GENERAL ASSEMBLY

INTRO TO DATA SCIENCE

LECTURE 10: ENSEMBLE TECHNIQUES

Francesco Mosconi

DAT16 SF // August 31, 2015

DATA SCIENCE IN THE NEWS

An example machine learning notebook

Notebook by Randal S. Olson

Supported by Jason H. Moore

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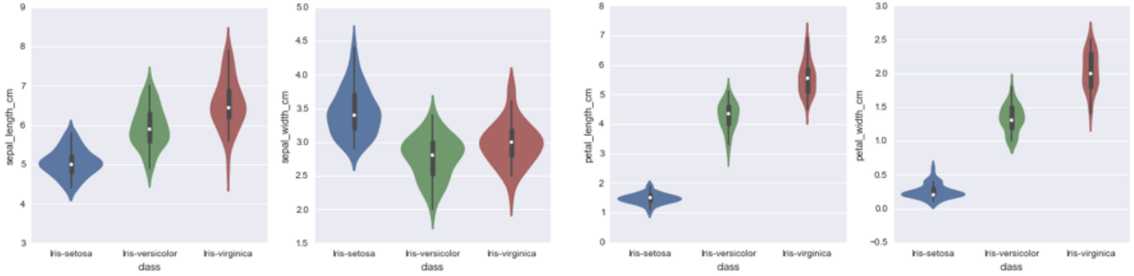
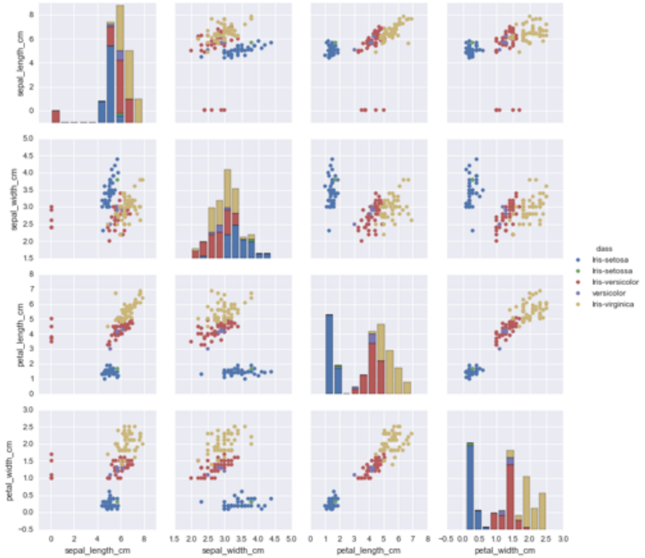
It is recommended to view this notebook in nbviewer for the best viewing experience.





https://github.com/rhiever/Data-Analysis-and-Machine-Learning-Projects/blob/master/example-data-science-notebook/Example%20Machine%20Learning%20Notebook.ipynb

Generating Poetry with PoetRNN

Aug 11, 2015

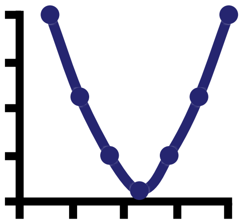
> *sunset home*
> *the bird of windows*
> *white the hand*

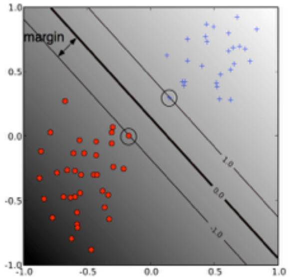
> *rain pond*
> *the light of shadow*
> *of the song*

http://sballas8.github.io/2015/08/11/Poet-RNN.html

LAST TIME:

I. SUPPORT VECTOR MACHINES (SVM)
II. LAB ON SVM
III. DECISION TREES
IV. LAB ON DECISION TREES





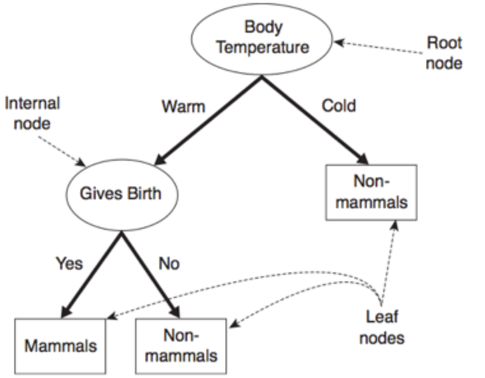


Figure 4.4. A decision tree for the mammal classification problem.

