RESTAURANT DELIVERY RECOMMENDATION ENGINE

HOW CAN GLOVO BUILD COMPETITIVE ADVANTAGE THROUGH RECOMMENDATION ENGINE?

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I. ABSTRACT

The objective of this report is to discuss the process of rebuilding the recommendation engine of Glovo's restaurant delivery. Since data was not publicly available for Glovo, I decided to use Yelp review dataset due to the similarity in nature of the two companies. Data was further transformed to match the business specificity of Glovo. The current shortcomings of Glovo Recommendation Engine are low serendipity & low novelty, lack of personalization and long tail distribution of review. Thus, a new Cascade Hybrid Model was built by ensemble Context Sensitive, Location-Based, Knowledge Based, Popularity, Random and Item Based Collaborative Filtering recommender. Each algorithm feeds on the refined recommendations of the previous algorithm to provide the most relevant list of recommendations.

This new system opens up new opportunities for Glovo to offer restaurants with Premium Listings, Target Advertisement and Promotion Packages. Additionally, the new engine aims to foster higher interactions of user with the platform, increasing user satisfaction, and ultimately increasing revenue for Glovo.

II. INTRODUCTION

As the society progress, people now are spending more time working and enjoying other activities, which means less time is allocated to cooking. With the help of digital development, we basically doing everything online, including eating. The trend of online food delivery has risen significantly for the past few years. According to a research by McKinsey&Co, online food delivery market enjoys a compound annual growth rate of 25% from 2015 to 2018[1].

Large opportunity carries fierce competition. In Spain alone, along with dozens of other smaller players, these four big players stood out: UberEats, Just Eat, Deliveroo and Glovo. These companies offer very similar delivery services and competing mainly on delivery fees and delivery time. Big players with greater financial power invest heavily to acquire more drivers and increase the market share. However, competing based on price is an unsustainable game and therefore, to compete in such a fierce environment, company need to build competitive advantage from a different angle. This is where a good restaurant recommendation engine become useful.

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[1] https://www.mckinsey.com/industries/high-tech/our-insights/the-changing-market-for-food-delivery

III. COMPANY BACKGROUND & BUSINESS MODEL

Glovo is a Spanish startup founded in 2015 and has become one of the fastest growing company in Europe. Glovo now operates in more than 70 cities in 20 countries within Europe and Latin America[2]. The value proposition of Glovo is to deliver anything that could be transferred in a bike within one hour. While Glovo offer delivery services for multiple categories of products such as pharmacies and supermarkets, the focus of our recommendation engine is on its top category, restaurant delivery[3].

Glovo earns money from transaction fees of every successful delivery. The fee is ranging from 1.9 to 5.5 euros depending on the distance. Furthermore, the startup has recently launched the Glovo Prime feature, where user can subscribe for free deliveries for 5.99 euros per month. While Glovo is growing at an accelerated pace, it faces very high competition from other more established players. To remain competitive, Glovo need to reinvent its current restaurant recommendation system in other to increase customer satisfaction, which is the key to retain customer in a platform. A user who repeatedly receives relevant restaurant recommendations from Glovo will be more satisfied with the experience and is more likely to use the platform again.

GLOVO APPS

With its distinctive yellow background, Glovo Apps is fairly user friendly. Simplicity one of the outstanding aspect of Glovo Apps comparing to the other competitors platform.

User can make an order within a few clicks. The account setup is straightforward, where the Apps will require user's personal details, bank account and delivery information.

Delivering fees varies across different services, depending on the distance of travelling, the complexity of the task and the timing of the order. Specifically, longer distance delivery has higher fees than standard delivery. More complex task such as medicine purchase charges higher fee. Also, user need to pay extra for late night orders (Out Of Business Hours).

