

MS&E 233

Game Theory, Data Science and AI

Lecture 13

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(by courtesy) Computer Science and Electrical Engineering

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Computational Game Theory for Complex Games

- 1
 - Basics of game theory and zero-sum games (T)
 - Basics of online learning theory (T)
 - Solving zero-sum games via online learning (T)
 - *HW1: implement simple algorithms to solve zero-sum games*
 - Applications to ML and AI (T+A)
 - *HW2: implement boosting as solving a zero-sum game*

- 2
 - Basics of extensive-form games
 - Solving extensive-form games via online learning (T)
 - *HW3: implement agents to solve very simple variants of poker*

- 3
 - General games, equilibria and online learning (T)
 - Online learning in general games
 - *HW4: implement no-regret algorithms that converge to correlated equilibria in general games*

Data Science for Auctions and Mechanisms

- 4
 - Basics and applications of auction theory (T+A)
 - Basic Auctions and Learning to bid in auctions (T)
 - *HW5: implement bandit algorithms to bid in ad auctions*

- 5
 - Optimal auctions and mechanisms (T)
 - Simple vs optimal mechanisms (T)
 - *HW6: implement simple and optimal auctions, analyze revenue empirically*

- 6
 - Basics of Statistical Learning Theory (T)
 - Optimizing Mechanisms from Samples (T)
 - *HW7: implement procedures to learn approximately optimal auctions from historical samples and in an online manner*

Further Topics

- 7
 - Econometrics in games and auctions (T+A)
 - A/B testing in markets (T+A)
 - *HW8: implement procedure to estimate values from bids in an auction, empirically analyze inaccuracy of A/B tests in markets*

Guest Lectures

- Mechanism Design for LLMs, Renato Paes Leme, Google Research
- Auto-bidding in Sponsored Search Auctions, Kshipra Bhawalkar, Google Research

Summarizing Last Lecture

Myerson's Theorem. When valuations are independently distributed, for any BIC, NNT and IR mechanism (and any BNE of a non-truthful mechanism), the payment contribution of each player is their expected virtual value

$$E[\hat{p}_i(v_i)] = E[\hat{x}_i(v_i) \cdot \phi_i(v_i)], \quad \phi_i(v_i) = v_i - \frac{1 - F_i(v_i)}{f_i(v_i)}$$

Corollary. When valuations are independently distributed, for any Bayes-Nash equilibrium of any non-truthful mechanism, the payment contribution of each player is their expected virtual value

$$E[\hat{p}_i(v)] = E[\hat{x}_i(v_i) \cdot \phi_i(v_i)], \quad \phi_i(v_i) = v_i - \frac{1 - F_i(v_i)}{f_i(v_i)}$$

Myerson's Optimal Auction. Assuming that virtual value functions are monotone non-decreasing, the mechanism that maximizes virtual welfare, achieves the largest possible revenue among all possible mechanisms and Bayes-Nash

$$x(v) = \operatorname{argmax}_{x \in X} \sum_i x \cdot \phi_i(v_i), \quad p_i(v) = v_i x_i(v) - \int_0^{v_i} x_i(z, v_{-i}) dz$$

$$\text{Rev} = E \left[\max_{x \in X} \sum_i x \cdot \phi_i(v_i) \right]$$

Optimal auction is

1) cumbersome, 2) hard to understand, 3) hard to explain, 4) does not always allocate to the highest value player, 5) discriminates a lot, 6) is many times counter-intuitive, 7) can seem unfair!

Second-Price with Player-Specific Reserves

- What if we simply run a second price auction but have different reserves for each bidder
- Each bidder i has a reserve price r_i
- Reject all bidders with bid below the reserve
- Among all bidders with value $v_i \geq r_i$, allocate to highest bidder
- Charge winner max of their reserve and the next highest surviving bid

Second-Price with Player-Specific Reserves

Theorem. There exist personalized reserve prices such that the above auction achieves at least $1/2$ of the optimal auction revenue!

