Lecture 12: Learning 2

http://cs.nju.edu.cn/yuy/course_ai18.ashx

Previously...

Learning

- Decision tree learning
- Nearest Neighbors
- Naive Bayes

Question:

why we can learn?

Classification

what can be observed:

on examples/training data:

$$\{(\boldsymbol{x}_1, y_1), \ldots, (\boldsymbol{x}_m, y_m)\} \quad y_i = f(\boldsymbol{x}_i)$$

e.g. training error

$$\epsilon_t = \frac{1}{m} \sum_{i=1}^{m} I(h(\boldsymbol{x}_i) \neq y_i)$$

what is expected:

over the whole distribution: generalization error

$$\epsilon_g = \mathbb{E}_x[I(h(\boldsymbol{x}) \neq f(\boldsymbol{x}))]$$

$$= \int_{\mathcal{X}} p(x) I(h(\boldsymbol{x}) \neq f(\boldsymbol{x}))] \mathrm{d}x$$

Regression

what can be observed:

on examples/training data:

$\{(\boldsymbol{x}_1, y_1), \ldots, (\boldsymbol{x}_m, y_m)\} \quad y_i = f(\boldsymbol{x}_i)$

e.g. training mean square error/MSE

$$\epsilon_t = \frac{1}{m}\sum_{i=1}^{m}(h(\boldsymbol{x}_i) - y_i)^2$$

what is expected:

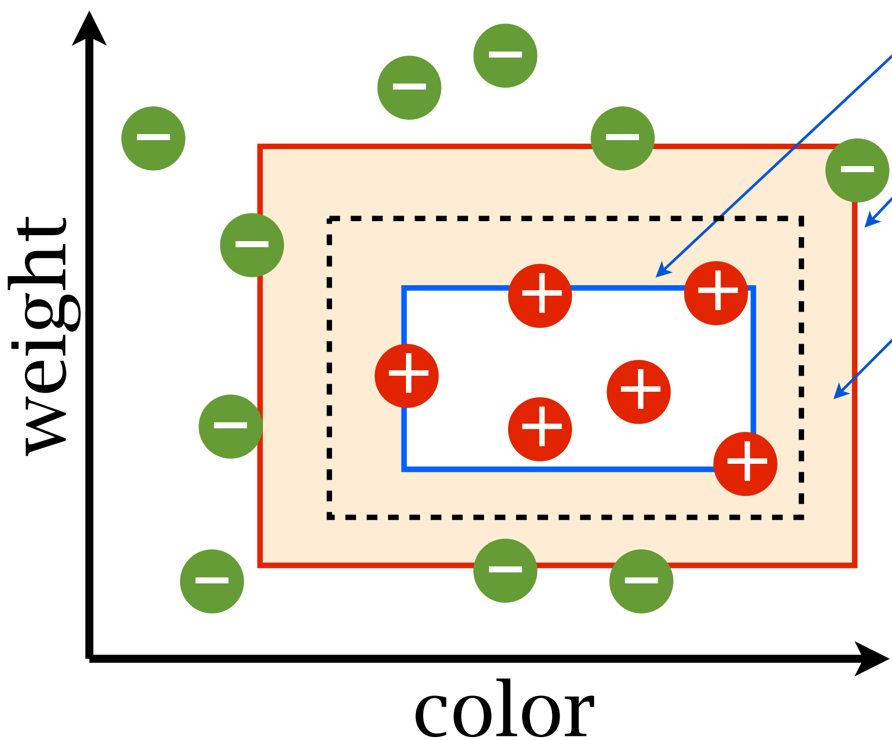
over the whole distribution: generalization MSE

$$\epsilon_g = \mathbb{E}_x(h(\boldsymbol{x}) \neq f(\boldsymbol{x}))^2$$

$$= \int_{\mathcal{X}} p(x)(h(\boldsymbol{x}) - f(\boldsymbol{x}))^2 \mathrm{d}x$$

The version space algorithm

an abstract view of learning algorithms



S: most specific hypothesis

G: most general hypothesis

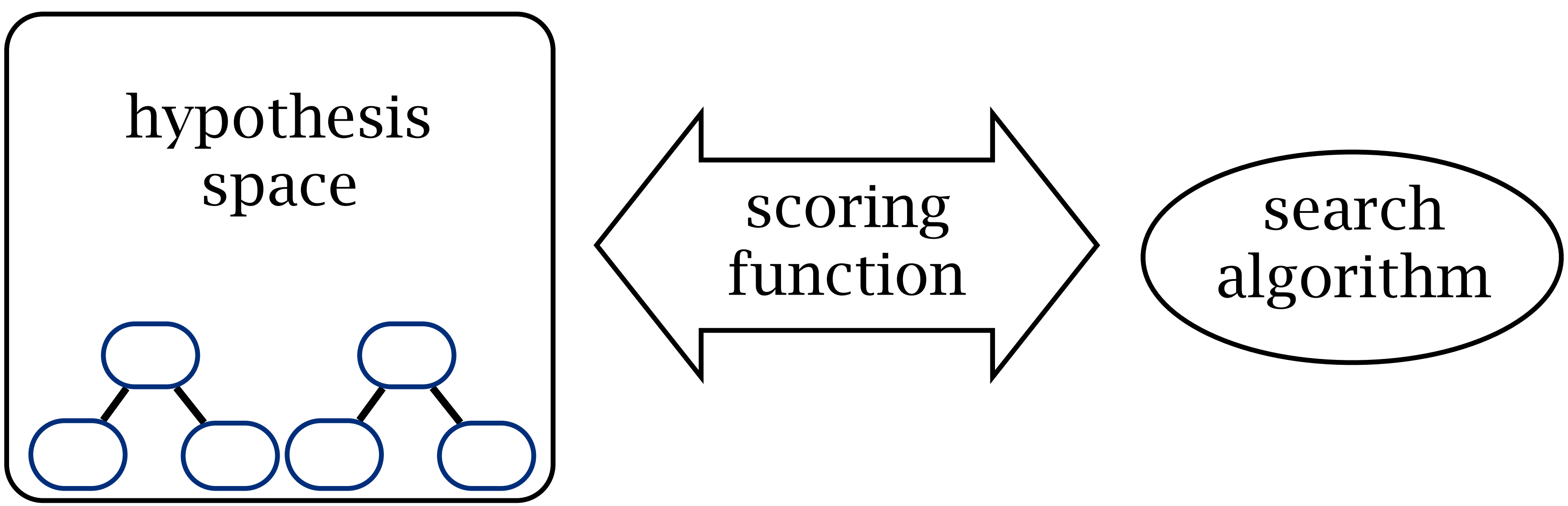
version space: consistent hypotheses [Mitchell, 1997]

remove the hypothesis that are inconsistent with the data, select a hypothesis according to learner's bias

