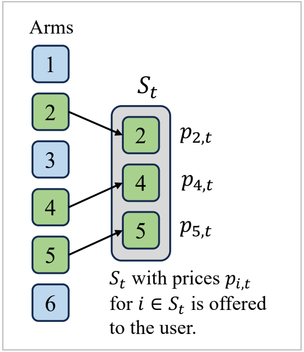
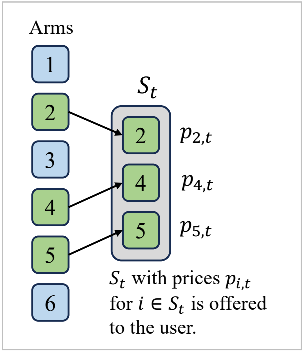
Dynamic Assortment Selection & Pricing with Censored Preference Feedback

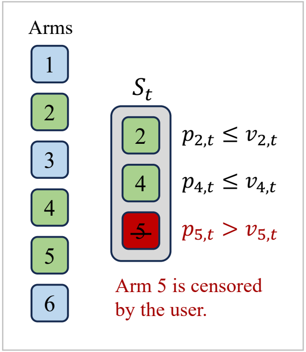
Jung-hun Kim, Min-hwan Oh
Seoul National University

Dynamic Assortment Selection and Pricing with Censored Preference Feedback

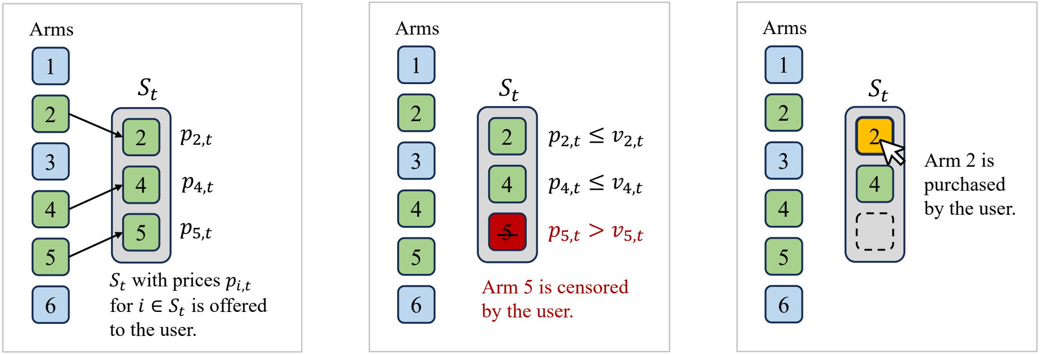


Dynamic Assortment Selection and Pricing with Censored Preference Feedback

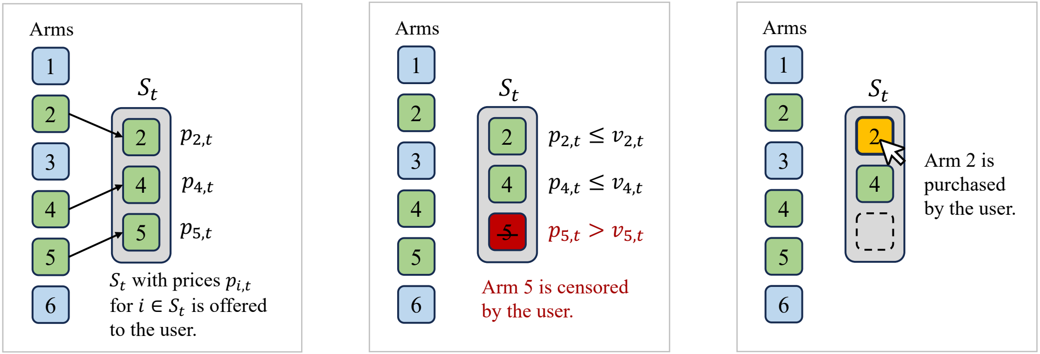




Dynamic Assortment Selection and Pricing with Censored Preference Feedback



Dynamic Assortment Selection and Pricing with Censored Preference Feedback



Motivating examples for this framework include

- e-commerce, hotel reservations, and air travel involving multiple products selection and pricing.

Purchase Model for Buyers

Definition 1 (Censored multinomial logit choice model)

Then, given S_t and p_t, the user purchases an arm $i \in S_t$ by paying $p_{i,t}$ according to the probability defined as follows:

$$\mathbb{P}_t(i|S_t, p_t) := \frac{\exp(v_{i,t} - \alpha_{i,t} p_{i,t}) \mathbb{1}(p_{i,t} \leq v_{i,t})}{1 + \sum_{j \in S_t} \exp(v_{j,t} - \alpha_{j,t} p_{j,t}) \mathbb{1}(p_{j,t} \leq v_{j,t})}, \tag{1}$$

where $v_{i,t}$ is the latent valuation for the buyer and $\alpha_{i,t}$ is the latent price sensitivity parameter of item i.

The expected revenue from purchased arm $i \in S_t$ is represented as $R_{i,t}(S_t) = p_{i,t} \mathbb{P}_t(i|S_t, p_t)$. Then, the overall expected revenue is formulated as

$$R_t(S_t, p_t) = \sum_{i \in S_t} R_{i,t}(S_t).$$

Summary of Our Contributions.

- We propose a novel framework for dynamic multi-product selection and pricing that incorporates a censored version of the multinomial logit (C-MNL) model.

Summary of Our Contributions.

- We propose a novel framework for dynamic multi-product selection and pricing that incorporates a censored version of the multinomial logit (C-MNL) model.
- We introduce a Lower Confidence Bound (LCB)-based pricing strategy to promote exploration by setting lower prices, avoiding buyer censorship, and facilitating the learning of buyer preferences and product valuations.

Summary of Our Contributions.

- We propose a novel framework for dynamic multi-product selection and pricing that incorporates a censored version of the multinomial logit (C-MNL) model.
- We introduce a Lower Confidence Bound (LCB)-based pricing strategy to promote exploration by setting lower prices, avoiding buyer censorship, and facilitating the learning of buyer preferences and product valuations.
- We develop two algorithms that combine LCB pricing with Upper Confidence Bound (UCB) or Thompson Sampling (TS) for assortment selection, achieving regret bounds of $\widetilde{O}(d^{\frac{3}{2}}\sqrt{T/\kappa})$ and $\widetilde{O}(d^{2}\sqrt{T/\kappa})$, respectively.

Summary of Our Contributions.

- We propose a novel framework for dynamic multi-product selection and pricing that incorporates a censored version of the multinomial logit (C-MNL) model.
- We introduce a Lower Confidence Bound (LCB)-based pricing strategy to promote exploration by setting lower prices, avoiding buyer censorship, and facilitating the learning of buyer preferences and product valuations.
- We develop two algorithms that combine LCB pricing with Upper Confidence Bound (UCB) or Thompson Sampling (TS) for assortment selection, achieving regret bounds of $\widetilde{O}(d^{\frac{3}{2}}\sqrt{T/\kappa})$ and $\widetilde{O}(d^{2}\sqrt{T/\kappa})$, respectively.
- We validate the effectiveness of our algorithms using synthetic datasets.

Thank You