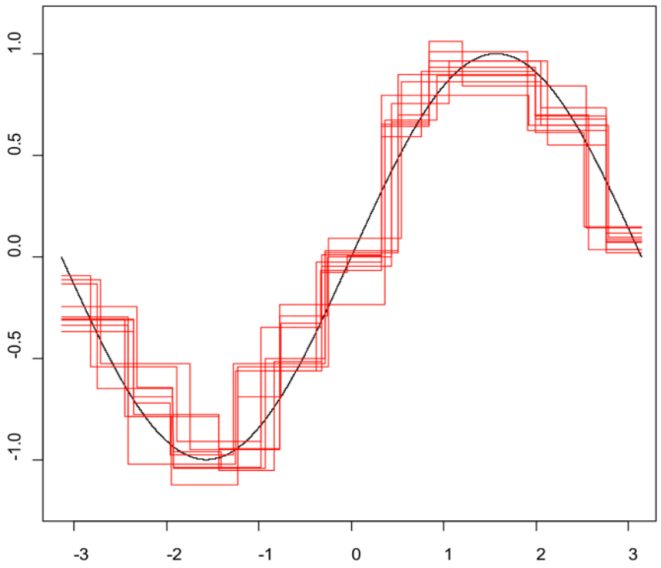
10 Regression Trees



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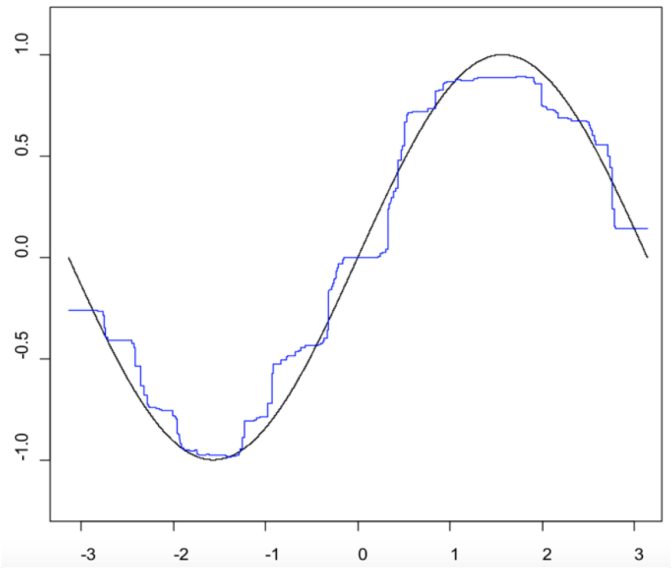
Average of 100 Regression Trees



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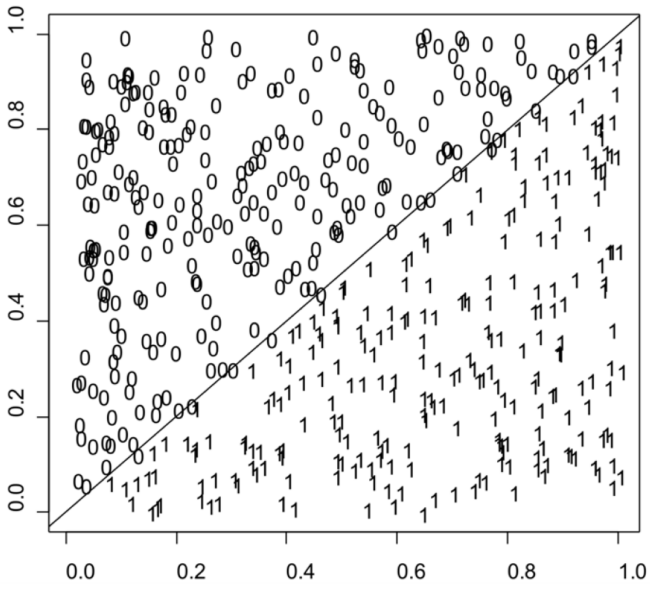
Hard problem for a single tree



