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

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

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

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

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

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

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

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 ½ 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

$$v_i^j \sim F_i, \qquad v^j \sim \boldsymbol{F} \stackrel{\text{def}}{=} F_1 \times \cdots \times F_n$$

- 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 $\epsilon(m) \to 0$ as the number of samples grows:

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

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

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

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

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

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

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

  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

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

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

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

- This approach is called Empirical Risk 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

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. $1-\delta$

$$\forall r \in [0,1]: \ |\mathrm{Rev}_m(r) - \mathrm{Rev}(r)| \le \epsilon_\delta(m)$$

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

$$|\mathrm{Rev}_m(r) - \mathrm{Rev}(r)| \le \epsilon_\delta(m)$$

- 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 Converges Suffices for No-Overfitting

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

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

- Empirical Risk Maximization reserve:

$$r_S = \operatorname*{argmax}_{r\in[0,1]} \mathrm{Rev}_m(r)$$

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

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

Uniform Converges Suffices for No-Overfitting

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

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

- By uniform convergence, with probability $1-\delta$:
$$\boxed{\mathrm{Rev(r_S)} \geq \mathrm{Rev}_m(r_S) - \epsilon_\delta(m)}$$
- Since, r_S optimizes the empirical objective
$$\boxed{\mathrm{Rev}_m(r_S) \geq \mathrm{Rev}_m(\eta)}$$
- By uniform convergence:
$$\mathrm{Rev}_m(\eta) \geq \mathrm{Rev}(\eta) - \epsilon_\delta(m)$$
- Putting it all together:
$$\mathrm{Rev}(r_s) \geq \mathrm{Rev}(\eta) - 2\epsilon_\delta(m)$$

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 $1-\delta$: $\mathrm{Rev}(\mathrm{r}_S) \geq \mathrm{Rev}_m(r_S) - \epsilon_\delta(m)$
- Cannot be argued solely using Law of Large Numbers: if we have i.i.d. X^j with mean $E[X]$

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

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

$$|\mathrm{Rev}_m(r) - \mathrm{Rev}(r)| = \left|\frac{1}{m}\sum_{j} r \cdot 1\{v^j \geq r\} - E[r \cdot 1\{v \geq r\}]\right| \to 0$$

- 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

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

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

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

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

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

- Probability that there exists reserve price whose empirical revenue is far from its population is at most δ

Uniform Convergence via Union Bound

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

Then with probability at least $1 - \delta$

$$\forall r \in \mathrm{Grid}_{\mathrm{K}}\colon |\mathrm{Rev}_m(r) - \mathrm{Rev}(r)| \le \epsilon_{\delta/K}(m) \overset{\text{def}}{=} \sqrt{\frac{\log(2K/\delta)}{2m}}$$

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 $1/K$

$$\mathrm{Rev}(r_K) \geq \mathrm{Rev}(r) - 1/K$$

Discretized ERM

- Let's modify ERM to optimize only over the grid
$$r_S = \max_{r \in \mathrm{Grid}_K} \mathrm{Rev}_m(r)$$
- We can apply the uniform convergence over the grid
$$\mathrm{Rev}(r_S) \geq \mathrm{Rev}_m(r_S) - \epsilon_{\delta/K}(m)$$
We cannot overfit, when optimizing over the grid of reserves
- Since, r_S optimizes the empirical objective over the grid
$$\mathrm{Rev}_m(r_S) \geq \mathrm{Rev}_m(\eta_K)$$
The *discretized monopoly reserve* is a **feasible** reserve in the grid but **was not chosen** by ERM.
- By uniform convergence over the grid:
$$\mathrm{Rev}_m(\eta_K) \geq \mathrm{Rev}(\eta_K) - \epsilon_\delta(m)$$
- By the discretization error argument:
$$\mathrm{Rev}(\eta_K) \geq \mathrm{Rev}(\eta) - 1/K$$

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

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

Choosing $K = 1/m$

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

Desideratum satisfied!
$\epsilon_\delta(m) \to 0$ 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?

