Online Retail Operations with Try-Before-You-Buy

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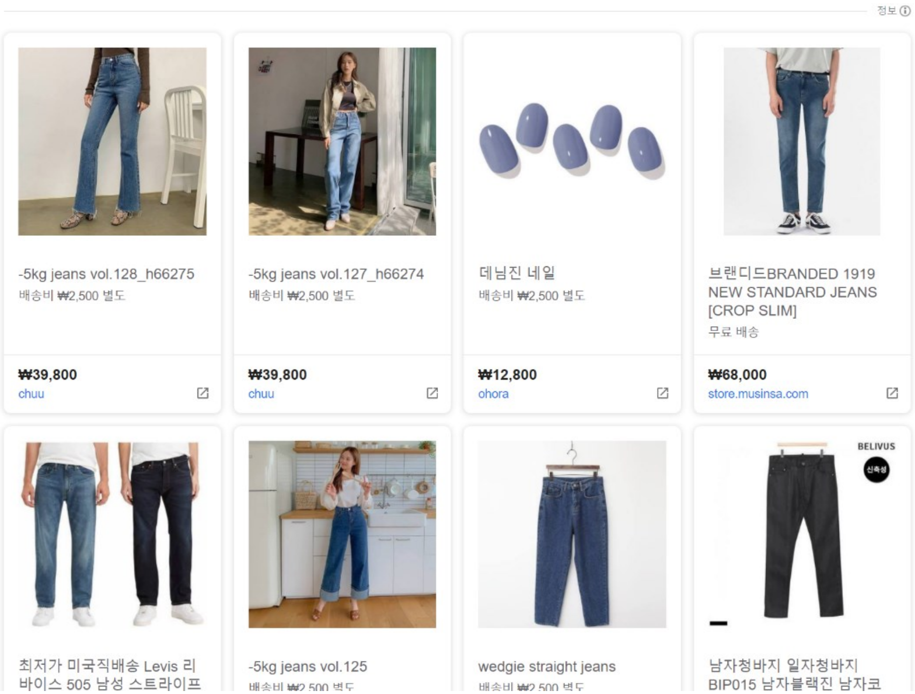
Motivation

Conventional online retail

- Its challenges include



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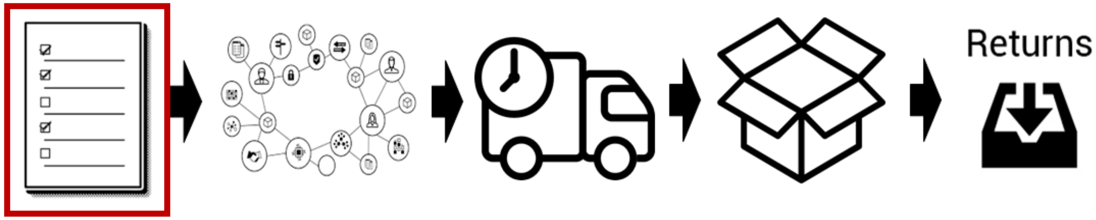
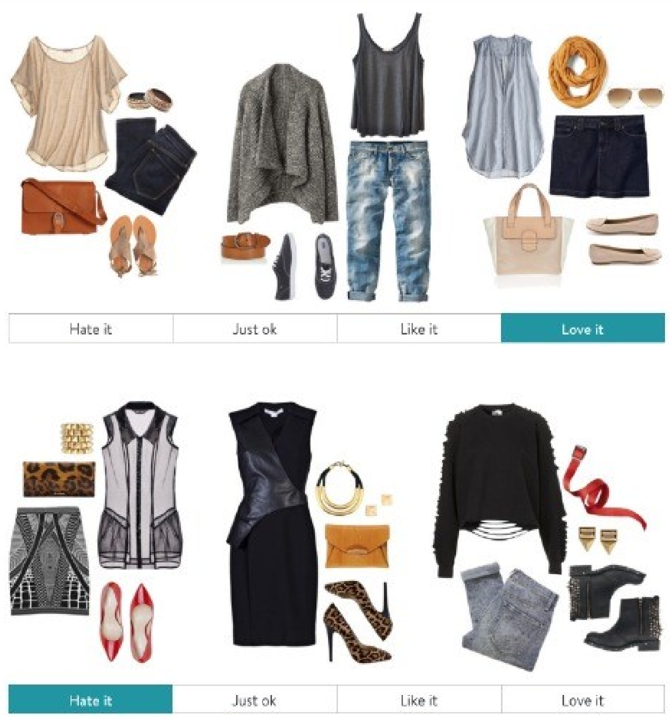
Try-Before-You-Buy (TBYB) Retail Strategy





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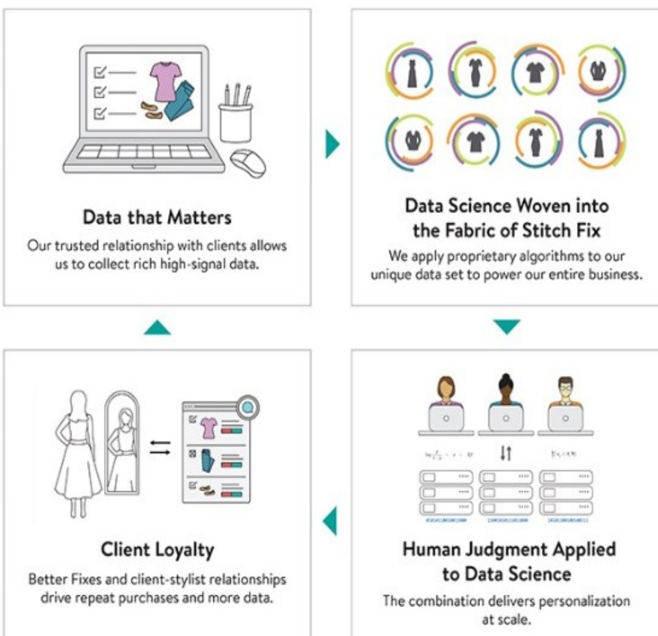

