

Random Forests™

Ensembles of bootstrapped, weakened trees

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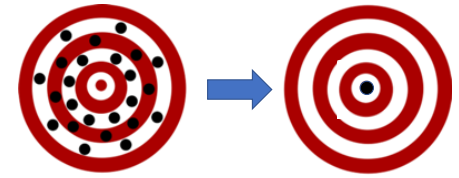
Leo Breiman (1996) introduced bagging
then Random Forests (2001)

<https://www.stat.berkeley.edu/~breiman/randomforest2001.pdf>

RF motivation

- Decision trees can often get training errors close to zero because we can grow very large trees to partition the feature space into tiny regions with 1 or just a few observations/samples; trees are very accurate on the training set and are **not biased** (not always systematically under-predicting or always over-predicting)
- The downside is that decision trees overfit like mad; or, using stats nerd terminology, decision trees have **high variance** and don't generalize well
- High variance implies model parameters (tree structure) vary a lot if we tweak the training data just a little bit

How can we increase generality?



- **Goal:** keep the high accuracy, but increase the generality
- Recall: simplifying models can increase generality at cost of some error
- So, let's weaken our decision tree model but in a way that makes predictions **noisy not biased**
- That means the model's prediction might be too high for one test case and too low in another
 - But, the model will not always be too low or always too high, which would be biased
 - The expected value of weakened model's prediction is same as full strength model
- To compensate for the noise and claw back some accuracy, make an ensemble of such weakened trees: the ensemble is **accurate on average**
- Ensemble predictions are the aggregate of the trees' predictions (average prediction or majority vote)

The key trick is amnesia

- Random forests are all about adding a bit of amnesia to the training process
- We will weaken trees by training each on a randomly selected subset of the training data: **bagged trees**
- Further, we will have training purposely forget about some features as we create decision nodes: **random forests**

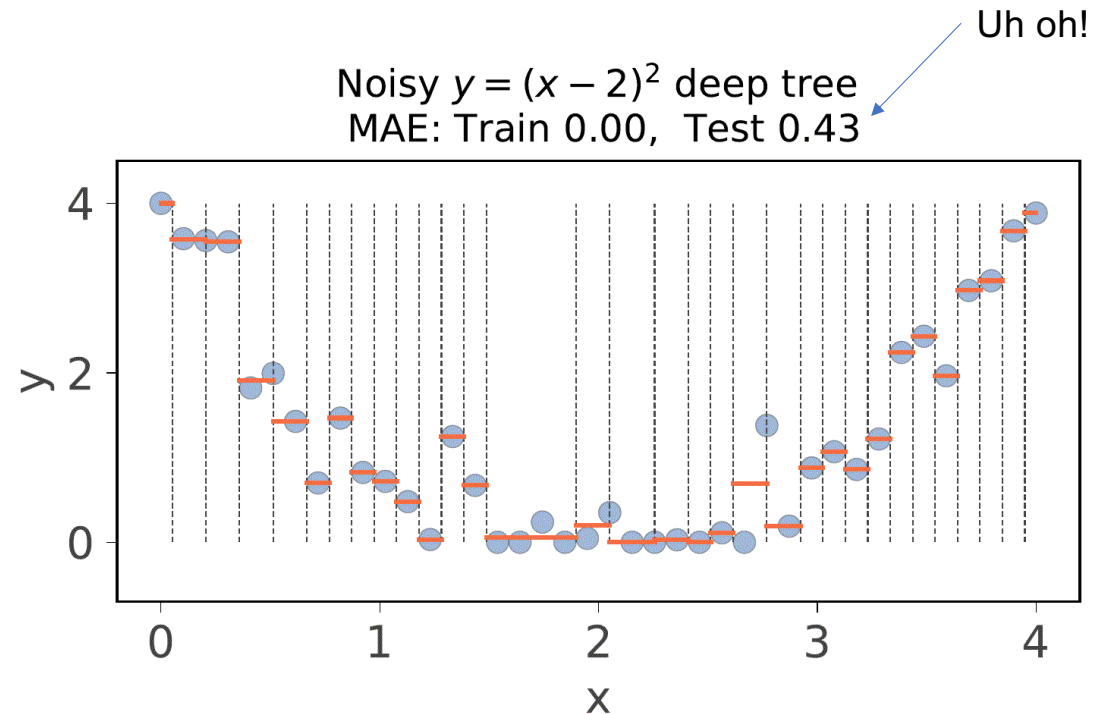


Analogy: Crowdsourcing SF house prices

- Recruit multiple real estate agents to build house price models in their heads by visiting lots of houses; then each agent can estimate prices of unvisited houses
- Agents choose and examine house subsets **independently**
- There will be some overlap in visited houses sets but the subsets will be *independent and identically distributed (i.i.d.)*
- An agent trained on large house set is very accurate
- An agent trained on an i.i.d. subset is not biased but is less accurate—a prediction for one house might be too low but a prediction for another house might be too high (avoiding bias)
- The variance of the ensemble average will be much tighter than the variance of an individual tree's prediction
- Averaging all agents' predictions reduces noise and is unbiased

