

Introduction to Machine Learning

Risk Minimization

Barnabás Póczos

What have we seen so far?

Several classification & regression algorithms seem to work fine on training datasets:

- Linear regression
- Gaussian Processes
- Naïve Bayes classifier
- Support Vector Machines

- How good are these algorithms on unknown test sets?
- How many training samples do we need to achieve small error?
- What is the smallest possible error we can achieve?

=> Learning Theory

Outline

- Risk and loss
 - Loss functions
 - Risk
 - Empirical risk vs True risk
 - Empirical Risk minimization
- Underfitting and Overfitting
- Classification
- Regression

Supervised Learning Setup

$\mathcal{D} = \{(X_1, Y_1), \dots, (X_n, Y_n)\}$ training data

$\{(X_{n+1}, Y_{n+1}), \dots, (X_m, Y_m)\}$ test data

Features: $X \in \mathcal{X} \subset \mathbb{R}^d$

Labels: $Y \in \mathcal{Y} \subset \mathbb{R}$

Generative model of the data: $X \sim \mu, \mu(A) = \Pr(X \in A)$
(train and test data) $Y \sim p(\cdot|X)$

Regression: Labels: $\mathcal{Y} = [a, b] \subset \mathbb{R}$, or $\mathcal{Y} = \mathbb{R}$

Classification: Labels: $\mathcal{Y} = \{0, 1\}$

Loss

$\mathcal{D} = \{(X_1, Y_1), \dots, (X_n, Y_n)\}$ training data

$\{(X_{n+1}, Y_{n+1}), \dots, (X_m, Y_m)\}$ test data

Loss function: $L(x, y, f(x))$

where $L : \mathcal{X} \times \mathcal{Y} \times \mathbb{R} \rightarrow [0, \infty]$

It measures how good we are on a particular (x,y) pair.

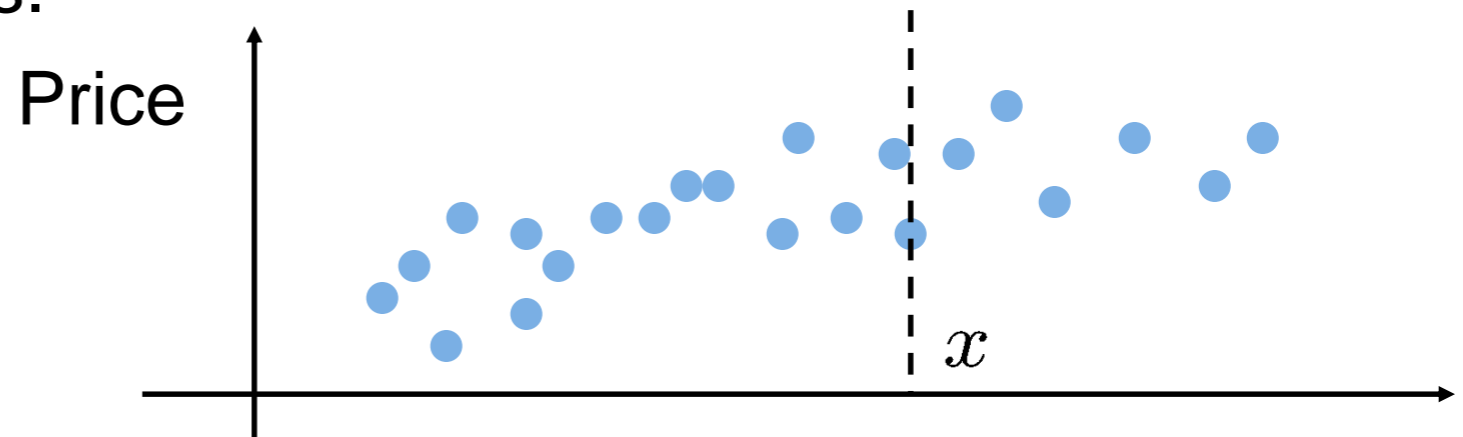
We want the loss $L(X_t, Y_t, f(X_t))$ to be small for many (X_t, Y_t) pairs in the test data.

Loss Examples

Classification loss:

$$L(x, y, f(x)) = \begin{cases} 1 & y \neq f(x) \\ 0 & y = f(x) \end{cases}$$

Regression: Predict house prices.

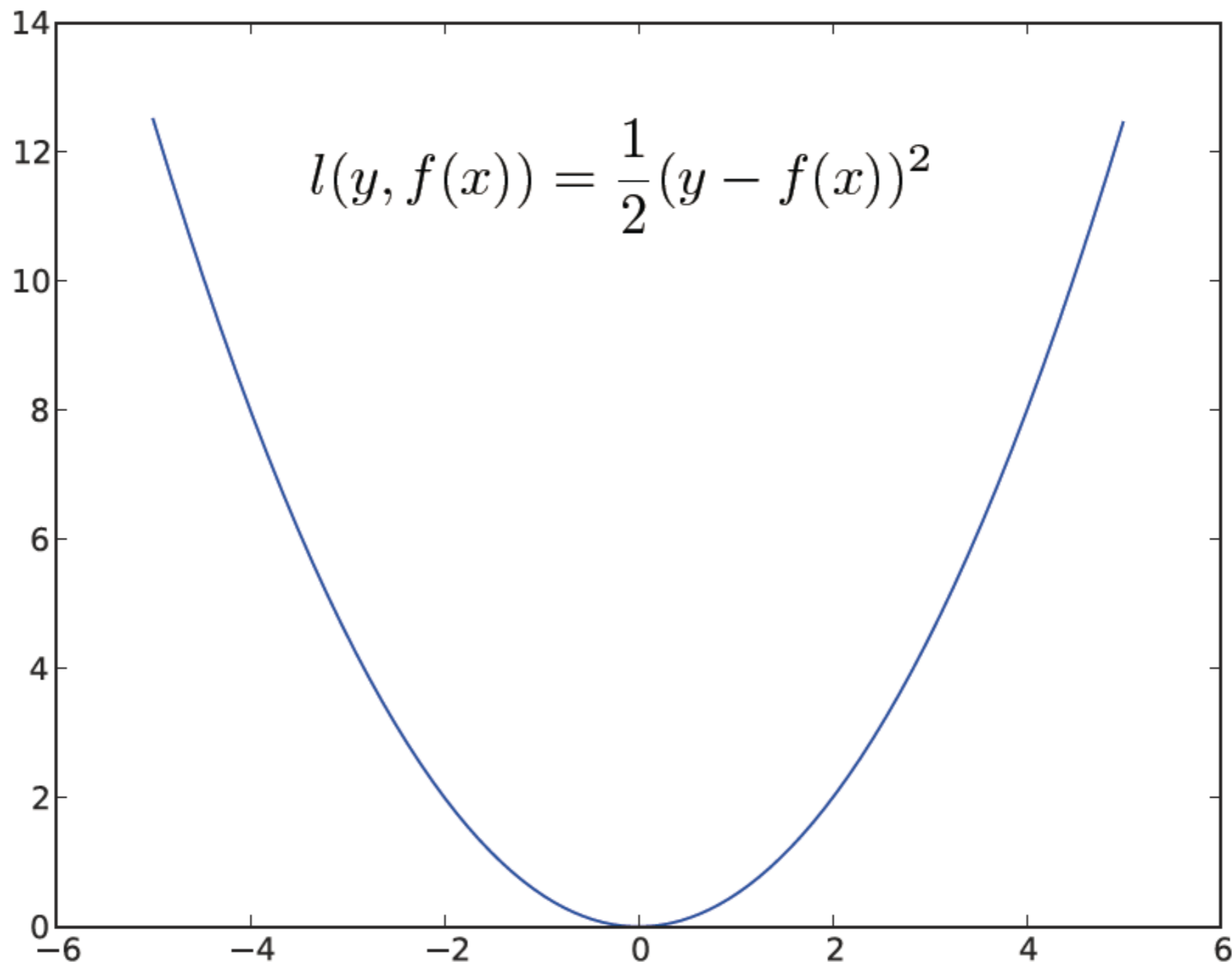


The price of house with feature x is $p(\cdot|x)$

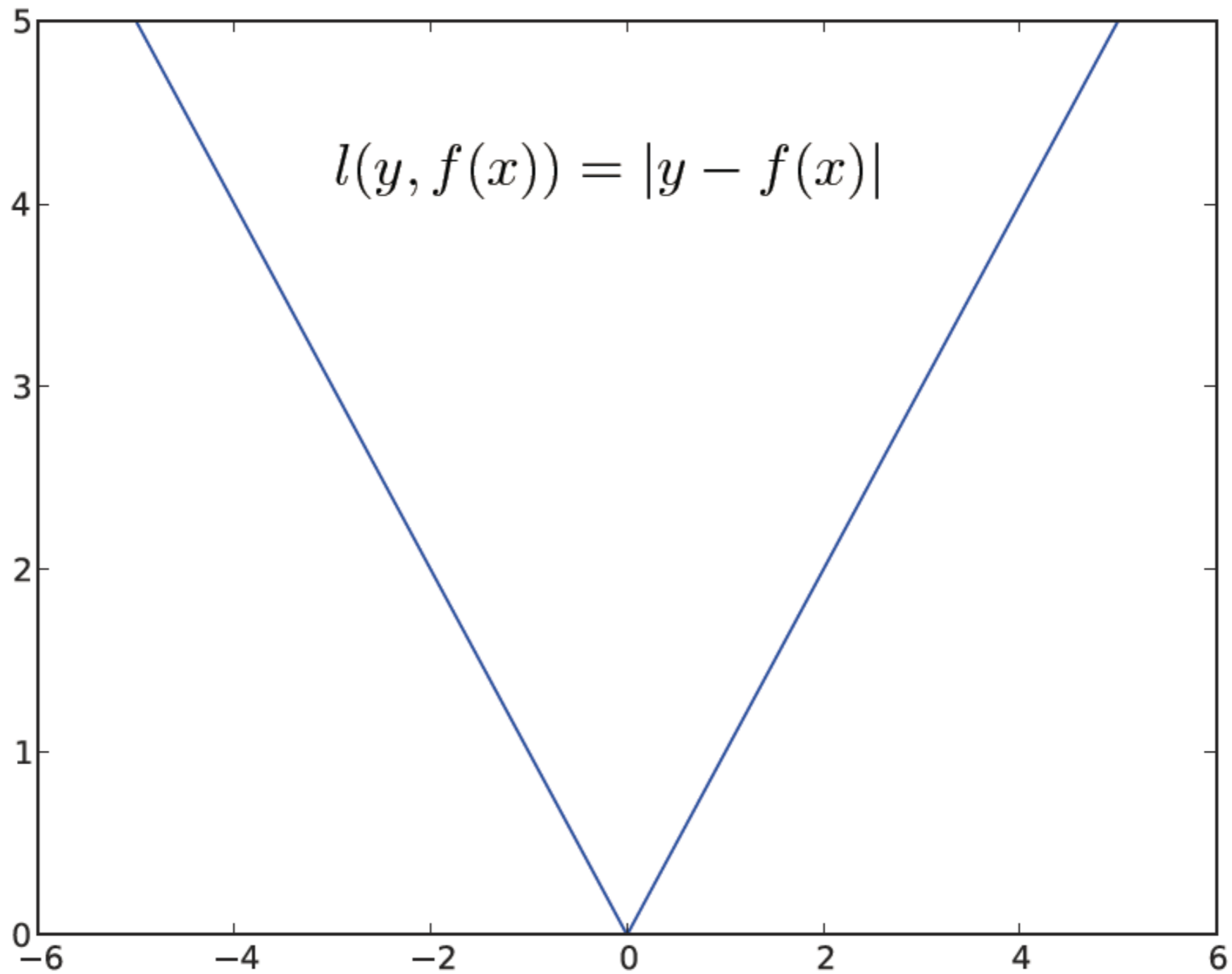
L₂ loss for regression: $L(x, y, f(x)) = (y - f(x))^2$