- It would have been ideal if we could argue about behavior of choices, on the given set of value samples, as opposed to the 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 $S = \{v^1, \ldots, v^m\}$ 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 $\epsilon(m) \to 0$ 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 $\epsilon(m) \to 0$ 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.

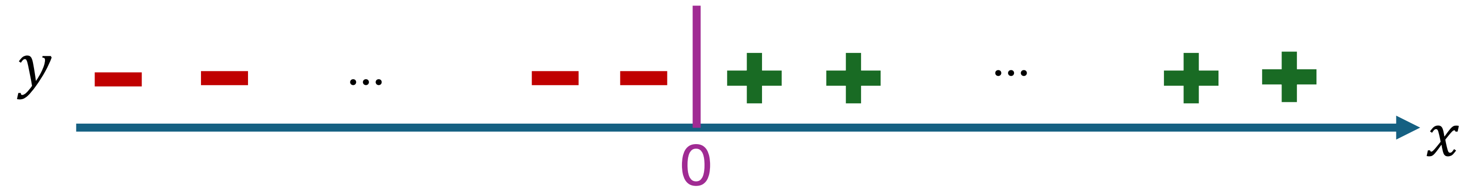
$$E_S[R(h_S)] \geq \max_{h\in H} R(h) - \epsilon(m)$$

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

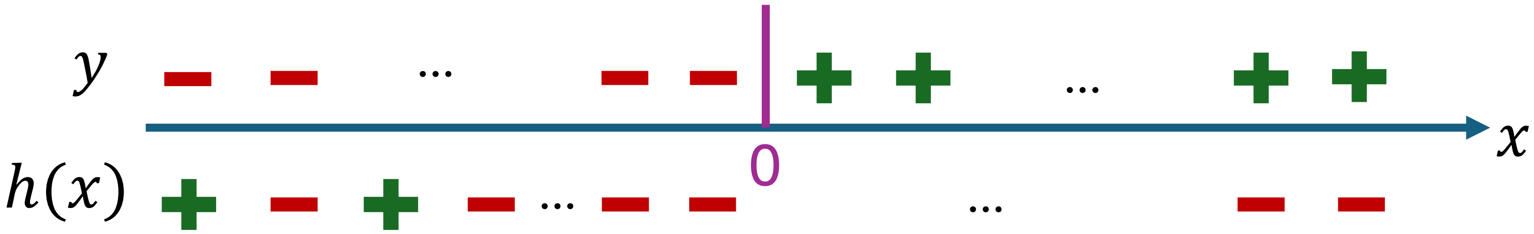
$$\text{w.p. } 1-\delta: \quad R(h_S) \geq \max_{h\in H} R(h) - \epsilon_\delta(m)$$

