Modeling Consumer Preferences and Price Sensitivities from Large-Scale Grocery Shopping Transaction Logs

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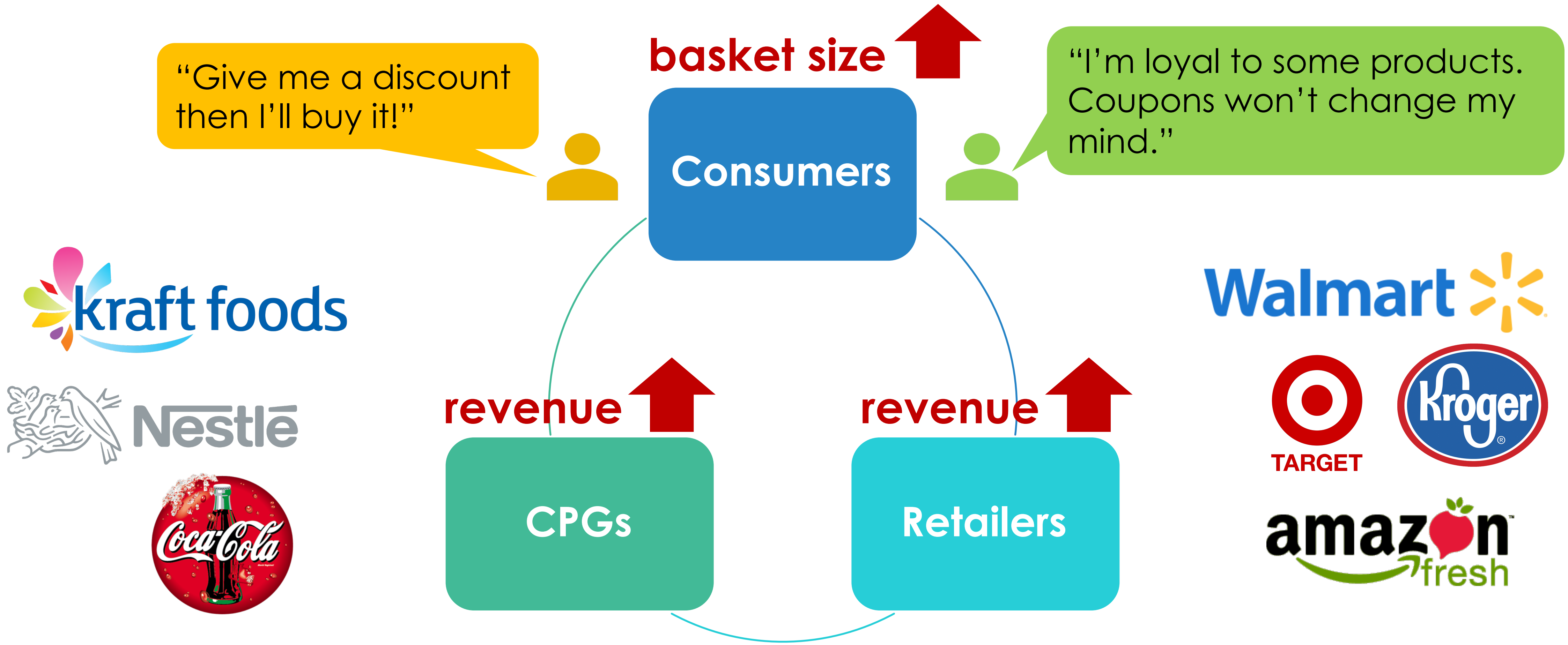
Right Products w. Right Coupons to Right Consumers!



*Transaction Logs (with **Price**!); Product info.; Demographics etc.* → **Consumer Behavior Model** *(preference & price sensitivity)* → *Optimizer* → *Product Recommendation; Personalized Promotion*

CPGs: consumer packaged goods companies

Preference & Price Sensitivity

. . . ⇨ **Consumer Behavior Model** *(preference & price sensitivity)* ⇨ . . .

