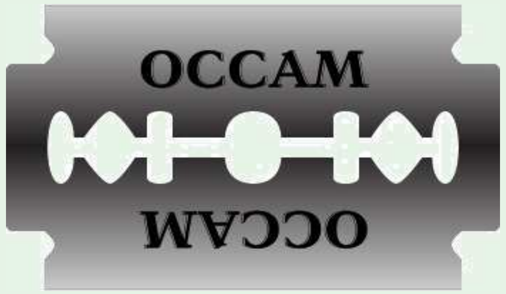
Review of Lecture 17

- Occam's Razor

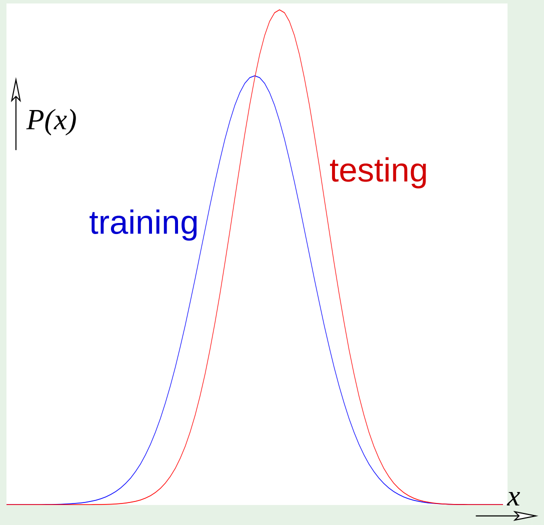
The simplest model that fits the data is also the most plausible.



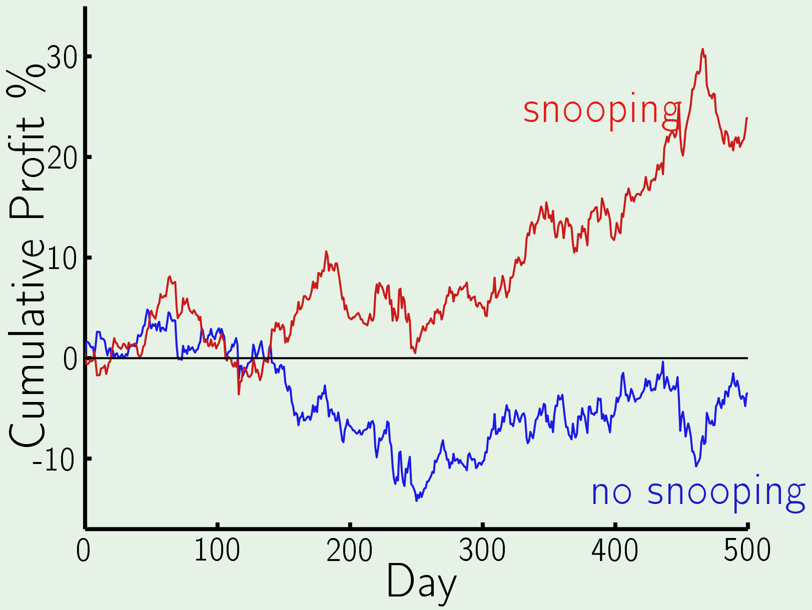
complexity of h $\longleftrightarrow$ complexity of $\mathcal{H}$

unlikely event $\longleftrightarrow$ significant if it happens

- Sampling bias



- Data snooping



Learning From Data

Yaser S. Abu-Mostafa
California Institute of Technology

Lecture 18: Epilogue

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Outline

- The map of machine learning
- Bayesian learning
- Aggregation methods
- Acknowledgments

It's a jungle out there

semi−supervised learning
overfitting
stochastic gradient descent
SVM
Q learning
Gaussian processes
deterministic noise
data snooping
distribution−free
linear regression
learning curves
collaborative filtering
VC dimension
mixture of expe
sampling bias
decision trees
nonlinear transformation
neural networks
no free
RBF
training versus testing
noisy targets
Bayesian prior
active learning
linear models
bias−variance tradeoff
weak learners
ordinal regression
logistic regression
data contamination
cross validation
ensemble learning
types of learning
perceptrons
hidden Markov mo
error measures
kernel methods
ploration versus exploitation
graphical models
is learning feasible?
soft−order constraint
clustering
weight decay
Boltzmann mach
regularization
Occam's razor

The map

THEORY

- VC
- bias−variance
- complexity
- bayesian

TECHNIQUES

models

- linear
- neural networks
- SVM
- nearest neighbors
- RBF
- gaussian processes
- SVD
- graphical models

methods

- regularization
- validation
- aggregation
- input processing (PCA etc.)