- Choose θ such that:

$$\Pr\left(\max_i \phi_i^+(v_i) \geq \theta\right) = 1/2$$

- Then set personalized reserve prices implied by:

$$\phi_i^+(v_i) \geq \theta \Leftrightarrow v_i \geq r_i$$

All these designs required knowledge
of distributions of values F_i !

What can we do if we only have
data from F_i ?

Learning Auctions from Samples

Learning from Samples

- We are given a set S of m samples of value profiles

$$S = \left\{ v^j = \left(v_1^j, \dots, v_n^j \right) \right\}_{j=1}^m$$

- Each sample is drawn i.i.d. from the distribution of values

$$v_i^j \sim F_i, \quad v^j \sim \mathbf{F} \stackrel{\text{def}}{=} F_1 \times \dots \times F_n$$

- Samples can be collected from historical runs of truthful auction
- Bids of each bidder in each of the m historical runs of the auction

Desiderata

- Without knowledge of distributions F_i , we want to produce a mechanism M_S , that achieves good revenue on these distributions
- For some $\epsilon(m) \rightarrow 0$ as the number of samples grows:

$$\text{Rev}(M_S) \stackrel{\text{def}}{=} E_{v \sim F} \left[\sum_i p_i^{M_S}(v) \right] \geq \text{OPT}(\mathbf{F}) - \epsilon(m)$$

- Either in expectation over the draw of the samples, i.e.

$$E_S[\text{Rev}(M_S)] \geq \text{OPT}(\mathbf{F}) - \epsilon(m)$$

- Or with high-probability over the draw of the samples, i.e.

$$\text{w. p. } 1 - \delta: \quad \text{Rev}(M_S) \geq \text{OPT}(\mathbf{F}) - \epsilon_\delta(m)$$

Easy Start: Pricing from Samples

Pricing from Samples

- Suppose we have **only one bidder** with $v \sim F$, for simplicity in $[0, 1]$
- Optimal mechanism is to post the **monopoly reserve price**
- The optimal price r is the one that maximizes

$$\text{Rev}(r) = E_{v \sim F}[r \cdot 1\{v \geq r\}] = r \Pr(v \geq r) = r (1 - F(r))$$

which is the monopoly reserve price η that solves:

$$\eta - \frac{1 - F(\eta)}{f(\eta)} = 0$$

- Choosing η **requires knowledge of the CDF F and the pdf f**
- **Can we optimize r if we have m samples of v ?**

The Obvious Algorithm

- We want to choose r that maximizes

$$\max_{r \in [0,1]} \text{Rev}(r) \stackrel{\text{def}}{=} E_{v \sim F}[r \cdot 1\{v \geq r\}], \quad (\text{population objective})$$

- With m samples S , we can optimize average revenue on samples!

$$\max_{r \in [0,1]} \text{Rev}_S(r) \stackrel{\text{def}}{=} \frac{1}{m} \sum_{j=1}^m r \cdot 1\{v^j \geq r\}, \quad (\text{empirical objective})$$

- This approach is called **Empirical Reward Maximization** (ERM)
- **Intuition.** Since each value is drawn from distribution F the empirical average over i.i.d. draws from F , by law of large numbers, should be very close to expected value

Same as Empirical Risk Minimization (ERM) in
Machine Learning (loss vs reward)

A Potential Problem with ERM

- The Law of Large Numbers applies if we wanted to **evaluate the revenue of a fixed reserve price**, we had in mind using the samples
- If we **optimize over a very large set of reserve prices**, then by random chance, it could be that we find a reserve price that has a large revenue on the samples, but small on the distribution
- This behavior is called **overfitting to the samples**
- We need to argue that overfitting cannot arise when we optimize over the reserve price!