The version space algorithm

an abstract view of learning algorithms

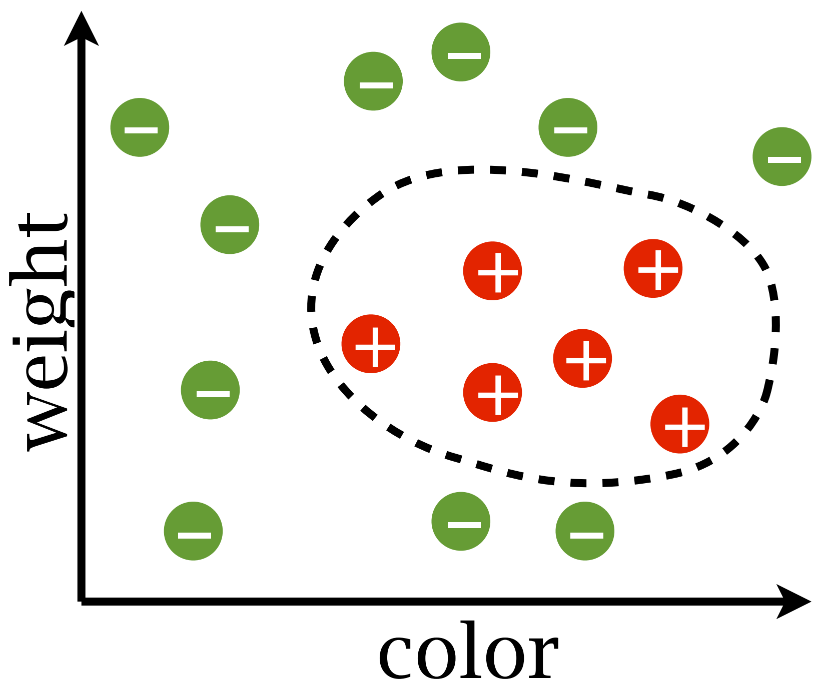
three components of a learning algorithm



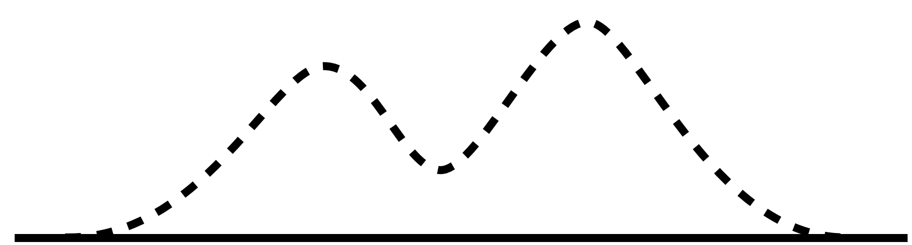
Theories

The i.i.d. assumption:

all training examples and future (test) examples are drawn *independently* from an *identical distribution*, the label is assigned by a *fixed ground-truth function*



unknown but fixed distribution D



Bias-variance dilemma

Suppose we have 100 training examples
but there can be different training sets

Start from the expected training MSE:

$$E_D[\epsilon_t] = E_D\left[\frac{1}{m}\sum_{i=1}^{m}(h(\boldsymbol{x}_i) - y_i)^2\right] = \frac{1}{m}\sum_{i=1}^{m} E_D\left[(h(\boldsymbol{x}_i) - y_i)^2\right]$$

(assume no noise)

$$\begin{aligned} & E_D\left[(h(\boldsymbol{x}) - f(\boldsymbol{x}))^2\right] \\ &= E_D\left[(h(\boldsymbol{x}) - E_D[h(\boldsymbol{x})] + E_D[h(\boldsymbol{x})] - f(\boldsymbol{x}))^2\right] \\ &= E_D\left[(h(\boldsymbol{x}) - E_D[h(\boldsymbol{x})])^2\right] + E_D\left[(E_D[h(\boldsymbol{x})] - f(\boldsymbol{x}))^2\right] \\ &\quad + E_D\left[2(h(\boldsymbol{x}) - E_D[h(\boldsymbol{x})])(E_D[h(\boldsymbol{x})] - f(\boldsymbol{x}))\right] \\ &= E_D\left[(h(\boldsymbol{x}) - E_D[h(\boldsymbol{x})])^2\right] + E_D\left[(E_D[h(\boldsymbol{x})] - f(\boldsymbol{x}))^2\right] \end{aligned}$$

