

Disentangling Attention and Utility Channels in Recommendations

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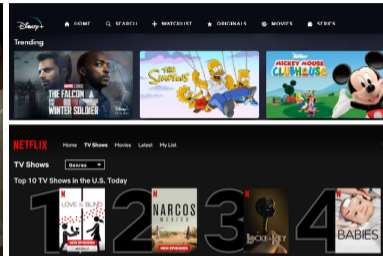
NET-A-PORTER LIVE™
What the world's most stylish women are buying now

[Black Boot](#)
[Black Bag](#)
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[Black Dress](#)

Top Reviewed

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- “Amazon’s Choice”
- “Superhost”
- “Etsy’s picks”
- “Best Seller”
- “Editor’s pick”
- ...



- Recommending a product often increases the sales of recommended products
 - Senecal and Nantel (2004): Wine/Calculators
 - Gupta and Harris (2010): Computer
 - Adomavicius et al (2018): Digital Music
 - Kawaguchi et al. (2019): Vending machine
 - Farronato et al. (2020): Home services
 - Rietveld et al. (2021): Microloans
 - Bairathi et al. (2022): Freelance
 - ...

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- But HOW?

- Recommendation influences the **awareness** set of consumer
 - Recommendation signage: Best Seller, Award Winner (e.g. Goodman et al, 2013)
 - (electronic) Word-of-mouth (e.g. Gupta and Harris, 2010)
 - Uninformative advertising (e.g. Mayzlin and Shin, 2011)
- Recommendation affects consumer's **valuation**
 - Consumer's Rating (Cosley et al, 2003)
 - Willingness to Pay (Adomavicius et al, 2018)
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How does recommendation affect choices through **attention** and **utility**?

What we do (today)

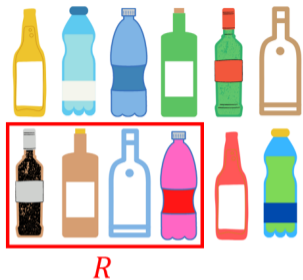
- Two channels in one model
- Accommodating observed phenomena
- Behaviorally distinguishing channels
- Full characterization (skipped)
- Evaluating recommendation (skipped)
- Auctioning recommendation (skipped)

Decision Problem



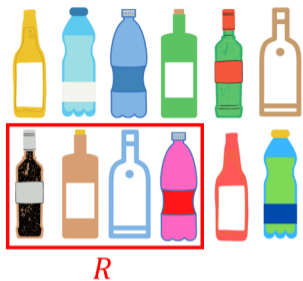
R

Decision Problem



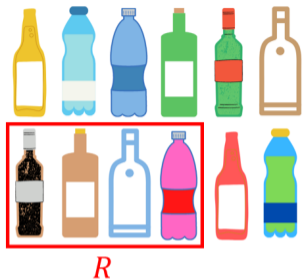
- X : Grand set of alternatives
- $S \subseteq X$: Set of available alternatives
- $R \subseteq S$: Recommended set of alternatives

Decision Problem



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Decision Problem



- X : Grand set of alternatives
- $S \subseteq X$: Set of available alternatives
- $R \subseteq S$: Recommended set of alternatives
- $\rho_S(x, R)$: Stochastic choice data
 - The probability that x is chosen when R is recommended in the set S
 - $\sum_{x \in S \cup \{o^*\}} \rho_S(x, R) = 1$, where o^* is a default/outside option.
- Domain of choice problem (skipped)

- Each alternative $x \in X$ has four parameters

$$u_R(x) = \begin{cases} u'(x) & \text{if } x \in R \\ u(x) & \text{otherwise} \end{cases} \quad \gamma_R(x) = \begin{cases} \gamma'(x) & \text{if } x \in R \\ \gamma(x) & \text{otherwise} \end{cases}$$

- $u_R(x) \in (0, \infty)$: The utility of x given recommended set R
- $\gamma_R(x) \in (0, 1)$: The likelihood to consider x given recommended set R

