

Adaptive Purchase Planner

By Team James



01

Our Idea

What is our product ?

Our Goals

What did we aim to achieve ?

02

03

Our Achievements

What did we achieve and how ?

Our Challenges

How was the learning journey ?

04



01. Our Idea

Your purchase partner that recommends what you might want to buy.



Some Facts



According to a survey, 56% of respondents go for grocery shopping 1-2 times a week.





02. Our Goals

Our expectations with the project,
our initial idea and planning.



Adaptiveness

- It understands from your previous purchases and recommends items.
- It suggests items you might need in few days
- It suggests new items you might also like based on other users' purchasing behaviour.

Features



Capture data

Allow users to either manually enter data, use OCR to scan receipts.



Recommendation Engine

Recommend products based on user purchasing behaviours

User Profiling

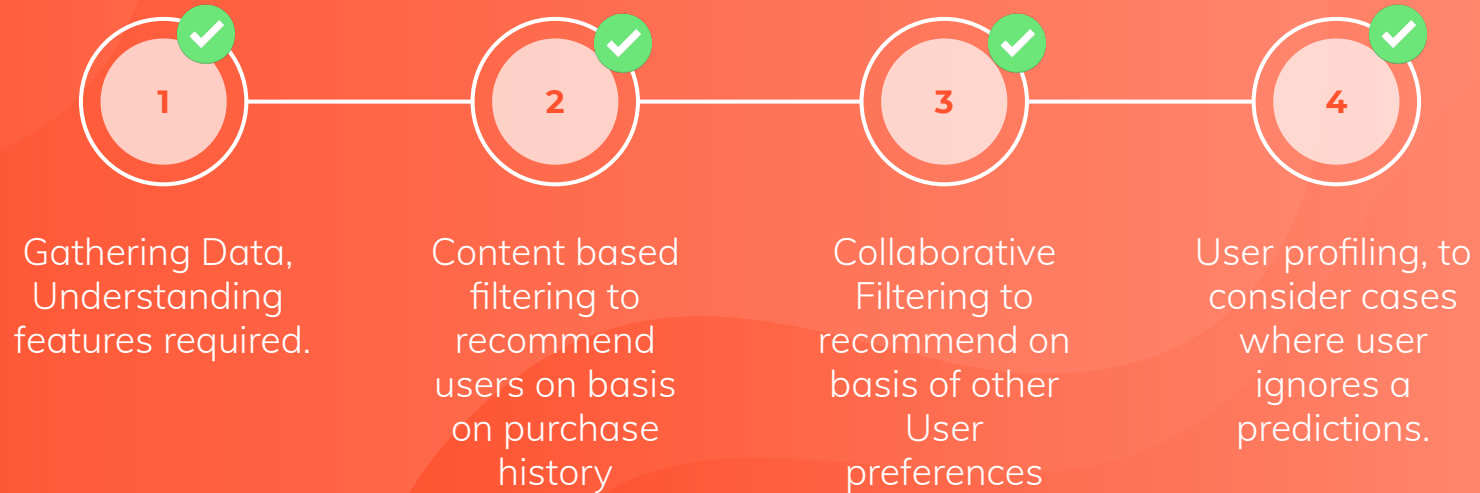
Understand, what items users ignore and update user models accordingly

03. Our achievements

Let's talk about what all we achieved and how?



Milestones





Approaches for User Modelling



01

Collaborative

For new users, Collaborative Modelling is used to recommend items that similar users purchase. This also serves as a fallback mechanism for irregular users.

02

Algorithmic

For regular users, we use algorithmic model to make recommendations using their behaviour.

03

**Machine
Learning**

When we have good amount of data of the user, we make predictions using an ML model. We then check the error gap between ML and Algorithmic model and predict the most likely accurate values.

Collaborative Filtering

Based on Other Users preferences.



Choose Features

We choose the following data as our features

- Age
- Gender
- Users' buy behaviour in all categories.

