

CSE 417T

Introduction to Machine Learning

Lecture 7

Instructor: Chien-Ju (CJ) Ho

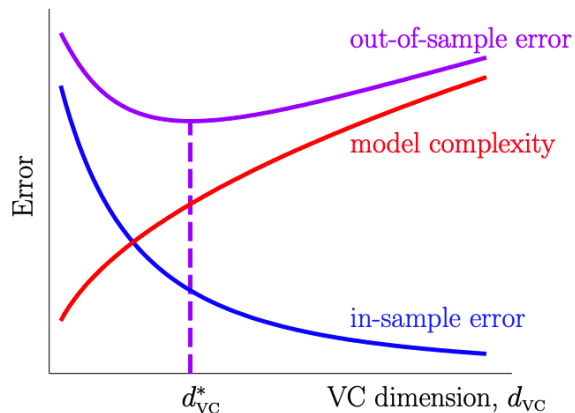
Logistics

- HW1: Due Sep 23
 - Reserve time if you have never used Gradescope
 - Check that submission is readable (if you scan your handwriting)
 - [Correctly assign pages](#) to each problem (you won't get points otherwise)
- HW2: Will be announce later this week
- Exam dates
 - Exam 1: October 27
 - We expect to finish the content for exam1 several lectures before the exam.
 - Exam 2: December 8

Recap

VC Generalization Bound

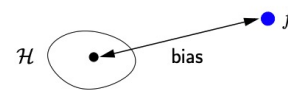
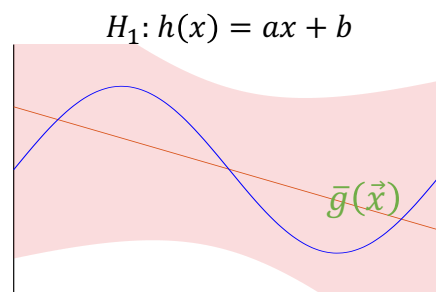
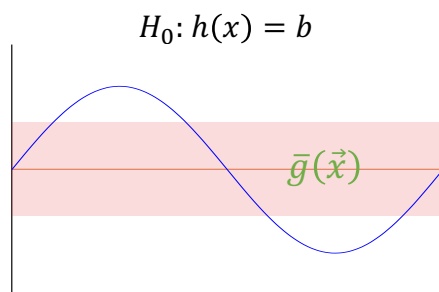
- VC Bound: $E_{out}(g) \leq E_{in}(g) + O\left(\sqrt{d_{vc} \frac{\ln N}{N}}\right)$
- Theoretically characterize the feasibility of learning
- The performance of your learning, i.e., $E_{out}(g)$, depends on
 - How well you fit your data ($E_{in}(g)$)
 - How well your $E_{in}(g)$ generalizes to $E_{out}(g)$



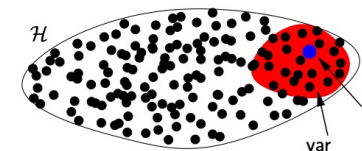
Bias-Variance Decomposition

$$\bullet \mathbb{E}_D[E_{out}(g^{(D)})] = \mathbb{E}_{\vec{x}} \left[\overset{\text{Bias}(\vec{x})}{(\bar{g}(\vec{x}) - f(\vec{x}))^2} \right] + \mathbb{E}_{\vec{x}} \left[\mathbb{E}_D \left[\overset{\text{Var}(\vec{x})}{(g^{(D)}(\vec{x}) - \bar{g}(\vec{x}))^2} \right] \right]$$

- The performance of your learning, i.e., $\mathbb{E}_D[E_{out}(g^{(D)})]$, depends on
 - How well you can fit your data using your hypothesis set (**bias**)
 - How stable your learning is for a randomly drawn dataset (**variance**)



Very small model



Very large model

Today's Lecture

The notes are not intended to be comprehensive. They should be accompanied by lectures and/or textbook.
Let me know if you spot errors.

Two Theories of Generalization

- VC Generalization Bound

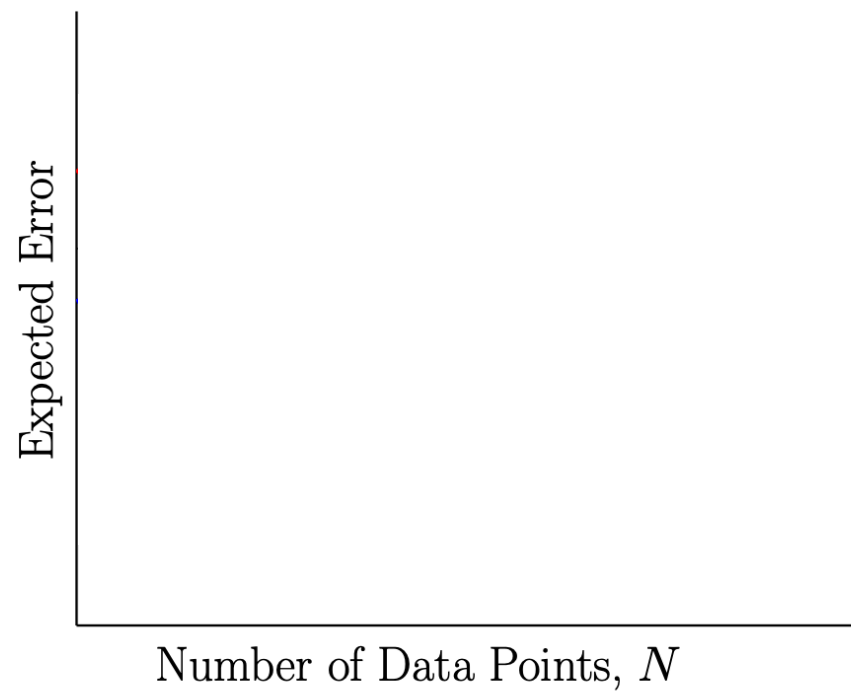
$$E_{out}(g) \leq E_{in}(g) + O\left(\sqrt{d_{vc} \frac{\ln N}{N}}\right)$$

- Bias-Variance Tradeoff

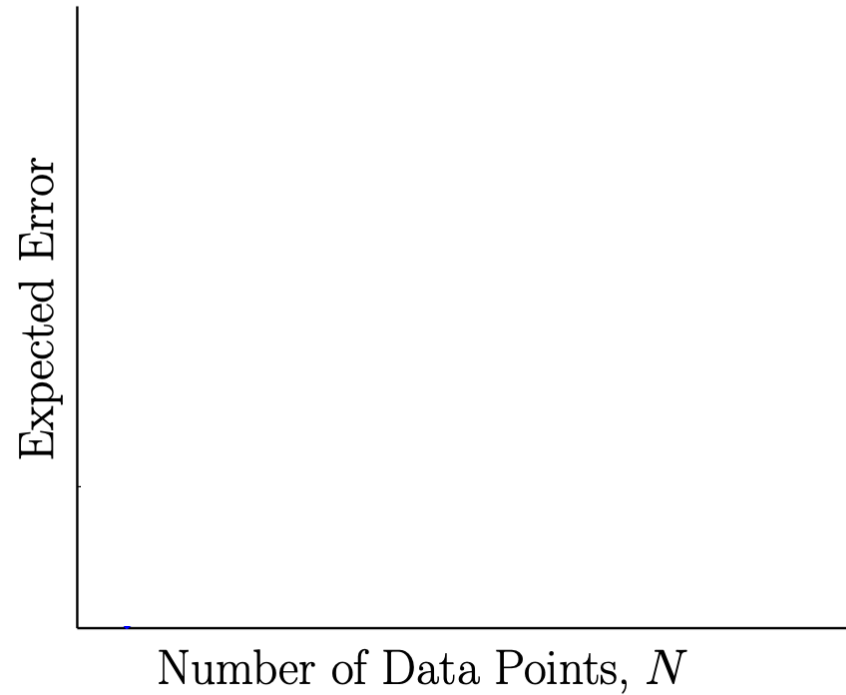
$$\mathbb{E}_D[E_{out}(g^{(D)})] = \mathbb{E}_{\vec{x}} \left[(\bar{g}(\vec{x}) - f(\vec{x}))^2 \right] + \mathbb{E}_{\vec{x}} \left[\mathbb{E}_D \left[(g^{(D)}(\vec{x}) - \bar{g}(\vec{x}))^2 \right] \right]$$