Basic Elements of Statistical Learning Theory

Uniform Convergence

- **Uniform Convergence.** Suppose that we show that, w.p. $1 - \delta$

$$\forall r \in [0,1]: |\text{Rev}_S(r) - \text{Rev}(r)| \leq \epsilon_\delta(m)$$

- **Alert.** Note that this is different than: $\forall r \in [0,1]$, w.p. $1 - \delta$

$$|\text{Rev}_S(r) - \text{Rev}(r)| \leq \epsilon_\delta(m)$$

- The first asks that with probability $1 - \delta$, the empirical revenue **of all reserve prices** is close to their population revenue
- The second asks that for a given reserve price, with probability $1 - \delta$ its empirical revenue is close to its population
- The second claims nothing about the probability of the **joint event** that this is satisfied for all prices simultaneously

Uniform Convergence Suffices for No-Overfitting

- **Uniform Convergence.** Suppose that we show that, w.p. $1 - \delta$

$$\forall r \in [0,1]: |\text{Rev}_S(r) - \text{Rev}(r)| \leq \epsilon_\delta(m)$$

- **Empirical Risk Maximization** reserve:

$$r_S = \underset{r \in [0,1]}{\text{argmax}} \text{Rev}_S(r)$$

Theorem. If uniform convergence holds then, w.p. $1 - \delta$

$$\text{Rev}(r_S) \geq \text{Rev}(\eta) - 2\epsilon_\delta(m) = \text{OPT}(F) - 2\epsilon_\delta(m)$$

Uniform Convergence Suffices for No-Overfitting

Theorem. If uniform convergence holds then, w.p. $1 - \delta$

$$\text{Rev}(r_S) \geq \text{Rev}(\eta) - 2\epsilon_\delta(m) = \text{OPT}(F) - 2\epsilon_\delta(m)$$

- By **uniform convergence**, with probability $1 - \delta$:

$$\text{Rev}(r_S) \geq \text{Rev}_S(r_S) - \epsilon_\delta(m)$$

- Since, r_S optimizes the **empirical objective**

$$\text{Rev}_S(r_S) \geq \text{Rev}_S(\eta)$$

- By **uniform convergence**:

$$\text{Rev}_S(\eta) \geq \text{Rev}(\eta) - \epsilon_\delta(m)$$

- Putting it all together:

$$\text{Rev}(r_S) \geq \text{Rev}(\eta) - 2\epsilon_\delta(m)$$

This is the no-overfitting property:

It **cannot be** that we found a reserve price that has *large empirical revenue* but very *small population revenue*

The *monopoly reserve* is a **feasible** reserve price but **was not chosen** by ERM. So, it must have had smaller empirical average revenue.

LLN vs Uniform Convergence

Crucial Argument: with probability $1 - \delta$: $\text{Rev}(r_S) \geq \text{Rev}_S(r_S) - \epsilon_\delta(m)$

- Cannot be argued solely using **Law of Large Numbers**: if we have i.i.d. X^j with mean $E[X]$

$$\left| \frac{1}{m} \sum_{j=1}^m X^j - E[X] \right| \rightarrow 0$$

- For reserve price r that is **chosen before looking at the samples**, define $X^j(r) = r \cdot 1\{v^j \geq r\}$

$$|\text{Rev}_S(r) - \text{Rev}(r)| = \left| \frac{1}{m} \sum_j r \cdot 1\{v^j \geq r\} - E[r \cdot 1\{v \geq r\}] \right| \rightarrow 0$$

- **Problem.** The reserve price r_S was **chosen by looking at all the samples** in S
 - If I tell you r_S you **learn something about the samples**
 - Conditional on r_S the **samples are no-longer i.i.d.**
- Uniform convergence, essentially means “*what I learn about S from r_S is not that much...*”

Concentration Inequalities and Uniform Convergence

- Concentration inequalities give us a stronger version of LLN
- **Chernoff-Hoeffding Bound.** If we have i.i.d. $X^j \in [0,1]$ with mean $E[X]$, w.p. $1 - \delta$:

$$\left| \frac{1}{m} \sum_{j=1}^m X^j - E[X] \right| \leq \epsilon_\delta(m) \stackrel{\text{def}}{=} \sqrt{\frac{\log(2/\delta)}{2m}}$$

