

# Prior-free Data Acquisition for Accurate Statistical Estimation

Yiling Chen, **Shuran Zheng**

Harvard University

June, 2019

*Acquiring data from self-interested individuals to estimate some statistic of a population*

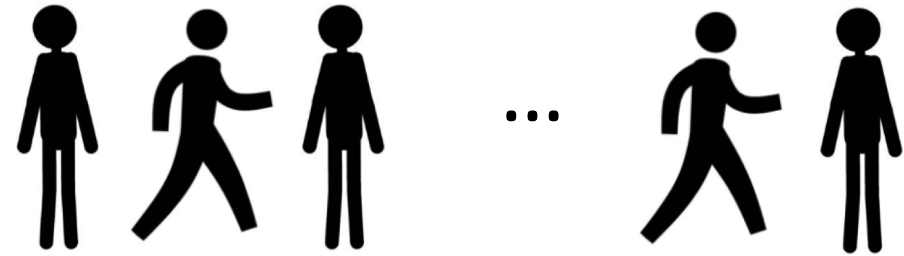
# Problem description

A data analyst



- Avg. daily workout time?
- Budget  $B$
- **No prior information** about the cost or data

$n$  data providers



- Incur **cost** to record workout time
- **Cost** and **data** arbitrarily correlated

# Model

## A data analyst

- Estimate the mean of some parameter of interest  $z$
- Budget  $B$
- **No** prior information of the cost (or data)

## $n$ data providers

- Incur **cost**  $c_i$  to acquire the data  $z_i$
- Cost and data arbitrarily **correlated**
- **Self-interested**

- For  $i = 1, \dots, n$ 
  1. The  $i$ -th data provider arrives (in random order).
  2. Decide a mechanism  $M_i$  to purchase the  $i$ -th data point  $z_i$  based on all observed history  $H_{i-1}$ ,
- Aggregate all collected information to output an estimator  $S$  of the population mean  $\frac{1}{n} \sum z_i$ .

# Problem description

- For  $i = 1, \dots, n$ 
  1. The  $i$ -th data holder arrives (in random order).
  2. Based on all observed history  $H_{i-1}$ , decide a mechanism  $M_i$  to purchase the  $i$ -th data point  $z_i$ .
- Aggregate all collected information to output an estimator  $S$  of the population mean  $\frac{1}{n} \sum z_i$ .
- Objective: output a good estimator  $S$ 
  - Unbiased point estimation: small variance
  - Interval estimation: minimize the length
- Constraint: expected spending  $\leq$  budget  $B$

Previous results: **known** cost distribution

***A simpler problem*** Roth and Schoenebeck [2012], Chen et al. [2018]:

- the marginal cost distribution is **known**
- find a **fixed** mechanism to purchase  $n$  data points
- **unbiased** estimator with minimum variance (in worst-case cost-data correlation)