Learning Curves

Simple Model

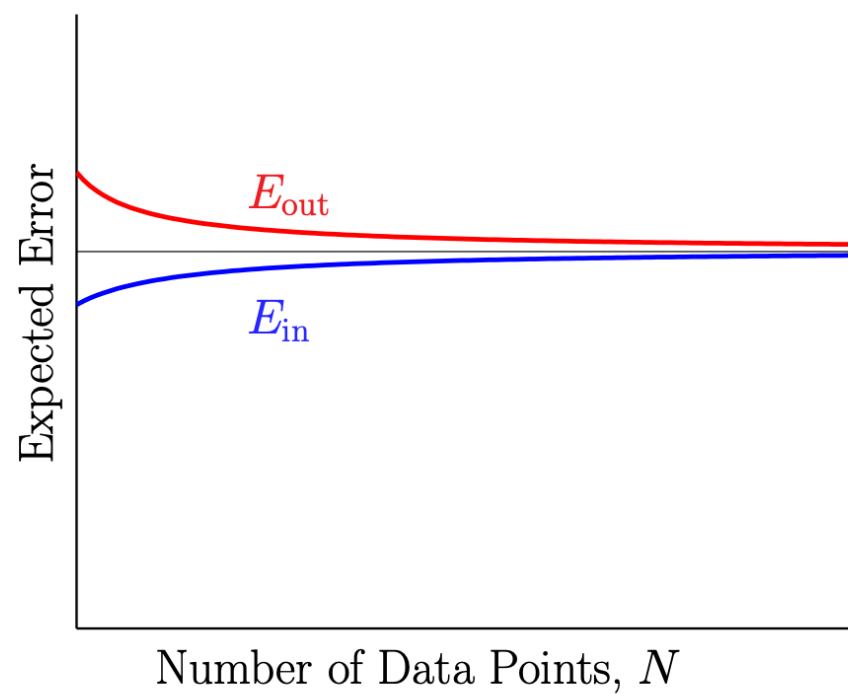


Complex Model

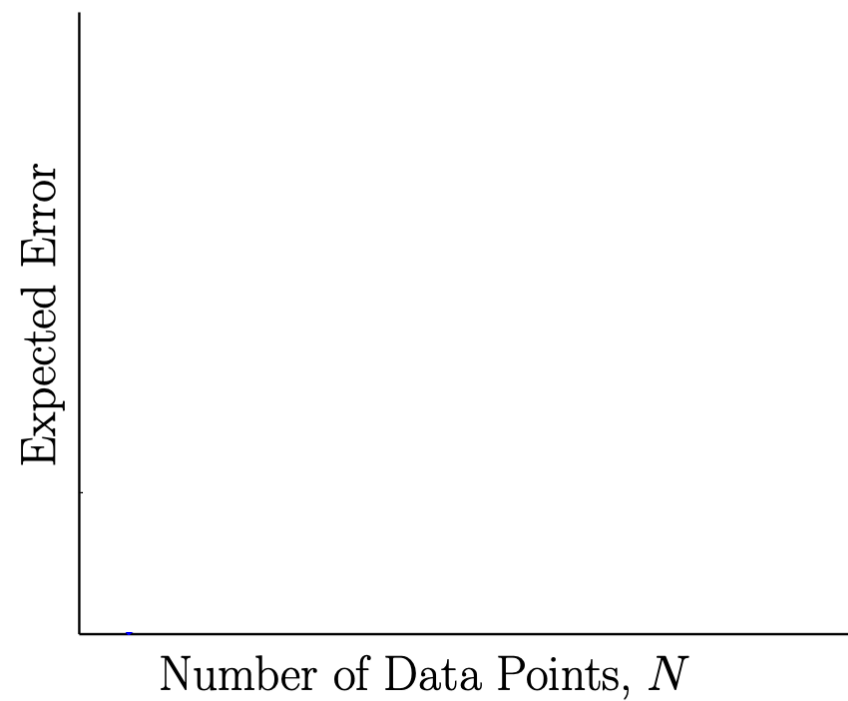


Learning Curves

Simple Model

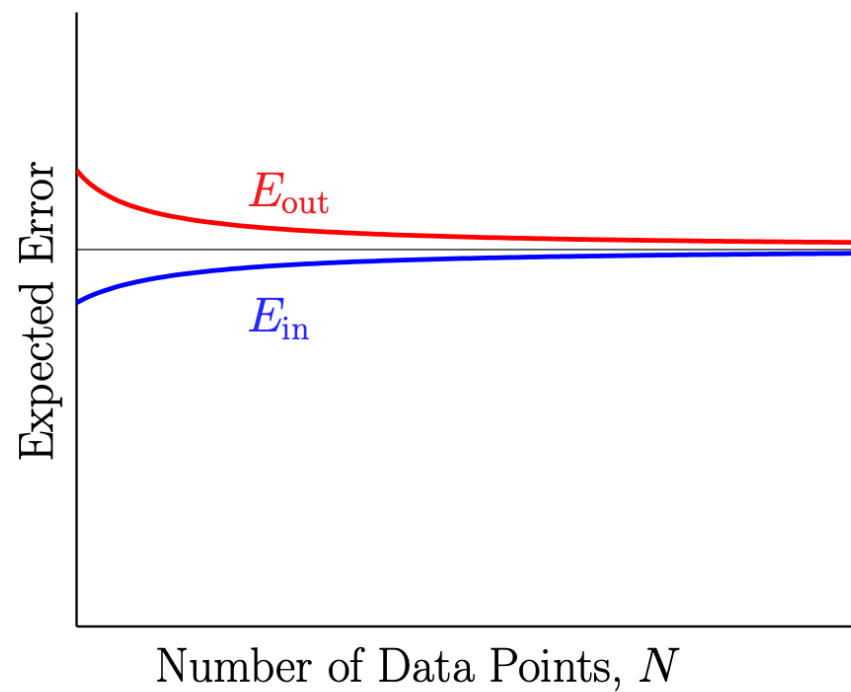


Complex Model

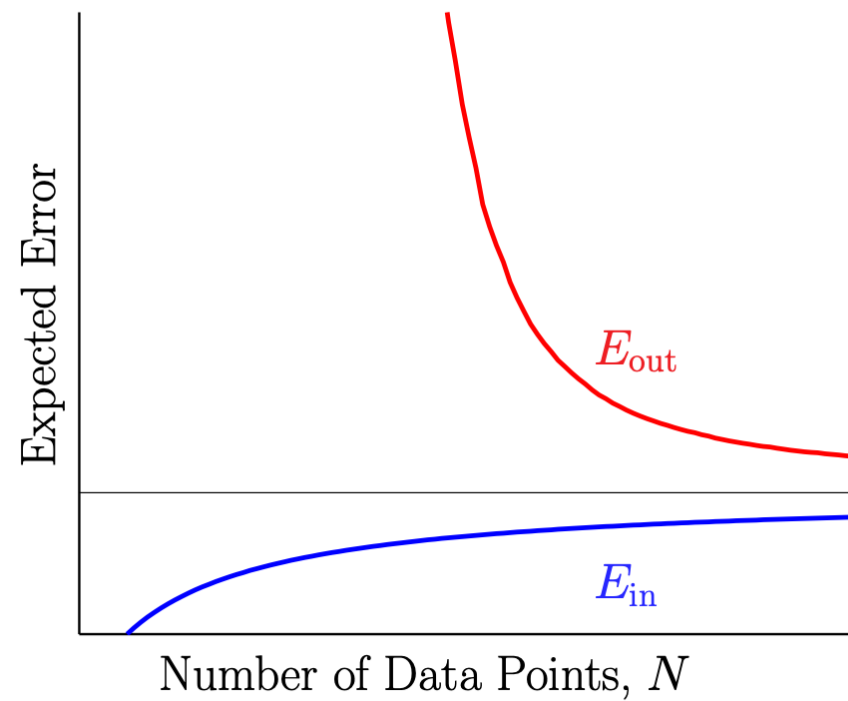


Learning Curves

Simple Model

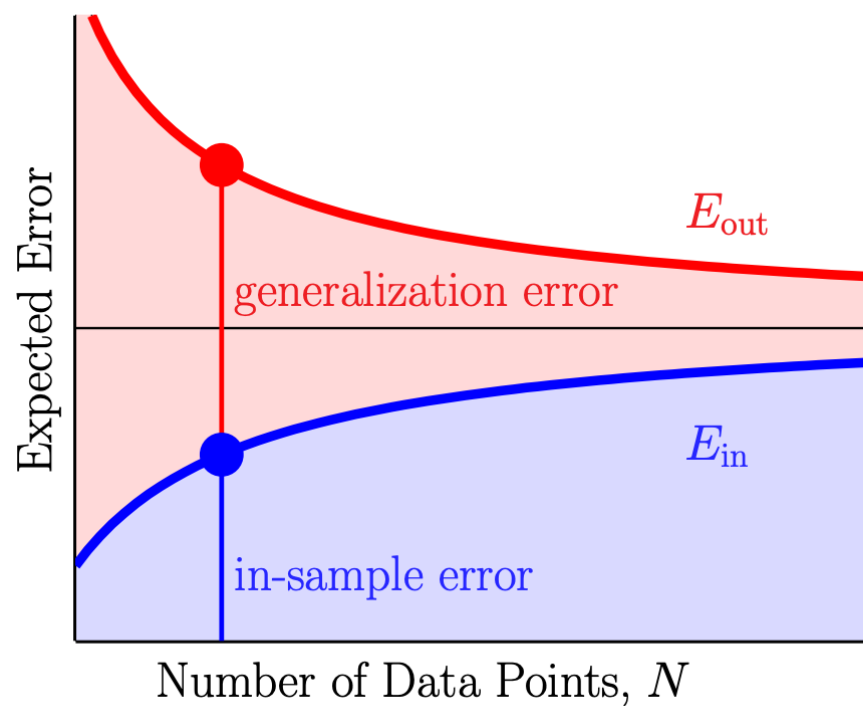


Complex Model



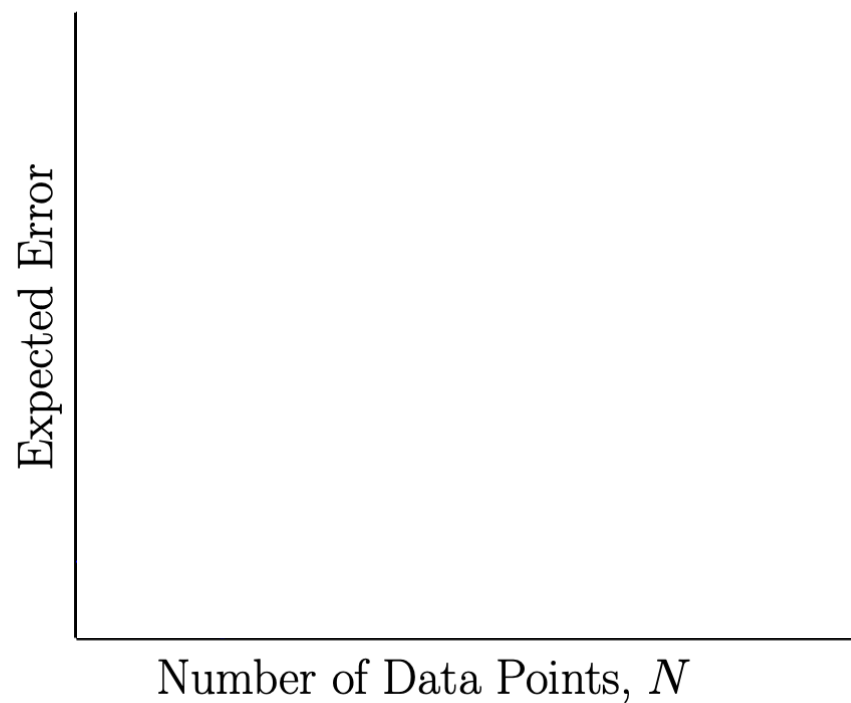
Learning Curves

