GENERAL ASSEMBLY

INTRO TO DATA SCIENCE

LECTURE 13: ENSEMBLE TECHNIQUES

LAST TIME:

- DIMENSIONALITY REDUCTION
- PRINCIPAL COMPONENT ANALYSIS

QUESTIONS?

I. ENSEMBLE TECHNIQUES
II. PROBLEMS IN CLASSIFICATION
III. BAGGING
IV. BOOSTING
V. RANDOM FORESTS

EXERCISE:
VI. RANDOM FORESTS

I. ENSEMBLE TECHNIQUES

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NOTE

Base classifiers and ensemble classifiers are sometimes called *weak learners* and *strong learners*.

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NOTE

Ideally, we would also like the base classifiers to be *unstable* to variations in the training set.

In other words, *high variance*.

II. PROBLEMS IN CLASSIFICATION

In any supervised learning task, our goal is to make predictions of the true classification function f *by learning the classifier* h.

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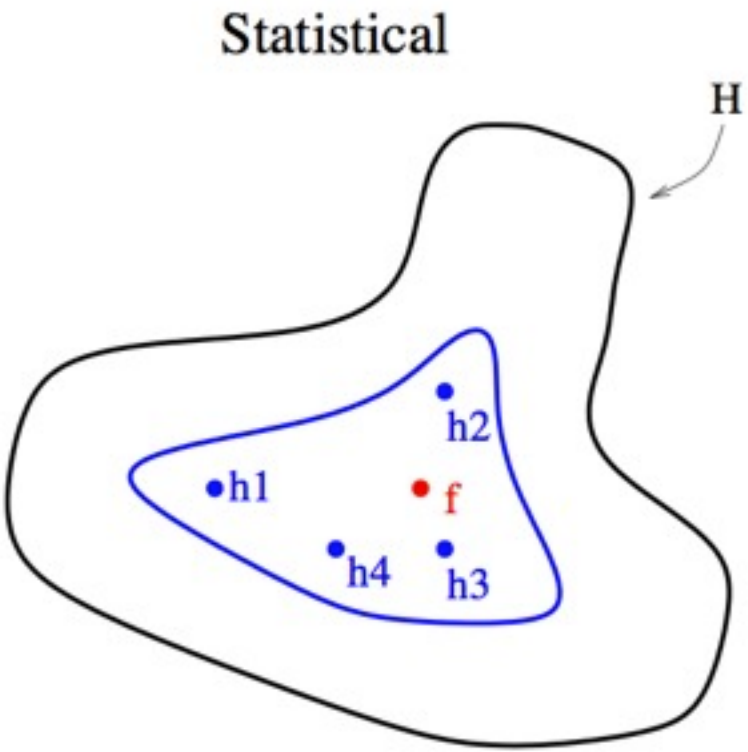
There are three main problems that can prevent this:

- *statistical problem*
- *computational problem*
- *representational problem*

If the amount of training data available is small, the base classifier will have difficulty converging to h.

An ensemble classifier can mitigate this problem by "averaging out" base classifier predictions to improve convergence.



NOTE

The true function *f* is best approximated as an average of the base classifiers.

source: http://www.cs.iastate.edu/~jtian/cs573/Papers/Dietterich-ensemble-00.pdf

Even with sufficient training data, it may still be computationally difficult to find the best classifier h.

For example, if our base classifier is a decision tree, an exhaustive search of the hypothesis space of all possible classifiers is extremely complex (NP-complete).

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NOTE

Recall that this is why we used a *heuristic algorithm* (greedy search).

