Rotman

RSM-8423 – Optimizing Supply Chain Management and Logistics

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HOT DELIVERY

A Case Study in Online Food Delivery Platforms

Source: https://www.appclonescript.com/online-food-delivery/

Introduction

Food delivery platforms such as *Uber Eats*, *DoorDash*, and *SkipTheDishes* have revolutionized the way how people order groceries and interact with restaurants, with an impressive year-on-year growth. For example, by the end of 2021 Uber Eats had already a market share of 29% of all the food delivery services across the United States, surpassing $8 billion in revenues and $30 billion in gross bookings (more statistics here). The second largest company in this space is DoorDash, who reported $4.8 billion in revenues in 2021 but, because of its aggressive restaurant and pricing strategy, controls 45% of the US food delivery market (stats here). (Of note is that Uber has made several attempts to merge with DoorDash in the past.)

While these companies have impressive growth and revenue, surprisingly Uber Eats, DoorDash, and other similar services *have never reported any profits, losing money every year*. This occurs because (a) they are primarily focusing on expanding the business and invest heavily in ads, promotions, and discounts; and (b) very little profit is made per order. The biggest expense delivery companies face is *paying drivers*, who receive a base fare based primarily on the **distance** they traverse. Thus, online food delivery companies invest heavily on data and routing prescriptive models to reduce their delivery costs, bringing to light new challenges in the field.

In this case study, your team was hired by the data analytics group at Uber Eats as consultants to propose a solution to a real-world *strategic* and *operational* problem that they face every day. Specifically, *how to assign drivers to orders based on estimates of their best-possible delivery routes.*

To help you in the analysis, the problem is broken into four parts that incrementally add more of the real-world features of the problem. Distance estimates are based on centroids of Toronto neighborhoods, a common practice where data is readily available. We suggest that you follow the flow provided by Parts I-IV to organize your work and evaluate trade-offs, highlighting the managerial insights you learn throughout the process. All problems should be formulated as mixed-integer linear programs and solved using PuLP (Gurobi is also acceptable if you feel adventurous).

Part I – Single-driver perspective

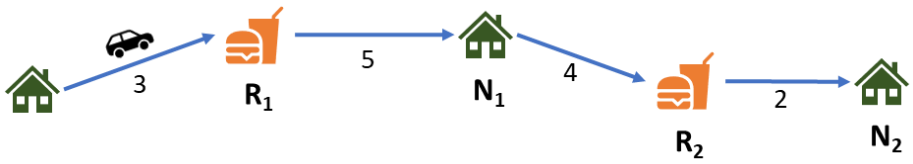
Once a delivery order arrives at the system, Uber Eats assigns it to a driver who picks the food at the restaurant and brings it to the customer. Uber Eats wishes to preemptively assign the driver to multiple pickups, based on the expected time the food will be prepared by the restaurant and the restaurant-customer distance. While the resulting order assignment may not be necessarily shared with the driver at once, it plays a critical role in estimating the best costs required to complete the delivery.

Your objective in Part I is to design a model that produces the optimal delivery route for a single driver, assuming their next few future orders have already been assigned by another system. Your solution must satisfy the following constraints and objective:

- The driver starts at the **Downtown Toronto (Rosedale)** neighborhood.
- The driver can carry multiple orders in their vehicle or transportation modal.
- After finishing all deliveries, the driver parks the car in the neighborhood where the last order has been placed, waiting for future orders.

- Your objective is to **minimize the total distance traversed by the driver**.

For example, the picture below depicts the example of a solution with two orders: one from restaurant R_1 to be delivered in neighborhood N_1, and another from restaurant R_2 to be delivered in neighborhood N_2. Distances are in kilometers. The driver first visits restaurant R_1 and delivers the food to N_1, and then picks up the food at R_2 and delivers to N_2. The total distance traversed by the driver in this solution is 3+5+4+2 = 14 km. Other solutions are possible, such as picking up both orders before delivering them.



The dataset contains two instances for you to evaluate your model, *part1_ordersA.csv* and *part1_ordersB.csv*. Discuss your solutions for each case, describing the route and total distance.