PARADIGMS

- supervised
- unsupervised
- reinforcement
- active
- online

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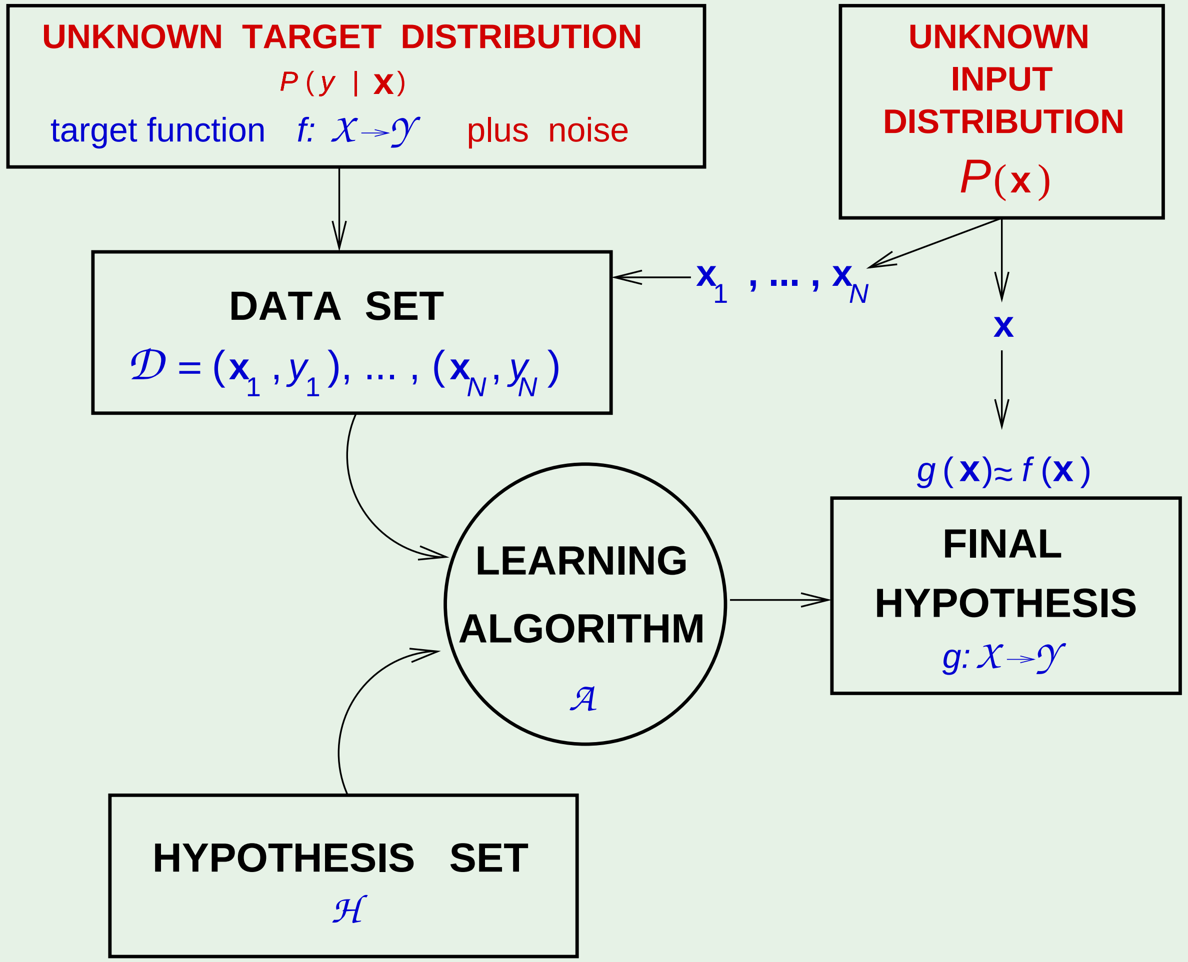
Probabilistic approach

Extend probabilistic role to all components

$P(\mathcal{D} \mid h = f)$ decides which h (likelihood)

How about $P(h = f \mid \mathcal{D})$?