L₁ loss for regression: $L(x, y, f(x)) = |y - f(x)|$

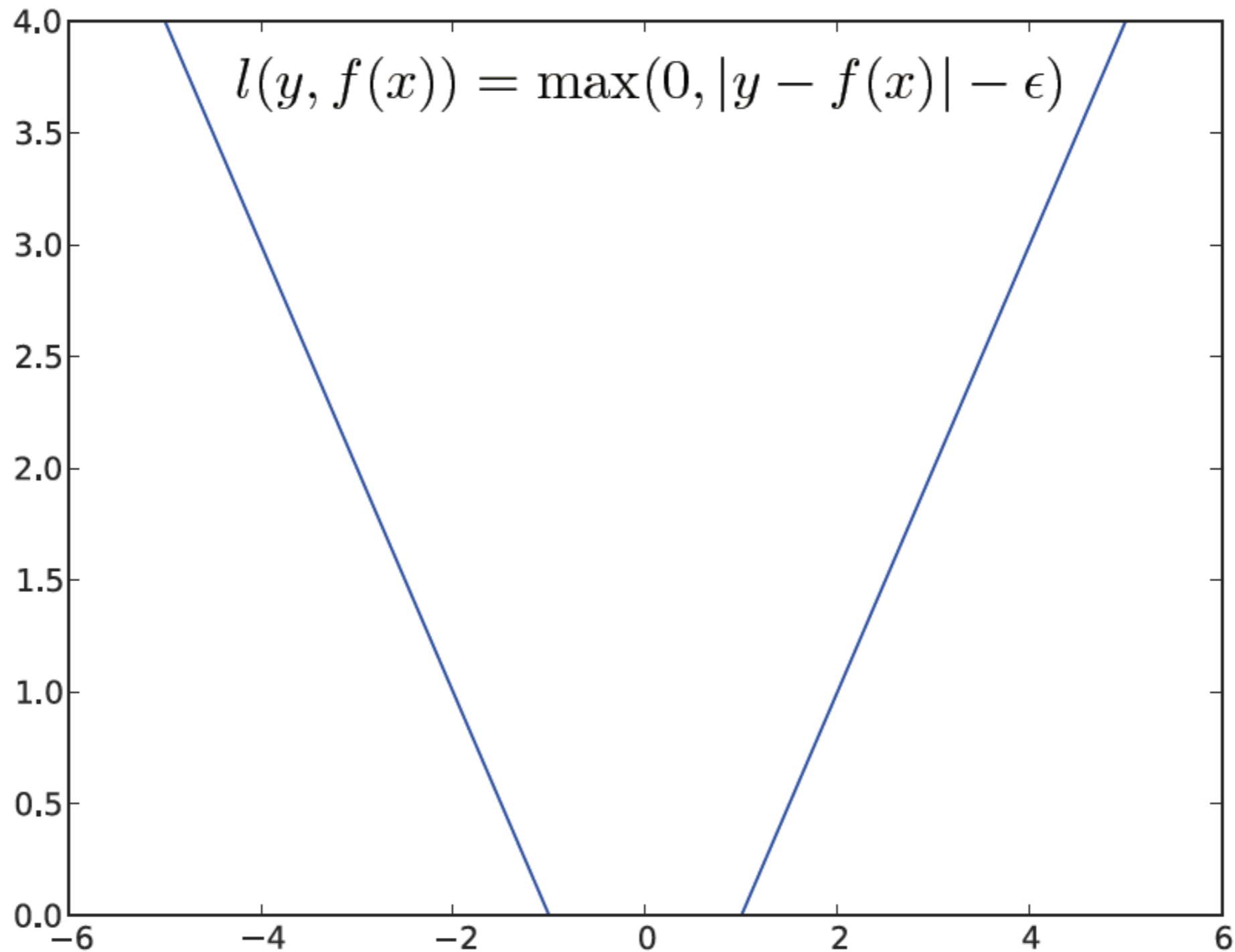
Squared loss, L_2 loss



L_1 loss

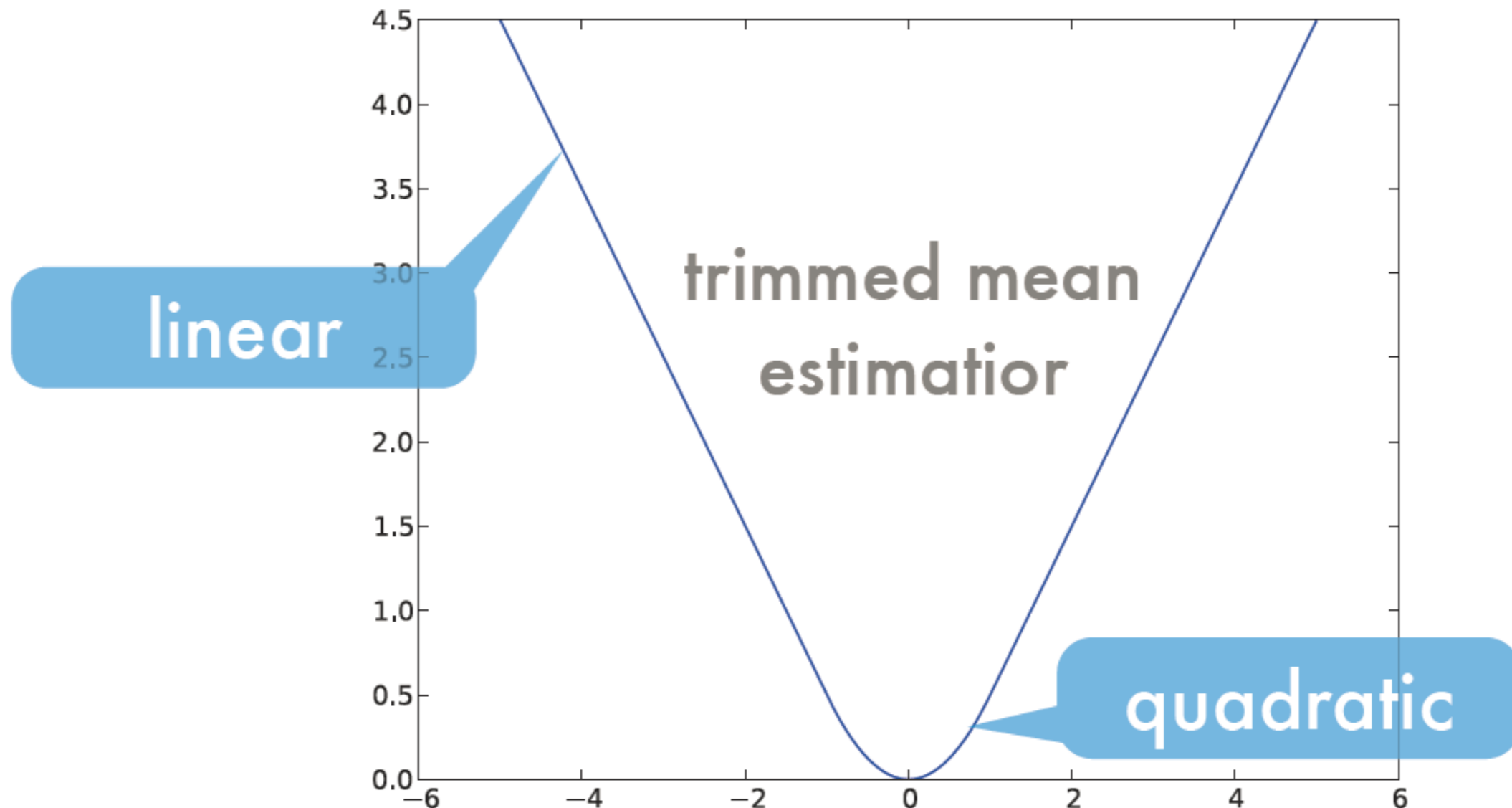


ϵ -insensitive loss



Huber's robust loss

$$l(y, f(x)) = \begin{cases} \frac{1}{2}(y - f(x))^2 & \text{if } |y - f(x)| < 1 \\ |y - f(x)| - \frac{1}{2} & \text{otherwise} \end{cases}$$



Risk

Risk of f classification/regression function:

$$R_{L,P}(f) = \int_{\mathcal{X} \times \mathcal{Y}} L(x, y, f(x)) dP(x, y) = \text{The expected loss}$$
$$= \mathbb{E}[L(X, Y, f(X))]$$

$p(y, x) dy dx$

$L(x, y, f(x))$: Loss function

$P(x, y)$: Distribution of the data.

Why do we care about this?

Why do we care about risk?

Risk of f classification/regression function:

$$\begin{aligned} R_{L,P}(f) &= \int_{\mathcal{X} \times \mathcal{Y}} L(x, y, f(x)) dP(x, y) && = \text{The expected loss} \\ &= \mathbb{E}[L(X, Y, f(X))] \end{aligned}$$

\swarrow
 $p(y, x) dy dx$

Our true goal is to minimize the loss of the test points!

$$f^* = \arg \min_f \frac{1}{m - n} \sum_{i=n+1}^m L(X_i, Y_i, f(X_i))$$

Usually we don't know the test points and their labels in advance..., but

$$\frac{1}{m - n} \sum_{i=n+1}^m L(X_i, Y_i, f(X_i)) \xrightarrow{m \rightarrow \infty} R_{L,P}(f) \quad (\text{LLN})$$

That is why our goal is to minimize the risk.

Risk Examples

Risk: $R_{L,P}(f) = \int_{\mathcal{X} \times \mathcal{Y}} L(x, y, f(x)) dP(x, y)$ The expected loss

Classification loss: $L(x, y, f(x)) = \begin{cases} 1 & y \neq f(x) \\ 0 & y = f(x) \end{cases}$

Risk of classification loss:

$$R_{L,P}(f) = \int_{\mathcal{X} \times \mathcal{Y}} L(x, y, f(x)) dP(x, y) = \mathbb{E}[\mathbf{1}_{\{f(X) \neq Y\}}] = \Pr(f(X) \neq Y)$$

L₂ loss for regression: $L(x, y, f(x)) = (y - f(x))^2$

Risk of L₂ loss: $R_{L,P}(f) = \mathbb{E}[(Y - f(X))^2]$

Bayes Risk

$$R_{L,P}(f) = \int_{\mathcal{X} \times \mathcal{Y}} L(x, y, f(x)) dP(x, y) \quad \text{The expected loss}$$

Definition: Bayes Risk

$$R_{L,P}^* = \inf_{f: \mathcal{X} \rightarrow \mathbb{R}} \int_{\mathcal{X} \times \mathcal{Y}} L(x, y, f(x)) dP(x, y)$$

← We consider all possible function f here

We don't know P , but we have i.i.d. training data sampled from P !

Goal of Learning:

Build a function f_D (using data D) whose risk $R_{L,P}(f_D)$ will be close to the Bayes risk $R_{L,P}^*$

The learning algorithm constructs this function f_D from the training data.

