CS685: Data Mining
Ensemble Methods

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- Classifiers of same or different types can be combined
- Same type: bagging, boosting
- Different type: stacking
- Assumes *no* class imbalance problem, i.e., classes are almost equally represented

Bagging

- Short form of bootstrap aggregating
- Suppose, initial training set size is d
- Create another training set of *same* size d by *sampling with replacement*
  - Equivalent to deleting some objects and replicating some others
- Repeat t times
- Build t classifiers of the *same* type on each of the training samples
- Use majority voting on the t classifiers for final classification

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- Random forests can be considered as a type of bagging

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- Thus, probability of *not* being chosen at all in any of the d tries is $(1 - 1/d)^d$
- For large d, $(1 - 1/d)^d \to 1/e = 0.368$
- Hence, probability that an object is chosen at least once, i.e., it is represented in the sample is $1 - 0.368 = 0.632$
- Hence, the method is called 0.632 bootstrap

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- Models are *not* built independently
- Each model is built *successively* on the previous ones
- Each new model concentrates more on the training objects mis-classified by previous models
- Each training set is of the *same* size d and is constructed using *sampling with replacement*

Adaboost

- A popular boosting algorithm is Adaboost
- Each training object is weighted (initially with the same weight)
- For a model, the *error* in classification is computed as the ratio of the sum of weights of mis-classified objects to total weight
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- For the next model, sampling with replacement is done using the new weights as probabilities

Updating the Weights

- Initially, the weights of training objects are same
- Thus, model 1 is built by simple sampling with replacement from training set
- Weights of all *correctly* classified objects are modified using the error e of the model

$$w(q) = w(q) \times \frac{e}{(1-e)} \text{ where } q \text{ is correctly classified}$$

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- Sampling is repeated till a suitable stopping criterion
- Final models are weighted for majority voting according to $log \frac{1-e_i}{e_i}$ where e_i is the error of model i

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- Bagging is simple
- Boosting progressively concentrates on harder training objects
- Boosting may overfit
- Assumes no *class imbalance*
- If a class is under-represented, it has to be *over-sampled*
- If a class is over-represented, it has to be *under-sampled*
- May need to take into account the relative populations while computing the mis-classification error

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- Individual classifiers are models of level 0
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- Level-1 classifier uses *only* the outputs of level-0 models, i.e., just their class labels and *not* the attributes of the training objects
- May use errors as well
- Level-1 classifier is thus just an arbiter
- It should be simple

Stacking

- For better results, training sample is divided into two parts D_0 and D_1
- Level-0 classifiers are trained using *only* D_0 and *not* D_1
- Level-1 classifier is trained using *only* D_1 and *not* D_0
  - D_1 training objects are simply passed through level-0 classifiers to get their outputs
  - These outputs act as inputs to the level-1 classifier
  - D_1 is not used for *training* level-0 classifiers at all