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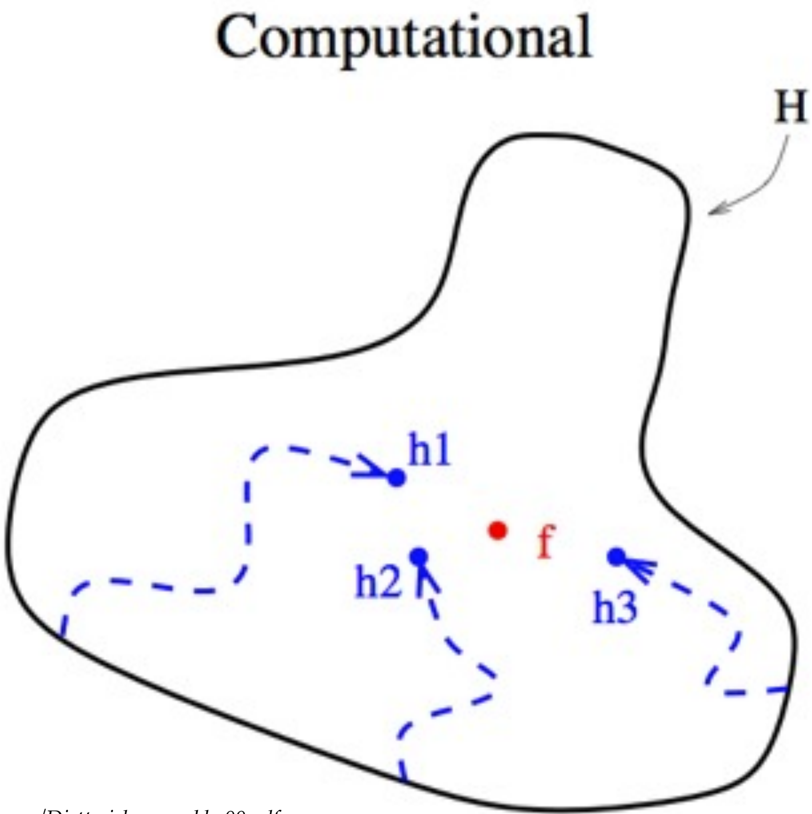
For example, if our base classifier is a decision tree, an exhaustive search of the hypothesis space of all possible classifiers is extremely complex (NP-complete).

An ensemble composed of several BC's with different starting points can provide a better approximation to f than any individual BC.



source: *http://www.cs.iastate.edu/~jtian/cs573/Papers/Dietterich-ensemble-00.pdf*

NOTE

The true function *f* is often best approximated by using several starting points to explore the hypothesis space.

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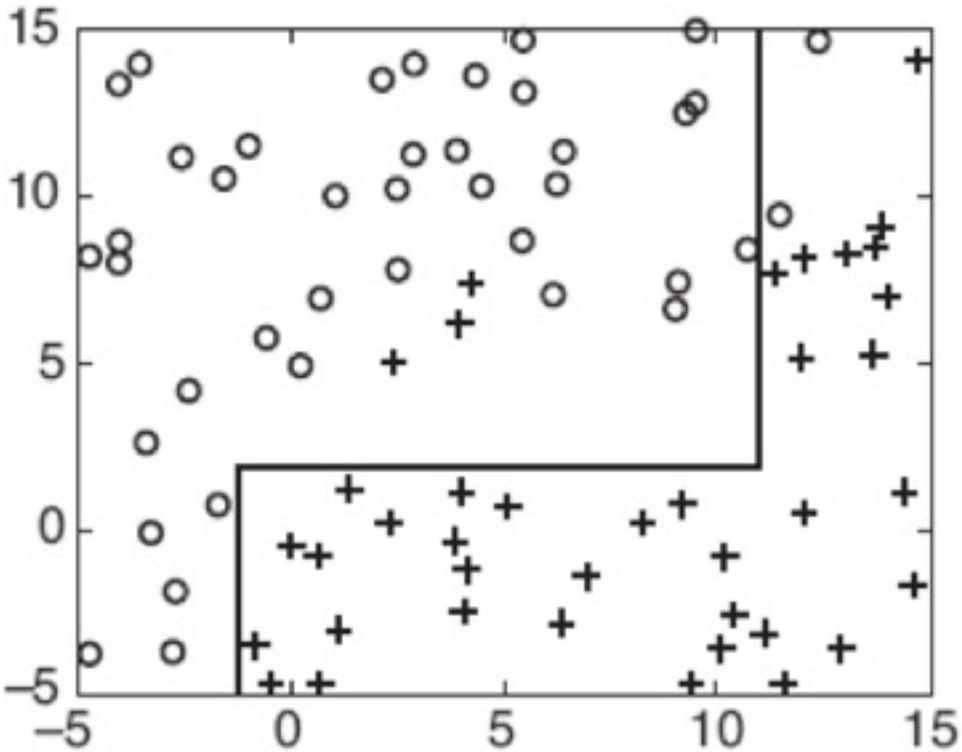
A decision tree works by forming a rectilinear partition of the feature space.

THE REPRESENTATIONAL PROBLEM – 2D DECISION TREE



NOTE

What is a *rectilinear* decision boundary?

One whose segments are *orthogonal* to the x & y axes.