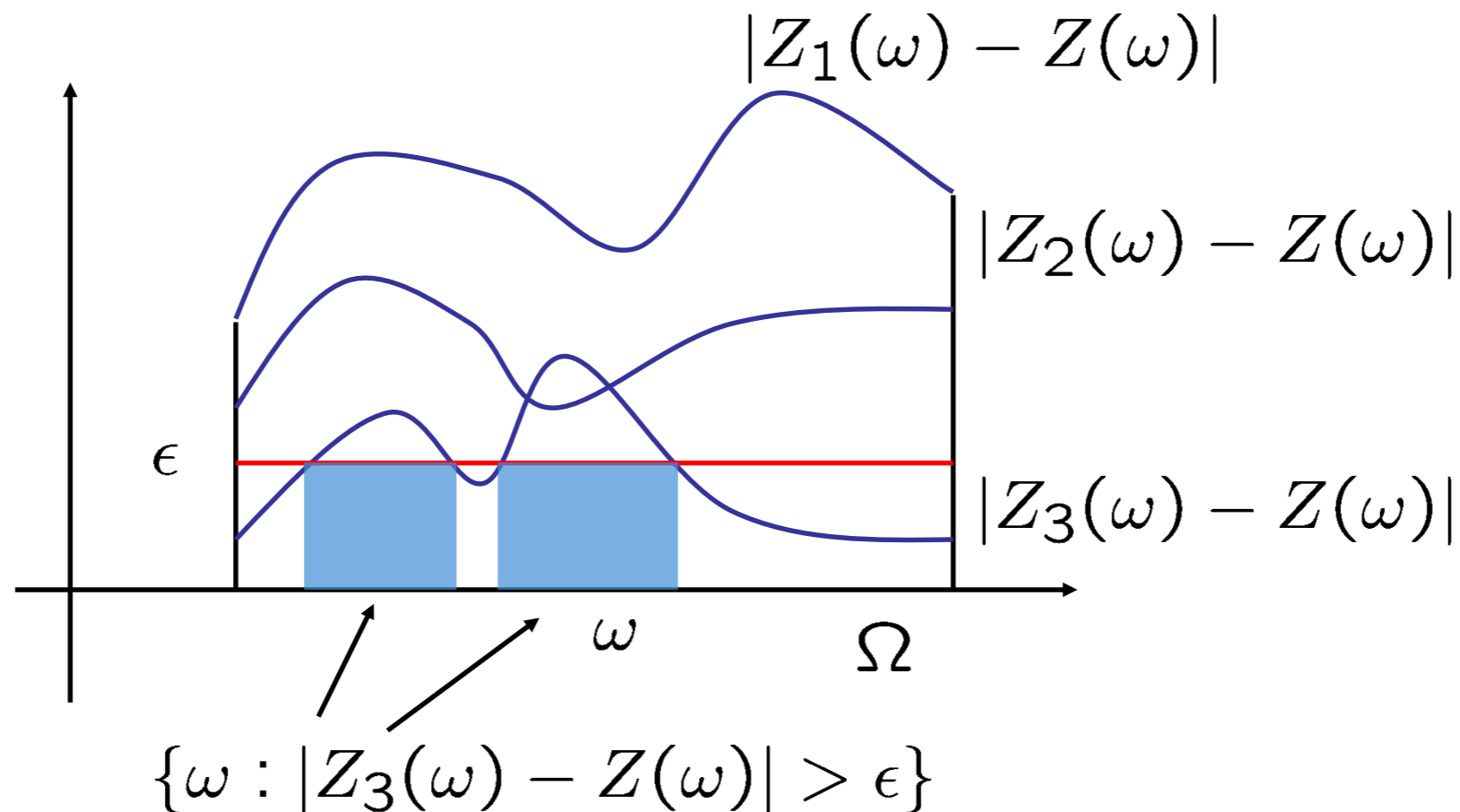
Convergence in Probability

Convergence in Probability

Notation: $Z_n \xrightarrow{p} Z$

Definition: $\forall \varepsilon > 0 \lim_{n \rightarrow \infty} \Pr(|Z_n - Z| \geq \varepsilon) = 0.$

$\forall \varepsilon > 0 \lim_{n \rightarrow \infty} \Pr(|Z_n - Z| < \varepsilon) = 1.$



This indeed measures how far the values of $Z_n(\omega)$ and $Z(\omega)$ are from each other.

Consistency of learning methods

Risk is a random variable: $R_{L,P}(f_D) = \mathbb{E}[L(X, Y, f_D(X)|D)]$

Definition:

A learning method is **universally consistent** if for all $P(X, Y)$ distributions the risk converges to the Bayes risk when we increase the sample size

$$R_{L,P}(f_D) \xrightarrow{p} R_{L,P}^* \text{ as } n \rightarrow \infty.$$

Stone's theorem 1977: Many classification, regression algorithms are universally consistent for certain loss functions under certain conditions: kNN, Parzen kernel regression, SVM,...

Yayyy!!! 😊

Wait! This doesn't tell us anything about the rates...

No Free Lunch!

Devroy 1982: For every consistent learning method and for every fixed convergence rate a_n , there exists $P(X, Y)$ distribution such that the convergence rate of this learning method on $P(X, Y)$ distributed data is slower than a_n

$R_{L,P}(f_D) \xrightarrow{p} R_{L,P}^*$ as $n \rightarrow \infty$ with slower rate than a_n



What can we do now?

Empirical Risk and True Risk

Empirical Risk

For simplicity, let $L(x, y, f(x)) = L(y, f(x))$

Shorthand:

True risk of f (deterministic): $R(f) = R_{L,P}(f) = \mathbb{E}[L(Y, f(X))]$

Bayes risk: $R^* = R_{L,P}^* = \inf_{f:\mathcal{X}\rightarrow\mathbb{R}} R(f)$

We don't know P , and hence we don't know $R(f)$ either.

Let us use the empirical counter part:

Empirical risk: $\hat{R}_n(f) = \frac{1}{n} \sum_{i=1}^n L(Y_i, f(X_i))$

Empirical Risk Minimization

$$R(f) = R_{L,P}(f) = \mathbb{E}[L(Y, f(X))] \quad R^* = R_{L,P}^* = \inf_{f:\mathcal{X}\rightarrow\mathbb{R}} R(f)$$

$$\hat{R}_n(f) = \frac{1}{n} \sum_{i=1}^n L(Y_i, f(X_i))$$

Law of Large Numbers:

For each fixed f , $\hat{R}_n(f) = \frac{1}{n} \sum_{i=1}^n L(Y_i, f(X_i)) \xrightarrow{n\rightarrow\infty} R(f)$

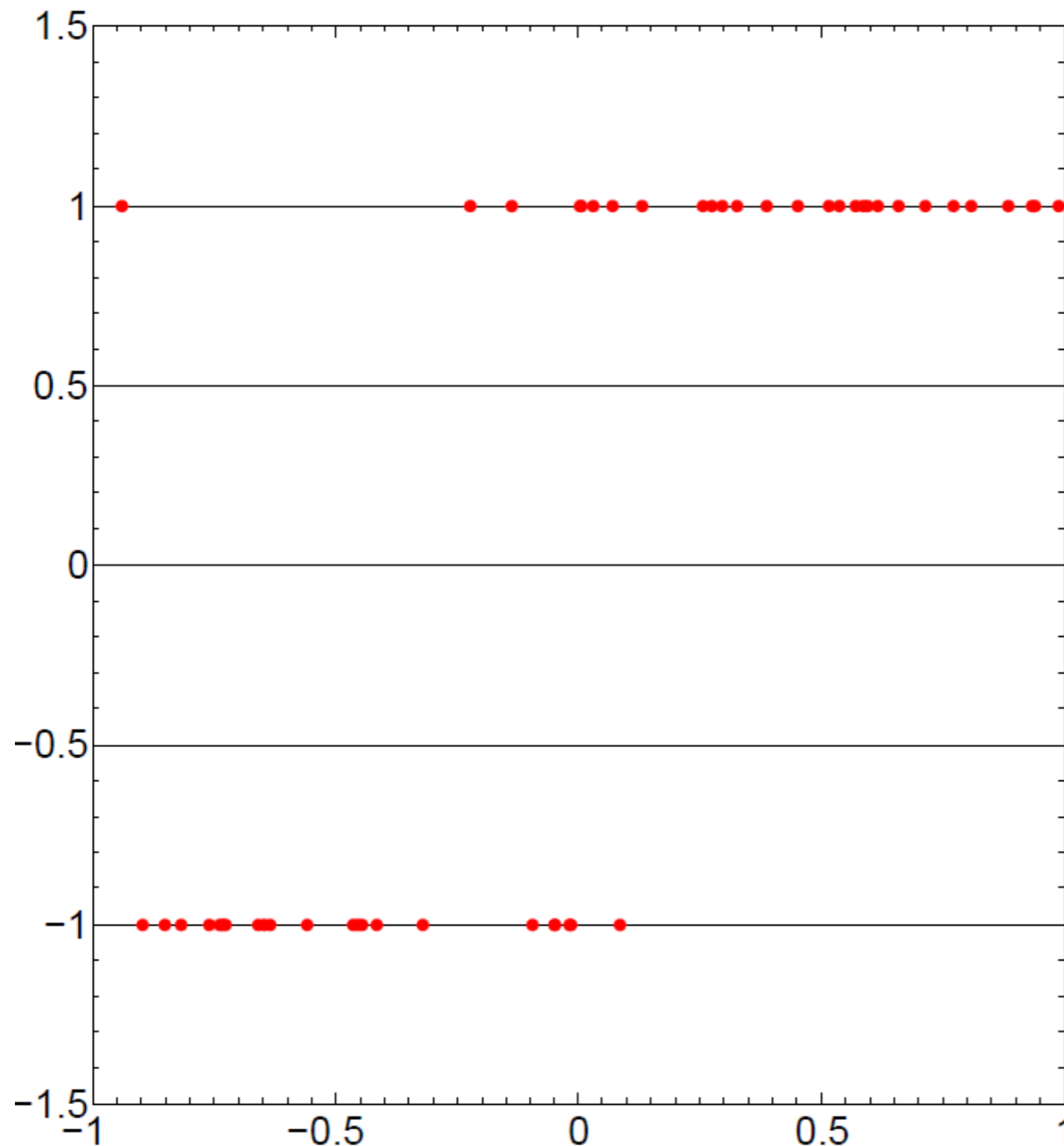
Empirical risk is converging to the Bayes risk

We need $\inf_{f:\mathcal{X}\rightarrow\mathbb{R}} R(f)$, so let us calculate $\inf_{f:\mathcal{X}\rightarrow\mathbb{R}} \hat{R}_n(f)$!

$$\inf_{f:\mathcal{X}\rightarrow\mathbb{R}} \hat{R}_n(f) = \inf_{f:\mathcal{X}\rightarrow\mathbb{R}} \frac{1}{n} \sum_{i=1}^n L(Y_i, f(X_i))$$

This is a **terrible idea** to optimize over all possible $f : \mathcal{X} \rightarrow \mathbb{R}$ functions! [Extreme overfitting]

