CS 391L: Machine Learning: Ensembles

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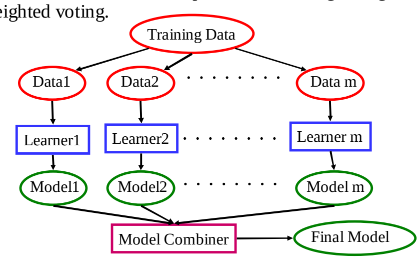
Learning Ensembles

- Learn multiple alternative definitions of a concept using different training data or different learning algorithms.
- Combine decisions of multiple definitions, e.g. using weighted voting.



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Value of Ensembles

- When combing multiple ***independent*** and ***diverse*** decisions each of which is at least more accurate than random guessing, random errors cancel each other out, correct decisions are reinforced.
- Human ensembles are demonstrably better
  - How many jelly beans in the jar?: Individual estimates vs. group average.
  - Who Wants to be a Millionaire: Expert friend vs. audience vote.

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Homogenous Ensembles

- Use a single, arbitrary learning algorithm but manipulate training data to make it learn multiple models.
  - Data1 ≠ Data2 ≠ … ≠ Data m
  - Learner1 = Learner2 = … = Learner m
- Different methods for changing training data:
  - Bagging: Resample training data
  - Boosting: Reweight training data
  - DECORATE: Add additional artificial training data
- In WEKA, these are called ***meta-learners***, they take a learning algorithm as an argument (***base learner***) and create a new learning algorithm.

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Bagging

- Create ensembles by repeatedly randomly resampling the training data (Brieman, 1996).
- Given a training set of size *n*, create *m* samples of size *n* by drawing *n* examples from the original data, ***with replacement***.
  - Each ***bootstrap sample*** will on average contain 63.2% of the unique training examples, the rest are replicates.
- Combine the *m* resulting models using simple majority vote.
- Decreases error by decreasing the variance in the results due to ***unstable learners***, algorithms (like decision trees) whose output can change dramatically when the training data is slightly changed.

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Boosting

- Originally developed by computational learning theorists to guarantee performance improvements on fitting training data for a ***weak learner*** that only needs to generate a hypothesis with a training accuracy greater than 0.5 (Schapire, 1990).
- Revised to be a practical algorithm, AdaBoost, for building ensembles that empirically improves generalization performance (Freund & Shapire, 1996).
- Examples are given weights. At each iteration, a new hypothesis is learned and the examples are reweighted to focus the system on examples that the most recently learned classifier got wrong.

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Boosting: Basic Algorithm

- General Loop:

  Set all examples to have equal uniform weights.
  For t from 1 to T do:
  Learn a hypothesis, h_t, from the weighted examples
  Decrease the weights of examples h_t classifies correctly
- Base (weak) learner must focus on correctly classifying the most highly weighted examples while strongly avoiding over-fitting.
- During testing, each of the T hypotheses get a weighted vote proportional to their accuracy on the training data.

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AdaBoost Pseudocode

TrainAdaBoost(D, BaseLearn)
For each example d_i in D let its weight w_i=1/|D|
Let H be an empty set of hypotheses
For t from 1 to T do:
Learn a hypothesis, h_t, from the weighted examples: h_t=BaseLearn(D)
Add h_t to H
Calculate the error, ε_t, of the hypothesis h_t as the total sum weight of the examples that it classifies incorrectly.
If $\varepsilon_t > 0.5$ then exit loop, else continue.
Let $\beta_t = \varepsilon_t \ / \ (1 - \varepsilon_t)$
Multiply the weights of the examples that h_t classifies correctly by β_t
Rescale the weights of all of the examples so the total sum weight remains 1.
Return H

TestAdaBoost(ex, H)
Let each hypothesis, h_t, in H vote for ex's classification with weight log(1/ β_t)
Return the class with the highest weighted vote total.

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Learning with Weighted Examples

- Generic approach is to replicate examples in the training set proportional to their weights (e.g. 10 replicates of an example with a weight of 0.01 and 100 for one with weight 0.1).
- Most algorithms can be enhanced to efficiently incorporate weights directly in the learning algorithm so that the effect is the same (e.g. implement the WeightedInstancesHandler interface in WEKA).
- For decision trees, for calculating information gain, when counting example i, simply increment the corresponding count by w_i rather than by 1.