VC Analysis



$$E_{out}(g) \leq E_{in}(g) + O\left(\sqrt{d_{vc} \frac{\ln N}{N}}\right)$$

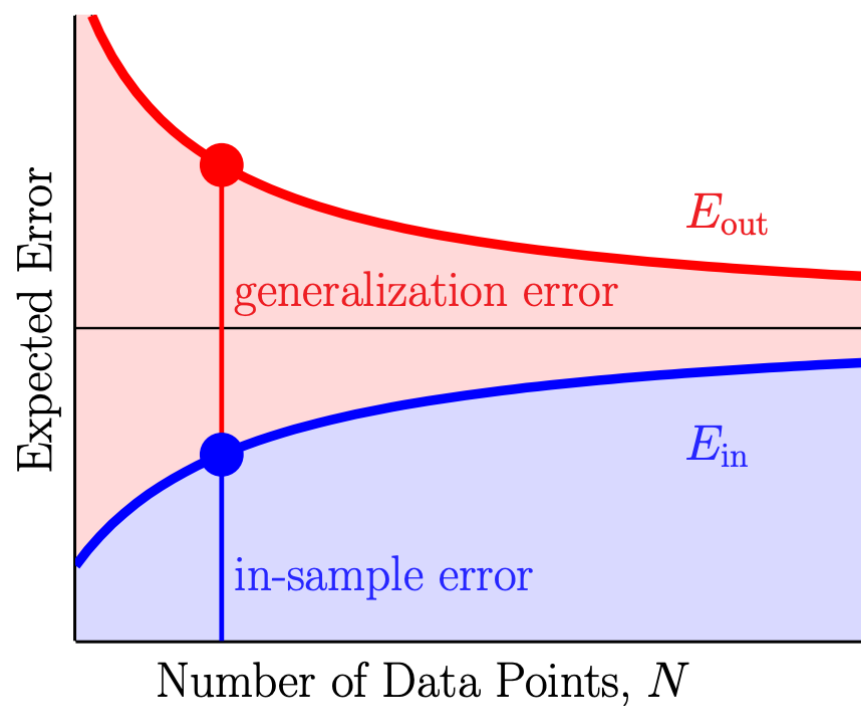
Bias-Variance Analysis



$$\begin{aligned} & \mathbb{E}_D[E_{out}(g^{(D)})] \\ &= \mathbb{E}_{\vec{x}} \left[(\bar{g}(\vec{x}) - f(\vec{x}))^2 \right] + \mathbb{E}_{\vec{x}} \left[\mathbb{E}_D \left[(g^{(D)}(\vec{x}) - \bar{g}(\vec{x}))^2 \right] \right] \end{aligned}$$

