

Optimal Bargaining on eBay Using Deep Reinforcement Learning

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What offer should I make?

“Best Offer” listings on eBay

This project

For any listing and at any point in the offer history, what offer maximizes the eventual payoff? For the seller? For the buyer?

- ▶ Characterize optimal behavior in a way that humans can use.

Larger goal

Tutorial for solving real-world dynamic decision problems.

- ▶ Where experimentation is infeasible but data are plentiful.

And characterizing the solutions.

Reinforcement learning

In each state, find the policy that maximizes the eventual payoff.

$$\pi(s) : s \rightarrow f(a)$$

Chess

- ▶ State: board position
- ▶ Action: allowable move
- ▶ Payoff: 1 for a win, 0 for a loss

Play randomly at first, reinforce actions that lead to higher payoffs.

Deep reinforcement learning

Approximates states from features.

$$\pi(\mathbf{x}) : \mathbf{x} \rightarrow f(a)$$

AlphaZero

“Best Offer” listings on eBay

- ▶ State: listing features + offer history
- ▶ Action: an offer
- ▶ Payoff: (tbd)

Can we train an algorithm to play optimally against human buyers and sellers on eBay?

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- ▶ Optimal \neq equilibrium

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Our approach:

1. Train neural nets to mimic human buyers and sellers.
2. Train reinforcement learning agents to play optimally against these simulated buyers and sellers.

Outline

1. Gameplay
2. Data
3. Simulator
4. Payoffs
5. RL seller

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Seller sets three prices

1. A **list price**, at which the item may be purchased immediately.
2. An optional **auto-accept price**, above which buyer offers are immediately accepted.
3. An optional **auto-reject price**, below which buyer offers are immediately rejected.

Order of operations (circa 2013)

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4. Repeat (2) & (3) until buyer and seller have each had 3 turns.

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4. Repeat (2) & (3) until buyer and seller have each had 3 turns.
5. After 3rd seller response, buyer faces take-it-or-leave-it offer.

A thread ends when...

1. An offer is accepted (on any thread).
2. The buyer walks (actively or passively).
3. The listing expires.

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Backus et al. (2020)

Universe of “Best Offer” listings on eBay from 2012-13.

- ▶ Complete offer histories for all negotiations.

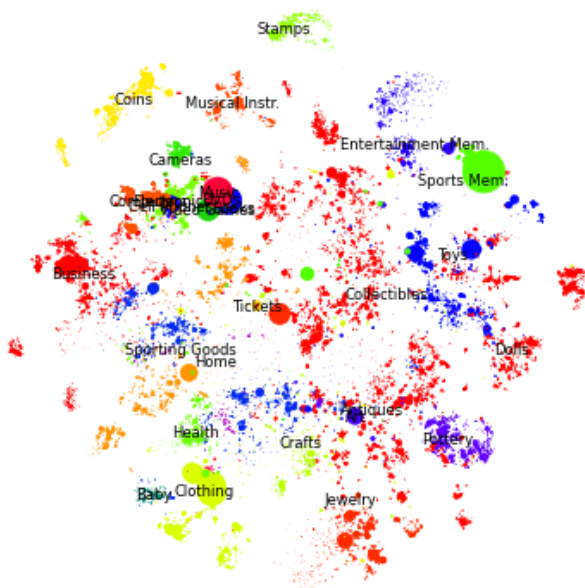
What else is in the data?

An incomplete list:

- ▶ List price and automatic thresholds.
- ▶ Category and subcategory.
- ▶ Listing start and end dates.
- ▶ Number of photos.
- ▶ Seller's rating.
- ▶ Offer timestamps.
- ▶ Whether a message is attached to the offer.

What's not in the data

- ▶ The photos themselves.
- ▶ The messages themselves.
- ▶ Item descriptions.



Data restrictions

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1. Plausibly unique listings (unique title): 28.6M
2. and fixed list price: 18.6M
3. and list price between \$9.95 and \$1000.00: 14.6M
4. and no other funny stuff: 13.4M

Partitions

13.4M listings, from 771.6k sellers, split into 4 partitions:

1. Simulator training: 75% of sellers
2. RL training: 10%
3. Validation: 5%
4. Test: 10%

All results that follow are from validation partition.

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Example listing

- ▶ \$100 list price
- ▶ \$60 auto-reject price
- ▶ No auto-accept price

In the data, the item sells for the list price to the first buyer.

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In the data, the item sells for the list price to the first buyer. Counterfactual:

1. Buyer 1 offers \$50.
2. Seller auto-rejects.
3. Buyer 1 offers \$75 of list price.
4. Buyer 2 purchases the item for the list price.

Overview

Simulate:

1. The arrival of buyers.
2. The offer path of each thread.

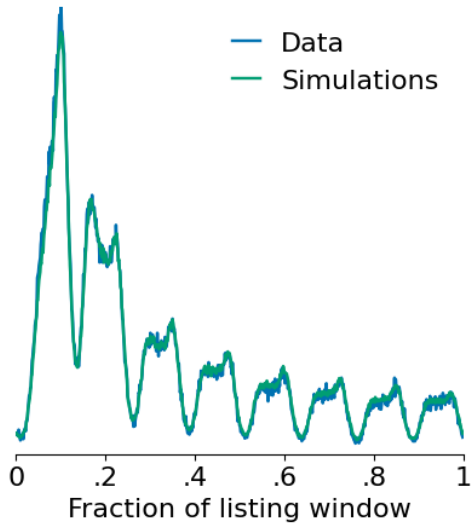
All features of the listing are held constant.

- ▶ e.g., list price and automatic thresholds

Listings expire after 1 week.

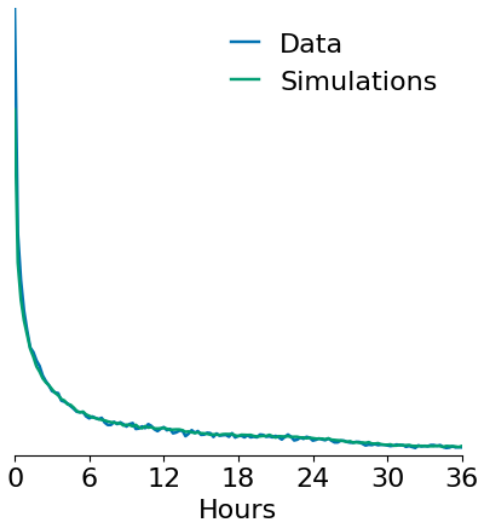
- ▶ Common listing duration in the data.