Build Model

We use K-means to find similar users

- Apply data scaling on every feature.
- Apply K-means clustering.
- Divide people into different groups.

Recommendation

Prediction based on similar users

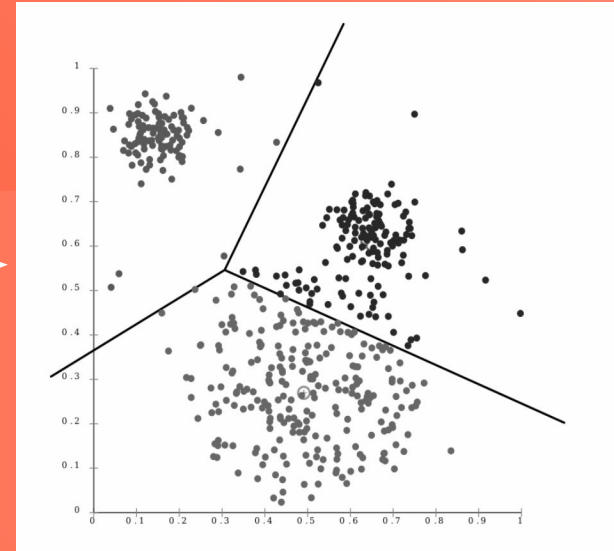
- Find all the similar users in the same group.
- Analyze users purchase behavior in the group.
- Recommendation based on group purchase behaviour.



CS7IS5-A-SEM202-201920 ADAPTIVE APPLICATIONS

	Sex	YOB	Food C	Dairy	Personal	Care	Food A	Food B	Cleaning	Beverages	Snacks
0	2	65	142	142		142	142	142	142	142	144
1	1	25	143	143		0	143	0	143	143	143
2	3	38	270	405		270	270	135	270	135	135
3	2	22	278	417		278	278	139	0	0	139
4	1	64	290	290		0	145	0	145	145	145
5	2	31	441	294		0	147	0	294	147	294
6	1	59	140	280		280	280	0	140	0	140
7	2	42	447	298		298	298	149	298	0	149
8	1	42	142	0		142	142	0	142	142	284
9	3	46	288	288		144	144	144	144	0	144
10	2	32	284	284		0	284	142	284	142	284
11	1	23	280	280		140	280	0	0	140	280
12	2	35	0	286		0	143	143	143	0	143
13	1	29	396	264		132	132	0	132	132	132
14	2	31	417	417		278	278	139	139	139	278
15	1	57	142	426		0	142	0	0	0	142
16	3	34	148	296		296	0	0	148	148	0
17	2	26	278	278		278	139	139	139	0	0
18	1	59	290	290		290	290	145	290	145	290
19	2	61	276	414		138	276	0	0	0	276

