23 Generalization theory / Overfitting

Generalization

How well does a learned function predict on future test examples?

How to choose hypothesis space H?

If H is too complex

- over-fitting
- small training error
- large test error
- very different functions have similar training error
- perturbing training data slightly yields very different optimal hypotheses

If H is too restricted

- under-fitting
- large training error
- large test error

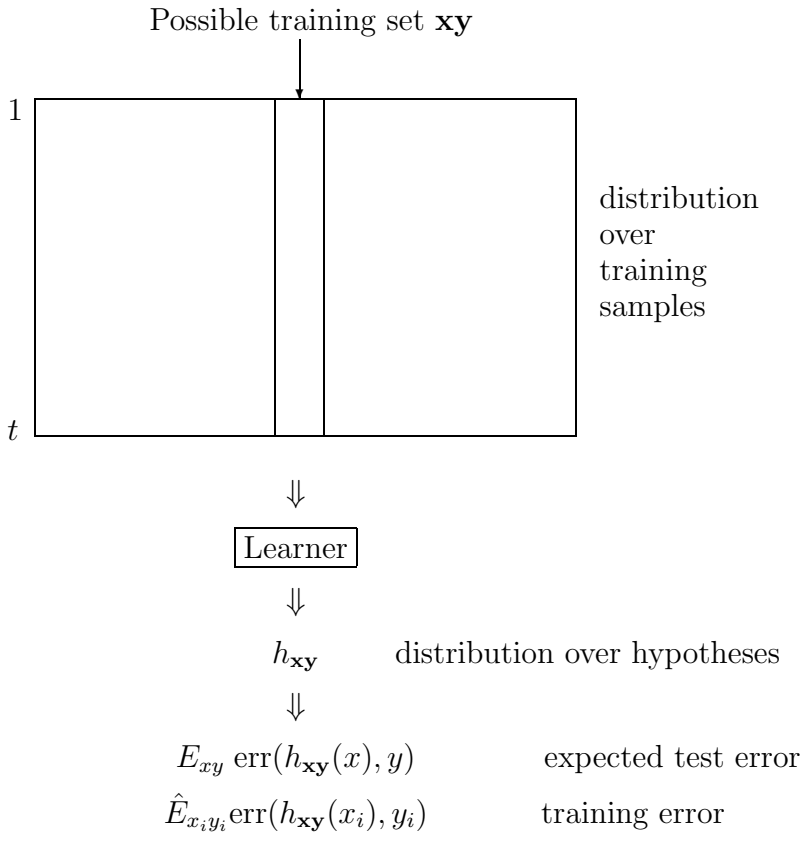
23.1 Introduction to statistical generalization theory

Mathematical model

independent identically distributed (IID) random examples

- Assume a fixed joint distribution P_{XY} over $X \times Y$
- Training examples $(x_1, y_1), \ldots, (x_t, y_t)$ independently drawn from P_{XY}
- Test examples independently drawn from same P_{XY}

Learner maps $(x_1, y_1) \ldots (x_t, y_t)$ to a hypothesis $h : X \to Y$



For squared prediction error

$$\mathrm{err}(\hat{y}, y) \;=\; (\hat{y} - y)^2$$

get

$$\begin{array}{lll} E_{\mathbf{xy}} E_{xy} \left(h_{\mathbf{xy}}(x) - y\right)^2 & \text{test error} & \\ \quad = \; E_{\mathbf{xy}} \hat{E}_{x_i y_i} \left(h_{\mathbf{xy}}(x_i) - y_i\right)^2 & \text{train error} & \left.\right\} \text{opt test err in } H \\ \quad + \; E_{\mathbf{xy}} \hat{E}_{x_i} \left(h_{\mathbf{xy}}(x_i) - h^*(x_i)\right)^2 & \text{train variance} & \\ \quad + \; E_{\mathbf{xy}} E_x \left(h_{\mathbf{xy}}(x) - h^*(x)\right)^2 & \text{variance} & \left.\right\} \text{hypothesis test err (all three terms)} \end{array}$$