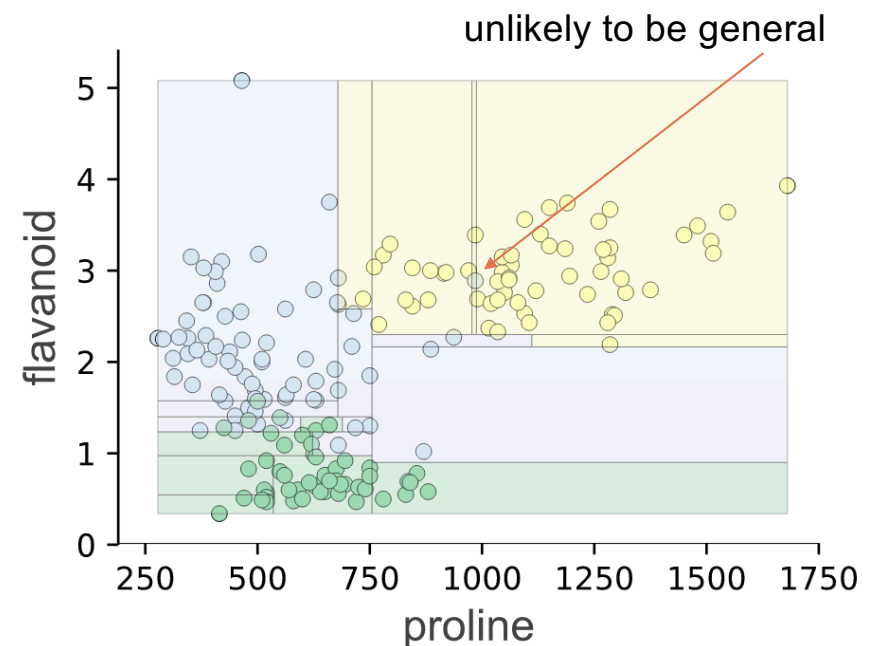
Ex: Overfit decision trees regressors

- Animation shows 1D feature space partitioning of i.i.d. sample sets
- Slightly different training data sets can yield very different decision trees
- Clearly the trees have gotten way too specific to the data set
- Notice how the training error is 0 but (20% hold out) test error is terrible!



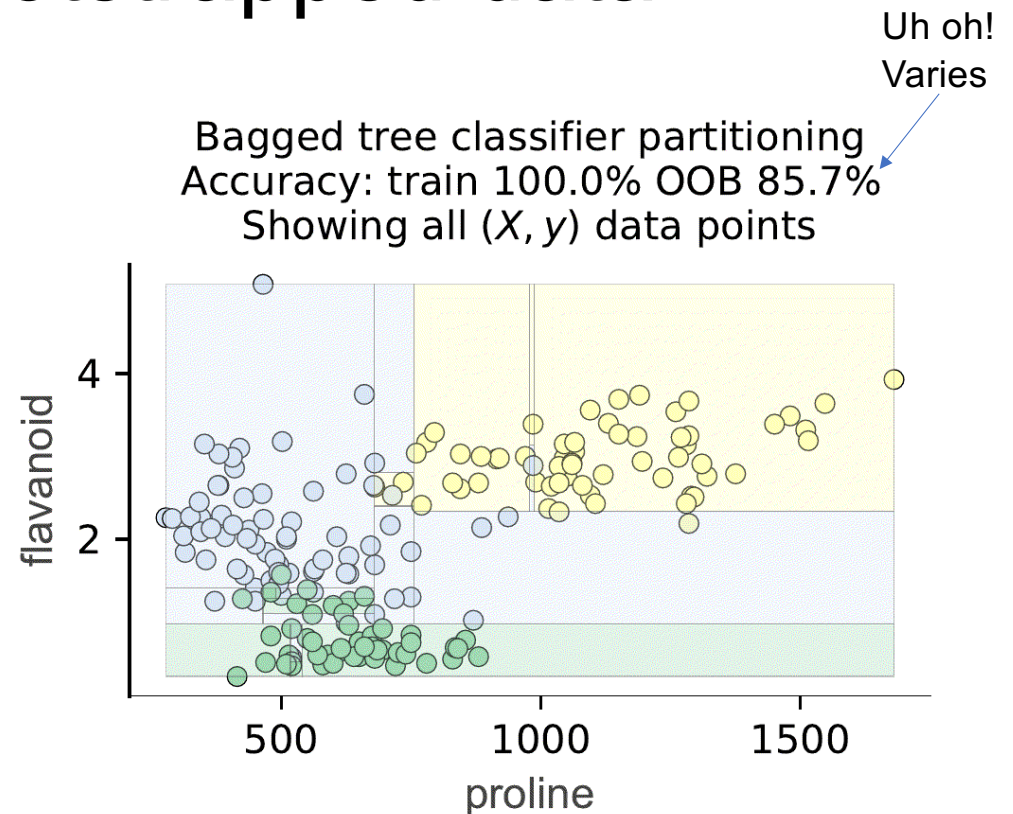
Ex: Overfit decision tree classifiers

- Here is a previous example where partitioning trapped a lonely blue in a sea of yellow
- In practice, we're given just one data set so let's do some sampling to get some i.i.d. "copies"
- Then see how different data sets give different partitioning (from different trees)



Partitioning from bootstrapped data[†]