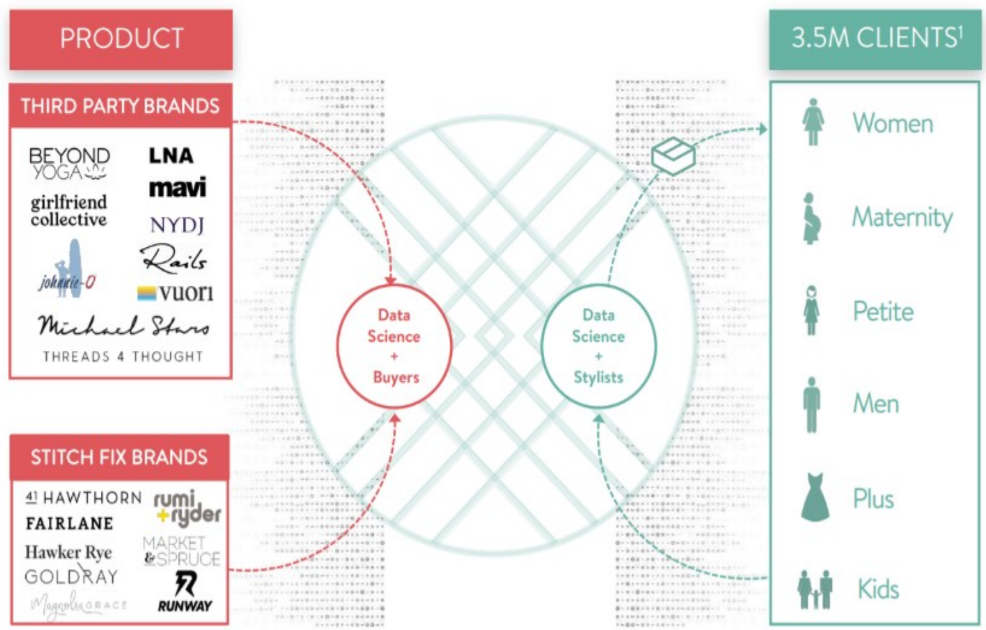

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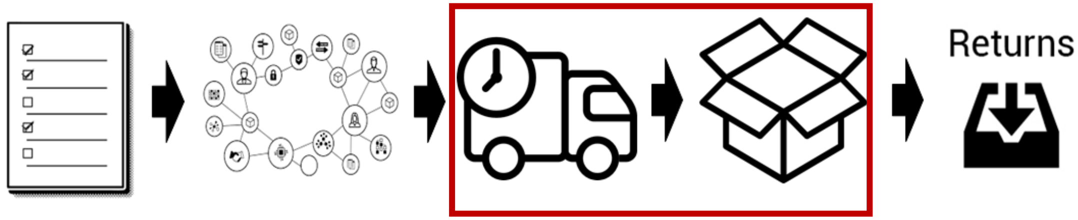


Motivation

Try-Before-You-Buy (TBYB) Retail Strategy

Returns

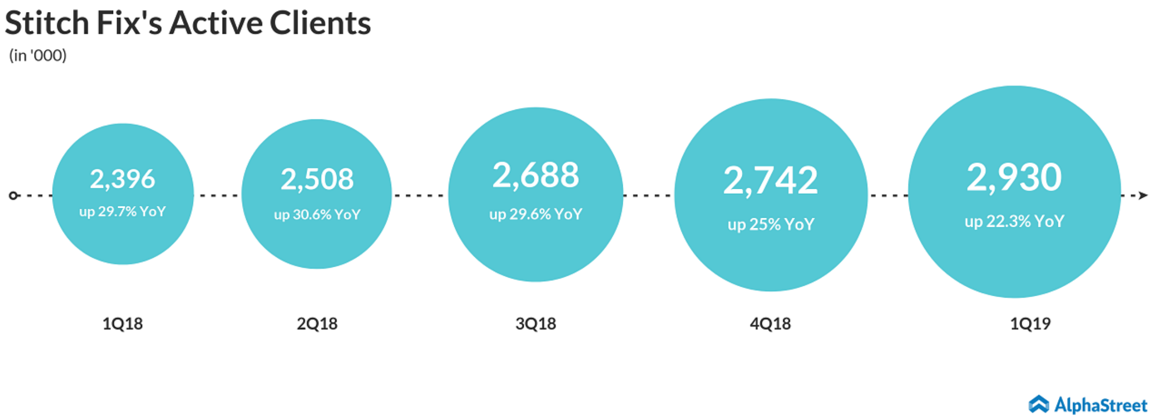
Returns are free and convenient

We offer free returns on all items purchased, including items you're trying on from your Fix delivery

- Place anything you don't want in the prepaid envelope included in your Fix delivery.
- Give your envelope to your mail carrier, drop it off at a blue USPS mailbox or bring it to your local post office.