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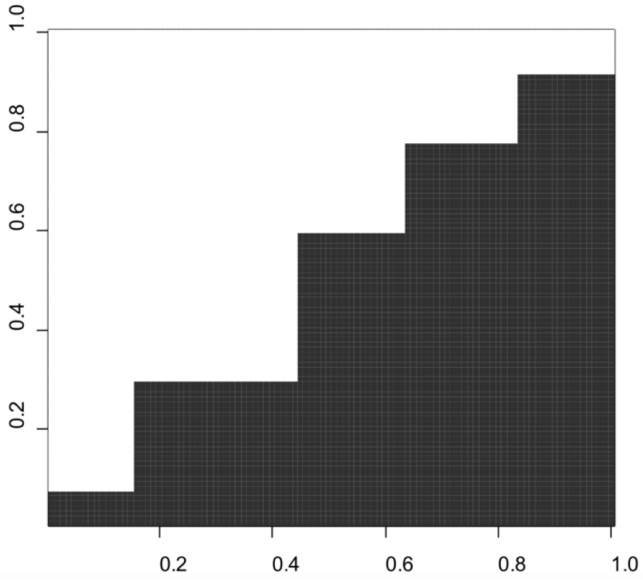
Single tree



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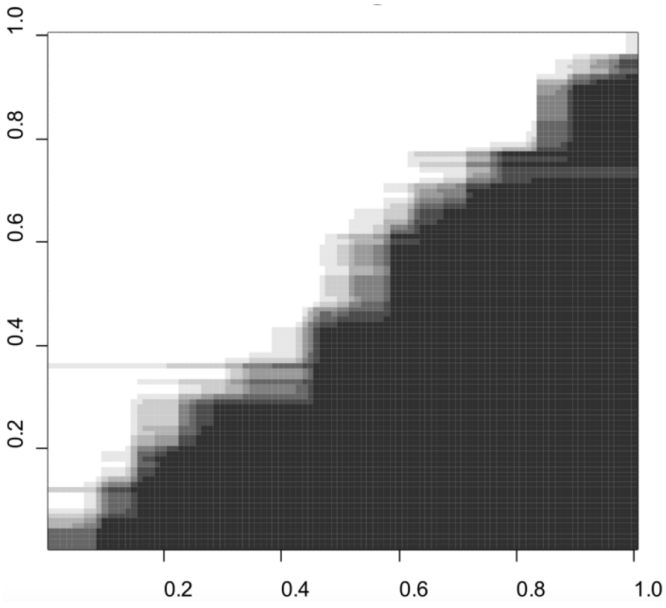
25 Averaged Trees



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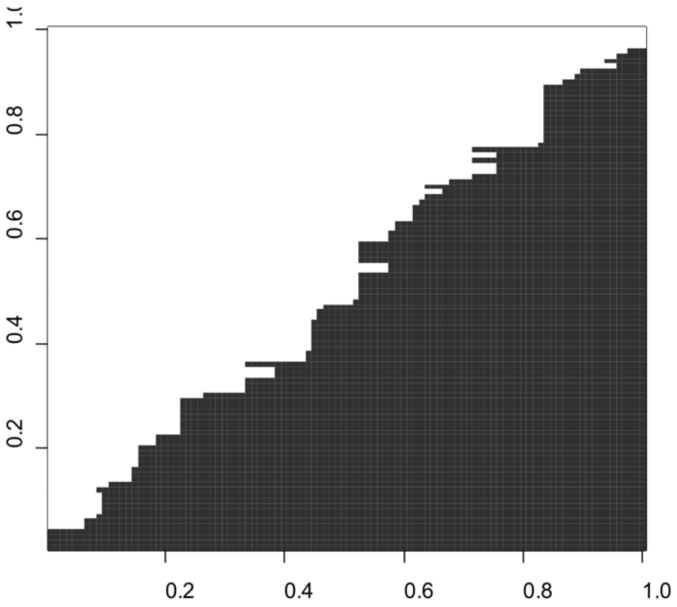
25 Voted Trees



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Bagging (Bootstrap Aggregating)

- Fit classification or regression models to bootstrap samples from the data and combine by voting (classification) or averaging (regression).

