Made-to-Order: Targeted Marketing in Fast-Food Using Collaborative Filtering

PURDUE UNIVERSITY | Mitchell E. Daniels, Jr. School of Business

Oluwayemisi Ajayi, Yuqiu Chen, Jason Crawford, Kamalika Das, Venkata Rahul Karumuri, Matthew A. Lanham
Purdue University, Mitchell E. Daniels, Jr. School of Business
ajayi4@purdue.edu; chen3485@purdue.edu; crawf136@purdue.edu; das192@purdue.edu; vkarumur@purdue.edu; lanhamm@purdue.edu

BUSINESS PROBLEM FRAMING

In a crowded market of fast-food chains, it's essential to stand out and appeal to customers better than the competition. One way to achieve this is by showing the customers are cared for and a more personalized experience them feel valued. Research indicates 54% of retailers claimed that product recommendations act as the key driver of the AOV (average order value) in customer purchase (Skovhøj, 2022). This study enables to **accurately predict when and what a customer will order next** allowing this food brand to target and cluster users more granularly results in following benefits:

⬆ Order Conversion | ⬆ Avg. Order Price | ⬇ Campaign Wastage

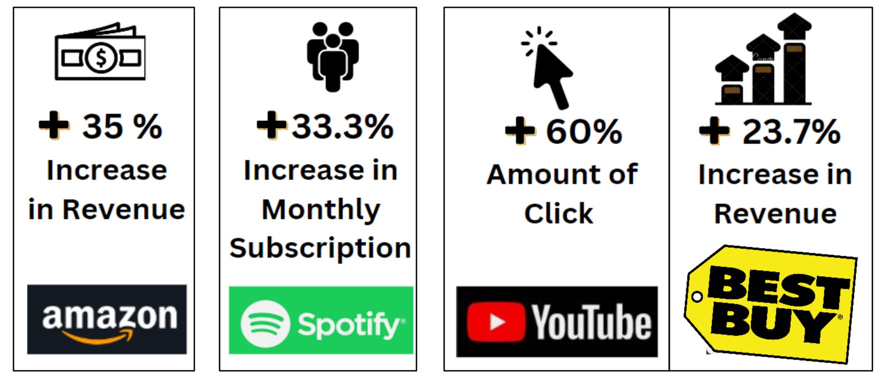

Fig. 1 *Recommendation algorithm significance statistics*

ANALYTIC PROBLEM FRAMING

Increase the conversion rate of customers and improve customer life cycle for the fast-food chain factoring the varying buying pattern from a vast pool of customers. Assuming, the sample transactional data reflects the fast-food entire customer persona and buying patterns accurately, the recommendation model built in this study successfully

1. Buckets users based on their potential next visit day

2. Predicting >=1 item of the bucket of products in the customer's next order

Collaborative Filtering

- Captures implicit/unseen relationships
- Higher accuracy when generating basket including previously ordered items
- More conservative in predicting new items

Content-based Filtering

- Explicitly captures similarities between items
- Higher accuracy when predicting unseen items
- More aggressive in predictions

