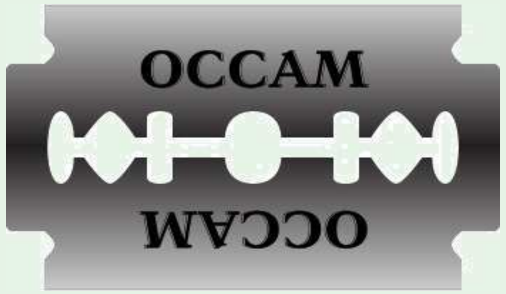
Review of Lecture 17

- Occam's Razor

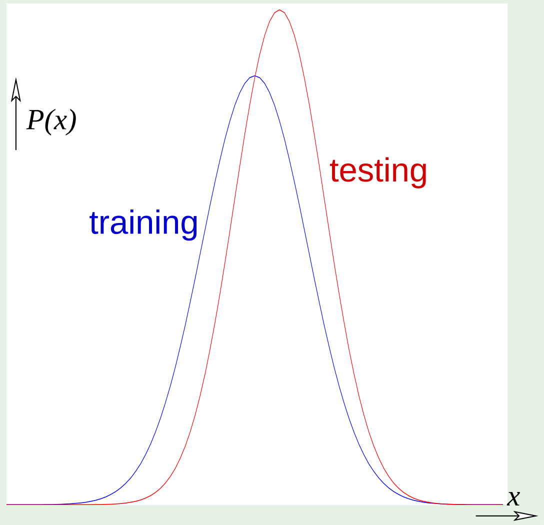
The simplest model that fits the data is also the most plausible.



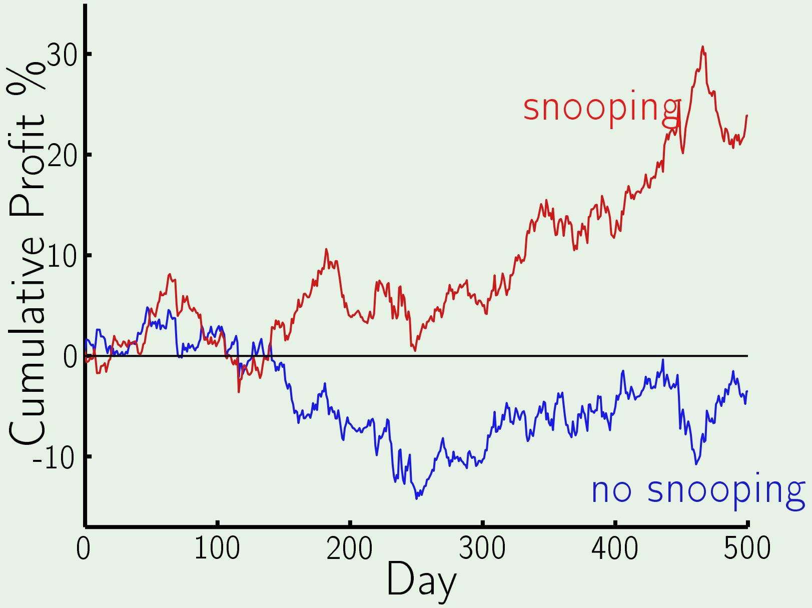
complexity of h $\longleftrightarrow$ complexity of $\mathcal{H}$

unlikely event $\longleftrightarrow$ significant if it happens

- Sampling bias



- Data snooping



Learning From Data

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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
VC dimension
collaborative filtering
mixture of expe
decision trees
nonlinear transformation
sampling bias
neural networks
no free
RBF
training versus testing
noisy targets
Bayesian prior
active learning
linear models
bias−variance tradeoff
weak learners
ordinal regression
cross validation
logistic regression
data contamination
ensemble learning
types of learning
perceptrons
hidden Markov mo
error measures
xploration versus exploitation
kernel methods
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