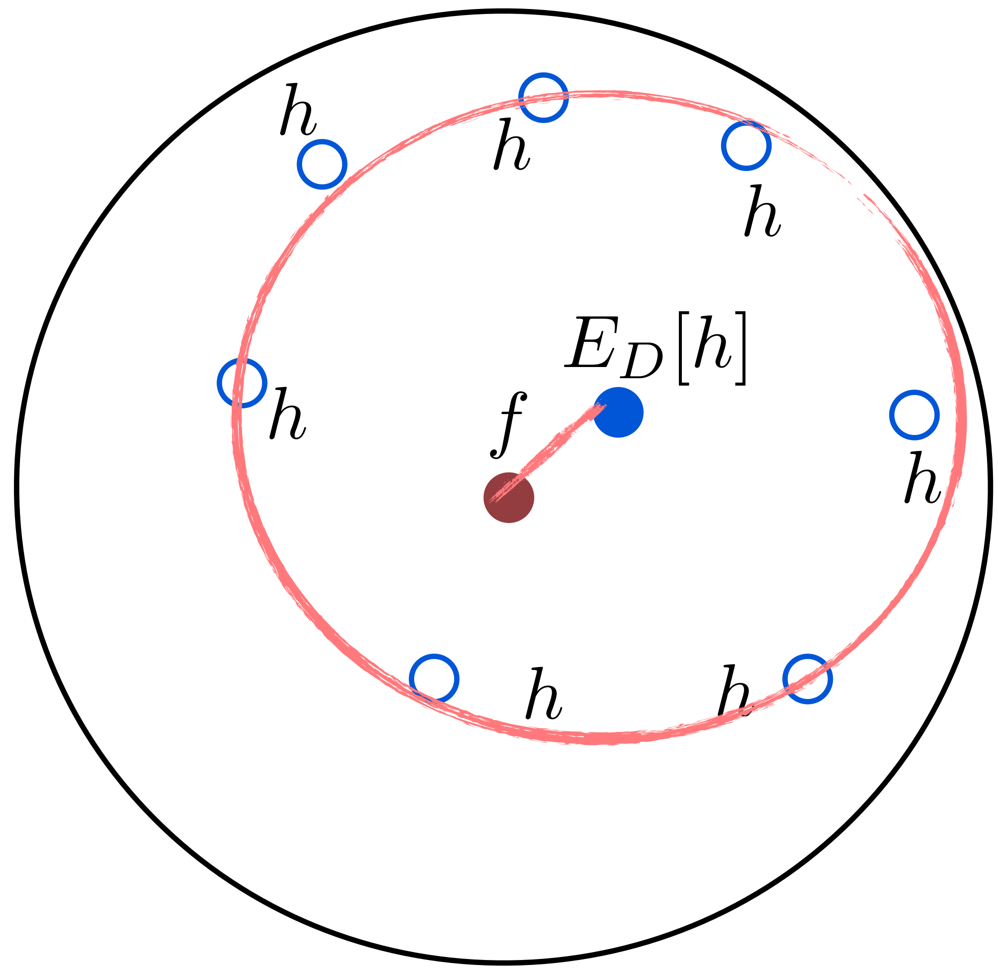
variance bias^2

Bias-variance dilemma

$E_D\left[(h(\boldsymbol{x}) - E_D[h(\boldsymbol{x})])^2\right]$ variance

$E_D\left[(E_D[h(\boldsymbol{x})] - f(\boldsymbol{x}))^2\right]$ bias^2

larger hypothesis space
=>
lower bias
but higher variance



hypothesis space

Bias-variance dilemma

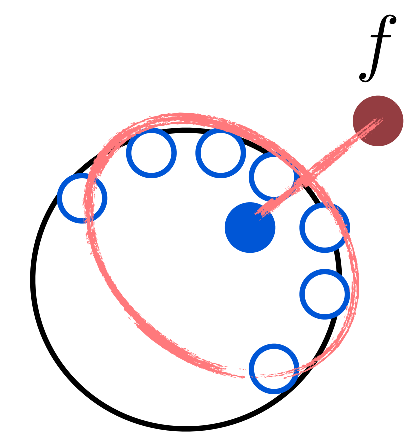
$$E_D\left[(h(\boldsymbol{x}) - E_D[h(\boldsymbol{x})])^2\right]$$

variance

$$E_D\left[(E_D[h(\boldsymbol{x})] - f(\boldsymbol{x}))^2\right]$$

bias^2

smaller hypothesis space
=>
smaller variance
but higher bias

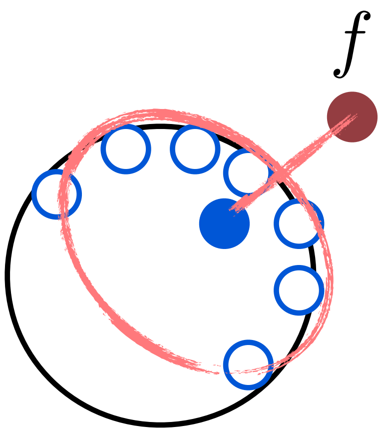


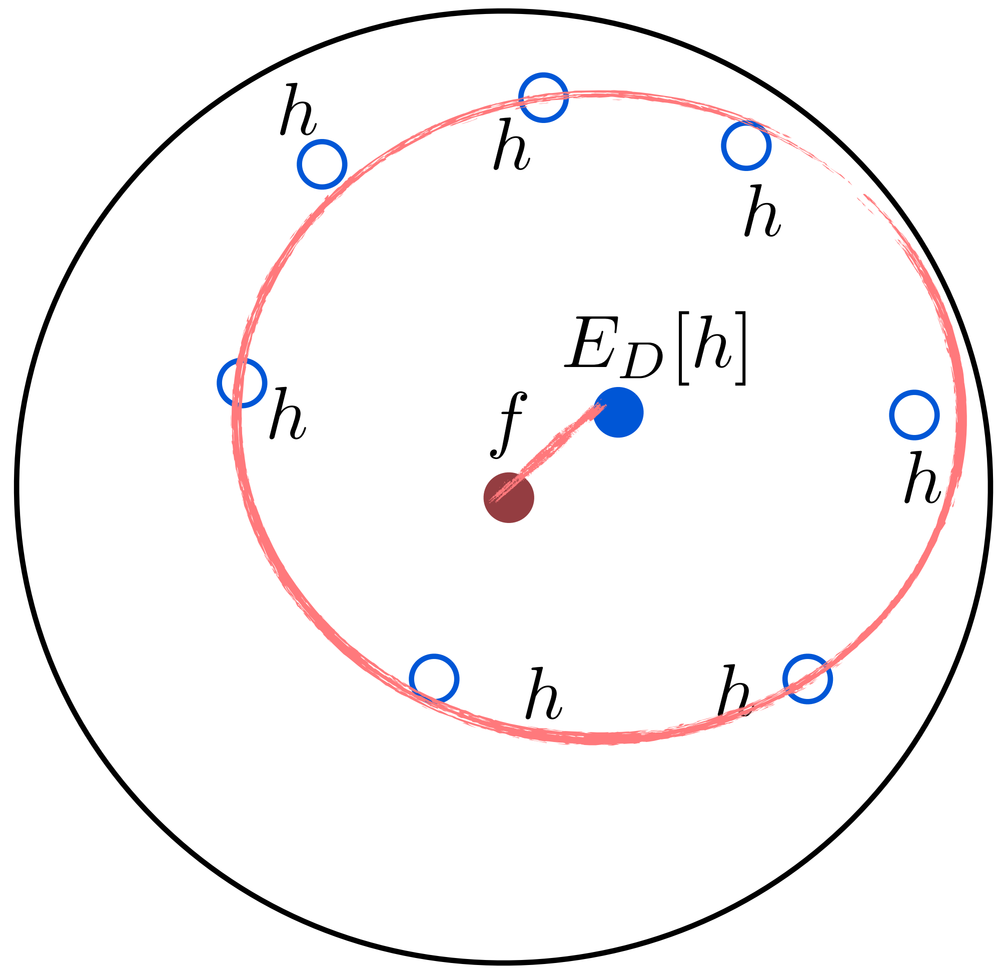
hypothesis space

Bias-variance dilemma

$$E_D\left[(h(\boldsymbol{x}) - E_D[h(\boldsymbol{x})])^2\right] \qquad E_D\left[(E_D[h(\boldsymbol{x})] - f(\boldsymbol{x}))^2\right]$$