Previous results: **known** cost distribution

***Naïve purchasing mechanisms:***

- Fixed price  $p$  so that the expected spending =  $B$

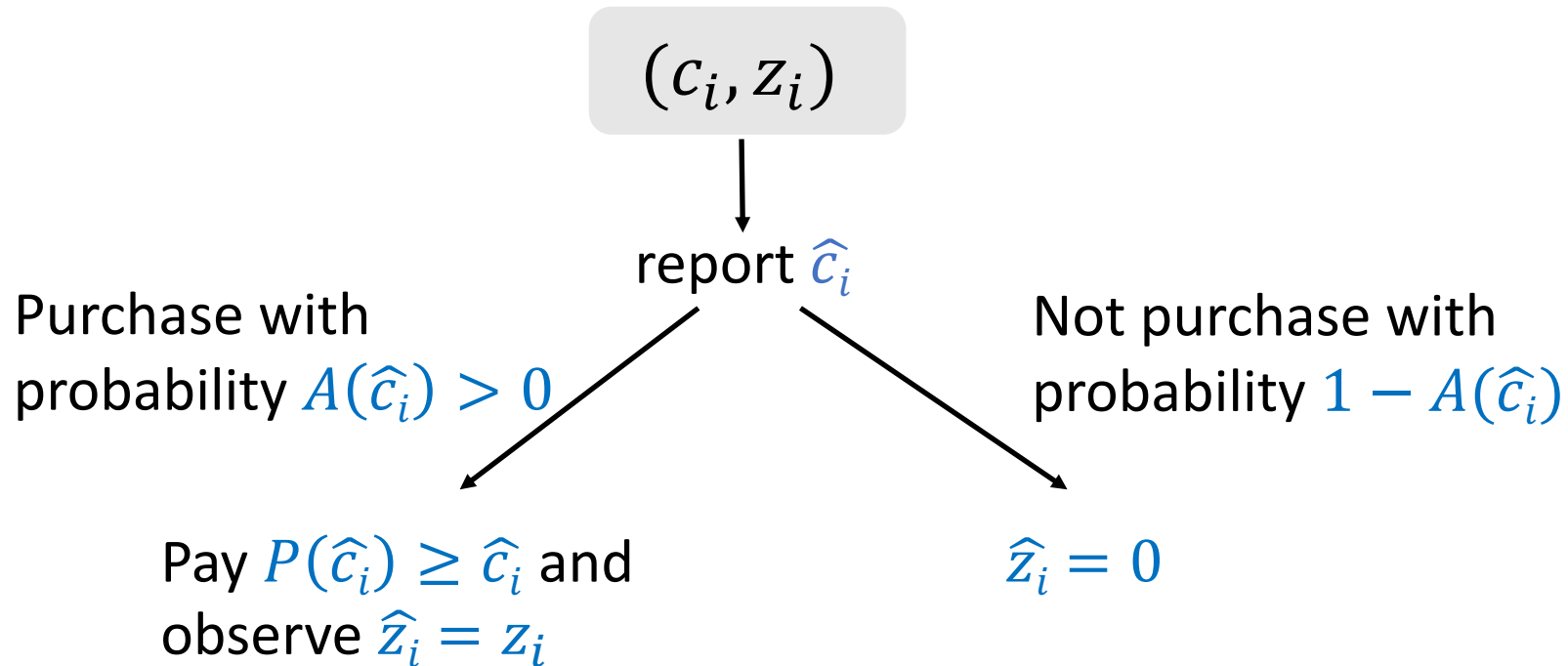
**Bias toward the low cost sub-population!**

- Purchase with a constant probability  $q$ , output  $\sum \hat{z}_i / q$

**Variance may not be optimal**

# Survey mechanisms from Roth and Schoenebeck [2012]

- Purchase data with different costs with different probabilities and prices



Horvitz-Thompson estimator:  $\frac{1}{n} \sum_{i=1}^n \frac{\hat{z}_i}{A(\hat{c}_i)}$



