Recommending restaurants for online food ordering

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***Abstract*— This report outlines a plan to design a restaurant recommendation model using real-world data from Akeed, which is a popular online food delivery application in Oman.**

I. INTRODUCTION

Online ordering is steadily increasing with many businesses developing their own websites and mobile applications to sell or using Shopify. With the abundance of products to buy, customers too must do more effort when deciding what to order. With platforms like Klaviyo and Mailchimp, it's easy to set up marketing campaigns to attract customers through multiple communication channels. However, what it is that you recommend to the customers still remains an area of ongoing research.

With this in mind, we aim to design a recommendation algorithm to market the most suitable restaurants or cloud kitchens to customers who wish to order food online. To provide personalized and adaptive recommendations, we would be using data specific to customers.

II. DATA

In Oman, Akeed is a delivery service app. Akeed's goal is to be the instant delivery and discovery platform for anything consumers require. Akeed approaches food delivery aspects by accepting an order, routing it to a restaurant, picking it up, and delivering it to the customer.

We have taken a dataset provided by Akeed for a Kaggle competition that included data for close to 35,000 customers who have made orders to at least one of the 100 vendors. There 135,234 orders recorded in the dataset.

Customer and vendor locations have been masked. The distances have been re-scaled, however nearby locations remain nearby. The average distance between one or more locations of a single customer is 3379 miles (re-scaled) and the average order amount is 15 Oman Riyals.

III. LITERATURE REVIEW

Most of the Recommendation systems suffer from limited content analysis, cold start problem, over-specialization, and sparsity. We plan to use various techniques to handle these bottlenecks in building an efficient model such as using collaborative filtering to reduce the sparsity of the data, ontology based model to eliminate cold-start problem, weighted sampling of k-neighbors that takes into consideration the similarity levels between the target user (or item) and the candidate neighbors to reduce overspecialization.

IV. HYPOTHESES/GOALS

One of our major goals is to understand customer behavior in the food ordering space. In this regard, we want to investigate in to questions such as

- Do customers prefer faster delivery times as compared to better vendor ratings?
- Can we segment customers by their preferences for more precise recommendations?
- Perform a RFM analysis on Akeed's customers to calculate lifetime values.
- Create baseline recommendation model and fine-tune it.

V. EXPECTATIONS AND RESULTS

Highly informed individuals using a recommendation model will likely know what they are looking for and expect recommendations to be accurate, whereas with a user that is exploring options will prefer less precision and more recall to explore possibilities. This makes it tricky to choose an appropriate metric for evaluating our model.

It is a good practice to report both the precision and recall as they tell complementary stories on how our recommendation model is working. For example, suppose there are a total number of 500 restaurants available, 100 of which a customer may like to order from. Model A recommends 70 out of the 100 relevant restaurants (recall = 0.7), while model B only recommends 2 of the 100 relevant restaurants (recall = 0.2). While A is suffering from lower precision, it also recommends some restaurants from those 400 irrelevant restaurants that the customer may not like, while model B recommends less irrelevant restaurants. Both models offer benefits, while one is conservative, the other may recommend a new restaurant to try.

VI. TIMELINE

Task	Target Date	Owner
Thorough literature review	17 Apr	Yuthika
EDA and unsupervised methods	20 Apr	Abhijeet
Build baseline recommendation model	20 Apr	Gurneet
Fine-tune recommendation model	22 Apr	Gaurav
Evaluate model results	24 Apr	Ayushi

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