Bootstrap sample $\Rightarrow$ $f_1(x)$
Bootstrap sample $\Rightarrow$ $f_2(x)$
Bootstrap sample $\Rightarrow$ $f_3(x)$
...
Bootstrap sample $\Rightarrow$ $f_M(x)$

MODEL AVERAGING

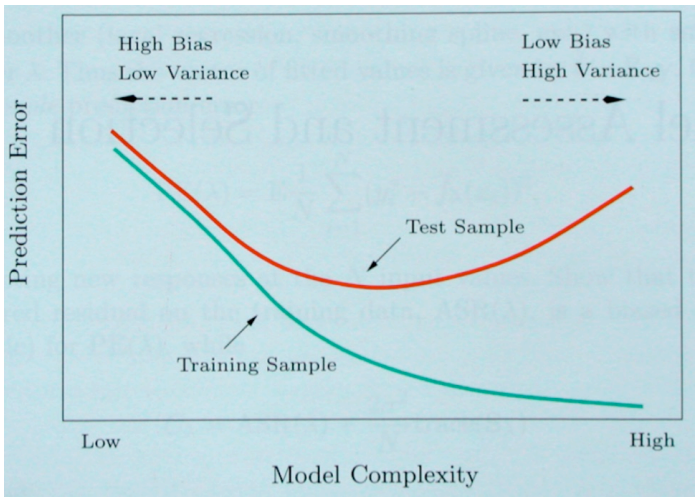
Combine $f_1(x),\ldots, f_M(x) \Rightarrow f(x)$

$f_i(x)$'s are "base learners"

Bagging (Bootstrap Aggregating)

- A bootstrap sample is chosen at random *with* replacement from the data.
- Some observations end up in the bootstrap sample more than once, while others are not included ("out of bag").
- Bagging reduces the *variance* of the base learner but has limited effect on the *bias*.
- It is most effective if we use *strong* base learners that have very little bias but high variance (unstable). E.g. trees.

Bias/variance tradeoff



Hastie, Tibshirani, Friedman "Elements of Statistical Learning" 2001

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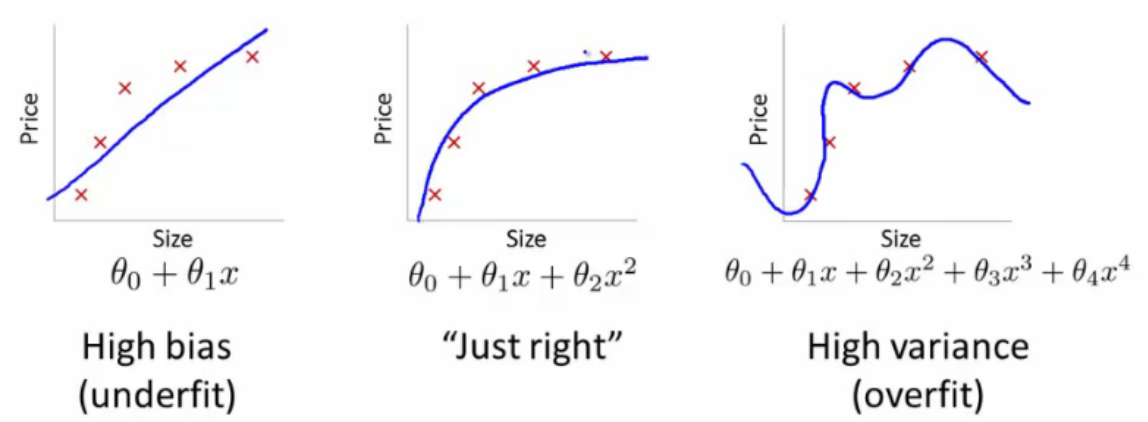
Example: bias vs variance