Suppose a set $R \subseteq S$ is recommended,

1. Within the choice set S , a consideration set $A \subseteq S$ emerges with probability (Manzini and Mariotti, 2014),

$$\prod_{y \in A} \gamma_R(y) \prod_{z \in S \setminus A} (1 - \gamma_R(z))$$

2. Within the consideration set A , the DM chooses an alternative x with probability (Luce 1959)

$$\frac{u_R(x)}{u_R(A)}$$

Parametric Recommendation Model

- The attention and utility parameters

$$u_R(x) = \begin{cases} u'(x) & \text{if } x \in R \\ u(x) & \text{otherwise} \end{cases} \quad \gamma_R(x) = \begin{cases} \gamma'(x) & \text{if } x \in R \\ \gamma(x) & \text{otherwise} \end{cases}$$

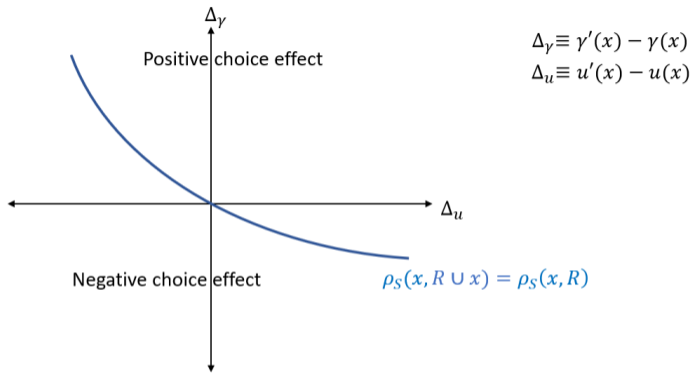
Definition

A probabilistic choice rule $\{\rho_S\}$ has a parametric recommendation representation if there exists functions $u_R : X \rightarrow \mathbb{R}_{++}$ and $\gamma_R : X \rightarrow (0, 1)$ such that for $x \in X$,

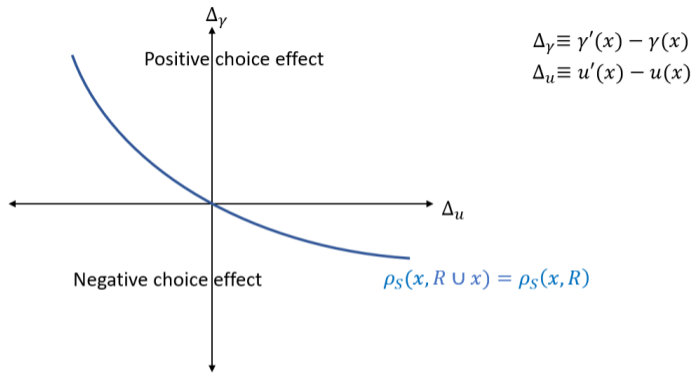
$$\rho_S(x, R) = \sum_{x \in A \subseteq S} \underbrace{\left[\prod_{y \in A} \gamma_R(y) \prod_{z \in S \setminus A} (1 - \gamma_R(z)) \right]}_{\text{Prob. of } A \text{ being the consideration set}} \underbrace{\frac{u_R(x)}{u_R(A)}}_{\text{Prob. of } x \text{ being chosen in } A}$$

- Manzini and Mariotti (2014) and Luce (1959)