Overfitting in Classification with ERM



Picture from David Pal

Generative model:

$$X \sim U[-1, 1]$$

$$\Pr(Y = 1 | X > 0) = 0.9$$

$$\Pr(Y = -1 | X > 0) = 0.1$$

$$\Pr(Y = 1 | X < 0) = 0.1$$

$$\Pr(Y = -1 | X < 0) = 0.9$$

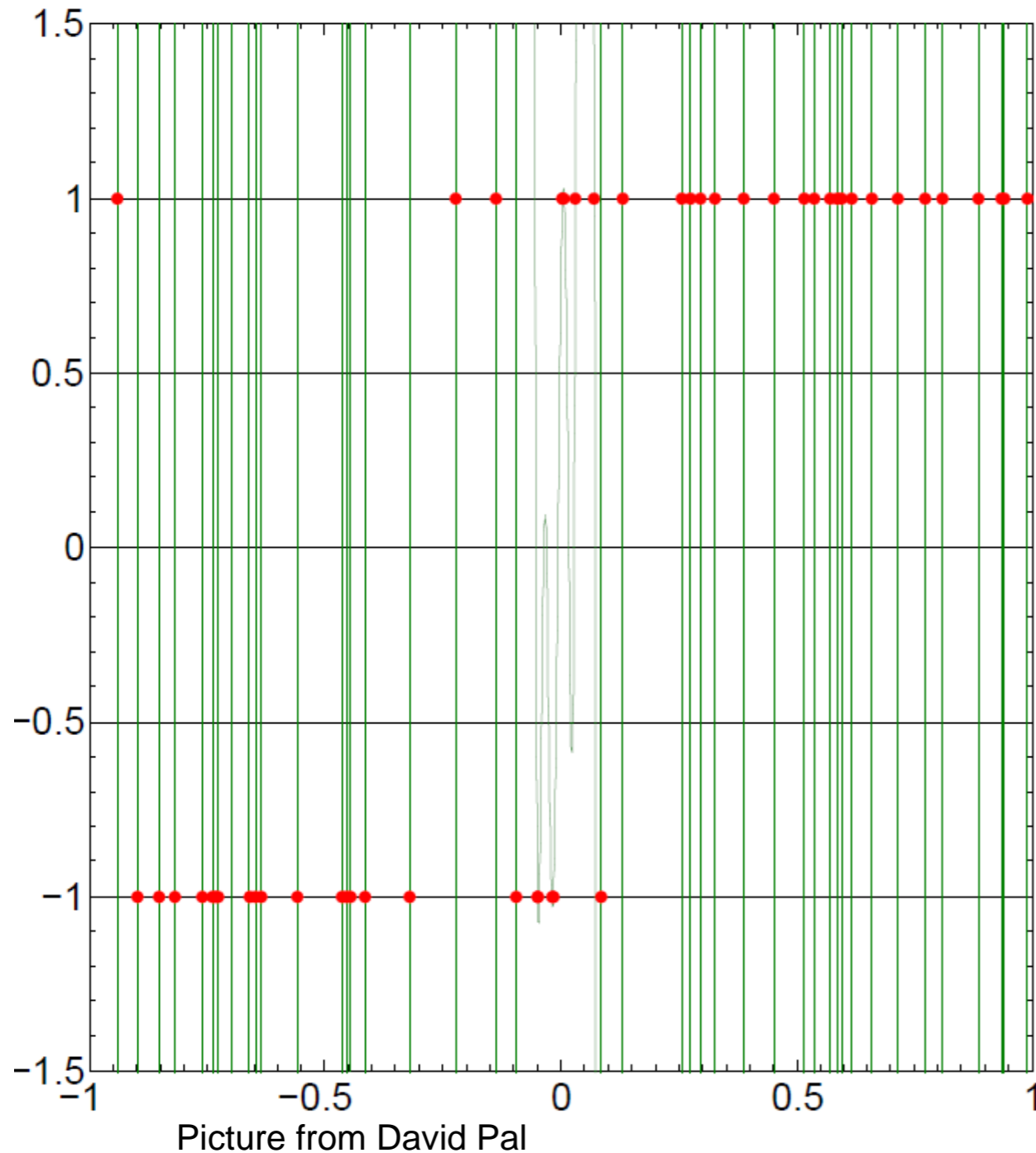
Bayes classifier:

$$f^* = \begin{cases} 1 & \text{if } x > 0 \\ -1 & \text{if } x \leq 0 \end{cases}$$

Bayes risk:

$$R^* = \Pr(Y \neq f^*(X)) = 0.1$$

Overfitting in Classification with ERM



n-order thresholded polynomials

$$\mathcal{F} = \left\{ f(x) = \text{sign} \left(\sum_{i=0}^n a_i x^i \right) \right\}$$

$$f_n^* = \arg \min_{f \in \mathcal{F}} \hat{R}_n(f)$$

Empirical risk:

$$\hat{R}_n(f_n^*) = 0$$

True risk of $f_n^* = 0.5$

$$R(f_n^*) = \Pr(Y \neq f_n^*(X)) = 0.5$$

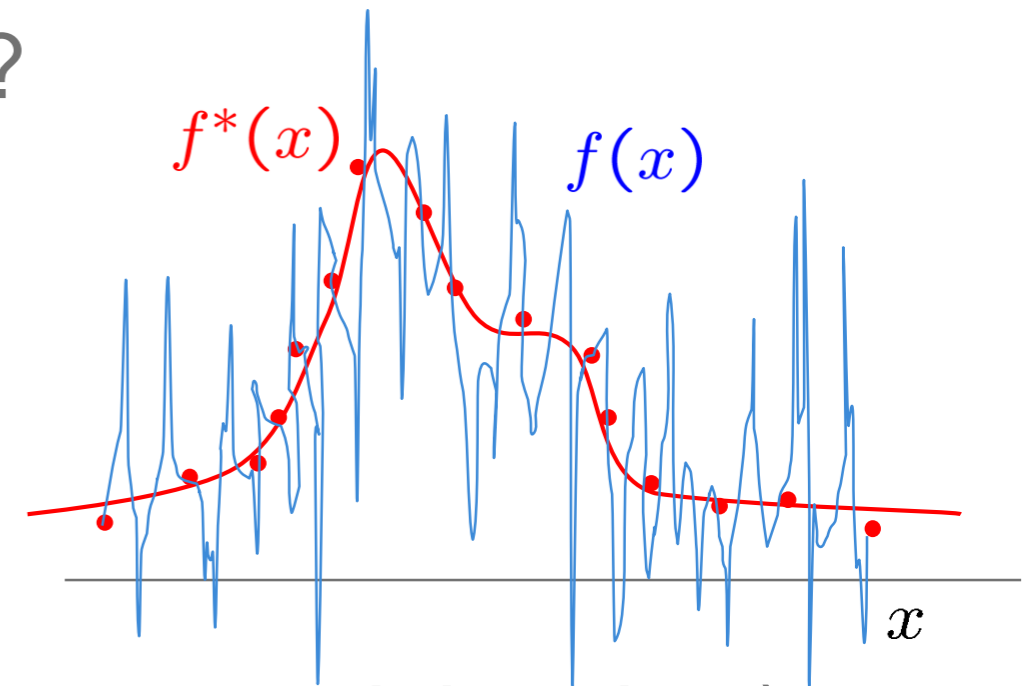
Bayes risk:

$$R^* = \Pr(Y \neq f^*(X)) = 0.1$$

Overfitting in Regression with ERM

Is the following predictor a good one?

$$f(x) = \begin{cases} Y_i, & x = X_i \text{ for } i = 1, \dots, n \\ \text{any value,} & \text{otherwise} \end{cases}$$



What is its empirical risk? (performance on training data)

zero !

What about true risk?

> zero

Will predict very poorly on new random test point:

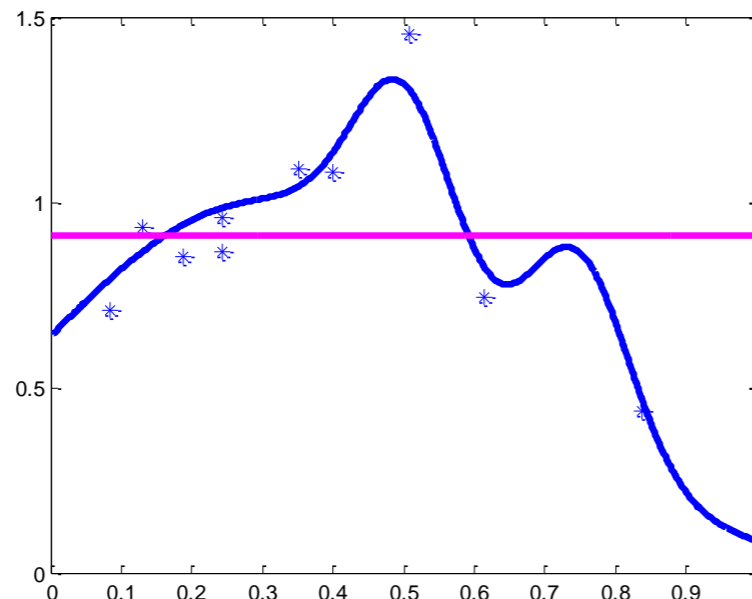
Large generalization error !

Overfitting in Regression

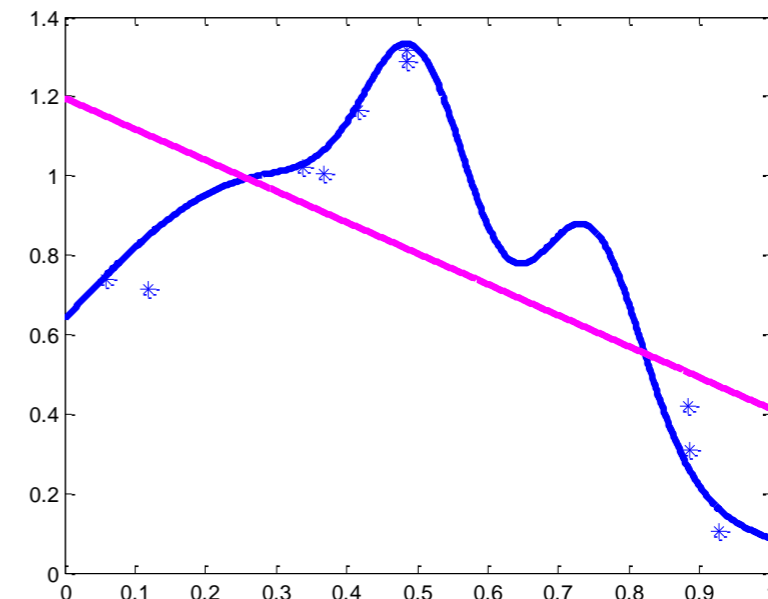
If we allow very complicated predictors, we could overfit the training data.

