Personalised recommendations to increase AOV of Instacart loyalists

Agenda

Introduction

- About Instacart
- Problem Statement

EDA

- Exploratory Data Analysis

Modelling

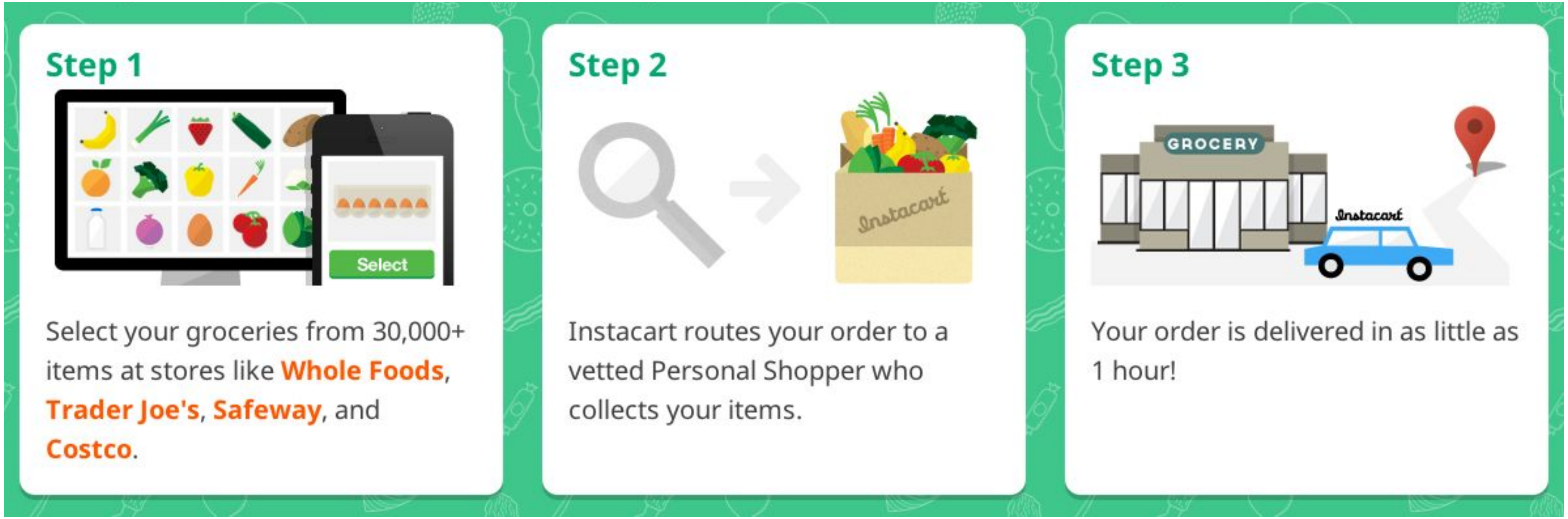
- Implementation of Recommender Systems
- Evaluation and Conclusion

