Inferring Private Valuations from Behavioral Data in Bilateral Sequential Bargaining

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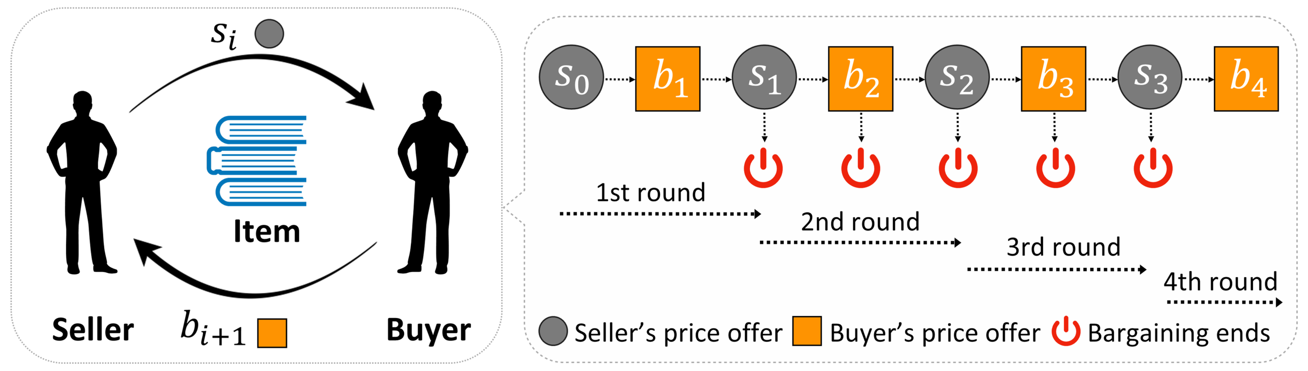
Background

Bilateral Sequential Bargaining:

- One seller and one buyer negotiate the price of an item. It exists many e-commerce platforms: Amazon, eBay, and Taobao.



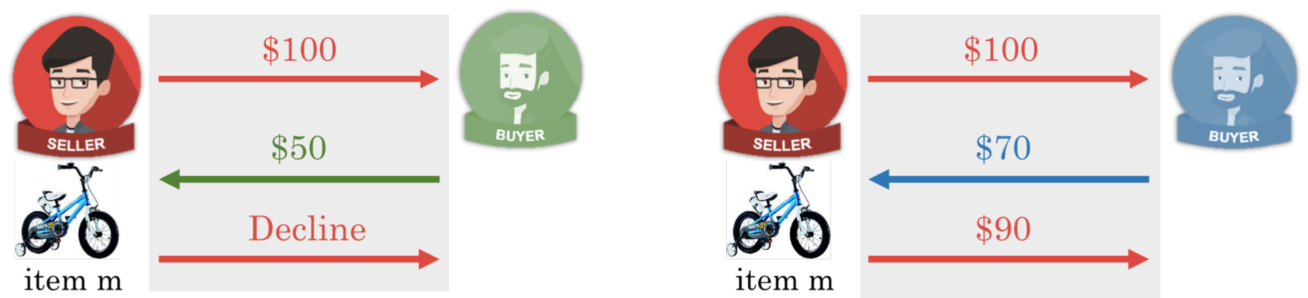
- Quantifying the optimality of bargaining mechanism needs to first know bargainers' private valuations on items, which is unobserved.

Our Goal: *Infer bargainers' private valuations from their behaviors.*

- We focus on seller private valuation inference.
- Existing equilibrium-based inference schemes rely on stong rationality assumptions, which are unsatisfied in real bargaining platforms.

Problem Formulation

- For item m of seller q, denote observed data as $\left\{\left(\boldsymbol{x}_i^{(qm)}, y_i^{(qm)}\right)\right\}_{i\in\mathcal{I}}$.
  - i: the index of a data point
  - $y_i^{(qm)}$: seller q's decision, i.e., accept, decline, or a counter-offer
  - $\boldsymbol{x}_i^{(qm)}$: offer history in the bargaining between seller q and a buyer



$\left(\boldsymbol{x}_1^{(qm)}, y_1^{(qm)}\right) = \left((100, 50), \text{Decline}\right)$ $\left(\boldsymbol{x}_2^{(qm)}, y_2^{(qm)}\right) = \left((100, 70), 90\right)$

$\left(\boldsymbol{x}_3^{(qm)}, y_3^{(qm)}\right) = \left((100, 70, 90, 75), \text{Accept}\right)$

- Denote seller q's valuation on item m as $v_q^{(m)}$ (unobservable).