- **Crucial.** The bound grows only logarithmically with $1/\delta$

Union Bound

- Suppose we had only K possible reserve prices $\left\{\frac{1}{K}, \frac{2}{K}, \frac{3}{K} \dots, 1\right\}$
- For each reserve price r on the grid, for any probability δ' , by Chernoff bound

$$\Pr((\text{Bad Event})_r) = \Pr\left(\left|\frac{1}{m} \sum_{j=1}^m X^j(r) - E[X(r)]\right| > \epsilon_{\delta'}(m)\right) \leq \delta'$$

- **Union Bound.** The probability of the union of events is at most the sum of the probabilities

$$\Pr(\cup_{r=1}^K (\text{Bad Event})_r) \leq \sum_{r=1}^K \Pr((\text{Bad Event})_r) \leq K \cdot \delta'$$

- Apply Chernoff bound with $\delta' = \delta/K$

$$\Pr(\cup_{r=1}^K (\text{Bad Event})_r) \leq \delta$$

- Probability(*exists reserve price whose empirical revenue is far from its population*) at most δ

Uniform Convergence via Union Bound

Theorem. Suppose we had K possible reserve prices $\text{Grid}_K \stackrel{\text{def}}{=} \left\{ \frac{1}{K}, \frac{2}{K}, \frac{3}{K}, \dots, 1 \right\}$

Then with probability at least $1 - \delta$

$$\forall r \in \text{Grid}_K: |\text{Rev}_S(r) - \text{Rev}(r)| \leq \epsilon_{\delta/K}(m) \stackrel{\text{def}}{=} \sqrt{\frac{\log(2K/\delta)}{2m}}$$

Problem. The optimal reserve η can potentially not be among these K reserves

Intuition. For a sufficiently large K , for any reserve price, we can find a reserve price on this discretized grid that achieves almost as good revenue

We don't lose much by optimizing over the grid!

Discretization

- For a reserve price r , pick largest reserve price below r on the grid
- Denote this discretization of r as r_K
- By doing so, you allocate to any value you used to allocate before
- For any such value you receive revenue at least $r - 1/K$
- Overall, you lose revenue at most $1/K$
$$\text{Rev}(r_K) \geq \text{Rev}(r) - 1/K$$

Discretized ERM

- Let's modify ERM to optimize only over the grid

$$r_S = \max_{r \in \text{Grid}_K} \text{Rev}_S(r)$$

- We can apply the **uniform convergence over the grid**

$$\text{Rev}(r_S) \geq \text{Rev}_S(r_S) - \epsilon_{\delta/K}(m)$$

We cannot overfit, when optimizing over the grid of reserves

- Since, r_S optimizes the empirical objective over the grid

$$\text{Rev}_S(r_S) \geq \text{Rev}_S(\eta_K)$$

The *discretized monopoly reserve* is a **feasible** reserve in the grid but **was not chosen** by ERM.

- By **uniform convergence over the grid**:

$$\text{Rev}_S(\eta_K) \geq \text{Rev}(\eta_K) - \epsilon_{\delta/K}(m)$$

- By the **discretization error argument**:

$$\text{Rev}(\eta_K) \geq \text{Rev}(\eta) - 1/K$$

Theorem. The revenue of the reserve price output by discretized ERM over the K -grid satisfies, with probability $1 - \delta$

$$\text{Rev}(r_S) \geq \text{OPT}(F) - 2 \sqrt{\frac{\log(2K/\delta)}{2m}} - \frac{1}{K}$$

Choosing $K = 1/m$

$$\text{Rev}(r_S) \geq \text{OPT}(F) - 3 \sqrt{\frac{\log(2m/\delta)}{2m}}$$

Desideratum satisfied!
 $\epsilon_\delta(m) \rightarrow 0$ as m grows

The Limits of Discretization

- Do we really need to optimize over the discrete grid?
- What if we insist on optimizing over $[0,1]$. Can we still overfit?
- Now that we have infinite possible reserves, we cannot apply the union bound argument ($K = \infty$)!
- How do we argue about optima over continuous, infinite cardinality spaces?

