Lecture 8

Start with a review: Quiz 1
Review of bagging and random forests
Implementing a random forest for linear outcome
If time, we will start conditional logistic regression

The material in this video is subject to the copyright of the owners of the material and is being provided for educational purposes under rules of fair use for registered students in this course only. No additional copies of the copyrighted work may be made or distributed.

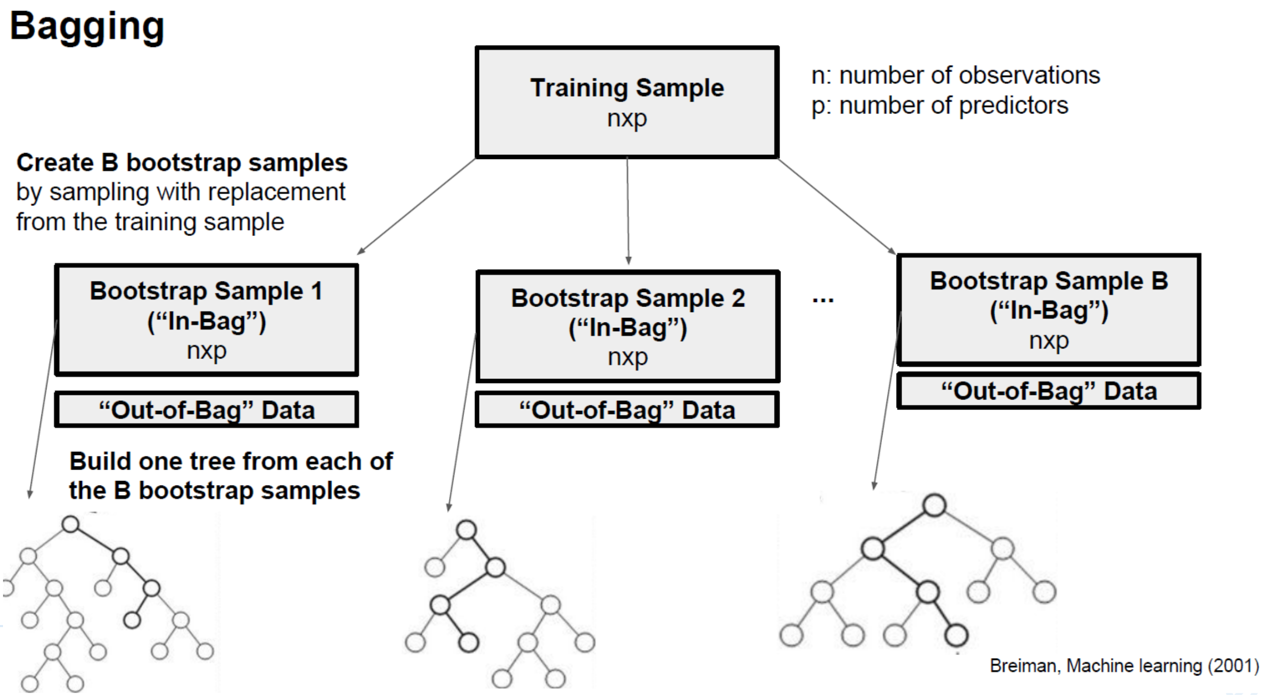
Lecture 7 Review:

- CART: Classification And Regression Trees
  - Made the link between the CART and a regression model
  - Examples with both linear and binary outcome
  - Compared CART to parametric model using AUC ROC

- Random forests
  - One issue with CART is sensitivity of predictions to small perturbations in X
  - CART results are highly variable
  - Ensemble learners: predictions based on averaging over many realizations of CART
  - Ensemble learners: improve accuracy and precision

