Decision Tree Learning (Part 2)

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Stopping criteria

We should form a leaf when
- all of the given subset of instances are of the same class
- we've exhausted all of the candidate splits

Is there a reason to stop earlier, or to prune back the tree?

How can we assess the accuracy of a tree?

- Can we just calculate the fraction of training examples that are correctly classified?

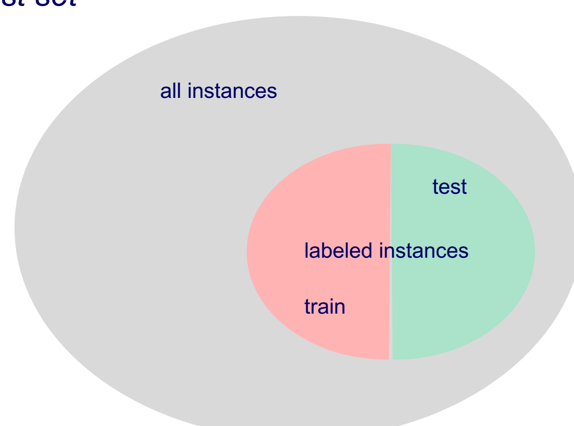
- Consider a problem domain in which instances are assigned labels at random with $P(Y = \mathrm{T}) = 0.5$

    - How accurate would a learned decision tree be on previously unseen instances?

    - How accurate would it be on its training set?

How can we assess the accuracy of a tree?

- to get an unbiased estimate of a learned model's accuracy, we must use a set of instances that are held-aside during learning
- this is called a *test set*



Overfitting

- consider error of model h over
  - training data: $error_D(h)$
  - entire distribution of data: $error(h)$

- model $h \in H$ *overfits* the training data if there is an alternative model $h' \in H$ such that

$$error(h) > error(h')$$

$$error_D(h) < error_D(h')$$

Overfitting

- the concept of overfitting is not specific to decision trees

- overfitting avoidance is one of the principal challenges in machine learning!

Overfitting with noisy data

suppose

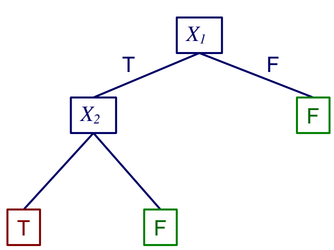
- the target concept is $Y = X_1 \wedge X_2$
- there is noise in some feature values
- we're given the following training set

X_1	X_2	X_3	X_4	X_5	…	Y
T	T	T	T	T	…	T
T	T	F	F	T	…	T
T	F	T	T	F	…	T
T	F	F	T	F	…	F
T	F	T	F	F	…	F
F	T	T	F	T	…	F

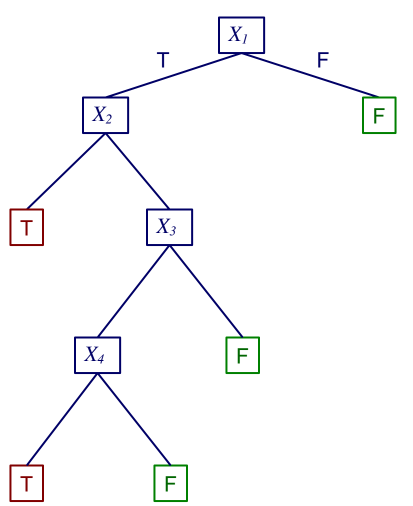
noisy value

Overfitting with noisy data

correct tree

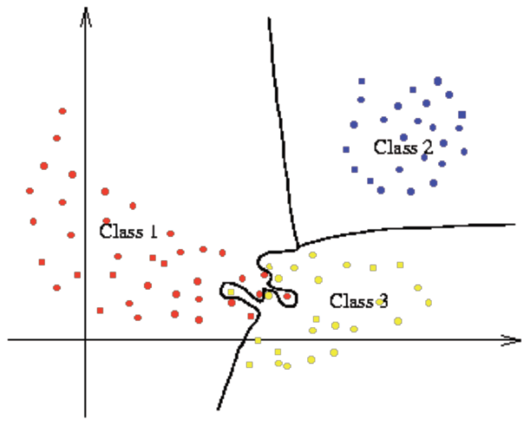


tree that fits noisy training data



Overfitting visualized

consider a problem with
- 2 continuous features
- 3 classes
- some noisy training instances

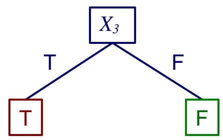


Overfitting with noise-free data

suppose
- the target concept is $Y = X_1 \wedge X_2$
- P(X_3 = T) = 0.5 for both classes
- P(Y = T) = 0.67
- we're given the following training set