Arrival time of first buyer

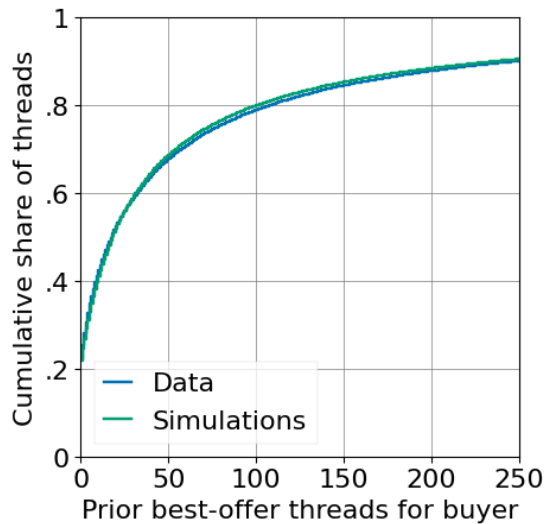


70% of listings expire without an arrival.

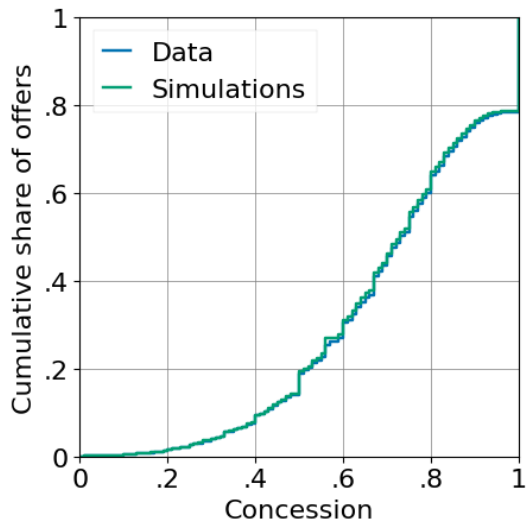
Interarrival time



Buyer experience



First buyer offer



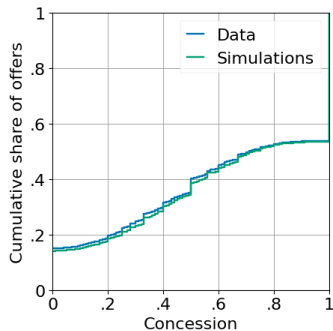
Offers as concessions

How much of the bargaining zone is conceded.

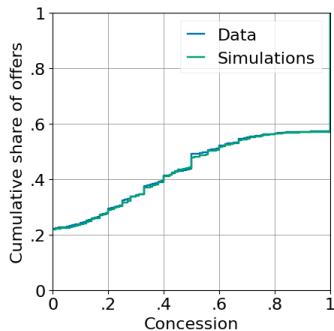
- ▶ e.g., buyer last offered \$50 and seller last offered \$100.
- ▶ \$60 buyer offer = 20% concession
- ▶ \$90 seller offer = 20% concession

Concessions: seller turns

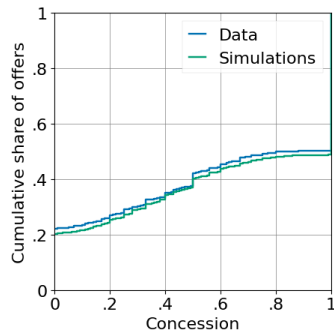
2



4



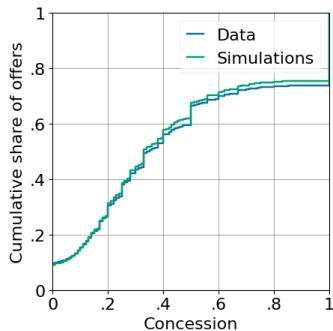
6



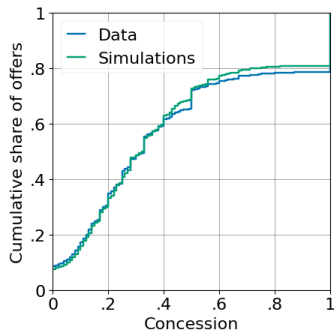
Note: excludes automatic offers and expirations.

Concessions: buyer turns

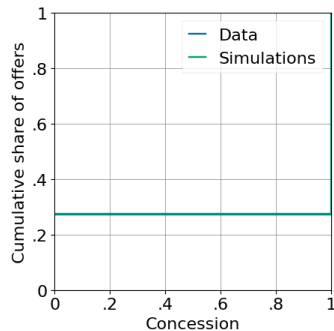
3



5



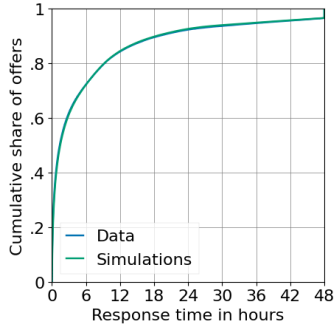
7



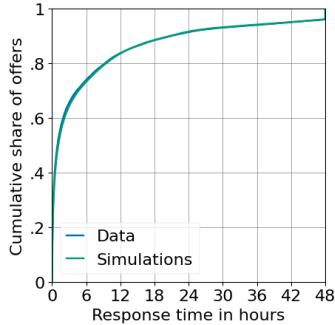
Note: excludes expirations.