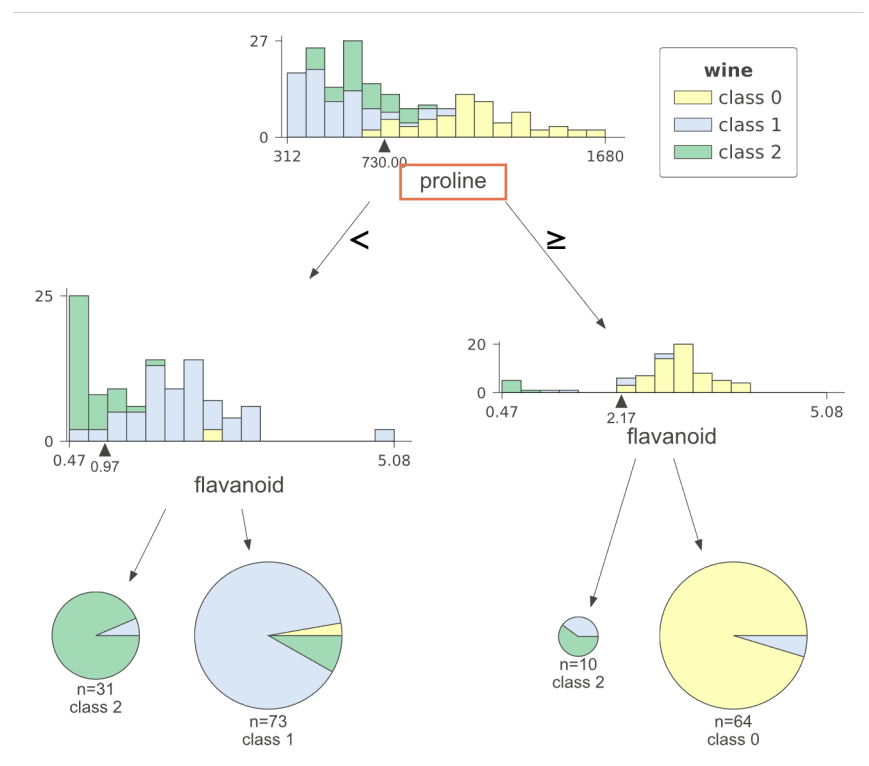
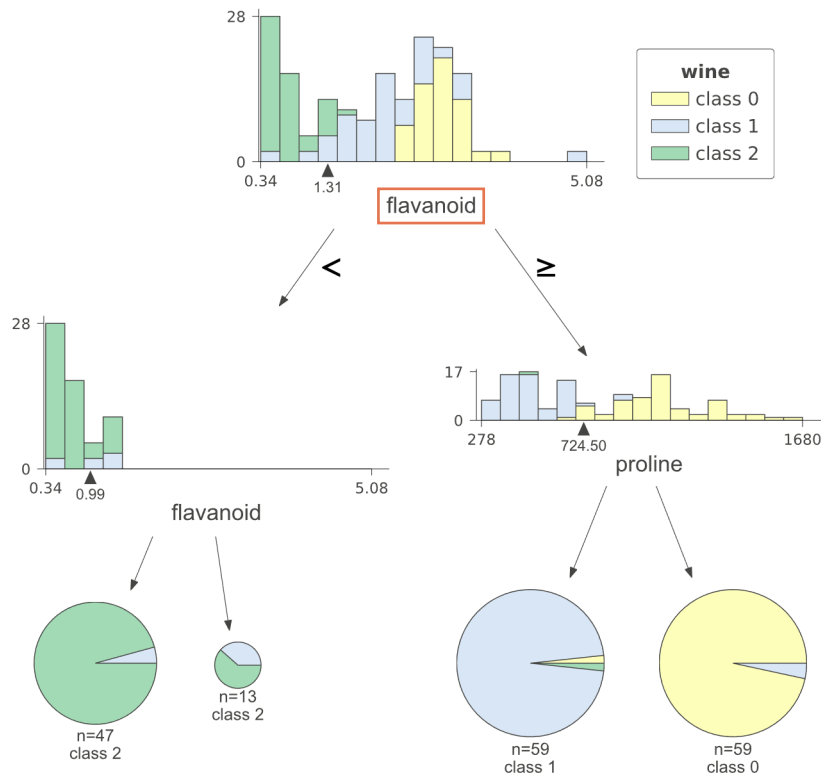
- *Bootstrap* (X, y) to simulate multiple i.i.d. data sets[†]
- Each set gets ~63% of unique (X, y) data (sample n records with replacement) *amnesia*
- Animation shows 2D feature space partitions from various bootstraps
- Partitioning clearly varies a lot between bootstraps
- *OOB* == "out of bag" (more later)



[†]Bootstraps are technically *conditionally independent*, conditioned on nature of original X , which could be weird by chance or by the way it was collected/obtained.

Bootstrapping gives slightly different trees

```
DecisionTreeClassifier(max_depth=2)
```



Same tree construction algorithm running on slightly different bootstraps

Aside: Code for bootstrapping

NumPy

```
# Bootstrap: sample with replacement  
n = len(y)  
idx = np.random.randint(0,n,size=n)  
X_train = X[idx]  
y_train = y[idx]
```

```
# get OOB (out-of-bag) samples  
mask = np.ones(n, dtype=bool)  
mask[idx] = False  
X_test = X[mask]  
y_test = y[mask]
```

Pandas

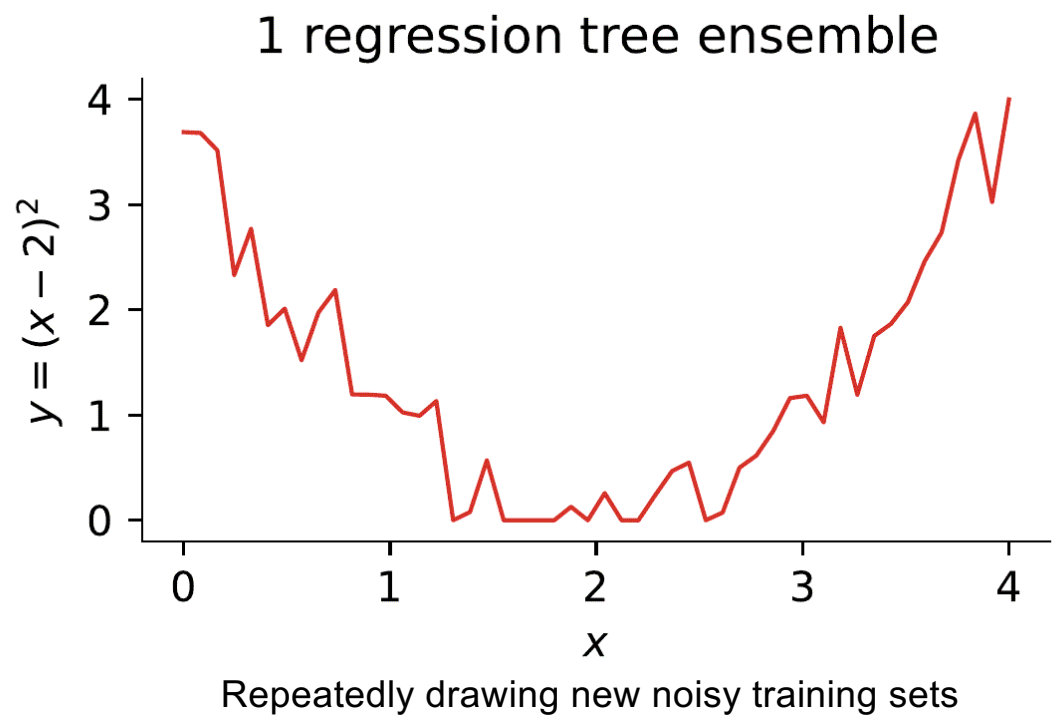
```
# If data in dataframe  
df = df.sample(len(df), replace=True)
```

