Adaptive Preference Measurement with Unstructured Data, with Applications to Adaptive Onboarding Surveys

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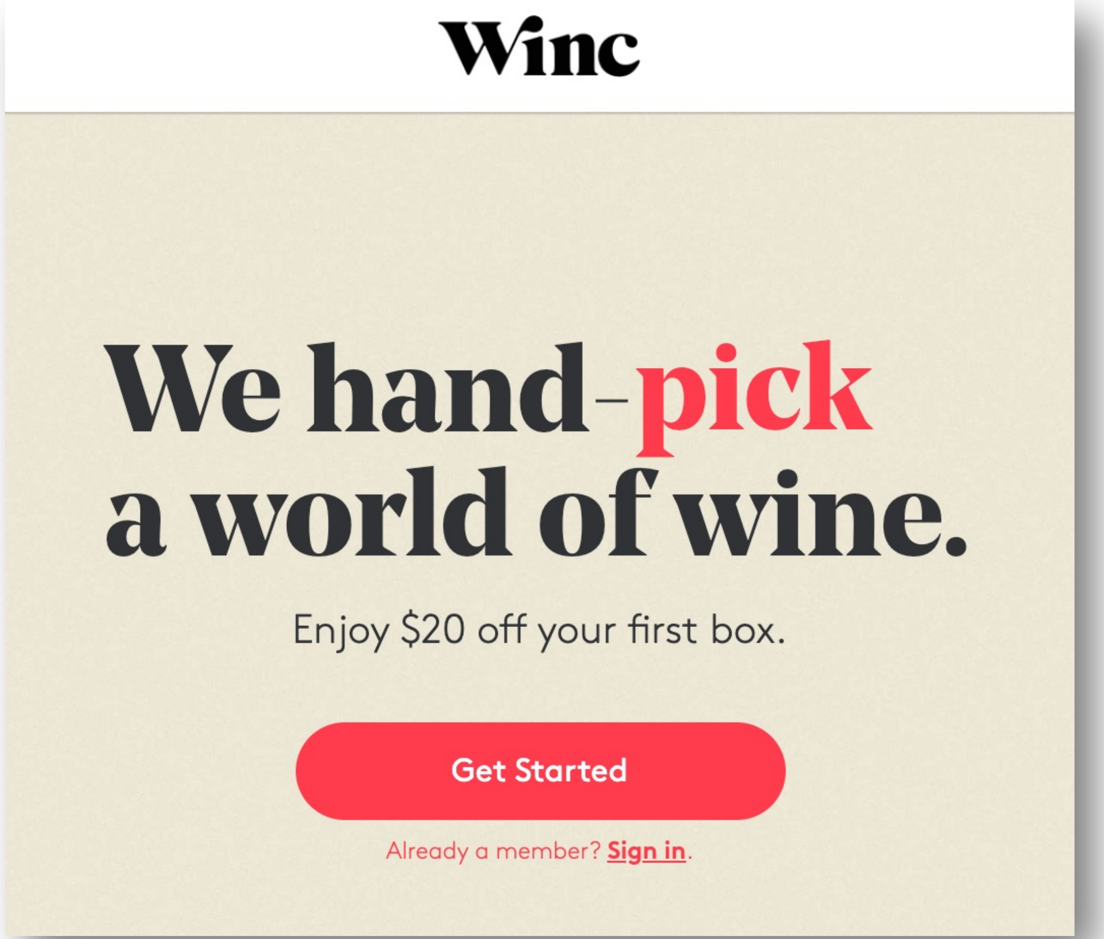
Subscription Boxes