Examples: Regression (Polynomial of order $k-1$ – degree k)

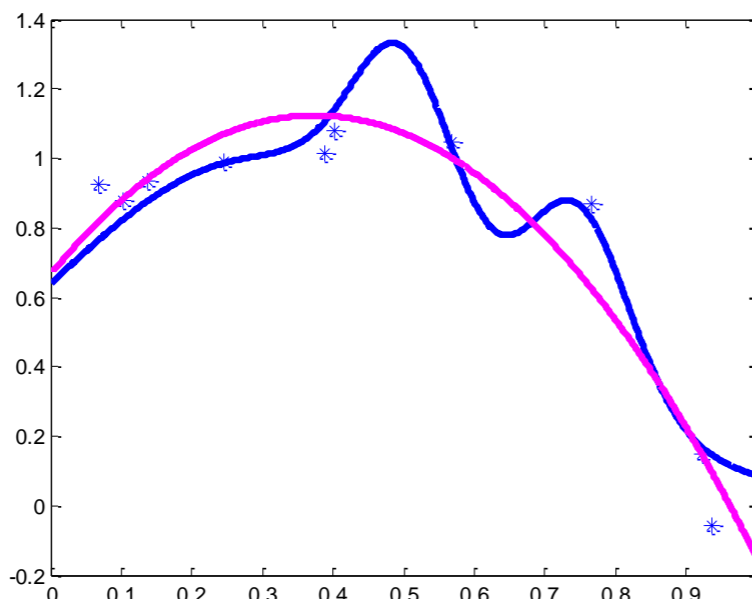
$k=1$
constant



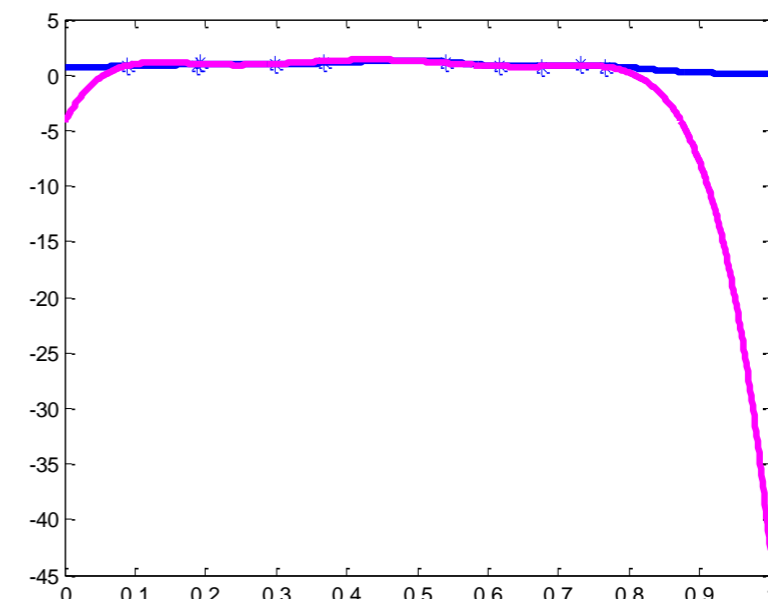
$k=2$
linear



$k=3$
quadratic



$k=7$
6th order



Solutions to Overfitting

Terrible idea to optimize over all possible $f : \mathcal{X} \rightarrow \mathbb{R}$ functions!
[Extreme overfitting]

\Rightarrow minimize over a smaller function set \mathcal{F} .

Empirical risk minimization over the function set \mathcal{F} .

$$f_n^* = \arg \min_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n L(Y_i, f(X_i))$$

Solutions to Overfitting

Structural Risk Minimization

Empirical risk minimization over the function set \mathcal{F} .

$$f_n^* = \arg \min_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n L(Y_i, f(X_i))$$

Notation: $R_{\mathcal{F}}^* = \inf_{f \in \mathcal{F}} \mathbb{E}[L(Y, f(X))]$ $\hat{R}_{n, \mathcal{F}}^* = \inf_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n L(Y_i, f(X_i))$

Risk Empirical risk

1st issue: $R_{\mathcal{F}}^* - R^* \geq 0$ needs to be small.
Risk in \mathcal{F} - Bayes risk (Model error, Approximation error)

Solution: Structural Risk Minimization (SRM)

Let \mathcal{F}_n increase with the sample size n ($\mathcal{F}_{n+1} \supset \mathcal{F}_n$), and let \mathcal{F}_{n+1} contain more complex functions than \mathcal{F}_n

Approximation error, Estimation error, PAC framework

Risk of the classifier f

$$R(f) - R(f^*) = \underbrace{R(f) - \inf_{f \in \mathcal{F}} R(f)}_{\text{Estimation error}} + \underbrace{\inf_{f \in \mathcal{F}} R(f) - R(f^*)}_{\text{Approximation error}}$$

R^* (Bayes risk) points to $R(f^*)$.
 $R_{\mathcal{F}}^*$ (Best classifier in \mathcal{F}) points to $\inf_{f \in \mathcal{F}} R(f)$.
 R^* (Bayes risk) also points to $R(f^*)$.

Probably Approximately Correct (PAC) learning framework

Learning algorithm produces $f_n^* = f_{n, \mathcal{F}}^*$ classifier. For each $\varepsilon, \delta > 0$

we want to find n large enough such that $\Pr(\underbrace{R(f_n^*) - \inf_{f \in \mathcal{F}} R(f)}_{\text{Estimation error}} > \varepsilon) < \delta$

Estimation error

Big Picture

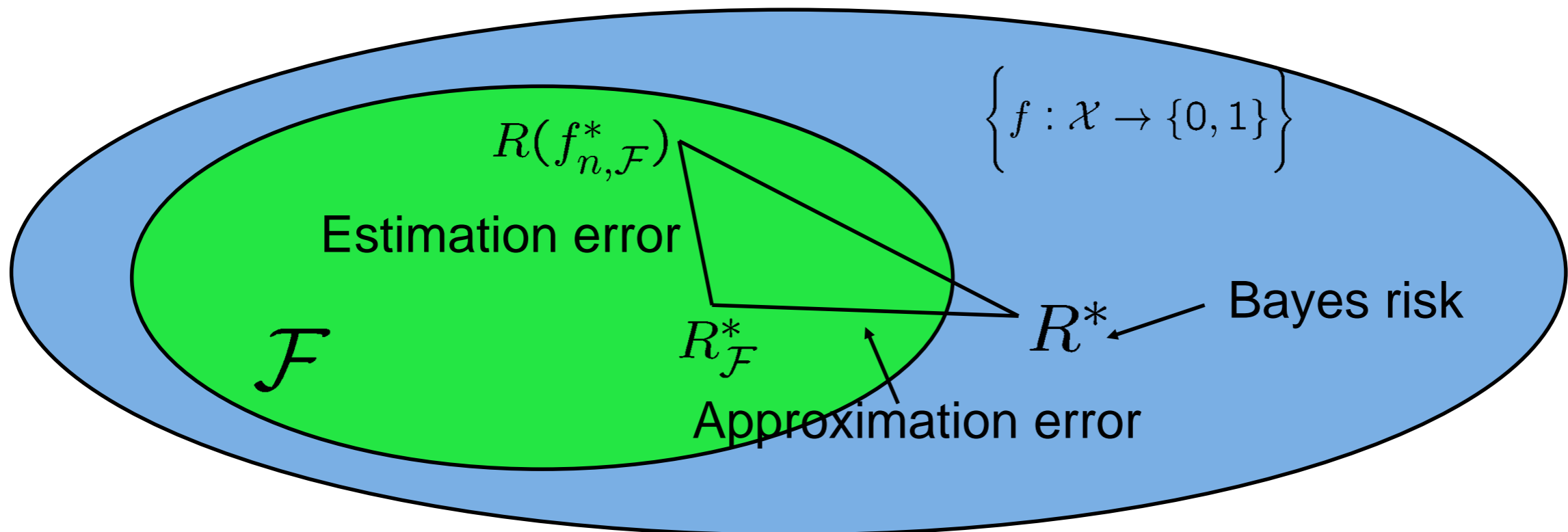
Ultimate goal: $R(f_n^*) - R^* = 0$

ERM: $f_n^* = f_{n,\mathcal{F}}^* = \arg \min_{f \in \mathcal{F}} \hat{R}_n(f) = \arg \min_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n L(Y_i, f(X_i))$

Risk of the classifier $f_{n,\mathcal{F}}^*$ Estimation error Approximation error

$$R(f_{n,\mathcal{F}}^*) - R^* = \underbrace{R(f_{n,\mathcal{F}}^*) - R_{\mathcal{F}}^*}_{\text{Estimation error}} + \underbrace{R_{\mathcal{F}}^* - R^*}_{\text{Approximation error}}$$

Bayes risk $R_{\mathcal{F}}^* = \inf_{g \in \mathcal{F}} R(g)$ Best classifier in \mathcal{F} Bayes risk



Solution to Overfitting

$$R_{\mathcal{F}}^* = \inf_{f \in \mathcal{F}} R(f) = \inf_{f \in \mathcal{F}} \mathbb{E}[L(Y, f(X))]$$

ERM on \mathcal{F} : $\hat{R}_{n, \mathcal{F}}^* = \inf_{f \in \mathcal{F}} \hat{R}_n(f) = \inf_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n L(Y_i, f(X_i))$

2nd issue: $\hat{R}_{n, \mathcal{F}}^* = \inf_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n L(Y_i, f(X_i))$

$\inf_{f \in \mathcal{F}} \hat{R}_n(f)$ might be a very difficult optimization problem in f
It might be not even convex in f

Solution:

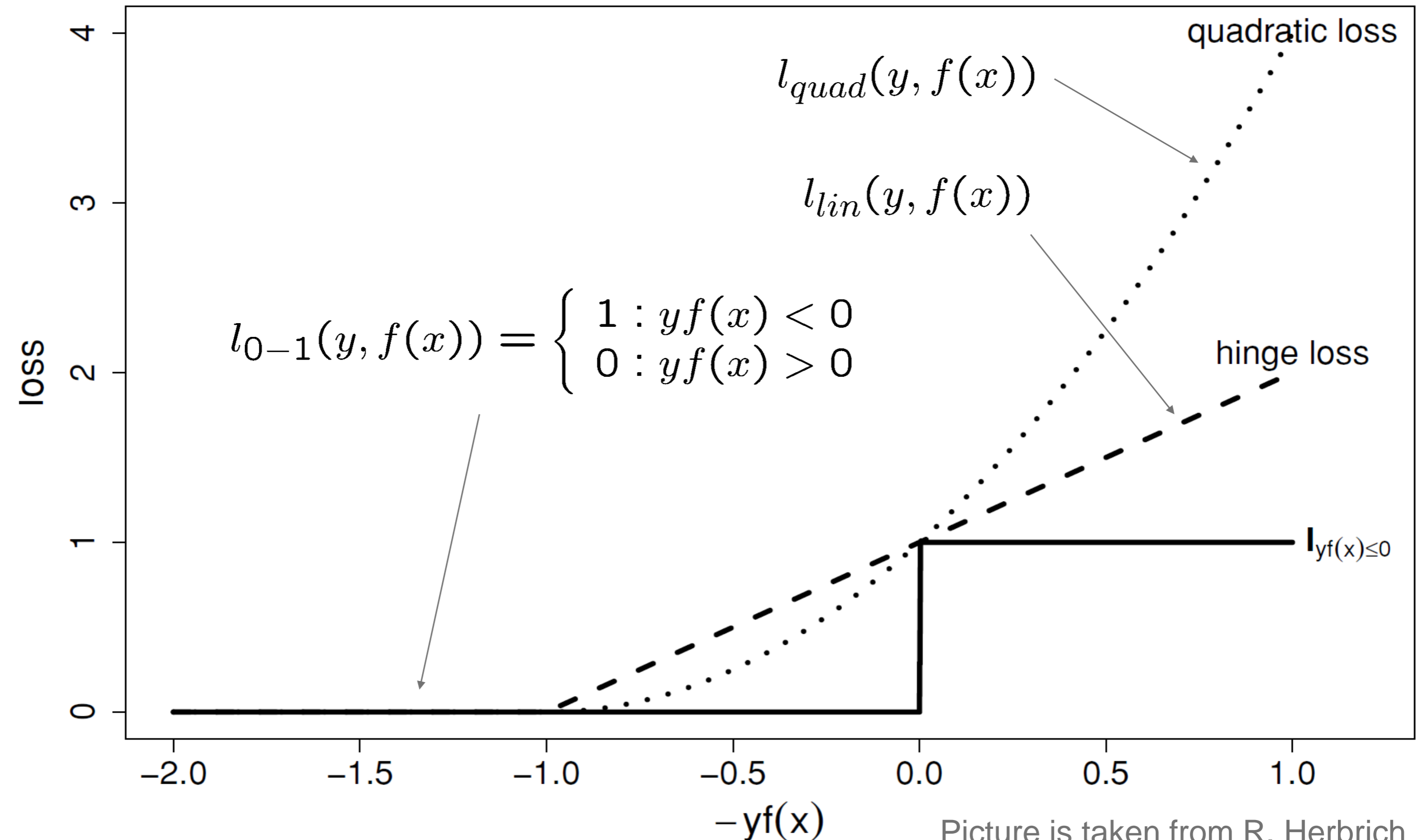
Choose loss function L such that $\hat{R}_n(f)$ will be convex in f

$$L(y, f(x)) = \begin{cases} 1 & y \neq f(x) \\ 0 & y = f(x) \end{cases} \Rightarrow \text{not convex } \hat{R}_n(f)$$