Bagged trees

Training trees on bootstrapped samples and aggregating predictions

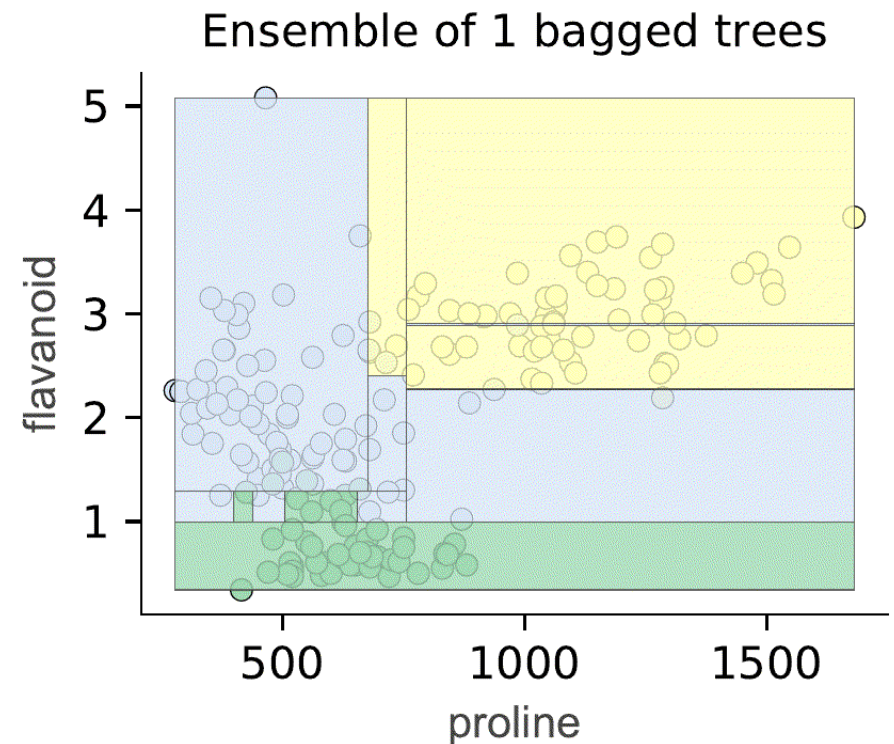
Ensemble of high-variance regression trees

- Animation shows how averaging the prediction of an ensemble of overfit trees actually produces a reasonable combined prediction
- As we add trees, the average prediction (red line) smooths out to the underlying quadratic distribution from which we draw noisy samples
- Note: variance of individual tree predictions stays high regardless of number of trees, but the variance of the ensemble average tightens (the magic of C.L.T.)



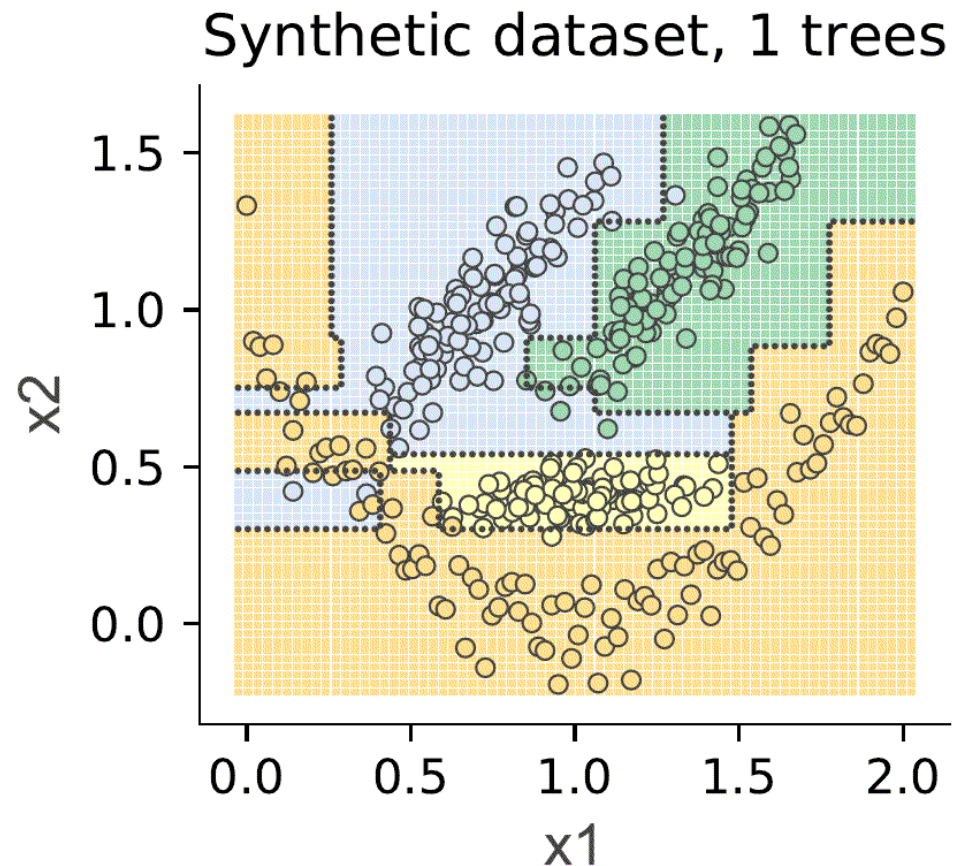
Ensemble of high-var. classification trees

- Animation shows overlapping prediction regions from multiple classifier trees
- Training data for each tree is bootstrapped from the original (X, y) data
- As we add trees, the averaged prediction regions become more stable and the decision boundaries more complex
- "Bag" is *bootstrap aggregation*



Ensemble classifier on synthetic data set

- Animation shows prediction regions from multiple bagged classifier trees
- Colored tiles indicate the probabilities of the various classes; e.g., yellow-orange color indicates uncertainty between those two classes
- What's prob. of class k at tile?
 - proportion of trees that predict k