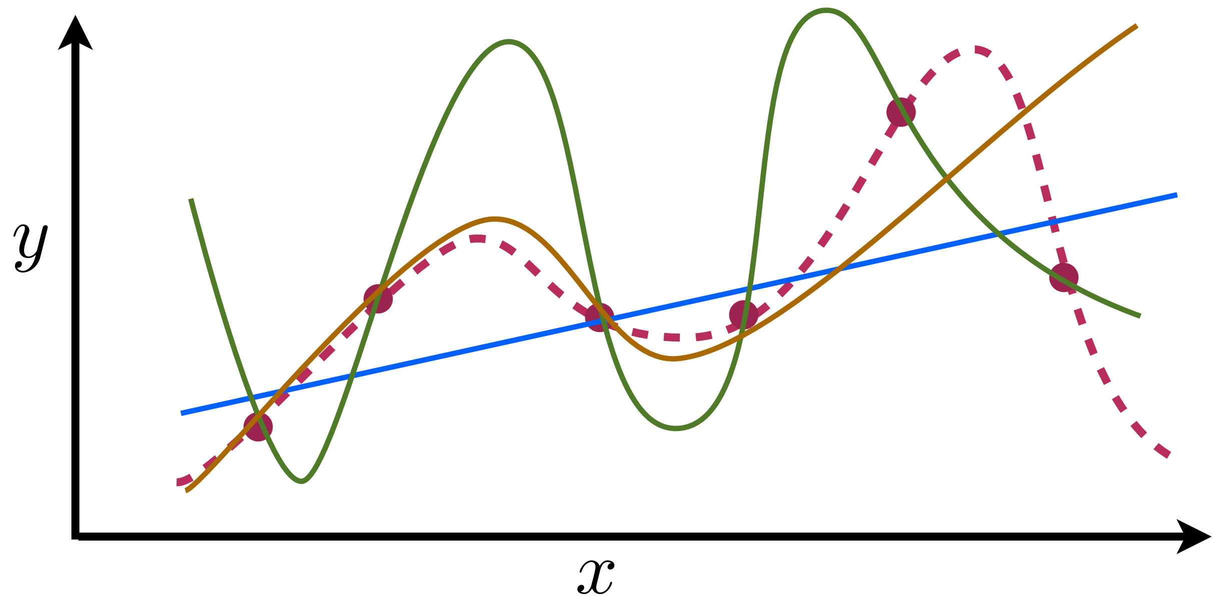
variance bias^2





Overfitting and underfitting

training error v.s. hypothesis space size



linear functions: high training error, small space

$$\{y = a + bx \mid a, b \in \mathbb{R}\}$$

higher polynomials: moderate training error, moderate space

$$\{y = a + bx + cx^2 + dx^3 \mid a, b, c, d \in \mathbb{R}\}$$

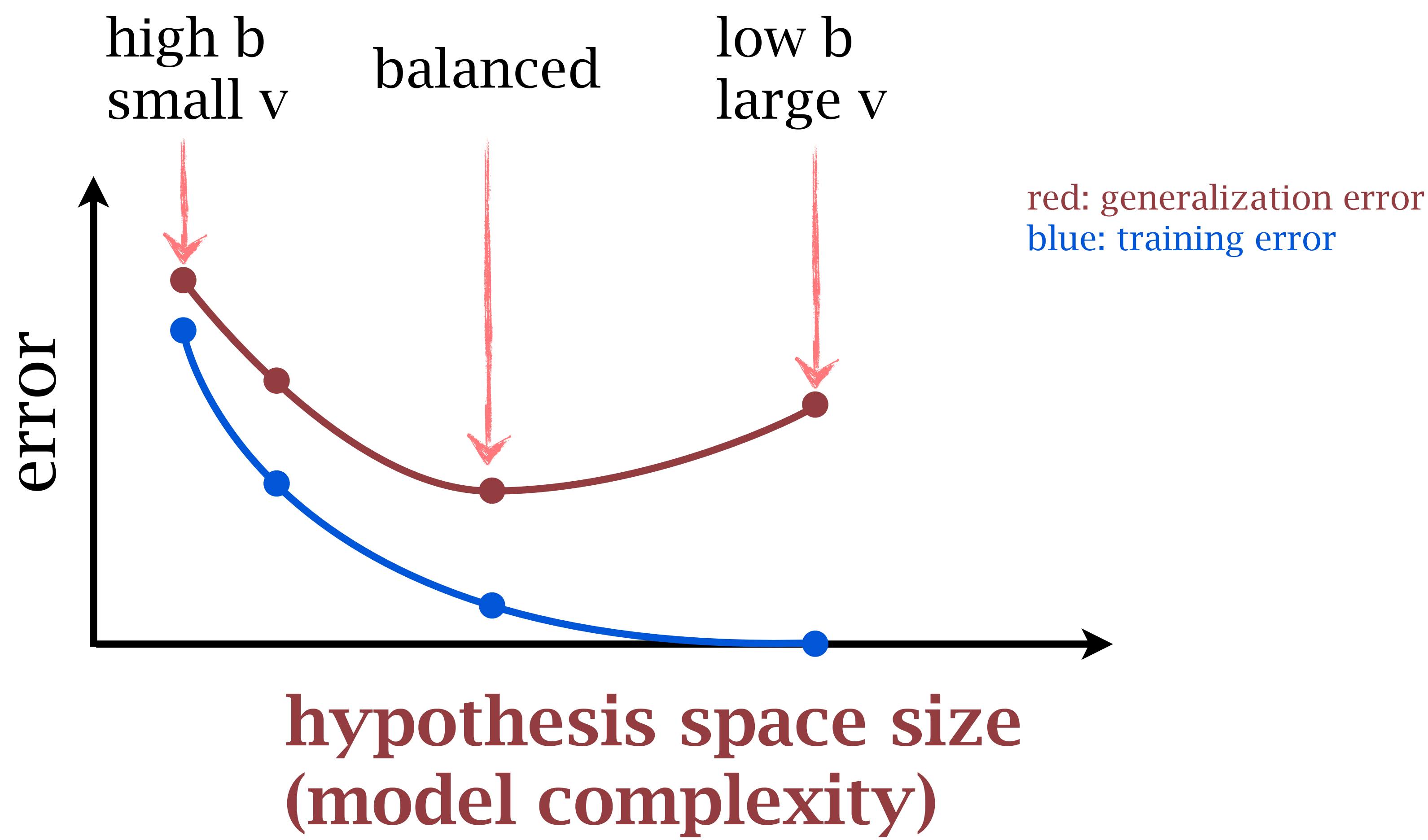
even higher order: no training error, large space

$$\{y = a + bx + cx^2 + dx^3 + ex^4 + fx^5 \mid a, b, c, d, e, f \in \mathbb{R}\}$$