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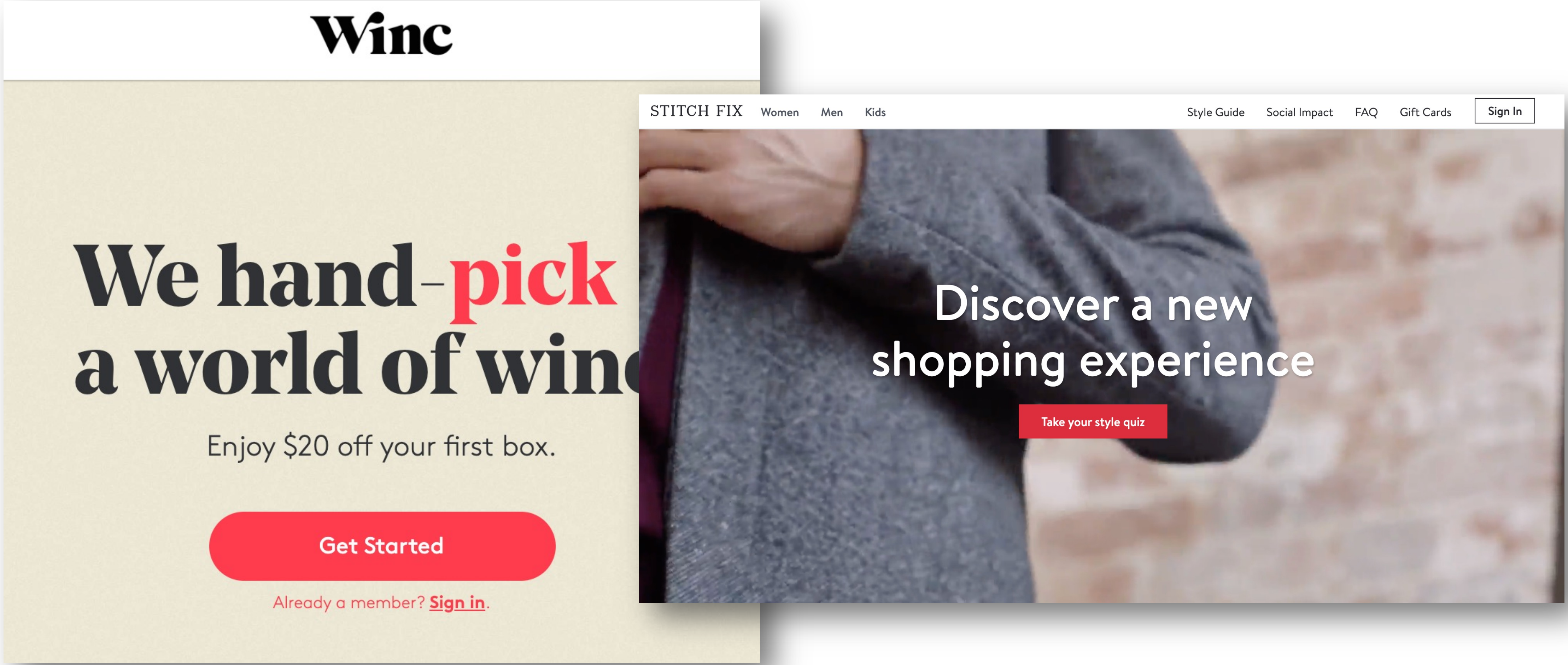
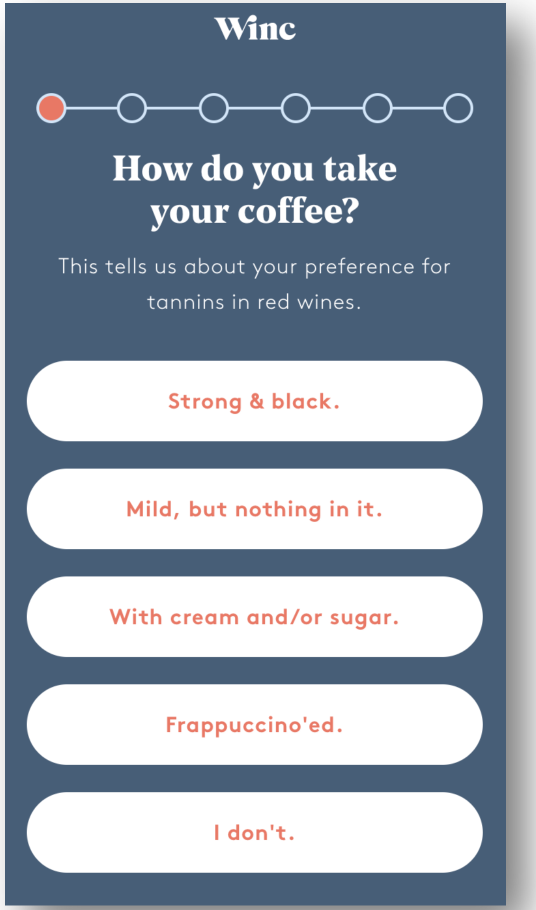
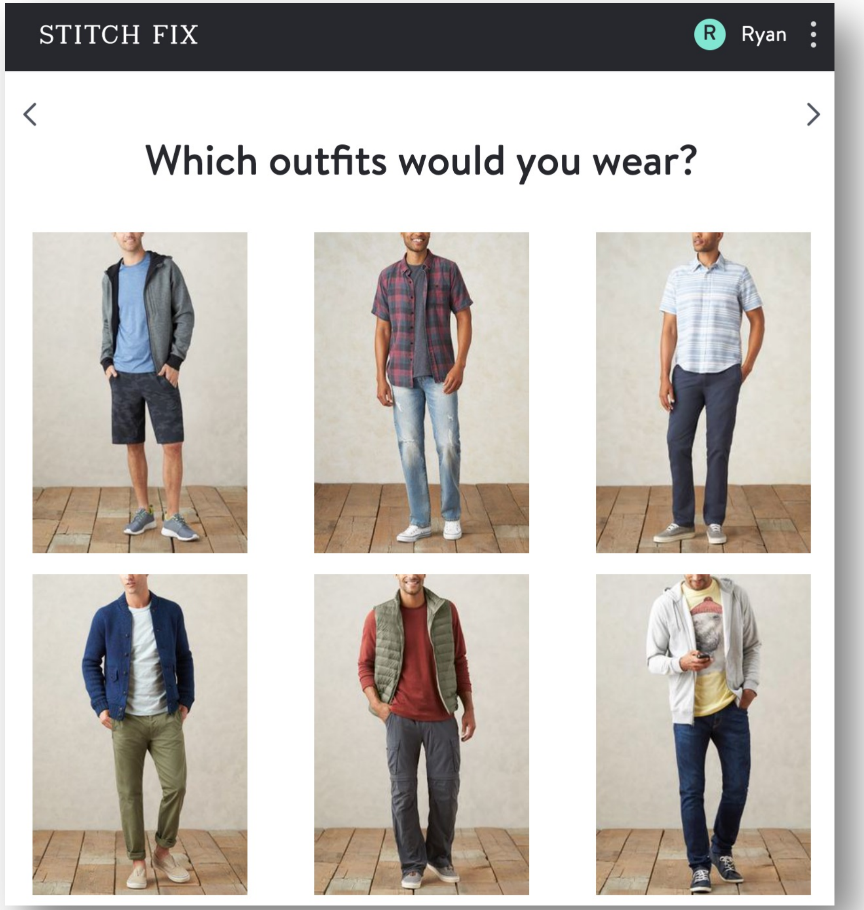


On-boarding Surveys





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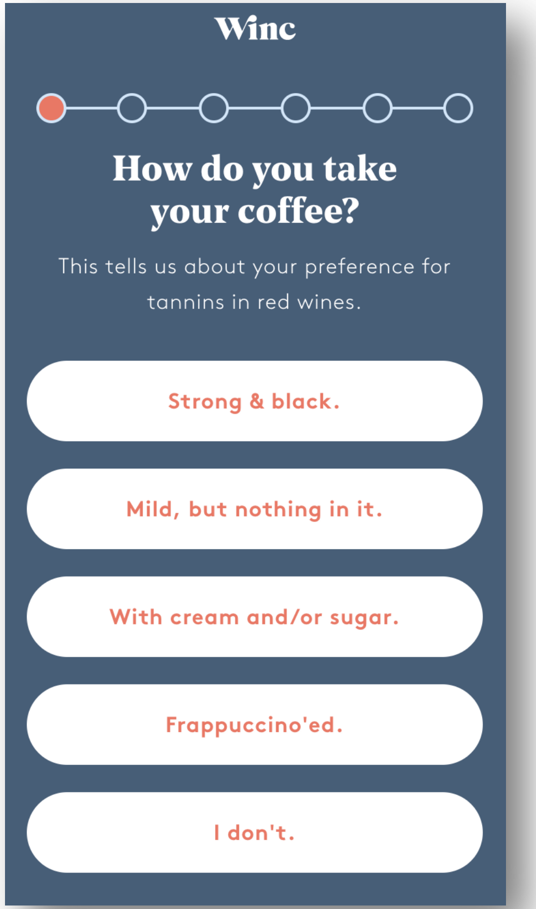