QUESTIONS?

WHAT WAS THE MOST INTERESTING THING YOU LEARNT?

WHAT WAS THE HARDEST TO GRASP?

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

EXERCISE:
VI. LAB

KEY OBJECTIVES

- UNDERSTAND THE POWER OF USING ENSEMBLE CLASSIFIERS
- KNOW THE DIFFERENCE BETWEEN A BASE CLASSIFIER AND AN ENSEMBLE CLASSIFIER
- UNDERSTAND WHAT BAGGING IS AND BE ABLE TO DESCRIBE IT
- UNDERSTAND WHAT BOOSTING IS AND BE ABLE TO DESCRIBE IT
- UNDERSTAND WHAT A RANDOM FOREST IS AND BE ABLE TO USE IT

I. ENSEMBLE TECHNIQUES

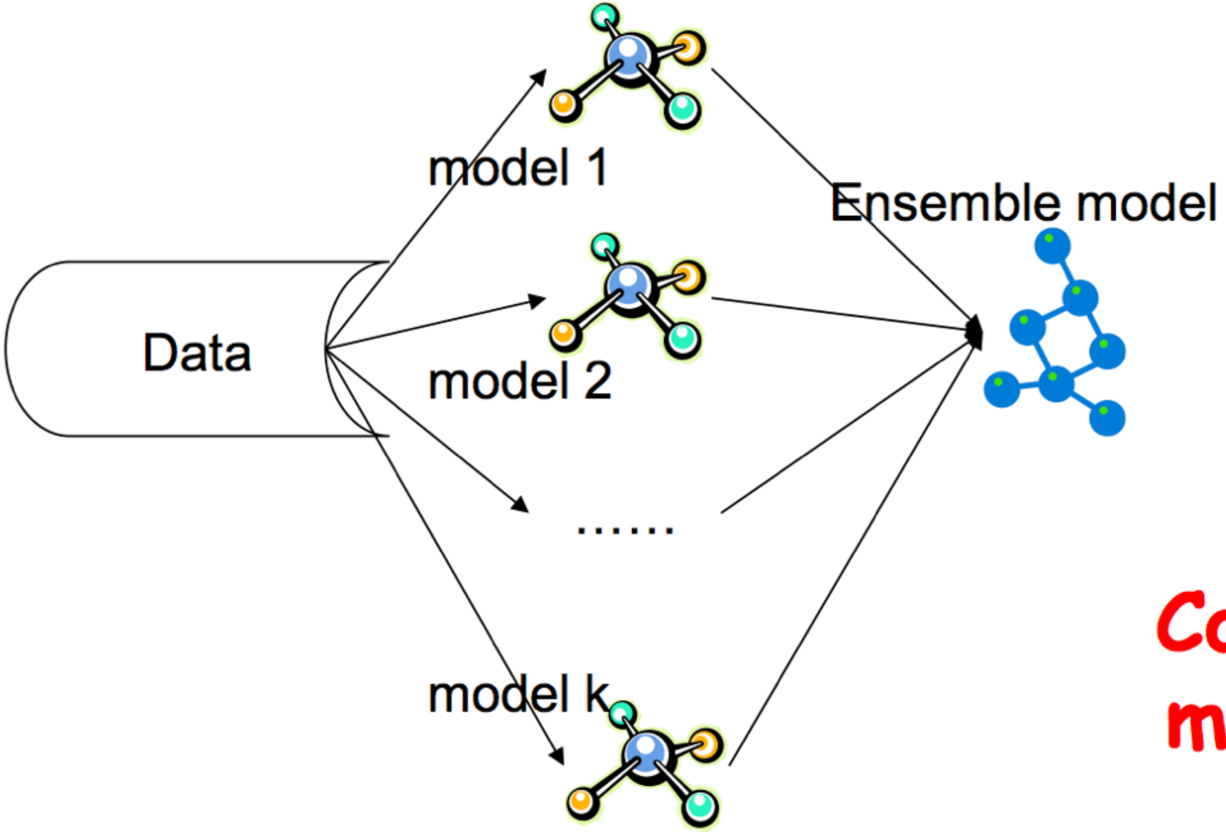
So far, we have only discussed individual classifiers

What are these?

