HIGH LEVEL DESIGN

MEAL RECOMMENDATION WIZARD

OVERVIEW

Part 1: Defining Buyer Persona

A User-Item collaborative filtering finds similarity in users based on similarity of items users purchased.

Part 2: Building Meal Recommendation Wizard

Using the user's current Cart contents and the predicted items user is most likely to buy next based on his purchase history.

ALGORITHM USED

PART 1: User Persona

A. Collaborative Filtering:

   a. User-Product Matrix:

      i. A User-Product matrix is built from the purchase history of users as below:

	Product1	Product2	Product3					Product M
User1	0	1	0	.	..	..	1	0
User2	1	0	0	.	..	..	0	1
.	.	.	.	.	..	..	..	..
.	.	.	.	.	..	..	..	..
User N	0	0	1	.	..	..	..	1

In this User-Product Matrix :
Cell[u][p] = 1 ;
If User 'u' has purchased product 'p'
Cell[u][p] = 0 ;
Otherwise

      ii. Each user is encoded into a vector like One Hot Encoding based on purchase history.

      iii. Similarity between users can be computed using cosine similarity or other similar metric with above encodings.

B. Associative Rule Learning:

Rule based ML learning method for discovering interesting relations between variables.

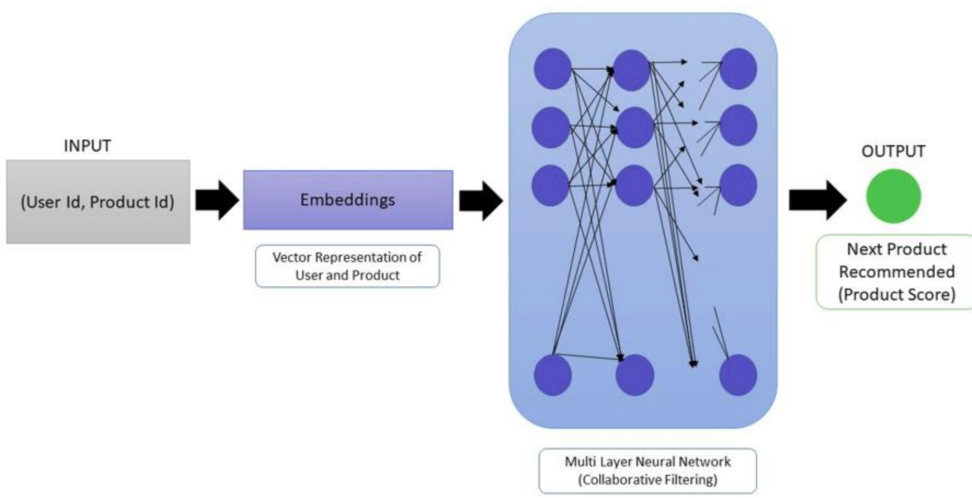
a. To improve buyer persona and personalize the recommendations based on factors like user's age, gender, health conditions, food preferences, etc. Users with similar information are most likely to have similar preferences.

C. Clustering:

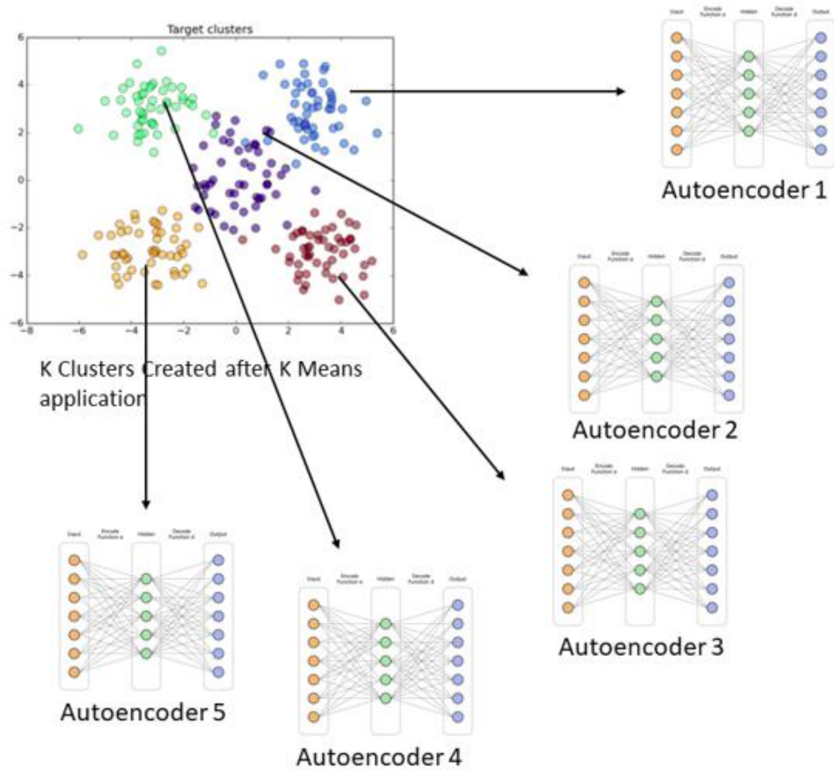
a. Any clustering algorithm like k-means can be applied on above user encodings to divide them into different clusters where cluster represents buyer persona.
b. More fileds can be added to above encodings representing personal information of user.
c. Weighted k-means or similar algorithm can be used to give more priority to more relevant fields.