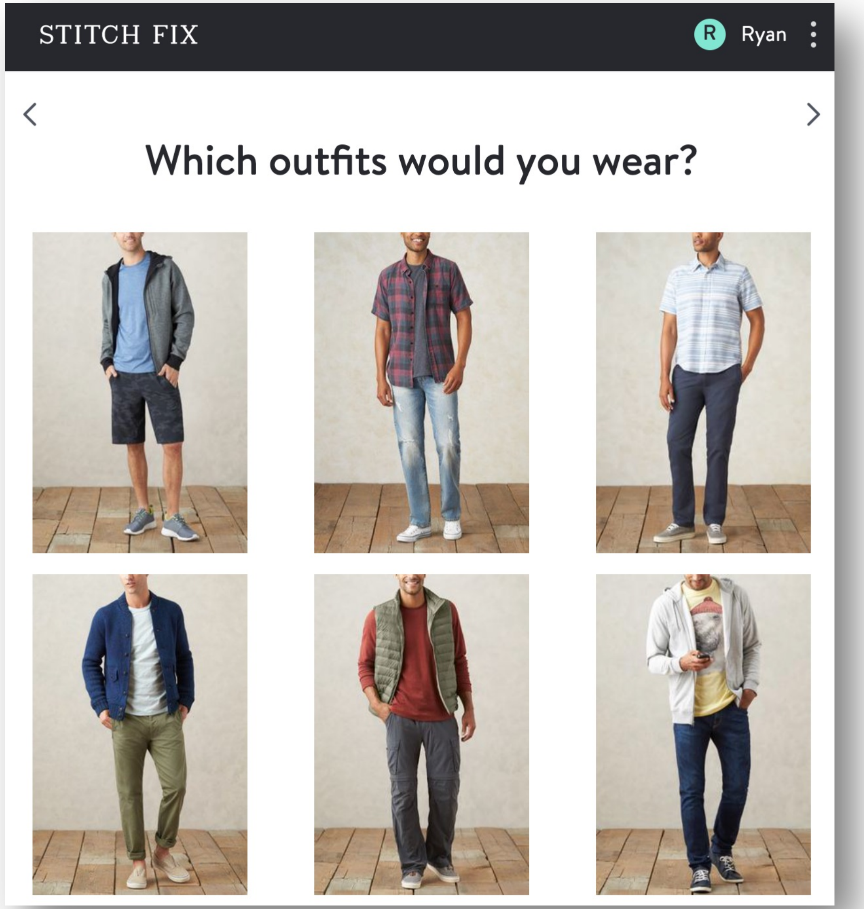

Different formats, same goal: **efficiently learn a user's preferences**

This Project

Representation Learning →

- Convert unstructured product data (images) to (numeric) vector representations

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Bayesian Optimization →

- Nonparametrically model person's utility function over representation space
- Adaptively select query points to reduce uncertainty

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=

Preference Measurement →

- Initializing recommendations and the on-boarding process
- Nonlinear preference prediction without resorting to pre-specified attributes/levels

Step 1: Representation Learning

Recommender-based

- Matrix factorization or modern neural collaborative filtering algorithms
- Produce representations of products as a “by-product” of learning: for person i, item j,

$$r_{ij} = u_i \cdot z_j$$

- Product representations are implicit: $z_1 = z_2$ if people tend to buy / like both products 1 and 2

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Feature-based

- Given features x_j, find a representation $z_j \in \mathbb{R}^K$ such that $x_j = f(z_j)$
- Numeric features: PCA
- Textual features:
  - Latent Dirichlet allocation
  - Embedding-based methods (doc2vec)
- Image features:
  - Variational autoencoders (VAE)
  - **Pre-trained / transfer learning**

Step 2: Bayesian Optimization

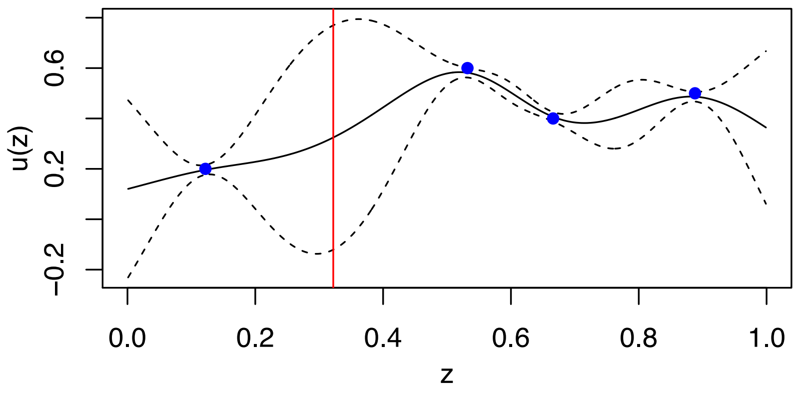
Quickly learn a user's utility over representations, u(z),
by having the user **rate** products

Model of the utility function:

$$u(z) \sim \mathcal{GP}(m(z), k(z, z'))$$

Likelihood of product ratings:

$$r_m \sim \mathcal{N}(u(z_{j_m}), \sigma)$$



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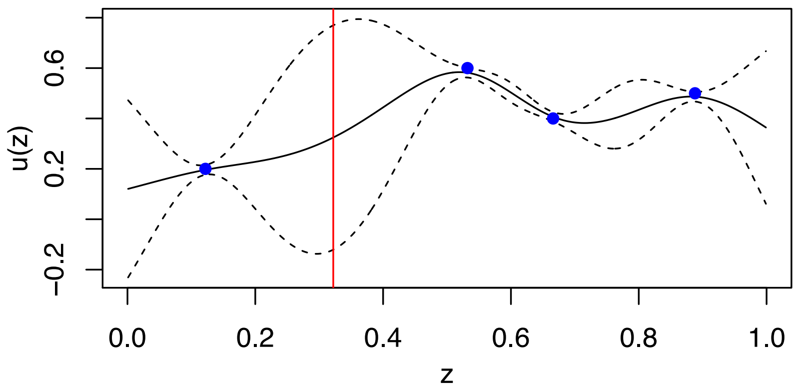
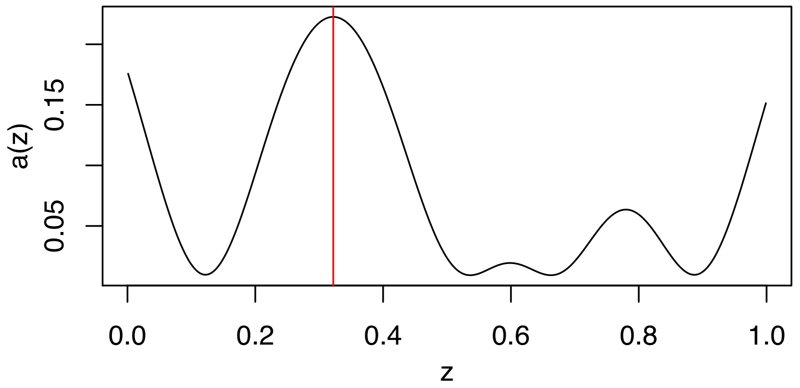
Acquisition function: select next user query based on uncertainty over u(x)

- Maximum Uncertainty (MU)
- Upper Confidence Bound (UCB)
- *Global Uncertainty Reduction (GUR)*





Experiments: Live Deployment of Method

Please rate the following dress
on a scale from 1-10.

Enter your rating for this dress

Submit

Which of these two dresses do you prefer?

or

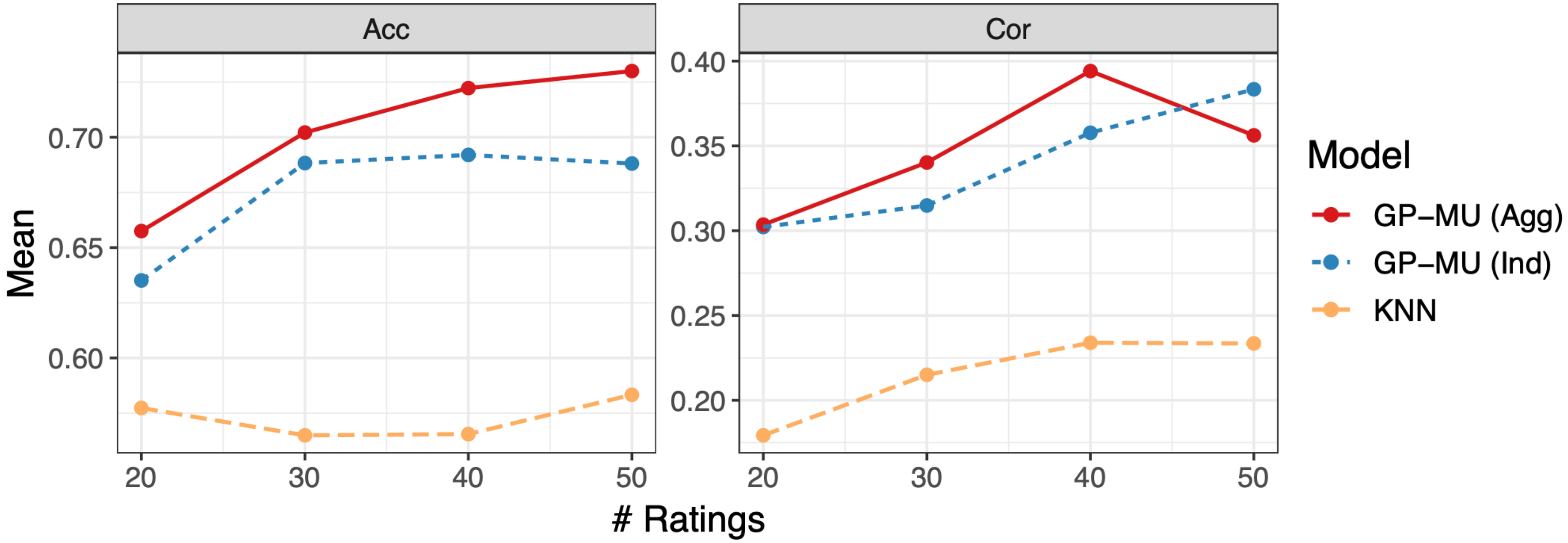
Enter your preference for the dresses

Strongly Prefer Left	Slightly Prefer left	Indifferent	Slightly Prefer Right	Strongly Prefer Right
○	○	○	○	○

Submit

Results

In live tests, we can identify meaningful utility functions **even with as few as 20 questions**, using just unstructured data



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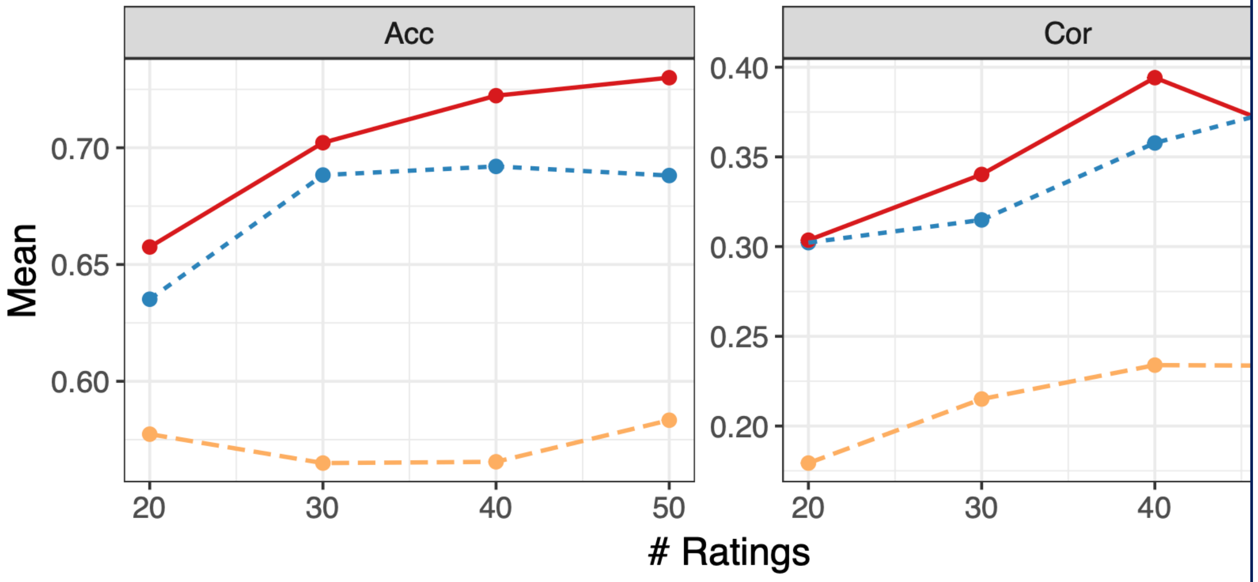

