Grocery Shopping Optimization

Group 2

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1. Introduction

Food insecurity can be defined as the inability to access sufficient, safe, and nutritious food that meets an individual's dietary needs for leading a healthy life. In 2017, 11.8% of American households were reported to be food insecure (Bahadur & Pai, 2020). When identifying groups who experience food insecurity, there are numerous factors to consider, such as the individual, social, and macro environments. Individually, eating habits are influenced by personal motivations and self-efficacy. Those with lower incomes tend to choose eating preferences based on taste rather than nutritional content (Bahadur & Pai, 2020). Social surroundings, such as norms and supports available, as well as the macroenvironment, including food production, agricultural policies, and economic price structures, will also play a role in dietary decisions. For example, the cost of nutrient-dense foods such as fruits and vegetables tends to increase rapidly compared to energy-dense foods such as chips and cookies. These are only a few factors that substantially impact whether or not an individual may experience food insecurity.

Although it has been identified as a symptom of poverty, this does not mean everyone suffering from food insecurity lives in poverty. In fact, two significant groups who are largely impacted include students and individuals with chronic illnesses. In North America, upwards of 47.2% of postsecondary students experience food insecurity (Broton & Cady, 2020). Often, food insecure students describe a balancing act characterized by the limit of time and money, resulting in many sacrificing food in the short term to gain the long-term socioeconomic success and stability associated with a postsecondary degree (Broton & Cady, 2020). Although they may have a preference for nutritious food, a working student may be too busy to research where to find the cheapest nutrient-rich foods. Alternatively, many students rely on frozen or pre-made meals from the grocery store and fast-food options to save time. Similarly, those who suffer from various chronic illnesses are also likely to suffer from food insecurity. Take the example of an individual with diabetes, where access to food does not guarantee security if food quality and preferences are ignored (Gucciardi et al., 2014). Like the student dilemma, the time it takes to research which grocery store carries the cheapest options that cater to their individual needs becomes an issue. The lack of time and resources to access this information can affect an individual's ability to manage their health, especially those that possess conditions with strict dietary regimens such as diabetes.

The goal of this project is to deliver these groups of individuals with a model that provides the lowest-cost grocery list per user by considering lifestyle factors such as desired nutritional intake and travel time. It is important to note that food insecurity is a highly complex issue which cannot simply be solved through one single method. There are many factors that have not been outlined which drive food insecurity worldwide. However, through this project, individuals will gain quick and easy access to the cheapest options that fit their personal needs in hopes to aid in lessening the gap between time, money, and food.

2. Problem Description

The basic model was built by minimizing the cost of purchasing grocery items and the cost of traveling to the grocery store, subject to transportation, nutrients, diversity, and allergy constraints. The objective of the model was that it would automatically determine one store the user should visit for groceries, as well as one recommended traveling mode to achieve the lowest cost. The later part, however, can also be pre-selected by the user. For our model, the user was assumed to reside on the campus of the University of Toronto, and thus, the origin of travel. The stores to be chosen are two Loblaws branches, two No Frills branches, one Metro branch, one Walmart branch, and one Grocery Gateway branch (Figure 2). The modes of transportation include driving, walking, biking, and public transport (Toronto subway). The user is assumed to have an allergy to peanuts to demonstrate the model's capability of excluding a particular type of ingredient.

2.1 Variables and Parameters Description

2.1.1 Parameters

We used capitalized letters for aggregated list of parameter names, such as names of nutrients; we used small letters for decision variables and grocery list related parameters, and Greek letters for transportation related constraints.

- S: List of stores, e.g., Loblaws and Walmart
- I_i: List of items in store i, where i belongs to S
- T: List of transportation modes, e.g., driving and walking
- N: List of nutrients, e.g., fats and sodium
- C: List of categories, e.g., K(legumes) and G(eggs)