PART 2: Prediction

- User and Product embeddings are used to learn an Autoencoder or similar deep learning model to predict product user most likely to buy next.



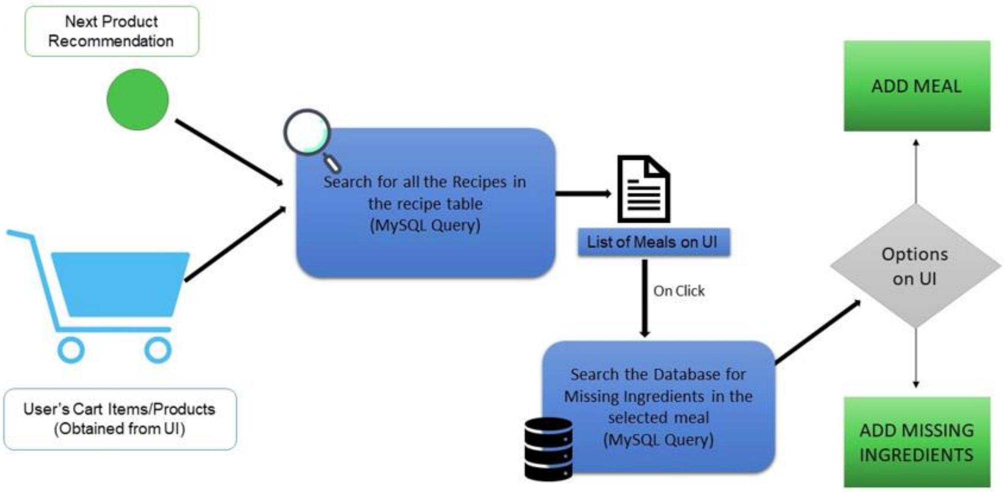
- To incorporate buyer's persona while predicting product, different autoencoder can be trained for different clusters.



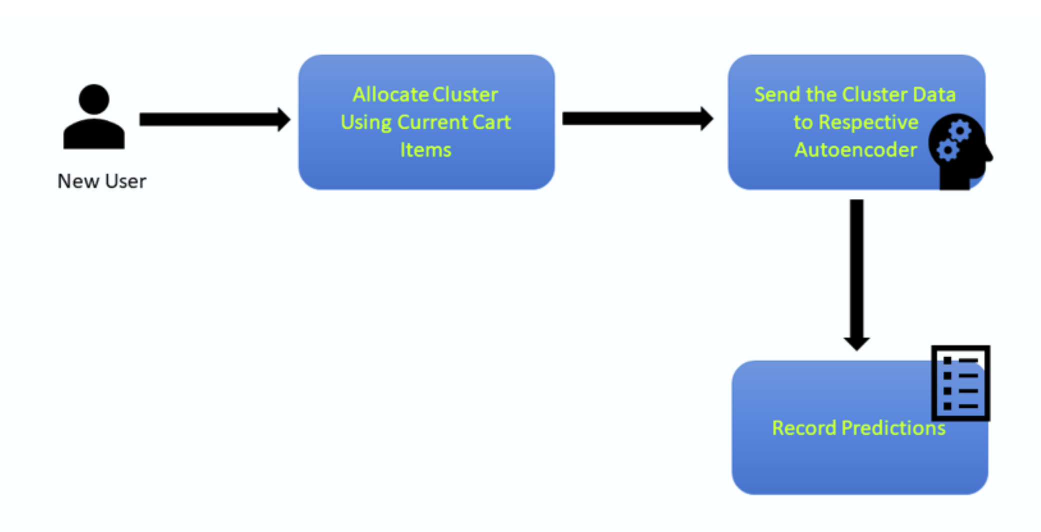
- Associative rule learning with Apriori algorithm to recommend products that a user will most likely purchase based on the set of products that are currently in his cart. For example, if a user buys bread and milk, he'll probably want butter.

PART 3: Meal Recommendation:

- Most suitable meals will be recommended to the user based on products predicted in part 2 and products in current cart as below:



- While querying database priority is given as below:
  - Common products > products currently in cart > predicted products
- In case of new user I.e. user with no purchase history, user is allotted to the cluster as per current cart products and/or personal information provided by the user. Predictions for new user can be less relevant in the beginning but will improve as purchase history grows.



DATASET:

Data can be generated synthetically as below:

- **User details:**
  - BuyerID, SalesID, SalesDate, ProductID, Quantity, CityID
- **Product details:**
  - Products: ProductID, ProductName, Category
  - Meal: MealID, MealName, Cuisine
  - Meal_Product: MealID, ProductID

Reference datasets:

- https://www.kaggle.com/naiara/sales-grocery-market-analysis
- https://www.kaggle.com/kaggle/recipe-ingredients-dataset
- https://cosylab.iiitd.edu.in/culinarydb/

EVALUATION METRICS:

Following metrics can be used to evaluate performance of the above recommendation system:

1. MAP: Indicates how relevant the list of recommended items is.
2. MAR: Indicates how well the recommender can recall all the items the user has purchased in the test set.
3. Coverage: Indicates the percent of items in the training data the model can recommend on a test set.
4. Personalization: Indicates how much personalized experience the model is offering to each user.
5. User-UI interaction analysis: How many meal recommendations are used by user from clicks.