Response time: seller turns

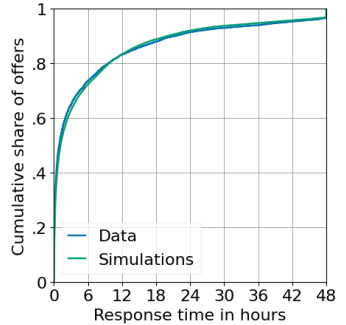
2



4



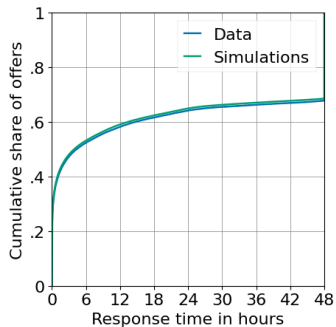
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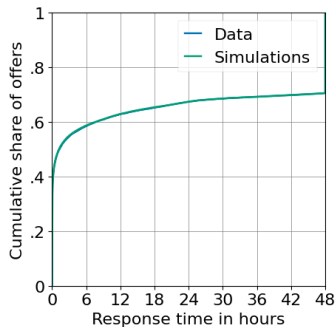
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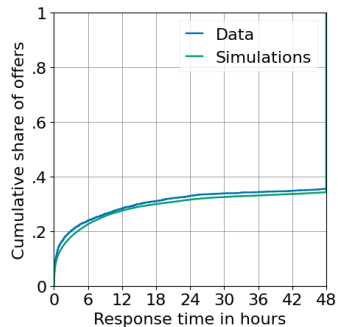
3