Rise of TBYB in practice

- Brightpearl (2018) reports that 8% of them are willing to adopt the TBYB strategy by the end of 2018



- Similarly, Birch Box attracted 2.5 million consumers (Del Rey, 2018)
- Amazon recently launched its own TBYB service named “personal shopper”

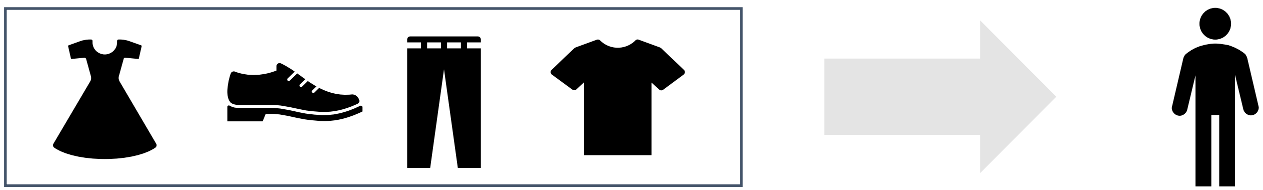
Dark side of TBYB

- Skyrocketing return

- “If they don’t prepare now, the impact on return rates could devastate online retailers that are already seeing their margins considerably squeezed.” (Fisher, 2019)

TBYB quantity decision

- Product return can be controlled by
  - Improving recommendation accuracy
  - Optimize return process
  - Adjusting number of items to include in a TBYB package



- The impact of TBYB quantity decision on the retailer: **sales revenue** + **return cost**

Motivation

TBYB quantity decision

- TBYB quantity in practice

STITCH FIX

5 items per package

TRUNK CLUB
A NORDSTROM COMPANY

6-10 items per package

personal shopper
by prime wardrobe

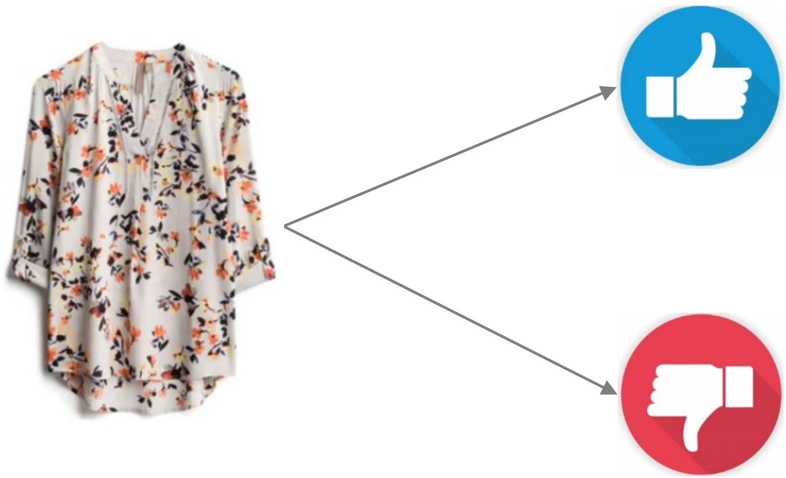
8 items per package

Objective 1: Model the TBYB retailer's quantity decision and understand the logic of optimal decision

Motivation

Recommendation accuracy and the quantity decision

- Recommendation accuracy

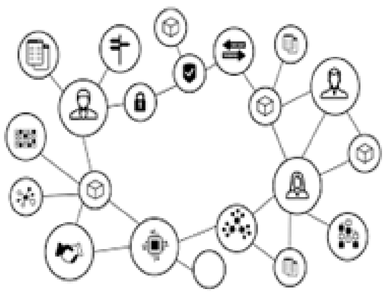


- Retailers put much effort in enhancing recommendation accuracy
  - "Given a dollar to invest in the company and the choice to use it for marketing, product, or data science, we'd almost always choose data science" (Allana Hale, Stitch Fix CEO)

Motivation

Recommendation accuracy and the quantity decision

- What is its impact on the TBYB quantity decision?



Improved accuracy

Send more or less?

Objective 2: In anticipation of a change in recommendation accuracy, uncover the relationship with the optimal quantity decision

Model

Consider a retailer selling its products belonging to a certain product category to a representative consumer

Sequence of events

The retailer sends n items to the representative consumer

The consumer determines the items to keep

The retailer's profit is realized based on sales/returns

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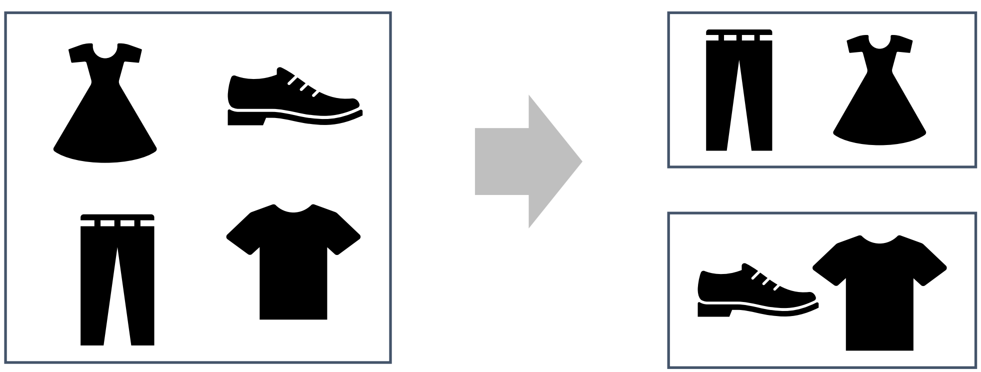