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Then it cannot be represented by finitely many rectilinear segments, and therefore the true decision boundary cannot be obtained by a decision tree classifier.

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However, it may be still be possible to approximate f or even to expand the space of representable functions using ensemble methods.

THE REPRESENTATIONAL PROBLEM – APPROXIMATION

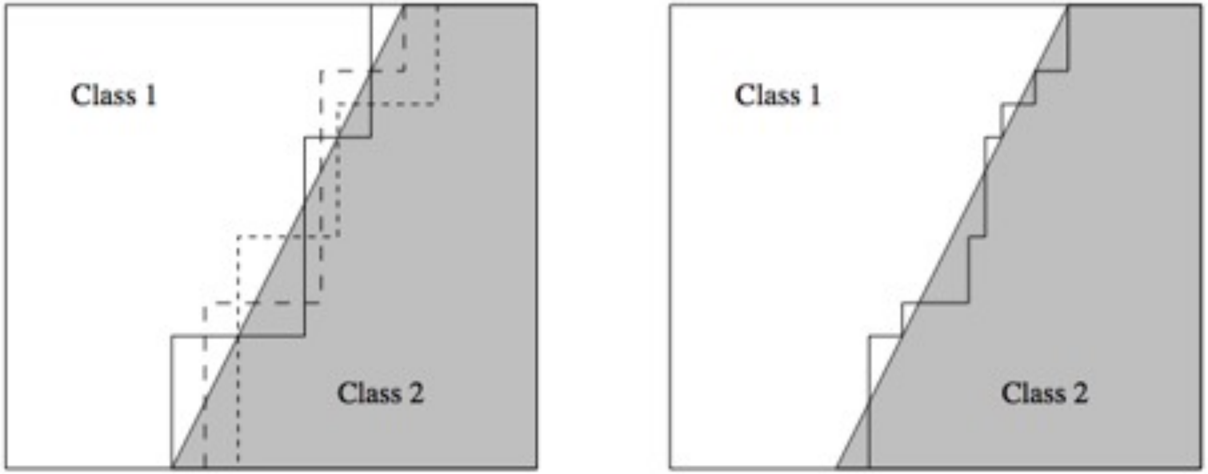
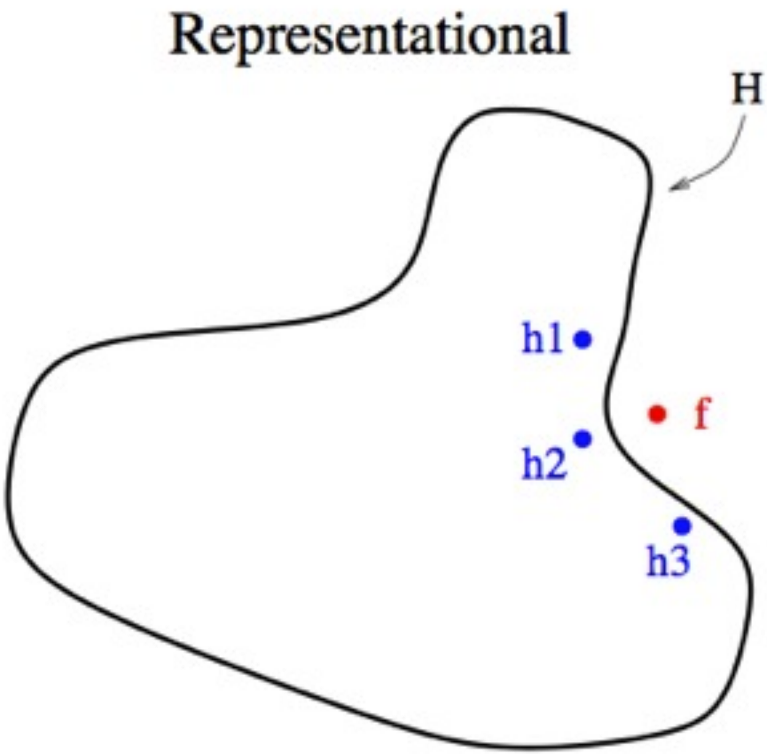


Fig. 4. The left figure shows the true diagonal decision boundary and three staircase approximations to it (of the kind that are created by decision tree algorithms). The right figure shows the voted decision boundary, which is a much better approximation to the diagonal boundary.

NOTE

An ensemble of decision trees can approximate a diagonal decision boundary.