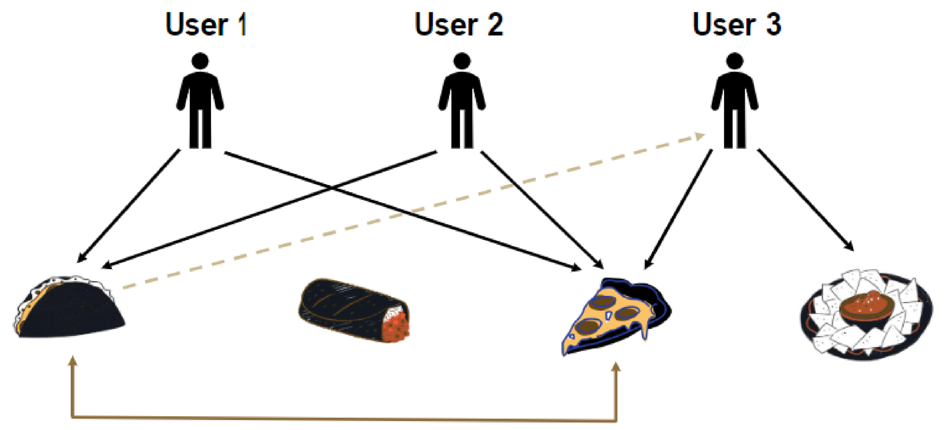

Fig. 2. *Collaborative filtering*

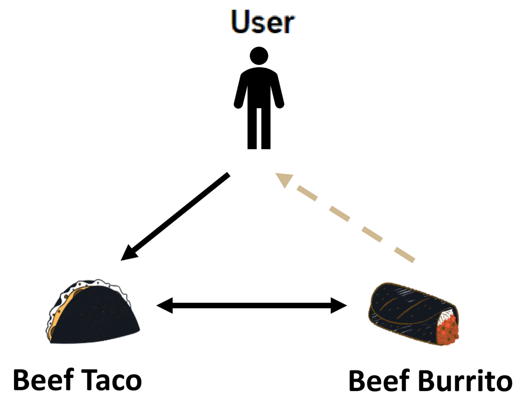

Fig. 3. *Content based filtering*

DATA

Feature Priority:

- Relationship between customers and products
- Date difference between orders

- Sample set is one year of transaction of transactions for 25,000 customers
- Orders bucketed by customer and item used in model to determine likelihood of ordering both previously seen and unseen items