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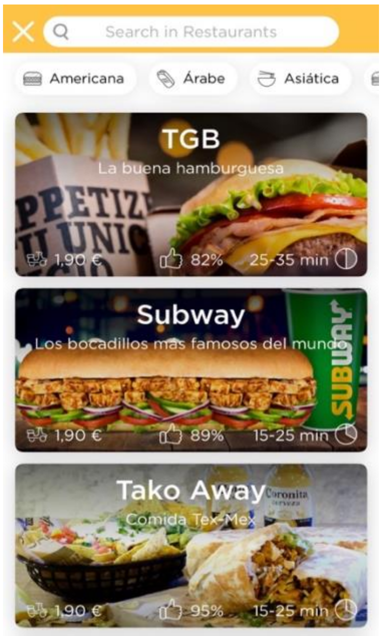
[2] https://techcrunch.com/2018/07/18/glovo-gets-134m-to-beef-up-its-on-demand-delivery-business/

[3] https://blog.dealroom.co/interview-with-sacha-michaud-co-founder-of-delivery-app-glovo/

The delivery fees is split between the platform and Glovers (carrier). Glovers can earn extra through tips and good rating from users. Glovo fosters the development of the gig economy, where Glovers enjoys flexible working hours in exchange for less employment benefits.

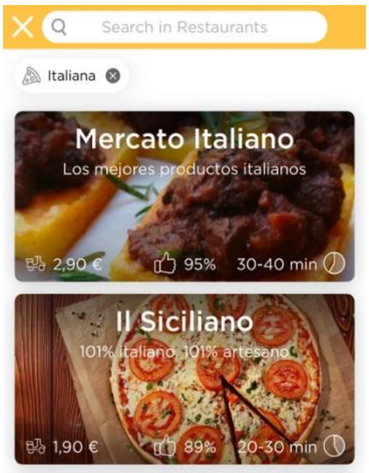
IV. CURRENT RECOMMENDATION ENGINE



Online Food Order Delivering is Glovo core business. As the user click on the “Food” section, they have a list of restaurant choices with information of delivery cost, delivery time and customer rating of the restaurant. This is where Glovo recommendation engine operates.

The core recommendation system of Glovo is a hybrid system of locational-based algorithm, popularity recommender and knowledge based recommender. At default mode, Glovo will recommend restaurants based on the location of customer and the popularity of the restaurant. In this case, the closest restaurants to my location is Subway, however TGB is at the top of the list due to its popularity.

Popularity algorithm is determined by the rating that users give to the restaurant for the order. At the end of each delivery, user can rate their experience with the restaurant by giving a “Thumb Up” for good experience or “Thumb Down” for bad experience. A rating of 82% means that out of the users who rate for this restaurant, 82% users positively.



Knowledge based recommender kicks in when user apply the filter bar for specific type of restaurant. In this case, user is giving explicit feedback for the recommender to suggest restaurants with attributes that match user criteria. For example, as I apply the “Italiana” filter, only Italian restaurant will be shown. Once again, the top listed restaurants are determined through popularity and location-based.

CORE PROBLEMS

1. Low serendipity & Low Novelty

Since the recommendation engine is popularity and locational based, user will repeatedly get the same recommendations. Specifically, popular restaurants that close to customer will be recommended again and again, reducing the novelty of the platform. The recommender has low serendipity due to the low diversity of the recommendations. This creates a long tail problem where less popular restaurants are unlikely to be recommended. This is costly for the business as its demotivate users explore new area of interests, restricting sales diversity. Additionally, user would not want to be recommended the same restaurant repeatedly as we have the tendency to try new food and explore new restaurants.