Private Valuation Inference Problem

Given each observable dataset $\left\{\left(\boldsymbol{x}_i^{(qm)}, y_i^{(qm)}\right)\right\}_{i\in\mathcal{I}}$ of seller q on item m, how to infer each $v_q^{(m)}$ for seller q on item m?

Private Valuation Inference Solution

- Denote seller q's bargaining behavior utilizing function $f_\theta^{(q)}$:

$$\underbrace{f_{\boldsymbol{\theta}}^{(q)}\left(v_q^{(m)}, \boldsymbol{x}_i^{(qm)}\right)}_{\text{predicted decision}} \rightarrow \underbrace{y_i^{(qm)}}_{\text{observed decision}}$$

If parameters θ are known, we can infer each $v_q^{(m)}$ by Bayes' Rule:

$$\Pr\left(v_m^{(q)} \middle| \left\{y_i^{(qm)}\right\}_{i\in\mathcal{I}}; \left\{\boldsymbol{x}_i^{(qm)}\right\}_{i\in\mathcal{I}}, \boldsymbol{\theta}\right) = \frac{\prod_{i\in\mathcal{I}} \Pr\left(y_i^{(qm)} \middle| v_m^{(q)}; \boldsymbol{x}_i^{(qm)}, \boldsymbol{\theta}\right) \Pr_{\text{prior}}\left(v_m^{(q)}\right)}{\sum_{\tilde{v}_m^{(q)}} \left(\prod_{i\in\mathcal{I}} \Pr\left(y_i^{(qm)} \middle| \tilde{v}_m^{(q)}; \boldsymbol{x}_i^{(qm)}, \boldsymbol{\theta}\right) \Pr_{\text{prior}}\left(\tilde{v}_m^{(q)}\right)\right)}.$$

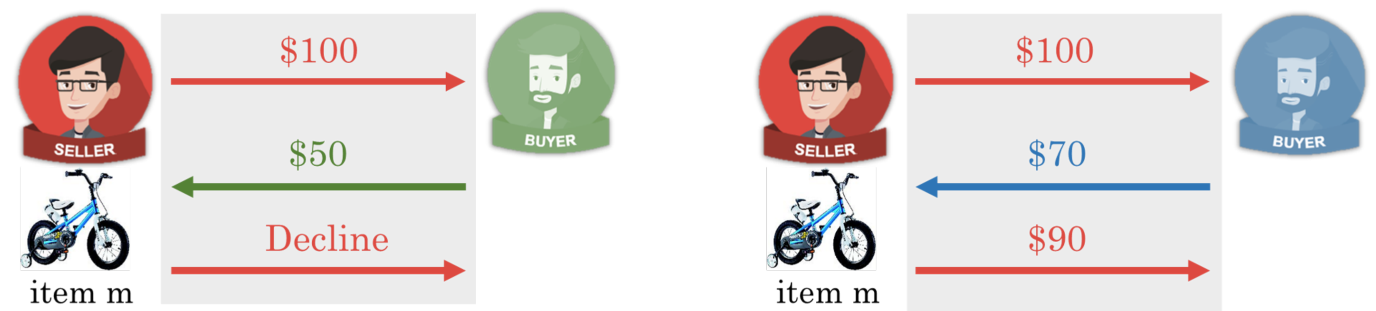
Our Solution: Model $f_{\boldsymbol{\theta}}^{(q)}$ via GRU network ($\boldsymbol{\theta}$ are trainable weights):

1. Minor rationality assumption: we assume that a seller never chooses strictly dominated decisions, deriving a feasible interval for $v_q^{(m)}$.
2. Learning of parameters $\boldsymbol{\theta}$: A novel loss function that is based on derived feasible intervals is proposed to guide GRU training.