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Experimental Results on Ensembles
(Freund & Schapire, 1996; Quinlan, 1996)

- Ensembles have been used to improve generalization accuracy on a wide variety of problems.
- On average, Boosting provides a larger increase in accuracy than Bagging.
- Boosting on rare occasions can degrade accuracy.
- Bagging more consistently provides a modest improvement.
- Boosting is particularly subject to over-fitting when there is significant noise in the training data.

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DECORATE
(Melville & Mooney, 2003)

- Change training data by adding new artificial training examples that encourage diversity in the resulting ensemble.
- Improves accuracy when the training set is small, and therefore resampling and reweighting the training set has limited ability to generate diverse alternative hypotheses.

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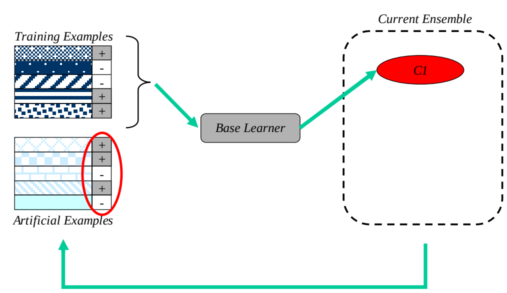
Overview of DECORATE



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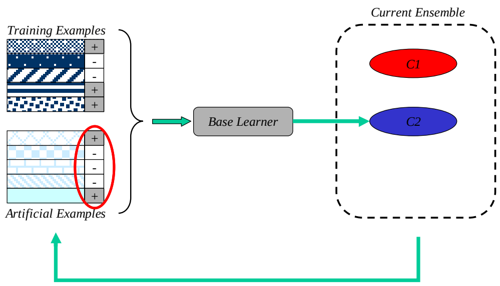
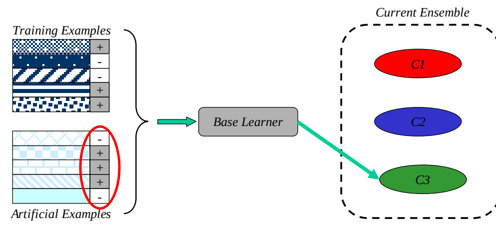


Overview of DECORATE



Ensembles and Active Learning

- Ensembles can be used to actively select good new training examples.
- Select the unlabeled example that causes the most disagreement amongst the members of the ensemble.
- Applicable to any ensemble method:
  - QueryByBagging
  - QueryByBoosting
  - ActiveDECORATE

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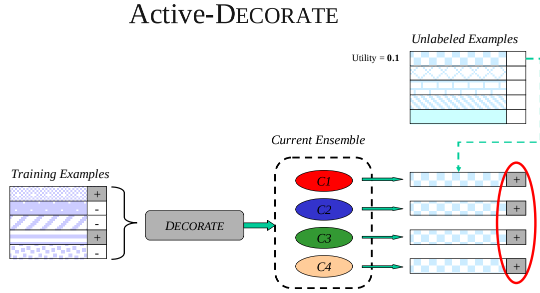
Active-DECORATE



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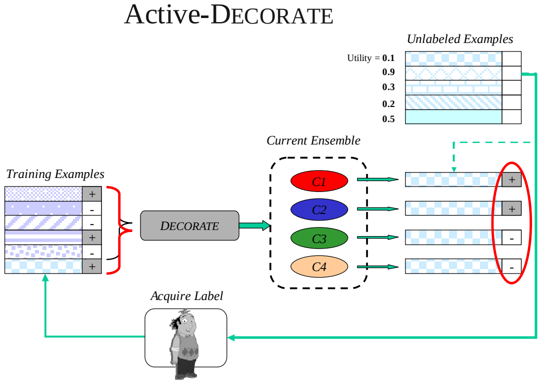
Active-DECORATE



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Issues in Ensembles

- Parallelism in Ensembles: Bagging is easily parallelized, Boosting is not.
- Variants of Boosting to handle noisy data.
- How “weak” should a base-learner for Boosting be?
- What is the theoretical explanation of boosting’s ability to improve generalization?
- Exactly how does the diversity of ensembles affect their generalization performance.
- Combining Boosting and Bagging.

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