2. Non Personalized Recommendations

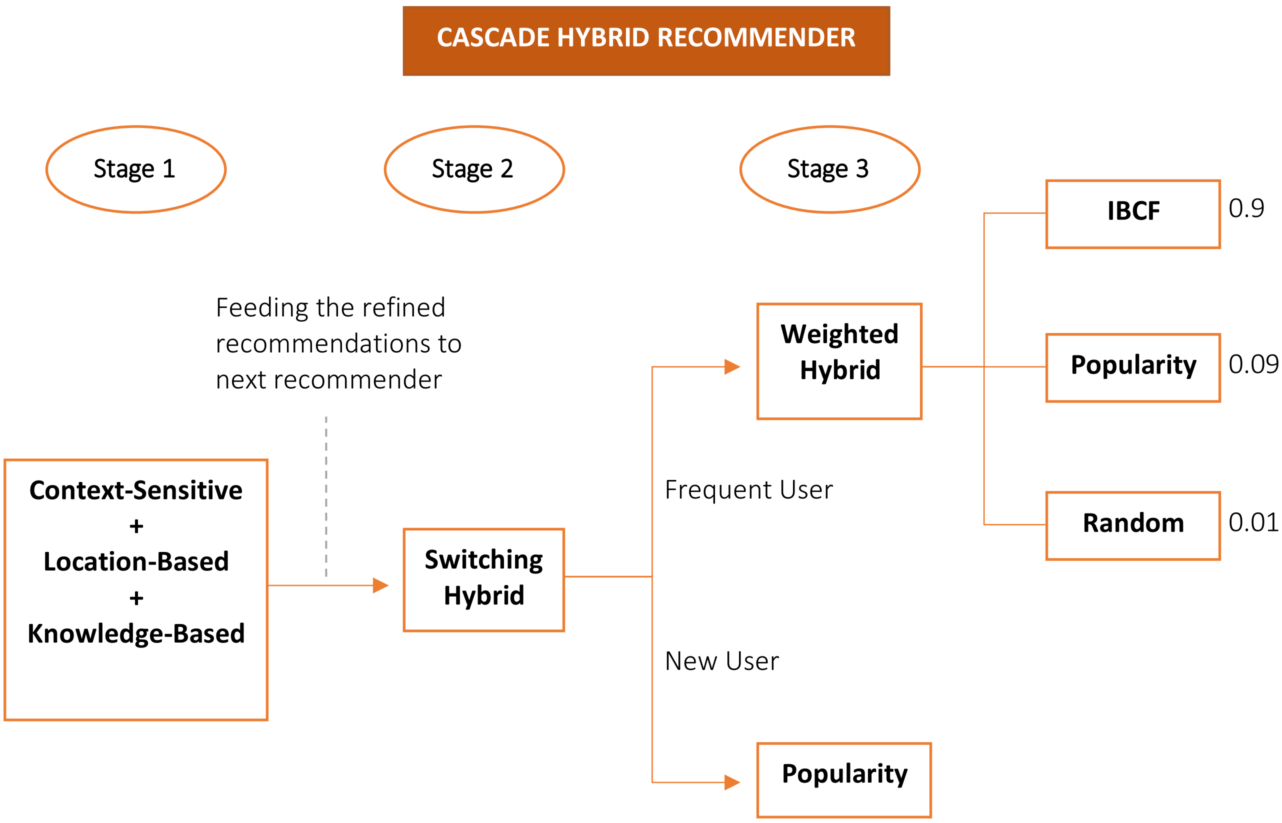
Recommendations based on popularity and location will rarely match user's taste. Given similar location, two user with different tastes will be given the same restaurant recommendations. While users can manually filter the recommendations to arrive at the list that matches their interest, current recommendation engine fails to capture the interaction between users and restaurants. This will better captured by incorporating collaborative filtering algorithm. From a business perspective, Glovo is likely to lose customers who received poor recommendations with low customization. These users will likely to migrate to competing platform, moving the potential source of data and revenue away from Glovo.

3. Unbalance Review Distribution

Most user on Glovo barely review. The majority of people review few times, while a small portion of user make up the majority of the review. At the same time, some restaurants received a lot of review while unpopular restaurant received less review. This could be due to the lack of incentive for customer to review. As customer review is not being feed into the recommendation engine, the interaction of the user and the reviewed restaurant is being discarded. On the other hand, a good recommendation system will take into account of this interaction, providing more relevant recommendations based on customer review. Ultimately, this will create a feedback loop where feedback from customer is being use to refine the algorithm.

V. REBUILDING GLOVO RECOMMENDATION ENGINE

The objective of the new recommendation engine is to resolve the shortcomings of the current engine. The new engine aims to offer higher serendipity, higher novelty, and more customized recommendations to the user. Additionally, the new model aims to leverage the power of customer and restaurants interactions, creating new business opportunity for Glovo. The diagram below outlines the core structure of the of Cascade Hybrid Recommender of Glovo. It ensembles 6 core algorithms: Context-Sensitive, Location-Based, Knowledge-Based, Item Based Collaborative Filtering, Popularity and Random. This is a Cascade Model as each recommender actively refines the recommendations made by the previous recommender[4]. We will discuss the algorithms in a deeper manner in the following section.