Introduction

About Instacart

Web and mobile-based

On-demand grocery delivery service



Big-selection grocers

NEW
Fairway
Delivery

NEW
The Food Emporium Shoppe
Delivery

NEW
The Market @ Mercedes House
Delivery

ALDI
Delivery • Pickup 18.9mi

The Food Emporium
Delivery

Key Food
Delivery • Pickup 6.0mi

Westside Market
Delivery

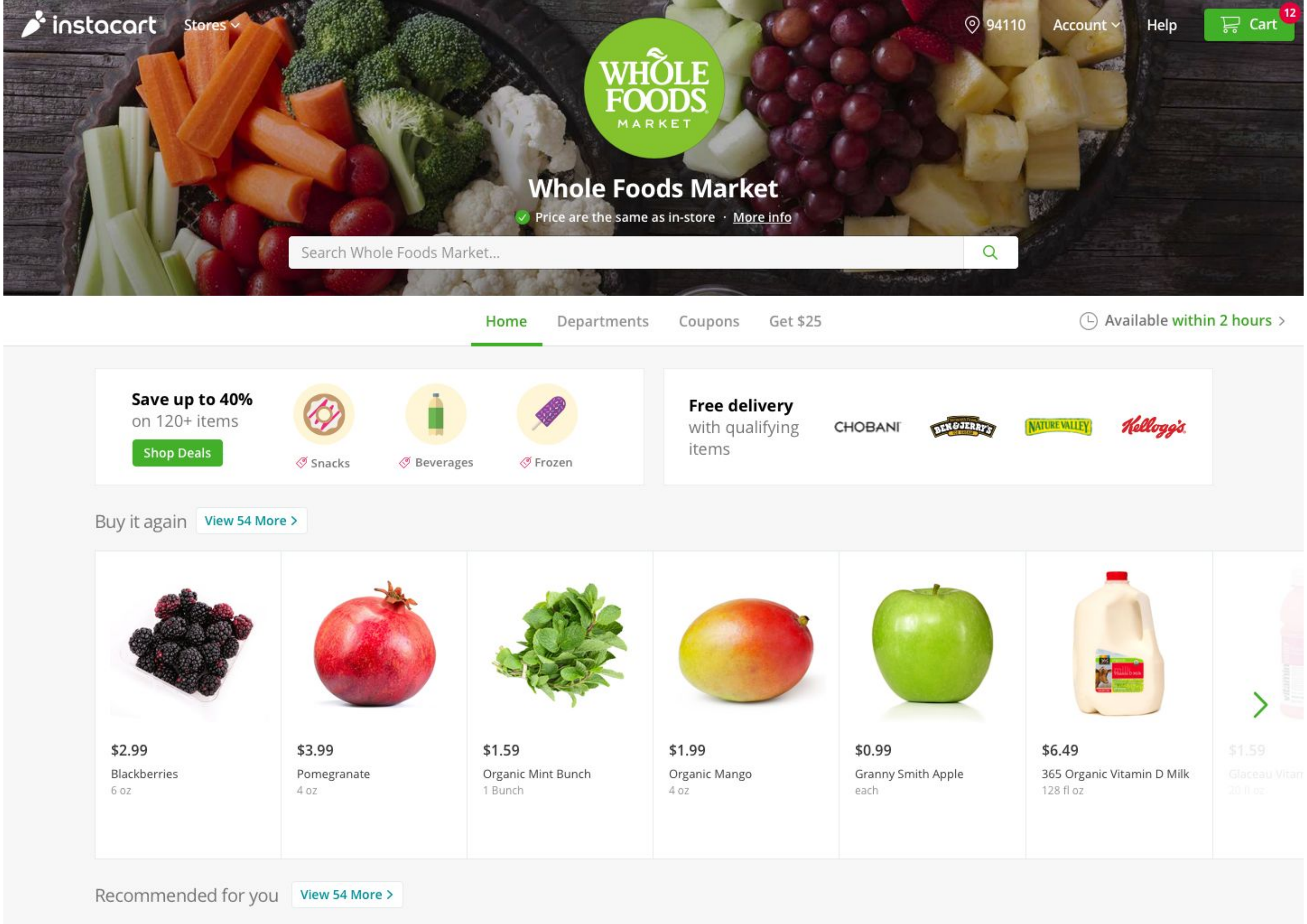
Food Universe
Delivery • Pickup 2.6mi

ShopRite
Delivery

Key Food Marketplace
Delivery

Wegmans
Delivery • Pickup 20.1mi

D'Agostino
Delivery

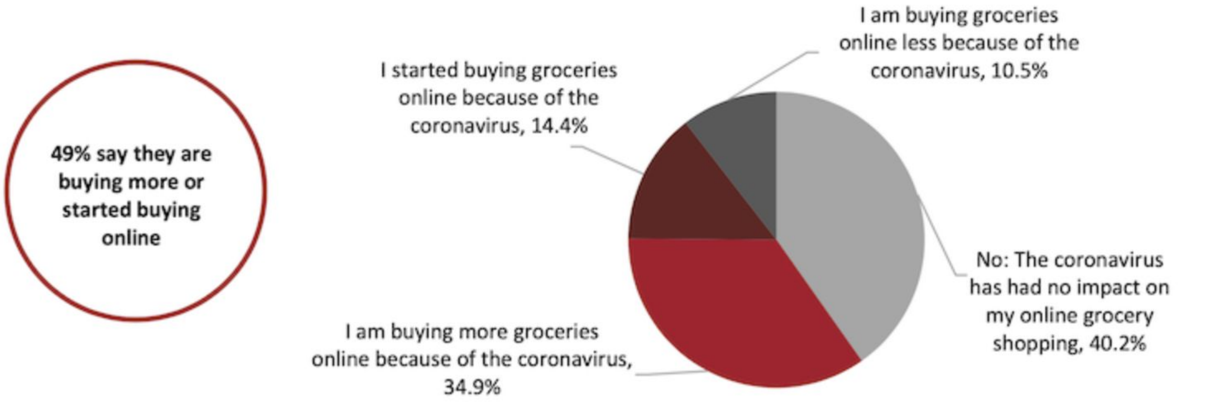


instacart
Stores
94110
Account
Help
Cart
12
WHOLE FOODS MARKET
Whole Foods Market
Price are the same as in-store · More info
Search Whole Foods Market...
Home
Departments
Coupons
Get $25
Available within 2 hours
Save up to 40%
on 120+ items
Shop Deals
Snacks
Beverages
Frozen
Free delivery
with qualifying items
CHOBANI
BEN & JERRY'S
NATURE VALLEY
Kellogg's
Buy it again
View 54 More
$2.99
Blackberries
6 oz
$3.99
Pomegranate
4 oz
$1.59
Organic Mint Bunch
1 Bunch
$1.99
Organic Mango
4 oz
$0.99
Granny Smith Apple
each
$6.49
365 Organic Vitamin D Milk
128 fl oz
Recommended for you
View 54 More

Problem Statement – The Digital Fight is On

As online grocery sales continue to surge, Instacart is facing increasing competition in the online grocery delivery space as many traditional grocers are rapidly expanding their online operations.

For example, Walmart has been expanding its online-order offering, with same-day delivery from 1,600 stores and pickup from 3,100 locations as of November 2019.



Base: 599 US Internet users aged 18+ who have bought groceries online in the past 12 months
Source: Coresight Research

Problem Statement – The Digital Fight is On

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How can Instacart improve their customer experience so as to retain the loyalty of their top customer base?

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How can Instacart improve their customer experience so as to retain the loyalty of their top customer base?

Through personalised recommendations!

EDA


instacart pickup
Kale& Avocados& Blueberries& Chocolate& Family.
instacart
instacart pickup
Order online, pickup here!
instacart.com