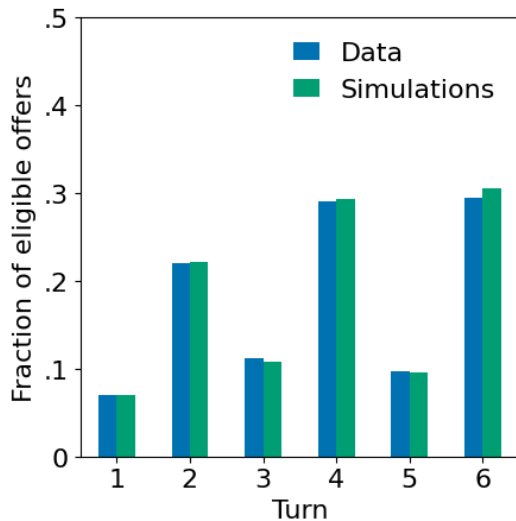
5



7

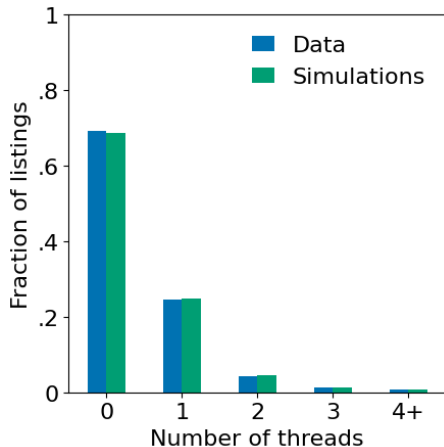


Message rates

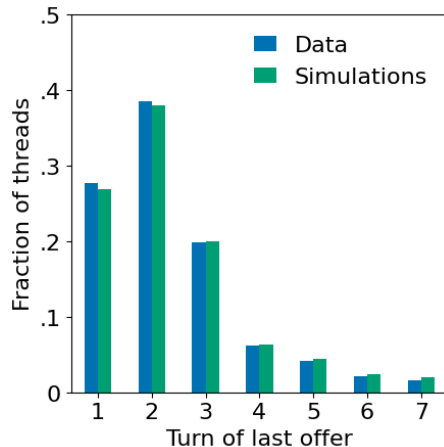


Summary statistics

(a) Threads per listing

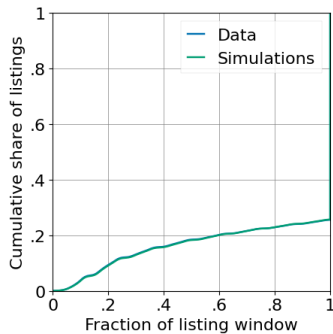


(b) Offers per thread

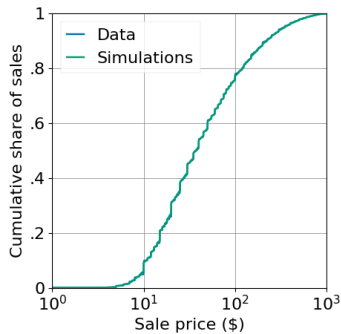


Sale time and price

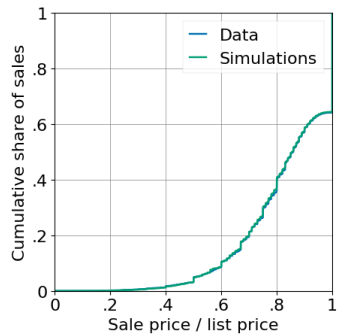
(a) Time to sale



(b) Sale price

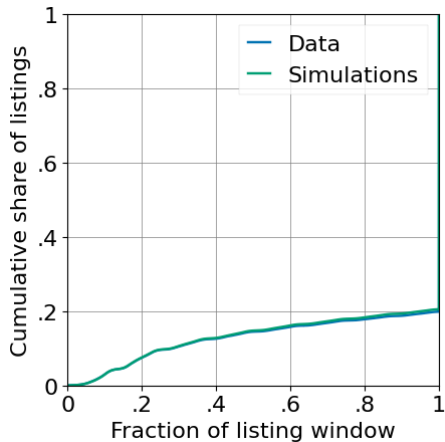


(c) Normalized

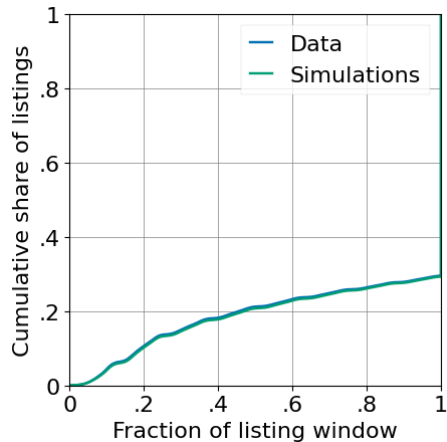


By category: time to sale

(a) Collectibles

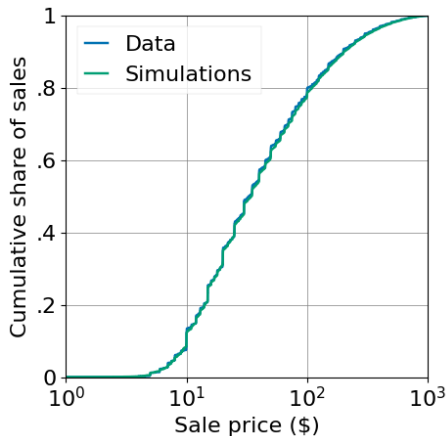


(b) Other

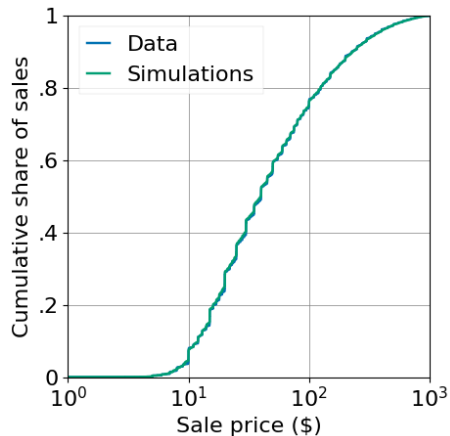


By category: sale price

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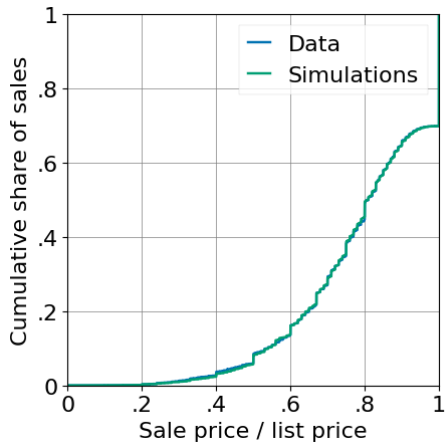


(b) Other

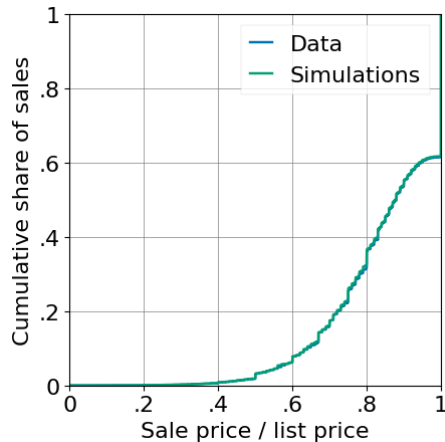


By category: normalized sale price

(a) Collectibles



(b) Other



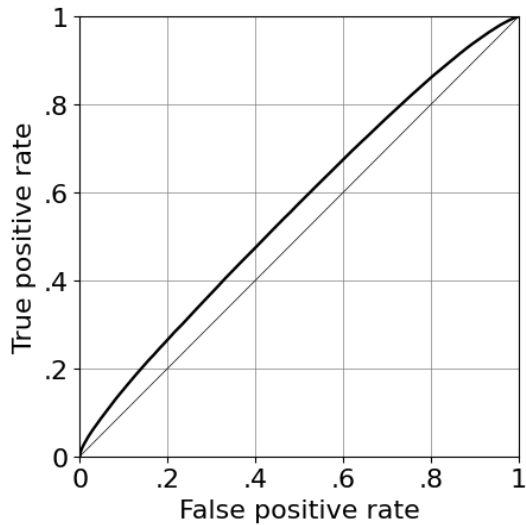
Discriminator

Observes a complete thread, either from data or simulations.

- ▶ Fixed listing features.
- ▶ Offer path.

Predicts the whether the thread is real or simulated.

Discriminator performance



AUC: 56%

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Buyer:

- ▶ item value less sale price, if buyer purchases item
- ▶ 0, otherwise

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- ▶ item value discounted by $\delta \in [0, 1]$, otherwise

What is an item's value?

- ▶ Calculate a “market value” for each item.
- ▶ Characterize optimal behavior under these values.

Values

$$v = P(\text{sale}) \cdot \mathbb{E}[\text{price}|\text{sale}] + (1 - P(\text{sale})) \cdot v$$

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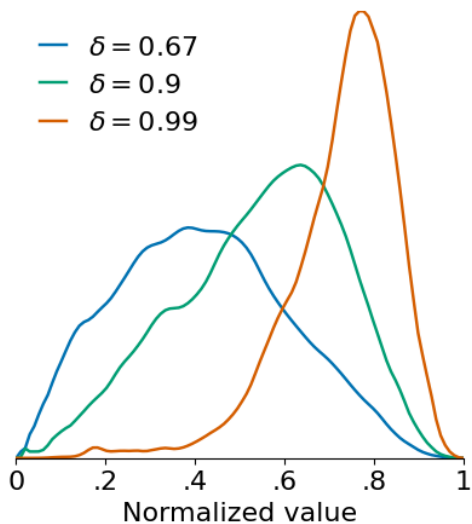
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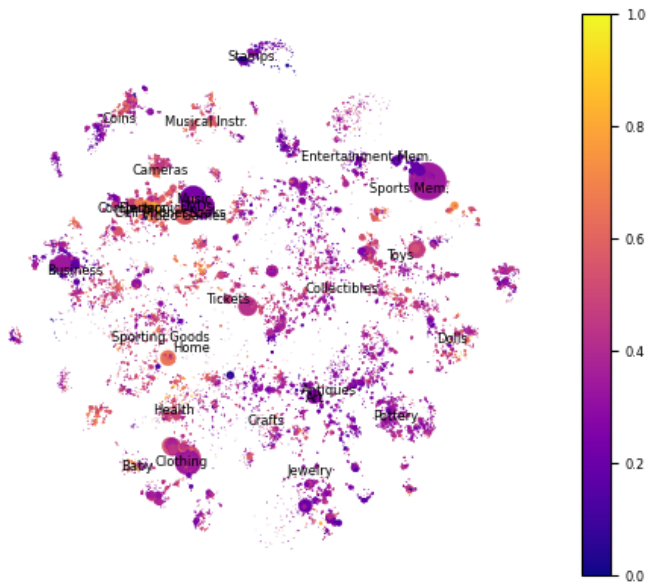
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- ▶ $\delta = 1 \rightarrow \text{value} = \mathbb{E}[\text{price}|\text{sale}]$

Simulate each listing to estimate $P(\text{sale})$ and $\mathbb{E}[\text{price}|\text{sale}]$.