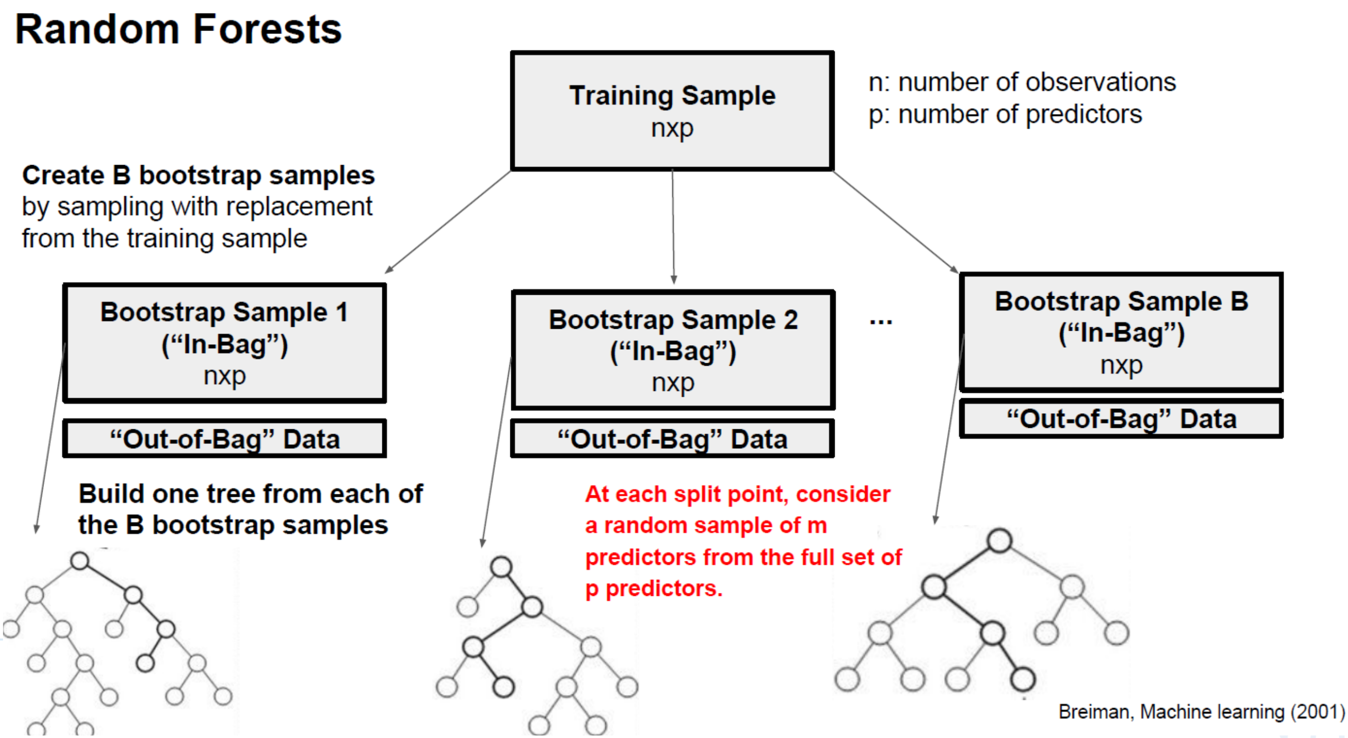
Ensemble Methods

- Bagging (**B**ootstrap **Agg**regat**ing**)
- Random Forests



Ensemble Methods

- Bagging (**B**ootstrap **Agg**regat**ing**)
- Random Forests



Out-of-bag samples

- Allows for internal cross-validation / evaluation of the quality of the ensemble method

- For a random forest constructed with B trees,

  - Each observation in the training data appears in
    - Roughly 2/3 of the trees / bootstrap samples
    - Roughly 1/3 of out-of-bag samples

  - Predicted values for observations in the training data are based on predictions made from the trees where the observation was an out-of-bag observation
    - Linear/continuous outcome: average prediction across all out-of-bag trees
    - Binary/categorical outcome: proportion of votes received for each level of the outcome across all out-of-bag trees, i.e. Pr(Y=y) for all y = 0, 1, …, and classification assigned as the y that yields the largest Pr(Y=y)

- Out-of-bag error is used to evaluate the tuning parameters for the ensemble learner
  - Linear/continuous outcome: mean squared error computed with out-of-bag prediction
  - Binary/categorical outcome: misclassification error computed with out-of-bag classification

Construction of random forest

- Parameters that we control
  - Number of variables considered at each split, m
    - Classification tree: floor square-root p
    - Regression tree: floor p/3
  - Number of trees

- Implementation:
  - To find m: set number of trees large (e.g. 500), identify minimum out-of-bag error for m = 1, 2, …, beyond default.
  - After finding m: check to see if your forest is sensitive to number of trees by plotting MSE or out-of-bag misclassification error as a function of number of trees.

Example: Predict log(expenditures + 1) in NMES

- See handout

Review of logistic regression assumptions

- And solutions to violations

- Mean model is correctly specified
  - Plot average predicted vs. observed proportions within quintiles or deciles of predicted values
  - Plot average predicted vs. observed proportions as a function continuous exposure
  - Summary tables of average predicted vs. observed proportions by level of categorical exposure
  - SOLUTION: change your mean model

- Observations are independent
  - More on this next Tuesday

- Variance is correctly specified
  - Under or over-dispersion
  - Var(Y) = p(1-p)
  - Compute Var(Y) and compare with predicted variance, overall or by select variables

- There are no "influencial" observations
  - DFFITS or DFBETAS

Review of logistic regression assumptions

- Variance is correctly specified
  - Logistic model assumes: Var(Y) = p(1-p)
  - Under or over-dispersion
  - Compute Var(Y) and compare with predicted variance, overall or by select variables
  - SOLUTION:
    - Bootstrap
    - GLM: family = “quasibinomial” assumes Var(Y) = ϕ x p x (1-p) where ϕ = 1/(n-k) sum of squared Pearson residuals

- There are no “influencial” observations
  - DFFITS or DFBETAS