where

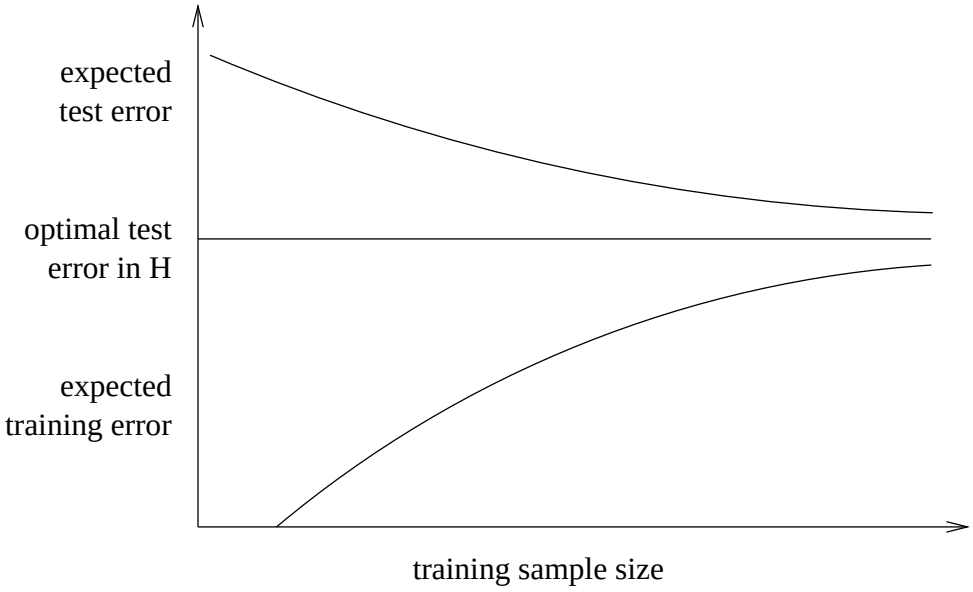
$$h^* \;=\; \arg\min_{h \in H} \; E_{xy} \left(h(x) - y\right)^2$$

$$H \quad \text{is} \quad \text{a closed linear space}$$

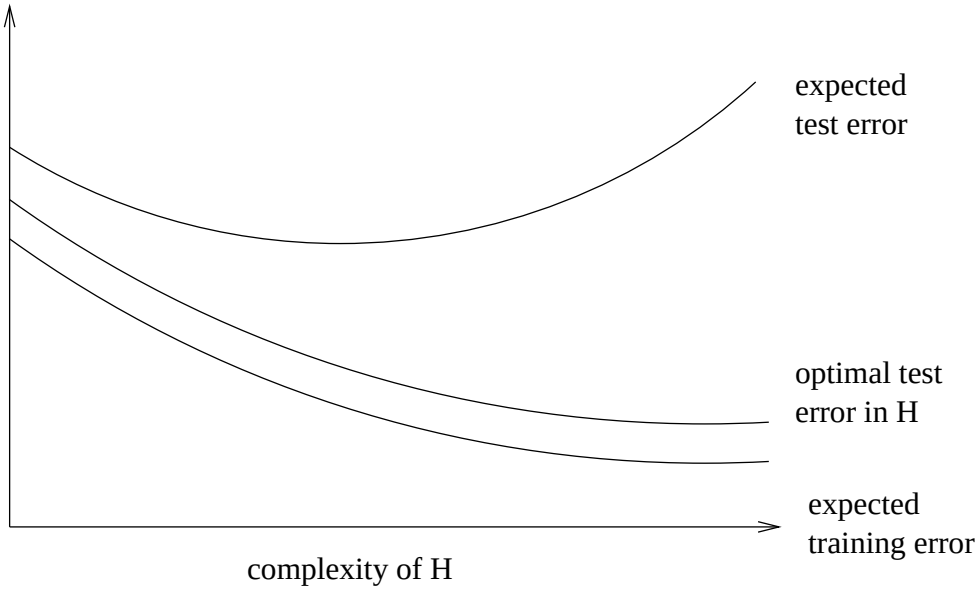
Immediate consequence

$$\begin{array}{lllll} \text{expected} & & \text{optimal} & & \text{expected} \\ \text{hypothesis} & \geq & \text{test} & \geq & \text{hypothesis} \\ \text{test} & & \text{error} & & \text{train} \\ \text{error} & & \text{in } H & & \text{error} \end{array}$$