PARADIGMS

- supervised
- unsupervised
- reinforcement
- active
- online

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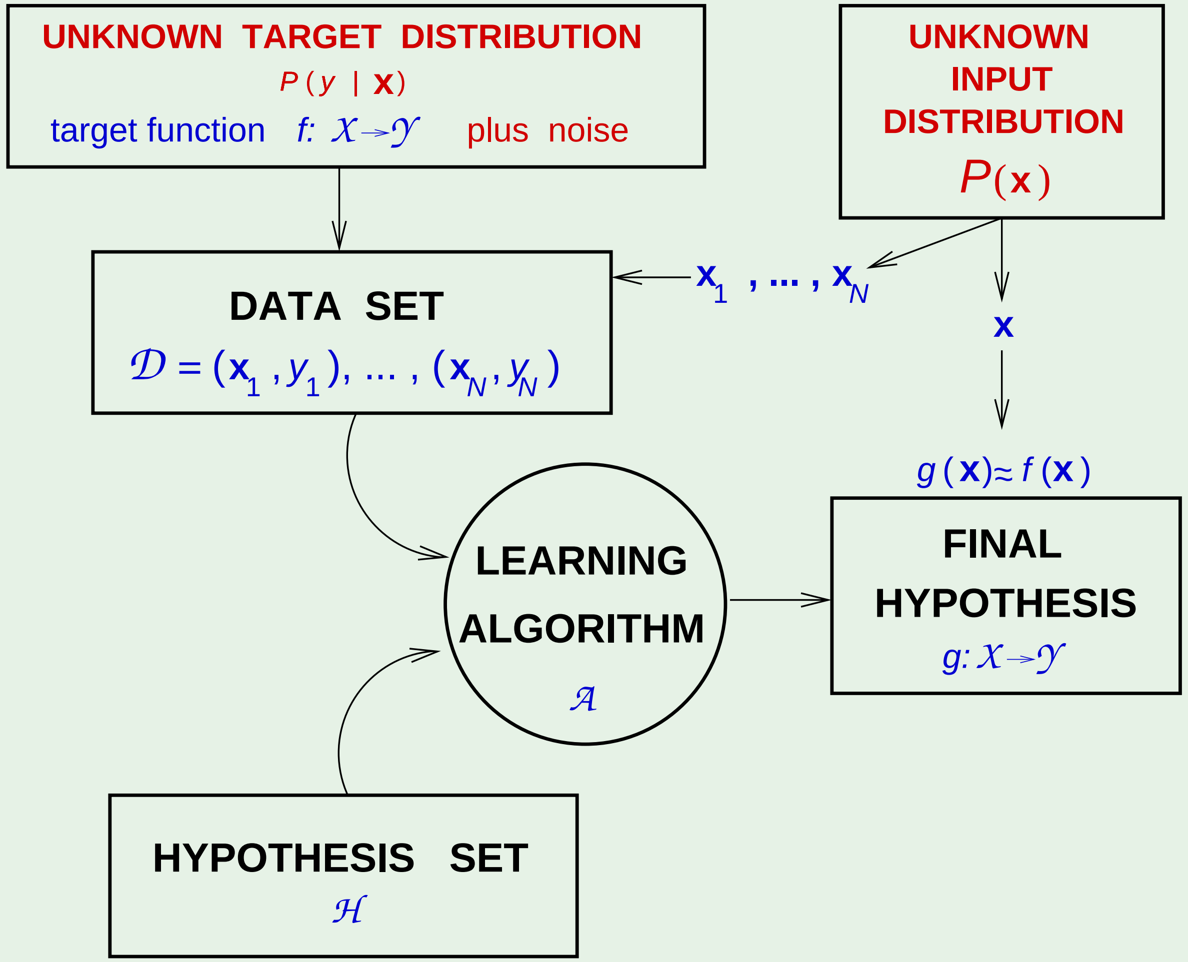
Probabilistic approach

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:

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

$P(h = f)$ 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 - $P(h = f)$

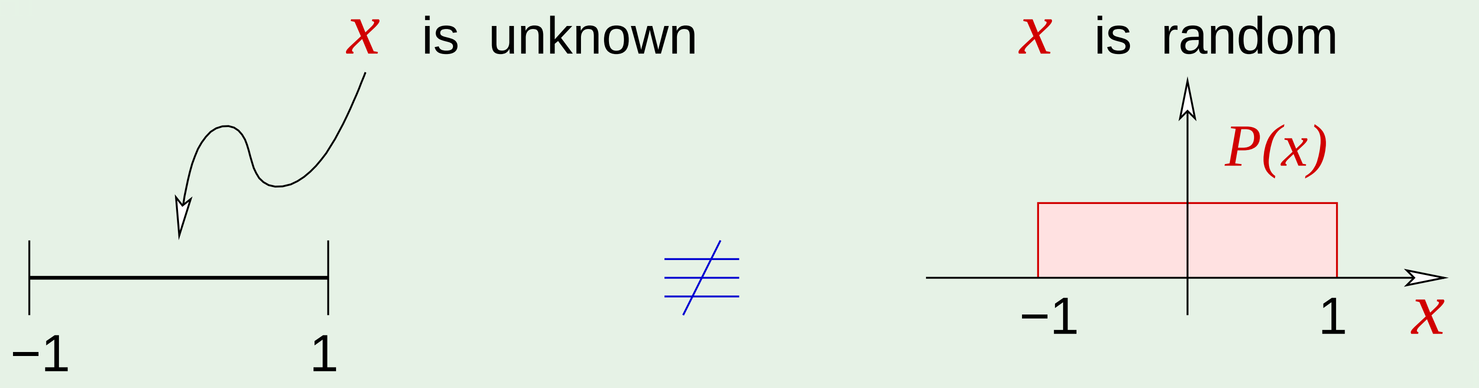
Given $\mathcal{D}$, we can compute $P(\mathcal{D} \mid h = f)$

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

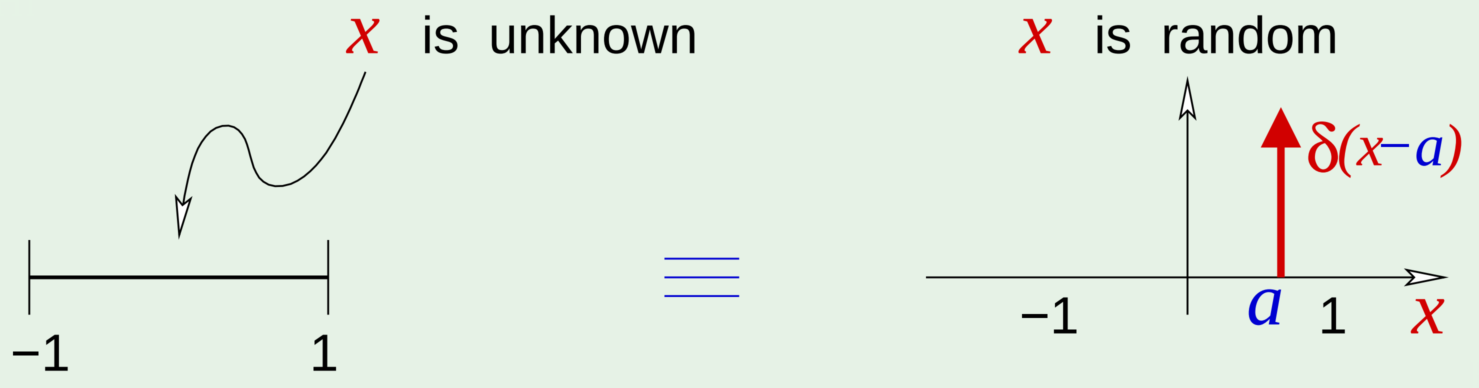
$$\propto \quad P(h = f)P(\mathcal{D} \mid h = f)$$