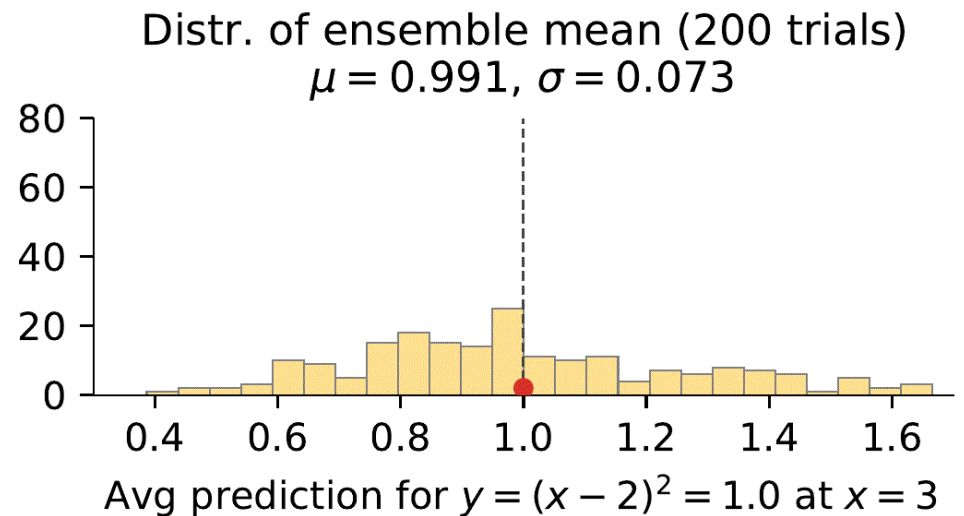
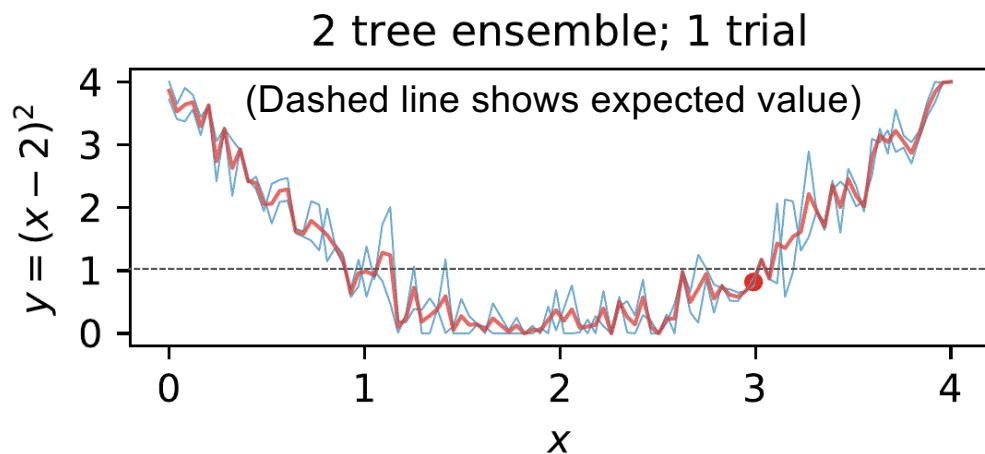
Animation uses experimental function I'm adding to dtreeviz

Ensemble's effect on bias and variance

- Train T trees on T i.i.d. X data sets
- Central limit theorem says that if variance of an i.i.d. random variable is σ^2 , the variance of the average of T such vars is σ^2/T
- So, as we add trees, the variance of the ensemble prediction will shrink, which means we squeeze out noise
- The average of the tree predictions is the same as the expected prediction from any tree trained on one of the X sets (since i.i.d.)
- Each tree gives noisy predictions, sometimes too low and sometimes too high, but is unbiased; so, ensemble is unbiased
- If weakened trees were biased, adding trees would increase bias

Ex: variance of ensemble prediction

- Animation shows tree and ensemble predictions on left for T trees; magnitude of noise in blue tree predictions doesn't change with the number of trees but red line get less noisy with more trees
- At $x = 3$, expected value of ensemble is 1.0; create 200 separate ensembles of size T and compute variance of ensemble predictions at $x = 3$; distribution of ensemble average shown on the right



Problem: trees are not independent thinkers

- With real estate agent analogy, we implicitly assumed agents were independent thinkers, and not clones
- But, decision trees are like robot clones and, given the same bit of data, yield the exact same bit of tree
- Imagine worst case: bootstrapping yields T identical sets so ensemble gives exactly the same prediction as any single tree
- In practice, if there is one strongly predictive var out of p , then all trees would be similar; initial root splits, and many others, would likely be same