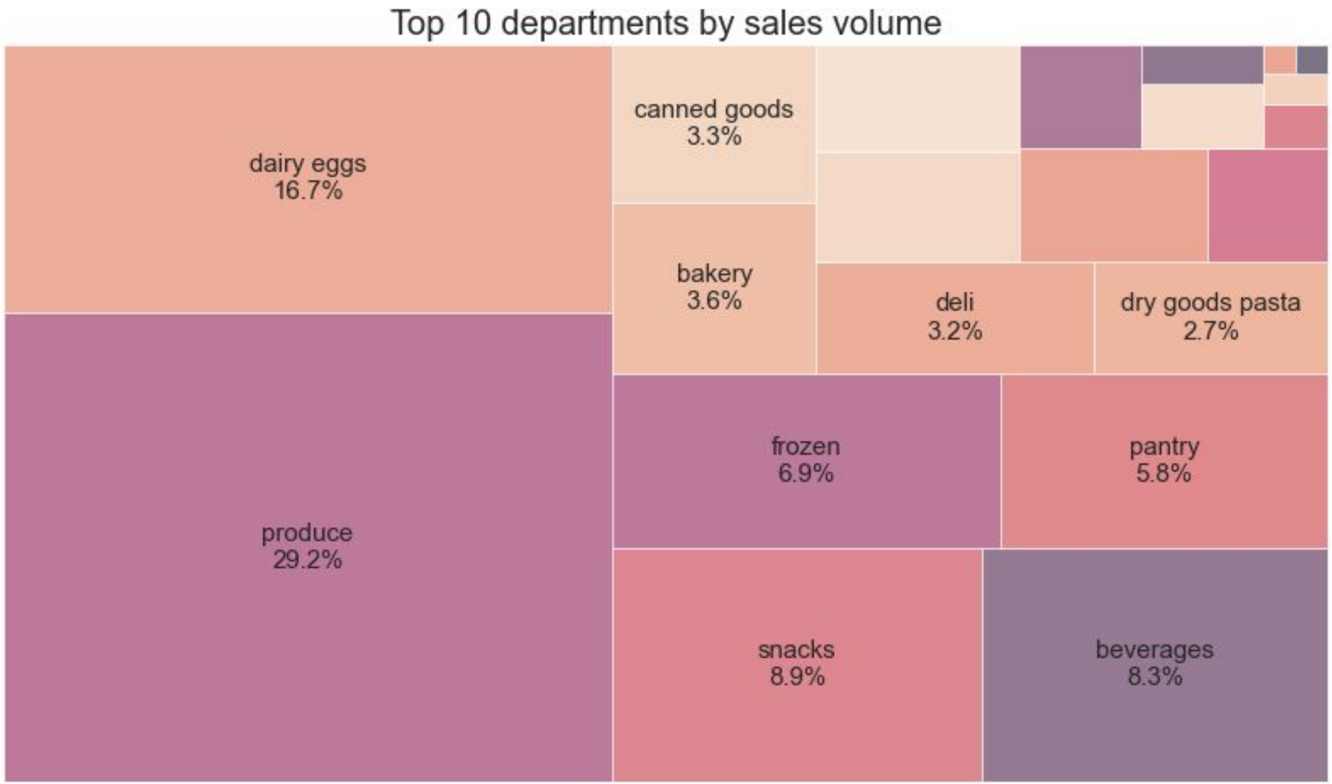
Dataset

33,819,106 rows, 12 columns

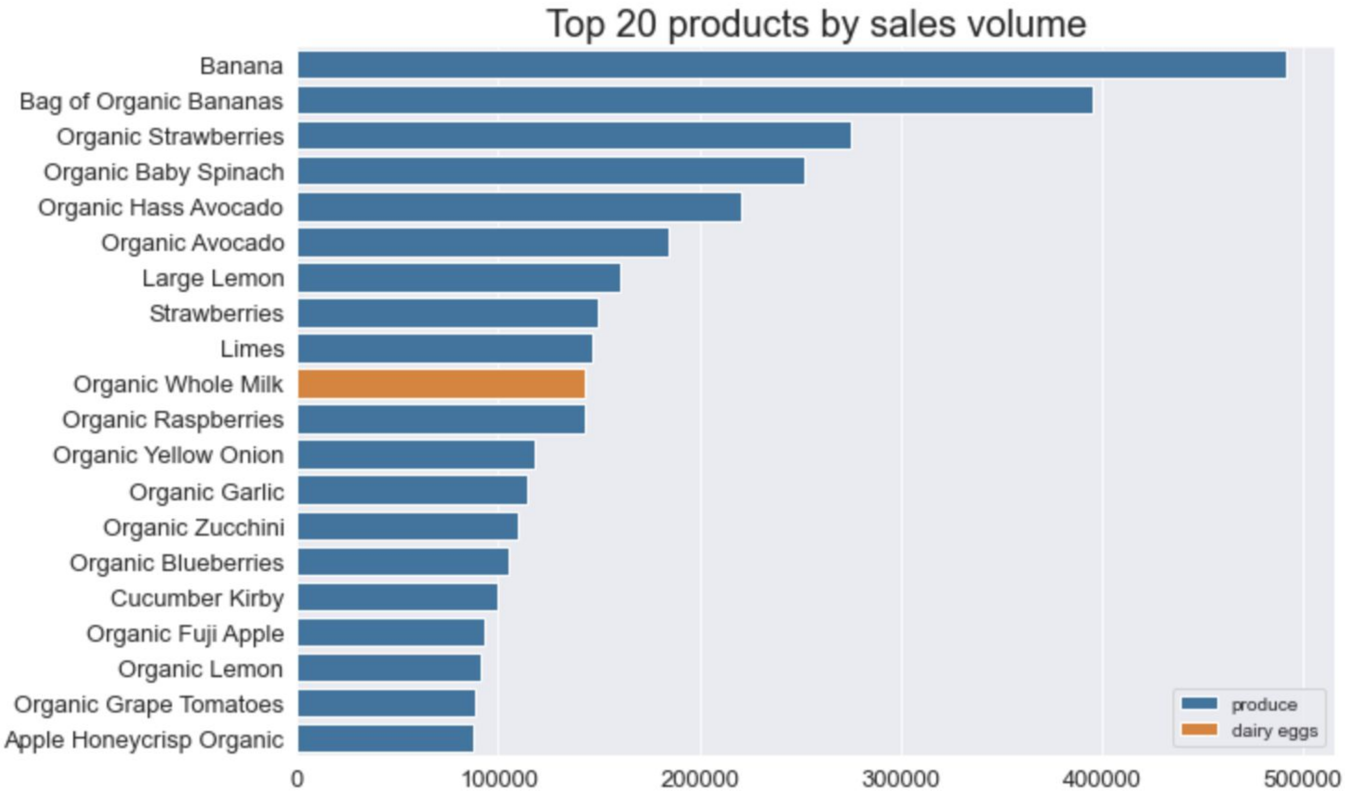
- Orders: 3.34 mil
- Users: 206,209
- Products: 49,688

