



Data Mining with Weka

Ensemble learning

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Ensemble learning

Committee structure: build different "experts," let them vote

- ❖ Often improves predictive performance
- ❖ Produces output that is hard to analyze
 - *but: there are approaches that aim to produce a single comprehensible structure*
- ❖ Methods
 - *Bagging*
 - *Randomization*
 - *Boosting*
 - *Stacking*

Ensemble learning

Bagging

- ❖ Several training sets of the same size
 - *produce them by sampling ... with replacement*
- ❖ Build model for each one
 - *use same machine learning scheme*
- ❖ Combine predictions by voting
(or, for regression, averaging)
- ❖ Very suitable for "unstable" learning schemes
 - *small change in training data can make big change in model*
 - *example: decision trees ... but not Naïve Bayes or instance-based learning*
- ❖ Weka: `meta>Bagging`
- ❖ E.g. with `glass.arff`
 - *J48* 66.8%
 - *Bagging (default parameters)* 72.4%

Ensemble learning

Randomization: random forests

- ❖ Randomize the algorithm, not the training data
 - *how you randomize depends on the algorithm*
- ❖ Random forests
 - *attribute selection for J48 decision tree: don't pick the best, pick randomly from the k best options*
 - *generally improves decision trees*
- ❖ Weka: `trees>RandomForests`
 - *options: number of trees (default 10); maximum depth of trees; number of attributes*
- ❖ E.g. with `glass.arff`
 - J48 66.8%
 - RandomForests (default parameters) 75.2%

Ensemble learning

Boosting

- ❖ Iterative: new models are influenced by performance of previously built ones
 - *extra weight for instances that are misclassified ("hard" ones)*
 - *encourage new model to become an "expert" for instances misclassified by earlier models*
 - *Intuitive justification: committee members should complement each other's expertise*
- ❖ Uses voting (or, for regression, averaging)
 - *but weights models according to their performance*
- ❖ Often dramatically improves performance
- ❖ Weka: `meta>AdaBoostM1`
- ❖ E.g. with `glass.arff`

– J48	66.8%
– AdaBoostM1 (using J48)	74.3%

Ensemble learning

Stacking

- ❖ Combine predictions of base learners using a *meta learner* (not voting)
 - *base learners: level-0 models*
 - *meta learner: level-1 model*
 - *predictions of base learners are input to meta learner*
- ❖ Base learners are usually different schemes
- ❖ Can't use predictions on training data to generate data for level-1 model!
 - *Instead use cross-validation-like scheme*
- ❖ Weka: **meta>Stacking**
 - and **StackingC**, more efficient version
 - *allow multiple level-0 models (by specifying a metaclassifier)*
- ❖ Quite hard to make stacking work well, but with **glass.arff** I got
 - J48 66.8%
 - StackingC: default metaclassifier + base classifiers IBk, PART, J48 72.5%

Ensemble learning

- ❖ Combining multiple models into "ensembles"
 - analogy with committees of humans
- ❖ Diversity helps, especially with "unstable" learners
 - when small changes in the training data can produce large changes in the learned model
- ❖ Create diversity by
 - Bagging: resampling the training set meta>Bagging
 - Random forests: alternative branches in decision trees trees>RandomForests
 - Boosting: focus on where the existing model makes errors meta>AdaBoostM1
 - Stacking: combine results using another learner (instead of voting) meta>Stacking