USER - 25K
ORDERS - 700K over full year
DATE + TIME
PRODUCT - 1.2M
PRICE
QUANTITY
MODIFICATIONS

Fig. 4. *Data structure*

METHODOLOGY

Software: Python

Libraries: surprise, XGBoost, scikit-learn

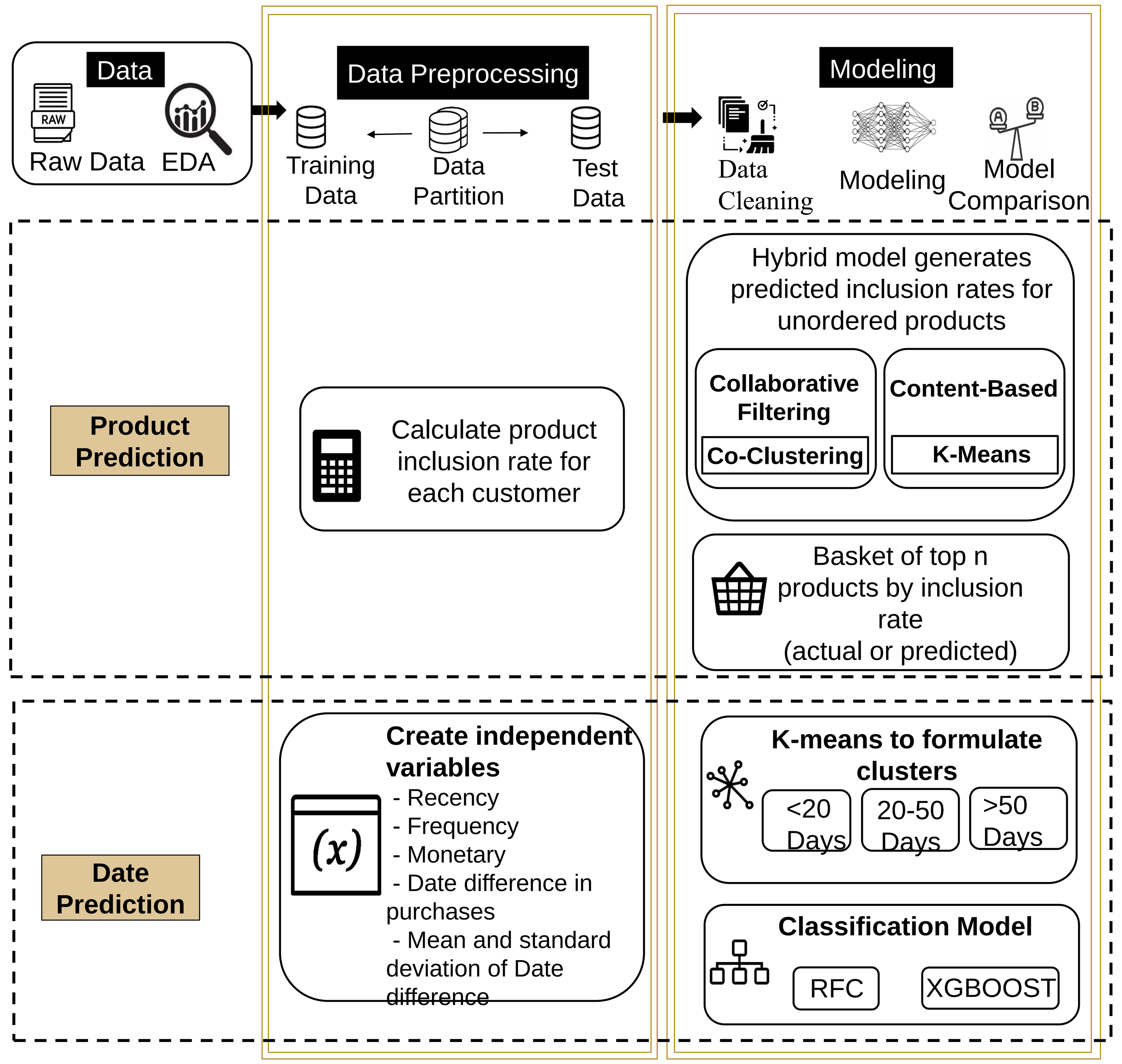

Fig. 5. *Overall Model methodology*

MODEL BUILDING

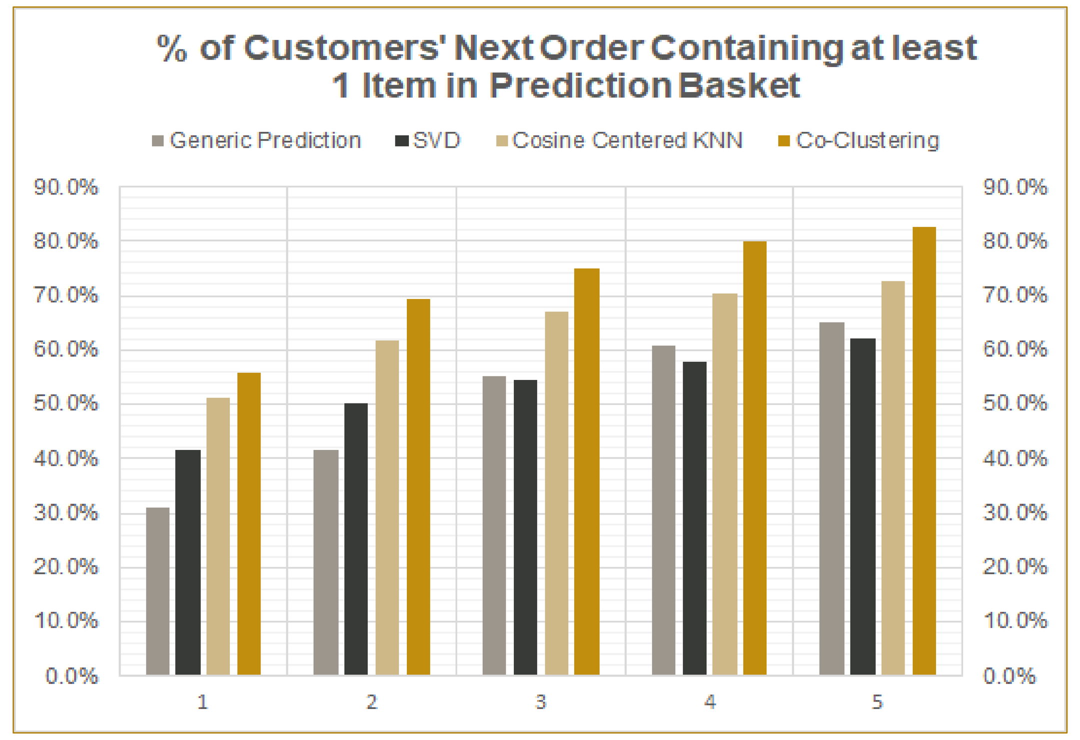

Fig 6. *Product prediction basket model accuracy*

Training Data
Q1-Q3 transactions
Prediction Data
Q4 transactions

Improvement Areas
- Penalize previously recommended products not ordered

- Baskets of n products predicted to be in the users' next order based on % order inclusion (actual for previously ordered items or predicted per collaborative filtering for unordered products).