- Preference: what kind of products people would like to buy
  - Recommender System
  - Purchase Probability / Quantity
- Price-sensitivity: what kind of products people would be more likely to buy if the price drops
  - Demanding System
  - $elasticity = (\frac{\Delta Quantity}{Quantity})/(\frac{\Delta Price}{Price})$ or $elasticity = (\frac{\Delta Probability}{Probability})/(\frac{\Delta Price}{Price})$
  - Price elasticity is usually negative, where larger absolute value -> more price sensitive

Challenges

- Recommender System
  - Price is barely considered
  - Interpretability
- Economics/Marketing
  - Scalability
  - Handcrafted consumer segmentation
- By connecting them …
  - Interpretable, Scalable, Personalized

Modeling Grocery Shopping Behavior

- **INPUT:** User ID, Item/Category ID, Features (temporal/geo info., item info.– price!, user demographics, etc.)
- **OUTPUT:** preference prediction, price elasticity

Category Purchase

1. Buy or not?

Yes!

Product Choice

2. Which product?

Selected!

Purchase Quantity

3. How many?

Method (Preference Scoring Function)

- A Unified Feature-Based Matrix Factorization (FMF): $link(Y(t)) = L(t) = \Phi(t)^T\Psi(t)$

price!

$$l_{i,u}(t) \approx \langle \phi_i(t), \psi_u(t)\rangle = \underbrace{\Big\langle w\ , \overbrace{\tilde{g}_{i,u}(t)}^{\text{global features}}\Big\rangle}_{\text{global effect}} + \underbrace{\Big\langle \overbrace{\tilde{\phi}_i^{(o)}(t)}^{\text{item features}},\ \psi_u^{(o)}\Big\rangle + \Big\langle \phi_i^{(o)}\ , \overbrace{\tilde{\psi}_u^{(o)}(t)}^{\text{user feature}}\Big\rangle}_{\text{observed item/user-specific effect}} + \underbrace{\Big\langle \phi_i^{(l)}, \psi_u^{(l)}\Big\rangle}_{\text{latent item-user interaction}}$$

Binary | Multi-Class | Positive Integer

Category Purchase

1. Buy or not?

('Logistic Regression')

Yes!

Product Choice

2. Which product?

('Multinomial Logistic')

Selected!

Purchase Quantity

3. How many?

('Poisson Regression')

Method (Advantages)

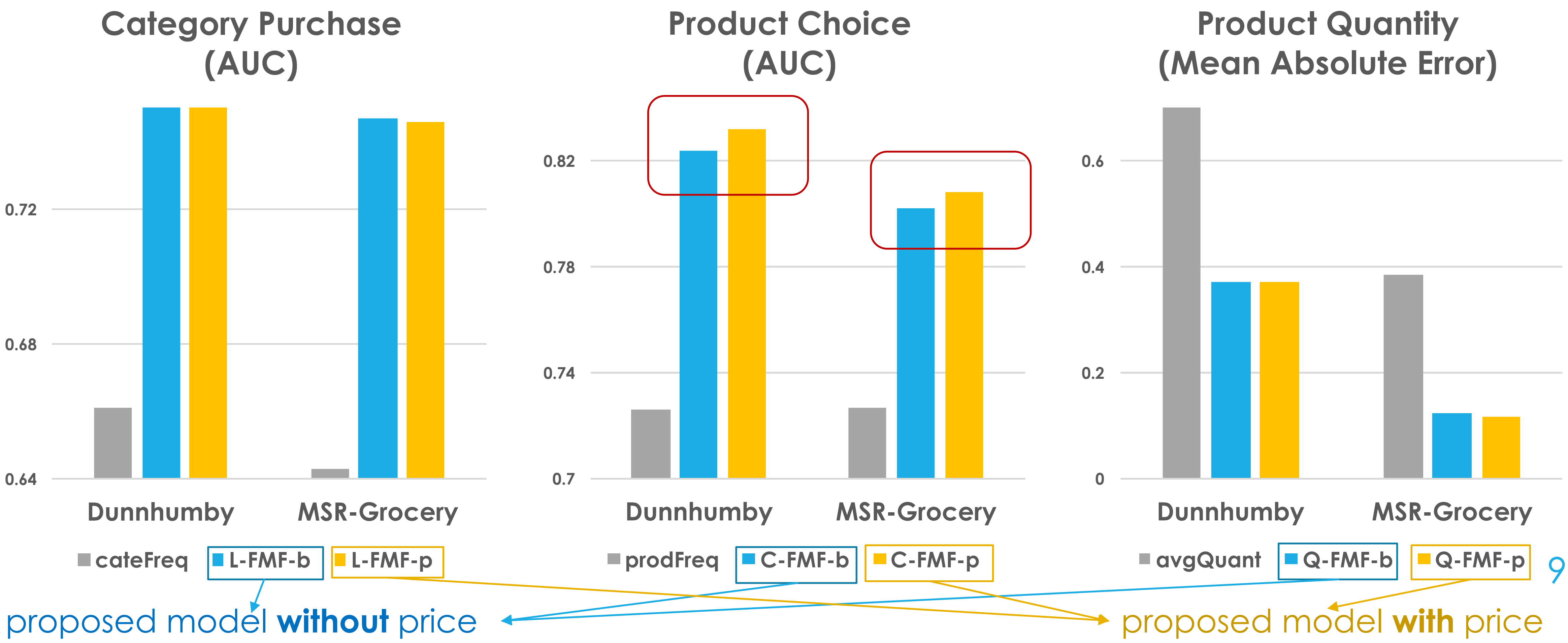
- Scalable
  - Inherit the scalability of Matrix Factorization
- Parallel
  - Three stages do not share parameters
- Flexible
  - Easy to adjust based on conditions
- Personalized
  - No need to do consumer segmentations beforehand