The prior

$P(h = f \mid \mathcal{D})$ requires an additional probability distribution:

$$P(h = f \mid \mathcal{D}) \quad = \quad \frac{P(\mathcal{D} \mid h = f)\; P(h = f)}{P(\mathcal{D})} \; \propto \; P(\mathcal{D} \mid h = f)\; P(h = f)$$

$P(h = f)$ is the **prior**

$P(h = f \mid \mathcal{D})$ is the **posterior**

Given the prior, we have the full distribution

Example of a prior

Consider a perceptron: h is determined by $\mathbf{w} = w_0, w_1, \cdots, w_d$

A possible prior on $\mathbf{w}$: Each w_i is independent, uniform over $[-1, 1]$

This determines the prior over h - $P(h = f)$

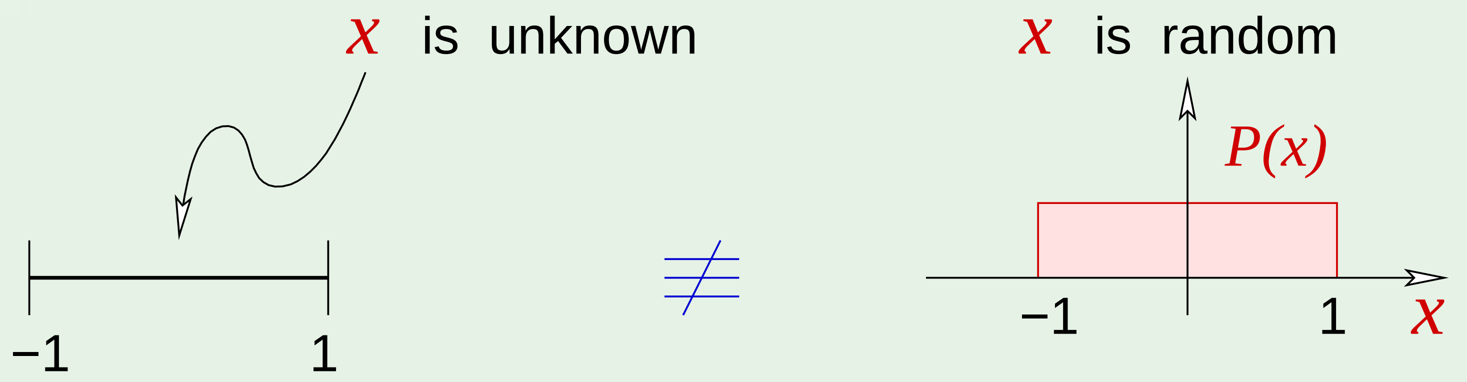
Given $\mathcal{D}$, we can compute $P(\mathcal{D} \mid h = f)$