Overfitting and bias-variance dilemma

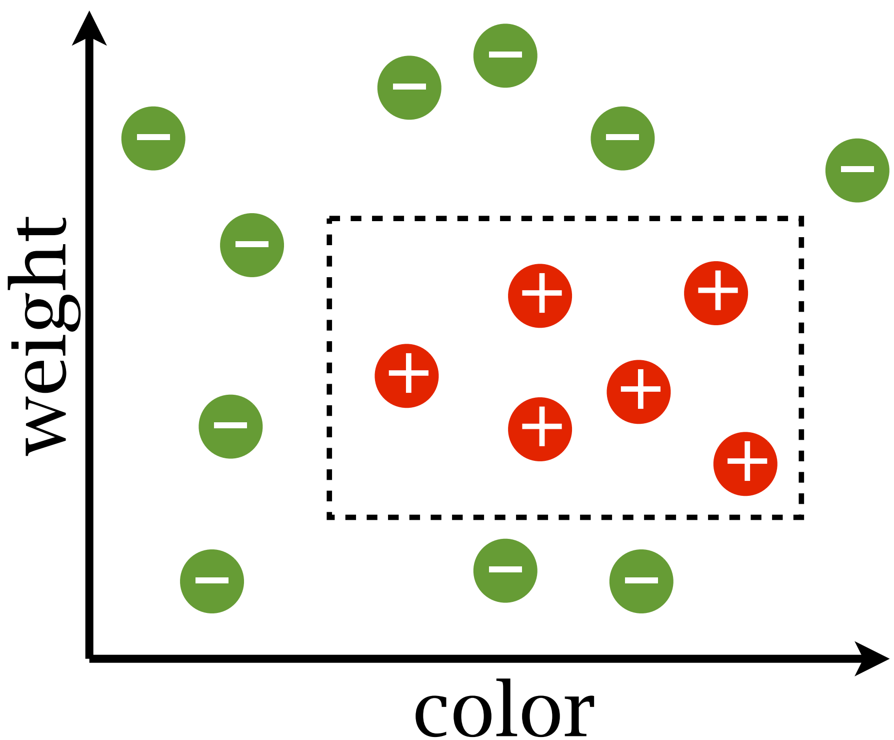
$$E_D\left[(h(\boldsymbol{x}) - E_D[h(\boldsymbol{x})])^2\right] \qquad E_D\left[(E_D[h(\boldsymbol{x})] - f(\boldsymbol{x}))^2\right]$$

variance　　　　bias^2



Generalization error

assume i.i.d. examples, and the ground-truth hypothesis is a box



the error of picking a consistent hypothesis:

with probability at least $1 - \delta$

$$\epsilon_g < \frac{1}{m} \cdot (\ln |\mathcal{H}| + \ln \frac{1}{\delta})$$

smaller generalization error:

- more examples
- smaller hypothesis space

Generalization error

for one *h*

What is the probability of h is consistent, $\epsilon_g(h) \geq \epsilon$

assume *h* is ***bad***: $\epsilon_g(h) \geq \epsilon$

h is consistent with 1 example:

$$P \leq 1 - \epsilon$$

h is consistent with ***m*** example:

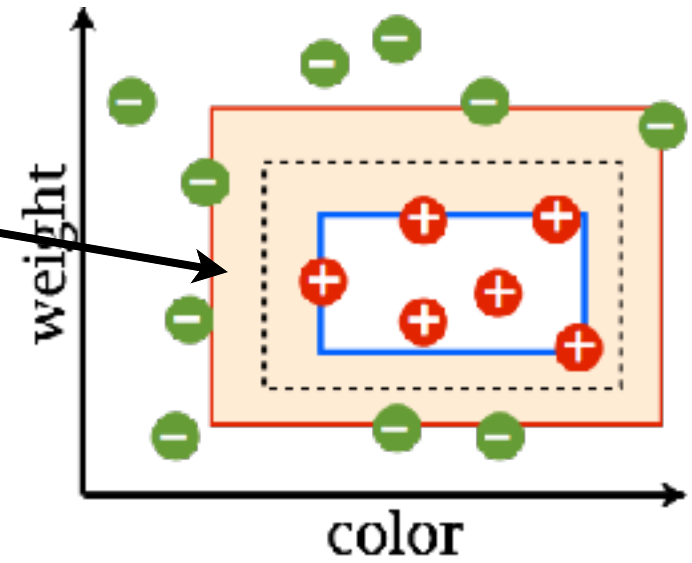
$$P \leq (1 - \epsilon)^m$$

Generalization error

h is consistent with ***m*** example:

$$P \leq (1-\epsilon)^m$$

There are ***k*** consistent hypotheses



Probability of choosing a bad one:

h_1 is chosen and h_1 is bad $P \leq (1-\epsilon)^m$

h_2 is chosen and h_2 is bad $P \leq (1-\epsilon)^m$

...

h_k is chosen and h_k is bad $P \leq (1-\epsilon)^m$

overall:

$\exists h$: *h* can be chosen (consistent) but is bad

Generalization error

h_1 is chosen and h_1 is bad $P \leq (1-\epsilon)^m$
h_2 is chosen and h_2 is bad $P \leq (1-\epsilon)^m$
...
h_k is chosen and h_k is bad $P \leq (1-\epsilon)^m$

overall:

$\exists h$: h can be chosen (consistent) but is bad

Union bound: $P(A \cup B) \leq P(A) + P(B)$

$$P(\exists h \text{ is consistent but bad}) \leq k \cdot (1-\epsilon)^m \leq |\mathcal{H}| \cdot (1-\epsilon)^m$$

Generalization error

$$P(\exists h \text{ is consistent but bad}) \leq k \cdot (1-\epsilon)^m \leq |\mathcal{H}| \cdot (1-\epsilon)^m$$

$$\Downarrow$$

$$P(\epsilon_g \geq \epsilon) \leq \underline{|\mathcal{H}| \cdot (1-\epsilon)^m}$$

