

An Integer Programming Application: Meal Plans using Fast Food Chains



OPR 620 Operation Research I

Group Project

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Executive Summary

College students have stereotypically poor eating habits, and scientific research supports this claim. While it may be tempting to propose eating healthier foods and setting aside more time to cook to college students with sub-par diets, this can be unrealistic due to constraints on a student's time, budget, and culinary knowledge. Given that, we would likely not be able to turn students away from convenience food, our objective is to optimize a diet consisting entirely of fast food and fast-casual restaurants. We have created a model wherein cost of food is minimized, while nutritional requirements are still met.

This model considers a sampling of establishments within walking distance of Drexel University. Our model provides three meals a day over the course of a number of days, with considerations made for variety – for instance, no restaurant may be visited more than once per day. Logistical concerns were made to keep our data set at a reasonable size, and also with nutrition in mind. Specifically, drinks were not included (soda and other beverages will only increase cost) and menu choices were limited in cases where restaurants had highly customizable menus (such as Chipotle).

To run our model, a user first inputs information about their vital statistics and goals, which generates nutritional requirements. This information is then copied to the code to be submitted to the NEOS server for computation.

This model works accurately, but there is room for improvement in efficiency. If the model can be adapted to run more efficiently, more user customizability can be implemented, including dietary restrictions (vegetarians, lactose intolerance, etc), restaurant preferences (perhaps I would like to eat Chipotle at least once per day), and the ability to tailor results to students who eat meals at unconventional times.

Problem Statement and Objective

If one was surveyed about the eating habits of college students, one of the phrases that would inevitably pop up is “the freshman 15,” referring to the idea that students usually gain 15 pounds during their first year. While this number may be fabricated, there is more than a nugget of truth to the idea. A study in the Journal of American College Health found that more than 50% of freshman students ate fried or high-fat fast foods at least three times in a week, and by the end of their sophomore year nearly 70% of the students studied had gained weight¹.

When separated between genders, we see more poor eating habits; only 40% of men are likely to cook their own food². They are also less likely to read food labels, and more

¹ (Racette, Deusinger, Strube, Highstein, & Deusinger, 2005)

² (Musingo, 2009)

likely to skip breakfast³. Women tend to consume less fiber and fewer servings of fruits and vegetables than men⁴.

One solution to a lack of nutritious meals would be for students to be more diligent in preparing their own food. This is problematic, however, given that many students may live on campus or in shared apartments with poorly outfitted kitchens and may not have sufficient culinary knowledge to work around these constraints. In addition, college students typically do not have excess money at their disposal, and the prospect of building a pantry of ingredients, purchasing pots and pans, and shopping for perishables on a regular basis may seem fiscally infeasible to a young student on their own for the first time. A study in the *Journal of Nutrition Education and Behavior* found that 59% of students were food insecure, meaning that they had insufficient access to adequate nutritional food due to socioeconomic conditions⁵.

Our objective is to provide a solution in which college students can eat convenience meals, minimize the costs, and still meet proper nutritional requirements. We will accomplish this by optimizing a diet consisting solely of fast-casual foods.

Methodology

Data Collection

A search of the website Grubhub.com in Drexel's area code reveals over 100 restaurants that will deliver food to area students⁶, and this number does not include fast food and fast casual locations such as Subway or Chipotle, nor the multitude of food trucks on campus. With so many options, it is not surprising that many students are not preparing their own meals.

In order to keep our project within scope, we needed to determine criteria to select which restaurants we would focus on:

- The restaurant needed to be located on or within walking distance of Drexel's campus
- The restaurant needed to have nutritional information available
- At least some of the restaurants needed to have a breakfast menu
- Both traditional fast-food and 'fast-casual' restaurants should be included to reflect the available landscape of options
- We would choose a total of 11 restaurants with which to create our data set

³ (Li, et al., 2012)

⁴ (Li, et al., 2012)

⁵ (Patton-López, López-Cevallos, Cancel-Tirado, & Vazquez, 2014)

⁶ This does not include "delivery services" that provide food from more traditional restaurants; if we include those, we find 275 restaurants within delivery distance.