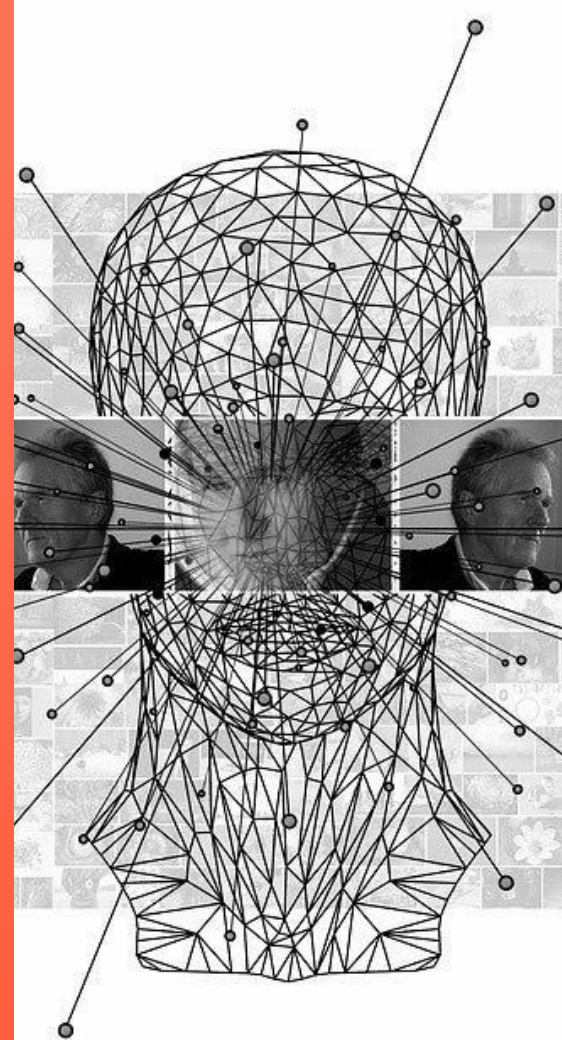
Data Before Scaling



K-means clustering

Content based (Algorithmic)

Purchase Behaviour

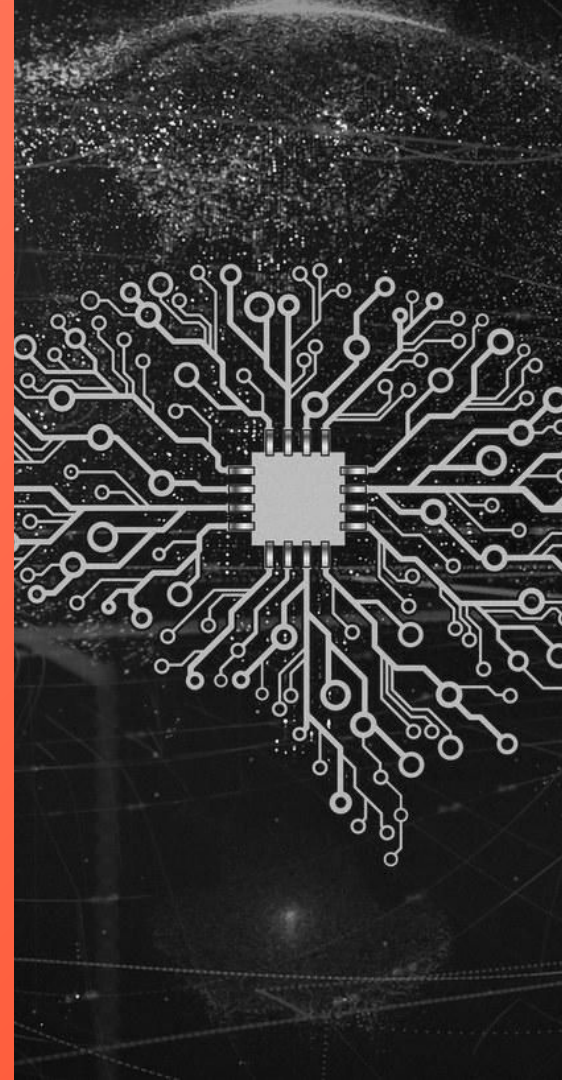


Implementation details

- Consider purchase dates of a product (and its size)
- Calculate the frequency of purchases (Difference between two purchases)
- Get the most frequent frequency for a product.
- Predict the next purchase date
 - ◆ Predict purchases to be made today
 - ◆ Predict purchases expected to be made in coming days
 - ◆ Analyse mispredictions.
 - Items ignored from the recommended list are considered as mispredictions.
 - Implemented Reminder system, where once a product is in ignored list (i.e., ignored on the day of purchase), it will be recommended twice before being permanently deleted from system.
 - The user has an option to explicitly remove an item from the ignored list so that the product is permanently deleted.

Content based (ML)

Purchase Behaviour



Implementation Details :

- Consider Product, size.
- Calculate Frequencies between purchase date
- Evaluate the most frequent frequency
- Perform One Hot Categorical encoding on features
- Train model using Linear Regression



04. Our Challenges

Let's discuss the hurdles and how we jumped them.



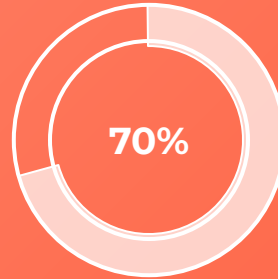
Was it tough?!