Putting them together, we get $P(h = f \mid \mathcal{D})$

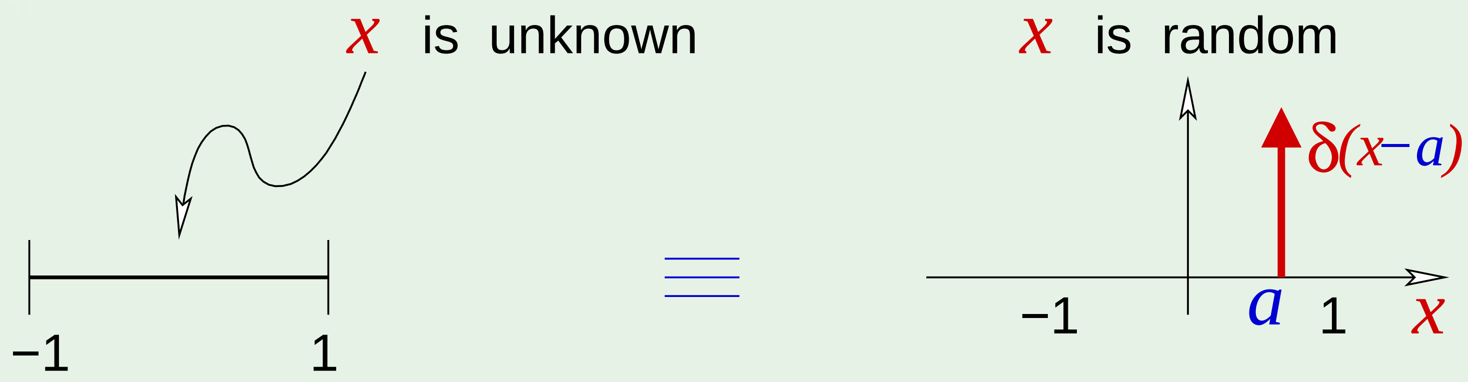
$$\propto \quad P(h = f)P(\mathcal{D} \mid h = f)$$

A prior is an assumption

Even the most "neutral" prior:



The true equivalent would be:



If we knew the prior

. . . we could compute $P(h = f \mid \mathcal{D})$ for every $h \in \mathcal{H}$

$\Longrightarrow$ we can find the most probable h given the data

we can derive $\mathbb{E}(h(\mathbf{x}))$ for every $\mathbf{x}$

we can derive the **error bar** for every $\mathbf{x}$

we can derive everything in a principled way

When is Bayesian learning justified?

1. The prior is **valid**

   trumps all other methods

2. The prior is **irrelevant**

   just a computational catalyst

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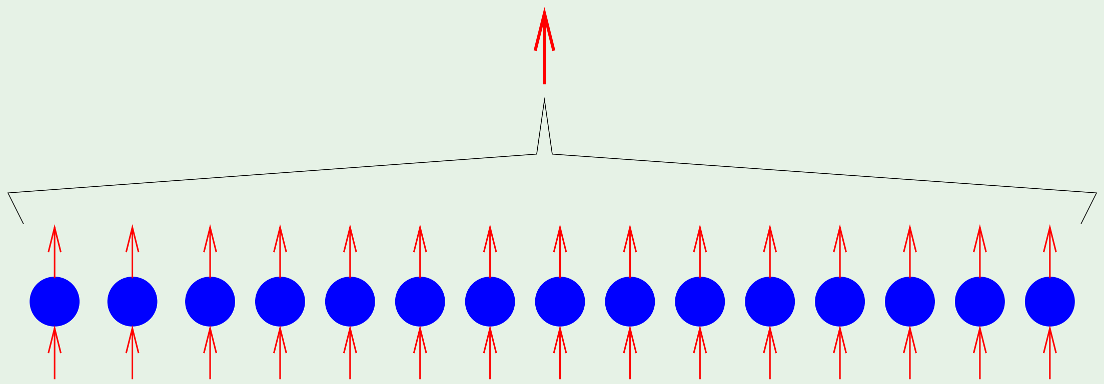
What is aggregation?

Combining different solutions $h_1, h_2, \cdots, h_T$ that were trained on $\mathcal{D}$:



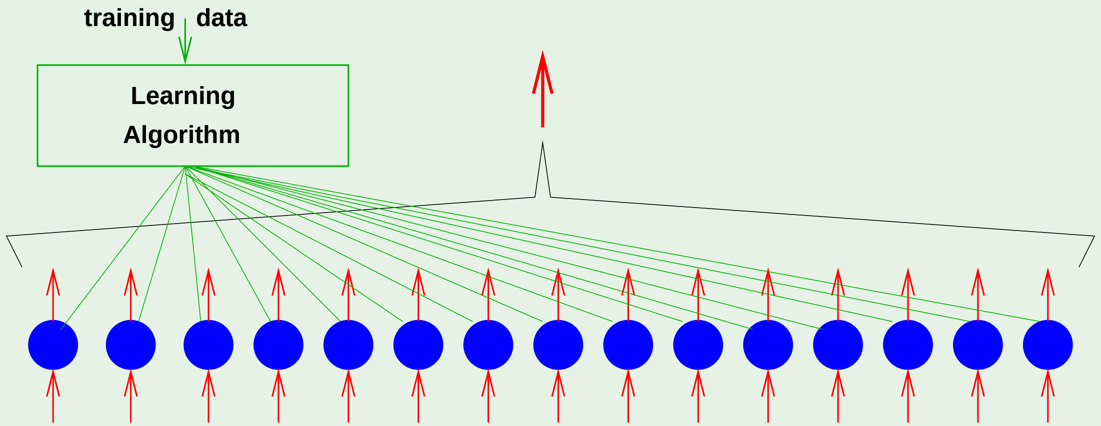
Regression: take an average

Classification: take a vote

a.k.a. *ensemble learning* and *boosting*

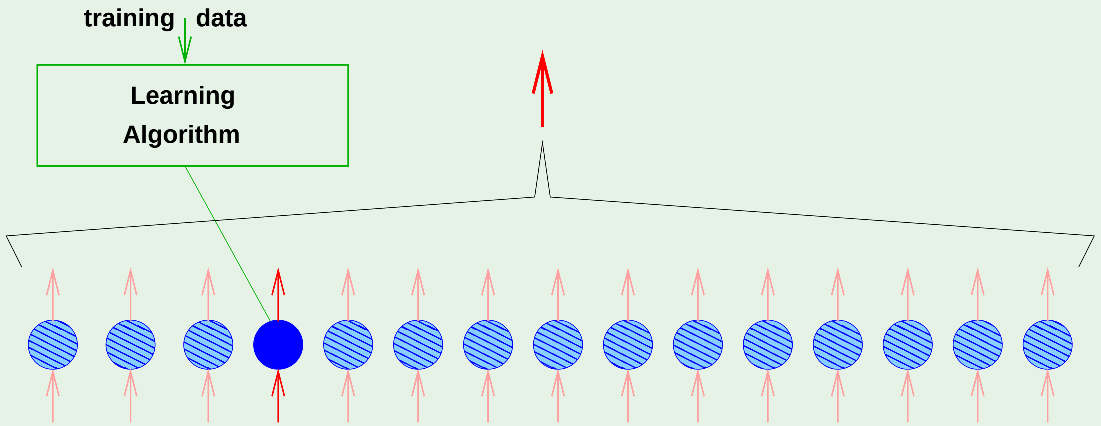
Different from 2-layer learning

In a 2-layer model, all units learn **jointly**:



In aggregation, they learn **independently** then get combined:

each unit attempts to contribute positively to approximating the function



each unit (could be separate hypotheses) tries to replicate the function

Two types of aggregation

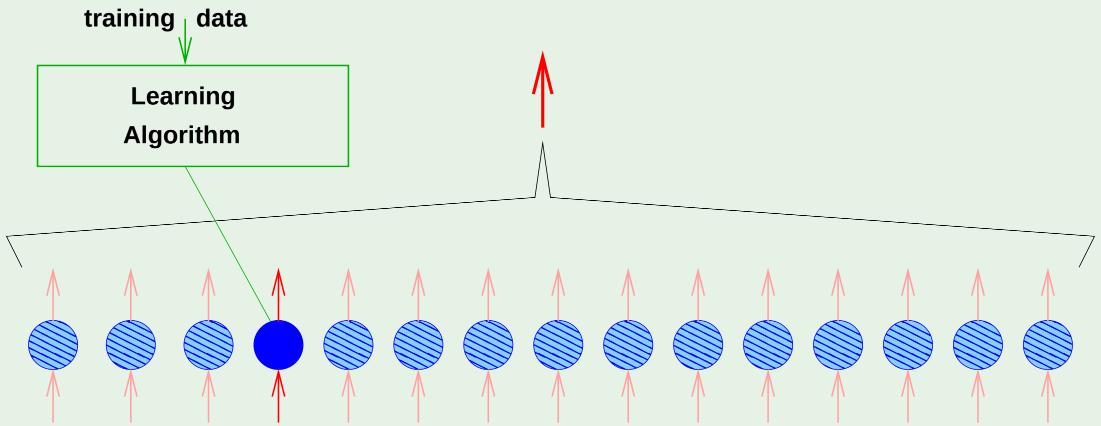
1. **After the fact:** combines existing solutions

they were developed solely with a view to performance individually, nobody was thinking of putting them together (so no one thought of deliberately getting a different model in order to contribute)