Sneak Peek

- Would have been ideal if we only have to argue about behavior of our optimization space, *on the given set of samples*
- As opposed to the unknown distribution of values
- What if we can find a small set of reserves and argue that for all reserves there is an approximately equivalent one in the small set, in terms of revenue on the samples
- Maybe then it suffices to invoke the union bound over the smaller space

Statistical Learning Theory

General Framework

- Given samples $S = \{v_1, \dots, v_m\}$ that are i.i.d. from distribution F
- Given a hypothesis/function space H
- Given a reward function $r(v; h)$
- Goal is to maximize the expected reward over distribution F
$$R(h) = E_{v \sim F}[r(v; h)]$$

Desiderata

- Without knowledge of distribution F , we want to produce a hypothesis h_S , that achieves good reward on this distribution
- For some $\epsilon(m) \rightarrow 0$ as the number of samples grows:

$$R(h_S) \stackrel{\text{def}}{=} E_{v \sim F}[r(v; h)] \geq \max_{h \in H} R(h) - \epsilon(m)$$

- Either in expectation over the draw of the samples, i.e.

$$E_S[R(h_S)] \geq \max_{h \in H} R(h) - \epsilon(m)$$

- Or with high-probability over the draw of the samples, i.e.

$$\text{w. p. } 1 - \delta: \quad R(h_S) \geq \max_{h \in H} R(h) - \epsilon_\delta(m)$$

Desiderata (Mechanism Design from Samples)

- Without knowledge of Distribution of value profiles F , we want to produce a hypothesis h_S , that achieves good Revenue on this distribution

- For some $\epsilon(m) \rightarrow 0$ as the number of samples grows:

$$R(h_S) \stackrel{\text{def}}{=} E_{v \sim F} \left[\sum_i p_i(v) \right] \geq \max_{h \in H} R(h) - \epsilon(m)$$

- Either in expectation over the draw of the samples, i.e.

$$E_S[R(h_S)] \geq \max_{h \in H} R(h) - \epsilon(m)$$

- Or with high-probability over the draw of the samples, i.e.

$$\text{w. p. } 1 - \delta: \quad R(h_S) \geq \max_{h \in H} R(h) - \epsilon_\delta(m)$$

The Obvious Algorithm

- We want to choose r that maximizes

$$\max_{h \in H} R(h) \stackrel{\text{def}}{=} E_{v \sim F}[r(v; h)], \quad (\text{population objective})$$

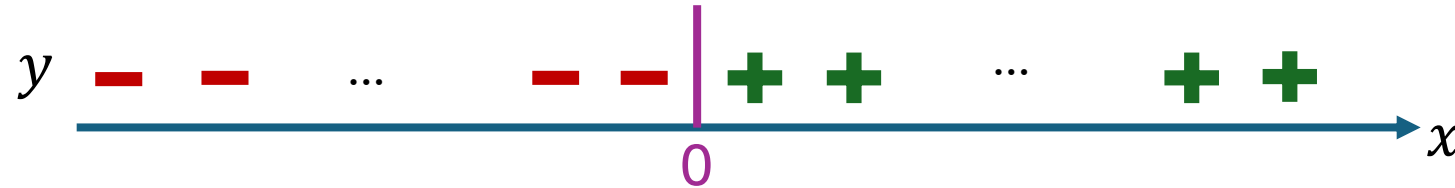
- With m samples, we can optimize average reward on samples!

$$\max_{h \in H} R_S(h) \stackrel{\text{def}}{=} \frac{1}{m} \sum_{j=1}^m r(v_j; h), \quad (\text{empirical objective})$$