order_id	user_id	order_number	order_dow	order_hour_of_day	days_since_prior_order	product_id	add_to_cart_order	reordered	product_name	department	aisle
2539329	1	1	2	8	NaN	196	1	0	Soda	beverages	soft drinks
2398795	1	2	3	7	15.0	196	1	1	Soda	beverages	soft drinks
473747	1	3	3	12	21.0	196	1	1	Soda	beverages	soft drinks

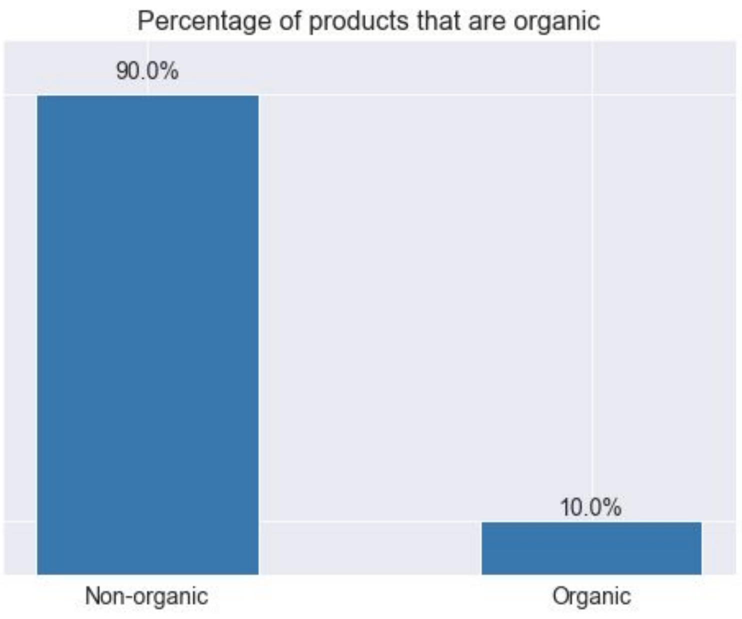
Sales by department



Top-selling items

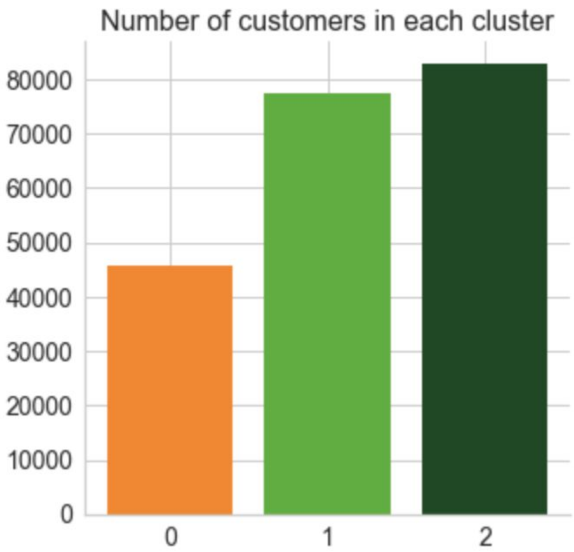


Organic items contribute a disproportionate amount to sales



Zooming in on Instacart's most loyal customers

Customer segments based on past transaction behaviour



Data reduction

EDA + customer clustering → **Data reduction** → **Utility matrix for recommenders**

