Bagging

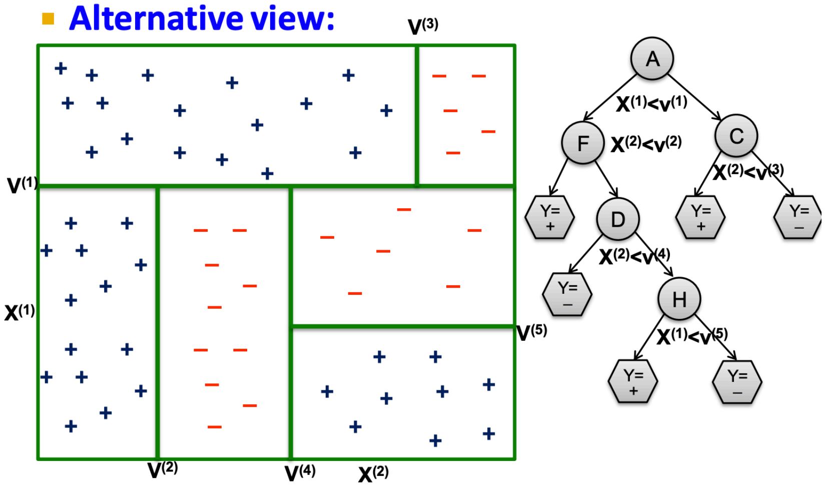
CSC 461: Machine Learning

Fall 2021

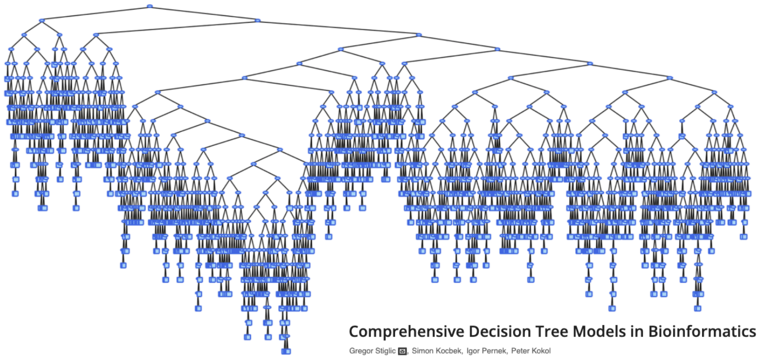
Prof. Marco Alvarez
University of Rhode Island

Feature space

- **Alternative view:**



Jure Leskovec, Stanford CS246: Mining Massive Datasets, http://cs246.stanford.edu



Comprehensive Decision Tree Models in Bioinformatics

Gregor Stiglic, Simon Kocbek, Igor Pernek, Peter Kokol

Published: March 30, 2012 • https://doi.org/10.1371/journal.pone.0033812

Complicated decision boundaries ==> Overfitting

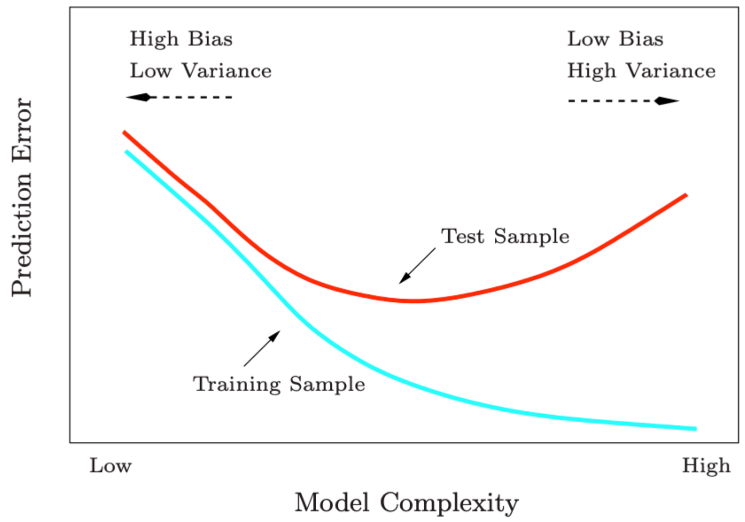
Trees problems

- Overfitting
- Unstable
  - ✓ slight changes of the data => different tree structures

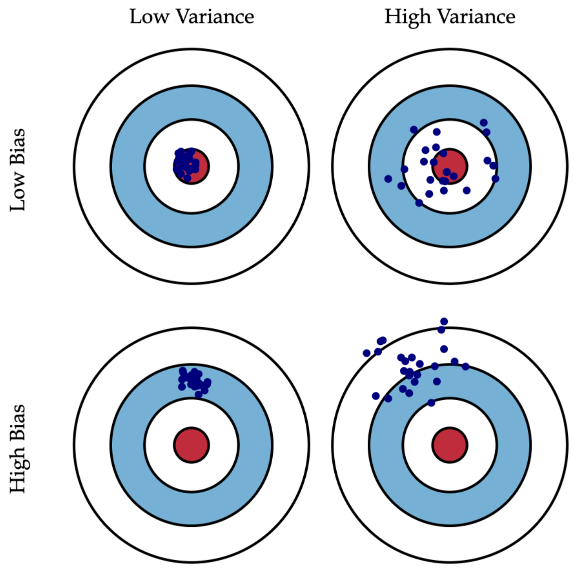
Bias-Variance decomposition

- Expected loss
  - ✓ **bias**: how wrong the expected prediction is
  - ✓ **variance**: the amount of variability in the predictions
  - ✓ **Bayes error**: the inherent unpredictability of the targets (e.g. noise)

$$\mathbb{E}[(y-t)^2] = \underset{\text{bias}}{(y^* - \mathbb{E}[y])^2} + \underset{\text{variance}}{\mathrm{Var}(y)} + \underset{\text{Bayes error}}{\mathrm{Var}(t)}$$



