

Classes on Tuesday (Nov 26)?

> One (long) lecture for project presentation or two separate lectures?

#### CS6501:Topics in Learning and Game Theory (Fall 2019)

Learning From Strategically Revealed Samples

Instructor: Haifeng Xu

Part of slides by Hanrui Zhang



Introduction and An Example

Formal Model and Results

Learning from Strategic Samples: Other Works

#### Academia in the Era of Tons Publications



The Trouble of Bob, a Professor of Rocket Science

#### Academia in the Era of Tons Publications



WWW. PHDCOMICS. COM

Current postdoc Charlie is happy . . .

#### Academia in the Era of Tons Publications

I got to pick best 3 papers to persuade Bob, so that he will hire Alice.



Charlie shall pick best 3 papers by Alice - I need to calibrate for that

They know what each other is thinking...

# Abstracting the Problem

- > Setup: (binary-)classify distributions with label  $l \in \{g, b\}$ 
  - Opposed to classic problem of classifying samples drawn from distributions
- Sol: accept good ones (l = g) and reject bad ones (l = b)
- Previous example: a postdoc candidate = a distribution (over papers)



#### Principal Reacts by Committing to a Policy

>Principal (Bob) commits to and announces a policy to agent Charlie

• He decides whether to accept *l* (hire Alice) based on agent's report



### **Agent's Problem**

> Has access to n(=50) samples (papers) from distribution l (Alice)

• Assume samples are i.i.d.

>Can choose m(= 3) samples as his report



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> Has access to n (= 50) samples (papers) from distribution l (Alice)

• Assume samples are i.i.d.

>Can choose m(= 3) samples as his report

Agent (Charlie) sends his report to Bob principal (Bob), aiming to persuade Bob to accept distribution *l* (Alice)



#### Principal Executes Based on His Policy

>Bob observes Charlie's report, and makes a decision according to the policy he announced



#### University admissions

· Students academic records are selectively revealed

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University admissions

Students academic records are selectively revealed

Classify loan lending decisions

· Borrowers will selectively report their features



University admissions

- Students academic records are selectively revealed
- Classify loan lending decisions
  - · Borrowers will selectively report their features
- Decide which restaurants to go based on Yelp rating
  - Platform may selectively showing you ratings
- Hiring job candidates in various scenarios

University admissions

- Students academic records are selectively revealed
- Classify loan lending decisions
  - · Borrowers will selectively report their features
- Decide which restaurants to go based on Yelp rating
  - Platform may selectively showing you ratings
- Hiring job candidates in various scenarios
- Note: this problem deserves study even you do classification manually instead of using an automated classifier
  - E.g., deciding where to hold the next Olympics based on photographs of different city locations



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#### The Model: Basic Setup

- ≻A distribution  $l \in \{g, b\}$  arrives, which can be good (l = g) or bad (l = b)
- >An agent has access to n i.i.d. samples from l, from which he chooses a subset of exactly m samples as his report
  - Agent's goal: persuade a principal to accept *l*
- > Principal observes agent's report, and decides whether to accept
  - Principal's goal: accept when l = g and reject when l = b
  - Want to minimize her probability of mistakes

#### The Model: the Timeline



>This is the same as distinguishing two distributions from samples

- You have m samples from distribution either g or b
- Want to tell which one it is, with high probability (you almost can never be 100% certain)

**Fact**: Let  $\epsilon = \max_{S} [g(S) - b(S)]$  be total variation (TV) distance between *g*, *b*. Then  $\Omega(1/\epsilon^2)$  samples to distinguish *g*, *b* with constant success probability.

Note:  $g(S) = \Pr_{x \sim g} (x \in S)$  is accumulated probability for  $x \in S$ 

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Formally,

$$||g-b||_{TV} = \int_{x:g(x)>b(x)} [g(x) - b(x)]dx$$



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#### Proof

First, compute 
$$S^* = \arg \max_{S} [g(S) - b(S)]$$

≻ Idea: try to estimate value of  $l(S^*)$  where  $l \in \{g, b\}$ 

- Why? This statistics has largest gap among g, b
- > How to estimate  $l(S^*)$  from samples?
  - Calculate fraction of samples in  $S^*$
- ≻  $\Omega(1/\epsilon^2)$  samples suffices to distinguish random variable  $g(S^*)$  from  $b(S^*)$



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#### Remarks

>When agent is not strategic, performance depends on TV distance in the form of  $\Omega\left(\frac{1}{\epsilon^2}\right)$ 



"Tough" World

>A good candidate writes a good paper w.p. 0.05

>A bad candidate writes a good paper w.p. 0.005

>All candidates have n = 50 papers, and the professor wants to read only m = 1 good candidate

**Q**: What is a reasonable principal policy?

"Tough" World

>A good candidate writes a good paper w.p. 0.05

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>All candidates have n = 50 papers, and the professor wants to read only m = 1 good candidate

**Q**: What is a reasonable principal policy?

Accept iff the reported paper is good

- Good candidate is accepted with prob  $p_g = 1 (1 0.05)^{50} \approx 0.92$
- A bad candidate is accepted with prob  $p_b = 1 (1 0.005)^{50} \approx 0.22$

>What happens if agent not strategic? → almost cannot distinguish

Strategic selection actually helps principal!

"Easy" World

≻A good candidate writes a good paper w.p. 0.05 0.95

≻A bad candidate writes a good paper w.p. <del>0.005</del> 0.05

>All candidates have n = 50 papers, and the professor wants to read only m = 1 good candidate

"Easy" World

≻A good candidate writes a good paper w.p. 0.05 0.95

≻A bad candidate writes a good paper w.p. 0.05

>All candidates have n = 50 papers, and the professor wants to read only m = 1 good candidate

Policy: Accept iff the reported paper is good

≻Good candidate is accepted with prob  $p_g = 1 - (1 - 0.95)^{50} \approx 1$ 

>A bad candidate is accepted with prob  $p_b = 1 - (1 - 0.05)^{50} \approx 0.92$ 

>What happens if agent not strategic?  $\rightarrow$  can distinguish easily

>Here, strategic selection hurts principal!

#### General Results: One Sample

**Theorem**: Any pareto optimal deterministic policy satisfies:

- 1. It orders sample space based on likelihood ratio g(x)/b(x)
- 2. Limiting acceptance probability satisfy:  $p_g + (1 p_b)^r = 1$ where  $r = \max_{x} g(x)/b(x)$  is maximum likelihood ratio

>That is, principle tries to use the "most distinguishable" sample



Pareto frontier when r = 3

Note: can define  
error rate = min 
$$\frac{p_b}{p_g}$$

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> That is, principle tries to use the "most distinguishable" sample

- >In strategic environment, likelihood ratio g(x)/b(x) matters
  - Opposed to TV distance in non-strategic setting

# Multiple Samples:

**Theorem**: There is a deterministic policy:

- 1. Which orders the sample space
- 2. Whose limiting error rate is at most  $\exp(-m(1-r^{-0.5})^2/2)$
- ≻This is not exactly optimal
- >But, error rate decrease exponentially in m
- ≻What is optimal like?
  - It is open, we don't know



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#### Many Other Work in this Space

>Learning from samples that are strategically transformed



#### Many Other Work in this Space

Strategic behaviors are costly



# When Strategic Behaviors are Costly

> How to induce the correct strategic behaviors



Paper: How Do Classifiers Induce Agents To Invest Effort Strategically by Kleinberg and Raghavan

# Thank You

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