Feasible Interval of Valuation

Assumption 1 *In the bargaining: (i) if a seller accepts a buyer's offer, the seller's valuation is no greater than the price; (ii) if a seller declines the buyer's offer in the last round, the seller's valuation is no less than the price; (iii) a seller never proposes a price less than his valuation.*

- Feasible interval is defined as the set of all possible valuation values satisfying above Assumption 1.



$50 \leq v_m^{(q)} \leq 100$ $\quad v_m^{(q)} \leq 90, \quad v_m^{(q)} \leq 75$

the feasible interval $\mathcal{V}_m^{(q)}$ of $v_m^{(q)}$ is $[50, 75]$.

- This assumption is much weaker than equilibrium ones. It only requires that players do not choose strictly dominated strategies.

Learning of Parameters $\boldsymbol{\theta}$

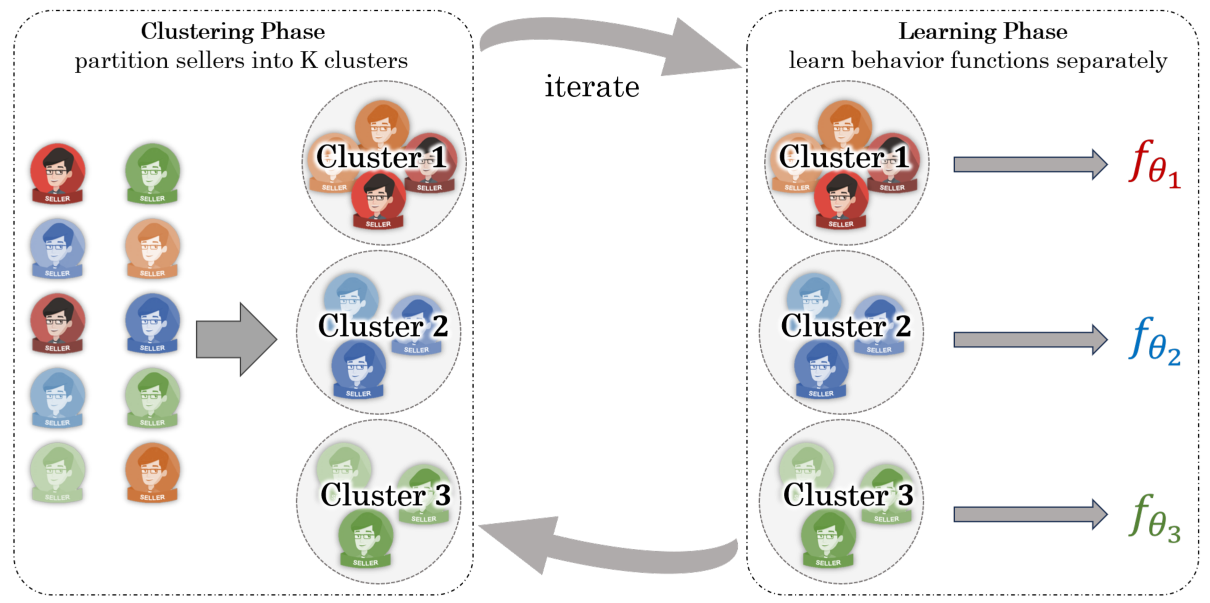
- Homogeneous behavior learning (BLUE): assume $f_{\boldsymbol{\theta}}^{(q)} = f_{\boldsymbol{\theta}}$ for all q. We learn $\boldsymbol{\theta}$ by minimizing a novel loss function on data:

$$\sum_{q\in\mathcal{Q}} \sum_{m\in\mathcal{M}} \sum_{i\in\mathcal{I}} \text{CrossEntropy}\left(f_{\boldsymbol{\theta}}\left(\tilde{v}_m^{(q)}, \boldsymbol{x}_i^{(qm)}\right), y_i^{(qm)}\right)$$

$$- \sum_{q\in\mathcal{Q}} \sum_{m\in\mathcal{M}} \sum_{i\in\mathcal{I}} \log \Pr\left(v_m^{(q)} \in \mathcal{V}_m^{(q)} \middle| y_i^{(qm)}; \boldsymbol{x}_i^{(qm)}, \boldsymbol{\theta}\right).$$