- $r_{i,j}$, for $i\forall S, j\forall I_i$: Price of item j in store i, where i belongs to S and j belongs to I_i
- δ_k, for $k\forall$T: Cost per meter of transportation for mode k, where k belongs to T
- β_i, for $i\forall S$: Distance in meter from the origin to store i, where i belongs to S
- $\mu_{i,k}$, for $i\forall S$, $k\forall$T: Traveling time in second from the origin to store i using transportation mode k, where i belongs to S and k belongs to T
- $n_{i,j,z}$, for $i\forall S, j\forall I_i, z\forall N$: Nutritional facts per item j of nutrient z in store i, where i belongs to S, j belongs to I_i, and z belongs to N
- $s_{i,j}$, for $i\forall S, j\forall I_i$: Numbers of serving per item j in store i, where i belongs to S and j belongs to I_i
- d_z, for $z\forall N$: Daily intake suggestion for nutrient z, where z belongs to N
- $c_{i,j,l}$, for $i\forall S, j\forall I_i, l\forall C$: A binary variables that indicates whether item j in store i belongs to category l, where i belongs to S, j belongs to I_i, and l belongs to C, i.e., $c_{i,j,l} = 1$ when item belongs to the category, and 0 otherwise
- p_l, for $l\forall C$: Minimal percentage of item should belong to category l, where l belongs to C.
- q: Maximum number of quantities. Set to 2 in the model
- γ: Maximum time in second that the user is willing to travel. Set to 2000 in the model
- $a_{i,j}$, for $i\forall S, j\forall I_i$: A binary variable that indicated whether item j in store i contains peanut as an ingredient, i.e., $a_{i,j} = 1$ when the item contains peanut, and 0 otherwise

2.1.2 Decision Variables

- $x_{i,j}$, for $i\forall S, j\forall I_i$: Quantity of items
- u_i, for $i\forall S$: A binary variable that indicates whether a store is selected by the model, i.e., $u_i = 1$ when store i, where i belongs to S, is selected by the model, and 0 otherwise.
- ρ_k, for $k\forall$T: A binary variable that indicates whether a mode of transportation is selected by the model, i.e., $\rho_k = 1$ when transportation k, where k belongs to T, is selected by the model, and 0 otherwise.

For our user, the model will choose a store (u_i) from S, with a list of items ($x_{i,j}$) from I_i, that satisfies the nutritional intake (d_z), category diversity (p_l), allergy ($a_{i,j}$) and maximum quantity (q) constraints. In addition, the model will also seek to minimize traveling cost by choosing a mode of transportation (ρ_k) from T that satisfies the maximum traveling time (γ) constraint.

2.2 Model Formulation

The objective function was composed of two parts. The first part was the cost of purchasing grocery items, which was calculated by the quantity of chosen items multiply the prices. The second part was the cost of traveling, which was calculated by the multiplication of traveling distance (β_i), traveling cost (δ_m), decision variable of the store (u_i), and decision variable of transportation mode (ρ_m). However, since the cost of public transport was always the same despite the distance, the traveling cost when taking public transport was only the multiplication of traveling cost (δ_n), decision variable of the store (u_i) and decision variable of transportation mode (ρ_n), where δ_n was \$6.5.

Objective:

$Minimize\ \sum_i Purchaing\ Cost_{i,j} + Traveling\ Cost_{i,m,n}$, for $i\forall S$

Purchasing Cost = $\sum_j x_{i,j} \times r_{i,j}$ for $j\forall I_i$

Traveling Cost = $\sum_m (u_i \times \rho_m \times \beta_i \times \delta_m) + (u_i \times \delta_n \times \rho_n)$ for $m\forall \mathrm{T}'$ and $n =$ $public\ transport$, where $\mathrm{T}' = \mathrm{T} - n$

Subject to:

(1.1) $\sum_j x_{i,j} \leq M \times u_i$

(1.2) $\sum_i u_i = 1$

(1.3) $\sum_i \sum_j x_{i,j} \times n_{i,j,z} \times s_{i,j} \leq d_z$ or $\sum_i \sum_j x_{i,j} \times n_{i,j,z} \times s_{i,j} \geq d_z$

(1.4) $x_{i,j} \leq q$

(1.5) $\sum_i \sum_j \frac{x_{i,j} \times c_{i,j,l}}{x_{i,j}} \geq p_l$

(1.6) $\sum_i \sum_j a_{i,j} = 0$

(2.1) $\sum_i \sum_k u_i \times \rho_k \times \mu_{i,k} \leq \gamma$

(2.2) $\sum_k \rho_k = 1$

for $i\forall S, j\forall I_i, k\forall \mathrm{T}, z\forall N, l\forall C$

M=999999999 (big M)