Given these requirements, we decided upon the following establishments:

- Chick-fil-A
- Chipotle
- Cosi
- Dunkin Donuts
- Jersey Mike's
- McDonald's
- Salad Works
- Shake Shack
- Starbucks
- Subway
- Wendy's

Nutritional data from each of these restaurants was gathered from their respective websites. The FDA requires that all restaurants of 20 or more locations offer the following nutritional information upon request:

- Calories
- Total Fat
- Trans Fat
- Sodium
- Fiber
- Protein
- Calories from Fat
- Saturated Fat
- Cholesterol
- Total Carbohydrates
- Sugar

This information was readily available, except for Cosi which did not disclose information regarding sugar content for their menu items. Given this inconsistency, we made the decision to discard Cosi from our data set.

In addition, a conscious decision was made to limit foods to standard menu offerings. Chipotle, for instance has over 1 million possible combinations of food available to order due to customization. In this instance, arbitrary decisions of what our burritos should consist of were necessary for the sake of scope.

Nutritional Requirements

In order to define the nutritional requirements for an individual, we must first set a framework to follow. Many fad diets have come in to fashion over the years, promising weight loss to those who eschew food items such as carbohydrates, fats, or gluten, or by consuming certain items such as shakes.

Essentially, if these diets work it is because those following them manage to eat less calories than they previously had. According to the Mayo Clinic, “Despite all the diet strategies out there, weight management still comes down to the calories you take in versus those you burn off.”⁷ In fact, from a perspective of strictly managing weight, a calorie is a calorie no matter where it comes from.⁸ An extreme example of this idea is

⁷ (Staff, n.d.)

⁸ (Buchholz & DA, 2004)

Kansas State University professor Mark Haub, who in 2010 lost 27 pounds on a diet focused on twinkies, Doritos and Oreos⁹.

In determining the caloric intake needed for a person, we must calculate basal metabolic rate (BMR) and total daily energy expenditure (TDEE). BMR is the amount of calories the human body needs to maintain its current weight if it is only providing vital functions (for instance, if that person was in a coma). BMR is determined by a person's sex, age, height and weight. While there is variation to metabolic rate, the majority of the population have a metabolic rate that exists within a variance of 200 to 300 calories.¹⁰ TDEE is the amount of calories needed to maintain weight factoring in daily activity and exercise.

Even though weight management is dependent on caloric intake, macronutrient and micronutrient intake are still important for overall health. Even the twinkie diet require Mark Haub to supplement with protein shakes, a multivitamin and vegetables. Macronutrients consist of protein, fat and carbohydrates. We will seek to build a diet which is inclusive of all three of the macronutrients. Protein is important for maintaining lean muscle mass while losing weight, or gaining muscle mass for someone who is gaining weight. In addition, protein is shown to increase satiety more so than fat or carbohydrates.¹¹ Excess intake of dietary fat has been linked to diseases such as diabetes and heart disease, however the human body relies on fat for essential functions.¹² While excess dietary fat is stored in the body as fat, when dietary fat consumption falls below 10% of total daily calories, the body begins converting carbohydrates to fat for storage.¹³ Carbohydrates are used as fuel by the body, and are converted to energy as well as supporting the central nervous system and our vital organs.¹⁴

Regarding intake levels for macronutrients, a person's daily protein intake should be in the range of 0.36 gram to 1 gram per pound of bodyweight. The low end of that spectrum is for sedentary individuals not seeking a change in body composition, while the higher end of that range should be targeted by anyone highly active or seeking to preserve lean muscle mass during weight loss.¹⁵

For fat intake, the USDA recommends that adults comprise 20 to 35% of their daily intake from fats, preferably with 10% or less of those calories coming from saturated fats.¹⁶

Once protein and fat intake levels have been calculated, carbohydrates form the remainder of calories. Given a person's personal dietary preferences, the ratio of fat to carbohydrate intake can be manipulated as one pleases (holding overall calorie intake

⁹ (Park, 2010)

¹⁰ (Resting Metabolic Rate, n.d.)