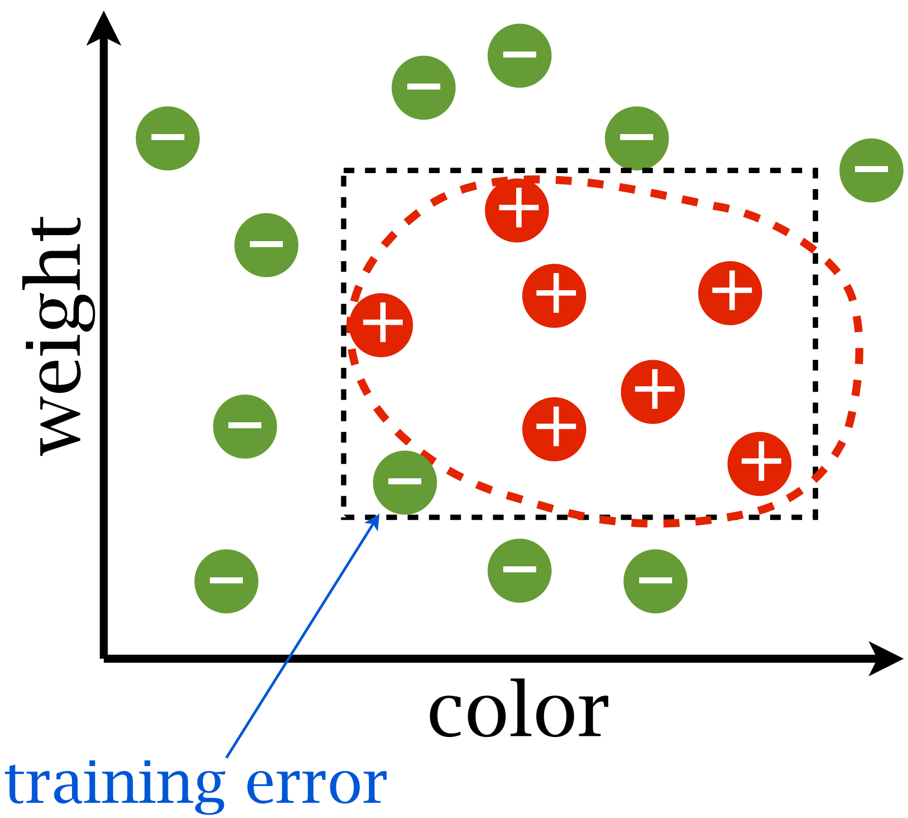
$$\delta$$

with probability at least $1-\delta$

$$\epsilon_g < \frac{1}{m} \cdot (\ln|\mathcal{H}| + \ln\frac{1}{\delta})$$

Inconsistent hypothesis

What if the ground-truth hypothesis is NOT a box: non-zero training error



with probability at least $1-\delta$

$$\epsilon_g < \epsilon_t + \sqrt{\frac{1}{m}\left(\ln|\mathcal{H}| + \ln\frac{1}{\delta}\right)}$$

smaller generalization error:

- more examples
- smaller hypothesis space
- **smaller training error**

Hoeffding's inequality

X be an i.i.d. random variable

$X_1, X_2, \ldots, X_m$ be m samples

$X_i \in [a, b]$

$$\frac{1}{m}\sum_{i=1}^{m} X_i - \mathbb{E}[X] \leftarrow \text{ difference between sum and expectation}$$

$$P(\frac{1}{m}\sum_{i=1}^{m} X_i - \mathbb{E}[X] \geq \epsilon) \leq \exp\left(-\frac{2\epsilon^2 m}{(b-a)^2}\right)$$

Generalization error

for one h

$$X_i = I(h(x_i) \neq f(x_i)) \in [0,1]$$

$$\frac{1}{m}\sum_{i=1}^{m} X_i \to \epsilon_t(h) \qquad\qquad \mathbb{E}[X_i] \to \epsilon_g(h)$$

$$P(\epsilon_t(h) - \epsilon_g(h) \geq \epsilon) \leq \exp\left(-2\epsilon^2 m\right)$$

$$P(\epsilon_t - \epsilon_g \geq \epsilon)$$

$$\leq P(\exists h \in |\mathcal{H}| : \epsilon_t(h) - \epsilon_g(h) \geq \epsilon) \leq \underbrace{|\mathcal{H}| \exp\left(-2\epsilon^2 m\right)}_{\delta}$$

with probability at least $1-\delta$

$$\epsilon_g < \epsilon_t + \sqrt{\frac{1}{2m} \cdot (\ln|\mathcal{H}| + \ln\frac{1}{\delta})}$$

Generalization error: Summary

assume i.i.d. examples

consistent hypothesis case:

with probability at least $1-\delta$

$$\epsilon_g < \frac{1}{m} \cdot (\ln |\mathcal{H}| + \ln \frac{1}{\delta})$$

inconsistent hypothesis case:

with probability at least $1-\delta$

$$\epsilon_g < \epsilon_t + \sqrt{\frac{1}{m}(\ln |\mathcal{H}| + \ln \frac{1}{\delta})}$$

generalization error:

- number of examples m
- training error ϵ_t
- hypothesis space complexity $\ln |\mathcal{H}|$

PAC-learning

Leslie Valiant
Turing Award (2010)
EATCS Award (2008)
Knuth Prize (1997)
Nevanlinna Prize (1986)

Probably approximately correct (PAC):

with probability at least $1-\delta$

$$\epsilon_g < \epsilon_t + \sqrt{\frac{1}{2m} \cdot (\ln |\mathcal{H}| + \ln \frac{1}{\delta})}$$

PAC-learnable: [Valiant, 1984]

A concept class $\mathcal{C}$ is PAC-learnable if exists a learning algorithm A such that for all $f \in \mathcal{C}$, $\epsilon > 0, \delta > 0$ and distribution D

$$P_D(\epsilon_g \leq \epsilon) \geq 1-\delta$$

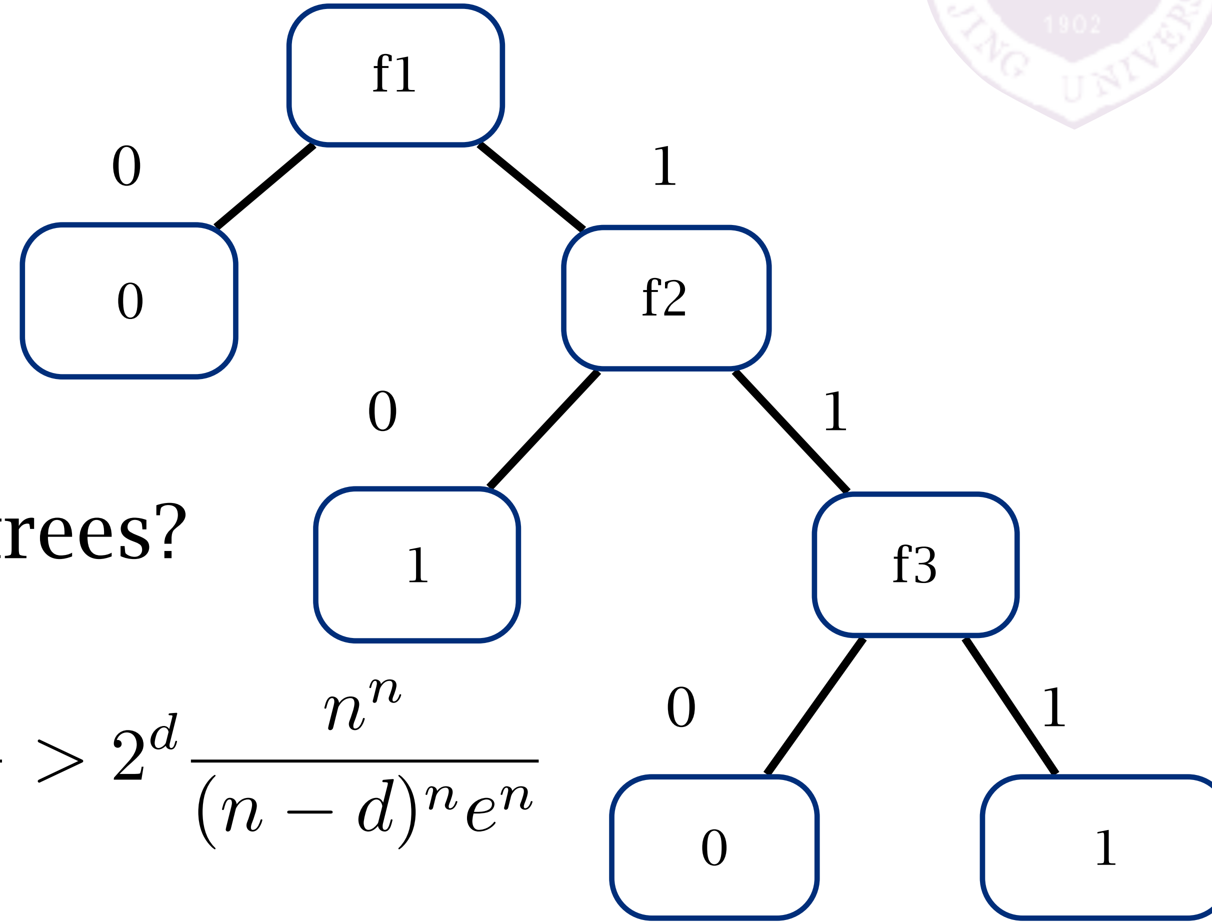
using $m = poly(1/\epsilon, 1/\delta)$ examples and polynomial time.