The Elements of Statistical Learning, Hastie, Tibshirani, Friedman, 2nd Ed.



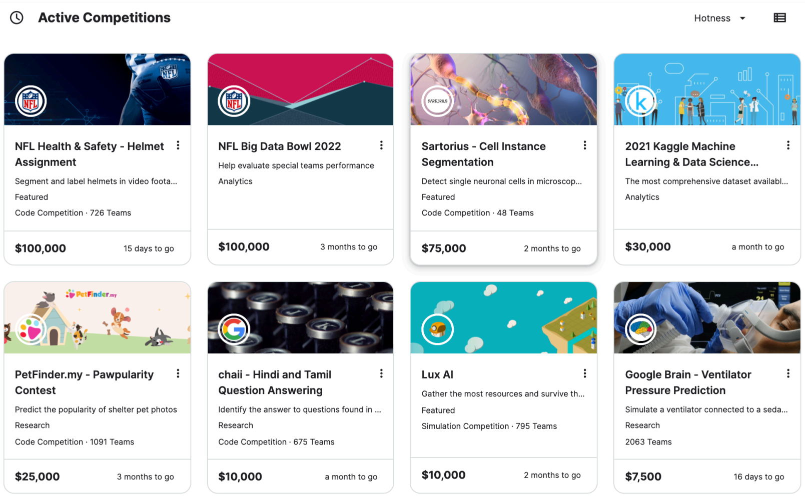
http://scott.fortmann-roe.com/docs/BiasVariance.html

Ensembles

- Set of hypotheses (e.g. classifiers)
  - ✓ individual predictions are combined into a final prediction, e.g. majority vote
- **Bagging (bootstrap aggregation)**
  - ✓ train models independently (**in parallel**) on random subsets of data
  - ✓ variance-reduction technique
- **Boosting**
  - ✓ train **weak** models **sequentially**, each focusing on examples misclassified by previous models
  - ✓ bias-reduction technique

Netflix prize

Kaggle competitions



Active Competitions

Hotness ▾

NFL Health & Safety - Helmet Assignment
Segment and label helmets in video foota...
Featured
Code Competition · 726 Teams
$100,000 15 days to go

NFL Big Data Bowl 2022
Help evaluate special teams performance
Analytics
$100,000 3 months to go

Sartorius - Cell Instance Segmentation
Detect single neuronal cells in microscop...
Featured
Code Competition · 48 Teams
$75,000 2 months to go

2021 Kaggle Machine Learning & Data Science...
The most comprehensive dataset availabl...
Analytics
$30,000 a month to go

PetFinder.my - Pawpularity Contest
Predict the popularity of shelter pet photos
Research
Code Competition · 1091 Teams
$25,000 3 months to go

chaii - Hindi and Tamil Question Answering
Identify the answer to questions found in ...
Research
Code Competition · 675 Teams
$10,000 a month to go

Lux AI
Gather the most resources and survive th...
Featured
Simulation Competition · 795 Teams
$10,000 2 months to go

Google Brain - Ventilator Pressure Prediction
Simulate a ventilator connected to a seda...
Research
2063 Teams
$7,500 16 days to go

Bootstrapping

- Assuming a dataset $\mathscr{D}$ with n examples
- Generate m datasets
  - ✓ sample n instances from $\mathscr{D}$ **with replacement** (bootstrap samples)
  - ✓ some elements will appear multiple times
  - ✓ some elements may not appear at all

probability of each element not being selected: $\left(1-\frac{1}{n}\right)^n$

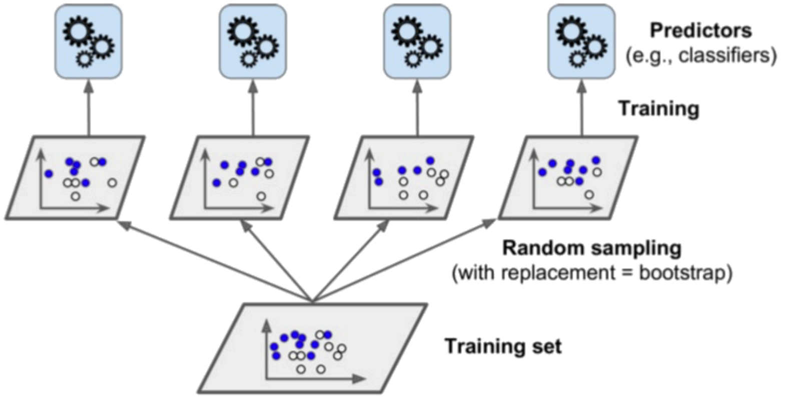
36.8% for large n

Exercise

- Write a script that generates a random sequence of N elements and creates M bootstrap samples from that sequence
  - ✓ can use `random.randint` and `random.choices`