¹¹ (Paddon-Jones, et al., 2008)

¹² (Lichtenstein AH1, et al., 1998)

¹³ (McDonald, n.d.)

¹⁴ (Macronutrients: the Importance of Carbohydrate, Protein, and Fat, n.d.)

¹⁵ (Editors' Guide for Protein Intake, n.d.)

¹⁶ (USDA, 2010)

constant) without effecting body composition during weight loss,¹⁷ or weight gain.¹⁸ However, it should be noted that for those with diseases such as diabetes, a relatively low-carb diet “has been shown to improve fasting plasma glucose and insulin levels, cholesterol levels, blood triglycerides, preserve muscle mass during weight loss, and other health markers.”¹⁹

Beyond the three major macronutrients, we will be tracking the amount of fiber, sugar, sodium and cholesterol in our model, based on USDA recommendations.²⁰

Results

A typical day of results run on a sampling of our data set gives the following solution:

Restaurant	Item	Price	Calories	Protein	Fat	Carbs	Sodium	Fiber	Sugar	Chol.
<i>Breakfast</i>										
Starbucks	Pumpkin Cookie	2.25	330	4	19	37	125	0	18	30
Starbucks	Oatmeal with Fresh Blueberries	3.45	220	5	2.5	43	125	5	13	0
Starbucks	Oatmeal with Fresh Blueberries	3.45	220	5	2.5	43	125	5	13	0
Starbucks	Oatmeal with Fresh Blueberries	3.45	220	5	2.5	43	125	5	13	0
<i>Lunch</i>										
McDonald's	Side Salad	1	20	1	0	4	10	1	2	0
McDonald's	Side Salad	1	20	1	0	4	10	1	2	0
McDonald's	Chicken McNuggets 4 Piece w/ Marinara Sauce	1.99	205	9	12	14	435	1	2	25
<i>Dinner</i>										
Subway	6" Oven Roasted Chicken	4.25	320	23	5	47	610	5	8	40
Subway	6" Oven Roasted Chicken	4.25	320	23	5	47	610	5	8	40
Total		25.09	1875	76	48.5	282	2175	28	79	135
Goals			2400	100	50	350	2200	30	80	250
Difference			525	24	1.5	68	25	2	1	115

¹⁷ (Brinkworth, Noakes, JD, JB, & PM, 2009)

¹⁸ (Lammert, et al., 2000)

¹⁹ (Are there health benefits of a low carb diet?, n.d.)

²⁰ (USDA, 2010)

A larger data set would give us a more efficient result – for instance, purchasing a 12” oven roasted chicken sub from Subway instead of 2 6” subs would result in saving \$2.25. The 12” version, however, was not used in this particular example.

Our resulting meal plan comes 500 calories beneath our goal of 2400 calories. If one is trying to lose weight (or does not mind losing weight), this would be great, as a 500 calorie daily deficit would result in the loss of 1 lb. per week. Given a larger data set, we would likely produce a result closer to our target of 2400 calories. For someone trying to strictly maintain or gain weight, we would need a result much closer to our target.

Given the lower calories, it is not surprising that our macronutrient intake is lower than our maximums. Our micronutrients come very close to our limits; one hypothesis when initially working on this problem was that hitting the USDA’s sodium recommendation of no more than 2200 milligrams would not be possible while eating fast food, however our solution comes just under.