[4] Aggarwal, C. (2018). *Recommender Systems*. New York: Springer.

STAGE 1: LOCATION BASED - CONTEXT SENSITIVE – KNOWLEDGE BASED

Delivery time is one of the core aspect of the competition among the food delivery companies. Customer expect their order to arrive within a defined timeframe. Late delivery often results in customer dissatisfaction, which might requires Glovo to refund or compensate for such poor service. Thus, recommended restaurants must located within a close periphery of the user's location. The Location Based Recommender allows us to refined the recommendations to only a certain geographic area. Ultimately, this ensures the engine to generate only relevant recommendations within customer neighborhood.

The type of food that user order changes throughout the day. For example, users are likely to enjoy something light in the morning or early afternoon, thus recommendations of pizza might not be ideal. Additionally, opening hour varies among restaurants. This is where Context-Sensitive recommender becomes useful, offering suggestions of restaurants are open when the customer want to make the order. For example, if a "frequent user" open the Glovo Apps in the morning, the engine will recommends relevant restaurants that offer breakfast. These restaurant will match with what the user' breakfast taste for previous order (IBCF). Further illustration in the section VI.

Another way that the user can interact with the platform is by applying a filter on the specific type of food that users would like to be recommended. The Knowledge Based Recommender processes performed on the basis of similarities between customer requirements and item descriptions, or the use of constraints specifying user requirements[5]. For example, if a "frequent user" apply "Mexican" as the filter, recommendations will contain nearby customized Mexican restaurants. Ultimately, the results of these three algorithms would then be used as the input for the later stage recommenders.

STAGE 2: SWITCHING HYBRID

The algorithm switches between various recommender systems depending on the number of review the user have made. In earlier phases, we apply popularity recommender system to avoid cold-start issues. In later phases, when more ratings are available, we will apply weighted hybrid model of item based collaborative filtering, popularity and random recommenders. Since IBCF is sensitive to cold start and require a certain amount of rating from user to perform well, popularity will step in to recommend nearby popular restaurants for new users.

[5] Aggarwal, C. (2018). *Recommender Systems*. New York: Springer.

Another way that our model resolve user cold start is from Knowledge Based Recommender where new user could apply filter on the specific type of restaurants. In this case, user will be recommended with popular restaurants that match their criteria.

STAGE 3: WEIGHTED HYBRID

For frequent users, we will apply Weighted Hybrid Recommender with the largest weight given to IBCF recommender. This is because collaborative filtering recommender helps improve the diversity of the recommendation, which is one of the shortcoming of the current system. IBCF utilize the past interactions between user and restaurants to recommended relevant restaurants that user is likely to like. Thus, IBCF is take into account of user's behavior while the other algorithms fail to achieve this.

A small portion of the weight is shared between Popularity and Random recommender. While IBCF is providing a more diverse recommended list, Popularity ensures that the certain restaurants in the list are trustworthy & popular in case the user is looking for something popular or mainstream. Random recommender is essential to increase the serendipity and novelty of the recommended list. Increasing serendipity often has long-term and strategic benefits to Glovo because of the possibility of discovering entirely new areas of interest. Also, Random recommender might help solve new restaurant cold start problem, as the new restaurant might be randomly recommended to a user. On the other hand, algorithms that provide serendipitous recommendations often tend to recommend irrelevant items. In many cases, the longer term and strategic benefits of serendipitous methods outweigh these short-term disadvantages.

We choose not to use UBCF which recommends restaurants base similar interest among users, it ends up recommend restaurants from different geographic region. In our case, we would want the recommendations to be within a confined geographic area of the user. IBCF gives more accurate and relevant recommendations. In the case of Glovo, IBCF offers higher **scalability** than UBCF as there are more users than restaurants, every time a new user sign up UBCF recommender need to be retrain, while it is only the case for IBCF if a new restaurant sign up.

VI. ILLUSTRATION USING R

Yelp dataset has 4.1M reviews and 947K tips by 1M users for 144K businesses. The business and review datasets were merged to create the rating dataset. This is further subset to include only ratings after 2015. While the geographic area of Yelp is in the U.S, the model was built to be scaled to any geographic region. The key data columns that were used to complete our model: Business_ID, Business_Name, City, State, Restaurant_Categories, User_ID, Review_ID, and Rating.