Random Forests

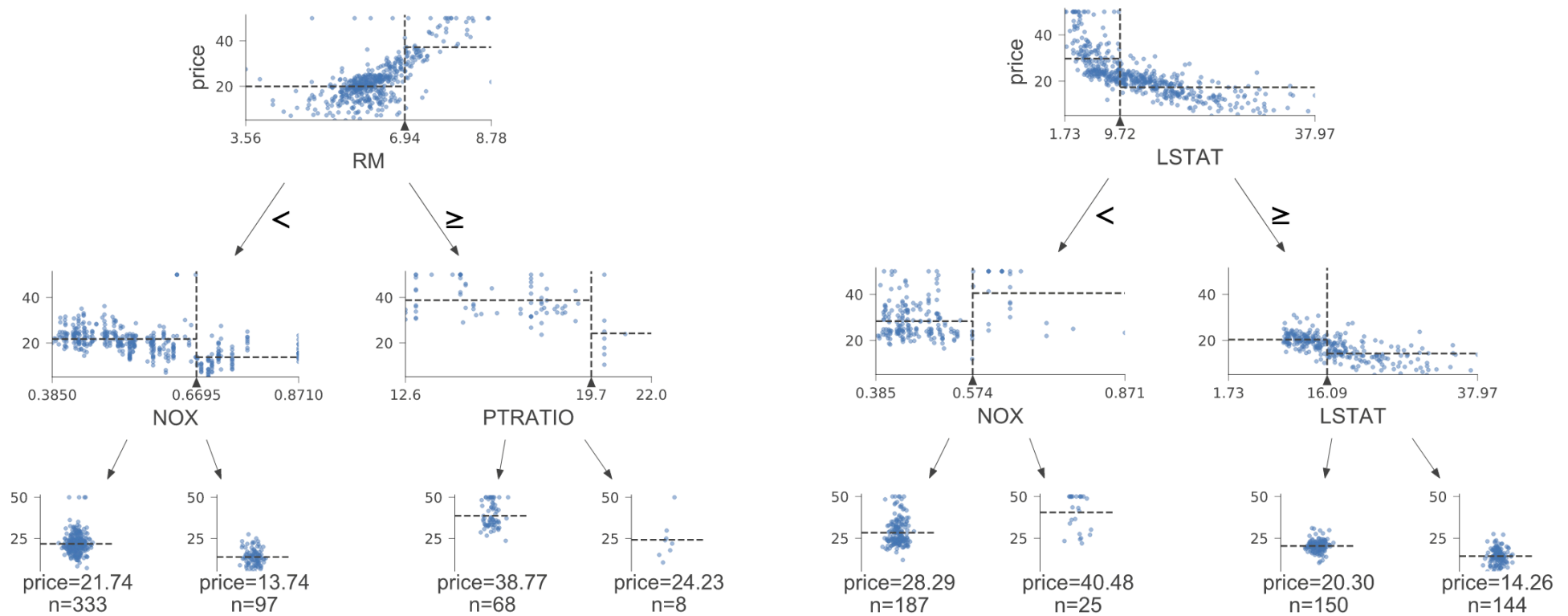
Ensembles of de-correlated bagged trees

Making trees independent thinkers

- Bagging overcomes most of the overfitting, but we can improve generality a little by further weakening the tree training process itself in an effort to make trees think more independently
- Restrict the available features when searching for a decision node split; choose from m randomly selected features (**amnesia** again!)
- Choose max features per split, $m \leq p$, such as $\text{sqrt}(p)$
- Make sure chance of selecting predictive variables (m/p) is high enough to find predictive variables (See ESLII p596)
- Let validation error be your guide to choosing m
- A *random forest* is then just an ensemble of decision trees trained on bootstraps and whose feature selection strategy has a bit of amnesia

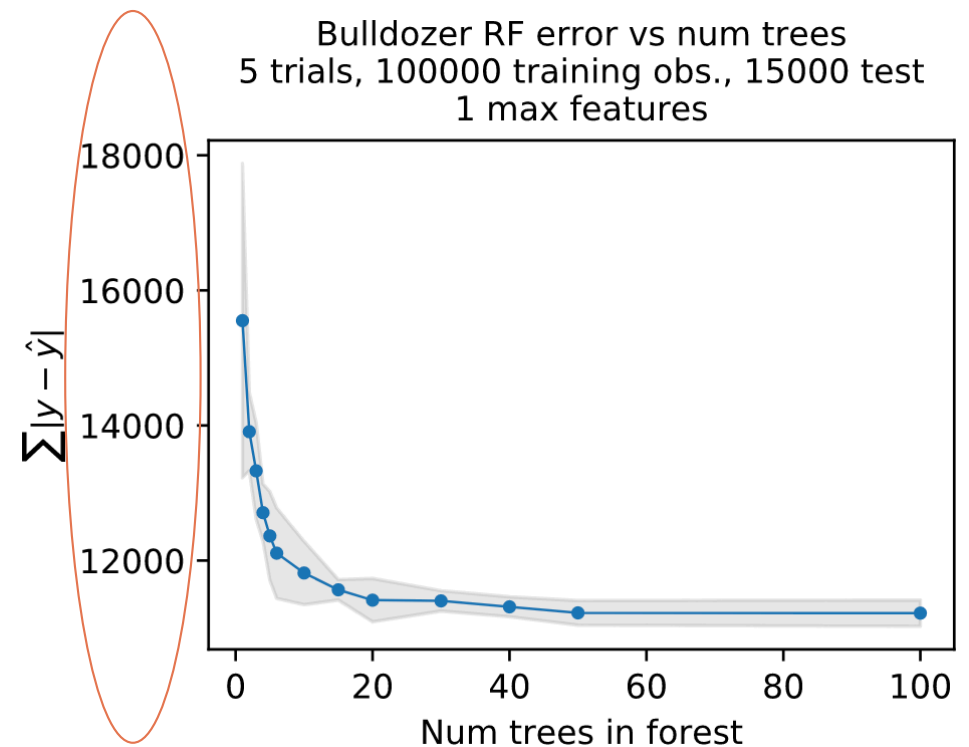
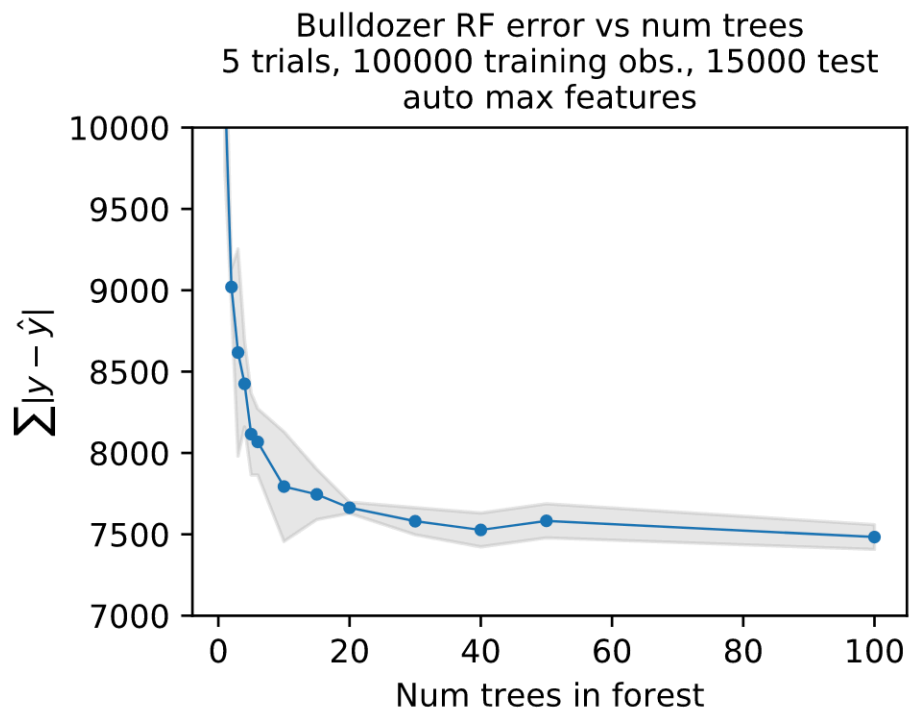
Ex: Effect of limiting feature set but using full data set

2 trees trained on **entire** Boston set with $m=5$ (of 13)