- Co-Clustering Prediction: at least one item in a **customer's next order in 75% of the test set with a basket of 3 items** vs 51% generically predicting the company's most popular items to all users

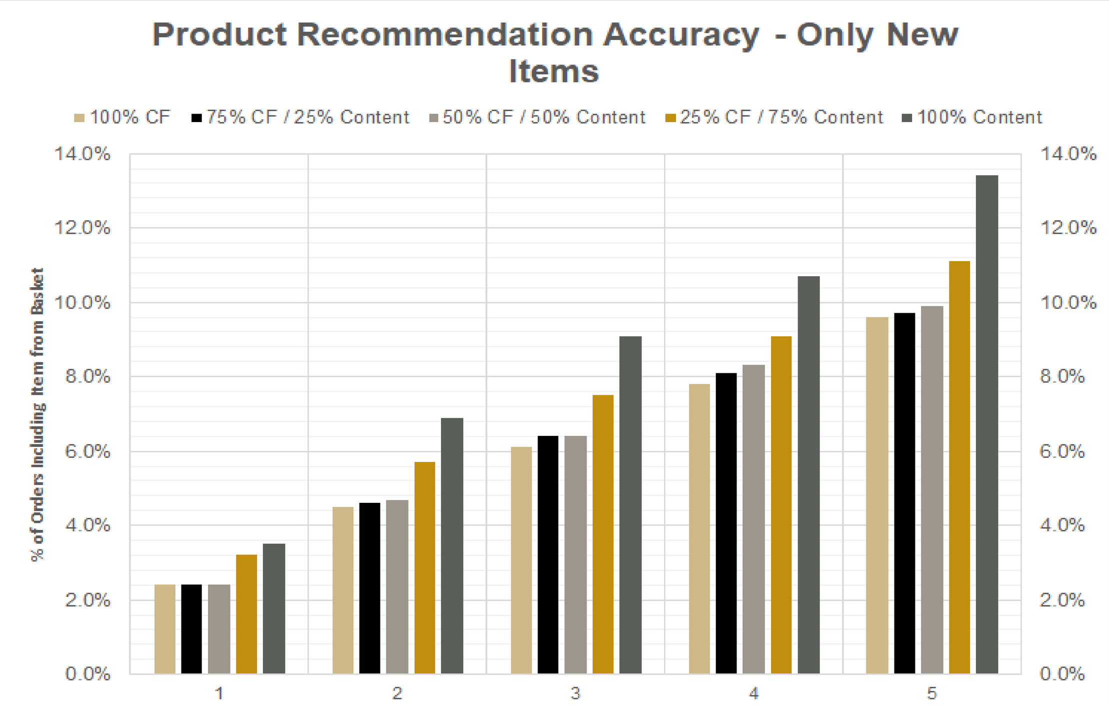

Fig 7. *Collaborative & content filtering predicting new items*

- Collaborative filtering is more accurate in predicting items from entire product universe
- Content-based approach **1.5x more accurate** than collaborative filtering at predicting basket of previously unordered items (across all recommendation basket sizes 1-5)