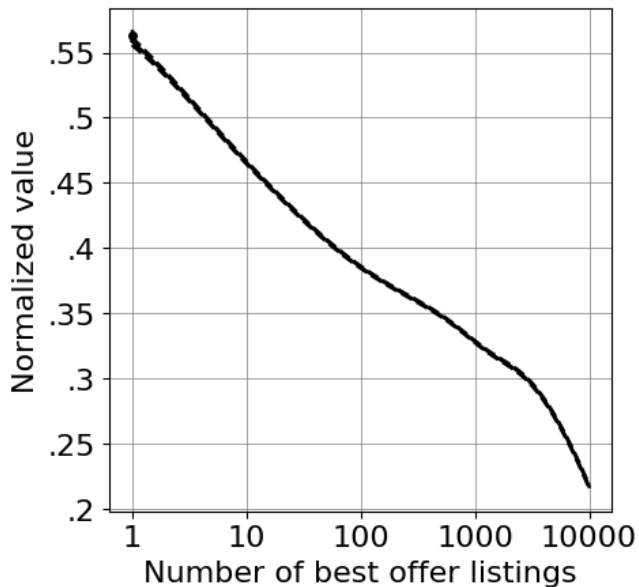
Normalized values



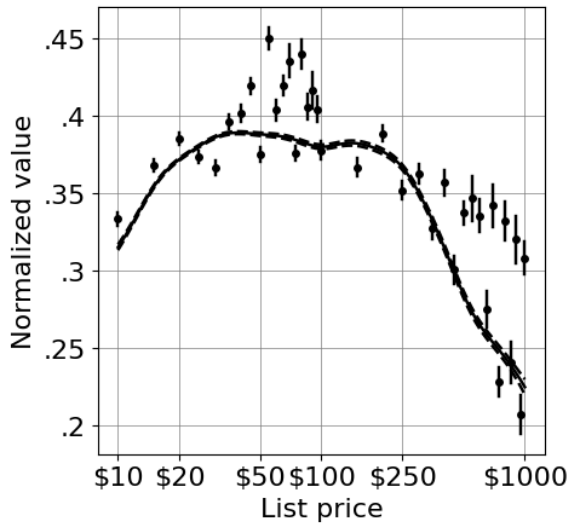
Category predicts value



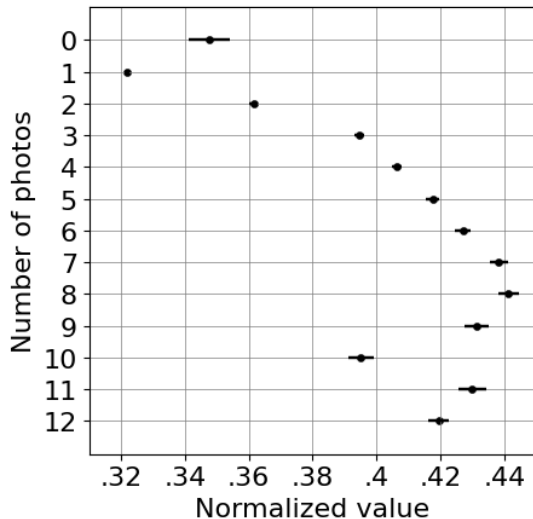
Seller experience predicts value



Round list prices have higher values



Listings with more photos generally have higher values



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Training procedure

$$\pi(\mathbf{x}) : \mathbf{x} \rightarrow f(a)$$

Initialize seller policy π .

1. Draw a listing from RL Training partition.
2. Simulate using π to draw seller offers.
3. If listing sells, payoff is sale price.
 - ▶ Otherwise payoff is δv .
4. Update π .

Repeat until π converges to deterministic policy.

- ▶ Simulate each listing in holdout partition 10 times.

Seller offers

$$\pi(\mathbf{x}) : \mathbf{x} \rightarrow f(a)$$

\mathbf{x} : features that are observable to seller.

- ▶ e.g., features that summarize offers on other threads.
- ▶ Excludes item value.

$a \in \{\text{expiration}, \text{reject}, \frac{1}{4}, \frac{1}{3}, \frac{2}{5}, \frac{1}{2}, \frac{3}{5}, \frac{2}{3}, \text{accept}\}$

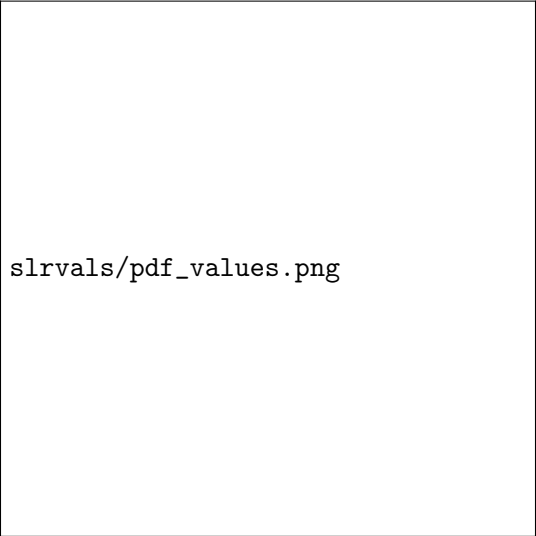
- ▶ Make offer when a human seller would.
- ▶ Cannot send a message.

Valid listings

A listing is valid if agent seller makes ≥ 1 non-automatic offer.

1. i.e., a buyer arrives and
2. make an offer between the automatic thresholds and
3. seller has an opportunity to respond before listing ends.

Values ($\delta = 0.67$)



slrvals/pdf_values.png

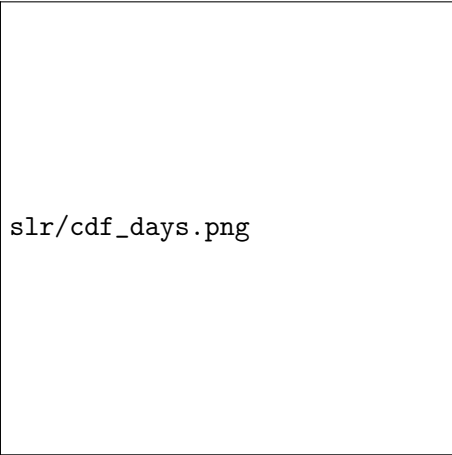
Sale prices ($\delta = 0.7$)



Avg normalized sale price (among sales): .76 in data / .83 for agent


Is the agent more patient than human sellers?