The first type of constraint was related to the grocery shopping list. Constraints (1.1) and (1.2) were to ensure that our model only chose one store to visit at a time. When $u_i = 0$, $x_{i,j} = 0$, and thus, this will make sure that when the model chooses not to visit a store, the quantity of all items purchased from that store will be zero. Constraint (1.3) controls the weekly intake of nutrients. For the macronutrients, the case of an athletic user interested in a high protein, high carb, and low fat diet was studied. It was assumed that the daily caloric intake of that user is 3,000 kcal per day. Keeping that in mind, we distributed the calories amongst fat, carb, protein, fibre at a 9:4:4:2 ratio, respectively, as those are the amounts of calories per gram of each macronutrient. The values of the weekly consumption of the remaining nutrients were based on the research of the U.S. Food & Drug Administration (FDA) and other institutions (U.S. FDA, 2022) (Harvard T.H. Chan, n.d.) (UCSF, n.d.). The final values of the weekly intake of each nutrient are demonstrated in Table 2.3.1 in the appendix. Constraints (1.4) and (1.5) served the purpose of diversifying the final output of the grocery list. Constraint (1.4) would set the maximum quantity of each item to 2, and constraint (1.5) made sure the user would get items from different categories, following a certain percentage calculated by the number of items in that category divided by the overall quantity of all items. The proportions specified in the model are displayed in Table 2.3.2 in the appendix. Constraint (1.6) corresponds to our assumption that the user is allergic to peanuts, and thus, the number of items with peanut in the ingredient should be zero.

The second type of constraint was related to traveling between the origin and store. Constraint (2.1) allowed the user to input the maximum amount of time they were willing to spend on traveling. Constraint (2.2) made sure that the model would select only one mode of transport at once.

3. Numerical Implementation & Results

3.1 Data Description and Manipulation

The data on which the optimization model was built was obtained from the University of Toronto's (UofT) Food Labelling Information Program (FLIP) curated by the L'Abbe Lab. Data in the FLIP database contains information about packaged food items across different stores in Toronto that is updated every 3-4 years. The application of our model was restricted to the data in the 2020 dataset, as it was the first dataset to map items to the retail stores and include item prices. The data also includes information about item characteristics, such as their food category, container weight, serving size, and nutritional value per serving.

The distance and time information were obtained by retrieving a distance matrix from the Google Maps API. Since our model assumes that the user will want to visit only one store when grocery shopping, only the distances of the shortest paths between the origin and all the seven stores and their corresponding travel times were kept. To facilitate the development of the model, the distance and travel time of the round trip between each store and the origin were calculated by adding the metrics of the trips in both ways. This process was repeated for four different modes of travel, namely driving, walking, biking, and public transport (Toronto subway) to make the model more inclusive and to reflect the reality of the different travel options available to different groups of society more closely. Tables 3.1.1, 3.1.2, 3.1.3 and 3.1.4 in the appendix show the total distances and travel times for a round trip between the origin and each store for every mode of travel.

Despite its richness, the 2020 FLIP dataset had many missing values in item characteristics that were vital for our model. In the attempt to make our data uniform across all items, we began by dropping all the items that had missing values in their pricing or in all their nutrient component values. We, later, discovered that some items had amounts of their nutrients defined but missed values in their calorie count. Since it makes no sense for an item to provide nutritional value without energy (calories), we dropped every item with a missing KCAL value before filling all the other missing nutrient entries with zeros. After that, we obtained dummy variables for the food category classification variable, TRA_Cat, to be able to integrate the information about categories in the constraints that help ensure a balanced variety in the recommended shopping list.

Upon its import, the dataset had three columns that reflect the size of an item: container size in grams, container size in milliliters, and container size as indicated on the package. The challenge rose in the last of these columns, where the size of a container was expressed in a plethora of ways (number of pieces, liters, kilograms, pounds, etc.). To solve this issue, we proceeded to convert the units in which the container sizes of these items were expressed to grams or milliliters. Container sizes expressed in the number of pieces, slices, portions, and many other unit-based measurements were dropped for the impracticality of quantifying the size of each unit in grams or milliliters. Only one exception to that process of item dismal was made in eggs, because we were able to assume that each egg weighs around 50 grams. Once all remaining item sizes were expressed in grams or millilitres, the column “container size as indicated on the package" was dropped. Moreover, by examining the preliminary results that our model yielded, we discovered that including big items produced infeasible results. This happened because the selection of such items would quickly meet most of the nutritional requirements specified, and hence left other constraints unfulfilled. Therefore, we dropped items with container sizes in grams greater than or equal to 1000 g.