X_1	X_2	X_3	X_4	X_5	…	Y
T	T	T	T	T	…	T
T	T	T	F	T	…	T
T	T	T	T	F	…	T
T	F	F	T	F	…	F
F	T	F	F	T	…	F

Overfitting with noise-free data

	training set accuracy	test set accuracy
	100%	50%
	60%	67%

- because the training set is a limited sample, there might be (combinations of) features that are correlated with the target concept by chance

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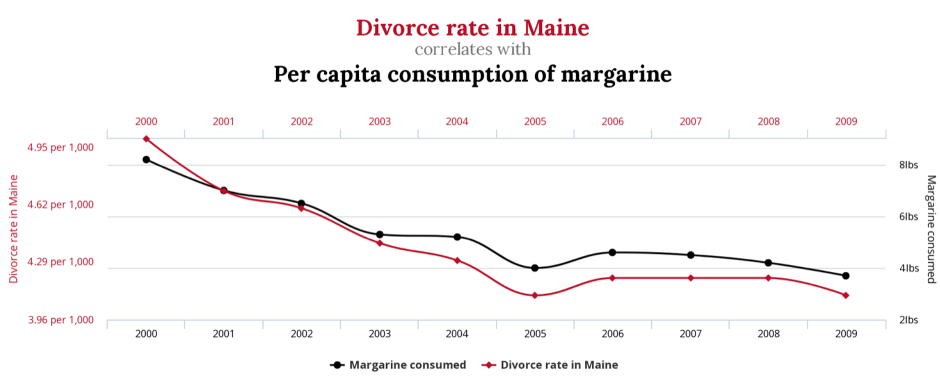

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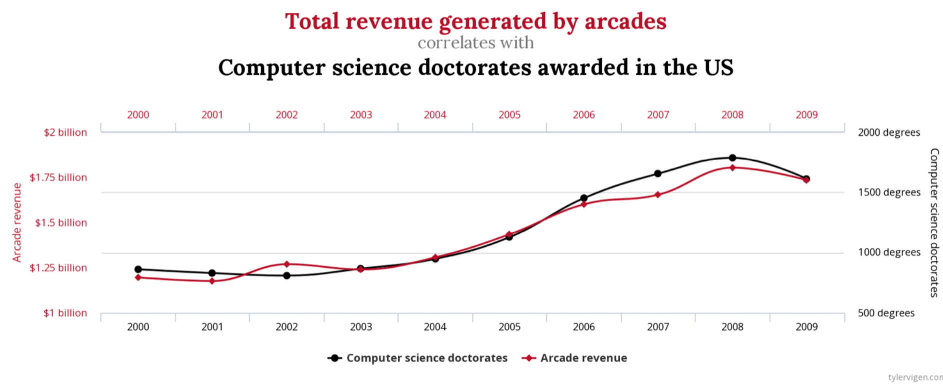

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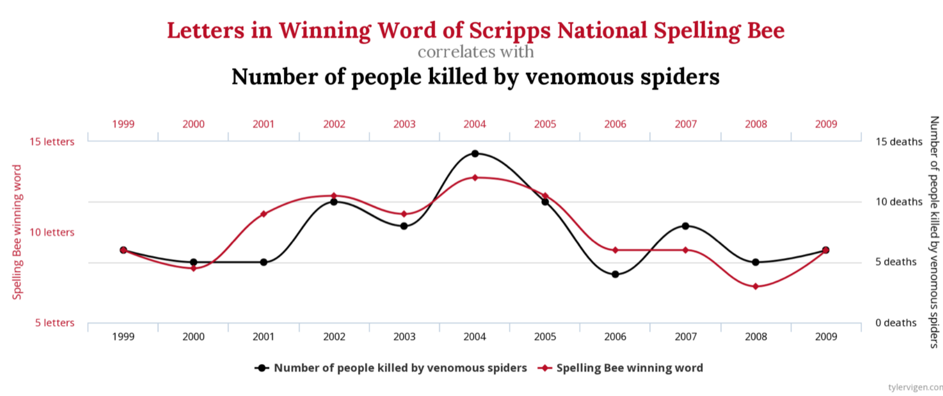
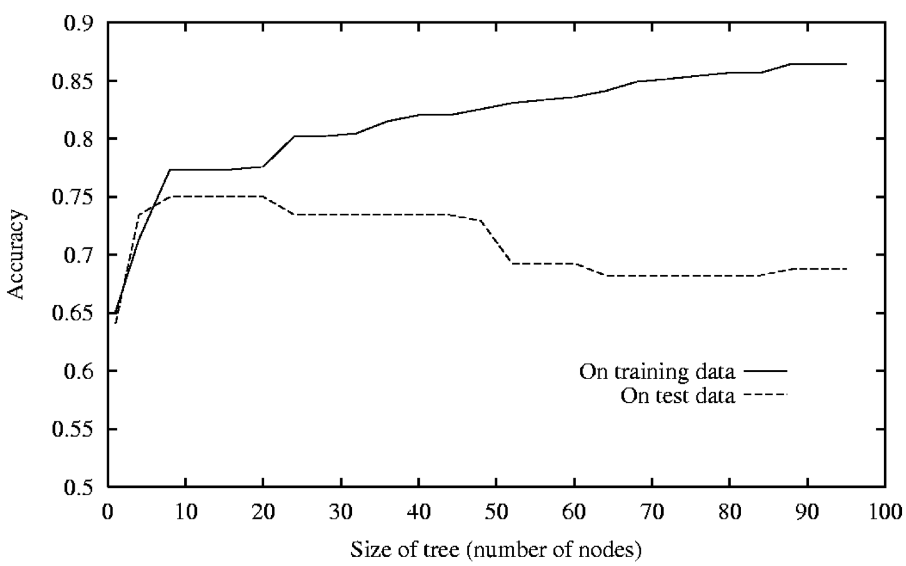