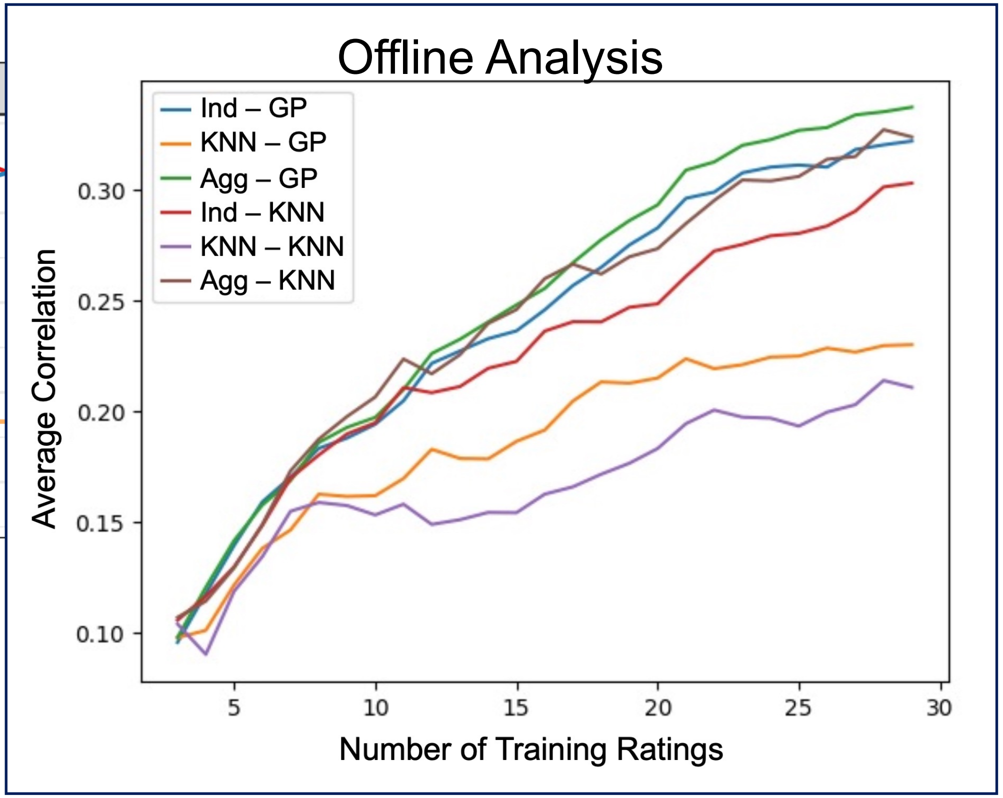

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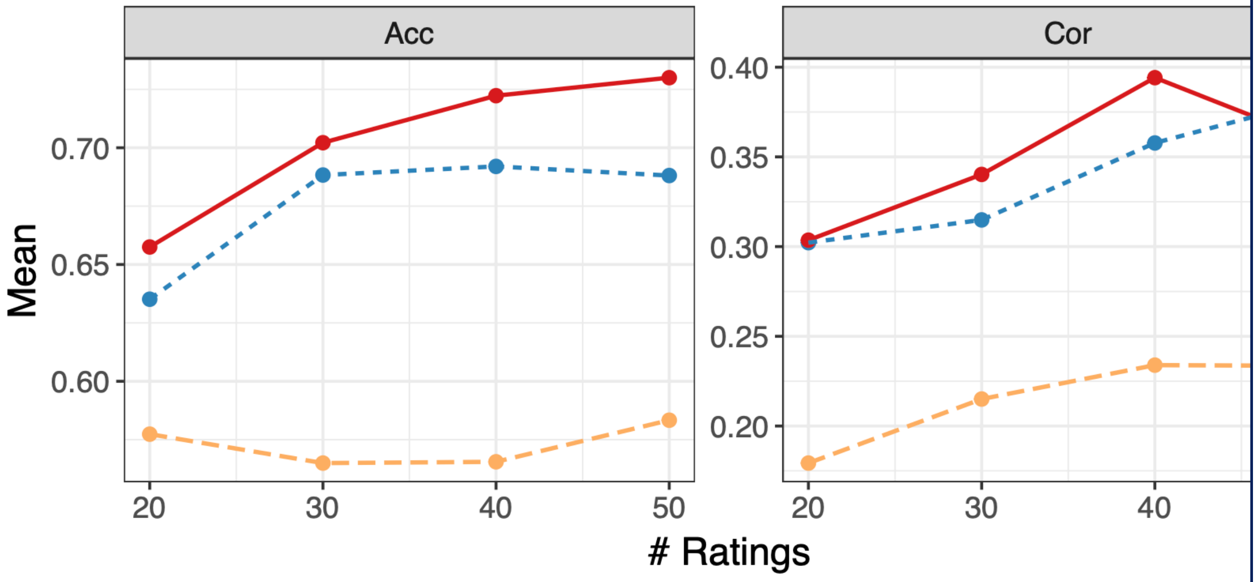