Orders: 3.34 mil

Users: 206,209

Products: 49,688

1. Drop products that were ordered <150 times
2. Drop orders with <4 items
3. Include only users with >20 orders, and keep only their last 20 orders

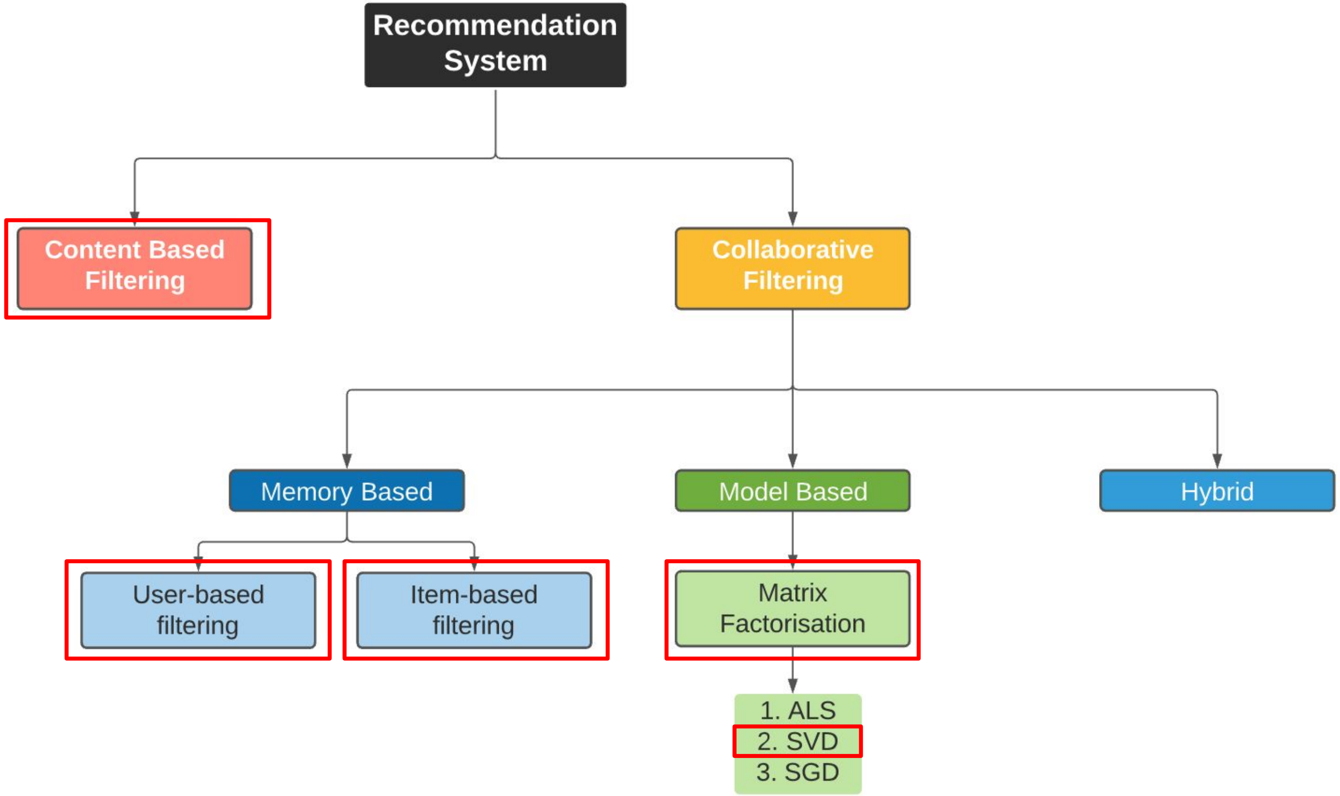
Orders: 830,980

Users: 41,549

Products: 16,859

Modelling

Recommender system types



General workings of Matrix Factorization

1. Decompose utility matrix

Decompose *M* into *U* and *V* such that *U*·*V* closely approximates *M* for known entries
(Number of latent factors *d* such that RMSE is minimised)