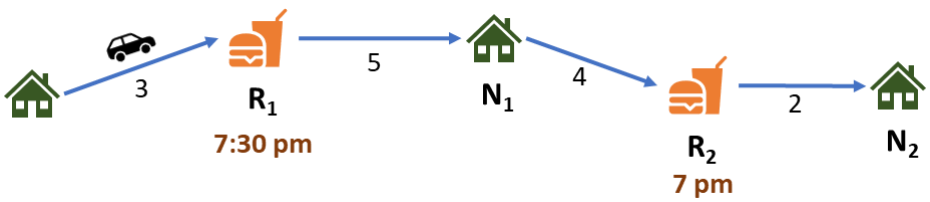
Part II – A matter of time

One of the main challenges in food delivery is *time*. First, the restaurant may require several minutes to prepare the order. Second, the time elapsed between the order being ready for pick up and when the customer receives it cannot be excessively high, which could be detrimental to the quality of the service and the food experience.

Your objective in Part II is to incorporate time into the model you developed in Part I. Specifically, every restaurant now places as estimated time when the food will be ready to pick up. Based on this value, we define the **customer wait time** as the time between when the food is ready to pick up, and when the driver arrives at the customer's address (in this case the neighborhood). Notice that this time does not consider food preparation/packaging because it cannot be optimized by Uber Eats.

Moreover, assume that the driver spends, on average, five minutes in each location waiting for the customer to pick up the order (e.g., waiting in the lobby of the customer's condominium).

The data group at Uber wishes to consider routes that impose a **limit "W" on the maximum average waiting time** of the orders assigned to the driver. For example, consider again the same illustrative route from Part 1, now with the time each order is expected to be released under the restaurant icons.



Assume that the driver's velocity is 20 km/h (considering traffic and stopping lights, for example). The customer waiting time for the first order that is picked up in the route (i.e., R_1) is 15 minutes: the order is ready at 7:30 pm, the same time it is picked up, and it takes 15 minutes for the driver to arrive at N_1 (at 7:45 pm). The waiting time for the second order is 68 minutes: the driver leaves N_1 at 7:50 pm, picks the order at 8:02 pm in R_2, and arrives at N_2 in 8:08 pm. The average waiting time is (15+68)/2 = 41.5 minutes.

The solution is feasible for W = 60 minutes, but infeasible for W = 30 minutes, for example.

We still wish to minimize total distance traversed. Augment your model to incorporate this time constraint, evaluating your solution on the instances in *part2_ordersA.csv* and *part2_ordersB.csv*. In particular:

1. How much more difficult does the problem become as W decreases or increases? Why?
2. Create a trade-off curve comparing **W** and **distance** for these instances. Why do you observe that particular shape? Furthermore, are they correlated? (Note: with this curve, you are trying to infer the *sensitivity* or *elasticity* of the total distance with respect to W).
3. What is the problem when considering the average waiting time? Propose and test an alternative metric to address the issue you identified, showing how the solution changed with your new measure.

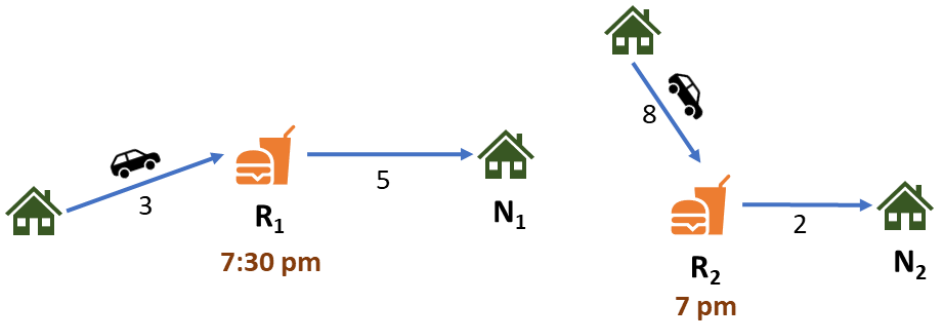
For this part, assume that the driver also starts at **Downtown Toronto (Rosedale)** and has an average velocity of **40 km/h**. Report the average waiting time for all your solutions.

Part III – The more the merrier

The routes calculated in Parts I and II help Uber Eats in estimating routing costs. The actual decision problem, however, is assigning orders to drivers based on such estimates.

Generalize your model from Part II to **multiple drivers**, that is, your model assigns orders to drivers as well as route them. Each driver has their own velocity based on their modal (walk, bicycle, or driving) and starting location described in the file **part3_drivers.csv**. Consider the average waiting time constraint from Part II (not your novel metric).