Future Considerations

- Research more efficient methods
 - Websites such as EatThisMuch.com are able to generate meal plans that meet nutritional requirements of their users in a matter of seconds
- Add in dietary restrictions
 - Add options for vegetarians, and for those with certain dietary needs (no pork, no dairy, etc)
- Add in more micronutrients
 - Ensure that potassium, vitamins and minerals were accounted for in our meal plan
 - This information was not directly available from the restaurants, as it is not required for them to report these numbers. It could be potentially difficult to obtain accurate information.
- Add more restaurants
 - Our data set consists of only a fraction of the options Drexel students have at their disposal.
 - This would require a more efficient method for calculating our model, as menu options would increase exponentially
- Add in additional preferences
 - For instance, if someone wanted Mexican food today, or wanted to avoid Chinese takeout
- Add a constraint that we cannot go to Chick-fil-A on a Sunday
 - Because it would be really depressing to be recommended Chick-fil-A only to realize that the restaurant is closed.
- Tailor to students schedules

- Use available restaurant opening/closing times to tailor to students schedules; especially since students may eat meals at unconventional times

Technical Report

Introduction / Rationale

A total of 1330 food items from 10 fast food restaurants were initially used in the model, among which 300 food items are from the Breakfast menu, and 1030 food items are from the Lunch & Dinner menu. The nutritional data and cost were also acquired for each food item. Our goal is to create a five-day meal plan to minimize the total cost and simultaneously maintain the daily nutritional goals that can be calculated through our Decision Support System. Maintaining the variety of foods will also allow for greater micronutrient variation. Taking all of these requirements into consideration, the following constraints were also established in order to create our model:

- Each day will consist of three meals
 - Since college students are more likely to skip breakfast, we wanted to enforce this as a rule
 - Our list of foods was split into breakfast, lunch, and dinner
- Each meal will consist of at least one item
 - Needed in order to enforce our criteria of three meals
- Our subject cannot go to the same restaurant more than once in a day
- Our subject cannot have the same item twice during the meal plan
- Each day will meet nutritional minimums
 - Nutritional minimums were set by our guidelines and calculated using our decision support system

One of the challenges we faced in implementing this model was running the code against our full data set. There were three restaurants that had a high number of menu items (Jersey Mike's had 600 accounting for different bread and size combinations) which we had to cut down. Jersey Mike's data set was cut from 600 options to 60 options.

We also eliminated items such as condiments and salad dressings. These items are considered free of charge at restaurants, and in order to minimize cost our model attempted to have our subjects eat a lunch consisting of balsamic vinaigrette. Similarly, we decided not to include beverages in our final dataset. This is from both a nutritional standpoint (sodas and sugary drinks from Starbucks would not have contributed to achieving goals), and from a logistical standpoint, as these would have added many more options to our data set, and generated their own constraints, forcing calculation time to increase even further.

Integer Linear Programming Model

There are two types of fundamental entities in our diet model: food items and nutrients. To formulate our diet model, we began by declaring the **sets**. We declared a set of nutrients denoted by *nutrients*. We split the total food items into three sets: *breakfastFoods* denotes the set of Breakfast Foods, *lunchFoods* denotes the set of Lunch Foods, and *dinnerFoods* denotes the set of Dinner Foods. The set *nutrients* contains eight elements, "Calories", "ProteinG", "Fatg", "Carbsg", "Sodmg", "Fiberg", "Sugarg", "Chlmg", representing the eight nutrients we focused on in the diet model. The elements of the set *breakfastFoods*, *lunchFoods*, *dinnerFoods* are composed of the food items in the dataset. We also denoted by *days* the set of days we are building the meal plan for, and *restaurants* the set of restaurants. The set *days* contains numerical elements 1 to 5, representing Day 1 to Day 5 of the meal plan. The set *restaurants* contains 10 elements: "Chick-Fi-La", "Chipotle", "Dunkin Donuts", "Jersey Mikes", "McDonalds", "Salad Works", "Shake Shack", "Starbucks", "Subway", and "Wendys", representing the 10 restaurants we are investigating in this model. We used the symbol *b*, *l*, and *d* to denote the individual food item in Breakfast, Lunch, and Dinner, respectively. We used the symbol *n* to denote the individual nutrient item.