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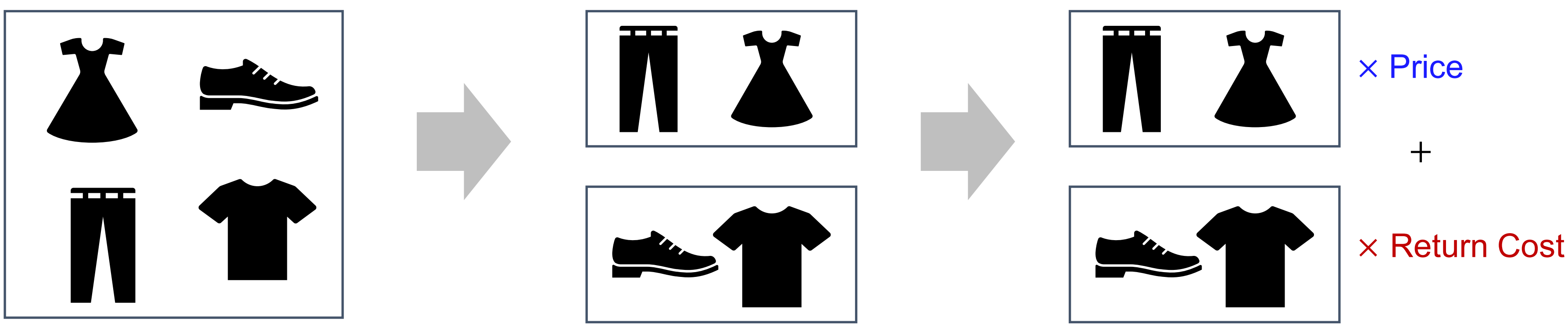


Model

Consumer Decision Process

- Consumer's utility for each product $i \in \{1, \ldots, n\}$: $u_i = \theta_i - p$

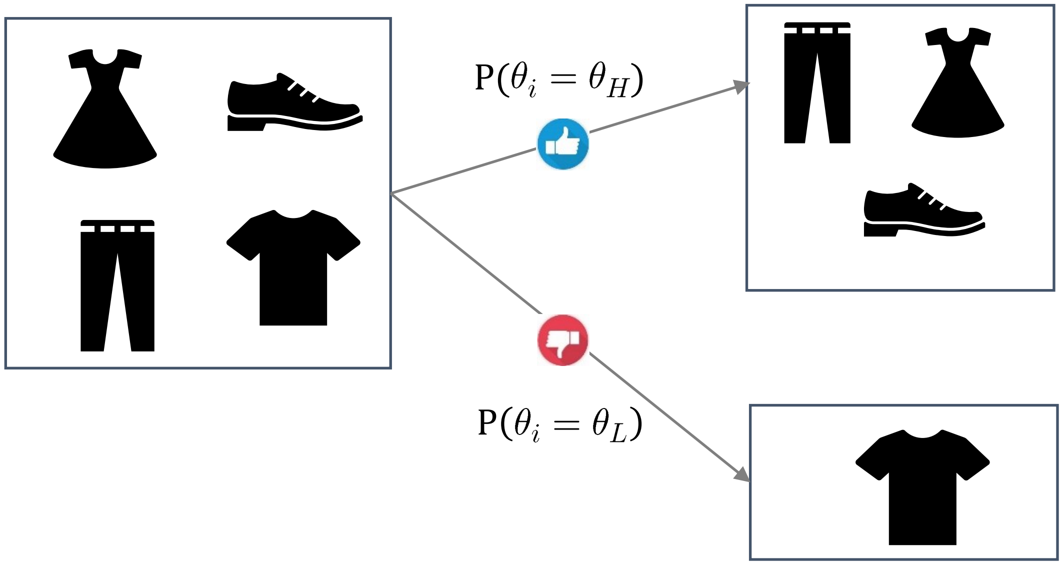
- For each item, θ_i is realized as either θ_H ("like") or θ_L ("dislike") depending on recommendation accuracy $\beta \in [0,1]$

- Model the decision as a 2-step process: categorization $\Rightarrow$ selection

Model

Consumer Decision Process

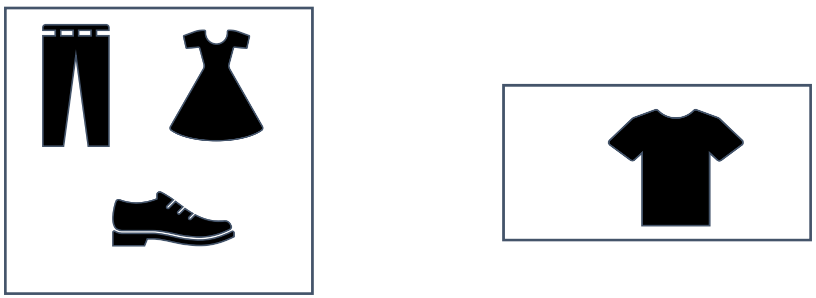
- **Categorization**: Group the products into the "like" category and "dislike" category



Model

Consumer Decision Process

- **Selection**: Purchase “like” items (l) up to her budget constraint (reflected as maximum purchase quantity x)
  - $l \geq x$ case: Purchase all the like ones



  - $x < l$ case: Purchase $x - l$ items and return remaining ones

  - In sum, purchase the quantity $\min\{l, x\}$

Model

The Retailer's Profit

- Profit is realized based on sales and return quantities

$$\Pi_R = p\mathsf{E}(q|n) - \alpha(n - \mathsf{E}(q|n)).$$

- Price p is assumed to be fixed
- Unit return cost α is assumed to be constant within a firm

Overview

- Consider $x = 1$ case first
  - Derive optimal TBYB quantity
  - Conduct sensitivity analysis w.r.t recommendation accuracy
- Then, extend the analysis to general x case
  - Focus on how the presence of x influences the results under $x = 1$ case
- As an extension, relax the random selection assumption

Consumer's Expected Purchase Quantity

- Obtained as:

On the receipt of n products, a consumer's expected purchase quantity $\mathsf{E}(q|n)$ is obtained

$$\mathsf{E}(q|n) = 1 - (1-\beta)^n. \qquad (4)$$

- Increasing in n and β

Optimal TBYB quantity decision

- Marginal benefit and cost of sending additional unit to the consumer

$$\frac{\partial \Pi_R(n)}{\partial n} = \underbrace{p\,\frac{\partial \mathsf{E}(q|n)}{\partial n}}_{\text{marginal sales benefit}} - \underbrace{\alpha\,\frac{\partial (n - \mathsf{E}(q|n))}{\partial n}}_{\text{marginal return cost}}.$$

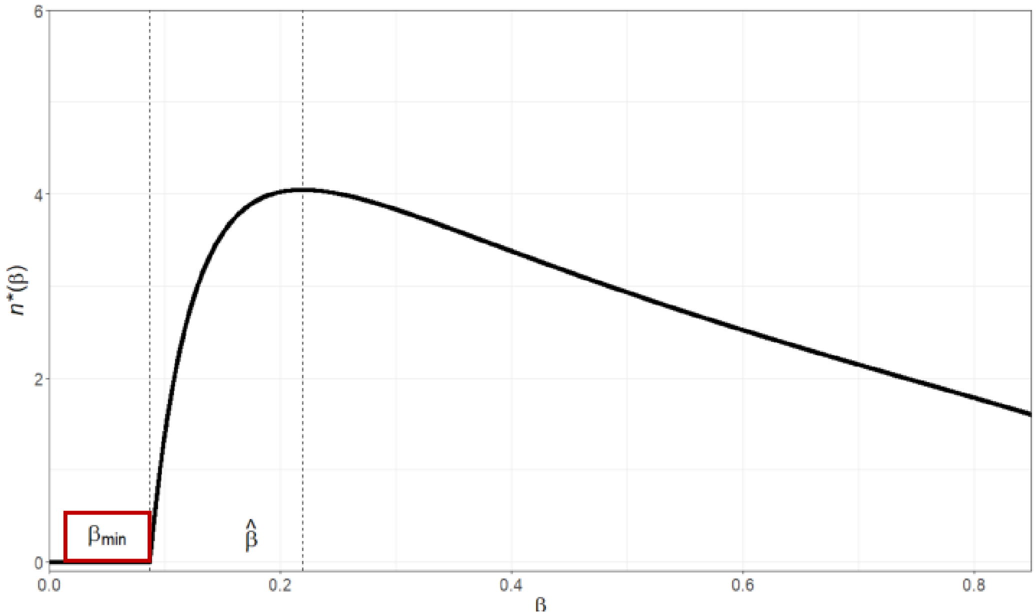
- Optimal decision
  - The quantity eliciting Marginal benefit $=$ Marginal cost
  - Obtained as:

The retailer's optimal TBYB quantity n^* that maximizes $\Pi_R(n)$ is obtained as

$$n^* = \begin{cases} \frac{\ln \frac{\alpha}{p+\alpha} - \ln(-\ln(1-\beta))}{\ln(1-\beta)} & \text{if} \quad \alpha < \frac{p \ln(1-\beta)^{-1}}{1+(1-\beta)}, \\ 0 & \text{otherwise.} \end{cases}$$

Impact of recommendation accuracy on the optimal TBYB quantity

The impact of recommendation accuracy (β) on the optimal TBYB quantity (n^*)



Minimum recommendation accuracy
(Entry barrier of TBYB)

Impact of recommendation accuracy on the optimal TBYB quantity

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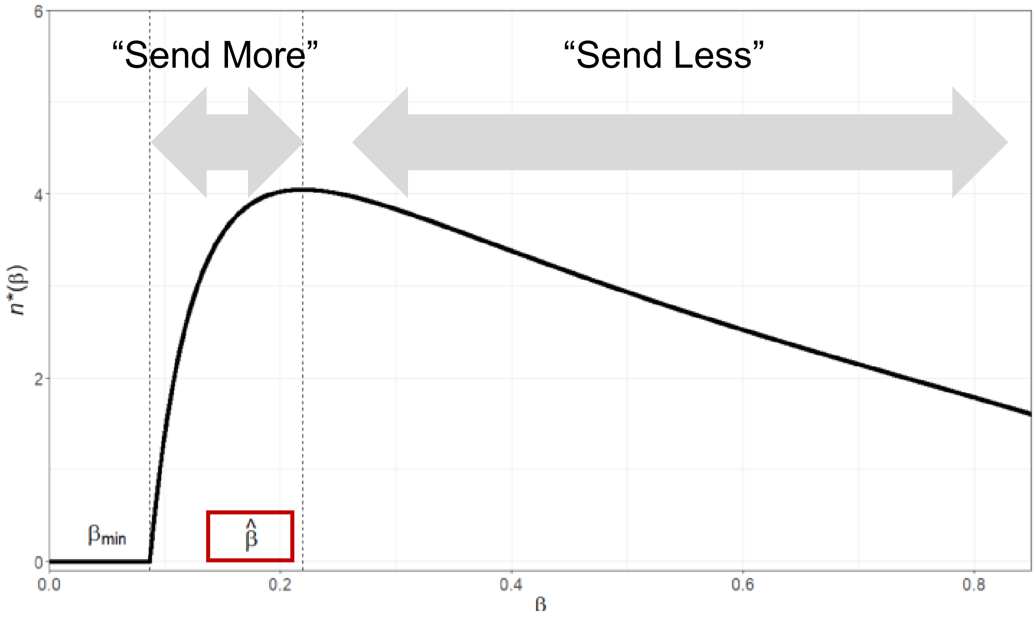