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 $h(x) \in \{-1,1\}$

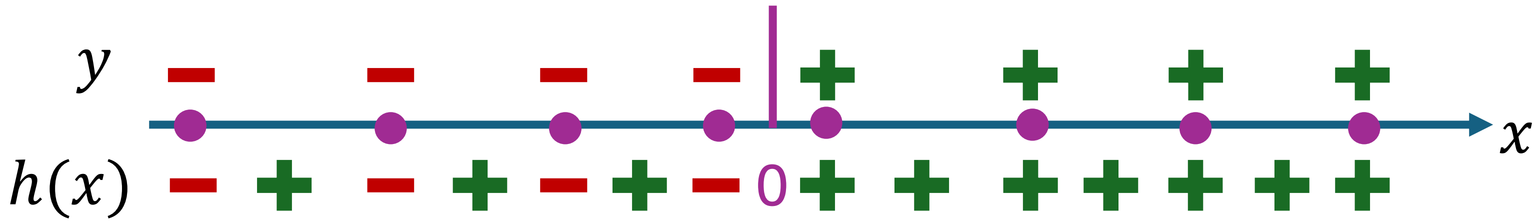


- That achieves good accuracy

$$r(v; h) = 1\{h(x) = y\}$$

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

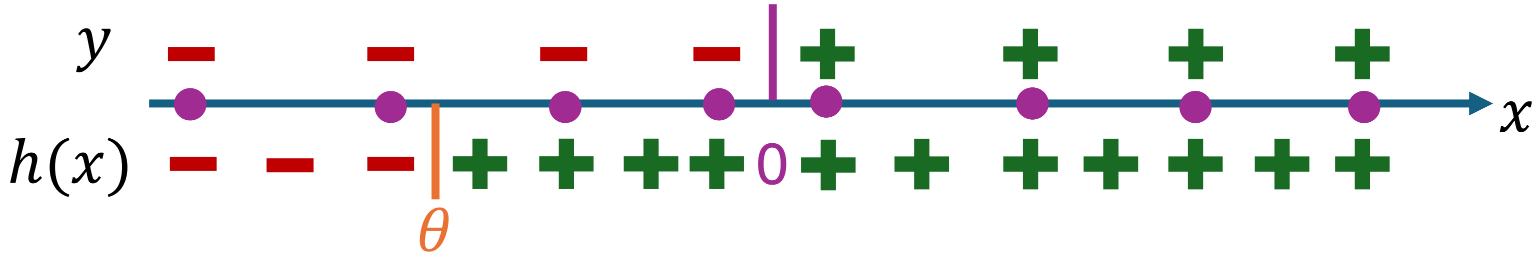


- The empirical average reward of this h_S is 1. The largest possible!
- The expected reward of this h_S is ½
- The discrepancy between the empirical reward of the ERM solution and its population reward never vanishes! Overifitting!

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

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

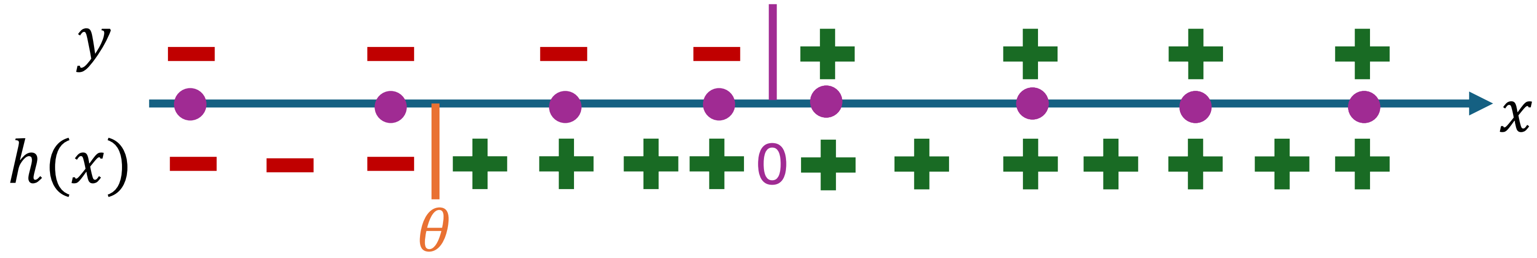


- Optimizing over such θ we will never be able to overfit
- How do we argue this?
- Discretization argument fails!
- No matter how we discretize, there exists a distribution of x that will have a very large discretization error

Representative Subsets on Samples

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

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



- 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
$$E_S[R(h_S)] \geq \max_{h \in H} R(h) - \epsilon(m)$$
- Representativeness: suppose that we can argue that
$$\mathrm{Rep} = E_S\left[\sup_h R_S(h_S) - R(h)\right] \leq \epsilon(m)$$
- 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 $h_* = \mathrm{argmax}_{h \in H} R(h)$ is feasible
$$E[R_S(h_S)] \geq \boxed{E[R_S(h_*)] = R(h_*)}$$