Accommodating Observed Behaviors

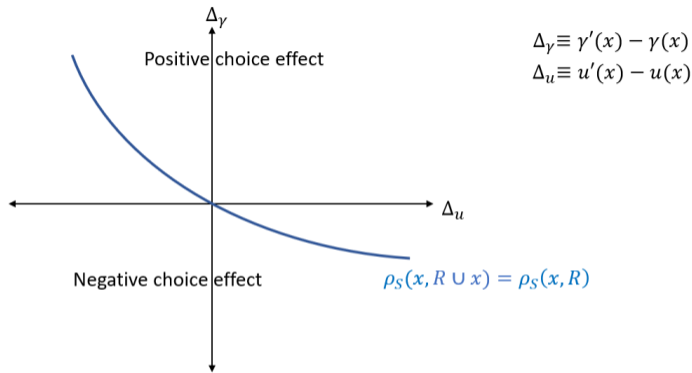


The zero-choice-effect curve



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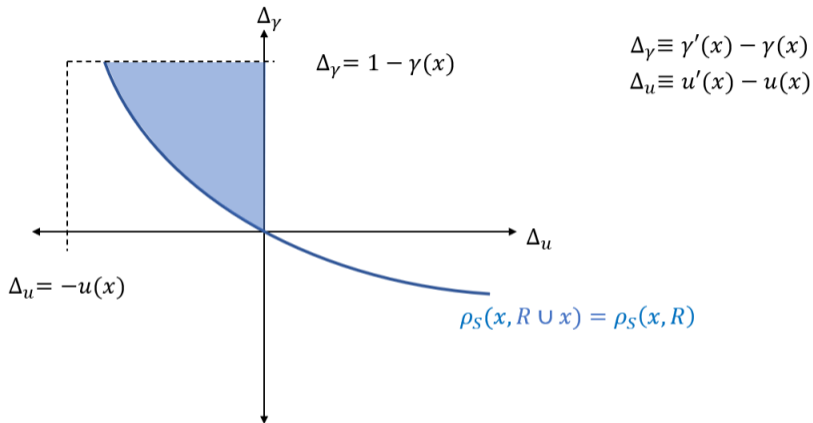
- Positive choice effect (coined by Kawaguchi et al., 2021): e.g. Goodman et al. (2013), Häubl and Trifts (2000), Rowley (2000), Senecal and Nantel (2004), and Vijayasathay and Jones (2000, 2001)



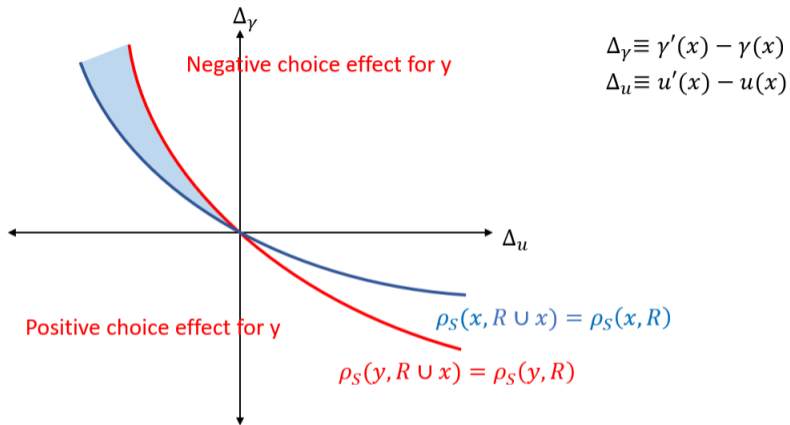
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- Negative choice effect(?)

Positive Effect of Negative Publicity

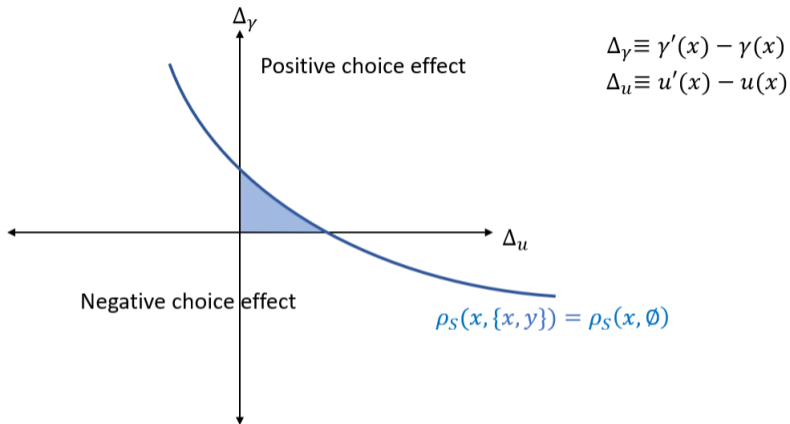


- Negative utility but positive attention effect
 - e.g. Allard et al. (2020), Berger et al. (2010), and Huang et al. (2023)