The objective is to minimize the **total distance traversed by all drivers**. For example, the solution below assigns the two orders from the previous examples to two distinct drivers, giving a total distance of 8 (first vehicle) + 10 (second vehicle) = 18 km.



Test your model on the instance *part3_small.csv*, collecting managerial insights from the solutions you obtained. In particular, answer the same questions 1-3 from Part II, in addition to

4. How does the solution change when you consider less drivers, including a single one? That is, what are the benefits/disadvantages to the distance and average waiting time?
5. Based on your insights from 1-4, how does that relate to the current driver strategies that Uber Eats and Door Dash implement?

Recall to report always the total distance and average time in your report.

Part IV – Scaling

In practice, Uber Eats not only needs to solve large-scale versions of the model you proposed in Part III, but also re-solve it several times throughout the day (e.g., when a driver cancel its current pick-ups).

The issue with your model in Part III is that the model does not scale to large-scale problems. Propose a simple but scalable heuristic based on the insights that you observed in the solutions of Parts I-III. Your heuristic may also leverage mathematical programming from Parts I-III, but that is not necessary.

Evaluate your method on the instance *part3_small.csv*, comparing its quality to the optimal solution you obtained in Part III. Fix **W = 120** for simplification.

Finally, use your heuristic to solve the instance *part4_large.csv* with *part4_drivers.csv* also with W=120, reporting the solution and the costs. Discuss (a) the applicability of your heuristic, and (b) how would your heuristic be used in practice. For your discussion, assume that your approach is run in an *online fashion*, i.e., it only considers the orders that are available in the system and no estimates of arriving orders (common in complex operational settings such as this).

The team with the best solution in terms of total distance will get a 15% bonus on the assignment (that is, their letter grade will be multiplied by 1.15). If two or more teams have the same distance, the team with the best average waiting time will be selected. Finally, if two or more teams have the same distance and waiting time, the team with the best report will be the winner. The solutions and waiting times must be clearly presented.

Data and further notes

You will also receive the file **regions.csv** with the geodata of the neighborhoods, and the file **distances.csv** with the distance in kilometers between two distinct neighborhoods. If you wish, you can use the Toronto geodata in this link (in GeoJSON) to plot your route in the map for visualization purposes.

It is extremely important that you build your models **incrementally**, always testing and inspecting solutions as much as possible. The models are not trivial. Please avoid implementing all constraints at once without testing and inspecting each portion of your model at a time.

The problems, even if small, are not easy to solve. If the runtime is taking too long, you can set a time limit with the code

```
model.solve(pulp.PULP_CBC_CMD(timeLimit=120))
```

where "120" represents the limit in seconds (you can use other numbers) and "model" is your PuLP formulation. The solver will halt at the time limit provided above with the best possible solution it could find during that time (if any). The total time elapsed after a solve() call can be obtained through the code

```
print("Time elapsed:", model.solutionTime)
```

All instances here (except *part3_large.csv*) are expected to be solved in less than two minutes. For the single-driver cases, taking more than 10 minutes could be indicative of problems in the formulation (possibly too many constraints). However, you may have different experiences based on your computer configuration. The solutions accepted in this case must be obtained within at least 10 minutes (600s).

Note: the solution is only optimal if the solver finishes **before** the time limit, even if PuLP says "optimal."

Deliverables

The deliverable for this case study are:

- A report in **PDF** format that addresses the managerial questions posed here. The report can be in any format that you desire. It must, however, include an executive summary and a **very clear** description of all the models you used. Your report must be at most 15 pages (or less), not counting the appendix (which can be of any length).

- The source code in **Python** with your analysis. Spreadsheets (e.g., Excel) and other tools are allowed for plotting purposes only. The code must be clearly organized so that we can replicate your results exactly.

Evaluation

Your report will be given a raw score out of 100 points using the following scheme:

- *Models* [40 points]: If the inventory models you designed are sound and adequate to the problem.
- *Analysis* [30 points]: if the analysis is sound and comprehensive, addressing the questions posed by the agency.
- *Implementation* [20 points]: If the implementation of your models is correct and free of errors or bugs. It must also be well organized and readable.
- *Writing* [10 points]: if the report is well-written and organized.

You will also receive a letter grade associated with your raw score, alongside an explanation of your mark. The letter grade is adjusted based on the relative performance of the class and the difficulty of the case study. Please check the syllabus for more information on the letter grade.