# Previous results: **known** cost distribution

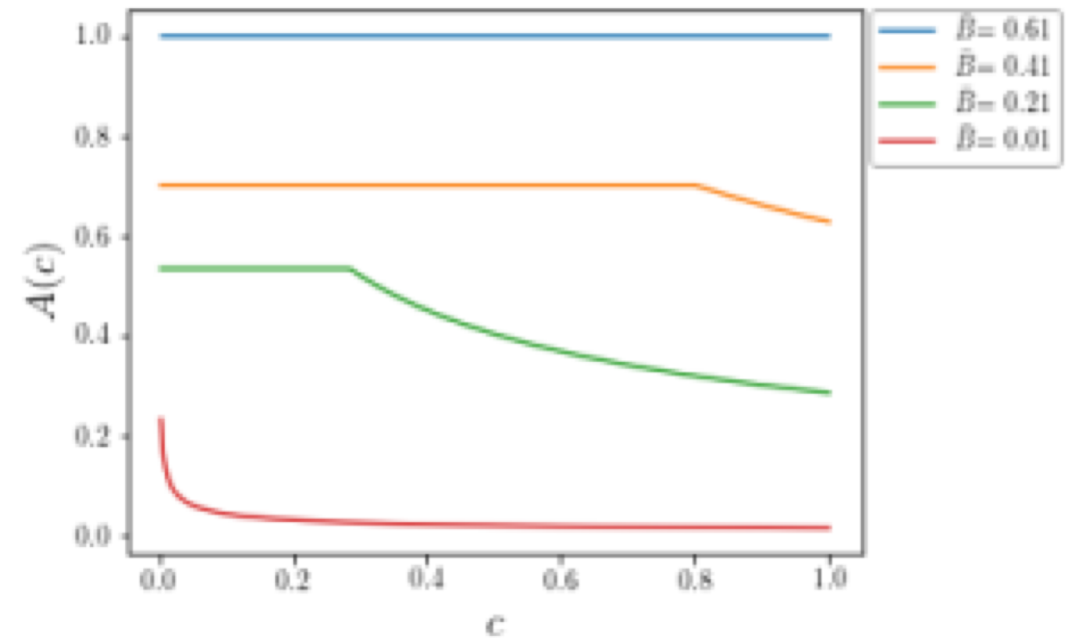
Horvitz-Thompson estimator:  $\frac{1}{n} \sum_{i=1}^n \frac{\hat{z}_i}{A(\hat{c}_i)}$

- Minimize the **variance** of the output Horvitz-Thompson estimator.
- $A(c), P(c)$  should satisfy
  - Individual rationality:  $P(c) \geq c$
  - Incentive compatibility
  - Budget feasibility:  $E_c[A(c)P(c)] \leq \bar{B}$

$$OPT(n, C, B) = (A^*, P^*)$$
$$C = \{c_1, \dots, c_n\}$$

# Previous results: **known** cost distribution

- Characterization of  $A^*(c)$  from Chen et al. [2018]
- Virtual costs  $\phi(c)$
- $A^*(c) \propto \frac{1}{\sqrt{\phi(c)}}$



# Unknown cost distribution: challenges

- $OPT(n, \mathcal{C}, B) = \underline{(A^*, P^*)}$
- Make purchasing decisions **without knowing future costs**
  - satisfy the **budget** constraint
  - optimize the **performance**
- Adjust the mechanism based on the observed costs