- Recommending x also makes other products more likely to be chosen
 - e.g. Bairathi et al. (2022) and Kawaguchi et al. (2021)

Crowding-Out Effect



- Supposing positive attention and utility effect for y
- A possible theoretical prediction

Behaviorally Distinguishing Channels

Increasing Recommendation Return to Size. For $x \in R \subseteq S \subseteq L$,

$$\frac{\rho_L(x, R)}{\rho_L(x, R \setminus x)} \geq \frac{\rho_S(x, R)}{\rho_S(x, R \setminus x)}$$

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Interpretations:

- Recommendation Return (Hence the name)

$$\frac{\rho_L(x, R) - \rho_L(x, R \setminus x)}{\rho_L(x, R \setminus x)} \geq \frac{\rho_S(x, R) - \rho_S(x, R \setminus x)}{\rho_S(x, R \setminus x)}$$

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- Regularity Comparison

$$\frac{\rho_L(x, R)}{\rho_S(x, R)} \geq \frac{\rho_L(x, R \setminus x)}{\rho_S(x, R \setminus x)}$$

where both $\frac{\rho_L(x, R)}{\rho_S(x, R)}$ and $\frac{\rho_L(x, R \setminus x)}{\rho_S(x, R \setminus x)} \leq 1$ by *regularity*.

Increasing Recommendation Return to Size. For $x \in R \subseteq S \subseteq L$,

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Theorem

Let (u_R, γ_R) be a parametric recommendation representation of $\{\rho_S\}$. Then, $u'(x) \geq u(x)$ for all x if and only if $\{\rho_S\}$ satisfies **Increasing Recommendation Return to Size**.

Positive Choice Effect at Singleton. For all x , $\rho_x(x, x) \geq \rho_x(x, \emptyset)$.

Theorem

Let (u_R, γ_R) be a parametric recommendation representation of $\{\rho_S\}$. Then, $\gamma'(x) \geq \gamma(x)$ for all x if and only if $\{\rho_S\}$ satisfies **Positive Choice Effect at Singleton**.

Positive Choice Effect

Within the model....

$\Delta_\gamma \geq 0$ and $\Delta_u \geq 0$ imply positive choice effect

Positive Choice Effect

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Not assuming the model....

Remark

For any choice probabilities $\{\rho_S\}$, **Increasing Recommendation Return to Size** and **Positive Choice Effect at Singleton** imply a positive choice effect (singleton recommendation).

Positive Choice Effect

Within the model....

$\Delta_\gamma \geq 0$ and $\Delta_u \geq 0$ imply positive choice effect

Not assuming the model....

Remark

For any choice probabilities $\{\rho_S\}$, **Increasing Recommendation Return to Size** and **Positive Choice Effect at Singleton** imply a positive choice effect (singleton recommendation).

- Idea:

$$\frac{\rho_L(x, x)}{\rho_L(x, \emptyset)} \geq \frac{\rho_S(x, x)}{\rho_S(x, \emptyset)} \geq \dots \geq \frac{\rho_x(x, x)}{\rho_x(x, \emptyset)} \geq 1$$

$$\Rightarrow \rho_S(x, x) \geq \rho_S(x, \emptyset)$$

Theorem

Suppose (u_R^1, γ_R^1) and (u_R^2, γ_R^2) are two parametric recommendation representations of the same choice probabilities, then $\gamma_R^1 = \gamma_R^2$ and $u_R^1 = \alpha u_R^2$ for some scalar $\alpha > 0$.

- Attention parameters are uniquely identified.
- Utility parameters are identified up to a positive scalar multiplication.

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Thank you for your attention!!!