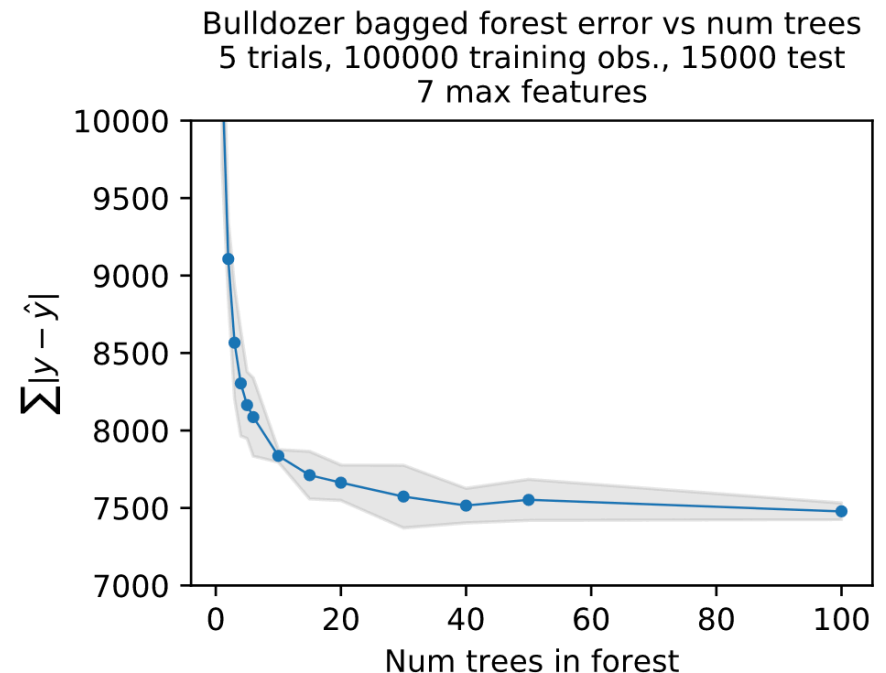
Choose from 5 randomly selected features during EACH split

If max_features too low, bad accuracy

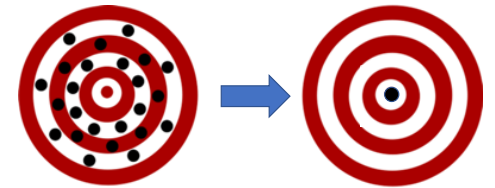


Effect of forest size on accuracy

- Why does accuracy improve greatly (initially) as we add trees?
 - Each tree sees only 2/3 of data so adding bootstrapped trees increases use of training data
- Why does accuracy asymptotically approach a minimum instead of continual improvement?
 - With enough trees, ensemble sees 100% of the training data; it's approaching the accuracy of single decision tree in ideal world



Properties (see *Breiman 2001*)



- p4 “*Random forests do not overfit as more trees are added*” **Why?**
 - Adding more trees actually REDUCES variance, and overfitting==variance
 - New trees get averaged in so each additional tree has less individual effect
 - New trees balance each other out, one might be too high, another too low
- p7 “*It's relatively robust to y outliers and X noise*” **Why?**
 - y outliers get shunted to their own leaf since doing so reducing loss function, particularly if squared-error is used
 - Noise vars aren't predictive so not chosen as split vars
- p10 Bagging helps more, the more unstable the model. **Why?**
 - Averaging is a smoothing operator, squeezing predictions to centroid
 - If model is low variance already, there is no point in bagging

Properties continued

- RFs are scale and range insensitive in features and target y **Why?**
 - Comparing feature values in decision nodes, not doing math on them
 - Computing mean or mode of y to predict
- ESLII p596 “*Classifiers are less sensitive to variance [than regressors]*” **Why?**
 - (not sure haha) I believe it has something to do with mode vs mean (mode is same until a threshold whereas mean is influenced by any value added, unless it is also the mean)

Bootstrapping vs subsampling

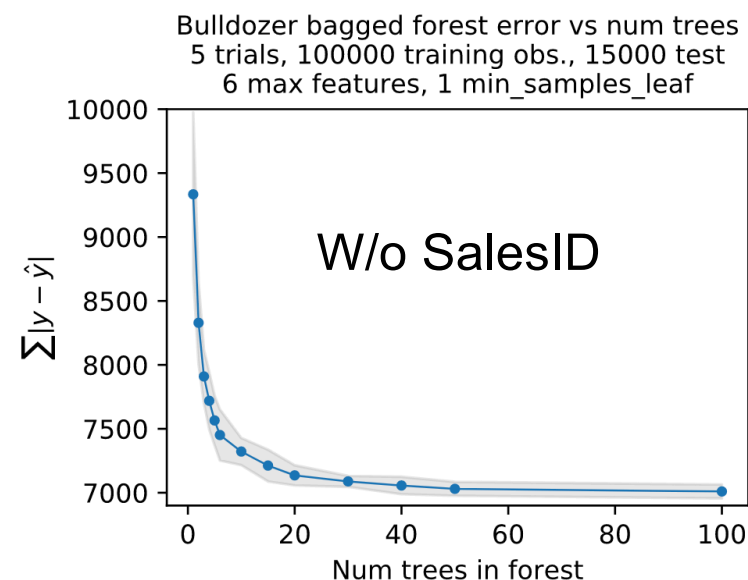
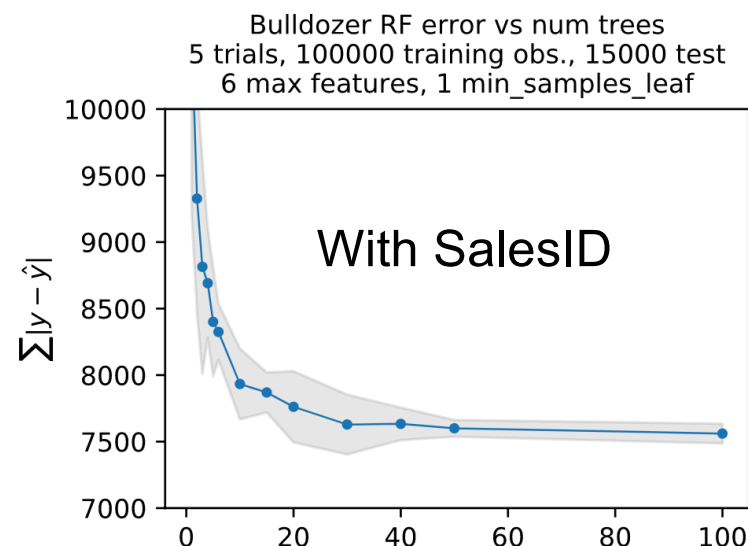
- Bootstrapping is sampling with replacement vs subsampling w/o replacement
- 🤔 Friedman and Hall (2000): subsampling also works, showing that training trees with $n/2$ subsamples is similar in bias/variance to bagging <http://statweb.stanford.edu/~jhf/ftp/bag.pdf>
- Smaller training set is a big win in terms of speed
- Using even smaller fractions of n improve generality (reduce variance) because trees are less correlated (they work on different data chunks); note that each tree would become less accurate as n subsample size decreases