Sets:

```
set breakfastFoods; #a set of breakfast Foods
set lunchFoods; #a set of lunch Foods
set dinnerFoods; #a set of dinner foods
set nutrients; #a set of nutrients
set days; #a set of days you are building meal plans for
set restaurants; #a set of Restaurants
```

Next, we declared the **parameters** in the model. There are three groups of parameters in the model: units of nutrients in each food item, cost of each food item, and daily nutritional goals for each nutrient. We used *bnutr*, *lnutr* and *dnutr* to denote the units of nutrients of food items in Breakfast, Lunch and Dinner, respectively. We used *bcost*, *lcost*, and *dcost* to denote the cost of food items in Breakfast, Lunch and Dinner, respectively. We denoted *nutriGoal* as the minimum units of nutrients required per day. In addition, we also declared additional three binary parameters *vB*, *vL* and *vD* as a linkage parameter associating each food items to each restaurant, with 1 indicating association, and 0 indicating no association.

Parameters:

```
param bnutr{breakfastFoods , nutrients} >= 0
    ## units of nutrients(n) in one item of b in Breakfast Food
    items.

param lnutr{lunchFoods , nutrients} >= 0;
    ## units of nutrients(n) in one item of b in Lunch Food items.
```

```

param dnutr{dinnerFoods , nutrients} >= 0;
    ## units of nutrients(n) in one item of b in Dinner Food items.

param nutrGoal{nutrients,days} >= 0;
    ## minimum units of nutrients (n) required per day for each
    nutrient.

param bcost{breakfastFoods} >= 0;
    ## cost of one item b in Breakfast Food items.

param lcost{lunchFoods} >= 0;

    ## cost of one item b in Lunch Food items.

param dcost{dinnerFoods} >= 0;

    ## cost of one item b in Dinner Food items.

param vB{breakfastFoods,restaurants};

    ## binary, matrix associated each Breakfast item to its
    associated restaurant with 1 or 0 if not associated.

param vL{lunchFoods,restaurants};
    ## binary, matrix associated each Breakfast item to its
    associated restaurant with 1 or 0 if not associated.

param vD{dinnerFoods,restaurants};
    ## binary, matrix associated each Breakfast item to its
    associated restaurant with 1 or 0 if not associated.

```

The set and parameters are known values from the dataset used in the model, next we defined the **decision variables** of the model, the values of which are to be determined by optimization. We used ***BX***, ***LX*** and ***DX*** to denote the number of food items purchased, and set these variables to be integer. The variable ***nutrSlack*** is denoted as the difference between the actual nutritional intake and the daily nutritional goal for each nutrient. Since the ***nutrSlack*** can be either positive or negative, we define ***nutriSlackVar*** as the absolute value of the slack variable. Another set of decision variables: ***BY***, ***LY***, and ***DY*** denotes the visit to a restaurant for Breakfast, Lunch and Dinner on a certain day, respectively. These set of decision variables are binary, with 1 indicating visit, 0 no visit.

Decision Variables:

```

var BX{breakfastFoods,days}    integer >= 0;
    ## the number of item b in Breakfast consumed on day t

var LX{lunchFoods,days}        integer >= 0;
    ## the number of item l in Lunch consumed on day t

var DX{dinnerFoods,days}       integer >= 0;

```

```

    ## the number of item d in Dinner consumed on day t

var nutrSlack{nutrients,days};
    ## the slack variable of nutrient n

var nutrSlackVar{nutrients,days};
    ## absolute value of the slack variable nutrSlack

var BY{restaurants , days} binary >= 0;
    ## binary for if the subject attended restaurant r on day t for
    Breakfast

var LY{restaurants , days} binary >= 0;
    ## binary for if the subject attended restaurant r on day t for
    Lunch

var DY{restaurants , days} binary >= 0;
    ## binary for if the subject attended restaurant r on day t for
    Dinner

```

The **objective** of this model is to minimize the total cost of food purchase in this five-day meal plan. There are two other components also included in the objective function. One is the total number of restaurant visits. Minimizing this component will ensure that if the subject purchased a food item from a restaurant, the visit to that restaurant will be forced to be 1, otherwise 0. The other component is the subtotal of the nutritional slack variables. We want to minimize the nutrition slack variables to ensure the actual nutritional intake in our meal plan as close to the nutritional goal as possible.