$$
\begin{array}{cc}
 & \text{items} \\
\text{users} & \begin{bmatrix} 5 & 2 & 4 & 4 & 3 \\ 3 & 1 & 2 & 4 & 1 \\ 2 & & 3 & 1 & 4 \\ 2 & 5 & 4 & 3 & 5 \\ 4 & 4 & 5 & 4 & \end{bmatrix}
\end{array}
=
\begin{array}{c}
\text{User latent factors} \\
\begin{bmatrix} u_{11} & u_{12} \\ u_{21} & u_{22} \\ u_{31} & u_{32} \\ u_{41} & u_{42} \\ u_{51} & u_{52} \end{bmatrix}
\end{array}
\times
\begin{array}{c}
\text{Item latent factors} \\
\begin{bmatrix} v_{11} & v_{12} & v_{13} & v_{14} & v_{15} \\ v_{21} & v_{22} & v_{23} & v_{24} & v_{25} \end{bmatrix}
\end{array}
$$

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$$

2. Recompose utility matrix

Use the entry in the product *UV* to estimate corresponding blank entries in *M*

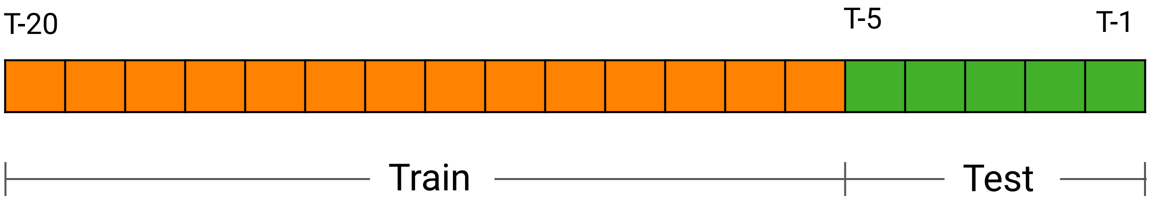
Recommender implementation

Each model generates 20 final recommendations for the target user

User-based	**CANDIDATE GENERATION** 1. Find user's 20 nearest neighbours 2. All past purchases of these 20 neighbours form potential recs	**RANKING** 1. Rank potential recs based on sales 2. Select the top 20 bestselling items as final recs
Item-based	**CANDIDATE GENERATION** 1. Select user's top 20 purchases 2. For each item, find 10 most similar items 3. 200 potential recs in total	**RANKING** Same procedure as above
SVD	Select the top 20 items with the highest scores from the reconstructed utility matrix.	

Train-test-split at the user level

E.g. user 32589's last 20 orders



Evaluating the recommender systems

- **Precision:** proportion of recommended items in the top-K set that were purchased by user
- **Recall:** proportion of the user's actual purchases that were in the recommendations

Baseline: Popularity model
Non-personalised – recommend the top 20 best-selling products

model	eval_set	F1	precision	recall
content-based	train	0.045174	0.116083	0.035937
content-based	test	0.046903	0.068783	0.038880
baseline	train	0.108100	0.264833	0.074087
baseline	test	0.114044	0.173317	0.091570
CF user-based	train	0.111239	0.270417	0.076457
CF user-based	test	0.117076	0.176683	0.094254
CF item-based	train	0.122490	0.289817	0.084993
CF item-based	test	0.129298	0.192200	0.105910
CF SVD	train	0.098514	0.239900	0.066857
CF SVD	test	0.114802	0.173033	0.093709

Top 20 recommendations for user 90623 (item-based CF)

product_name	department
Red Peppers	produce
Organic Red Bell Pepper	produce
Organic Small Bunch Celery	produce
Organic Garnet Sweet Potato (Yam)	produce
Half & Half	dairy eggs
Organic Avocado	produce
Organic Lemon	produce
Sparkling Water Grapefruit	beverages
Carrots	produce
Organic Cilantro	produce
Fresh Cauliflower	produce
Organic Baby Spinach	produce
Organic Hass Avocado	produce
Bag of Organic Bananas	produce
Organic Zucchini	produce
Banana	produce
Organic Garlic	produce
Organic Yellow Onion	produce
Limes	produce
Organic Raspberries	produce