Due to the specificity of our use case, we needed to form a link between the size of the container and the serving size of each item. This was necessary to better present the number of nutrients each complete item offers when consumed and the amount each item contributes to the overall weekly nutritional intake desired by the user. Hence, for the items the serving sizes of which were expressed in grams or milliliters, the number of servings in each container was calculated by dividing the container size by the serving size. Then, the items with serving sizes expressed in other units were discarded.

Finally, the data was converted into a dictionary of dictionaries for easier access, with each sub-dictionary referring to a single store. Each store dictionary was indexed by the store code found in the original dataset and consisted of multiple lists that represented data about each store and the items it offered. Table 3.1.5 in the appendix demonstrates the final format of the dictionaries corresponding to each store.

3.2 Numerical Results

Our team used Gurobi 9.5.2 and Python 3.8.8 to create the linear grocery trip minimization problem. For loops were used throughout the model to ensure that every item contained in all six grocery stores is considered.

The output of the linear optimization model determined Joe's No Frills as the optimal grocery to shop at along with biking as the optimal mode of transportation. These results satisfy the travelling time constraint as well as minimize the travelling cost. Table 3.2.1 in the appendix displays the items to be purchased by the user so that they attain their nutritional goals. Table 3.2.2 in the appendix displays the total nutritional facts of the grocery store items in the model output. The total cost of all the items at Joe's No Frills is $28.36.

4. Problem Extensions

4.1 Multiple Stops

Currently, our model assumes users want to purchase all their items from one location. The model considers the distance between a user and six grocery stores as well as the time related to various transportation modes. However, due to different pricing strategies, visiting multiple stores may reduce the overall cost of a user's grocery bill. On average, Canadian households visit 2.3 stores to purchase their weekly groceries (Retail Council of Canada, 2019). This extension would be beneficial as the time it takes to travel between multiple grocery stores may be worth it for a user on a tight budget. The addition of this focuses on adding routes a user can take and the travel time associated with each route and mode. Specifically, a user would input the number of stores they are willing to visit in one trip, and the model would identify which combination of grocery stores would provide the cheapest items according to the nutrition and allergy constraints while also considering the user's desired travel time and the length of each mode. Figure 4.1 depicts a comparison between the original model output and this extension, assuming the user is willing to visit up to 2 grocery stores, wants to save money by walking, and sets the desired travel time of 75 minutes.

As shown, if a user is willing to spend an extra 35 minutes on travel, they can reduce the cost of their total grocery bill. Although this extension allows for greater customization and considers the unique needs of each user, its ability to work alongside our current desired travel time constraint is user dependent. Even if they are willing to visit multiple stores, if a short, desired travel time is set, the model will likely tell a user to visit one store or to drive. Therefore, when setting up multiple stores, users should consider extending their desired travel time to save on their grocery bills. However, as a note, this extension still does not consider other complexities such as the cost of gas or the cost of parking in a major city.

4.2 User Consumption

When shopping for groceries, consumers are likely to have items or recipes in mind that call for specific ingredients. Even though our current model allows users to choose what to include or exclude in the final output, it does not take into account the proportions of each item that will be consumed during the week due to the absence of data on consumer eating behaviors. This results in the recommendation of items that will not realistically be consumed in one week. For example, one of the outputs that we obtained as we tested our model was canola oil. Even though the nutritional value of the bottle of oil does not disrupt the nutrition constraints, it is not logical for anyone to consume a bottle of canola oil in one week. The presence of a matrix that provides a rough estimate of the user's eating behavior would allow the model to account for the proportions of an item that will be consumed, and thus, provide more suitable recommendations. Such data would also allow the user to account certain recipes he/she might want to make. By knowing the recipe proportions and the amount of meals the user plans to prepare, the model can ensure that the user requirements are fulfilled accordingly.