Objective:

```

minimize fun:
    sum{b in breakfastFoods,t in days} bcost[b]*BX[b,t]
    + sum{l in lunchFoods,t in days} lcost[l]*LX[l,t]
    + sum{d in dinnerFoods,t in days} dcost[d]*DX[d,t]
    + 0.01*sum{r in restaurants , t in days} (BY[r,t]+LY[r,t]+DY[r,t])
    + sum{n in nutrients,t in days} nutrSlackVar[n,t]

```

After defining the decision variable and objective function of the model, the final part is to define the **constraints**. The following constraints were added to the model.

- Binary Linking Constraints use the linkage variables to connect the food item purchase and the restaurant visit. If the subject purchased a food item from a restaurant, the subject must visit the restaurant. As mentioned in the objective function, since we are minimizing the total visits to restaurants, therefore if the subject did not purchase a food item from a restaurant, the subject must not visit the restaurant.
- We also added constraints to make sure the at least one item is purchased per meal, the subject does not purchase the same item more than once in the five-day

- meal plan. The subject cannot go to the same restaurant more than once in a day, and can only go to one restaurant per meal.
- The Nutritional goal constraint ensures that we get close to the daily nutritional goal for all nutrients.
 - The Food variety constraint ensures the variety of food purchase in the five-day meal plan.

Constraints:
Binary Linking Constraints
<pre> subject to linkBY {b in breakfastFoods, t in days, r in restaurants}: vB[b,r]*BX[b,t] - 100000000*BY[r,t] <= 0; subject to linkLY {l in lunchFoods, t in days, r in restaurants}: vL[l,r]*LX[l,t] - 100000000*LY[r,t] <= 0; subject to linkDY {d in dinnerFoods, t in days, r in restaurants}: vD[d,r]*DX[d,t] - 100000000*DY[r,t] <= 0; </pre>
Purchase at least one item per meal
<pre> subject to eatBreakfast {t in days}: sum {b in breakfastFoods} BX[b,t] >= 1; subject to eatLunch {t in days}: sum {l in lunchFoods} LX[l,t] >= 1; subject to eatDinner {t in days}: sum {d in dinnerFoods} DX[d,t] >= 1; </pre>
#Budget Constraints
<pre> subject to budgetConstraint {t in days}: sum {b in breakfastFoods} bcost[b]*BX[b,t] sum {l in lunchFoods} lcost[l]*LX[l,t] sum {d in dinnerFoods} dcost[d]*DX[d,t] <= 100; </pre>
Nutritional Slack Absolute Value
<pre> subject to slackabscon1 {n in nutrients, t in days}: nutrSlackVar[n,t] >= nutrSlack[n,t]; subject to slackabscon2 {n in nutrients, t in days}: nutrSlackVar[n,t] >= -nutrSlack[n,t]; </pre>
Nutritional Goals Constraints
<pre> subject to getCloseToNutrGoals {t in days, n in nutrients}: sum {b in breakfastFoods} (bnutr[b,n]*BX[b,t]) sum {l in lunchFoods} (lnutr[l,n]*LX[l,t]) sum {d in dinnerFoods} (dnutr[d,n]*DX[d,t]) nutrSlackVar[n,t] = nutrGoal[n,t]; </pre>
#Hard Calories Minimum Constraints
<pre> subject to meetCalories {t in days}: sum {b in breakfastFoods} (bnutr[b,'Calories']*BX[b,t]) sum {l in lunchFoods} (lnutr[l,'Calories']*LX[l,t]) </pre>

```
sum {d in dinnerFoods} (dnutr[d, 'Calories'] * DX[d, t])
>= nutrGoal['Calories', t];
```