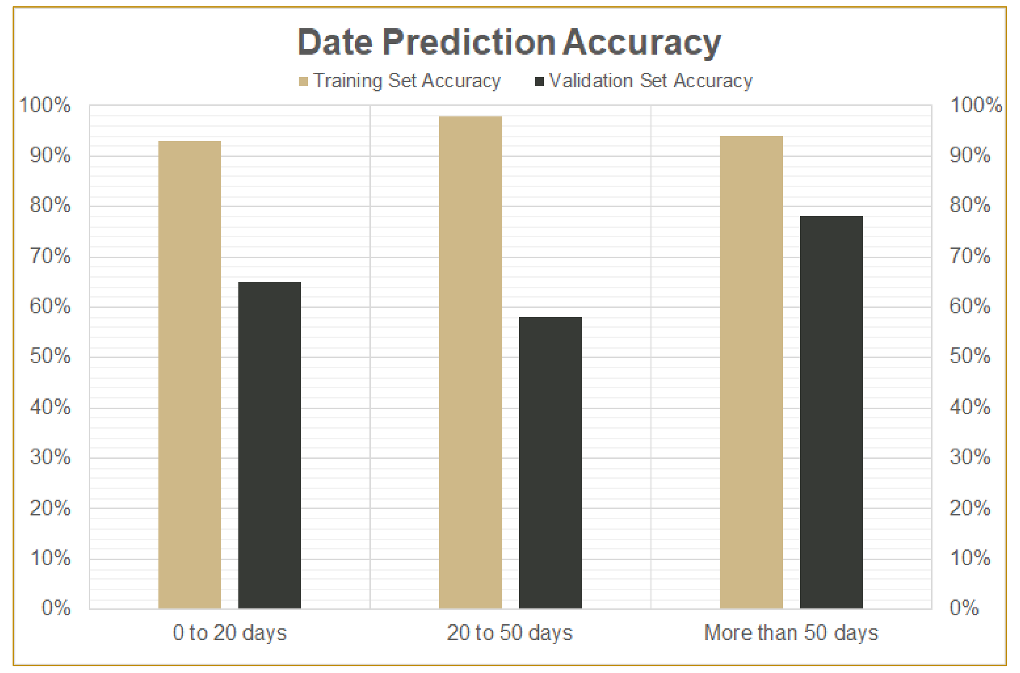

Fig 8. *Date prediction clustering accuracy*

- Classification model most accurate in predicting those in cluster ordering >50 days in future
- Training on Q1-Q3 transaction history
- Prediction designed to parse customers likely ordering in the few weeks

Improvement Areas
- Retain accuracy while creating more granular clusters

BUSINESS IMPACT ASSESSMENT

To translate the effect of increased prediction accuracy on **conversion rates and per-order spending**, the below **A/B test** presents customers with one of two advertisements: one informed by the personalized customer prediction baskets and one for the brand's most popular products across users nationwide