(a) Time to sale



slr/cdf_days.png

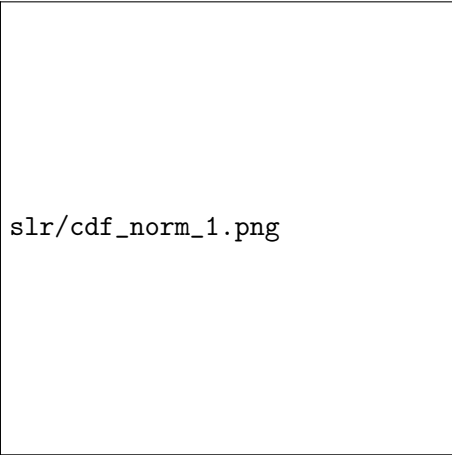
(b) Threads per listing



slr/bar_threads.png

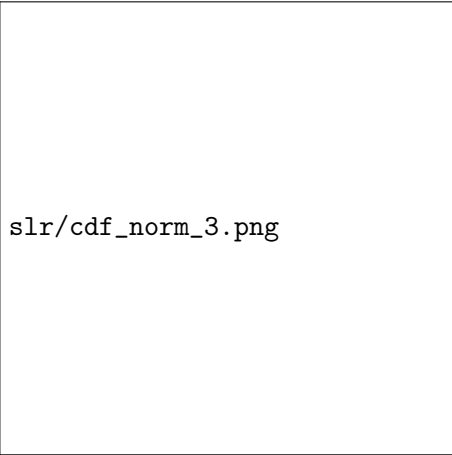
Agent seller induces full-price offers on turn 3

(a) Turn 1



slr/cdf_norm_1.png


(b) Turn 3



slr/cdf_norm_3.png


Humans and agent diverge in turn 2

(a) Accept rate



turn2/response_accept.png

(b) Reject rate

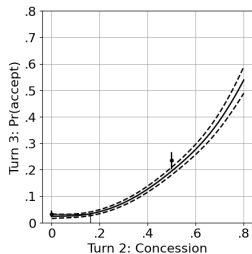


slr2/response_reject.png

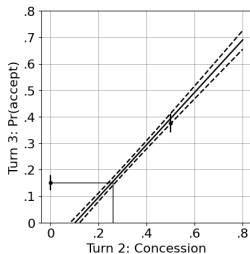
Note: excludes auto-accepts and auto-rejects.

Turn 2 rejects induce accepts

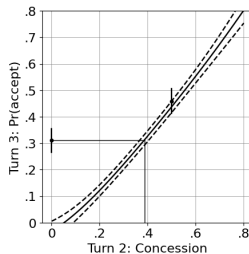
$$\frac{\text{First buyer offer}}{\text{list price}} = \frac{1}{2}$$



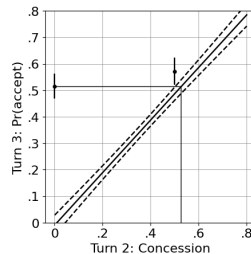
$$\frac{\text{First buyer offer}}{\text{list price}} = \frac{2}{3}$$



$$\frac{\text{First buyer offer}}{\text{list price}} = \frac{3}{4}$$



$$\frac{\text{First buyer offer}}{\text{list price}} = \frac{4}{5}$$



Summary so far

Human sellers accept higher first offers at higher rates.

- ▶ Consistent with comparing offer to reservation value or goal.

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The agent seller rejects higher first offers at higher rates.

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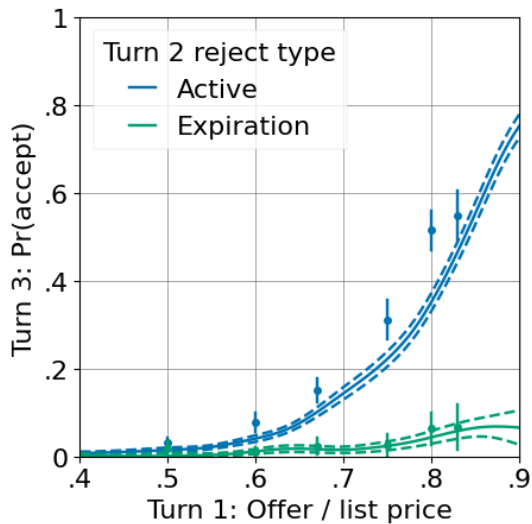
The agent seller rejects higher first offers at higher rates.

- ▶ Consistent with inferring willingness to pay from offer.

Rejections induce higher accept rates than small concessions.

- ▶ Consistent with a price integrity hypothesis.

Don't play hard to get



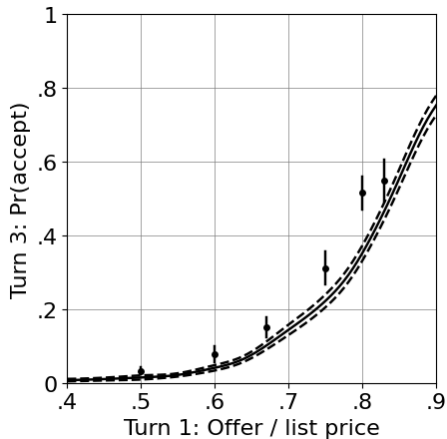
Reject rates

	Turn 2		Turn 4		Turn 6	
	Data	Agent	Data	Agent	Data	Agent
Expire	.04	-	.04	-	.03	-
Reject	.14	.63	.22	-	.22	-

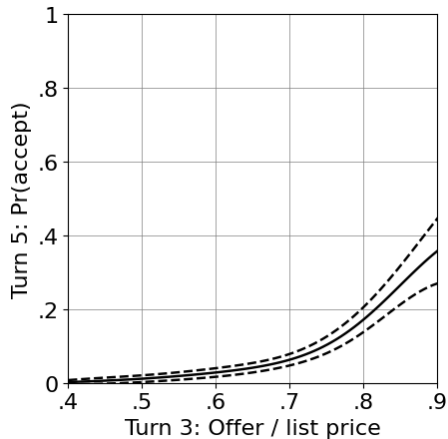
Note: excludes auto-rejects.