Hinge loss \Rightarrow convex $\hat{R}_n(f)$

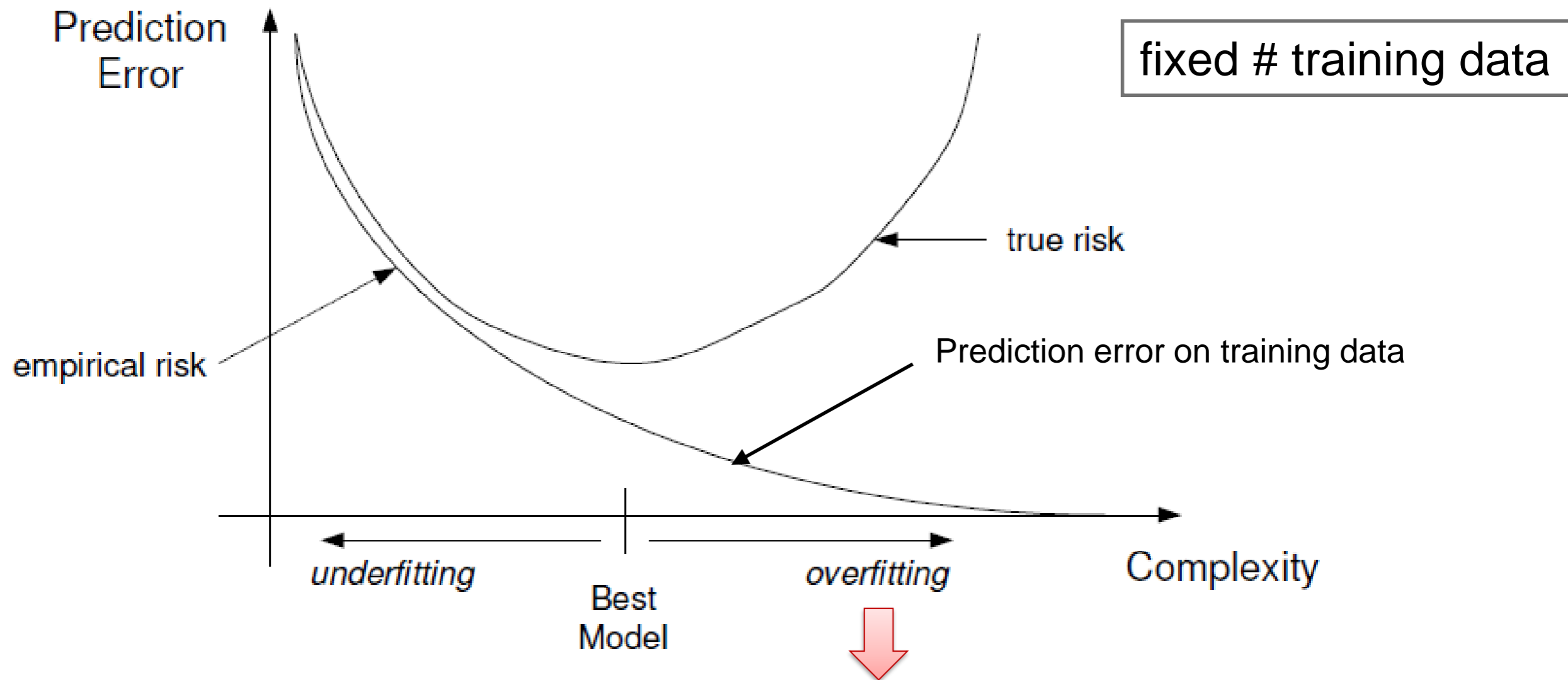
Quadratic loss \Rightarrow convex $\hat{R}_n(f)$

Approximation with the Hinge loss and quadratic loss



Effect of Model Complexity

If we allow very complicated predictors, we could overfit the training data.

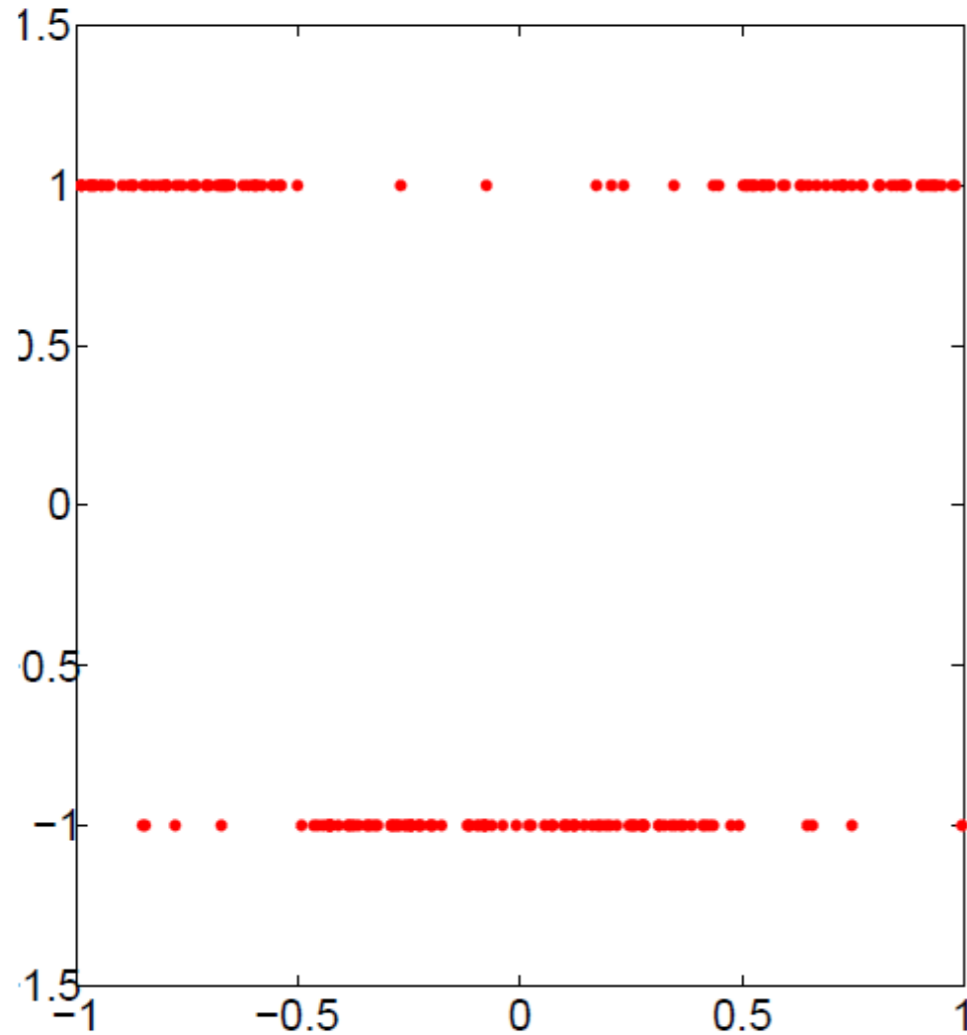


Empirical risk is no longer a good indicator of true risk

Underfitting

Let \mathcal{F} be the class of thresholded polynomials of degree at most one.

$$\mathcal{F} = \{f : f(x) = \text{sign}(ax + b), a, b \in \mathbb{R}\}$$



$$X \sim U[-1, 1]$$

$$\Pr(Y = +1 | X \in (-0.5, 0.5)) = 0.9$$

$$\Pr(Y = -1 | X \in (-0.5, 0.5)) = 0.1$$

$$\Pr(Y = +1 | X \notin (-0.5, 0.5)) = 0.1$$

$$\Pr(Y = -1 | X \notin (-0.5, 0.5)) = 0.9$$

$$f^*(x) = \begin{cases} 1 & \text{if } x \notin (-0.5, 0.5) \\ -1 & \text{if } x \in (-0.5, 0.5) \end{cases}$$

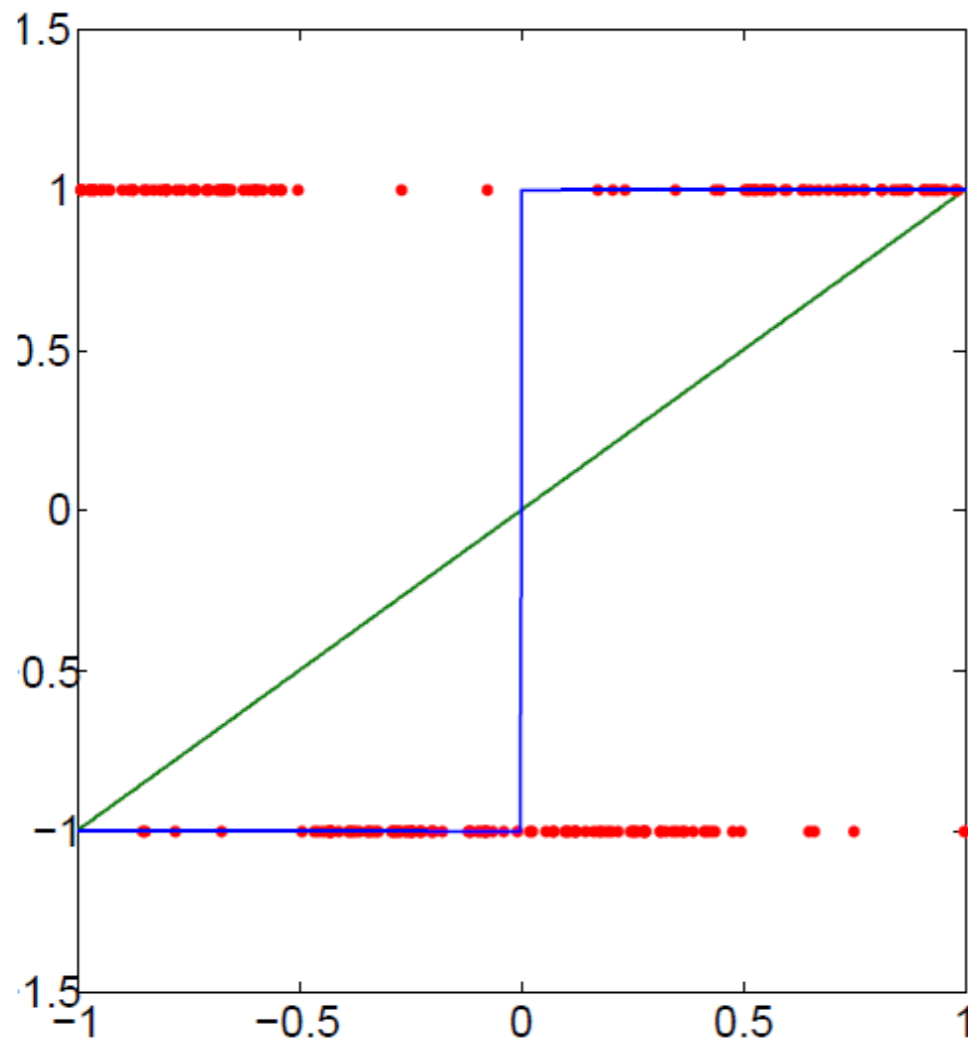
$$R_{\mathcal{F}}^* = \inf_{f \in \mathcal{F}} R(f) = \inf_{f \in \mathcal{F}} \mathbb{E}[L(Y, f(X))]$$