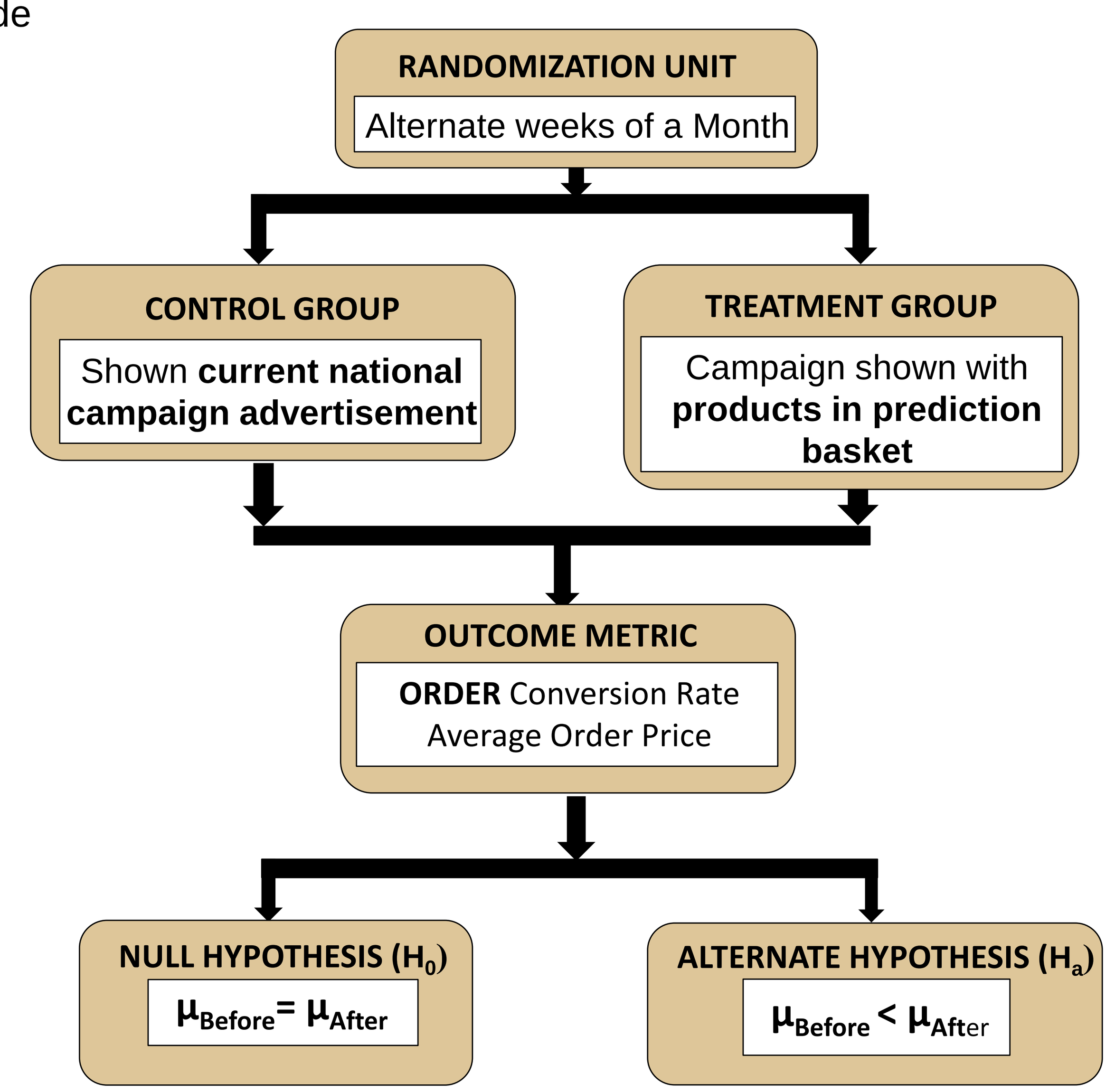

Fig 9. *A/B testing to measure business efficacy*

CONCLUSIONS

GOAL : **Predict When and What a Customer will Order Next**

METHOD : **Collaborative Filtering and K-Means Clustering**

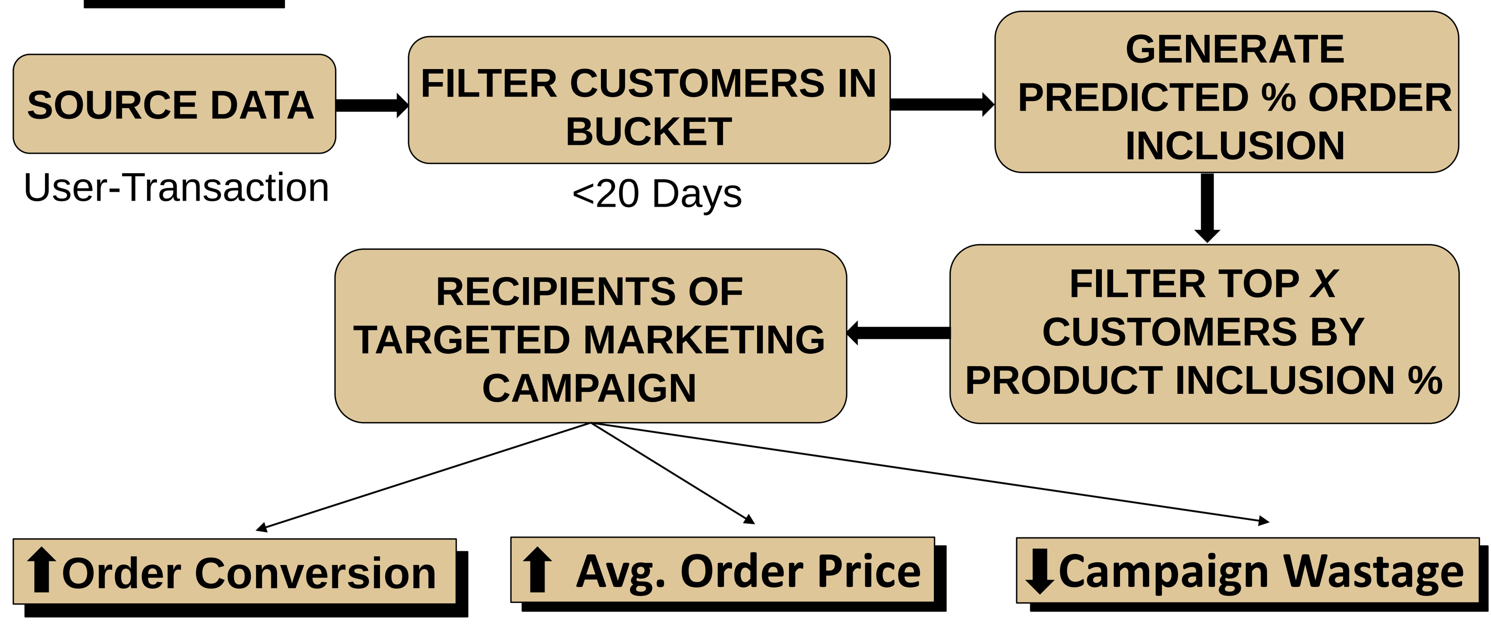

Fig 10. *Use case of model*

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