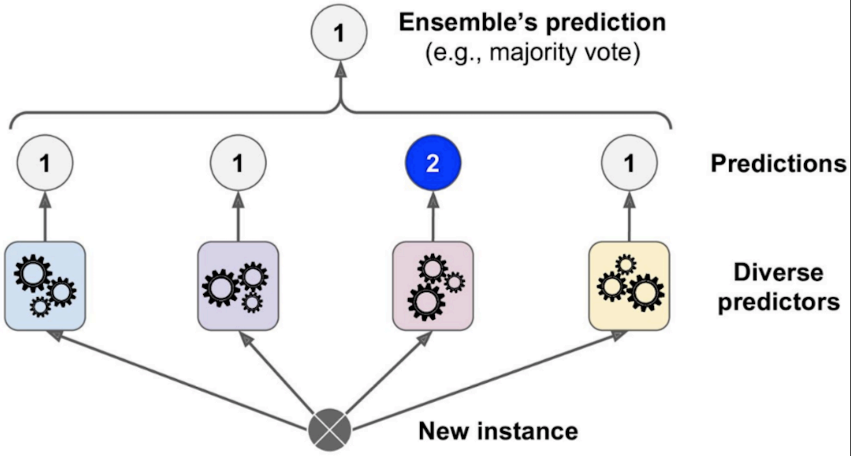
Random Forests

Bootstrapping



https://www.bpesquet.fr/mlhandbook/algorithms/decision_trees_and_random_forests.html

Inference



https://www.bpesquet.fr/mlhandbook/algorithms/decision_trees_and_random_forests.html

Random Forest

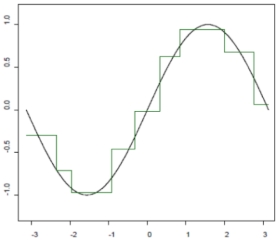
- Ensemble
  - ✓ create *m* trees trained from bootstrap "samples"
  - ✓ majority vote for prediction
- Benefits
  - ✓ reduces overfitting — low variance, however it has little effect on bias
- Combines **example diversity** with **feature diversity**

Algorithm

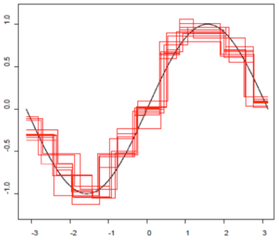
```
Algorithm RandomForest($D, T, d$) – train an ensemble of tree models from bootstrap samples and random subspaces.
Input   : data set $D$; ensemble size $T$; subspace dimension $d$.
Output  : ensemble of tree models whose predictions are to be combined by
          voting or averaging.
for $t = 1$ to $T$ do
    build a bootstrap sample $D_t$ from $D$ by sampling $|D|$ data points with
    replacement;
    select $d$ features at random and reduce dimensionality of $D_t$ accordingly;
    train a tree model $M_t$ on $D_t$ without pruning;
end
return $\{M_t | 1 \leq t \leq T\}$
```

from: Machine Learning Making Sense of Data, http://people.cs.bris.ac.uk/~flach/mlbook/

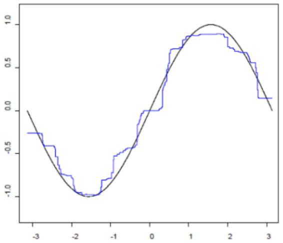
Regression example



1 tree

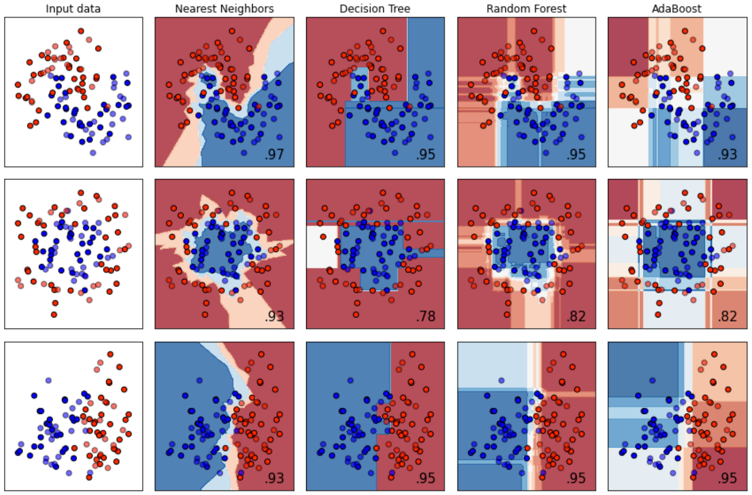


10 trees



average

Comparing classifiers



Issues

- Fitting ensembles can be computationally intensive
  - ✓ can use *max_depth* to alleviate
- Naively averaging or taking a majority both may not be optimal
  - ✓ stay tuned: **boosting**