What is your favorite?

How can we come up with a better model?

Can we combine multiple classifiers to produce a better classifier?



Combine multiple models into one!

source: http://www.cse.buffalo.edu/~jing/sdm10ensemble.htm

MOTIVATOR FROM LECTURE 1

NETFLIX CHALLENGE

award $1 million to anyone who can improve movie recommendation by 10%

Supervised learning task

– Training data is a set of users and ratings (1,2,3,4,5 stars) those users have given to movies.

source: http://www.cse.buffalo.edu/~jing/sdm10ensemble.htm

Supervised learning task

– Construct a classifier that given a user and an unrated movie, correctly classifies that movie as either 1, 2, 3, 4, or 5 stars

source: http://www.cse.buffalo.edu/~jing/sdm10ensemble.htm

At first, single-model methods are developed, and performances are improved

source: http://www.cse.buffalo.edu/~jing/sdm10ensemble.htm

However, improvements slowed down

source: http://www.cse.buffalo.edu/~jing/sdm10ensemble.htm

Later, individuals and teams merged their results, and significant improvements are observed

source: http://www.cse.buffalo.edu/~jing/sdm10ensemble.htm

Leaderboard

Rank	Team Name	Best Test Score	% Improvement	Best Submit Time
Grand Prize - RMSE = 0.8567 - Winning Team: BellKor's Pragmatic Chaos				
1	BellKor's Pragmatic Chaos	0.8567	10.06	2009-07-26 18:18:28
2	The Ensemble	0.8567	10.06	2009-07-26 18:38:22
3	Grand Prize Team	0.8582	9.90	2009-07-10 21:24:40
4	Opera Solutions and Vandelay United	0.8588	9.84	2009-07-10 01:12:31
5	Vandelay Industries !	0.8591	9.81	2009-07-10 00:32:20
6	PragmaticTheory	0.8594	9.77	2009-06-24 12:06:56
7	BellKor in BigChaos	0.8601	9.70	2009-05-13 08:14:09
8	Dace_	0.8612	9.59	2009-07-24 17:18:43
9	Feeds2	0.8622	9.48	2009-07-12 13:11:51
10	BigChaos	0.8623	9.47	2009-04-07 12:33:59
12	BellKor	0.8624	9.46	2009-07-26 17:19:11
Progress Prize 2008 - RMSE = 0.8627 - Winning Team: BellKor in BigChaos				
13	xiangliang	0.8642	9.27	2009-07-15 14:53:22
14	Gravity	0.8643	9.26	2009-04-22 18:31:32
15	Ces	0.8651	9.18	2009-06-21 19:24:53
Progress Prize 2007 - RMSE = 0.8723 - Winning Team: KorBell				
Cinematch score - RMSE = 0.9525				

"Our final solution (RMSE=0.8712) consists of blending 107 individual results. "

"Predictive accuracy is substantially improved when blending multiple predictors. Our experience is that most efforts should be concentrated in deriving substantially different approaches, rather than refining a single technique. "

source: http://www.cse.buffalo.edu/~jing/sdm10ensemble.htm

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A: Methods of improving classification accuracy by aggregating predictions over several base classifiers.

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NOTE

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

In order for an ensemble classifier to outperform a single base classifier, the following conditions must be met:

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1) **accuracy**: *base classifiers outperform random guessing*

2) **diversity**: *misclassifications must occur on different training examples*

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1) **accuracy**: *low bias*

2) **diversity**: *uncorrelated*

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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.