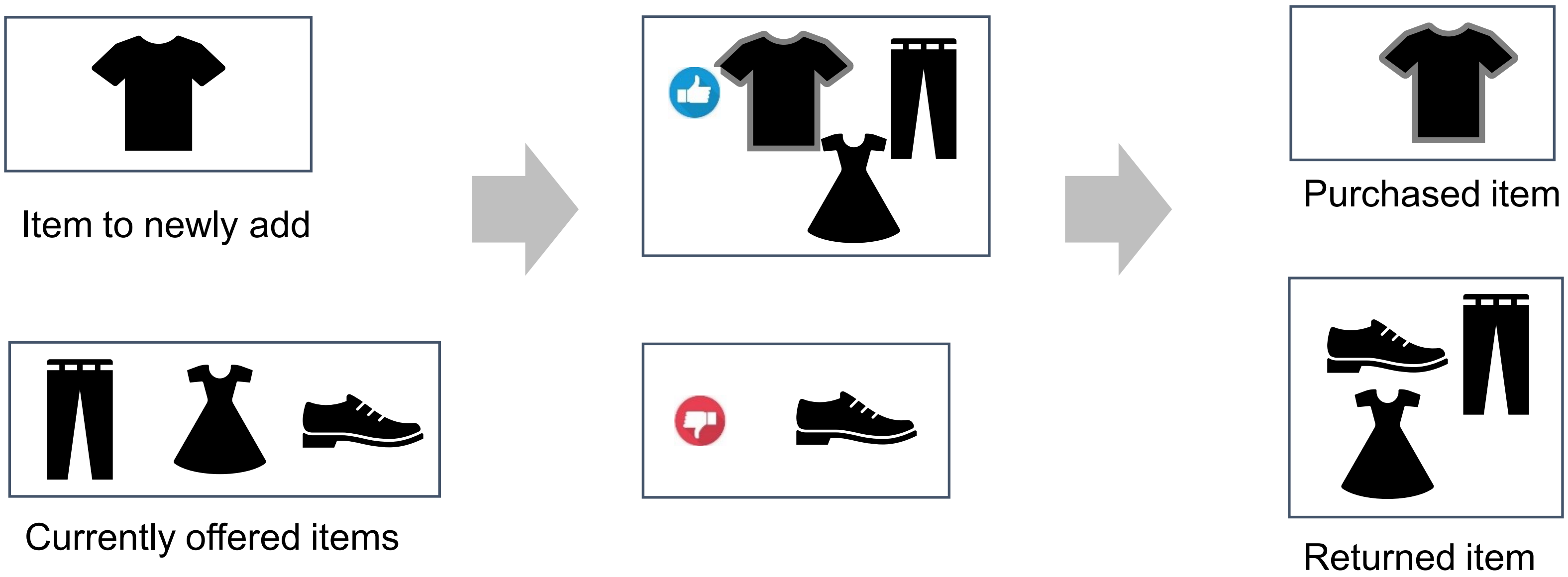
From "Send More" ($\frac{\partial n^*(\beta)}{\partial \beta} > 0$) to "Send Less" ($\frac{\partial n^*(\beta)}{\partial \beta} < 0$)

Results

Impact of recommendation accuracy on the optimal TBYB quantity

- With respect to an increment in β, does the retailer find it profitable to send an additional item?
  - $\text{Prob(the new item is purchased)}$ matters!

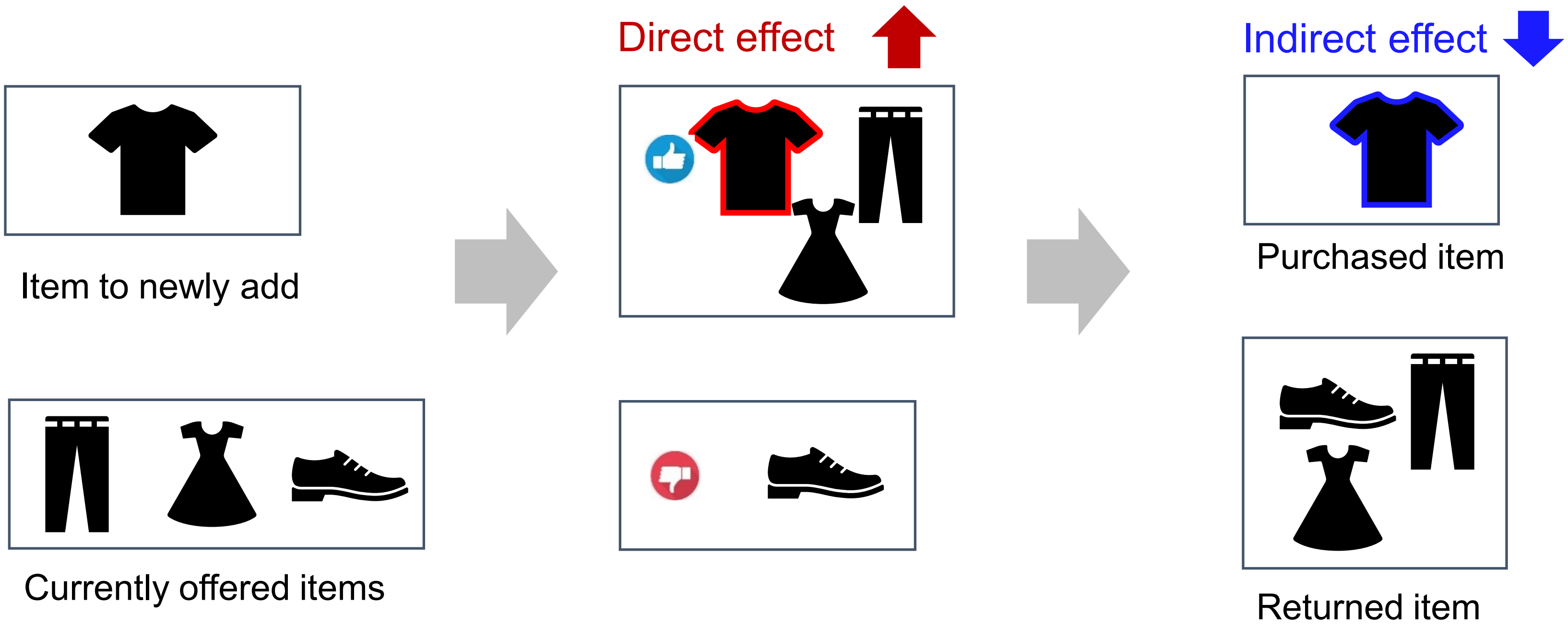
- The new one is purchased only if following conditions are met:



Results

Impact of recommendation accuracy on the optimal TBYB quantity

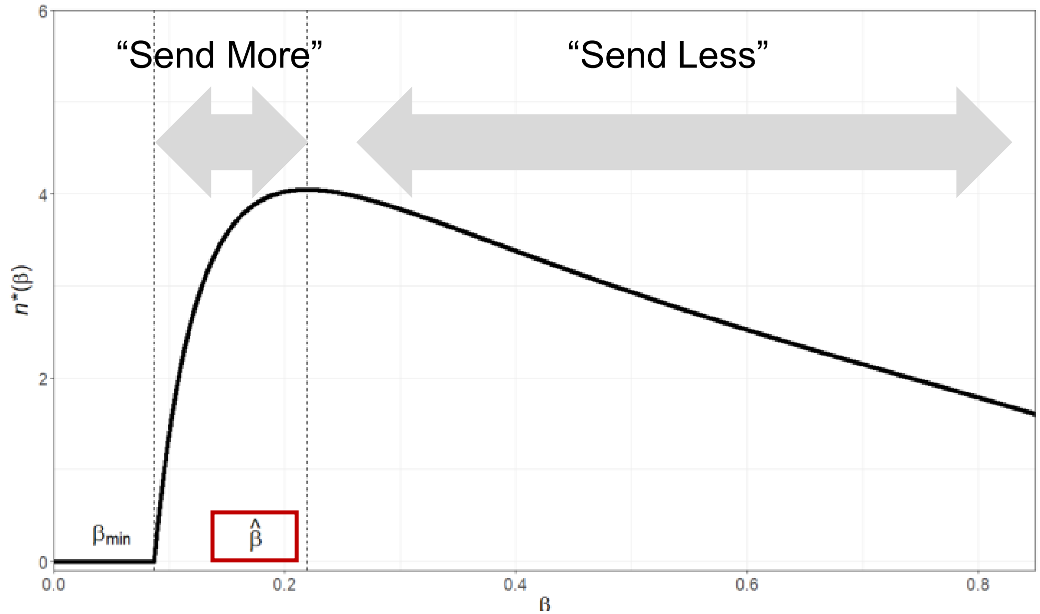
- Enhanced accuracy causes two countering effects on the probability:
  - Increase the prob of becoming "like" (**direct effect**)
  - Reduce the prob of being chosen instead of others (**indirect effect**)



  - Relative size between the two depend on # of currently offered items

Impact of recommendation accuracy on the optimal TBYB quantity

The impact of recommendation accuracy (β) on the optimal TBYB quantity (n^*)



direct effect $>$ indirect effect

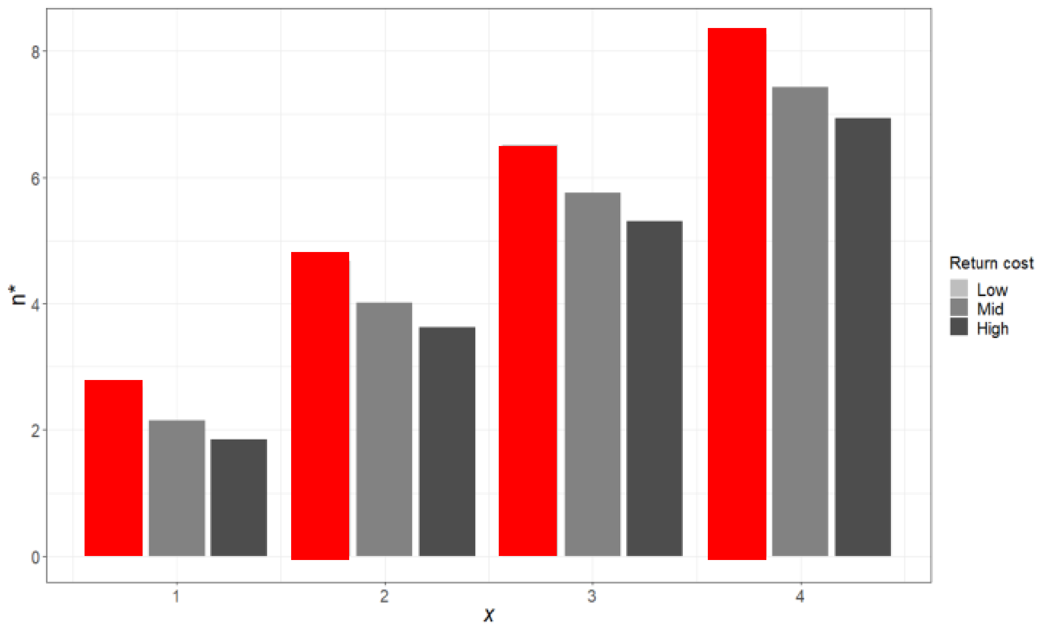
direct effect $<$ indirect effect

Results

Generalization: Maximum purchase quantity $x \geq 2$

- Result 1: Having higher budget increases the optimal TBYB quantity

Figure 2: The effect of maximum purchase quantity (x) and return cost (α) on the optimal TBYB quantity (n^*)