In addition to the model extensions mentioned, additions to the dataset would have augmented the use case immensely. The suggested dataset modifications are discussed in the following list:

1. Adding claims in the data, such as if an item is gluten-free, vegetarian, or vegan, would enable users to customize the output of products to their specific dietary restrictions. In 2017 these claims were manually tracked for each item in the FLIP dataset. Since the 2020 data was scraped, it did not include these claims, however, the 2020 dataset was used for this project as it was more thorough in other aspects. We could not match claims to items between 2017 and 2020 as they each included different store locations and products. However, if current datasets still had these item claims, users could better find specific items related to their dietary needs.
2. Currently, the dataset only includes packaged foods. This leaves out produce products from our final grocery list output, which is unrealistic. The addition of these items would allow the model to make decisions that more closely the eating habits of more groups in society.
3. Although each item is categorized into groups: legume, meat, eggs, vegetable, fruit, or bakery item, more detailed groups would aid in improving this model. Specific categories, such as cereals or chicken products, could be included so that users can identify items they want. For example, this would ensure that the user can eat cereal for breakfast, but the model will find the cereal that best minimizes the price and aligns with set nutritional constraints.
4. The uniformity of product IDs and category IDs across different stores would be helpful in comparing prices. In the application of the Traveling Salesman Problem, for proposed multi-stop extension, uniform IDs would allow the model to identify items bought in one store and ensure no repetitions are made. Coupling product and category IDs would further assure that the same products across brands would not be recommended multiple times.

5. Recommendations & Conclusions

The purpose of this project is to provide people with an accessible way to obtain cheaper food while satisfying nutritional requirements. Therefore, to make the whole process more convenient, we recommend developing a mobile application that focuses on customizing the grocery shopping list for an individual user at the lowest cost. Building upon the basis of our model, the application should include three major functionalities.

- Customization: Allow users to input their personal information, such as age, weight, height, and workout habits. The application will automatically calculate the best nutritional intake suggestion to ensure a healthy diet.
- Dietary Preferences: The algorithm will also seek to meet all the preferences that a particular user has. For instance, referring to the previous section, more claims, such as vegan and gluten-free. Users can also incorporate specific recipes into their diets.
- Traveling Preferences: To ensure users can easily access the recommended locations, they are encouraged to specify their preferred traveling method, traveling time, as well as the maximum number of stores they are willing to visit.

Despite the promising vista, in reality, there are many bottlenecks limiting the feasibility of the application. Data integrity and data security are the two main barriers. As previously mentioned, the FLIP dataset only contains package food. This is because the nutritional data of not packaged food are difficult to obtain, as, for example, the amount of fat in different chocolate cakes can vary largely from store and brand. Furthermore, it is hard to imagine that many stores will be willing to share data about their product information, especially for the usage of allowing consumers to compare prices.

Through months of exploring and trying out, this project has improved our comfortability with Gurobi and Python. We learned how to build a more complex model and, more importantly, use linear optimization to solve real-world issues. We also have come to know why it is incredibly challenging to attain a universal solution despite a large population are suffering from food insecurity. However, we hope this project can fuel this endeavor and, in the future, help to make healthy food more accessible to more people.