Recommended items that were in user's past purchases (first 15 of last 20 orders):
['Organic Zucchini', 'Organic Small Bunch Celery', 'Organic Yellow Onion']

Recommended items that were in user's last 5 orders:
['Organic Yellow Onion', 'Organic Zucchini', 'Organic Small Bunch Celery', 'Organic Baby Spinach']

All items in user's last 5 orders:
['Organic Southwest Salad', 'Pure Cane Golden Brown Sugar', 'Sprouted Whole Wheat Bread', 'Large Grade AA Cage Free Eggs', 'Organic Baby Spinach', 'Rosemary Mini Croccantini', 'Maple Quinoa Cluster With Chia Seeds', 'Almonds & Sea Salt in Dark Chocolate', 'Organic Yellow Onion', 'Sparkling Water Berry', 'Organic Reduced Fat 2% Milk', 'Organic Dark Chocolate Peanut Butter Cups', 'Feta Cheese Crumbles', 'Boneless Skinless Chicken Breast', 'Organic Low Fat Cottage Cheese', 'Organic Mayonnaise', 'Black Beans No Salt Added', 'Snickerdoodle Cookie with Salted Caramel Ice Cream Sandwich', 'Boomchickapop Sea Salt Popcorn', 'Organic Traditional Flour Tortillas', 'Organic Asian Chopped Salad Kit', 'Pure Castile Peppermint Soap', 'Macaroni Shells & White Cheddar Cheese', 'California Sourdough Bread', 'Gluten Free Mushroom Risotto Bowl', 'Organic Rainbow Carrots', 'Organic Long Grain White Rice', 'Organic Sour Cream', 'Lemon Hummus', 'Organic Zucchini', 'Uncured Genoa Salami', 'Organic Strained Tomatoes', 'Butter', 'Corn Bread Mix', 'Salsa Verde', 'Sour Cream & Onion Potato Chips', 'Organic Baby Rainbow Carrots', 'Roasted & Salted Almonds', 'Mango Soft Serve Fruit Pops', 'Organic Butternut Squash', 'Smoked Turkey Breast Slices', 'Organic Raw Unfiltered Apple Cider Vinegar', 'Raw Sauerkraut', 'Double Chocolate Chip Cookies with Dirty Mint Chip Ice Cream', 'Organic Green Cabbage', 'Manhattan Style Whole Kosher Pickles', 'Fire Log', 'Peach Pear Flavored Sparkling Water', 'Yellow Onions']

Recommendations need to be made contextual

In reality, e-commerce retailers employ different product recommendation strategies for different pages on the site, such as:

- **Homepage**: "Recently viewed" / "Buy it again" / "Recommended For You"
- **Category pages**: "Most Popular in Category" / "Recommended For You" (category-specific)
- **Product detail pages (PDPs)**: "Similar Products" / "Often Bought Together"
- **Cart pages**: "Often Bought Together" (showcasing products that are slightly cheaper than those in a user's cart can lead to quick purchase decisions)
- **Search results page**: Results returned from search queries can also be considered a form of recommendation. These items are ranked by probability of purchase.

More granularity needed to truly personalise the recommendations

The recommendations generated may not be user-specific enough – we need to set additional rules to generate smarter recommendations.

- We wouldn't want to recommend non-vegan items to a vegan customer.
- Consumers who have high average order values can be recommended more highly profitable items in order to maximise revenue.
- We don't want to recommend items from the user's most recent basket, especially for items that are not weekly purchase items.

Consider diversity of recommendations too

- My recommendation systems are biased towards recommending items that have relatively high sales volume, so they are probably unable to surface truly novel items that have not been discovered by many other people.
- We can improve the diversity of recommendations by recommending these long-tail items to increase the novelty factor for the user.
- Include recommendations from stores customers may have never shopped from previously. This is appropriate for customers who have a high unique-items-to-total-items ratio.

Thanks :)