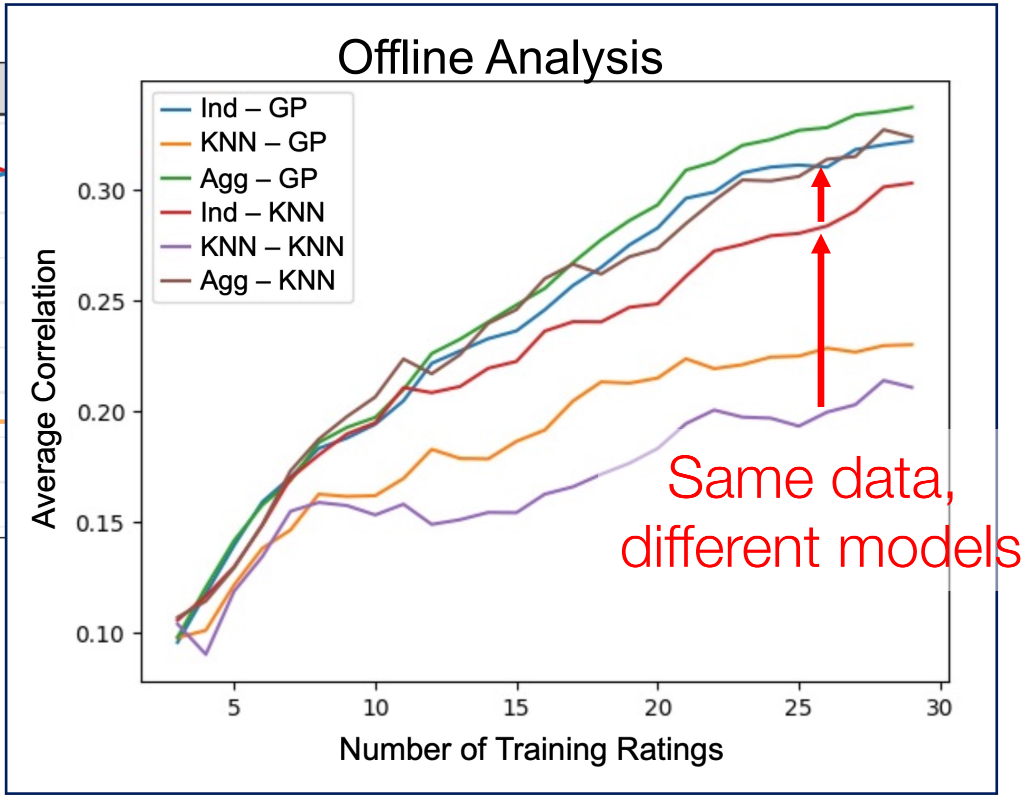

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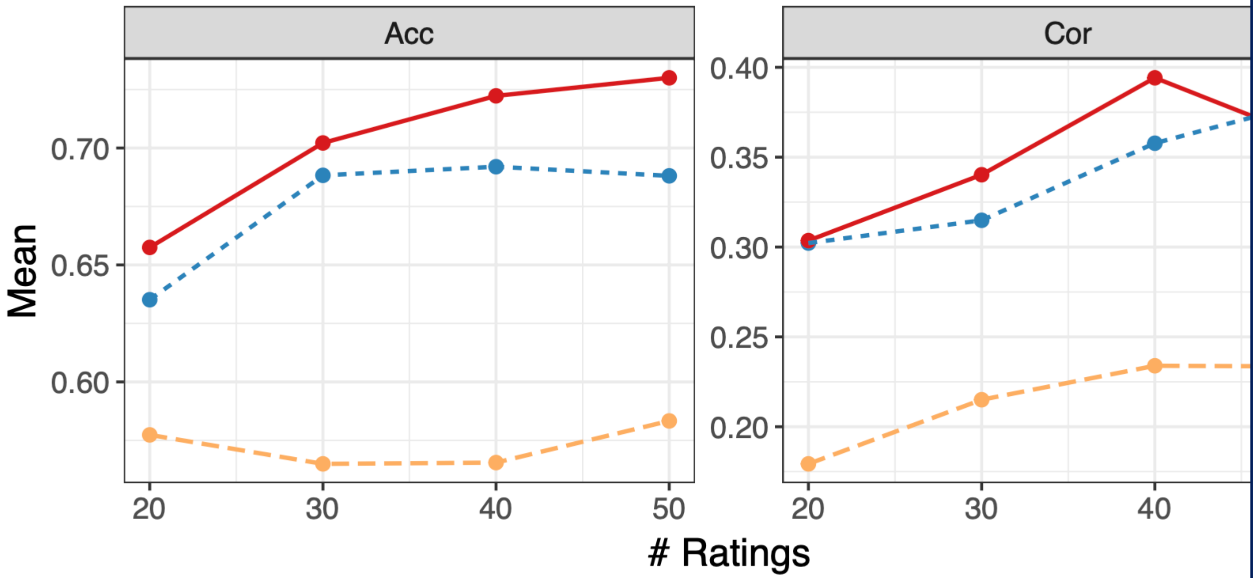