h_* does not depend on the samples

$$\sum_j E[h(v^j; h_*)] = E[h(v; h_*)] = R(h_*)$$

If we can bound representativeness

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

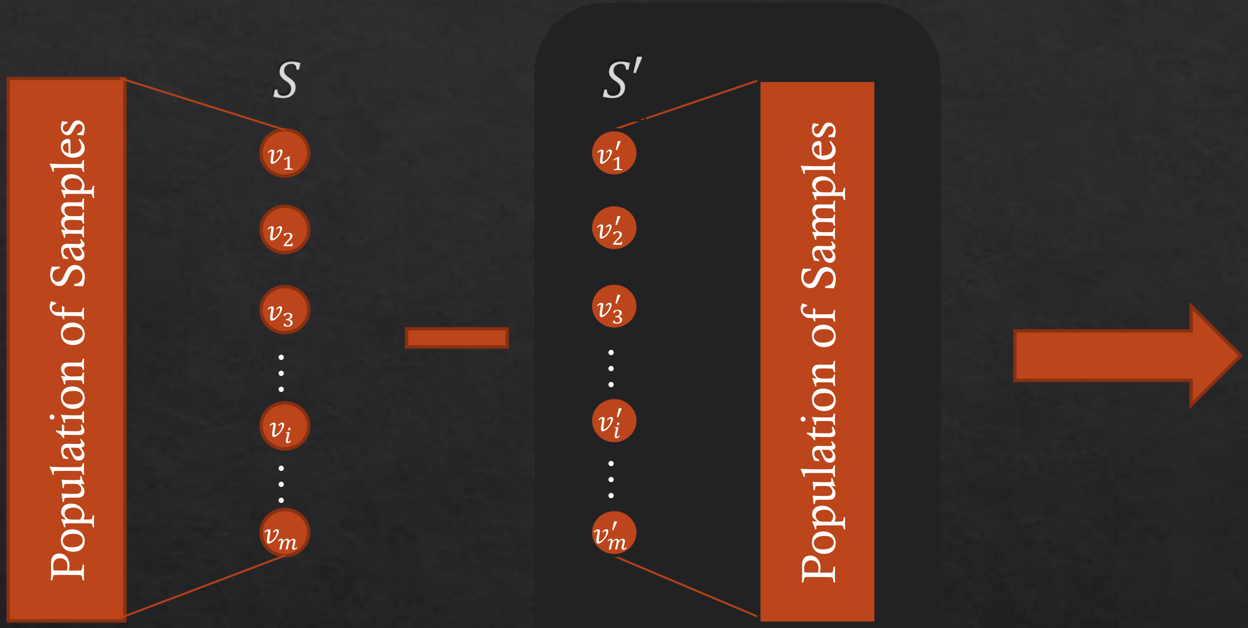
Then we can bound expected performance

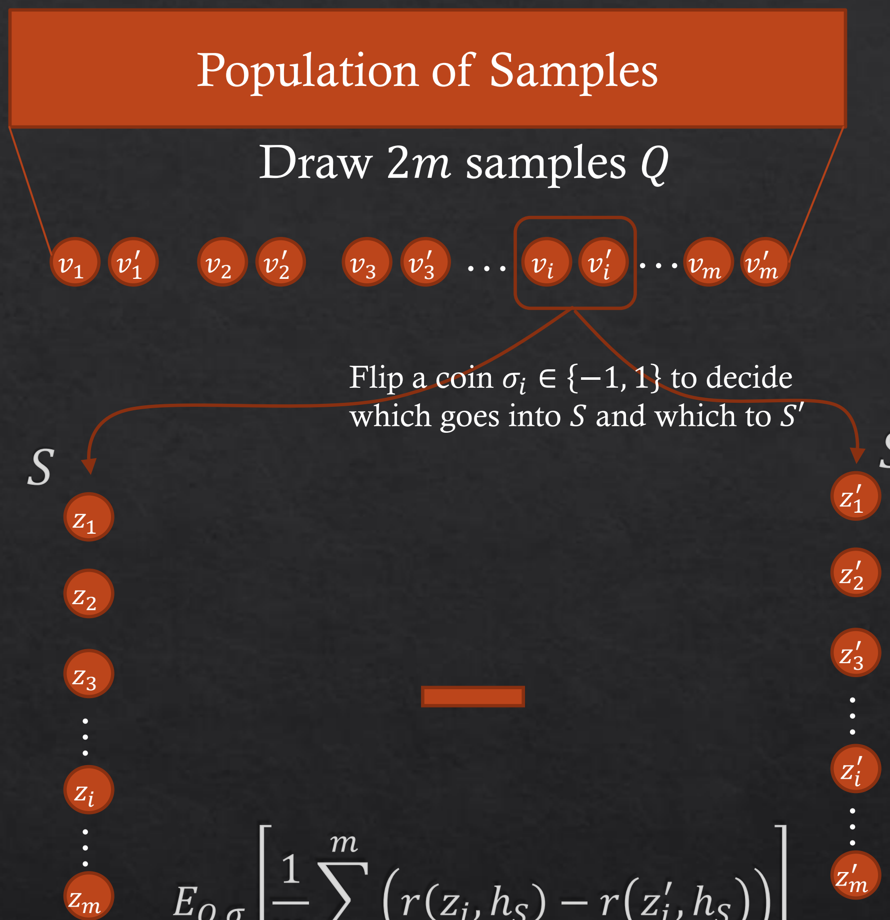
$$E[R(h_S)] \ge E[R(h_*)] - \epsilon(m)$$

$$E[R_S(h_S) - R_D(h_S)]$$

$$E\left[R_S(h_S) - E_{S'}\left[R_{S'}(h_S)\right]\right]$$

$$E_{S,S'}\left[R_S(h_S) - R_{S'}(h_S)\right]$$





$$E_{Q,\sigma}\left[\frac{1}{m}\sum_{i=1}^{m}\left(r(z_i, h_S) - r(z_i', h_S)\right)\right]$$

$$E_{Q,\sigma}\left[\frac{1}{m}\sum_{i=1}^{m}\sigma_i \cdot \left(r(v_i, h_S) - r(v_i', h_S)\right)\right]$$

$$E_{Q,\sigma}\left[\sup_{h\in H}\frac{1}{m}\sum_{i=1}^{m}\sigma_i \cdot \left(r(v_i, h) - r(v_i', h)\right)\right]$$

Choose $h \in H$ to maximize average reward on S

Learner

Choose $h \in H$ to maximize the average difference