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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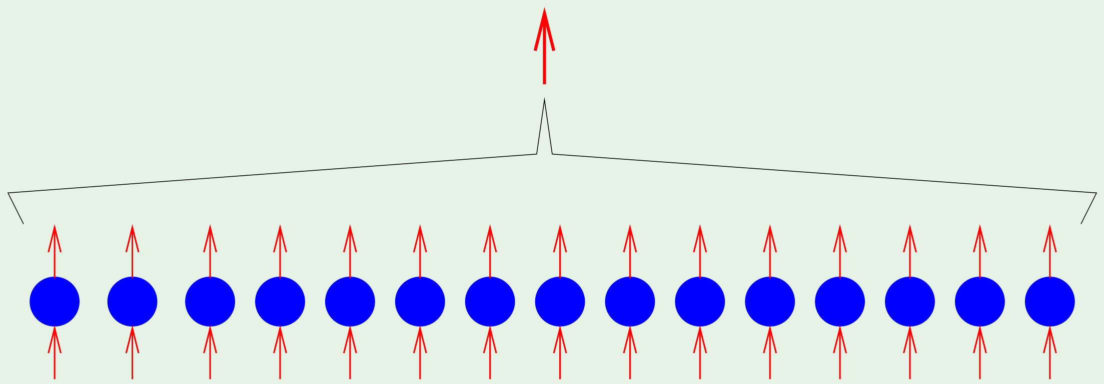
What is aggregation?

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



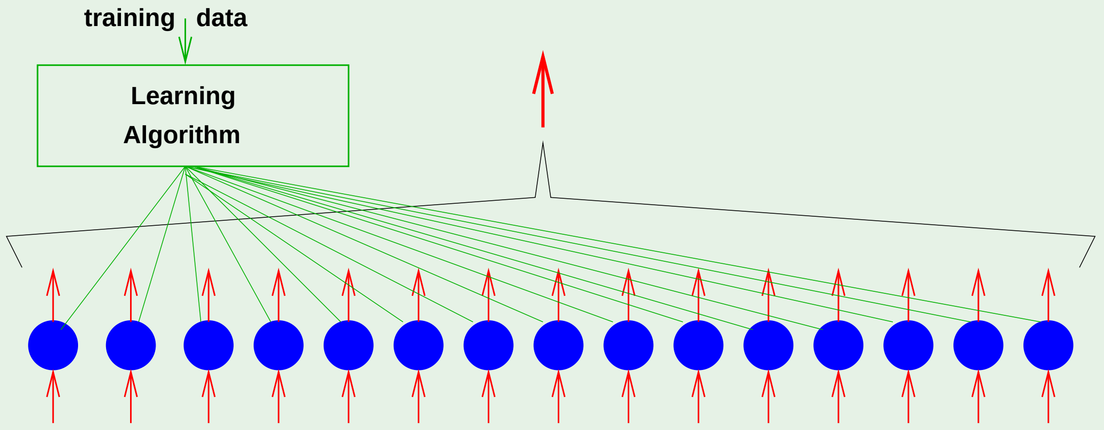
Regression: take an average

Classification: take a vote

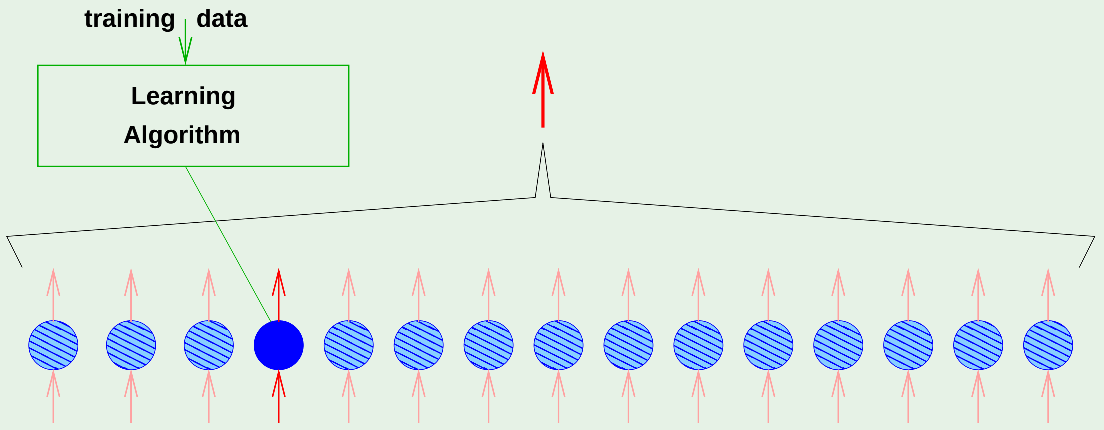
a.k.a. *ensemble learning* and *boosting*