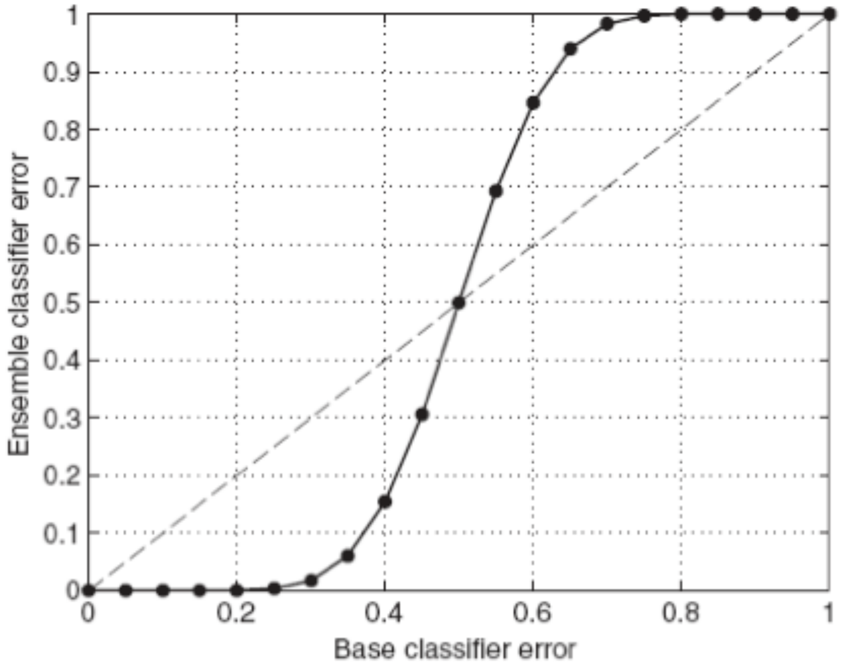

Figure 5.30. Comparison between errors of base classifiers and errors of the ensemble classifier.

NOTE

dashed line = perfectly correlated bc's (no improvement using ensemble)

solid line = perfectly uncorrelated bc's (some improvement for unbiased bc's)

Quick check

what base classifiers would you combine to have very different perspectives?

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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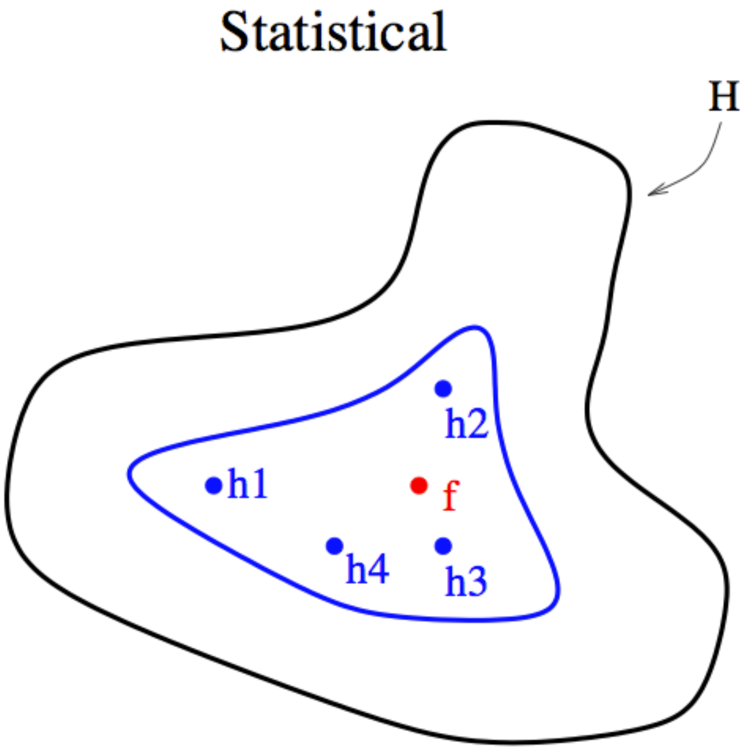
There are three main problems that can prevent this:

- *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.