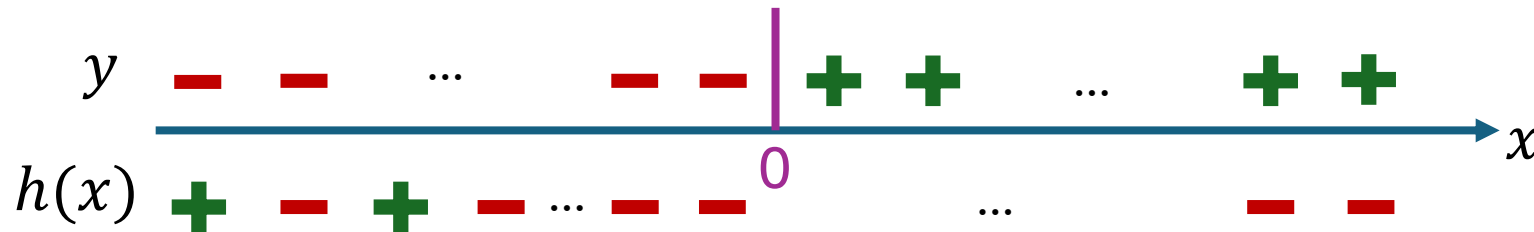
- This approach is called **Empirical Reward Maximization** (ERM)
- **Intuition.** Since each value is drawn from distribution F the empirical average over i.i.d. draws from F , by law of large numbers, should be very close to expected value

Standard Classification Example

- Suppose samples $v = (x, y)$ where $x \sim U[-1, 1]$ and $y \in \{-1, 1\}$



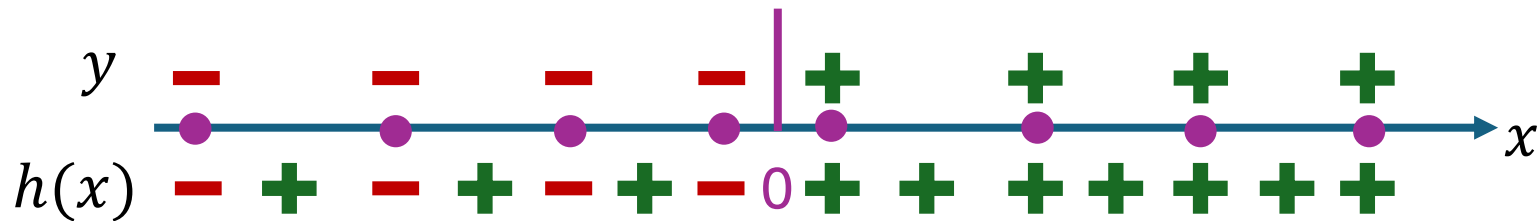
- We want to choose a “labeling” function $h(x) \in \{-1, 1\}$



- That achieves good accuracy
$$r(v; h) = 1\{h(x) = y\}$$

ERM Gone Bad

- Suppose we choose the following h_S : label all samples correctly and predict +1 for any value that is not on the samples

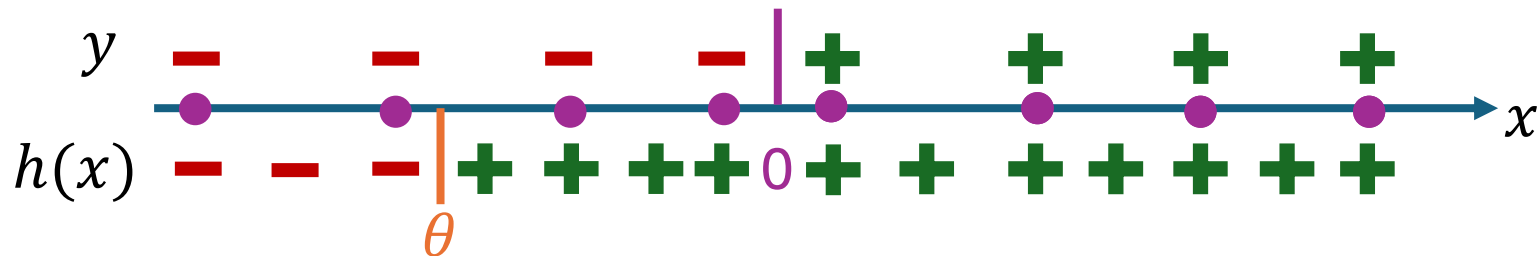


- The empirical average reward of this h_S is 1. The largest possible!
- The expected reward of this h_S is $\frac{1}{2}$
- The discrepancy between the empirical reward of the ERM solution and its population reward never vanishes! Overfitting!