Restaurant Visit Constraints

```
subject to restaurantVariety {r in restaurants, t in days}:
    (BY[r, t] + LY[r, t] + DY[r, t]) <= 1;

    ## cannot go to the same restaurant more than once in a day

subject to oneRestarauntForBreakfast {t in days}:
    sum {r in restaurants} BY[r, t] <= 1;

subject to oneRestarauntForLunch {t in days}:
    sum {r in restaurants} LY[r, t] <= 1;

subject to oneRestarauntForDinner {t in days}:
    sum {r in restaurants} DY[r, t] <= 1;

    ## Can only go to one restaurant per meal
```

Food Variety Constraints

```
subject to c13 {b in breakfastFoods}:
    sum {t in days} (BX[b, t]) <= 1;

subject to c14 {l in lunchFoods}:
    sum {t in days} (LX[l, t]) <= 1;

subject to c15 {d in dinnerFoods}:
    sum {t in days} (DX[d, t]) <= 1;

    ## Cannot have the same item more than once during the plan
```

Computational Result

Presolve eliminates 104733 constraints and 15 variables.

Adjusted problem:

11850 variables:

11770 binary variables

80 linear variables

14144 constraints, all linear; 137590 nonzeros

40 equality constraints

14104 inequality constraints

1 linear objective; 11690 nonzeros.

Gurobi 6.5.0: threads=4

outlev=1

Optimize a model with 14144 rows, 11850 columns and 137590 nonzeros

Coefficient statistics:

Matrix range [5e-01, 1e+08]

Objective range [1e-02, 1e+01]

Bounds range [1e+00, 1e+00]

RHS range [1e+00, 2e+03]

Presolve removed 4573 rows and 3805 columns
 Presolve time: 0.73s
 Presolved: 9571 rows, 8045 columns, 92605 nonzeros
 Variable types: 0 continuous, 8045 integer (8005 binary)
 Found heuristic solution: objective 9259.7100000
 Found heuristic solution: objective 8143.3500000

Meal Plan:

Day	Meal Type	Restaurant	Food Item
1	Breakfast		
1	Lunch		
1	Dinner		
2	Breakfast		
2	Lunch		
2	Dinner		
3	Breakfast		
3	Lunch		
3	Dinner		
4	Breakfast		
4	Lunch		
4	Dinner		
5	Breakfast		
5	Lunch		
5	Dinner		

Decision Support System

In order to optimize our dietary plan to an individual's needs, we need to intake that person's vital statistics and goals. We implement this system using a spreadsheet to calculate the relevant nutritional requirements and output those numbers into a format which can then be copied and pasted into the existing AMPL code.

Basal Metabolic Rate (BMR) is calculated using the following inputs and formula²¹:

- Sex
- Weight
- Height
- Age

For men: $BMR = 10 * \text{weight (kg)} + 6.25 * \text{height (cm)} - 5 * \text{age (years)} + 5$

For women: $BMR = 10 * \text{weight (kg)} + 6.25 * \text{height (cm)} - 5 * \text{age (years)} - 161$

Note that in our system, weight and height are automatically converted from pounds and inches respectively.