Experiments (Datasets)

- Dunnhumby (household-level data) [1]
  - 531,201 product transactions, 98,020 trips, 799 users, 4,247 products, 108 stores, 104 categories
  - Features: price, day-of-week, household demographics, product info etc.
- MSR-Grocery (individual, convenient store)
  - 152,021 products transactions, 53,075 trips, 1,288 users, 1,929 products, 55 categories
  - Features: price, day-of-week, product info etc.

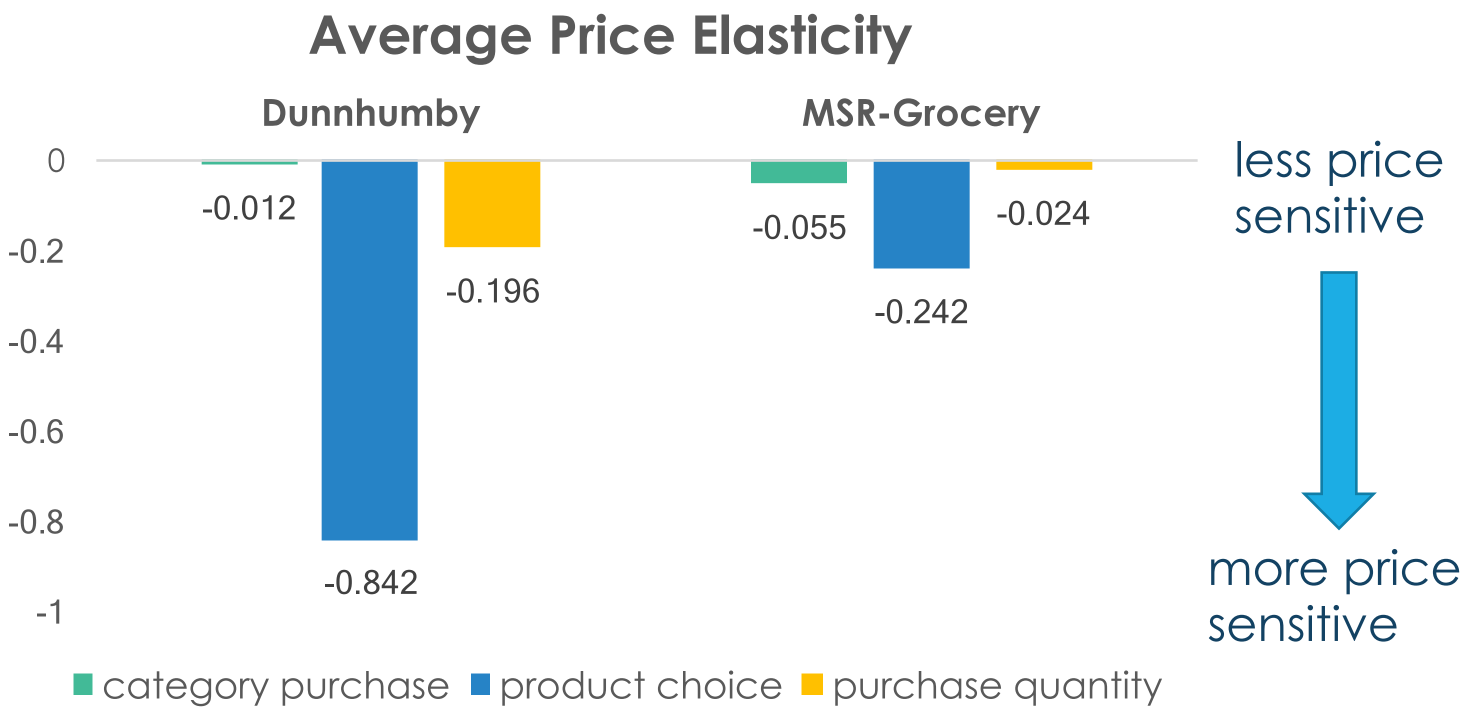
[1] https://www.dunnhumby.com/sourcefiles