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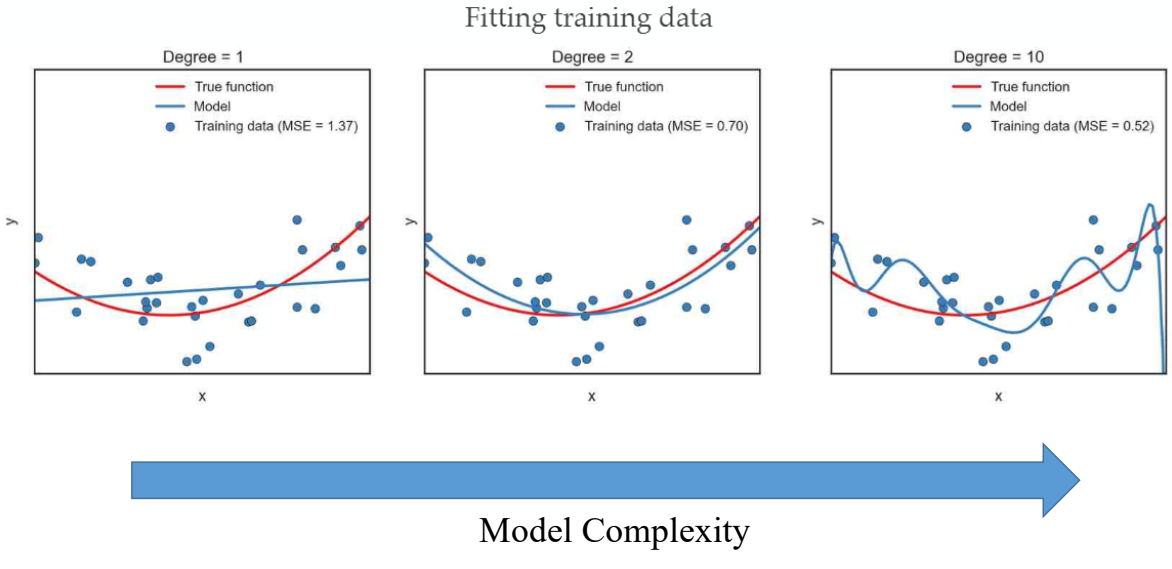
Example: bias vs variance



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Reducing variance without increasing bias

- Averaging reduces variance:

$$\mathrm{var}\left(\bar{X}\right) = \frac{\mathrm{var}\left(X\right)}{n}$$

Average models to reduce model variance

One problem

- Only one training set
- Where do multiple models come from?

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Bagging: bootstrap aggregation

- Take repeated bootstrap samples from training set D.
- Bootstrap sampling: Given set D containing N training examples, create D' by drawing N examples at random with replacement from D.

- Bagging:
  - Create k bootstrap samples D_1 … D_k
  - Train distinct classifier on each D_i
  - Classify new instance by majority vote / average

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Random forest algorithm

Grow a **forest** of many trees. (R default is 500)

Grow each tree on an independent **bootstrap sample*** from the training data.

At each node:

1. Select ***m*** variables **at random** out of all ***M*** possible variables (independently for each node).
2. Find the best split on the selected ***m*** variables.

Grow the trees to maximum depth (classification).

Vote/average the trees to get predictions for new data.

*Sample N cases at random with replacement.

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RF Predictor

- A case in the training data is *not* in the bootstrap sample for about one third of the trees (we say the case is "out of bag" or "oob"). Vote (or average) the predictions of *these trees* to give ***the RF predictor.***
- The ***oob error rate*** is the error rate of the ***RF predictor.***
- The ***oob confusion matrix*** is obtained from the ***RF predictor.***
- For new cases, vote (or average) *all* the trees to get the ***RF predictor.***

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Advantages

- Accuracy – Random forest is competitive with the best known machine learning methods
- Stability – If we change the data little, the individual trees may change but the forest is relatively stable it is combination of many trees

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RF Predictor

For example, suppose we fit 1000 trees, and a case is out-of-bag in 339 of them, of which:

283 say "class 1"

56 say "class 2"

The RF predictor for this case is class 1.

The "oob" error gives an estimate of test set error (generalization error) as trees are added to the ensemble.