NOTE

Ensemble classifiers can be effective even if the true decision boundary lies outside the hypothesis space.

Q: How do you create an ensemble classifier?

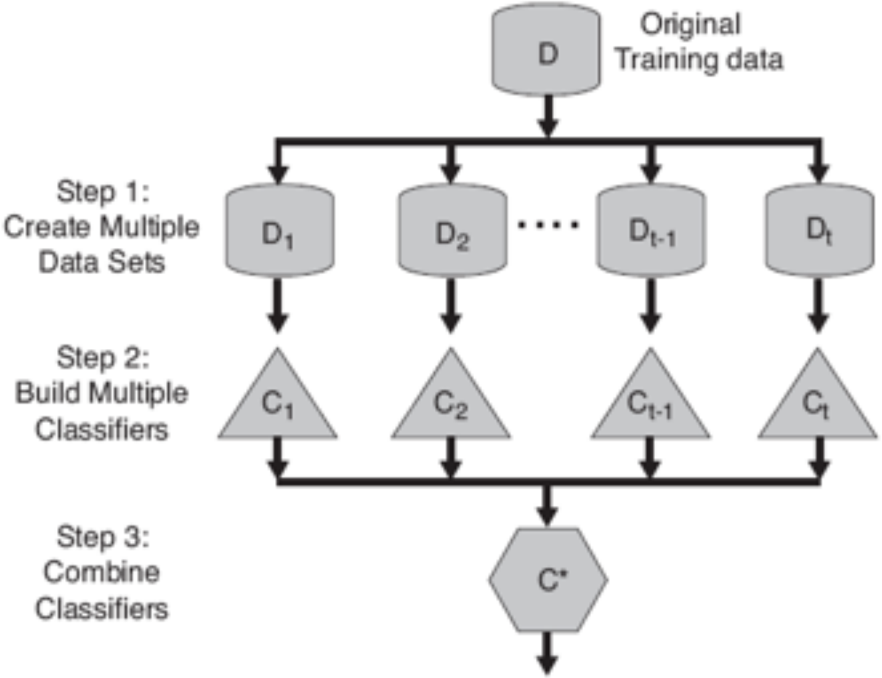


Figure 5.31. A logical view of the ensemble learning method.

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A: There are several ways to do this:

- *manipulating the training set*
- *manipulating the output labels*
- *manipulating the learning algorithm itself*

We will talk about a few examples of each of these.

III. BAGGING

Bagging *(bootstrap aggregating) is a method that involves manipulating the training set by* **resampling***.*

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We learn k base classifiers on k different samples of training data.

These samples are independently created by resampling the training data using uniform weights (eg, a uniform **sampling distribution***).*

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Each training sample is the same size as the original training set.

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Resampling means that some training records may appear in a sample more than once, or even not at all.

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We learn k *base classifiers on* k *different samples of training data.*

These samples are independently created by resampling the training data using uniform weights (eg, a uniform **sampling distribution***).*

The final prediction is made by taking a majority vote across bc's.

Bagging reduces the variance in our generalization error by aggregating multiple base classifiers together (provided they satisfy our earlier requirements).

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If the base classifier is stable, then the ensemble error is primarily due to bc bias, and bagging may not be effective.

Since each sample of training data is equally likely, bagging is not very susceptible to overfitting with noisy data.

IV. BOOSTING

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NOTE

The bc's focus more and more closely on records that are difficult to classify as the sequence of iterations progresses.

Thus the bc's are faced with progressively more difficult learning problems.

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These omitted records will likely be misclassified, and given greater weight in subsequent iterations once the sampling distribution is updated.

So even if a record is left out at one stage, it will be emphasized later.

Updating the sampling distribution and forming an ensemble prediction leads to a nonlinear combination of the base classifiers.

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By explicitly trying to optimize the weighted ensemble vote, boosting attacks the representation problem head-on.

V. RANDOM FORESTS

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For a small number of features, we can also create linear combinations of features and select splits from the enhanced feature set (Forest-RC).

Or, we can select splitting features completely at random (Forest-RI).

Random forests are about as accurate as AdaBoost, more robust to noise, and can also have better runtime than other ensemble methods (since the feature space is reduced in some cases).

Wisdom of Crowds

IBM's WATSON

Nate Silver's election models

Kaggle competitions

EX: ENSEMBLE METHODS IN SCIKIT-LEARN