Results (Preference)



Results (Price Elasticity)

- Product choice is the most price sensitive stage
- Consumers in *Dunnhumby* (households) are less price sensitive in category purchase, but more price sensitive in product choice and quantity, than those in MSR-Grocery (convenient store)



Coupons are primarily effective "within category"!

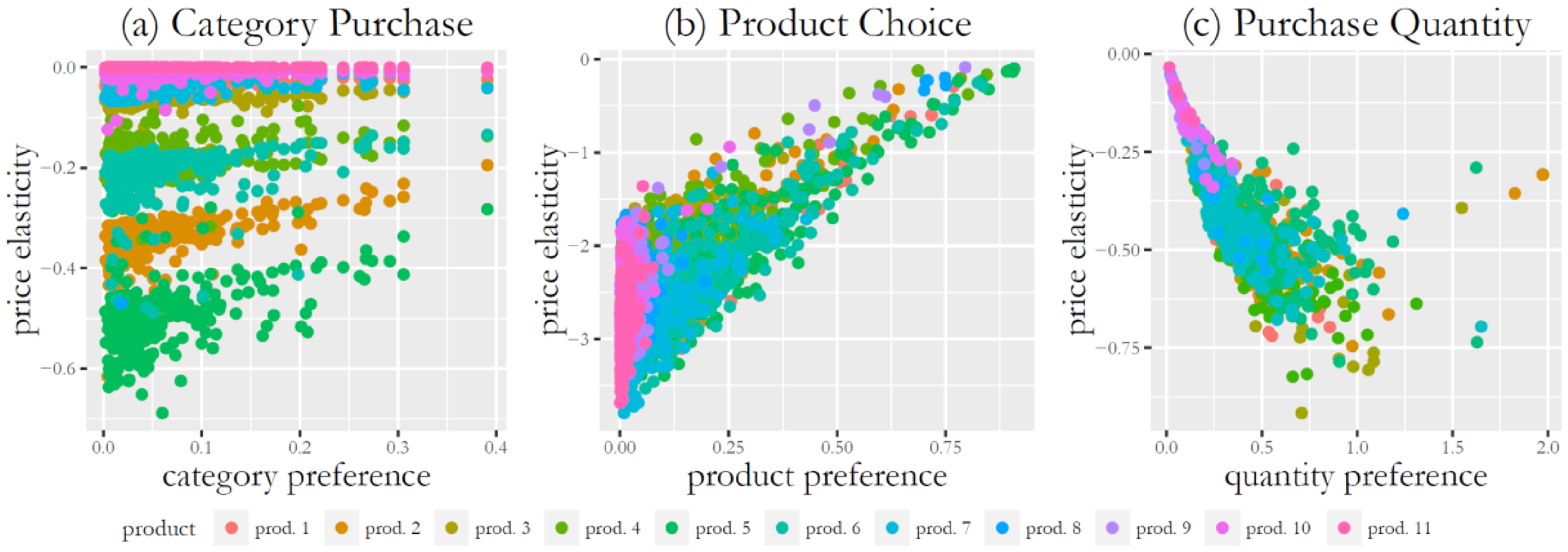
Case Study: Bacon

X-axis: 10 users (randomly selected) Y-axis: 11 bacon products ordered by price (bottom to top)