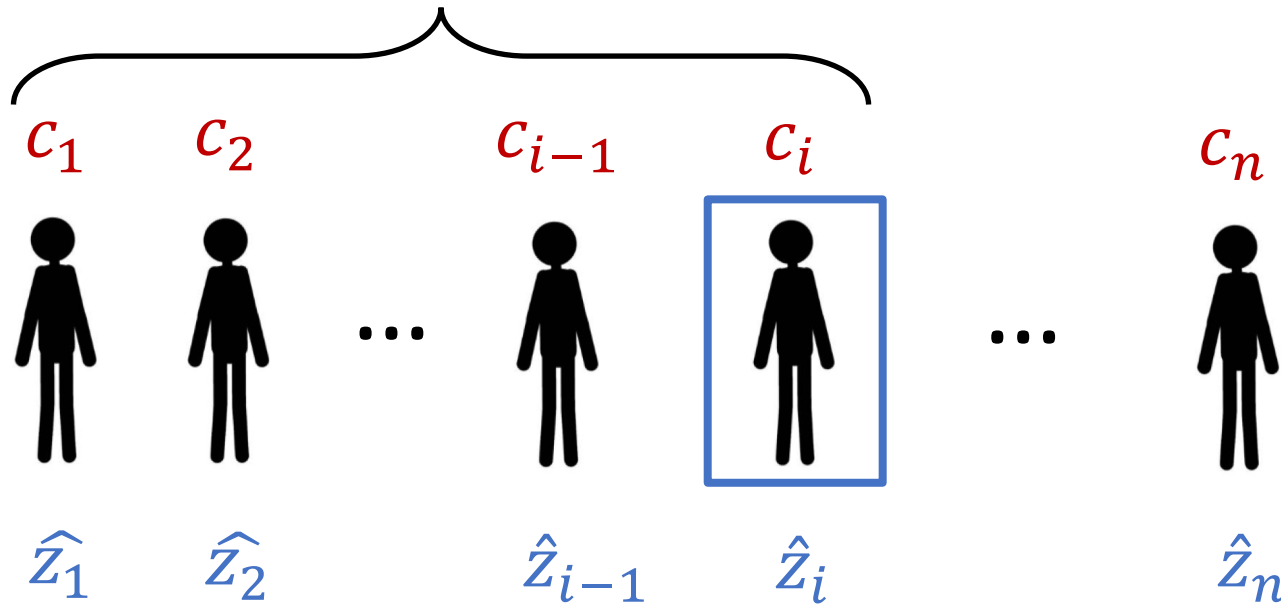
# Our contribution

- Prior-free mechanism design
  - Performance matches that of the optimal mechanism, which knows the true cost distribution, **within a constant factor**.
- Confidence interval estimator

# Prior-free mechanisms: algorithm

- At round  $i$ , use a survey mechanism  $M_i$

$$APPROX(i, \{c_1, \dots, c_{i-1}, \bar{C}\}, B_i) \approx OPT(i, \{c_1, \dots, c_{i-1}, \bar{C}\}, B_i)$$



Output  $\frac{1}{n} \sum_{i=1}^n \frac{\hat{z}_i}{A^i(\hat{c}_i)}$

# Prior-free mechanisms: result

**Theorem:** When we use  $B_i \propto \sqrt{i}$ , our mechanism is

- IC and IR,
- with expected total spending no more than  $B$ ,
- and performance no worse than a constant factor times the benchmark  $OPT(n + 1, \{c_1, \dots, c_n, \bar{C}\}, B)$ .

# Prior-free mechanisms: proof ideas

- At round  $i$ , use a survey mechanism  $M_i$

Step #1: Decompose the variance into per-round “loss”

Variance of  $S \approx E[\text{loss}(M_1)] + E[\text{loss}(M_2)] + \dots + E[\text{loss}(M_n)]$

$$E[\text{loss}(M_i)] = E\left[\frac{1}{A^i(\hat{c}_i)}\right]$$

# Prior-free mechanisms: proof ideas

Step #2: Compare the loss of our mechanism with the loss of the benchmark

- $L(n, C, B)$  = expected loss of using  $APPROX(n, C, B)$  when the data holder's cost is randomly chosen from  $C$

Properties of  $L(n, C, B)$ :