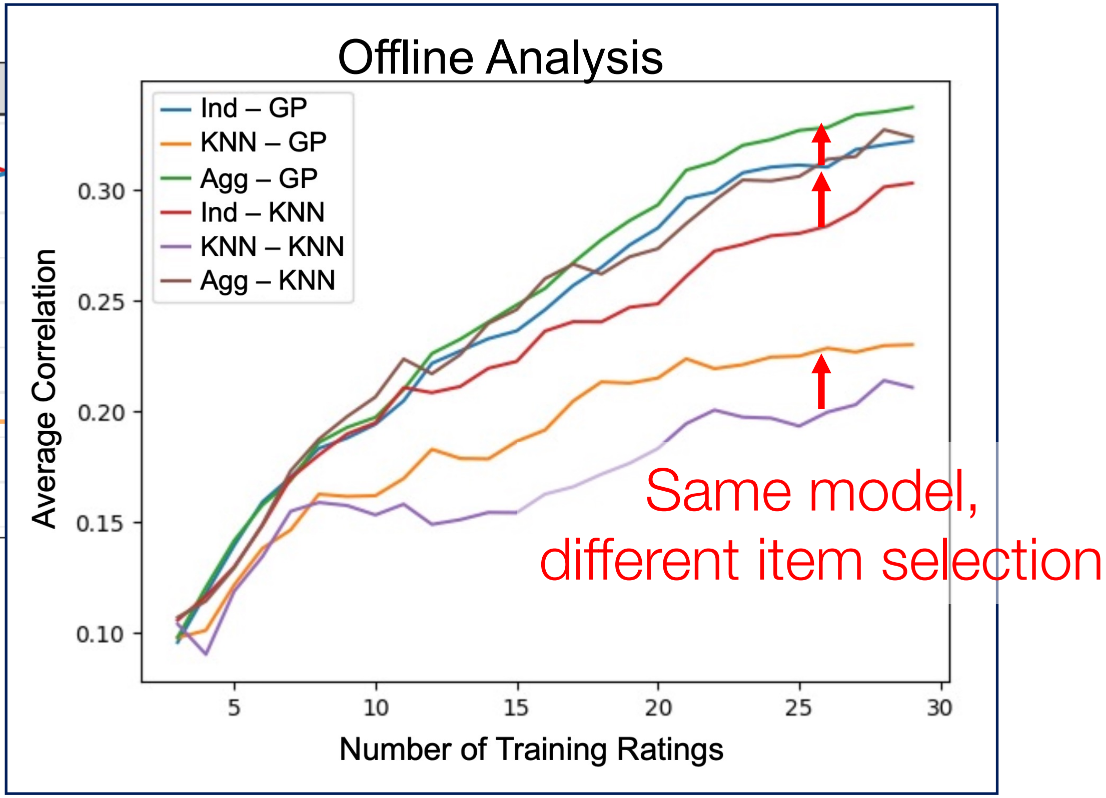

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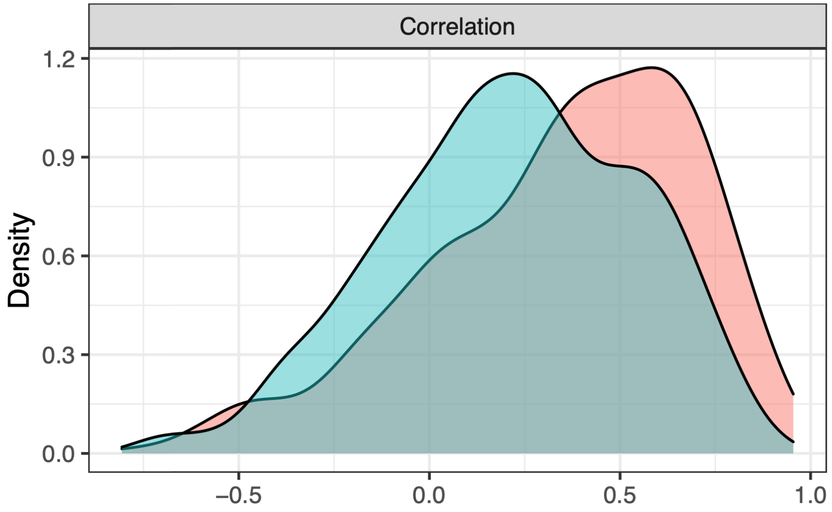

Figure 1: Distribution of individual-level correlations between predicted and actual item ratings for our method (red) versus a simple benchmark (blue)

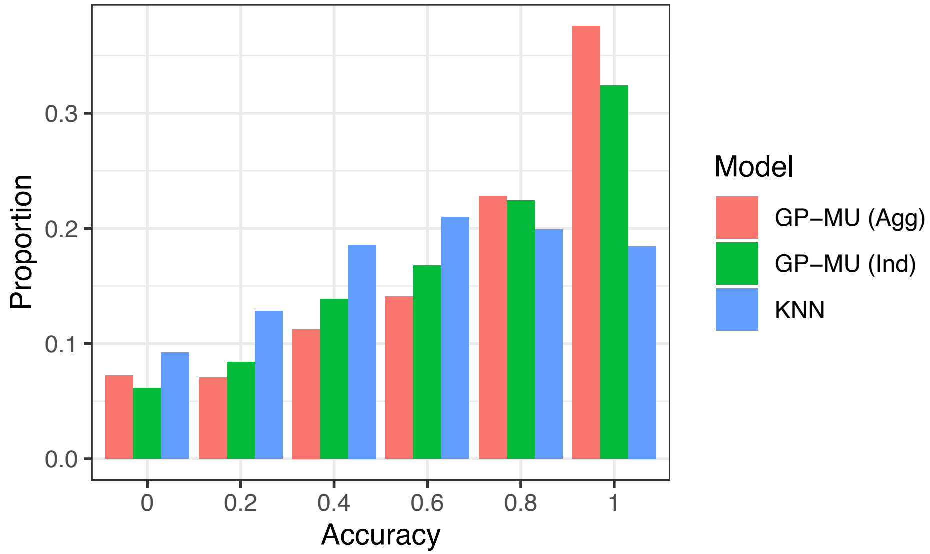

Figure 2: Comparison of three models in terms of correctly classifying whether a consumer would like 5 items. KNN is a k-nearest neighbors benchmark.

Interpretation: Implications for Research

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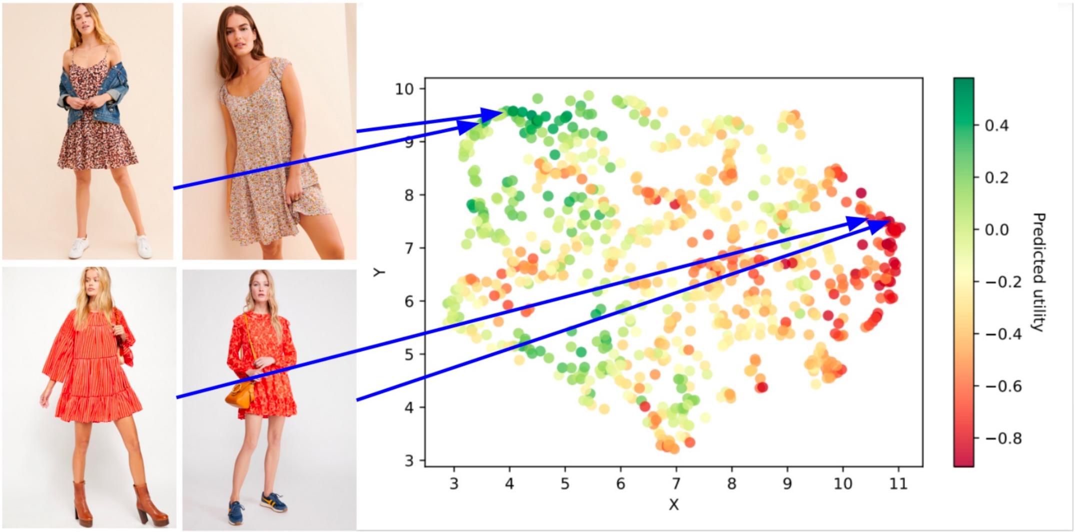
UMAP + Item Visualization