THE STATISTICAL PROBLEM



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

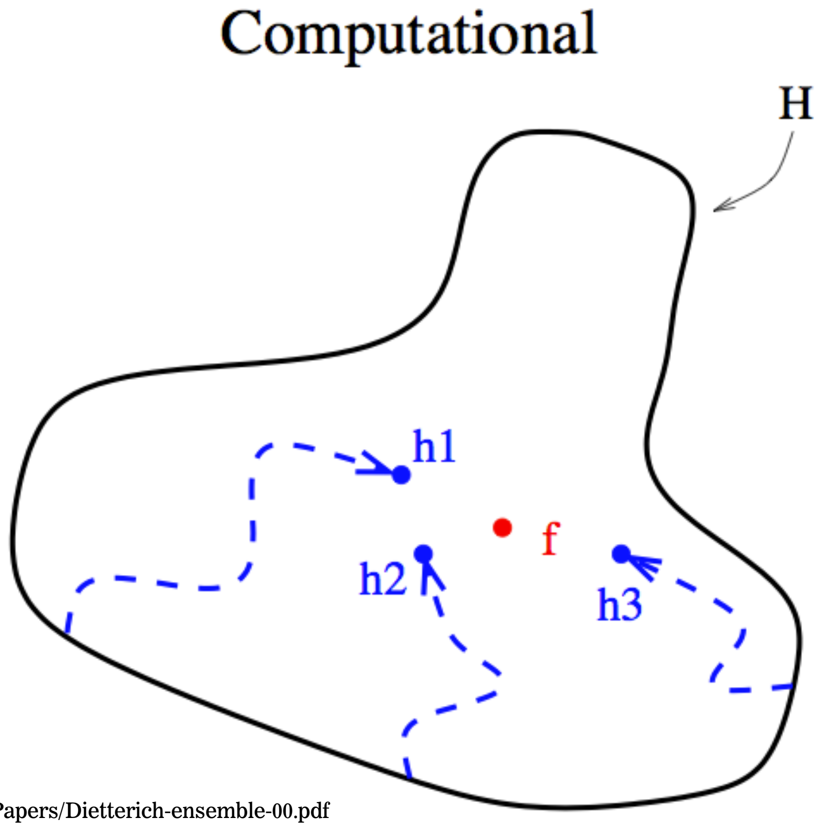
Recall that this is why we used a heuristic algorithm (greedy search).

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).

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

THE COMPUTATIONAL PROBLEM



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.

Sometimes f *cannot be expressed in terms of our hypothesis at all.*

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To illustrate this, suppose we use a decision tree as our base classifier.

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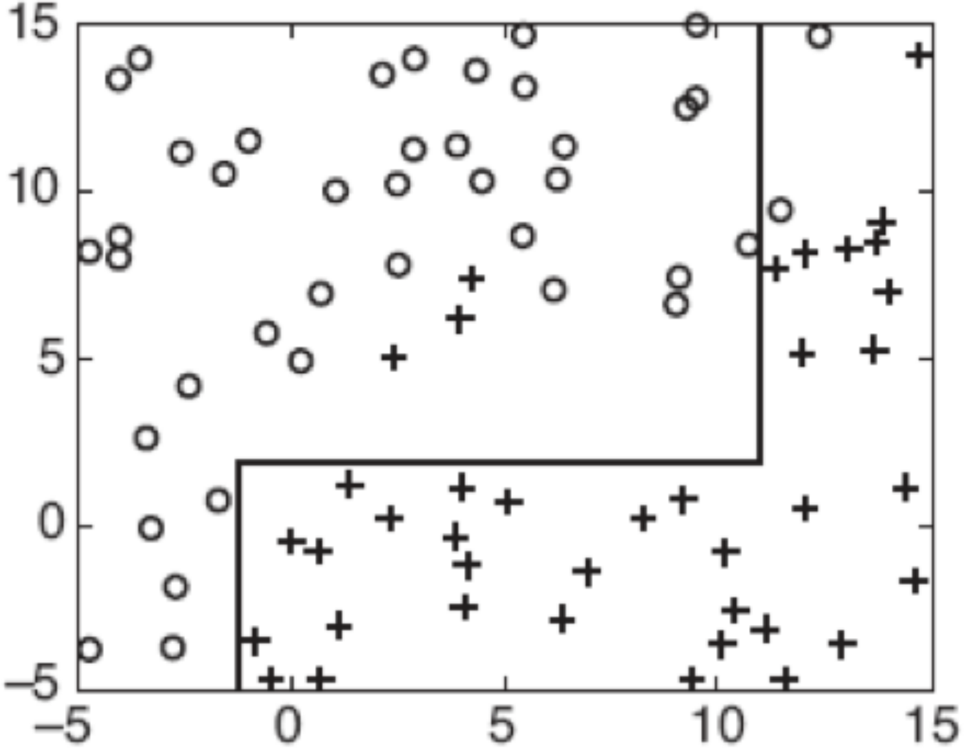
A decision tree works by forming a rectilinear partition of the feature space.