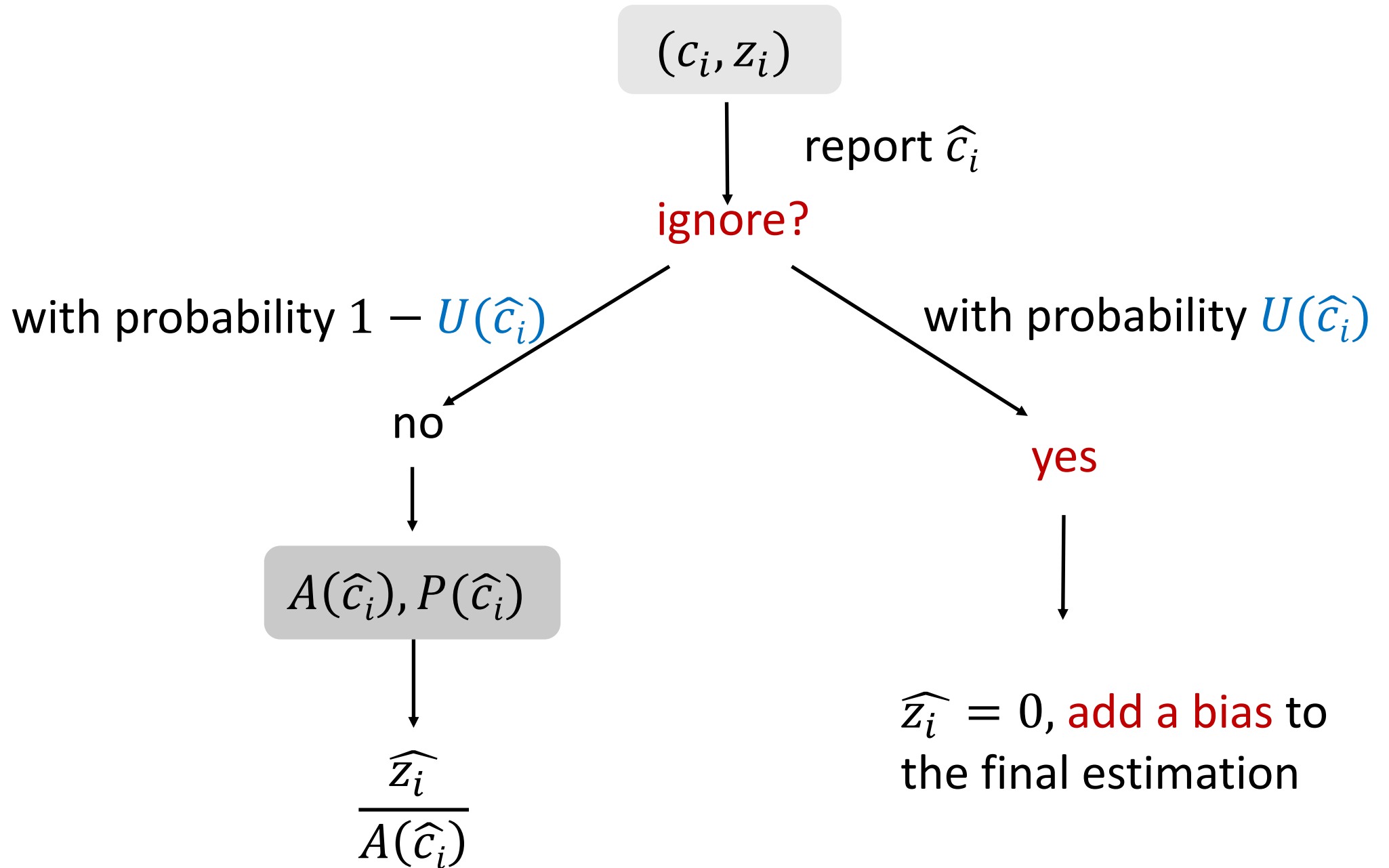
1.  $L(n, C, B/k) \leq k \cdot L(n, C, B)$  for any  $n, C, B, k$
2. Let  $S$  be a random subset  $\subseteq C$  with  $|S| = k$ ,  
$$E_S[L(k, S, B)] \leq L(n, C, B)$$

- At round  $i$ , allocate budget  $B_i$ , the expected loss  $\leq L(n, C, B) \cdot \frac{B}{B_i}$
- Choose  $B_i \propto \sqrt{i}$ , total "loss"  $\leq \text{constant} \cdot \text{benchmark}$



# Confidence interval estimator

- Allow the estimator to be biased
- Ignore some high-cost data points
- Bias-variance tradeoff
- Optimal confidence interval: minimize the worst-case expected length.



# Confidence interval estimator

- Characterization of a 2-approximation of the optimal confidence interval **when the cost distribution is known**
- **Online** mechanism that matches the benchmark **within a constant factor**

Thanks & Questions?

# First estimate the costs

- Truthfulness guarantee weaker
- Difficult to estimate  $\phi(c)$

# Questions

- Bandits with knapsack (dynamic pricing):
  - Action space too large
  - Regret dependent on  $|A|$
- Online convex optimization
  - Put the violation of budget constraint into objective function: cannot be decomposed into per round loss function
  - Online convex optimization (with long-term budget): unknown budget constraint  $\rightarrow$  unknown  $X$