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- Ensemble learning technique
 - multiple base models are combined
 - to improve accuracy and stability
 - to avoid overfitting
- Random forest = set of decision trees
 - a number of decision trees are built at training time
 - the class is assigned by majority voting





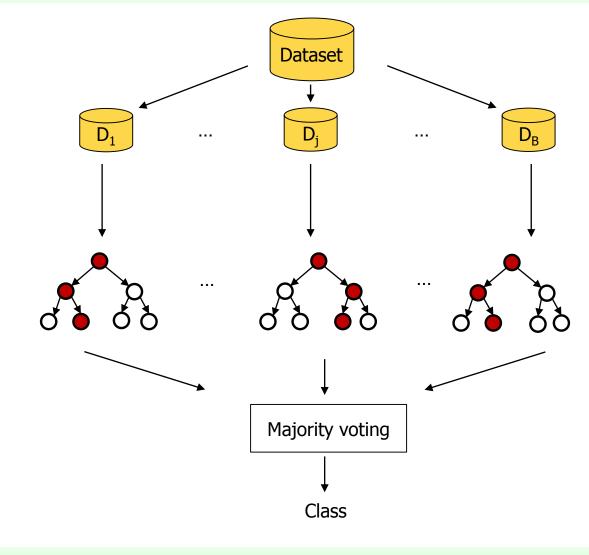
Original Training data

Random subsets

Multiple decision trees

For each subset, a tree is learned on a *random* set of features

Aggregating classifiers







Bootstrap aggregation

- Given a training set D of n instances, it selects B times a random sample with replacement from D and trains trees on these dataset samples
 - For b = 1, ..., B
 - Sample with replacement n' training examples, $n' \le n$
 - A dataset subset D_h is generated
 - Train a classification tree on D_b



Feature Bagging

- Selects, for each candidate split in the learning process, a *random* subset of the features
 - being p the number of features, \sqrt{p} features are typically selected
- Trees are decorrelated
 - Feature subsets are sampled randomly, hence different features could be selected as best attribute for the split





Random Forest – Algorithm Recap

- Given a training set D of n instances with p features
- For b = 1, ..., B
 - Sample randomly with replacement n' training examples. A subset D_b is generated
 - Train a classification tree on D_b
 - During the tree construction, for each candidate split
 - $m \ll p$ random features are selected (typically m $\approx \sqrt{p}$)
 - ullet the best split is computed among these m features
- Class is assigned by majority voting among the B predictions





Strong points

- higher accuracy than decision trees
- fast training phase
- robust to noise and outliers
- provides global feature importance, i.e. an estimate of which features are important in the classification

Weak points

- results can be difficult to interpret
 - A prediction is given by hundreds of trees
 - but at least we have an indication through feature importance