1. minimize distance between predicted and observed decisions
2. maximize probability that inferred $v_m^{(q)}$ lies infeasible interval

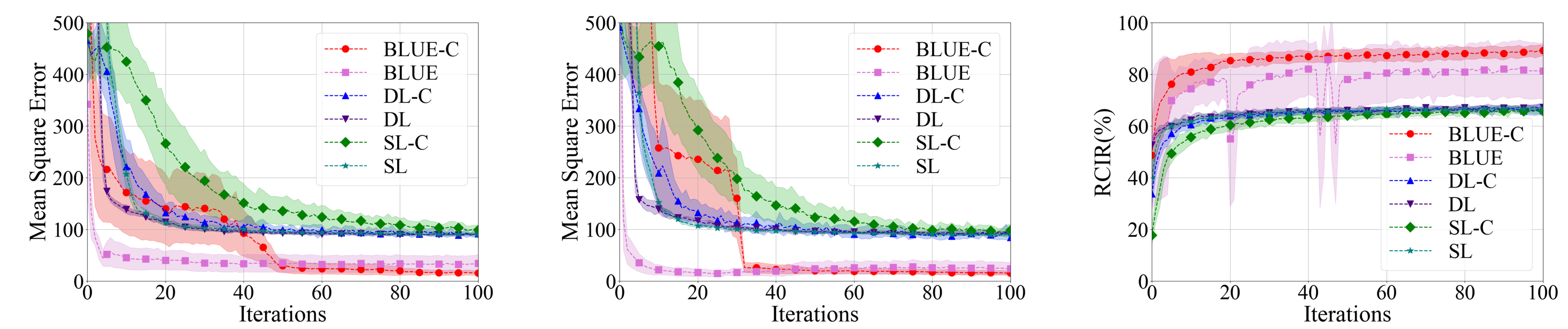
- Heterogeneous behavior learning (BLUE-C), i.e., $f_{\boldsymbol{\theta}}^{(q)} \neq f_{\boldsymbol{\theta}}^{(k)}$ exists.



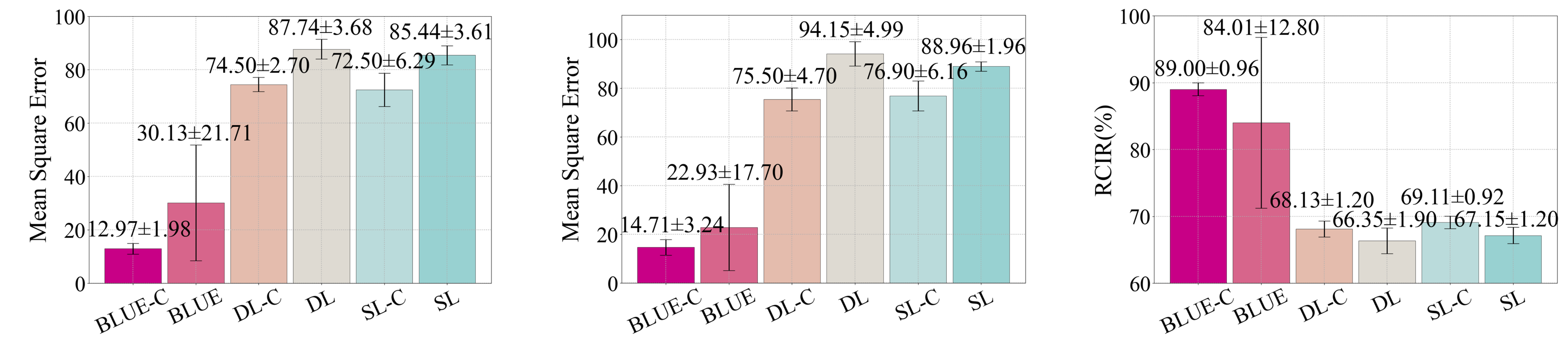
Experiments & Results

Inference Performance on Synthetic and Real Datasets:

- Synthetic data: MSE between inferred valuation and actual value
- Real data: the percentage of inferred valuations belonging to the feasible intervals (RCIR)



Comparable performance to other methods on validation datasets.



Best inference performance among all methods on testing datasets.

More results on other experiments can be found in our paper.