Active rejections don't have same effect in later turns

(a) Active rejections in turn 2

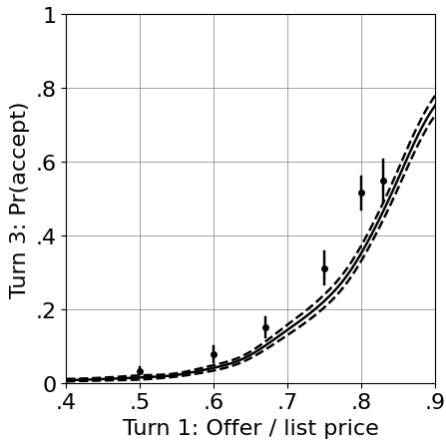


(b) Active rejections in turns 2 & 4

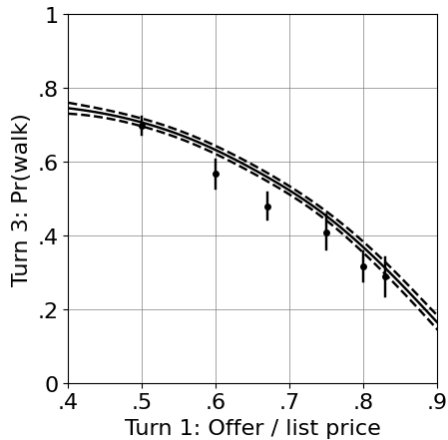


A more complete picture

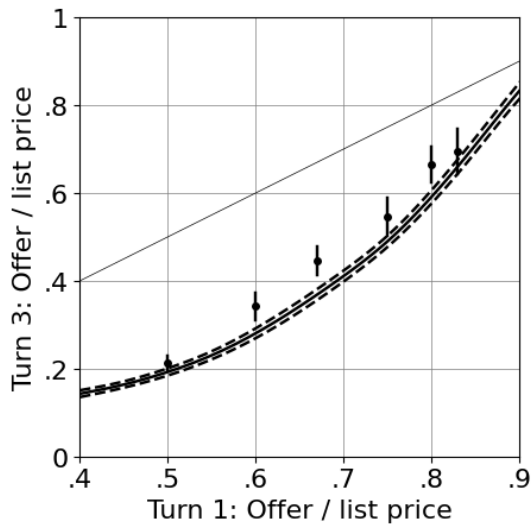
Some buyers accept...



...but others walk.



A more complete picture



Bargaining is a dynamic problem

Goal is to maximize *eventual* payoff.

- ▶ Not to maximize counterparty's response in next turn.

Bargaining is a dynamic problem

Goal is to maximize *eventual* payoff.


- Not to maximize counterparty's response in next turn.

The payoff to the rejecting on turn 2 comes from:

1. Buyer acceptances on turn 3.
2. Agreements with the same buyer in a later turn.
3. An agreement with another buyer.

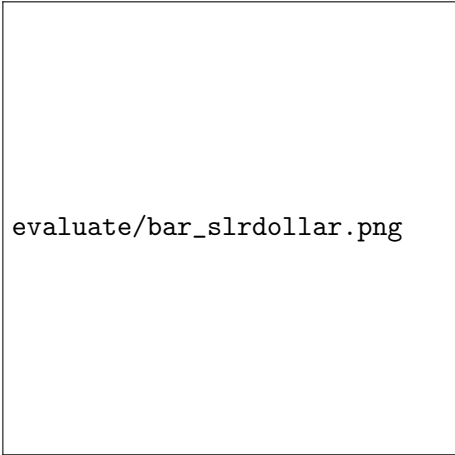
Is there a simple agent that does almost as well?

(a) Normalized reward



evaluate/bar_slrnorm.png

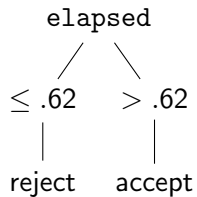
(b) Dollar reward



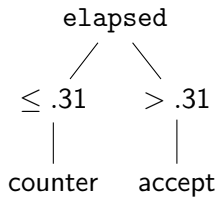
evaluate/bar_slrdollar.png

Heuristic agent

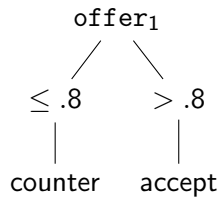
Turn 2



Turn 4

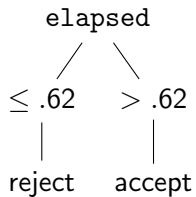


Turn 6

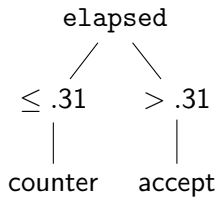


Heuristic agent

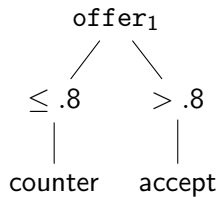
Turn 2



Turn 4



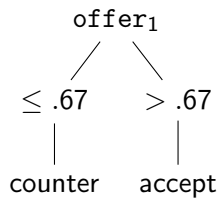
Turn 6



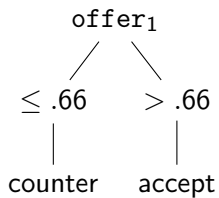
Reject early, concede later.