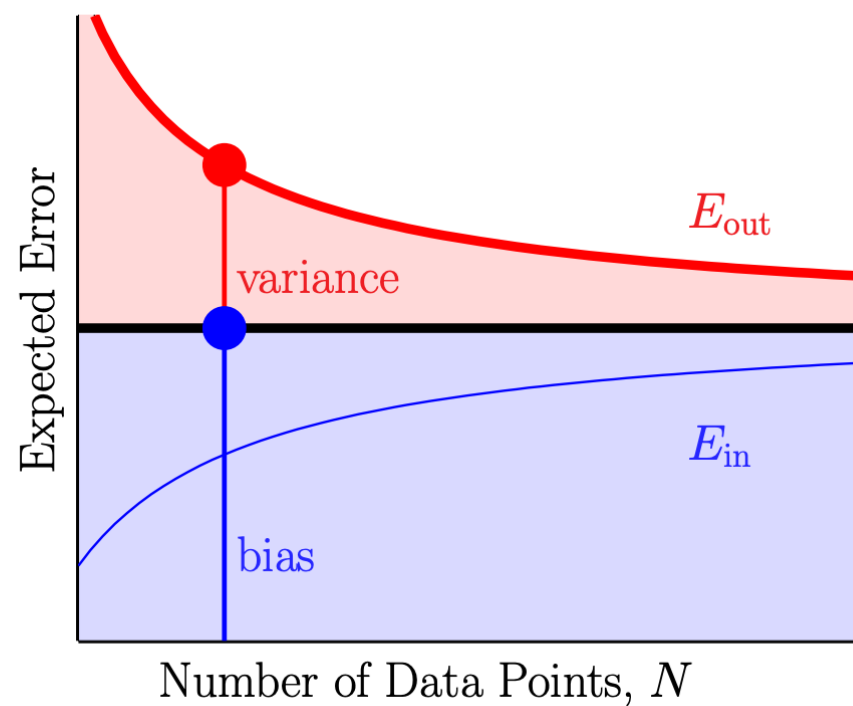
Learning Curves

VC Analysis

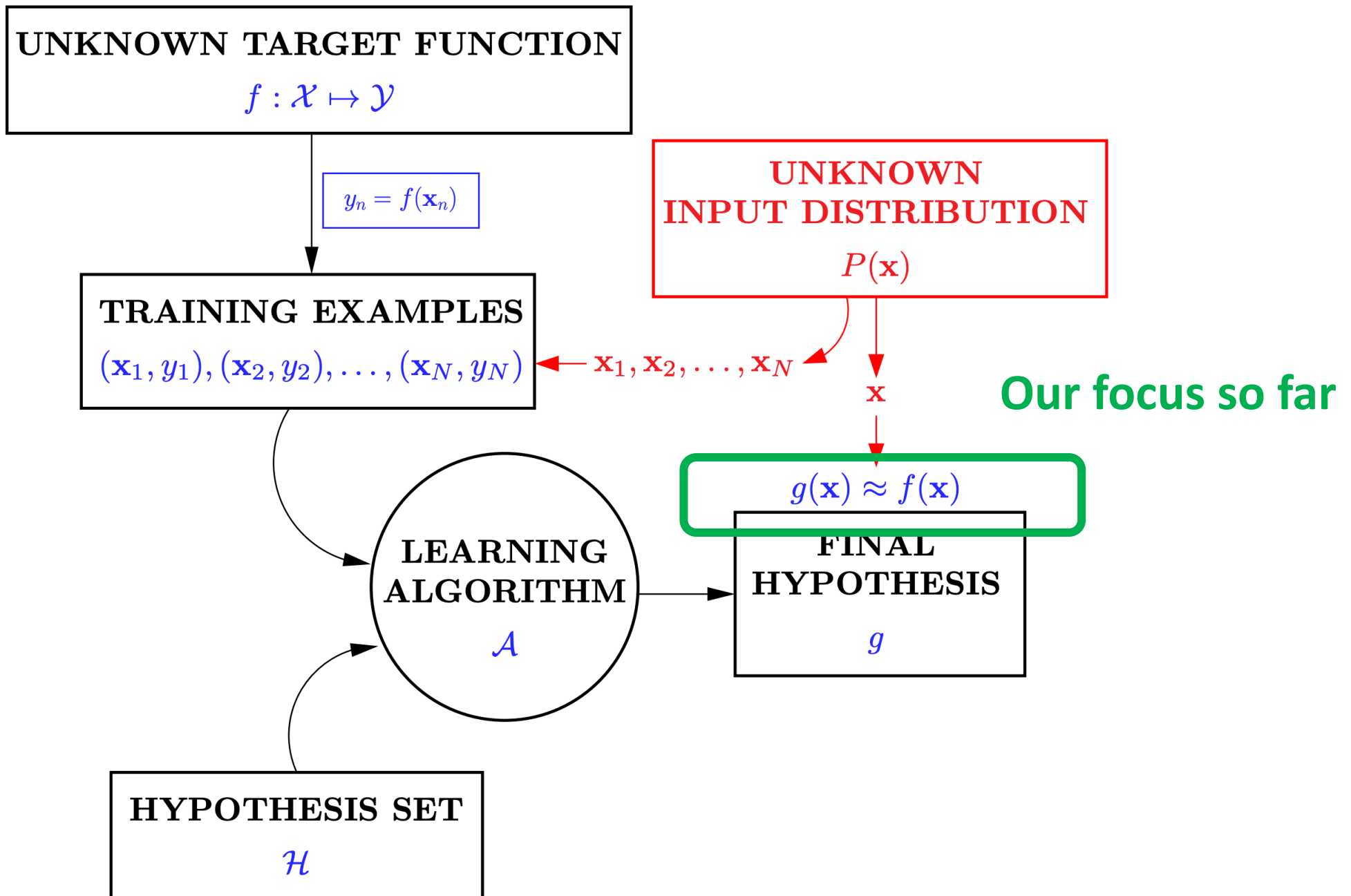


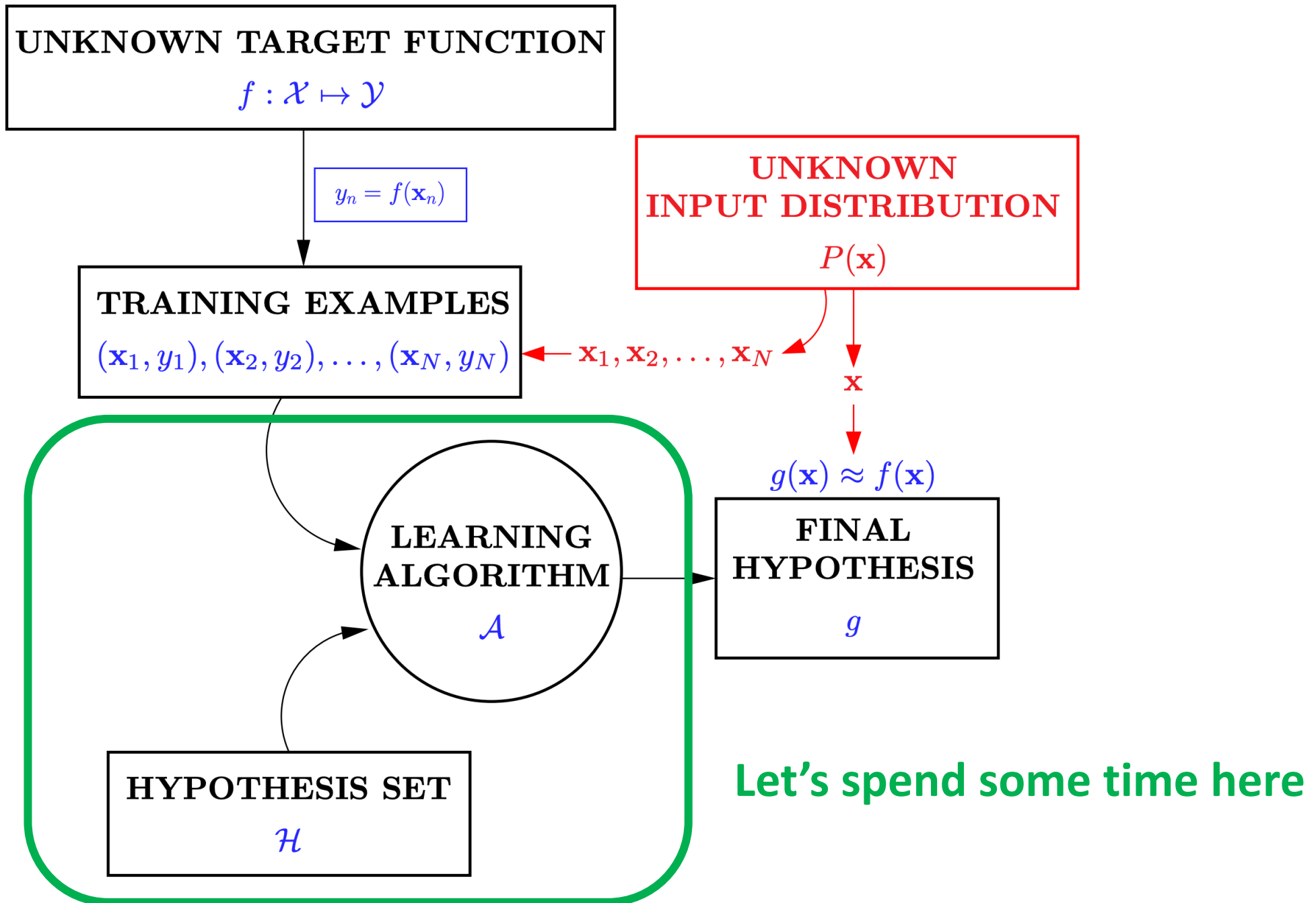
$$E_{out}(g) \leq E_{in}(g) + O\left(\sqrt{d_{vc} \frac{\ln N}{N}}\right)$$