Learning algorithms revisit

Decision Tree

Tree depth and the possibilities

features: *n*
feature type: binary
depth: *d*<*n*



How many different trees?

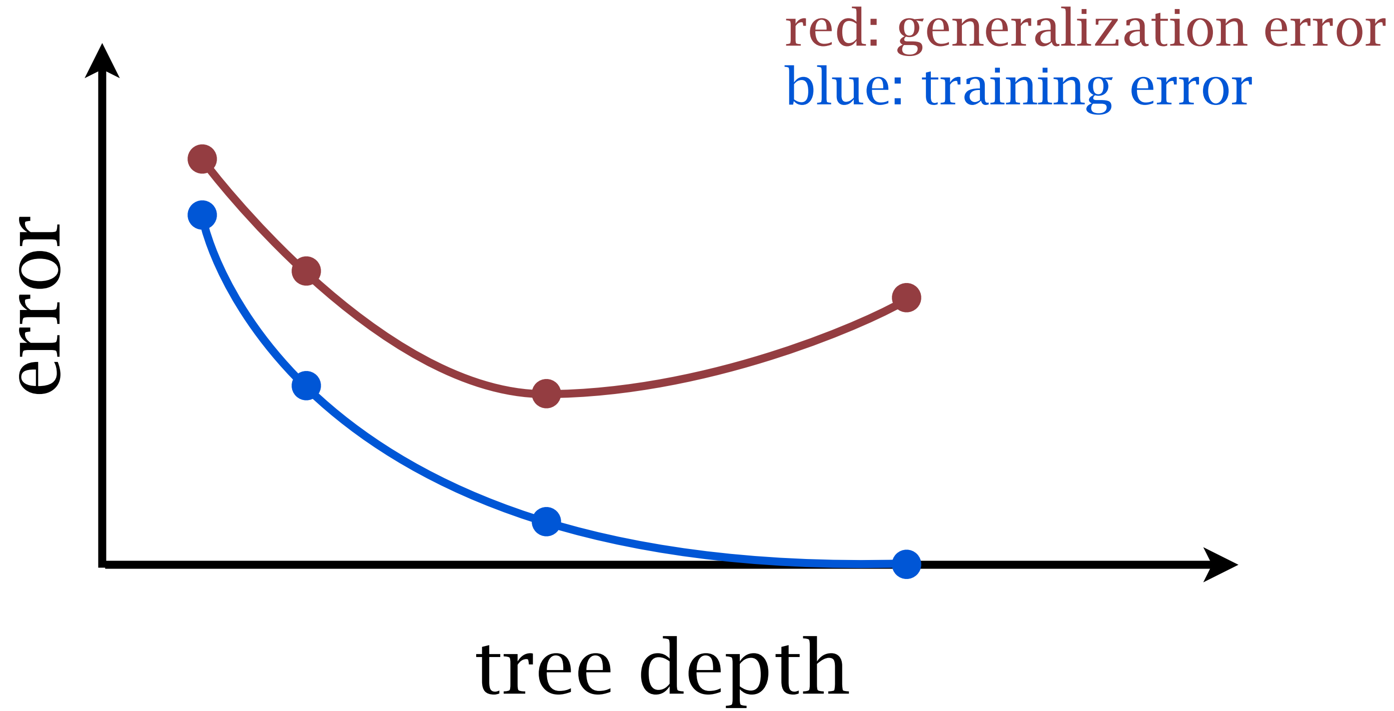
one-branch: $2^d \frac{n!}{(n-d)!} > 2^d \frac{n^n}{(n-d)^n e^n}$