Bayes risk = 0.1

Underfitting

$$\mathcal{F} = \{f : f(x) = \text{sign}(ax + b), a, b \in \mathbb{R}\}$$

Best linear classifier:



$$\begin{aligned} R_{\mathcal{F}}^* &= R(f_{\mathcal{F}}^*) = \inf_{f \in \mathcal{F}} \Pr[Y \neq f(X)] \\ &= \frac{1}{4} \times 0.9 + \frac{1}{4} \times 0.1 + \frac{1}{4} \times 0.9 + \frac{1}{4} \times 0.1 = 0.5 \end{aligned}$$

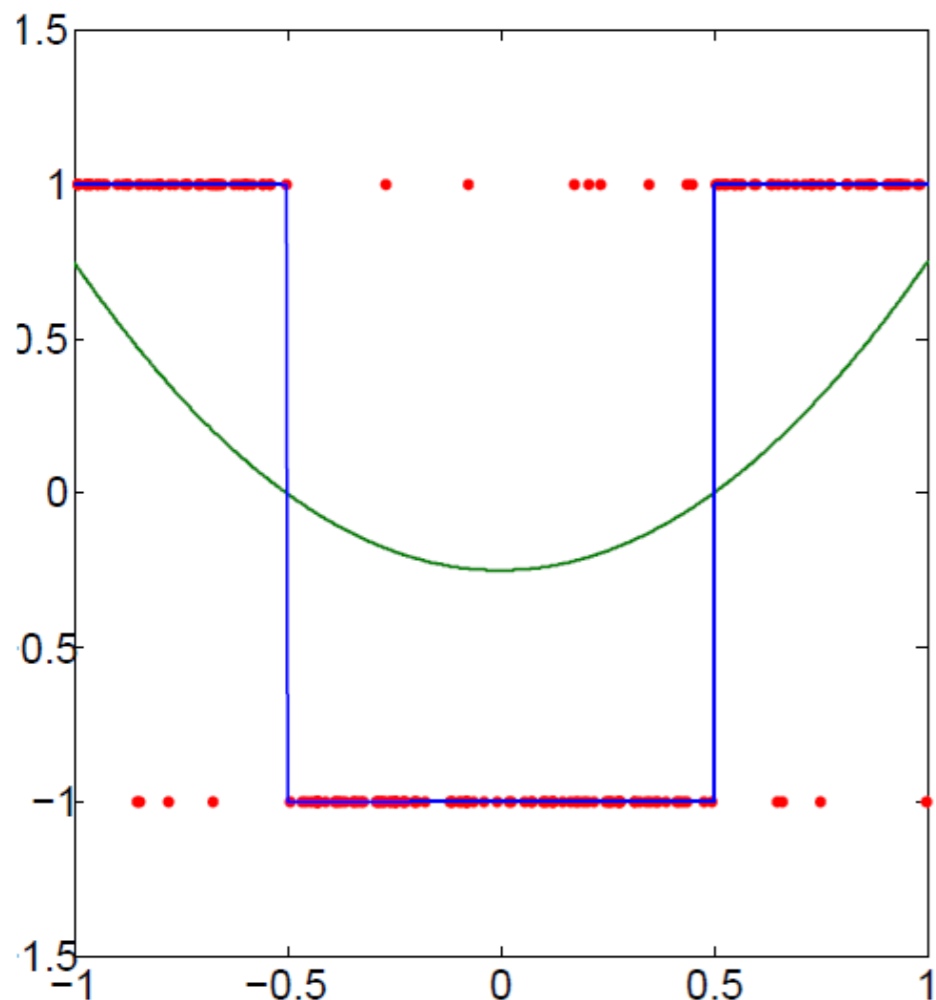
The empirical risk of the best linear classifier:

$$\hat{R}_n(f_{\mathcal{F}}^*) \approx 0.5$$

Underfitting

$$\mathcal{F} = \{f : f(x) = \text{sign}(ax^2 + bx + c), a, b, c \in \mathbb{R}\}$$

Best quadratic classifier:



$$f_{\mathcal{F}}^* = \text{sign}((x - 0.5)(x + 0.5))$$

$$\begin{aligned} R_{\mathcal{F}}^* &= R(f_{\mathcal{F}}^*) = \inf_{f \in \mathcal{F}} \Pr[Y \neq f(X)] \\ &= \frac{1}{4} \times 0.1 + \frac{1}{4} \times 0.1 + \frac{1}{4} \times 0.1 + \frac{1}{4} \times 0.1 = 0.1 \end{aligned}$$

Same as the Bayes risk) good fit!

Classification using the 0-1 loss

The Bayes Classifier

$$L(y, f(x)) = \begin{cases} 1 & y \neq f(x) \\ 0 & y = f(x) \end{cases}$$

$$\begin{aligned} R^* &= \inf_{f: \mathcal{X} \rightarrow \mathbb{R}} R(f) \\ &= \inf_{f: \mathcal{X} \rightarrow \mathbb{R}} \mathbb{E}[L(Y, f(X))] \\ &= \inf_{f: \mathcal{X} \rightarrow \mathbb{R}} \Pr(Y \neq f(X)) \end{aligned}$$

$$\begin{aligned} f^* &= \arg \inf_{f: \mathcal{X} \rightarrow \mathbb{R}} R(f) \\ &= \arg \inf_{f: \mathcal{X} \rightarrow \mathbb{R}} \mathbb{E}[L(Y, f(X))] \\ &= \arg \inf_{f: \mathcal{X} \rightarrow \mathbb{R}} \Pr(Y \neq f(X)) \end{aligned}$$

Lemma I: $\Pr(Y \neq f^*(X)) \leq \Pr(Y \neq f(X)) \quad \forall f$

$$\text{Lemma II: } f^* = \begin{cases} 1 & \text{if } \eta(x) > 1/2 \\ 0 & \eta(x) \leq 1/2 \end{cases} \quad \eta(x) = \mathbb{E}[Y = 1|x]$$

Proofs

Lemma I: Trivial from definition

Lemma II: Surprisingly long calculation

The Bayes Classifier

$$R(f) = \Pr[Y \neq f(X)]$$

$$R^* = R(f^*) = \inf_{f: \mathcal{X} \rightarrow \mathbb{R}} R(f)$$

$$f^* = \arg \min_{f: \mathcal{X} \rightarrow \mathbb{R}} R(f)$$

$$R_{\mathcal{F}}^* = R(f_{\mathcal{F}}^*) = \inf_{f \in \mathcal{F}} R(f)$$

$$f_{\mathcal{F}}^* = \arg \min_{f \in \mathcal{F}} R(f)$$

$$\hat{R}_n(f) = \frac{1}{n} \sum_{i=1}^n \mathbf{1}_{\{Y_i \neq f(X_i)\}}$$

$$\hat{R}_{n, \mathcal{F}}^* = \inf_{f \in \mathcal{F}} \hat{R}_n(f)$$

$$f_{n, \mathcal{F}}^* = \arg \min_{f \in \mathcal{F}} \hat{R}_n(f)$$

This is what the learning algorithm produces

We will need these definitions, please copy it!

$R(f)$ = Risk

R^* = Bayes risk

$\hat{R}_n(f)$ = Empirical risk

f^* = Bayes classifier

$f_n^* = f_{n, \mathcal{F}}^*$ = the classifier that the learning algorithm produces

The Bayes Classifier

$$R(f) = \Pr[Y \neq f(X)]$$

$$R^* = R(f^*) = \inf_{f: \mathcal{X} \rightarrow \mathbb{R}} R(f)$$

$$f^* = \arg \min_{f: \mathcal{X} \rightarrow \mathbb{R}} R(f)$$

$$R_{\mathcal{F}}^* = R(f_{\mathcal{F}}^*) = \inf_{f \in \mathcal{F}} R(f)$$

$$f_{\mathcal{F}}^* = \arg \min_{f \in \mathcal{F}} R(f)$$

$$\hat{R}_n(f) = \frac{1}{n} \sum_{i=1}^n \mathbf{1}_{\{Y_i \neq f(X_i)\}}$$

$$\hat{R}_{n, \mathcal{F}}^* = \inf_{f \in \mathcal{F}} \hat{R}_n(f)$$

$$f_{n, \mathcal{F}}^* = \arg \min_{f \in \mathcal{F}} \hat{R}_n(f)$$

This is what the learning algorithm produces

Theorem I: Bound on the Estimation error

The true risk of what the learning algorithm produces

$$|R(f_{n, \mathcal{F}}^*) - R_{\mathcal{F}}^*| \leq 2 \sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)|$$

How far $f_{n, \mathcal{F}}^*$ is from the optimal in \mathcal{F}

$\sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)|$ can be used to get an upper bound for this

Proof of Theorem 1

Theorem I: Bound on the Estimation error

The true risk of what the learning algorithm produces

$$|R(f_{n,\mathcal{F}}^*) - R_{\mathcal{F}}^*| \leq 2 \sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)|$$

How far $f_{n,\mathcal{F}}^*$ is from the optimal in \mathcal{F}

Proof:

The Bayes Classifier

$$R(f) = \Pr[Y \neq f(X)]$$

$$R^* = R(f^*) = \inf_{f: \mathcal{X} \rightarrow \mathbb{R}} R(f)$$

$$f^* = \arg \inf_{f: \mathcal{X} \rightarrow \mathbb{R}} R(f)$$

$$R_{\mathcal{F}}^* = R(f_{\mathcal{F}}^*) = \inf_{f \in \mathcal{F}} R(f)$$

$$f_{\mathcal{F}}^* = \arg \inf_{f \in \mathcal{F}} R(f)$$

$$\hat{R}_n(f) = \frac{1}{n} \sum_{i=1}^n \mathbf{1}_{\{Y_i \neq f(X_i)\}}$$

$$\hat{R}_{n, \mathcal{F}}^* = \inf_{f \in \mathcal{F}} \hat{R}_n(f)$$

$$f_{n, \mathcal{F}}^* = \arg \min_{f \in \mathcal{F}} \hat{R}_n(f)$$

This is what the learning algorithm produces

Theorem II:

$$|\hat{R}_n(f_{n, \mathcal{F}}^*) - R(f_{n, \mathcal{F}}^*)| \leq \sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)|$$

How far the empirical risk of $f_{n, \mathcal{F}}^*$ is from its true risk.

$\sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)|$ can be used to get an upper bound for this

Proofs

Theorem I: Not so long calculations.