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7. Appendix

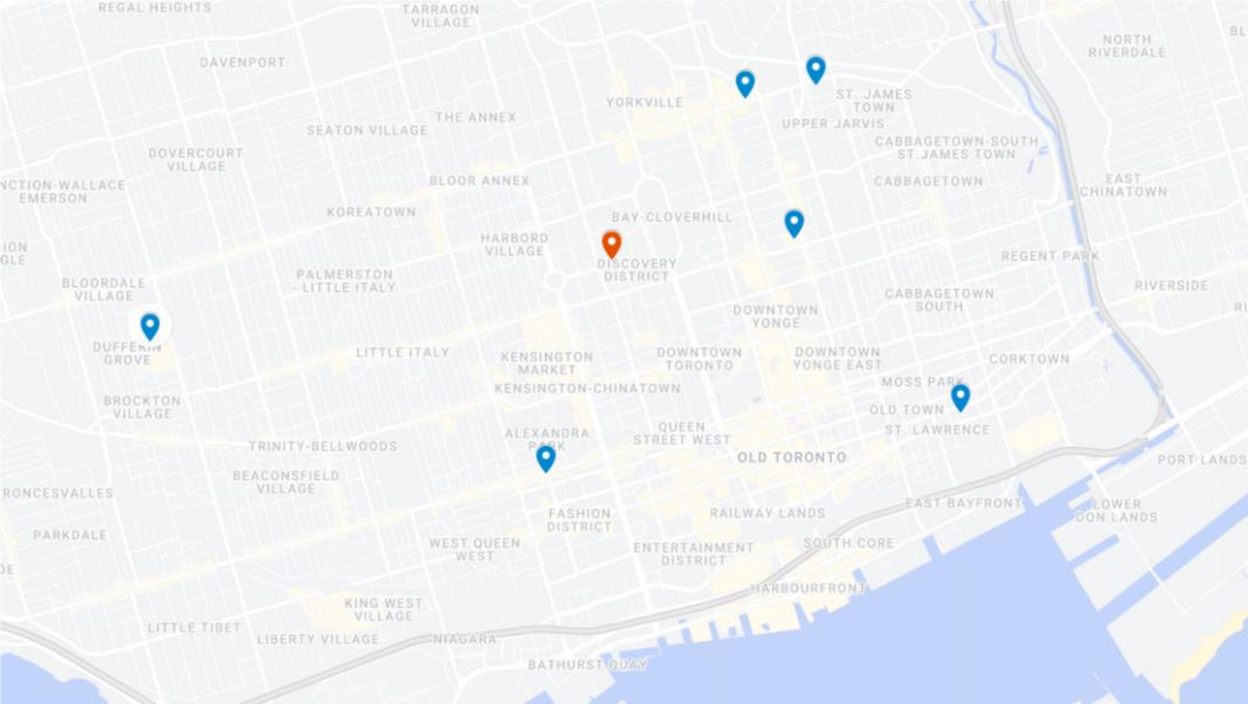


Figure 2 Locations of stores with respect to the origin

Food Component	Weekly Values
Calories	≤21000 grams
Fat	≥500 grams
Saturated Fat	≥ 140 grams
Trans Fat	≤20 grams
Cholesterol	≤2200 milligrams
Sodium	≤16100 milligrams
Carbohydrates	≥2000 grams
Fiber	≥100 grams
Sugar	≤252 grams
Protein	≥1400 grams

Table 2.3.1 Weekly nutritional intake of examined user

TRA Category	Percentage
Legumes	≥5%
Meat products or substitutes	≥20%
Eggs	≥5%
Vegetables	≥10%
Fruits	≥10%
Products	≥10%
Beverages	≥3%
Grain Products	≥10%

Table 2.3.2 Minimum percentages for each category

Store	Travel Distance (m)	Travel Duration (s)
Loblaws MLG	4356	1012
No Frills	7482	1705
No Frills Joe's	5520	1483
Walmart	51655	3777
Grocery Gateway	8676	1754
Loblaws	2155	2669
Metro	3836	911

Table 3.1.1. Total distance and travel time between the origin and each store for driving

Store	Travel Distance (m)	Travel Duration (s)
Loblaws MLG	2826	2199
No Frills	7112	5516
No Frills Joe's	4613	3483
Walmart	38150	28753
Grocery Gateway	7520	5730
Loblaws	4628	3517
Metro	2472	1913

Table 3.1.2. Total distance and travel time between the origin and each store for walking

Store	Travel Distance (m)	Travel Duration (s)
Loblaws MLG	9431	2754
No Frills	8506	3950
No Frills Joe's	6267	2520
Walmart	44893	7989
Grocery Gateway	9140	2988
Loblaws	4628	3517
Metro	2472	1913

Table 3.1.3. Total distance and travel time between the origin and each store for the subway

Store	Travel Distance (m)	Travel Duration (s)
Loblaws MLG	3191	816
No Frills	7579	2073
No Frills Joe's	5395	1373
Walmart	40373	8685
Grocery Gateway	8776	1935
Loblaws	4668	1023
Metro	2837	707

Table 3.1.4. Total distance and travel time between the origin and each store for biking