The first illustration of the model is applied to a frequent user who lives in Las Vegas and loves fast food. He has made 10 ratings on Western Restaurants. First, Location Based Recommender refines the recommended list to only Las Vegas. Since he is a has make more than the threshold level of rating, Weighted Hybrid Model with IBCF algorithm was applied to provide the recommended list of 10 restaurants based in Las Vegas. Most of the recommended restaurants match the user taste for Western based foods. However, there are a few interesting recommendations about Asian and Mediterranean restaurants. This illustrates fairly well the improvement in diversity, serendipity and novelty of the recommendation. Detail resulted could be found in Appendix 1.

The second illustration of the model is applied to a new user who is from Las Vegas. This user has made two reviews and is using the platform in the morning to look for Juice & Smoothies. In this case, Context Sensitive Recommender kicks in to refine recommended list to only restaurants that open for breakfast. Knowledge Based Recommender is applied to further refine the lists to include only restaurants that offer Juice & Smoothies. Since this is a new user, Popularity recommender is later applied to provide a list of popular restaurants that offer Juice and Smoothies in Las Vegas. This illustrates how the model can deal with user cold start and provide relevant recommendations that fits the context and matches user interest.

VII. FUTURE REVENUE OPPORTUNITIES

Since the recommendation engine is now more dynamic and diverse, not only popular restaurants will appear on the recommended list. Glovo can give edge to vendors who are willing to pay by offering Premium Listings. Vendors could then pay Glovo to be on top of the recommended lists or to appear in more often in the recommended list.

Also, as Glovo will have a better understanding of customer preference, it could advise Paid Vendors to attract more customers through targeted advertisements. Specifically, restaurants can have dynamic cover photos that changes depending on the target group. This is a strategy that Netflix is applying to showcase its movie, where the cover photo changes depending the user[6].

Glovo can launch "Glovo Deal" program where restaurants can buy deals and gift certificates to offer customer attractive discounts at their business. This has been successfully adopted by Yelp, where they charges 30% of the paid amount in case of deals and 10% in case of certificates[7].

NON ALGORITHMIC SOLUTIONS

Review can be increased using incentive system. Create feedback loops of review by providing incentive for user to review. This should be send 30 minutes after the confirmation of delivery, ensuring that user already enjoy the food, and recommendation is given on a merit basis. Also, Glovo could learn from Yelp in how active reviewers are recognized as Yelp Elite, which members enjoy exclusive benefits. In this case, Glovo can motivate users to review by granting free delivery to active reviewers or free membership of the Glovo Prime.

While Restaurant Cold Start problem could be solved using knowledge based or random recommender, a more effective non algorithmic solution is to create a section dedicated to new restaurants. Glovo could launch the "New Restaurants In Town" section which will appear below the normal recommended list. As users scroll down the recommended list, they could have a chance to explore the "New Restaurant In Town" section. This allows new restaurants to have more exposure in the platform thus increase the likelihood of them being rated.

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[6] https://www.vox.com/2018/11/21/18106394/why-your-netflix-thumbnail-coverart-changes

[7] https://www.feedough.com/yelp-business-model-how-does-yelp-make-money/

ROOM FOR IMPROVEMENT

At this point, our engine is giving recommendation at the "City" level, however, it will be more accurate to have the Location Based Recommender refine at the "Neighborhood" level. Since delivery time is extremely important for Glovo, the recommended lists need to be within approximately 1 hour delivery time. This problem could be resolved with more accurate data at the neighborhood level.

Similarly, Context-Sensitive Recommender will function more effectively with detail information of restaurant opening time. However, the current dataset doesn't provide this information. In the case of Glovo, this could be easily incorporate since restaurant needs to provide operating time when signing up with the platform.

Currently, the engine have not incorporate any attack model to ensure robust and stability. A recommender system is stable and robust when the recommendations are not significantly affected in the presence of attacks such as fake ratings or when the patterns in the data evolve significantly over time. This could be resolved by either adopting push or nuke attack method, where they designed to "nuke" items or lower the weight of fake ratings in the system[8].