Bias-Variance Analysis



$$\begin{aligned} & \mathbb{E}_D[E_{out}(g^{(D)})] \\ &= \mathbb{E}_{\vec{x}} \left[(\bar{g}(\vec{x}) - f(\vec{x}))^2 \right] + \mathbb{E}_{\vec{x}} \left[\mathbb{E}_D \left[(g^{(D)}(\vec{x}) - \bar{g}(\vec{x}))^2 \right] \right] \end{aligned}$$





Linear Models

Linear Models

This is why it's called linear models

- H contains hypothesis $h(\vec{x})$ as **some function of** $\vec{w}^T \vec{x}$

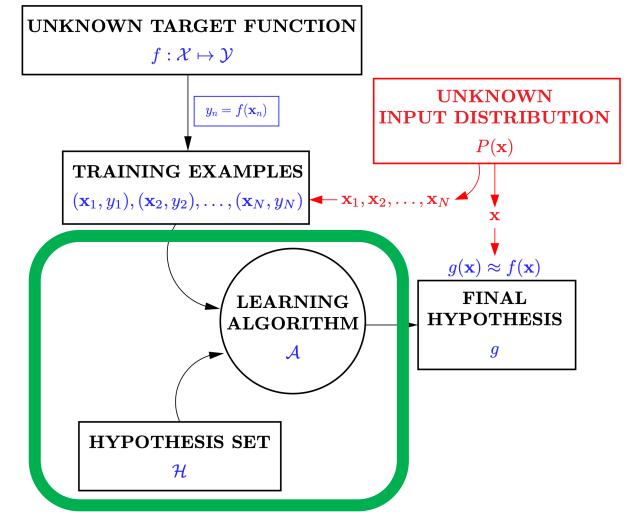
| | Domain | Model | Credit Card Example |
|-----------------------|--------------------|---|---------------------|
| Linear Classification | $y \in \{-1, +1\}$ | $H = \{h(\vec{x}) = \text{sign}(\vec{w}^T \vec{x})\}$ | Good customer? |
| Linear Regression | $y \in \mathbb{R}$ | $H = \{h(\vec{x}) = \vec{w}^T \vec{x}\}$ | Credit line |
| Logistic Regression | $y \in [0,1]$ | $H = \{h(\vec{x}) = \theta(\vec{w}^T \vec{x})\}$ | Prob. of default |

$$\theta(s) = \frac{e^s}{1 + e^s}$$

- Linear models:
 - Simple models => Good generalization error
- Reminder:
 - We will **interchangeably use** h and \vec{w} to represent a hypothesis in linear models

Learning Algorithm?

- Goal of the algorithm: Find $g \in H$ that minimizes $E_{out}(g)$
(We don't know E_{out})
- Common algorithms:
 - $g = \operatorname{argmin}_{h \in H} E_{in}(h)$
 - Works well when the model is simple (generalization error is small)
 - Will focus on this in the discussion of linear models
 - $g = \operatorname{argmin}_{h \in H} \{E_{in}(h) + \Omega(h)\}$
 - $\Omega(h)$: penalty for complex h
 - Will discuss this when we get to LFD Section 4



$$\text{VC Bound: } E_{out}(g) \leq E_{in}(g) + O\left(\sqrt{d_{vc} \frac{\ln N}{N}}\right)$$

- **Optimization** is a key component in machine learning

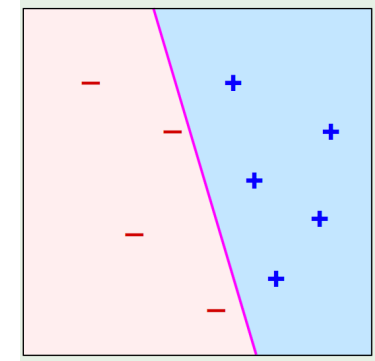
Linear Classification

| | Domain | Model |
|-----------------------|--------------------|---|
| Linear Classification | $y \in \{-1, +1\}$ | $H = \{h(\vec{x}) = \text{sign}(\vec{w}^T \vec{x})\}$ |
| Linear Regression | $y \in \mathbb{R}$ | $H = \{h(\vec{x}) = \vec{w}^T \vec{x}\}$ |
| Logistic Regression | $y \in [0,1]$ | $H = \{h(\vec{x}) = \theta(\vec{w}^T \vec{x})\}$ |

Linear Classification (Perceptron)

- Formulation

- Hypothesis set $H = \{h(\vec{x}) = \text{sign}(\vec{w}^T \vec{x})\}$
- Error measure: binary error $e(h(\vec{x}), y) = \mathbb{I}[h(\vec{x}) \neq y]$



- Property

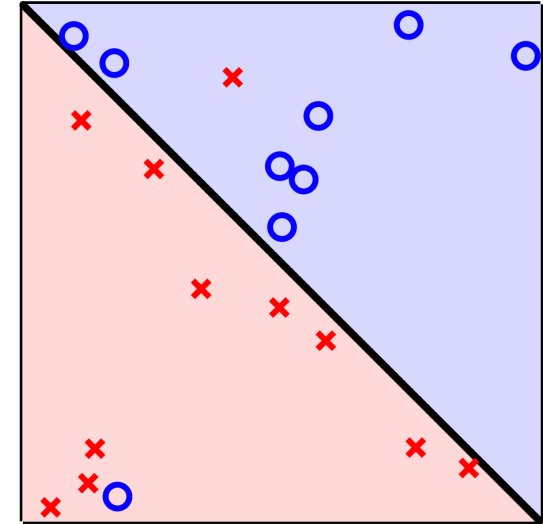
- Simple model (Fact: the VC dimension of d-dim perceptron is d+1)
- Good generalization error

- When data is linearly separable

- Run PLA
 - => find g with $E_{in}(g) = 0$
 - => $E_{out}(g)$ is close to $E_{in}(g) = 0$