23.2 Learning curves

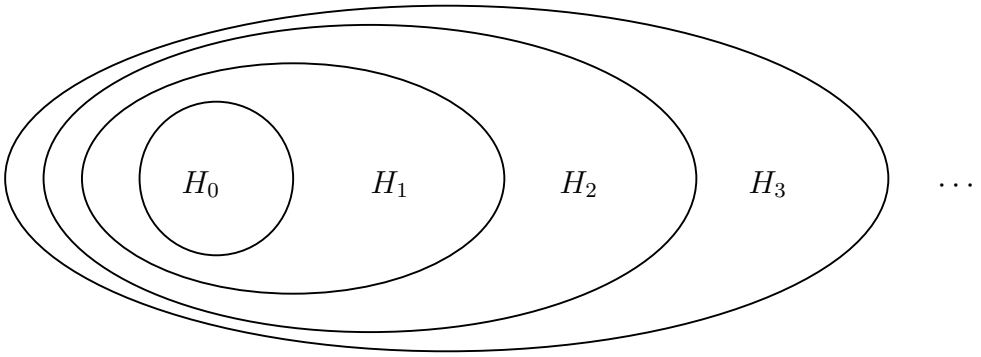


23.3 Overfitting curves



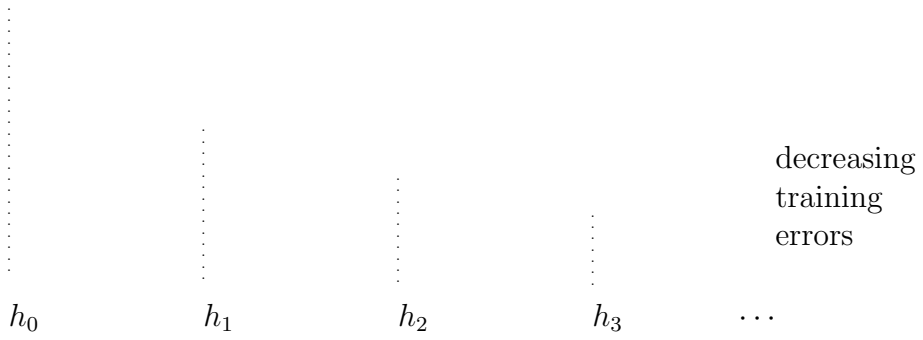
23.4 Automatic complexity control

Model selection



How to choose the right complexity level?

Given data, get



which hypothesis to choose?

- choose too early: under-fit
- choose too late: over-fit

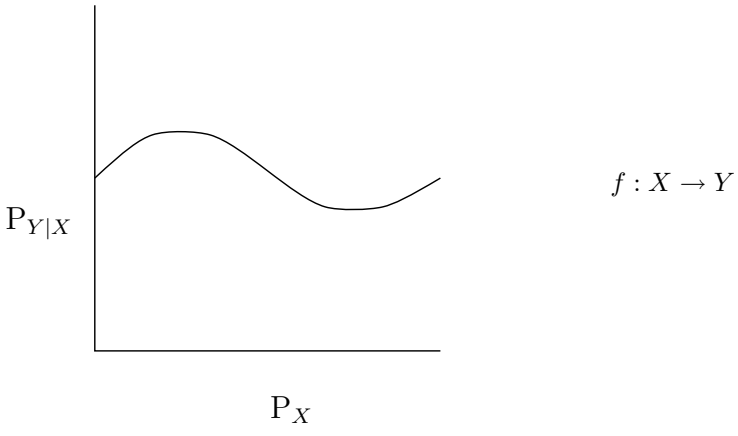
strategy 1: complexity penalization

- guess at variances
- training errors say nothing about variances
- penalty(i) approximates variance at complexity level i
- minimize: training_error(i) + penalty(i)

Strategy 2: Hold out testing

- Split training data into pseudo-train and pseudo-test set
- Train on pseudo-train and test each hypothesis $h_0, h_1, ...$ on the held-out pseudo-test
- Hold-out test gives an *unbiased* estimate of test error
- Pick i with best hold-out test
- Re-train at complexity level i on all the data

Strategy 3: Metric space



Assume we know P_X (which can be estimated from unlabeled data $x_1, x_2, ...$)

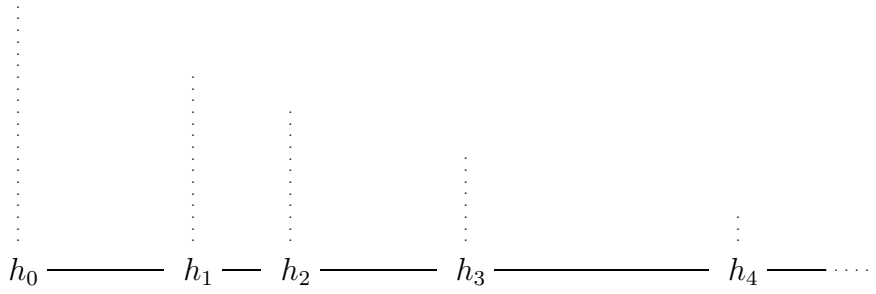
Defines a *metric* on H

$$d(h,g) = \sqrt{\int_x (h(x)-g(x))^2 \; d\mathrm{P}_X}$$

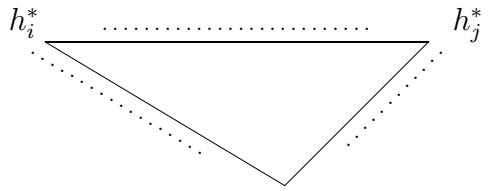
$$d(h,\mathrm{P}_{Y|X}) = \sqrt{\int_x \int_y (h(x)-y)^2 \; d\mathrm{P}_{Y|x} d\mathrm{P}_X}$$

Goal is to minimize $d(h,\mathrm{P}_{Y|X})$

Given data, get



Have 2 metrics, real and estimated



$\mathrm{P}_{Y|X}$

Adjust $\hat{d}(h_i, P_{Y|X})$ by multiplying it by $\max_{j<i} \dfrac{d(h_i,h_j)}{\hat{d}(h_i,h_j)}$

Readings

Hastie, Tibshirani, Friedman: Sections 2.9, 5.1–5.5

Schuurmans, D. and Southey, F. (2001) Metric-based methods for adaptive model selection and regularization. *Machine Learning*, 48(1-3): 51–84.