Economics of Algorithms

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All models are wrong, but some are useful.

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Chapter 1 Recommender Systems

1.1 [Dinerstein et al.(2018)]: Consumer Price Search and Platform Design in Internet Commerce

There is a redesign of eBay:

- Before the redesign: ranking according to a relevance algorithm.
- After the redesign: first prompting consumers to identify an exact product, then comparing seller listings of that product head-to-head, ranked (mostly) by price.

1.2 Conceptual Framework

Trade-off between guiding consumers to their most desired products and strengthening seller incentives to provide better product attributes.

There are J sellers. Each product j has a fixed vector of attributes x_j and a posted price p_j (determined by the seller). Each consumer i arrives at the platform is defined by a vector of characteristics ξ_i ($\sim F$). Each consumer has a unit demand and decides which product to purchase, or not to purchase at all. Consumer i's utility from product j is given by $u(x_j, p_j; \xi_i)$.

The platform sets an awareness/visibility function $a_{ij} \in [0, 1]$, where a_{ij} is the probability that product j is being considered by consumer i.

Assumption 1.1

$a_{ij} = a_j = a(p_j, x_j; p_{-j}, x_{-j})$ for all i. That is, the platform presents products to consumers based on their prices and attributes, but does not discriminate presentation across consumers (may generate discrimination ex post).

The platform charges sellers a transaction fee T and a fraction t of the transaction price.

The platform design implies choice sets $L \in 2^J$ for consumers. The probability of the choice set L being aware of is given by $a_L = \left(\prod_{j\in L} a_j\right)\left(\prod_{j\notin L}(1-a_j)\right)$.

The overall demand for product is given by

$$D_j(p_j, p_{-j}) = \sum_{L\in 2^J} a_L D_j(p_j, p_{-j}; L),$$

where

$$D_j(p_j, p_{-j}; L) = \int \mathbf{1}\left\{u(x_j, p_j; \xi_i) \geq x_k, p_k; \xi_i\right\} dF(\xi_i).$$

The seller j sets p_j to maximize profits,

$$\pi_j = \max_{p_j} D_j(p_j, p_{-j})\left((1-t)p_j - c_j - T\right),$$

leading to the F.O.C.,

$$p_j = \frac{c_j + T}{1-t} - \left(\frac{\partial D_j(p_j, p_{-j})}{\partial p_j}\right)^{-1} D_j(p_j, p_{-j}).$$

where

$$\frac{\partial D_j(p_j, p_{-j})}{\partial p_j} = \sum_L a_L \frac{\partial D_j(p_j, p_{-j}; L)}{\partial p_j} + \sum_L \frac{\partial a_L}{\partial p_j} D_j(p_j, p_{-j}; L).$$

Chapter 2 Identification of Prediction Errors

2.1 [Rambachan(2024)]: Identifying Prediction Mistakes in Observational Data

Uncovering systematic prediction mistakes in empirical settings is challenging because

1. the decision maker's preferences and
2. the information set

are unknown to us.

2.1.1 Expected Utility Maximization at Accurate Beliefs

A decision maker (DM) makes a binary choice $c \in \{0, 1\}$ for each individual, which is summarized by characteristics $x \in \mathcal{X}$ and an unknown outcome $y^* \in \mathcal{Y}$ (observable when $c = 1$).

Example 2.1 (Pretrial Release)

A judge decides whether to detain ore release defendants $C \in \{0, 1\}$. The outcome $Y^* \in \{0, 1\}$ is whether a defendant would fail to appear in court if released. X is the recorded information of the defendant.

Example 2.2 (Medical Testing and Diagnosis)

$C \in \{0, 1\}$ is whether to conduct a test. $Y^* \in \{0, 1\}$ is whether the patient had a heart attack. X is the recorded information of the patient.

Example 2.3 (Hiring)

$C \in \{0, 1\}$ is whether to hire a candidate. Y^* is a vector of on-the-job productivity measures. X is the recorded information of the candidate.

These three variables are summarized by a joint distribution, $(X, C, Y^*) \sim P(\cdot)$. We assume finite full support of x, i.e. there is a $\delta > 0$ such that $P(x) := P(X = x) \geq \delta, \forall x \in \mathcal{X}$. As the Y^* is only observable when $C = 1$. We define

$$Y := C \cdot Y^*$$

The observable data is the joint distribution $(X, C, Y) \sim P(\cdot)$. The DM's conditional choice probabilities are

$$\pi_c(x) := P(C = c | X = x), c \in \{0, 1\}, x \in \mathcal{X}$$

The observable conditional outcome probabilities are

$$P_1(y^* \mid x) := P(Y^* = y^* \mid C = 1, X = x), y^* \in \mathcal{Y}, x \in \mathcal{X}$$

The $P_0(y^* \mid x)$ and the true outcome probabilities $P(y^* \mid x)$ are not identified due to the missing-data problem.

Assumptions

Note *In the main context of paper: (i). The decision maker makes a binary choice $c \in \{0, 1\}$ for each individual; (ii). The decision maker's choice does not have a direct causal effect on the outcome.*

Assumption 2.1 (Bounds on the Unobserved Conditional Outcome Probabilities)

For each $x \in \mathcal{X}$, there exists a known subset $\mathcal{B} \subseteq \Delta\mathcal{Y}$ such that $P_0(\cdot \mid x) \in \mathcal{B}_x$.

Given this assumption, the identified set for the true outcome probabilities given $x \in \mathcal{X}$, denoted by

$$\mathcal{H}(P(\cdot \mid x); \mathcal{B}_x) := \big\{\tilde{P}(\cdot \mid x) \in \Delta\mathcal{Y} : \tilde{P}(y^* \mid x) = \tilde{P}_0(y^* \mid x)\pi_0(x) + P_1(y^* \mid x)\pi_1(x), \\ \forall y^* \in \mathcal{Y} \text{ and for some } \tilde{P}_0(\cdot \mid x) \in \mathcal{B}_x\big\}$$

Bibliography

[Dinerstein et al.(2018)] Dinerstein, M., Einav, L., Levin, J., and Sundaresan, N. (2018). Consumer price search and platform design in internet commerce. *American Economic Review*, 108(7):1820–1859.

[Rambachan(2024)] Rambachan, A. (2024). Identifying prediction mistakes in observational data. *The Quarterly Journal of Economics*, page qjae013.