THE REPRESENTATIONAL PROBLEM – 2D DECISION TREE



NOTE

What is a rectilinear decision boundary?

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

But what if f *is a diagonal line?*

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

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

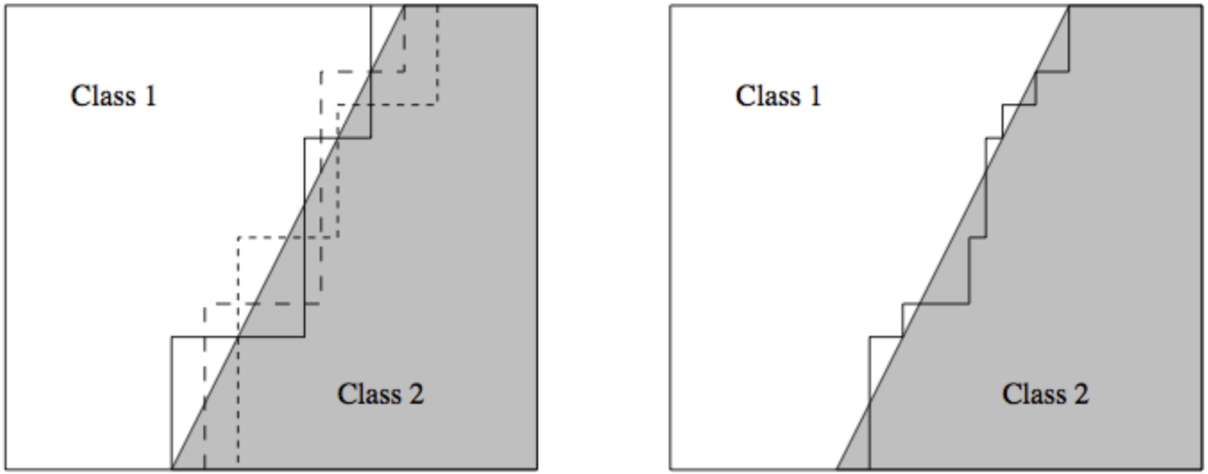
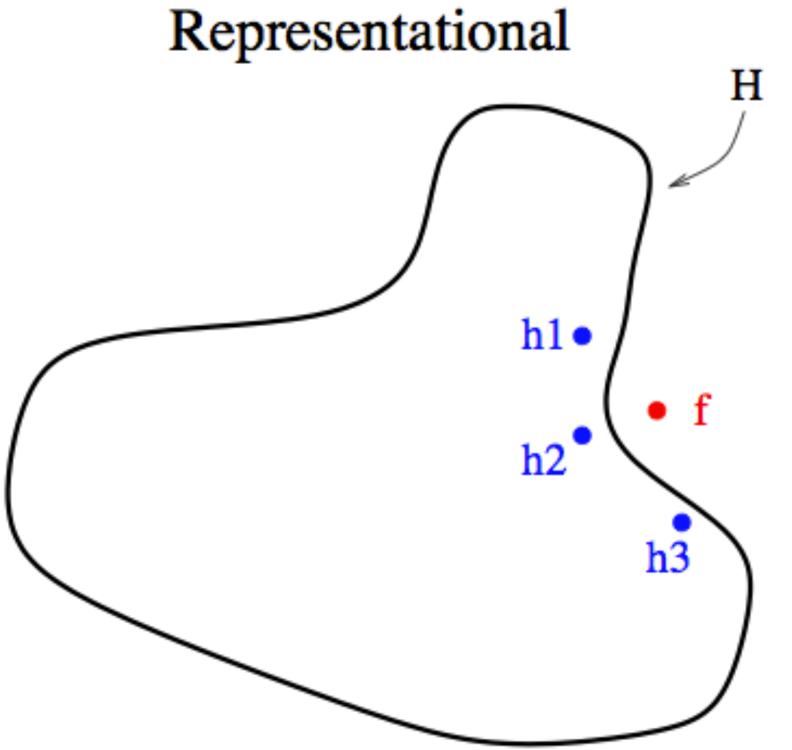