- Different consumers may have different price sensitivities
- Do category promotions on popular products

Case Study: Bacon

Preference vs Price Elasticity

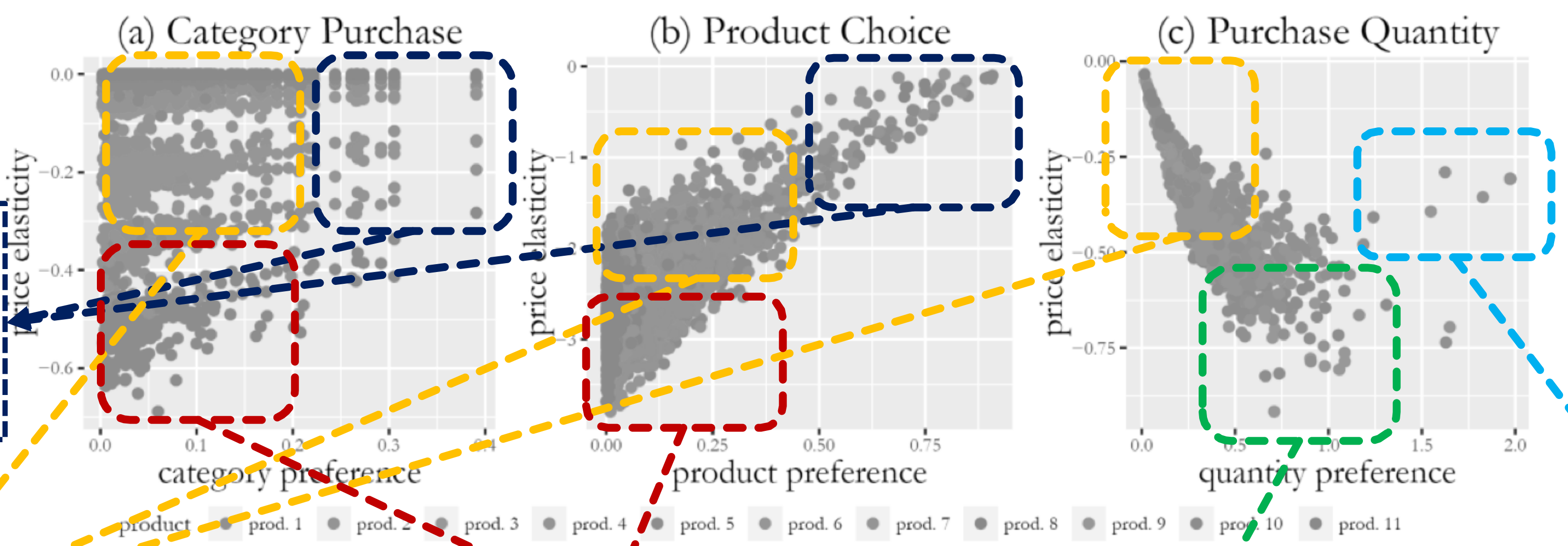


less price sensitive

more price sensitive

Case Study: Bacon

Preference vs Price Elasticity



High preference
Price **insensitive**
(they like it no matter how expensive it is)

less price sensitive

more price sensitive

Low preference
Price **insensitive**
(they dislike it)

Low preference
Price **sensitive**
(price is too high to afford)

Mid preference
Price **sensitive**
(aggressive buyer)

High preference
Price **insensitive**
(budget limit)

Conclusion and Future

- Three purchase stages
  - category purchase, product choice, purchase quantity
- A nested feature-based matrix factorization model (FMF)
  - Personalized
- Lots of economic insights
  - Coupons are primarily effective "within category"

- Temporal-aware model – long-term purchase patterns
- Complementary and Substitutes
- Optimization strategy to generate personalized coupons so that utilities can be maximized

Thanks!

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