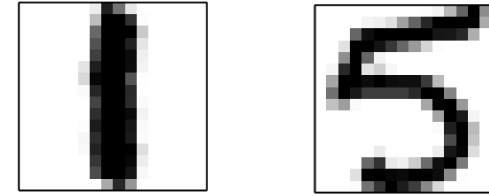
Non-Separable Data

- Generally a hard problem
 - Minimizing E_{in} is NP-hard
 - Reason: binary error is discrete and hard to optimize
- Alternative approaches
 - Pocket algorithm
 - Run PLA for a finite pre-determined T rounds
 - Keep track of the best weights \vec{w}^* ($\vec{w}(t)$) that minimizes E_{in}
 - Engineering the features to make data closer to be separable
 - Feature engineering (requiring domain knowledge, e.g., see LFD Example 3.1)
 - Non-linear transformation (will discuss this in later lectures)
 - Changing the problem formulation
 - Treat it as a logistic regression problem (what's the probability for the label to be +1)
 - Another example: Support vector machines in 2nd half of the semester



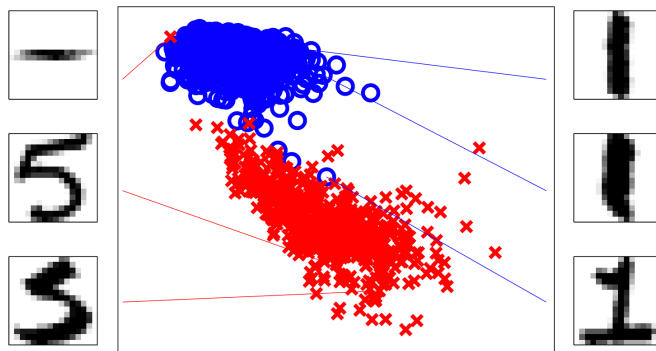
Example on Feature Engineering

- Task: Classify handwritten digits of 1 and 5



- Linearly separable?

- What are the features \vec{x} ?
 - Each pixel as a feature (deep neural network takes this approach. requires a lot of data)
 - $\vec{x} = (\text{intensity}, \text{symmetry})$



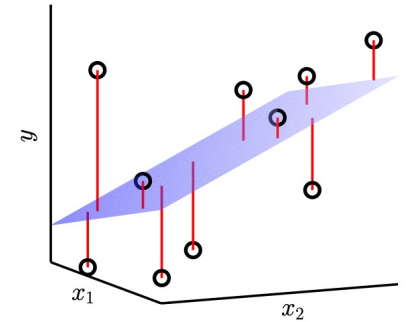
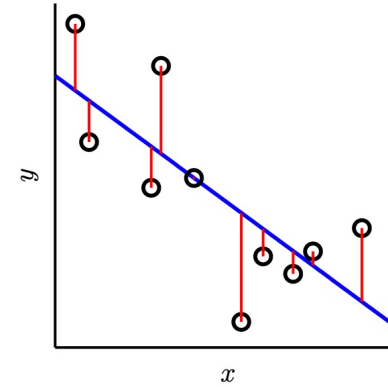
Feature engineering is a practical issue in applied ML but not the focus of this course (requires domain knowledge).

Linear Regression

| | Domain | Model |
|-----------------------|--------------------|---|
| Linear Classification | $y \in \{-1, +1\}$ | $H = \{h(\vec{x}) = \text{sign}(\vec{w}^T \vec{x})\}$ |
| Linear Regression | $y \in \mathbb{R}$ | $H = \{h(\vec{x}) = \vec{w}^T \vec{x}\}$ |
| Logistic Regression | $y \in [0,1]$ | $H = \{h(\vec{x}) = \theta(\vec{w}^T \vec{x})\}$ |


Linear Regression

- Formulation
 - Hypothesis set $H = \{h(\vec{x}) = \vec{w}^T \vec{x}\}$
 - Squared error $e(h(\vec{x}), y) = (h(\vec{x}) - y)^2$
- Given dataset $D = \{(\vec{x}_1, y_1), \dots, (\vec{x}_N, y_N)\}$
 - $E_{in}(\vec{w}) = \frac{1}{N} \sum_{n=1}^N (\vec{w}^T \vec{x}_n - y_n)^2$
- Goal: find $\vec{w}_{lin} = \operatorname{argmin}_{\vec{w}} E_{in}(\vec{w})$



Matrix Representation

- $D = \{(\vec{x}_1, y_1), \dots, (\vec{x}_N, y_N)\}$

- $X = \begin{bmatrix} \vec{x}_1^T \\ \vdots \\ \vec{x}_N^T \end{bmatrix} = \begin{bmatrix} x_{1,0} & x_{1,1} & \cdots & x_{1,d} \\ x_{2,0} & x_{2,1} & \cdots & x_{2,d} \\ \vdots & \vdots & \ddots & \vdots \\ x_{N,0} & x_{N,1} & \cdots & x_{N,d} \end{bmatrix}$ 

$x_{n,i}$: the i -th element
of vector \vec{x}_n

- $\vec{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix}$

Predictions made
by hypothesis \vec{w}

$$X\vec{w} = \begin{bmatrix} \vec{x}_1^T \vec{w} \\ \vdots \\ \vec{x}_N^T \vec{w} \end{bmatrix}$$

$$X\vec{w} - \vec{y} = \begin{bmatrix} \vec{x}_1^T \vec{w} - y_1 \\ \vdots \\ \vec{x}_N^T \vec{w} - y_N \end{bmatrix}$$

Rewriting the In-Sample Error In Matrix Form

$$E_{in}(\vec{w}) = \frac{1}{N} \sum_{n=1}^N (\vec{w}^T \vec{x}_n - y_n)^2$$

$$X = \begin{bmatrix} \vec{x}_1^T \\ \vdots \\ \vec{x}_N^T \end{bmatrix}; \quad \vec{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix}$$

$$X\vec{w} = \begin{bmatrix} \vec{x}_1^T \vec{w} \\ \vdots \\ \vec{x}_N^T \vec{w} \end{bmatrix}$$

$$X\vec{w} - \vec{y} = \begin{bmatrix} \vec{x}_1^T \vec{w} - y_1 \\ \vdots \\ \vec{x}_N^T \vec{w} - y_N \end{bmatrix}$$

$$= \frac{1}{N} \sum_{n=1}^N (\vec{x}_n^T \vec{w} - y_n)^2$$

$$\|\vec{z}\| = \sqrt{\vec{z}^T \vec{z}} = \sqrt{\sum_{i=1}^d z_i^2}$$
$$\|\vec{z}\|^2 = \vec{z}^T \vec{z} = \sum_{i=1}^d z_i^2$$

$$= \frac{1}{N} \|X\vec{w} - \vec{y}\|^2$$

$$= \frac{1}{N} (X\vec{w} - \vec{y})^T (X\vec{w} - \vec{y})$$

$$\longrightarrow E_{in}(\vec{w}) = \frac{1}{N} \left((X\vec{w})^T - \vec{y}^T \right) (X\vec{w} - \vec{y})$$
$$= \frac{1}{N} (\vec{w}^T X^T X \vec{w} - 2\vec{w}^T X^T \vec{y} + \vec{y}^T \vec{y})$$

How to find $\vec{w}_{lin} = \operatorname{argmin}_{\vec{w}} E_{in}(\vec{w})$?