full-tree: $2^{2^d} \prod_{i=0}^{d-1} \frac{(n-i)!}{(n-d-i)!}$

the possibility of trees grows very fast with *d*

The overfitting phenomena

-- the divergence between infinite and finite samples



Pruning

To make decision tree less complex

Pre-pruning: early stop

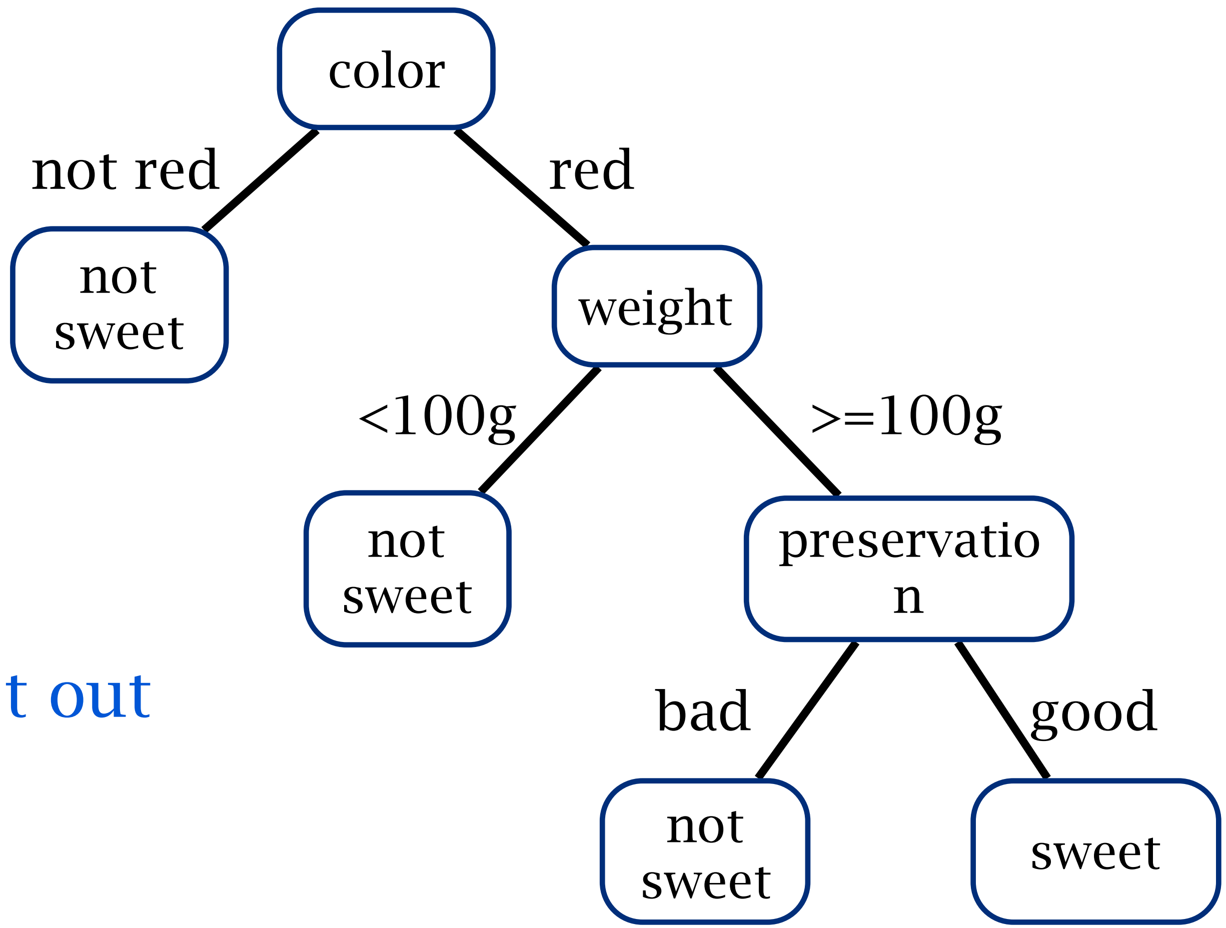
- minimum data in leaf
- maximum depth
- maximum accuracy

Post-pruning: prune full grown DT

reduced error pruning

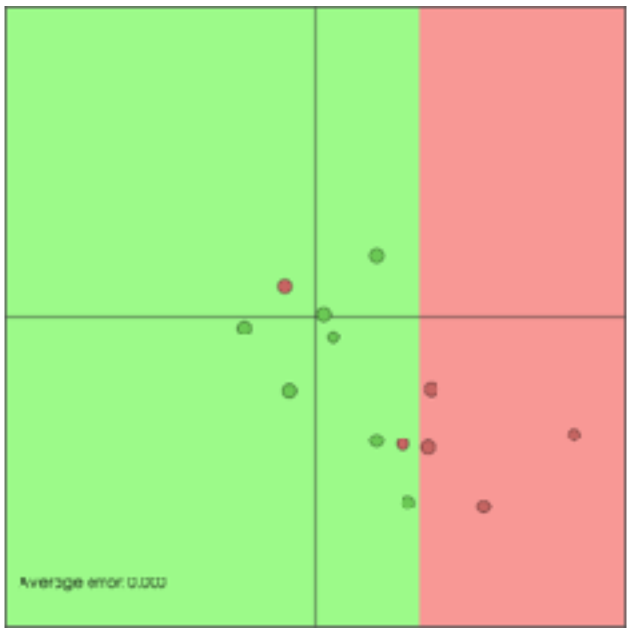
Reduced error pruning

1. Grow a decision tree
2. For every node starting from the leaves
3. Try to make the node leaf, if does not increase the error, keep as the leaf

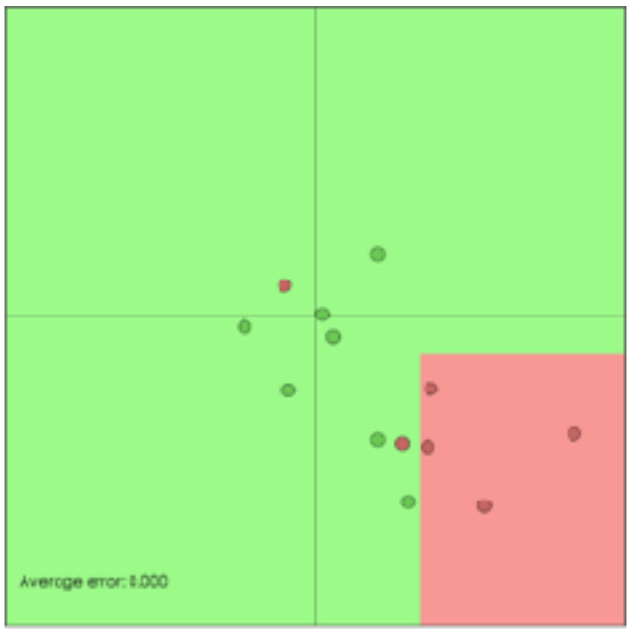


could split a validation set out from the training set to evaluate the error

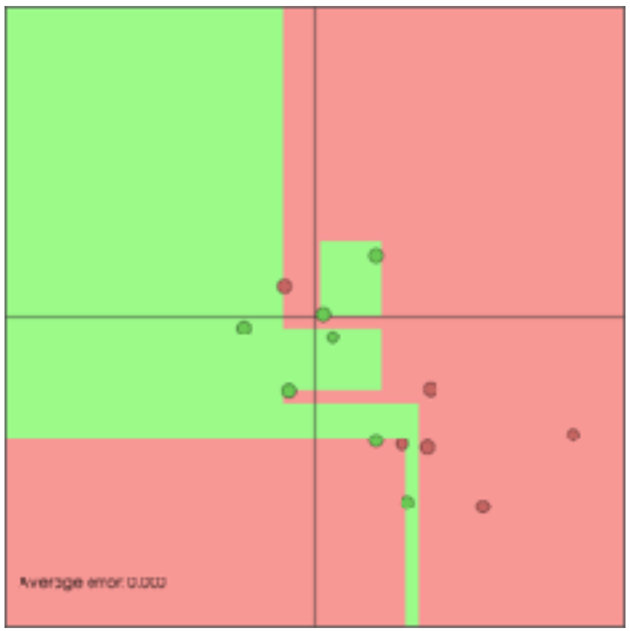
DT boundary visualization



decision stump



max depth=2



max depth=12

Oblique decision tree

choose a linear combination in each node:

axis parallel:
$X_1 > 0.5$

oblique:
$0.2\ X_1 + 0.7\ X_2 + 0.1\ X_3 > 0.5$

was hard to train