Theorem II: Trivial

Corollary:

$$|\hat{R}_n(f_{n,\mathcal{F}}^*) - R_{\mathcal{F}}^*| \leq 3 \sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)|$$

True risk of the best possible classifier in \mathcal{F} (unknown)

Empirical risk of the learned classifier $f_{n,\mathcal{F}}^*$ (known)

Main message:

It's enough to derive upper bounds for

$$\sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)|$$

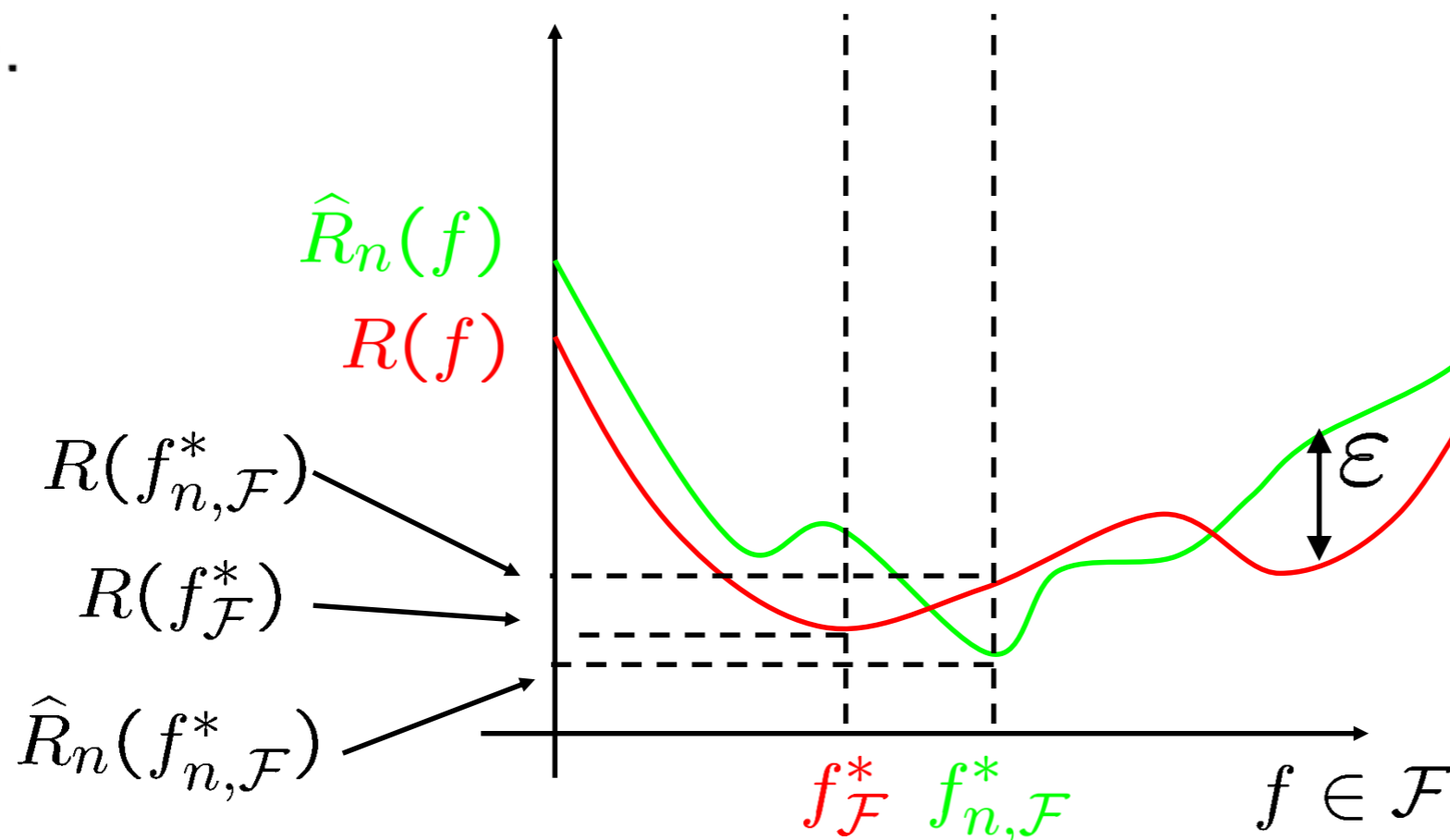
Illustration of the Risks

$$|\hat{R}_n(f_{n,\mathcal{F}}^*) - R(f_{n,\mathcal{F}}^*)| \leq \sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)| = \varepsilon$$

$$|R(f_{n,\mathcal{F}}^*) - R(f_{\mathcal{F}}^*)| \leq 2 \sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)| = 2\varepsilon$$

$$|\hat{R}_n(f_{n,\mathcal{F}}^*) - R(f_{\mathcal{F}}^*)| \leq 3 \sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)| = 3\varepsilon$$

$\sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)|$ can be used to get an upper bound for these.



It's enough to derive upper bounds for

$$\sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)|$$

**It is a random variable that we need to bound!
We will bound it with tail bounds!**

Hoeffding's inequality (1963)

$$\left. \begin{array}{l} Z_1, \dots, Z_n \text{ independent} \\ Z_i \in [a_i, b_i] \\ \varepsilon > 0 \end{array} \right\} \Rightarrow$$

$$\Rightarrow \Pr\left(\left|\frac{1}{n} \sum_{i=1}^n (Z_i - \mathbb{E}[Z_i])\right| > \varepsilon\right) \leq 2 \exp\left(\frac{-2n\varepsilon^2}{\frac{1}{n} \sum_{i=1}^n (b_i - a_i)^2}\right)$$

Special case

$$Z_i \text{ is Bernoulli}(p) \Rightarrow \sum_{i=1}^n Z_i \text{ is Binomial}(n, p)$$

$$\Rightarrow \Pr\left(\left|\sum_{i=1}^n \frac{1}{n} (Z_i - \mathbb{E}[Z_i])\right| > \varepsilon\right) \leq 2 \exp\left(\frac{-2n\varepsilon^2}{\frac{1}{n} \sum_{i=1}^n (1 - 0)^2}\right) = 2 \exp(-2n\varepsilon^2)$$

Binomial distributions

Our goal is to bound $\sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)|$

$$\hat{R}_n(f) = \frac{1}{n} \sum_{i=1}^n \mathbf{1}_{\{Y_i \neq f(X_i)\}} \Rightarrow n\hat{R}_n(f) = \sum_{i=1}^n \mathbf{1}_{\{Y_i \neq f(X_i)\}} \sim \text{Binom}(n, p)$$

where $p = \mathbb{E}[\mathbf{1}_{\{Y \neq f(X)\}}] = \Pr(Y \neq f(X)) = R(f)$ ↙ Bernoulli(p)

Let $Z_i = \mathbf{1}_{\{Y_i \neq f(X_i)\}} \sim \text{Bernoulli}(p)$

$$\Rightarrow |\hat{R}_n(f) - R(f)| = \left| \frac{1}{n} \sum_{i=1}^n \mathbf{1}_{\{Y_i \neq f(X_i)\}} - p \right| = \left| \frac{1}{n} \sum_{i=1}^n Z_i - \mathbb{E}[Z_i] \right|$$

Therefore, from Hoeffding we have:

$$\Pr(|\hat{R}_n(f) - R(f)| > \varepsilon) \leq 2 \exp(-2n\varepsilon^2)$$

Yuppie!!!

Inversion

From Hoeffding we have:

$$\Pr(|\hat{R}_n(f) - R(f)| \geq \varepsilon) \leq 2 \exp(-2n\varepsilon^2)$$

$$\begin{aligned} \text{Let } 2 \exp(-2n\varepsilon^2) &\leq \delta \\ -2n\varepsilon^2 &\leq \log(\delta/2) \\ \varepsilon^2 &\geq \frac{\log(2/\delta)}{2n} \end{aligned}$$

Therefore,

$$\begin{aligned} \Pr\left(|\hat{R}_n(f) - R(f)| \geq \sqrt{\frac{\log(2/\delta)}{2n}}\right) &\leq \delta \\ \Pr\left(|\hat{R}_n(f) - R(f)| < \sqrt{\frac{\log(2/\delta)}{2n}}\right) &\geq 1 - \delta \end{aligned}$$

Usually $\delta = 0.05$ (5%), and $1 - \delta = 0.95$ (95%)

Union Bound

Our goal is to bound: $\sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)|$

We already know: $\Pr(|\hat{R}_n(f) - R(f)| > \varepsilon) \leq 2 \exp(-2n\varepsilon^2)$

Theorem: [tail bound on the ‘deviation’ in the worst case]

Let $\mathcal{F} = \{f : \mathcal{X} \rightarrow \{0, 1\}\}$, and $|\mathcal{F}| \leq N$

$$\Rightarrow \Pr \left(\sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)| > \varepsilon \right) \leq 2N \exp(-2n\varepsilon^2)$$

Worst case error

This is not the worst classifier in terms of classification accuracy!

Worst case means that the empirical risk of classifier f is the furthest from its true risk!

Proof: $\Pr(A \cup B) \leq \Pr(A) + \Pr(B)$

$$\Pr \left(\sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)| > \varepsilon \right) = \Pr \left(\bigcup_{f \in \mathcal{F}} \{|\hat{R}_n(f) - R(f)| > \varepsilon\} \right)$$

$$\Pr \left(\bigcup_{f \in \mathcal{F}} \{|\hat{R}_n(f) - R(f)| > \varepsilon\} \right) \leq \sum_{f \in \mathcal{F}} \Pr(|\hat{R}_n(f) - R(f)| > \varepsilon)$$

Inversion of Union Bound

We already know: Let $\mathcal{F} = \{f : \mathcal{X} \rightarrow \{0, 1\}\}$, and $|\mathcal{F}| \leq N$

$$\Rightarrow \Pr \left(\sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)| > \varepsilon \right) \leq 2N \exp(-2n\varepsilon^2)$$

Let $2N \exp(-2n\varepsilon^2) \leq \delta \Rightarrow -2n\varepsilon^2 \leq \log(\delta/(2N)) \Rightarrow \varepsilon^2 \geq \frac{\log(2N/\delta)}{2n}$

Therefore,

$$\Pr \left(\sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)| \geq \sqrt{\frac{\log(N) + \log(2/\delta)}{2n}} \right) \leq \delta$$

$$\Pr \left(\sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)| < \sqrt{\frac{\log(N) + \log(2/\delta)}{2n}} \right) \geq 1 - \delta$$

Inversion of Union Bound

$$\Pr \left(\sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)| \geq \sqrt{\frac{\log(N) + \log(2/\delta)}{2n}} \right) \leq \delta$$

$$\Pr \left(\sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)| < \sqrt{\frac{\log(N) + \log(2/\delta)}{2n}} \right) \geq 1 - \delta$$

- The larger the N , the looser the bound
- This result is distribution free: True for all $P(X, Y)$ distributions
- It is useless if N is big, or infinite... (e.g. all possible hyperplanes)

We will see later how to fix that. (Hint: McDiarmid, VC dimension...)

The Expected Error

Our goal is to bound: $\sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)|$

We already know: $\Pr\left(\sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)| > \varepsilon\right) \leq 2N \exp(-2n\varepsilon^2)$

(Tail bound, Concentration inequality)

Theorem: [Expected 'deviation' in the worst case]

Let $\mathcal{F} = \{f : \mathcal{X} \rightarrow \{0, 1\}\}$, and $|\mathcal{F}| \leq N$

$$\Rightarrow \mathbb{E} \left[\sup_{f \in \mathcal{F}} |\hat{R}_n(f) - R(f)| \right] \leq \sqrt{\frac{\log(2N)}{2n}}$$

Worst case deviation

This is not the worst classifier in terms of classification accuracy!

Worst case means that the empirical risk of classifier f is the furthest from its true risk!

Proof: we already know a tail bound. If $Y \geq 0$, then $\mathbb{E}[Y] = \int_0^{\infty} \Pr(Y \geq z) dz$

(From that actually we get a bit weaker inequality... oh well)

Thanks for your attention 😊