- Given $E_{in}(\vec{w}) = \frac{1}{N} (\vec{w}^T X^T X \vec{w} - 2 \vec{w}^T X^T \vec{y} + \vec{y}^T \vec{y})$
- Solve for $\nabla_{\vec{w}} E_{in}(\vec{w}) = 0$
 - Think about what you'll do for one-dimensional case

- Derivations

- $E_{in}(\vec{w}) = \frac{1}{N} (\vec{w}^T X^T X \vec{w} - 2 \vec{w}^T X^T \vec{y} + \vec{y}^T \vec{y})$

- $\nabla_{\vec{w}} E_{in}(\vec{w}) = \frac{1}{N} (2X^T X \vec{w} - 2X^T \vec{y})$

- $\nabla_{\vec{w}} E_{in}(\vec{w}_{lin}) = 0 \implies X^T X \vec{w}_{lin} = X^T \vec{y}$

$$\nabla f(\vec{w}) = \nabla_{\vec{w}} f(\vec{w}) = \begin{bmatrix} \frac{\partial}{\partial w_0} f(\vec{w}) \\ \frac{\partial}{\partial w_1} f(\vec{w}) \\ \vdots \\ \frac{\partial}{\partial w_d} f(\vec{w}) \end{bmatrix}$$

- $X^T X \vec{w}_{lin} = X^T \vec{y}$
 - Two cases:
 - If $X^T X$ is **invertible** (When $N \gg d$, most of the time, it is invertible)
 - $\vec{w}_{lin} = (X^T X)^{-1} X^T \vec{y}$
 - If $X^T X$ is not invertible
 - Requires special handling (See LFD Problem 3.15 for an example)
 - In practice
 - Define X^\dagger as the pseudo-inverse of X
 - When $X^T X$ is invertible, $X^\dagger = (X^T X)^{-1} X^T$
 - When $X^T X$ is not invertible, “handle” it appropriately (usually done in the library for you)
- Linear regression algorithm (a single step algorithm):
 - $\vec{w}_{lin} = X^\dagger \vec{y}$

Linear Regression “Algorithm”

- Input: $D = \{(\vec{x}_1, y_1), (\vec{x}_2, y_2), \dots, (\vec{x}_N, y_N)\}$

1. Construct X and \vec{y}

2. Compute the pseudo-inverse of X : X^\dagger
($X^\dagger = (X^T X)^{-1} X^T$ when $(X^T X)$ is invertible)

3. Compute $\vec{w}_{lin} = X^\dagger \vec{y}$

- Output: \vec{w}_{lin}

Short Discussion

Linear Regression “Algorithm”

- Input: $D = \{(\vec{x}_1, y_1), (\vec{x}_2, y_2), \dots, (\vec{x}_N, y_N)\}$

1. Construct X and \vec{y}

2. Compute the pseudo-inverse of X : X^\dagger
($X^\dagger = (X^T X)^{-1} X^T$ when $(X^T X)$ is invertible)

3. Compute $\vec{w}_{lin} = X^\dagger \vec{y}$

- Output: \vec{w}_{lin}

- What happens in 0-dimensional model
 - $\vec{x} = (x_0)$
 - Given $D = \{(\vec{x}_1, y_1), (\vec{x}_2, y_2), \dots, (\vec{x}_N, y_N)\}$
 - What's \vec{w}_{lin}

Short Discussion

Linear Regression “Algorithm”

- Input: $D = \{(\vec{x}_1, y_1), (\vec{x}_2, y_2), \dots, (\vec{x}_N, y_N)\}$

1. Construct X and \vec{y}

2. Compute the pseudo-inverse of X : X^\dagger
($X^\dagger = (X^T X)^{-1} X^T$ when $(X^T X)$ is invertible)

3. Compute $\vec{w}_{lin} = X^\dagger \vec{y}$

- Output: \vec{w}_{lin}

- Special case of **zero-dimensional** space

$$X = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} \Rightarrow X^T X = N \Rightarrow (X^T X)^{-1} = 1/N$$

$$\vec{w}_{lin} = (X^T X)^{-1} X^T \vec{y}$$

$$= \begin{bmatrix} \frac{1}{N} & \dots & \frac{1}{N} \end{bmatrix} \begin{bmatrix} y_1 \\ \vdots \\ y_N \end{bmatrix} = \frac{1}{N} \sum_{n=1}^N y_n$$

Squared error \Rightarrow mean

Discussion

- Linear regression generalizes very well
 - Under mild conditions (See LFD Exercise 3.4 for an example)

$$E_{out}(g) = E_{in}(g) + O\left(\frac{d}{N}\right)$$

- Use regression for classification
 - Note that $\{-1, +1\} \subset \mathbb{R}$
 - Use linear regression to find $\vec{w}_{lin} = (X^T X)^{-1} X^T \vec{y}$ for data with $y \in \{-1, +1\}$
 - Use \vec{w}_{lin} for classification: $g(\vec{x}) = \text{sign}(\vec{w}_{lin}^T \vec{x})$
 - Alternatively, use \vec{w}_{lin} as the initialization for Pocket Algorithm

Logistic Regression

| | Domain | Model |
|-----------------------|--------------------|---|
| Linear Classification | $y \in \{-1, +1\}$ | $H = \{h(\vec{x}) = \text{sign}(\vec{w}^T \vec{x})\}$ |
| Linear Regression | $y \in \mathbb{R}$ | $H = \{h(\vec{x}) = \vec{w}^T \vec{x}\}$ |
| Logistic Regression | $y \in [0,1]$ | $H = \{h(\vec{x}) = \theta(\vec{w}^T \vec{x})\}$ |

Logistic Regression: Predicting a Probability

- Will this patient have a heart attack within the next year?

| | |
|-------------|-----------------|
| age | 62 years |
| gender | male |
| blood sugar | 120 mg/dL40,000 |
| HDL | 50 |
| LDL | 120 |
| Mass | 190 lbs |
| Height | 5' 10'' |
| ... | ... |

Classification: Yes/No

Logistic regression: Probability of Yes

- A hypothesis $h(\vec{x})$ outputs a value in $[0,1]$
 - Interpreting it as the probability of yes

Logistic Regression: Predicting a Probability

- Hypothesis set $H = \{h(\vec{x}) = \theta(\vec{w}^T \vec{x})\}$
 - Want θ to map from $(-\infty, \infty)$ to $[0,1]$

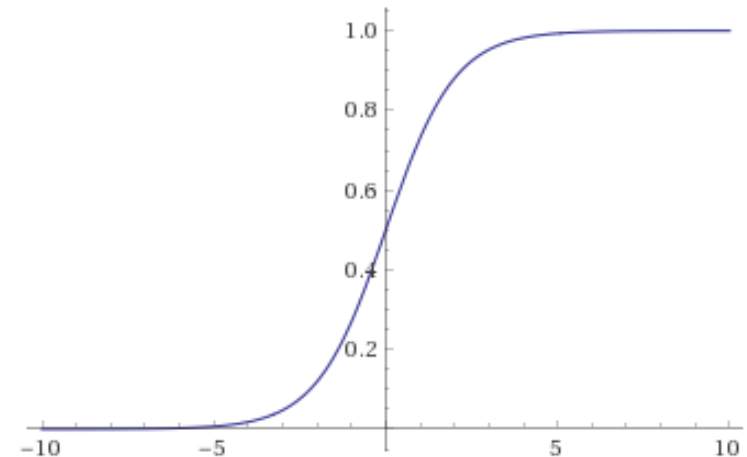
- $\theta(s) = \frac{e^s}{1+e^s} = \frac{1}{1+e^{-s}}$

- A sigmoid function ("S"-shaped function)

- $\theta(s) = \begin{cases} 1 & \text{when } s \rightarrow \infty \\ 0.5 & \text{when } s = 0 \\ 0 & \text{when } s \rightarrow -\infty \end{cases}$

- Useful property

- $1 - \theta(s) = \frac{1+e^s}{1+e^s} - \frac{e^s}{1+e^s} = \frac{1}{1+e^s} = \theta(-s)$



What Kind of Dataset do We Get?