RF Tuning strategy

- Good news: very little tuning needed
- Start with maybe 20 trees and work upwards til validation error stops getting better; or just pick 100
- Sklearn uses `max_features= sqrt(p)` by default; try dropping this to `log(p)`, or similar; ESLII suggests $p/3$ for regression and `sqrt(p)` for classification
- Try adjusting min samples per leaf: 1, 3, 5, 10, 25, 100
- Goal: minimize validation error
- Can also try grid search, but I never bother; Start with num trees, then tune the others

Feature engineering beats model tuning

- SalesID: unique record ID, and is never seen again in future predictions
- Is that useful for prediction? No
- Does the model think it's useful? Yes
- Model is overfit not on noise but on falsely-predictive feature
 - Could be that sales ID correlates with inflation or change in type of models sold in auction creates “trend” in sale prices
- A case where using LESS data improves the model a lot (\$500 diff)
- Dropping useless features also often gives a small bump



The RF algorithms

Fitting RFs

Algorithm: $RFfit(X, y, loss, ntrees, max_features, min_samples_leaf)$
 for $i = 1..ntrees$ **do**
 $X', y' = bootstrap(X, y, size = |X|)$
 $T_i = RFdtreefit(X', y', loss, max_features, min_samples_leaf)$
 end

For regression, pass in $loss = \text{MSE or stddev}$

For classifier, pass in $loss = \text{gini}$

Fitting a single tree in RF

Same as decision tree except
we pass `max_features` to
`RFbestsplit()`

Algorithm: $RFdtreefit(X, y, loss, \text{max_features}, \text{min_samples_leaf})$

if $|X| \leq \text{min_samples_leaf}$ **then** return `Leaf(y)`

$col, split = RFbestsplit(X, y, loss, \text{max_features})$

if $col = -1$ **then** return `Leaf(y)`

$lchild = RFdtreefit(X[X_{col} \leq split], y[X_{col} \leq split], \dots)$

$rchild = RFdtreefit(X[X_{col} > split], y[X_{col} > split], \dots)$

return `DecisionNode(col, split, lchild, rchild)`

Finding best split in decision node in RF

Algorithm: *RFbestsplit*($X, y, \text{loss}, \text{max_features}$)

$\text{best} = (\text{col} = -1, \text{split} = -1, \text{loss} = \text{loss}(y))$

$\text{vars} = \text{pick } \text{max_features} \text{ variables from all } p$

for $\text{col} \in \text{vars}$ **do**

$\text{candidates} = \text{randomly pick } k \ll n \text{ values from } X_{\text{col}}$

foreach $\text{split} \in \text{candidates}$ **do**

$\text{yl} = y[X_{\text{col}} \leq \text{split}]$

$\text{yr} = y[X_{\text{col}} > \text{split}]$

if $|\text{yl}| < \text{min_samples_leaf}$ **or** $|\text{yr}| < \text{min_samples_leaf}$ **then continue**

$l = \frac{|\text{yl}| \times \text{loss}(\text{yl}) + |\text{yr}| \times \text{loss}(\text{yr})}{|y|}$ (weighted average of subregion losses)

if $l = 0$ **then return** col, split

if $l < \text{best}[\text{loss}]$ **then** $\text{best} = (\text{col}, \text{split}, l)$

end

end

return $\text{best}[\text{col}], \text{best}[\text{split}]$

Only diff with decision tree

Pick, say, 11 not all possible X values. We get better generality and code is much faster!

Should pick midpoint between split value and next smallest X

Simplest RF prediction (ESLII p588)

- But doesn't use all information to make best prediction
- Should use weighted averages / votes

Regression: $\hat{f}_{\text{rf}}^B(x) = \frac{1}{B} \sum_{b=1}^B T_b(x).$

Classification: Let $\hat{C}_b(x)$ be the class prediction of the b th random-forest tree. Then $\hat{C}_{\text{rf}}^B(x) = \text{majority vote } \{\hat{C}_b(x)\}_1^B.$

RF prediction

Weighted average of y values
among the leaves reached by
running x down each tree

Algorithm: $RFpredict_{regr}(\{T_1..T_{ntrees}\}, x)$

Let $leaves = \{leaf(T_t, x) \mid \forall t = 1..ntrees\}$

$nobs = \sum_{t=1}^{ntrees} |leaves_t|$

$y_{sum} = \sum_{t=1}^{ntrees} \sum_{y \in leaves_t} y$

return $\frac{1}{nobs} y_{sum}$

Count all y votes among the leaves
reached by running x down each tree

Algorithm: $RFpredict_{class}(\{T_1..T_{ntrees}\}, x)$

$counts[k] = 0 \mid \forall \text{ classes } k$

foreach $t = 1..ntrees$ **do**

$leaf = leaf(T_t, x)$ (*leaf reached by x*)

foreach $y \in leaf$ **do**

$counts[y] += 1$ (*track count of leaf modes*)

end

end

return $\text{argmax}(counts)$

Extremely randomized trees (Geurts *et al* 2006)

- The variable/value pair is highly sensitive to the training set, and responsible for much of error rate
- “*The optimal cut-point was shown to depend very strongly on the particular learning sample used...this cut-point variance appeared to be responsible for a significant part of the error rates of tree-based methods.*” <https://link.springer.com/article/10.1007/s10994-006-6226-1>
- Geurts wondered if more randomness could reduce variance further
- Pick random split value in $\min(X[:,j]) \dots \max(X[:,j])$, ignoring y !
- Like RF, select $m \leq p$ variables and choose var/value with lowest loss
- Fits using entire X training set, not bootstrap and not subsample (trying to increase accuracy of prediction/decrease noise)
- Our use of just 11 (not n) X candidate values in the project is similar (an effort to reduce variance and increase speed)

RF advantages

- Ensemble of decision trees trained on different bootstraps and sometimes forgetting about features during training
- Prediction is ensemble average or majority vote (weighted)
- Easy to understand, efficient, excellent accuracy, interpretable
- Very little tuning is required
- Gracefully handles categorical variables, no need to normalize numerical variables
- Robust to noise in X, y and nonpredictive variables
- Built-in out of bag validation sets
- Negative: cannot extrapolate beyond support data