Data	Data Scale	Data Type	Data Description
Distance	Store	Integer (4 dictionary entries, one for each travel mode)	Distance to store and back using the said travel mode in meters
Travel Time	Store	Integer (4 dictionary entries, one for each travel mode)	Time to store and back using the said travel mode in seconds
Product Names	Item	List of strings	Names of products in the store
Item Price	Item	List of floats	Prices of each product in the store
Number of Servings	Item	List of floats	The number of servings in each item
NFT	Item	List of floats (15 lists, one for each nutrient)	Amount of the nutrient in a serving of each item
Ingredients	Item	List of strings	Ingredients found in each item
TRA categories	Item	List of binary integers (26 lists, one for each food category)	Food category to which each item belongs (1 means belongs to said category)

Table 3.1.5 Every store's data dictionary used in building the optimization model.

Food Product	**Quantity**
Sparkling Passion Fruit Beverage	1
Parle Krackjack Cookies	1
Pear J Sparkling Pear Drink	1
Grade A White Eggs, Large	1
Hazelnut Wafers	1
Whole Leaf Spinach	1
Chicken Hot Dogs	2
Luncheon Meat	1
Whole Flaxseed	1
Sliced Mushrooms	1
Yellow Split Peas	2
Lupini Beans	2

Table 3.2.1 Final grocery shopping output from linear optimization model

Nutrient	Value
Calories (kcal)	20991
Protein (g)	1401
Fat (g)	841
Trans Fat (g)	2
Saturated Fat (g)	143
Carbohydrates (g)	2175
Fibre	1049
Sugar (g)	240
Sodium (mg)	12985
Cholesterol (mg)	2196
Vitamin A (mg)	593
Vitamin C (mg	169
Calcium (mg)	8838
Iron (mg)	224
Potassium (mg)	41795

Table 3.2.2 Total nutritional information from the grocery items outputted by the model

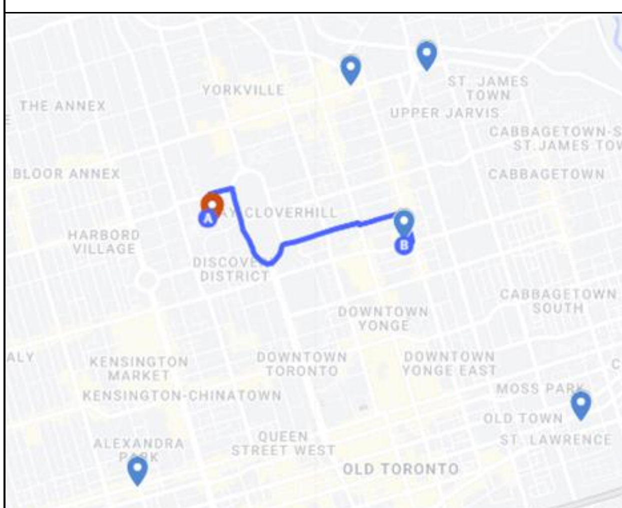
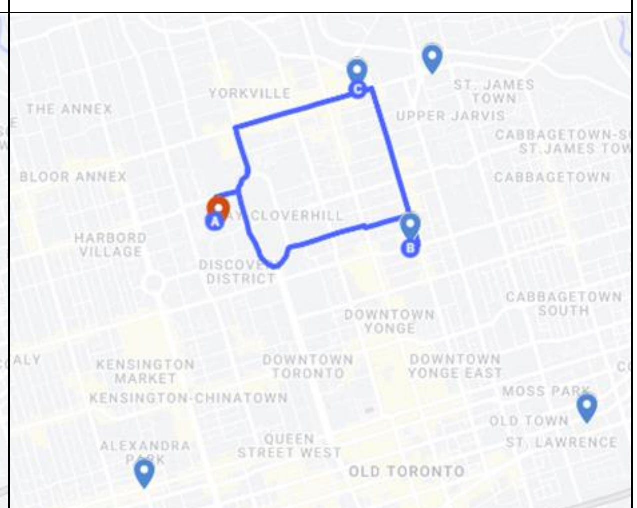
<table>
<tr><th>Original Model</th><th>Model Extension</th></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Mode of Transportation: Walk (30 minutes)</td><td>Mode of Transportation: Walk (65 minutes)</td></tr>
</table>

Figure 4.1 Contrast between the model choosing one grocery store versus multiple