Different from 2-layer learning

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



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



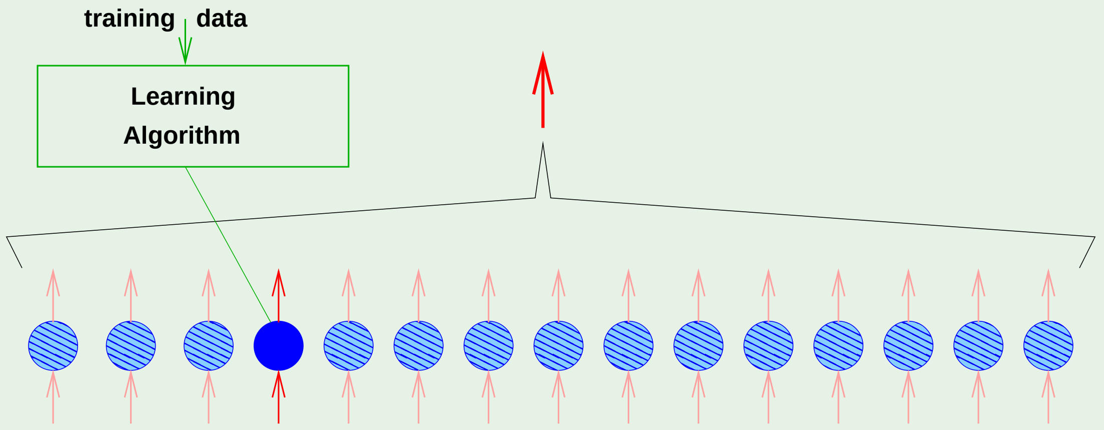
Two types of aggregation

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

   Example. Netflix teams merging "blending"

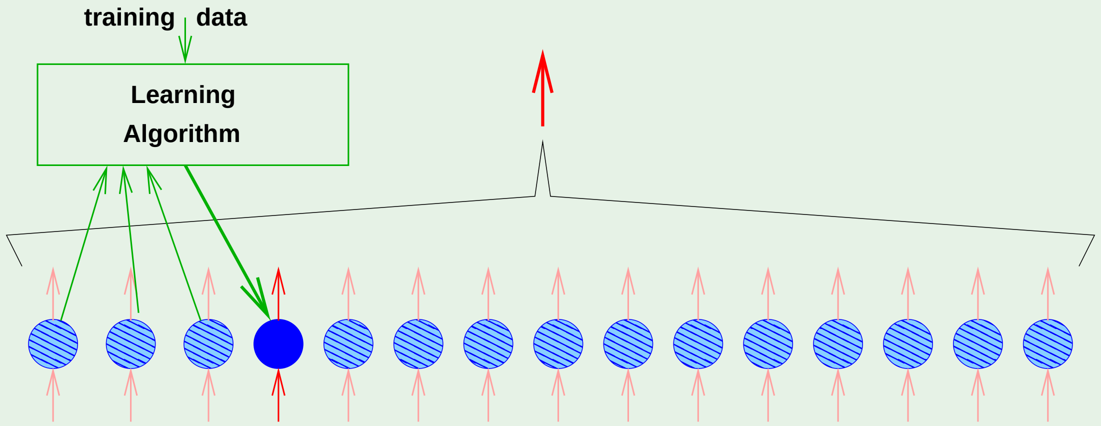
2. **Before the fact:** creates solutions to be combined

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



Decorrelation - boosting

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



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

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?

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Course content

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To the fond memory of

Faiza A. Ibrahim