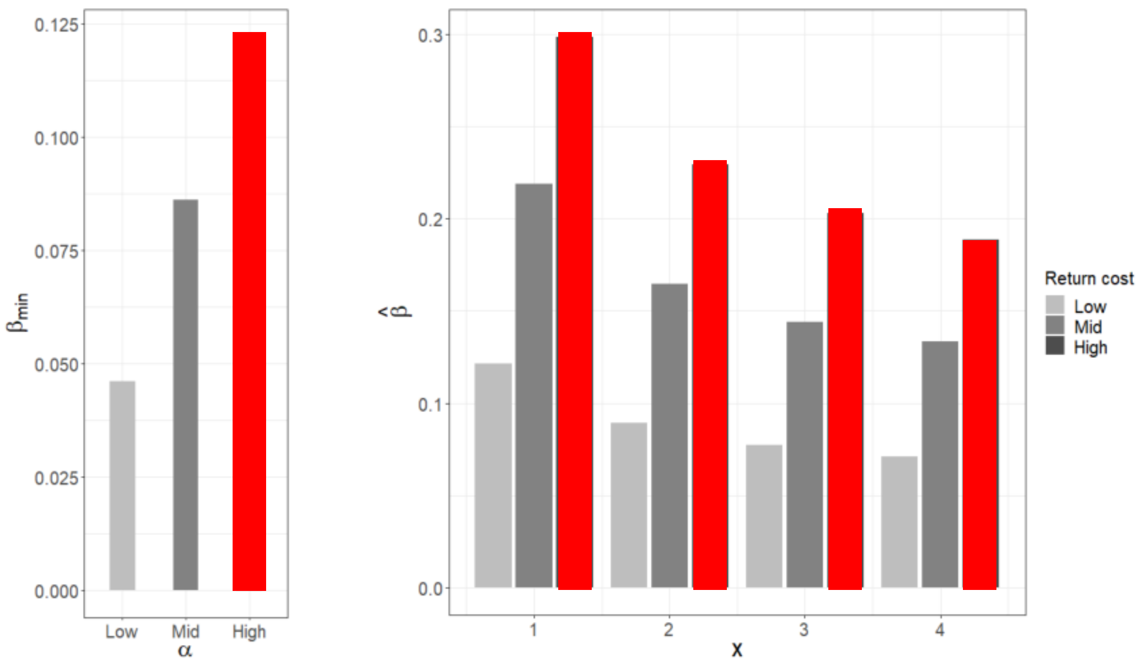


- Implication: TBYB quantity personalization

Generalization: Maximum purchase quantity $x \geq 2$

- Result 2: Impact of x on min accuracy β_{min} and switching point $\widehat{\beta}$

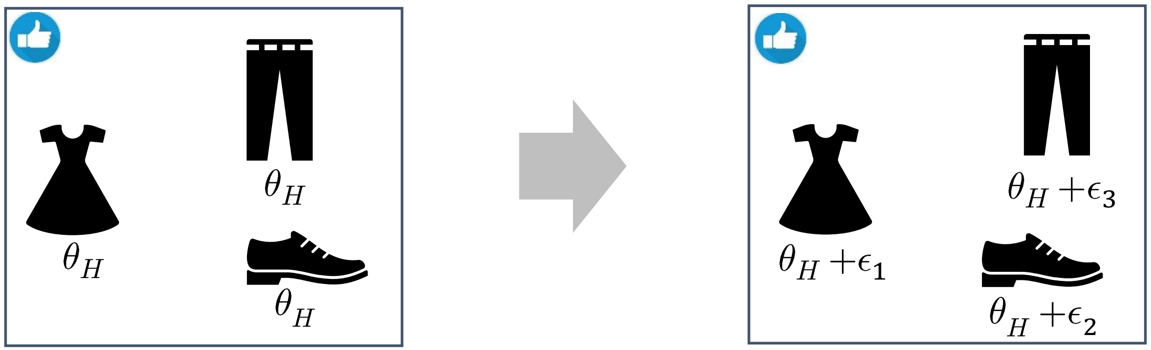
Figure 3: The effect of maximum purchase quantity (x) and return cost (α) on the minimum recommendation accuracy (β_{min}) and switching point ($\hat{\beta}$)



- Sufficient investment in recommendation accuracy is a prerequisite for implementing TBYB retail

Extension: Heterogeneous Valuation among the “Like” Items

- Model



  - θ_H is replaced with $\theta_H + \epsilon_i$ where ϵ_i is drawn from $U[-\bar{\epsilon}, \bar{\epsilon}]$

- Analysis
  - Now the consumer chooses the purchase item by comparing the utilities across the “like” items
  - Overall, key insight under $x = 1$ case continue to hold

Conclusion

What we do:

- Consider a retailer's TBYB quantity decision
- Develop a stylized model of quantity decision taking account consumers' purchase decision process
- Analyze optimal quantity decision as well as the relationship between the recommendation accuracy and the optimal quantity

One of the first study to address TBYB retailer's problem in its operations management