Data generated vs real world data



Data was mocked with
fair amount of
randomness.

Predicting Recommendation using machine learning



Feature engineering
played important role

Scanning Receipts and parsing values.

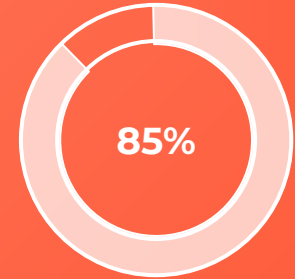


Image to text conversion
was easy but parsing
each record from receipt
was tough.



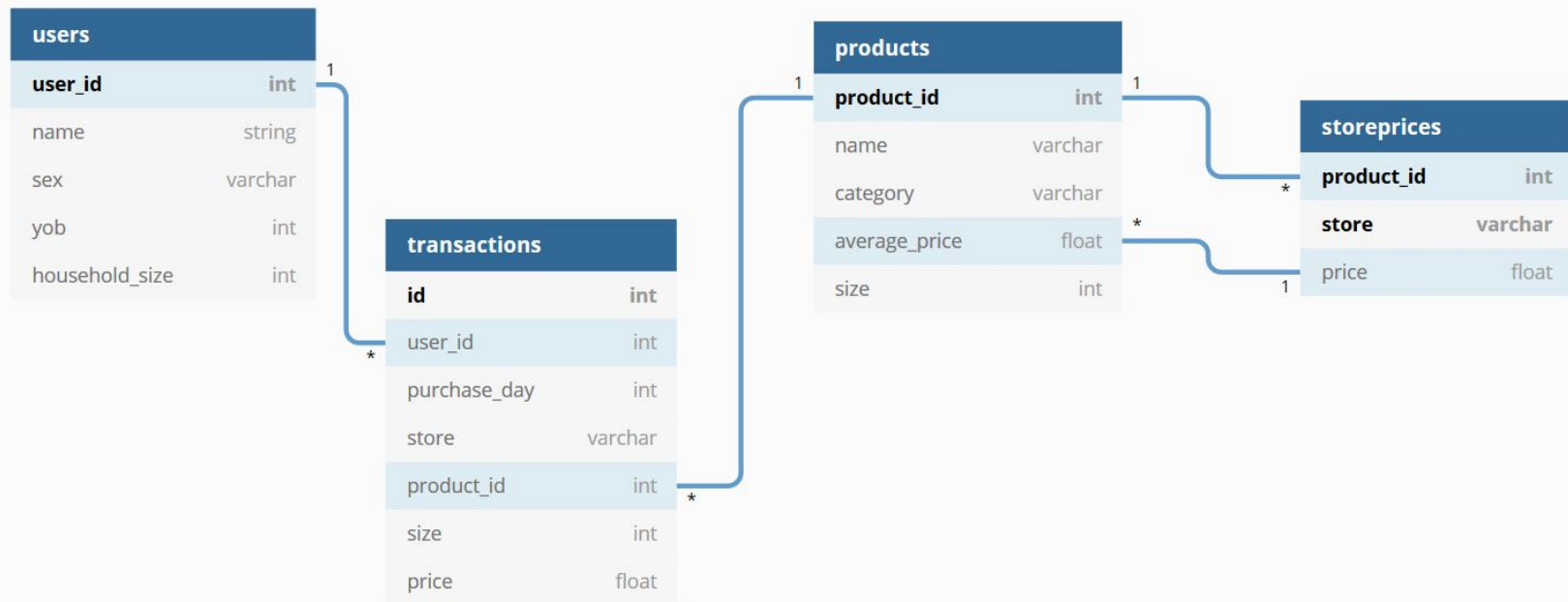
Thanks!

Do you have any questions?

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The Mocked Data



Attempted to mock a loose correlation between household size, product liking and a pseudo random tendency to visit a store. Data for about 500 days for 50 users was generated.