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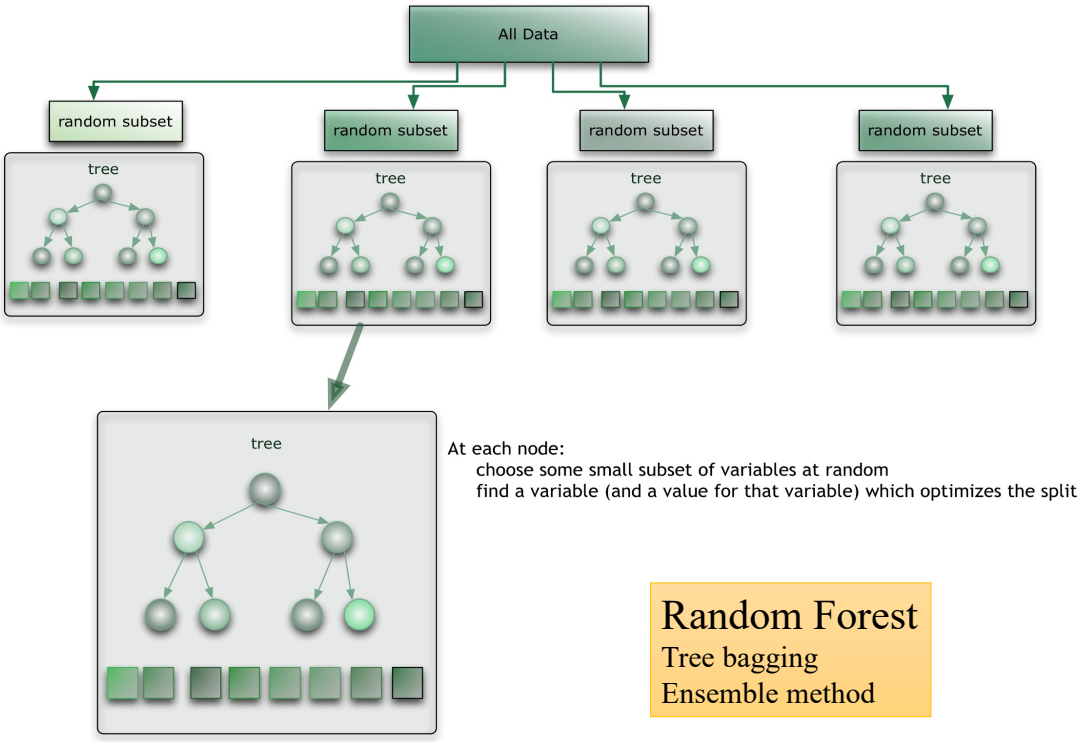

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R: Separate training and test data (Again)

```
bankData.train <- sample_frac(bankData, 0.6)
training.ind <- as.integer(rownames(bankData.train))
bankData.test <- bankData[-training.ind,]
```

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R: Build a random forest

```
library(randomForest)
rf <- randomForest(y ~ ., data = bankData.train)
rf
```

```
Call:
 randomForest(formula = y ~ ., data = bankData.train)
               Type of random forest: classification
                     Number of trees: 500
No. of variables tried at each split: 4

        OOB estimate of  error rate: 9.15%
Confusion matrix:
       no  yes class.error
no  23135  845   0.0352377
yes  1638 1509   0.5204957
```

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Prediction

```
res <- predict(rf, bankData.test)
confusionMatrix(res,
                bankData.test$y,
                positive = "yes",
                mode  = "prec_recall")
```

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```
          Reference
Prediction    no   yes
       no  15294  1031
       yes   648  1111

               Accuracy : 0.9072
                 95% CI : (0.9028, 0.9113)
    No Information Rate : 0.8816
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.5181
 Mcnemar's Test P-Value : < 2.2e-16

              Precision : 0.63161
                 Recall : 0.51867
                     F1 : 0.56960
```

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Activity: Decision tree and random forest

- Use 3-credit-approval data
- Separate data into 60:40 for training:testing
- Build a decision tree and a random forest
- Evaluate the model accuracy

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Thank you

Question?

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