- Dataset $D = \{(\vec{x}_1, y_1), \dots, (\vec{x}_N, y_N)\}$

$\vec{x} =$

| | |
|-------------|-----------------|
| age | 62 years |
| gender | male |
| blood sugar | 120 mg/dL40,000 |
| HDL | 50 |
| LDL | 120 |
| Mass | 190 lbs |
| Height | 5' 10" |
| ... | ... |

- What are the values of y_n ?
 - Ideally, we want to have y_n to be the probability value
 - In practice, we **cannot measure a probability**
 - We can only see the occurrence of an event and infer the probability
 - (We often only observe whether the person had heart attack, we don't observe the "probability")
- Need to address the case when $y_n \in \{-1, +1\}$ in the given dataset D

Error Measure: Quantifying $g \approx f$

Side note:

You probably can guess why the property $1 - \theta(s) = \theta(-s)$ might be helpful

- Target function $f(\vec{x}) = \Pr(y = +1|\vec{x})$

- Another way to write it: $\Pr(y|\vec{x}) = \begin{cases} f(\vec{x}) & \text{for } y = +1 \\ 1 - f(\vec{x}) & \text{for } y = -1 \end{cases}$

- How do we define the error measure to quantify $g \approx f$
 - Ideally, we want it to be **meaningful**
 - Binary error for classification: tell us the number of mistakes we make
 - Squared error for regression: the error minimizer is the "mean (average)"
 - We also want it to be **easy to optimize**

Cross Entropy Error

$$E_{in}(\vec{w}) = \frac{1}{N} \sum_{n=1}^N \ln(1 + e^{-y_n \vec{w}^T \vec{x}_n})$$

- It looks complicated, but
 - It has nice interpretations (min error => max likelihood)
 - It is easy to optimize (continuous, differentiable, convex)

Minimizing Cross Entropy Error



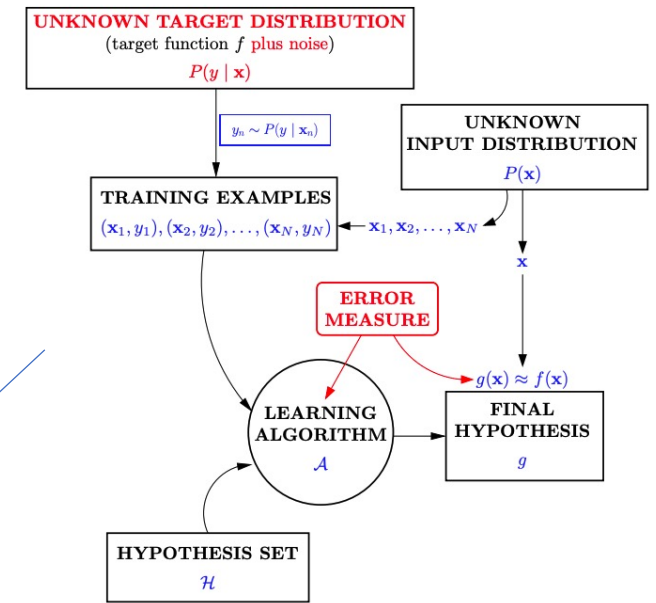
Maximizing Likelihood

Maximum Likelihood Estimation

- Likelihood $\Pr(D|h)$
 - The probability of seeing dataset D if D is generated according to h
 - $\Pr(D|h) = \Pr((\vec{x}_1, y_1), \dots, (\vec{x}_N, y_N)|h)$
 - Maximum likelihood estimation (MLE)
 - $g = \operatorname{argmax}_{h \in H} \Pr(D|h)$
- Sidenote: Two different concepts in ML
 - Likelihood: $\Pr(D|h)$ [Focus of this course]
 - Posterior: $\Pr(h|D)$ [Focus of Bayesian machine learning: More in 515T]
- Connection: $\Pr(h|D) = \frac{\Pr(h)\Pr(D|h)}{\Pr(D)}$
 - Prior $\Pr(h)$: the additional assumption Bayesian ML makes

Write Down the Likelihood

- How are $D = \{(\vec{x}_1, y_1), \dots, (\vec{x}_N, y_N)\}$ generated?
 - $(\vec{x}_1, \dots, \vec{x}_N)$ are i.i.d. drawn from a distribution
 - (y_1, \dots, y_N) are labeled according to target function $f(\vec{x})$



- Likelihood $\Pr(D|h)$
 - The probability of seeing dataset D if D is generated according to h
 - $\Pr(D|h) = \Pr((\vec{x}_1, y_1), \dots, (\vec{x}_N, y_N)|h)$
$$= \Pr(\vec{x}_1, \dots, \vec{x}_N) \Pr((y_1, \dots, y_N)|(\vec{x}_1, \dots, \vec{x}_N), h)$$
$$= \prod_{n=1}^N \Pr(\vec{x}_n) \prod_{n=1}^N \Pr(y_n|\vec{x}_n, h)$$

(Assumption of independent data)

Maximum Likelihood

- Choosing the hypothesis that maximizes the likelihood

- $g = \operatorname{argmax}_{h \in H} \Pr(D|h)$
 $= \operatorname{argmax}_{h \in H} \prod_{n=1}^N \Pr(\vec{x}_n) \prod_{n=1}^N \Pr(y_n|\vec{x}_n, h)$
 $= \operatorname{argmax}_{h \in H} \prod_{n=1}^N \Pr(y_n|\vec{x}_n, h)$

$\prod_{n=1}^N \Pr(\vec{x}_n)$ doesn't depend on h

- We interpret $h(\vec{x})$ as the probability of $y = +1$

- $\Pr(y|\vec{x}, h) = \begin{cases} h(\vec{x}) = \theta(\vec{w}^T \vec{x}) & \text{for } y = +1 \\ 1 - h(\vec{x}) = 1 - \theta(\vec{w}^T \vec{x}) & \text{for } y = -1 \end{cases}$

- Since $1 - \theta(s) = \theta(-s)$

- $\Pr(y|\vec{x}, h) = \theta(y \vec{w}^T \vec{x})$

Maximum Likelihood

- Choosing the hypothesis that maximizes the likelihood

- $g = \operatorname{argmax}_{h \in H} \Pr(D|h)$
 $= \operatorname{argmax}_{h \in H} \prod_{n=1}^N \Pr(y_n | \vec{x}_n, h)$

- $\vec{w}^* = \operatorname{argmax}_{\vec{w}} \prod_{n=1}^N \theta(y_n \vec{w}^T \vec{x}_n)$
 $= \operatorname{argmax}_{\vec{w}} \ln(\prod_{n=1}^N \theta(y_n \vec{w}^T \vec{x}_n))$
 $= \operatorname{argmax}_{\vec{w}} \sum_{n=1}^N \ln(\theta(y_n \vec{w}^T \vec{x}_n))$
 $= \operatorname{argmin}_{\vec{w}} - \sum_{n=1}^N \ln(\theta(y_n \vec{w}^T \vec{x}_n))$
 $= \operatorname{argmin}_{\vec{w}} \sum_{n=1}^N \ln \frac{1}{\theta(y_n \vec{w}^T \vec{x}_n)}$
 $= \operatorname{argmin}_{\vec{w}} \sum_{n=1}^N \ln(1 + e^{-y_n \vec{w}^T \vec{x}_n})$
 $= \operatorname{argmin}_{\vec{w}} \frac{1}{N} \sum_{n=1}^N \ln(1 + e^{-y_n \vec{w}^T \vec{x}_n})$

$$\theta(s) = \frac{e^s}{1+e^s} = \frac{1}{1+e^{-s}}$$

$$E_{in}(\vec{w}) = \frac{1}{N} \sum_{n=1}^N \ln(1 + e^{-y_n \vec{w}^T \vec{x}_n})$$

Cross Entropy Error

$$E_{in}(\vec{w}) = \frac{1}{N} \sum_{n=1}^N \ln(1 + e^{-y_n \vec{w}^T \vec{x}_n})$$

- Minimizing $E_{in}(\vec{w})$ is the same as maximizing likelihood
- Next question: How to solve $\vec{w}^* = \operatorname{argmin}_{\vec{w}} E_{in}(\vec{w})$
 - Answer: Solve for $\nabla_{\vec{w}} E_{in}(\vec{w}) = 0$
 - No single-step solution like we have in linear regression