Heuristic human agent

Turn 2



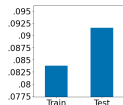
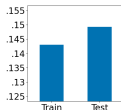
Turn 4



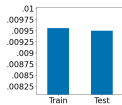
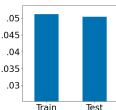
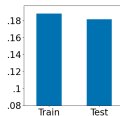
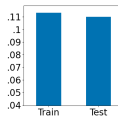
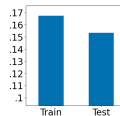
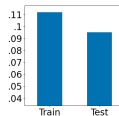
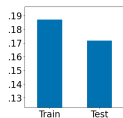
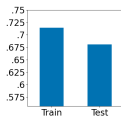
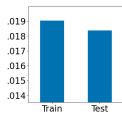
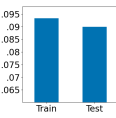
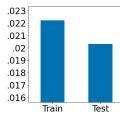
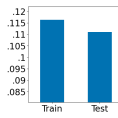
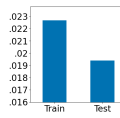
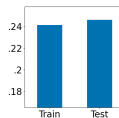
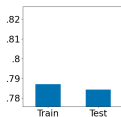
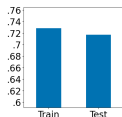
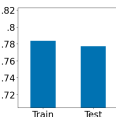
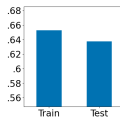
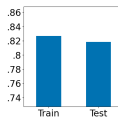
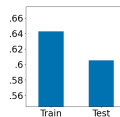
Turn 6

accept

Appendix

arrival₀arrival₁

byr_hist

con₁con₂con₃con₄con₅con₆con₇delay₂delay₃delay₄delay₅delay₆delay₇msg₁msg₂msg₃msg₄msg₅msg₆

When does agent seller make offers?

2

slr/cdf_delay_2.png

4

slr/cdf_delay_4.png

6

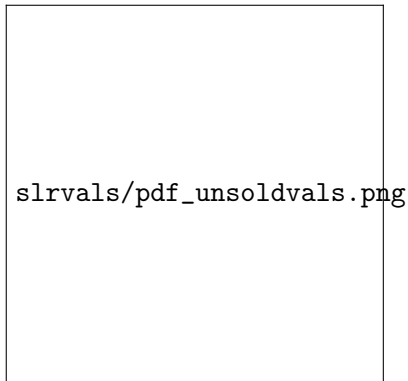
slr/cdf_delay_6.png

Drawn from turn-specific distribution for simulated seller.

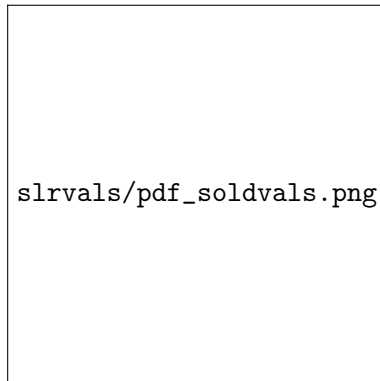
- Conditional on delay < 48 hours.

Values ($\delta = 0.7$)

(a) Unsold items




(b) Sold items



80.7% of valid listings sell in data vs. 80.3% for agent.

Sale prices

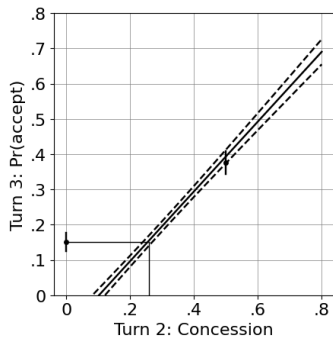


slr/cdf_lstgprice.png

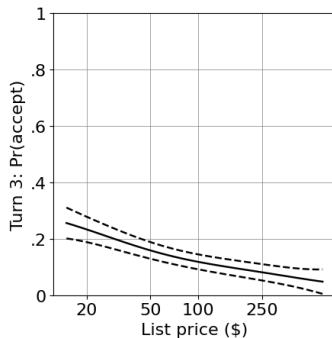
Turn 3 accept rates

$$\frac{\text{First buyer offer}}{\text{list price}} = \frac{2}{3}$$

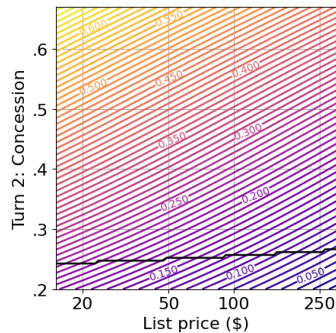
Overall



After a reject, by price



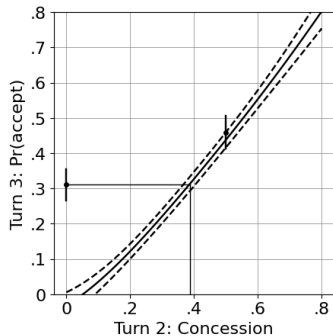
By price and seller response



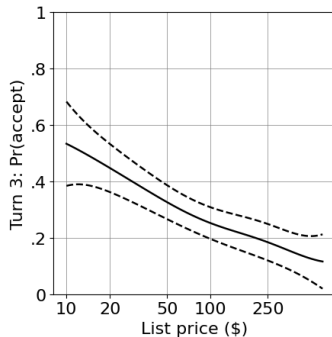
Turn 3 accept rates

$$\frac{\text{First buyer offer}}{\text{list price}} = \frac{3}{4}$$

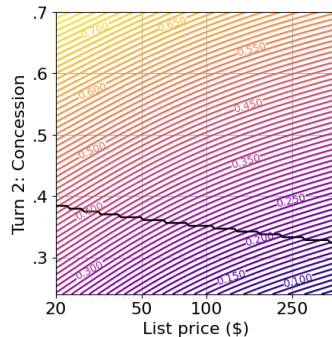
Overall



After a reject, by price




By price and seller response



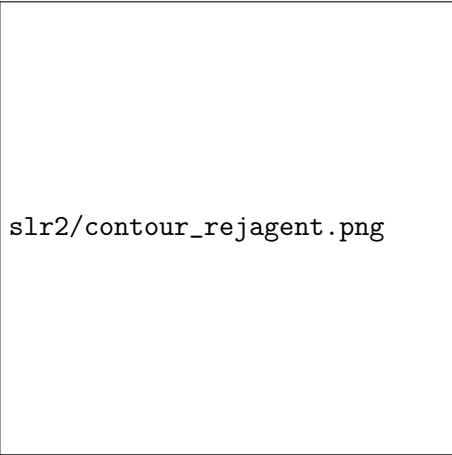
Turn 2 rejection rates

(a) Data



slr2/contour_rejdata.png

(b) Agent



slr2/contour_rejagent.png