Adversary

Symmetrization

- We can upper bound representativeness by

$$Rep \leq E_{S,S',\sigma}\left[\max_{h\in H}\frac{1}{m}\sum_{j=1}^{m}\sigma_j\left(r(v_j;h)-r\left(v_j';h\right)\right)\right]$$

- We can upper bound by splitting the max into the two separate

$$\mathrm{Rep} \leq E_{S,\sigma}\left[\max_{h\in H}\frac{1}{m}\sum_{j=1}^{m}\sigma_j r(v_j;h)\right]+E_{S',\sigma}\left[\max_{h\in H}-\frac{1}{m}\sum_{j=1}^{m}\sigma_j r\left(v_j';h\right)\right]$$

- But these two quantities are the same

$$\mathrm{Rep} \leq \boxed{2\,E_{S,\sigma}\left[\max_{h\in H}\frac{1}{m}\sum_{j=1}^{m}\sigma_j r(v_j;h)\right]}$$

Rademacher Complexity of Hypothesis Space H

Empirical Rademacher Complexity

- Empirical Rademacher complexity of a hypothesis space H on a set of samples S:

$$\mathrm{Rad}(S, H) \coloneqq 2E_\sigma\left[\sup_h \frac{1}{m}\sum_{i=1}^{m} \sigma_i \cdot r(v_i, h)\right]$$