CONCLUSION

To remain competitive in the food delivering sector, it is essential for Glovo to revamp its current recommendation engine. Customers are becoming more and more overwhelm with the amount of restaurant options that they could choose, thus a good recommendation need to make this process easier. The current engine faces with the shortcoming of low diversity and fail to capture past behavior of users. Thus the recommended lists are not personalized and similar for user living in the same area.

A new Cascade Hybrid Model is designed to offer higher serendipity, higher novelty and more personalized recommended lists. Recommendations are constantly refine based on the location, context and the filter that the user applied. Different recommender mechanisms are applied depending on the status and background of the user. This system aims to deliver higher customer satisfaction while opening up new business opportunity for Glovo with restaurants. The engine could be further improved through gathering more granular data and adopting more robust attack models.

[8] Aggarwal, C. (2018). *Recommender Systems*. New York: Springer.

APPENDIX 1: ILLUSTRATION FOR FREQUENT USER

User Rating List

Business Name	Rating	Location	Business Categories
The Melting Pot-Las Vegas	2	Las Vegas	Restaurants, Breakfast & Brunch, American (New), American (Traditional)
Pieology Pizzeria	5	Las Vegas	Pizza, Fast Food, Restaurants
Hash House A Go Go	4	Las Vegas	Barbeque, Restaurants
Omelet House	4	Las Vegas	Food, Restaurants, French, Breakfast & Brunch, Cafes, Bakeries, Coffee & Tea
Bacon Bar	5	Las Vegas	Fast Food, Burgers, Restaurants
Feast Buffet	3	Las Vegas	American (New), American (Traditional), Sports Bars, Bars, Nightlife, Diners, Restaurants
The Original Sunrise Cafe	3	Las Vegas	Food, Italian, Salad, Restaurants, Pizza
The Palazzo Las Vegas	5	Las Vegas	Italian, Restaurants, Nightlife, Pizza, Bars
Pinball Hall Of Fame	4	Las Vegas	Barbeque, Event Planning & Services, Food, Pizza, Restaurants, Food Delivery Services, Italian, Chicken Wings, Caterers
Senor Frog's	4	Las Vegas	Restaurants, Chicken Wings, Cajun/Creole, Fast Food, Chicken Shop

Recommendation List

Business Name	Location	Business Categories
Pokeman	Las Vegas	Hawaiian, Japanese, Sushi Bars, Food, Poke, Restaurants
Tacos El Gordo	Las Vegas	Mexican, Tacos, Restaurants
MAMAOH	Las Vegas	Korean, Restaurants, Asian Fusion
N9NE Steakhouse	Las Vegas	Seafood, Steakhouses, American (Traditional), Restaurants
Lola's A Louisana Kitchen	Las Vegas	Breakfast & Brunch, Restaurants, Cajun/Creole
Mario's Westside Market	Las Vegas	Veterinarians, Grocery, Food, Pets, Restaurants, Soul Food
Joes Seafood Prime Steak & Stone Crab	Las Vegas	Steakhouses, Nightlife, Seafood, Restaurants, Bars, Wine Bars
Golden Flower Chinese Cuisine	Las Vegas	Restaurants, Chinese
The Fat Greek	Las Vegas	Cafes, Restaurants, Mediterranean, Food, Bakeries, Greek
Karaoke Q Studio	Las Vegas	Barbeque, Nightlife, Karaoke, Bars, Asian Fusion, Lounges, Korean, Beer Bar, Restaurants

APPENDIX 2: ILLUSTRATION FOR NEW USER

User Rating List

Business Name	Rating	Location	Business Categories
Bruxie	5	Las Vegas	Desserts, Food, Breakfast & Brunch, Waffles, Sandwiches, Restaurants
Cabo Wabo Cantina	5	Las Vegas	Arts & Entertainment, Mexican, Breakfast & Brunch, Nightlife, Restaurants, Music Venues, Bars

Recommendation List

Business Name	Location	Business Categories
SkinnyFATS	Las Vegas	Food Delivery Services, Juice Bars & Smoothies, American (Traditional), Delis, Breakfast & Brunch, American (New)
Grouchy John's Coffee	Las Vegas	Food Trucks, Breakfast & Brunch, Cafes, Food, Bagels, Juice Bars & Smoothies, Coffee & Tea