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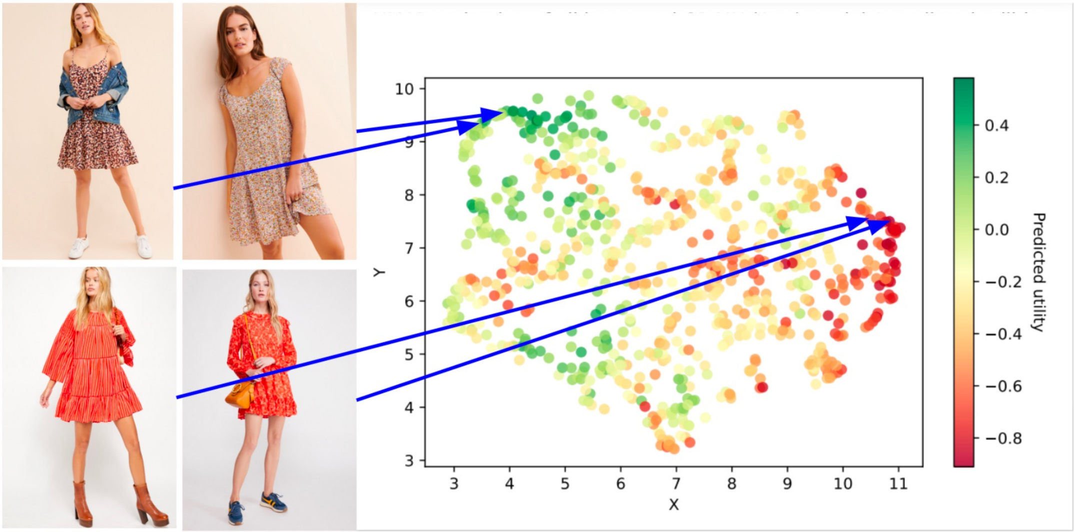
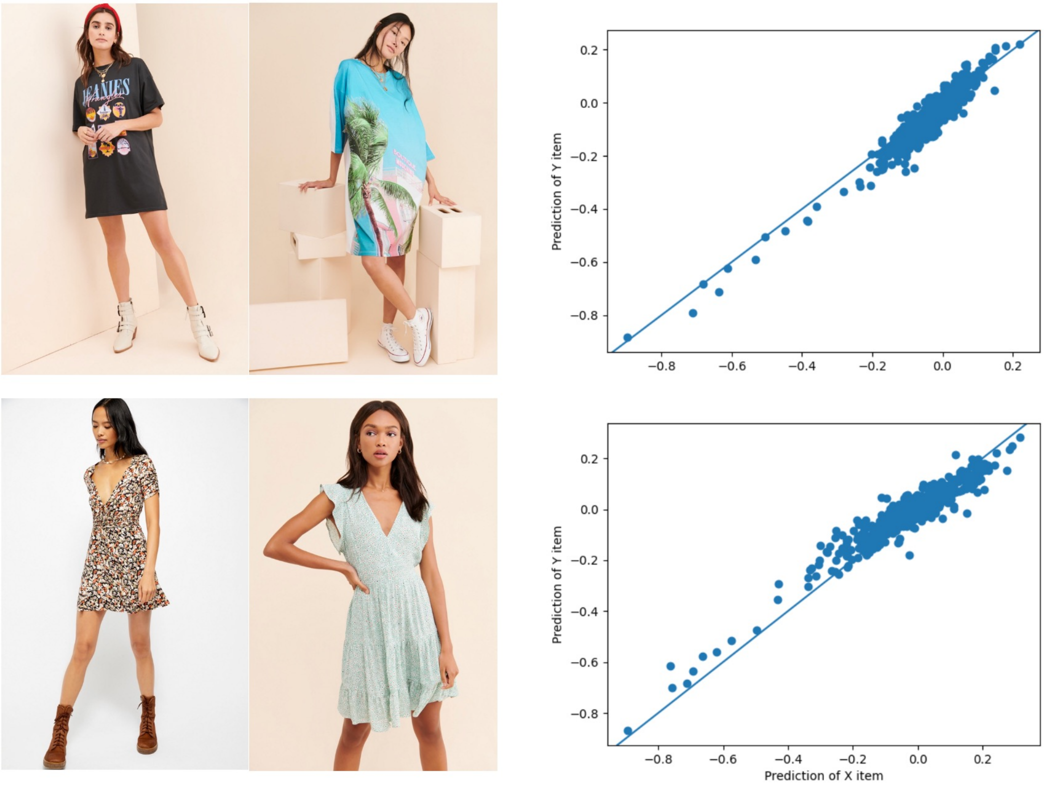


Paired Predictions



X Y

Connecting Theory and Practice

- Our work leverages cutting edge methods for adaptive question design, built on decades of research on adaptive conjoint, and recent developments in the use of unstructured data

- We develop this methodology in a modern, applied context, to solve an increasingly prevalent problem in practice, especially for subscription industries

- The method works in real-time, using real world relevant data, without making unrealistic assumptions about firm data, or consumer preferences

- We introduce practical methodologies for interpreting the results, allowing firms to turn complex, messy data into actionable insights

Thank you!

Questions / comments?

ryandew@wharton.upenn.edu

Working paper available

Special thanks to:

Wharton
University of Pennsylvania
ANALYTICS AT WHARTON

WHARTON BEHAVIORAL LAB

Additional Slides

Algorithm

Algorithm 1: Adaptive Preference Measurement

Data: Representations z_j for products $j = 1, ..., J$, number of initial (random) ratings M_0, number of total ratings M

Ask user to rate M_0 initial products, $j_1, j_2, ..., j_{M_0}$

Optimize GP hyperparameters using Equation 7, and compute initial estimate estimate of $u(z)$ using Equation 4

for $m = 1, \ldots, M$ **do**

- Select next item for user to rate by $j_m = \arg\max_j a(z_j)$
- Show user item j_m, obtain rating r_m
- (Optional) Optimize GP hyperparameters using Equation 7 and the full history of ratings
- Update estimate of $u(z)$ using Equation 4 and the full history of ratings
- Update acquisition function $a(z)$ based on $u(z)$

return *User's utility function* $u(z)$

Step 1: Have the user rate some (random) initial products

Step 2: Initialize our model of u(z) using those initial product ratings

Repeat:

- Show next item based on the acquisition function
- Update posterior estimate of u(z) using full history