Example. Netflix teams merging "blending"

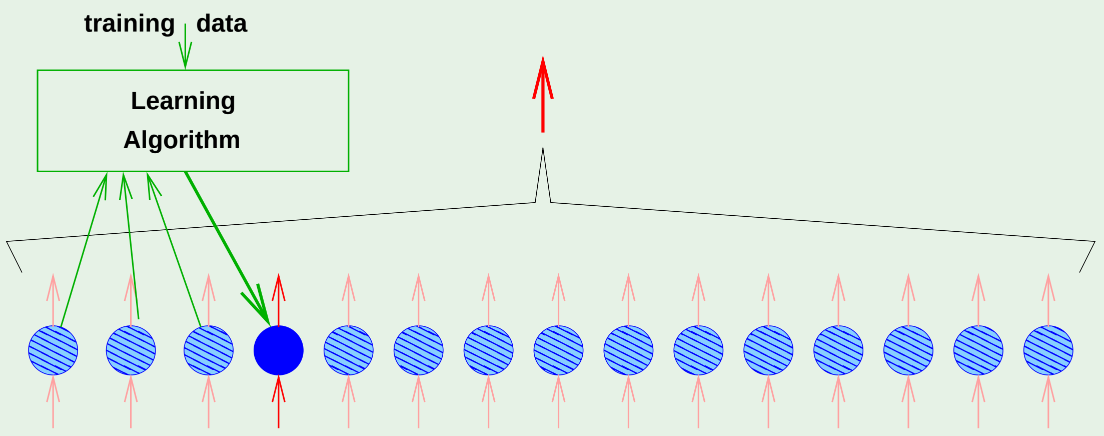
2. **Before the fact:** creates solutions to be combined

Example. Bagging - resampling $\mathcal{D}$



Decorrelation - boosting

Create $h_1, \cdots, h_t, \cdots$ sequentially: Make h_t decorrelated with previous h's:



Say we have so far 60% correct (in classification) and 40% wrong combining the first few hypotheses. To make the next h fairly independent of the previous, emphasize the examples from D we did badly on (give them bigger weights in training) and deemphasize the ones we got right, so as far as the new distribution is concerned, it looks like we have a weighted error of 50% (as if it were a random guess). So taking this distribution and learn on it and get better than 50%, the new hypothesis is adding value to what we had before.

Emphasize points in $\mathcal{D}$ that were misclassified

Choose weight of h_t based on $E_{\text{in}}(h_t)$

Blending - after the fact

For regression, $h_1, h_2, \cdots, h_T \longrightarrow$ $g(\mathbf{x}) = \sum_{t=1}^{T} \alpha_t \, h_t(\mathbf{x})$

If we use MSE, algorithm to choose alpha's will be

Principled choice of α_t's: minimize the error on an "aggregation data set" pseudo-inverse

Some α_t's can come out negative

Most valuable h_t in the blend?

You evaluate the performance of the summation both with and without each h_t - the difference is the contribution of the solution. So if there are two h_t doing identically the same thing, taking one out just means the other hypothesis will contribute everything that is needed. Meanwhile those hypotheses which are more diverse/fringe often have greater actual contribution to the blend, even if the individual performance of the model on the problem is not as good..

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Course content

Professor **Malik Magdon-Ismail**, *RPI*

Professor **Hsuan-Tien Lin**, *NTU*

Course staff

Carlos Gonzalez (*Head TA*)

Ron Appel

Costis Sideris

Doris Xin

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To the fond memory of

Faiza A. Ibrahim