Fig. 4. The left figure shows the true diagonal decision boundary and three staircase approximations to it (of the kind that are created by decision tree algorithms). The right figure shows the voted decision boundary, which is a much better approximation to the diagonal boundary.

NOTE

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

THE REPRESENTATIONAL PROBLEM – EXPANDING THE HYPOTHESIS SPACE



NOTE

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

CREATING AN ENSEMBLE PREDICTION

Q: How do you create an ensemble classifier?

CREATING AN ENSEMBLE PREDICTION

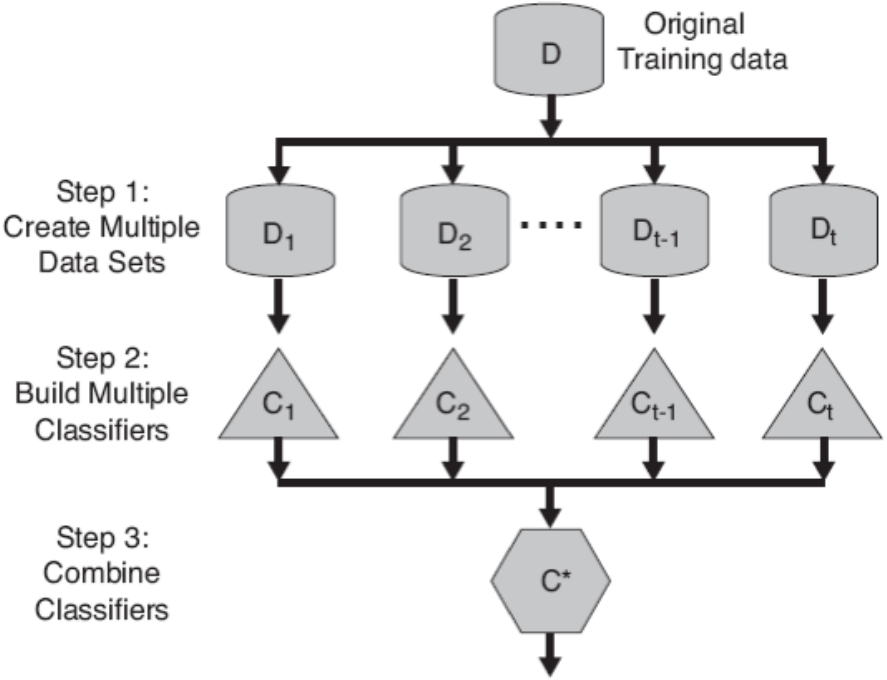


Figure 5.31. A logical view of the ensemble learning method.

Q: How do you generate several base classifiers?

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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.

Quick check

What could go wrong when you use decision trees for classification?

How could you mitigate the problem?

Discuss with the person next to you

LAB 1

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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NOTE

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

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NOTE

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 EXAMPLE

Original	1	2	3	4	5	6	7	8
Training set 1	2	7	8	3	7	6	3	1
Training set 2	7	8	5	6	4	2	7	1
Training set 3	3	6	2	7	5	6	2	2
Training set 4	4	5	1	4	6	4	3	8

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.

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.

The final prediction is constructed by a weighted vote (where the weights for a bc depends on its training error).

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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 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.

RANDOM FORESTS

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but how?

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One way to do this is to randomly choose one of the top k *features to split each node.*

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 boosting methods, more robust to noise, and can also have better runtime than other ensemble methods (since the feature space is reduced in some cases).

Quick check

Is there a startup that provides random forests as a service?

If so, what's their competitive advantage?

search the web and find an answer…

LAB