ERM Over Threshold Functions

- Suppose we restrict to optimizing over threshold functions
- Label every $x \geq \theta$ with $+1$ and every $x \leq \theta$ with -1

$$H = \{x \rightarrow 1(x > \theta) - 1(x \leq \theta) : \theta \in \Theta\}$$

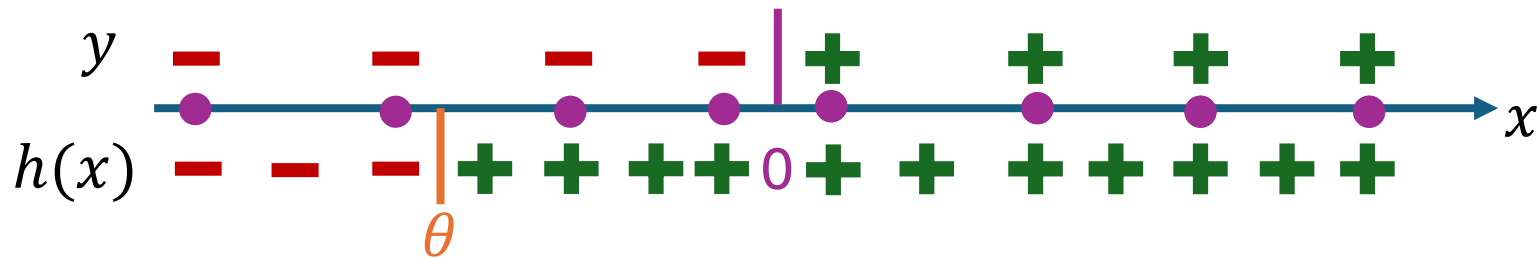


- Optimizing over such θ we will never be able to overfit
- How do we argue this?
- Discretization argument fails!
- No matter how we discretize, there exists a distribution of x that will have a very large discretization error

Sufficient Hypothesis Subspace on Samples

- Suppose we restrict to optimizing over threshold functions
- Label every $x \geq \theta$ with $+1$ and every $x < \theta$ with -1

$$H = \{x \rightarrow 1(x \geq \theta) - 1(x < \theta) : \theta \in \Theta\}$$



- Given the m samples, then on the samples there are at most $m + 1$ equivalent hypothesis: choose the threshold on the sample (or $\theta = 1$)
- Every other hypothesis produces the exact same labeling of the samples and achieves the same empirical reward
- Is there an argument that only takes union bound over this set?

Back to the General Framework

- We will try to argue the expected performance

$$E_S[R(h_S)] \geq \max_{h \in H} R(h) - \epsilon(m)$$

- Expected Sample Average *Representativeness*: suppose that

$$\text{Rep} = E_S \left[\sup_{h \in H} R_S(h) - R(h) \right] \leq \epsilon(m)$$

How good is the sample average objective in terms of representing the population expectation, in the worst case over H

- Then we can prove expected error of $\epsilon(m)$

$$E_S[R(h_S)] = E[R_S(h_S)] - E[R_S(h_S) - R(h_S)] \geq E[R_S(h_S)] - \epsilon(m)$$

- Since h_S optimizes $R_S(h)$ and $h_* = \operatorname{argmax}_{h \in H} R(h)$ is feasible

$$E[R_S(h_S)] \geq E[R_S(h_*)] = R(h_*)$$

h_* does not depend on the samples

$$E[R_S(h_*)] \stackrel{\text{def}}{=} \frac{1}{m} \sum_j E[h(v^j; h_*)] = E[h(v; h_*)] = R(h_*)$$

If we can bound representativeness

$$\text{Rep} = E_S \left[\sup_h R_S(h) - R(h) \right] \leq \epsilon(m)$$

Then we can bound expected performance

$$E[R(h_S)] \geq E[R(h_*)] - \epsilon(m)$$