Overfitting in decision trees



Avoiding overfitting in DT learning

two general strategies to avoid overfitting

1. *early stopping*: stop if further splitting not justified by a statistical test
   - Quinlan's original approach in ID3

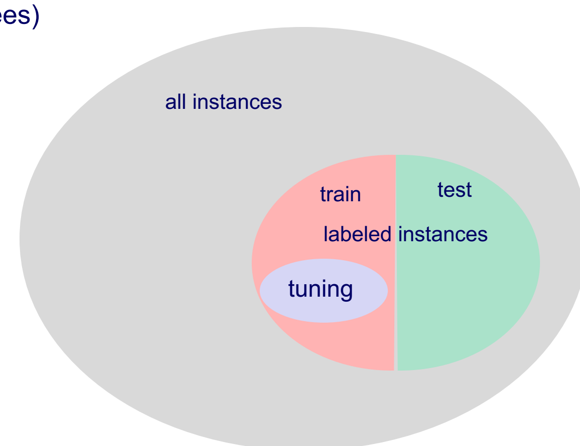
2. *post-pruning*: grow a large tree, then prune back some nodes
   - more robust to myopia of greedy tree learning

Pruning in C4.5

1. split given data into training and *tuning* (*validation*) sets
2. grow a complete tree
3. do until further pruning is harmful
   - evaluate impact on tuning-set accuracy of pruning each node
   - greedily remove the one that most improves tuning-set accuracy

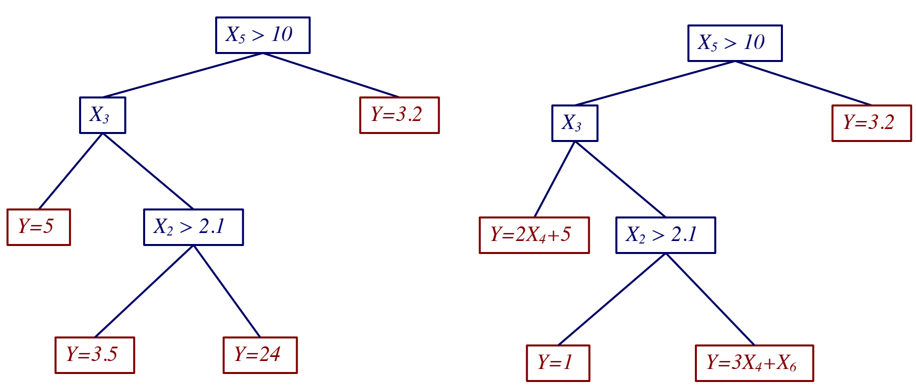
Tuning sets

- a *tuning set* (a.k.a. *validation set*) is a subset of the training set that is held aside
  - not used for primary training process (e.g. tree growing)
  - but used to select among models (e.g. trees pruned to varying degrees)



Regression trees

- in a regression tree, leaves have functions that predict numeric values instead of class labels
- the form of these functions depends on the method
  - CART uses constants
  - some methods use linear functions (model trees)



Regression trees in CART

- CART does *least squares regression* which tries to minimize

$$\sum_{i=1}^{|D|}\left(y^{(i)} - \hat{y}^{(i)}\right)^2 = \sum_{L \in \text{leaves}} \sum_{i \in L}\left(y^{(i)} - \hat{y}^{(i)}\right)^2$$

target value for i^{th} training instance

value predicted by tree for i^{th} training instance (average value of y for training instances reaching the leaf)

- at each internal node, CART chooses the split that most reduces this quantity

Comments on decision tree learning

- widely used approach
- many variations
- fast in practice
- provides humanly comprehensible models when trees are not too big
- insensitive to monotone transformations of numeric features
- standard methods learn axis-parallel hypotheses*
- standard methods not suited to on-line setting*
- usually not among most accurate learning methods

* although variants exist that are exceptions to this