- We have thus proven that:

$$E[R(h_S)] \geq R(h_*) - E_S[\mathrm{Rad}(S, H)]$$

- For any fixed h, the sum $\frac{1}{m}\sum_{i=1}^{m} \sigma_i \cdot r(v_i, h)$ is a sum of i.i.d. mean zero r.v.s
- By a Chernoff-Hoeffding bound it concentrates, i.e. at most $O\left(\sqrt{\frac{\log(2/\delta)}{2m}}\right)$
- If H was finite then by union bound, the supremum $O\left(\sqrt{\frac{\log(2|H|/\delta)}{2m}}\right)$

Massart's lemma. For any finite hypothesis space H: $\mathrm{Rad}(S, H) \leq 2\sqrt{\frac{2\log(|H|)}{m}}$

Growth Rate

- Crucially: if we can find a subset of functions H_ϵ that approximate well or such that the behavior of any function in H is equivalent to some function in H_ϵ on the sample S, then union bound only over H_ϵ
- Growth rate $\tau(m, H)$: the size of the smallest function space H_ϵ that satisfies the above equivalence property on a sample of size m
- For threshold classifiers: $\tau(m, H) = m + 1$
- Thus for threshold classifiers: $\mathrm{Rad}(S, H) \leq O\left(\sqrt{\frac{\log(2|H|/\delta)}{2m}}\right)$

On-sample Discretization Lemma

- Given a set of samples S, suppose that there is a subset H_ϵ such that for any $h \in H$, there exists an $h_\epsilon \in H_\epsilon$, such that for all $v_i \in S$: $|r(v_i, h) - r(v_i, h_\epsilon)| \leq \epsilon$
- Then:

$$\text{Rad}(S, H) \leq R(S, H_\epsilon) + 2\epsilon$$

- Proof:

$$\text{Rad}(S, H) = E_\sigma\left[\sup_h \frac{2}{m}\sum_{i=1}^{m} \sigma_i \cdot r(v_i, h)\right]$$

$$\leq E_\sigma\left[\sup_{h\in H} \frac{2}{m}\sum_{i=1}^{m} \sigma_i \cdot r(v_i, h_\epsilon)\right] + 2\epsilon \leq E_\sigma\left[\sup_{h\in H_\epsilon} \frac{2}{m}\sum_{i=1}^{m} \sigma_i \cdot r(v_i, h)\right] + 2\epsilon = R(S, H_\epsilon) + 2\epsilon$$

Back to Pricing

- It suffices to consider prices on the union of the samples and the ϵ grid to approximate the behavior of $r(p, v)$ on the samples to within $\epsilon = 1/m$

$$\mathrm{Rad}(S, H) \le 2\sqrt{\frac{2\log\left(m + \frac{1}{\epsilon}\right)}{m}} + \epsilon \le 3\sqrt{\frac{2\log(2m)}{m}}$$

ϵ v_1 2ϵ v_2 3ϵ 4ϵ v_3 5ϵ 6ϵ … v_4

Single-Item Auction

- Consider a single-item auction with n i.i.d. bidders and regular distribution
- By Myerson's theorem, optimal auction is second-price with a reserve-price
- On any given sample, we can consider H_ϵ to be the ϵ-grid, plus the $n \cdot m$ values of the bidders

$$\mathrm{Rad}(S, H) \leq 2\sqrt{\frac{2\log\left(n \cdot m + \frac{1}{\epsilon}\right)}{m}} + \epsilon \leq 3\sqrt{\frac{2\log(2n \cdot m)}{m}}$$

Next lecture

- Single-item auction with n asymmetric bidders and regular distributions
- What is the sample complexity of learning the optimal auction?
- Now the optimal mechanism is defined via n monotone virtual value functions
- Can we compete with the optimal revenue with m samples?

- We will examine a variant of the growth-rate and the symmetrization analysis, which combined with a discretization argument, will give us rates of the form:

$$\left(\frac{2\log(2n \cdot m)}{m}\right)^{\frac{1}{3}}$$

- We will give an overview of recent results in single and multi-dimensional mechanism design from samples that go beyond the basic statistical learning theory