²¹ (Orlov, 2015)

Given a person's BMR, we now factor in their daily activity to determine their Total Daily Energy Expenditure (TDEE) using the following formula²²:

Amount of Exercise/Activity	Description	TDEE/ Maintenance
Sedentary	Little or no Exercise/ desk job	$TDEE = 1.2 \times BMR$
Lightly active	Light exercise/ sports 1 – 3 days/ week	$TDEE = 1.3 \times BMR$
Moderately active	Moderate Exercise, sports 3 – 5 days/ week	$TDEE = 1.5 \times BMR$
Very active	Heavy Exercise/ sports 6 – 7 days/ week	$TDEE = 1.7 \times BMR$
Extremely active	Very heavy exercise/ physical job/ training 2 x/ day	$TDEE = 1.9 \times BMR$

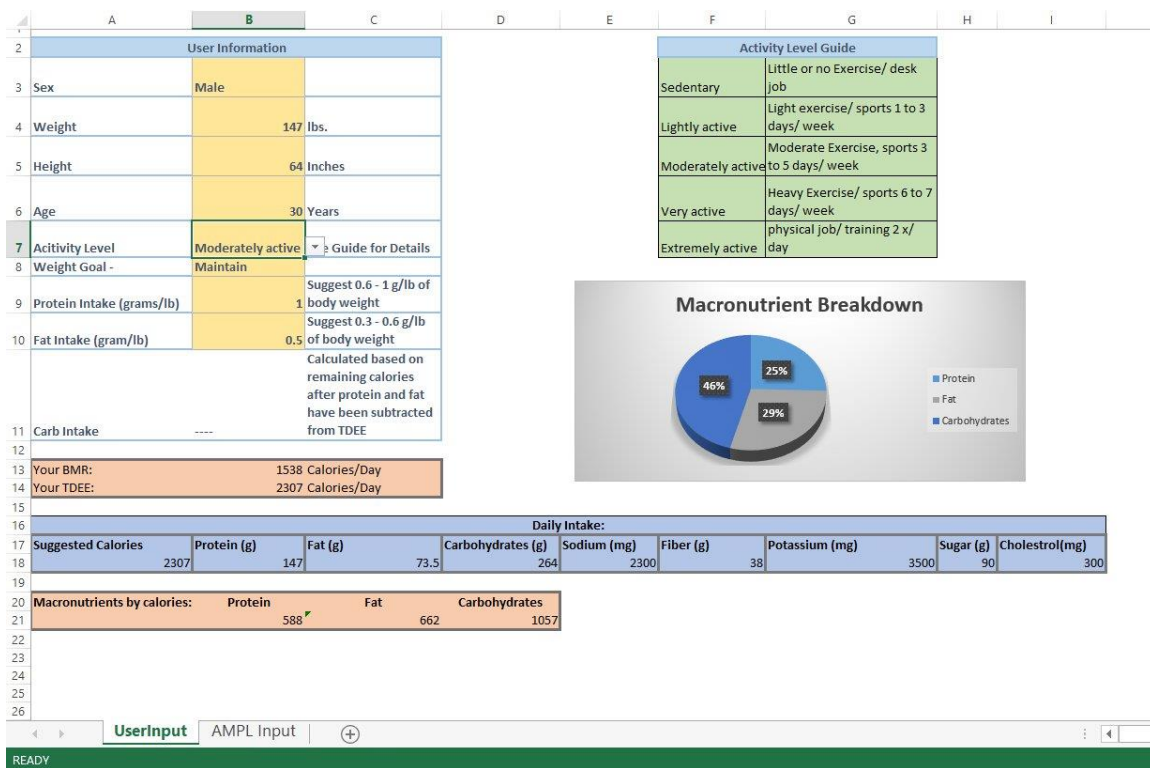
The last step in determining a person's daily caloric intake goal is to modify their TDEE using the following table:

Goal	Daily Intake
Lose 2 lbs/week	Calories = $TDEE - 1000$
Lose 1 lb/week	Calories = $TDEE - 500$
Maintain Weight	Calories = $TDEE$
Gain 0.5 lbs/week	Calories = $TDEE + 250$
Gain 1 lb/week	Calories = $TDEE + 500$

Next, we calculate the subject's macronutrient goals (in grams). Based on our framework and personal preferences, we would suggest a protein intake between 0.6 – 0.8 g/lb of body weight per day, and 0.4 g/lb of body weight per day. Carbohydrate intake will comprise the remainder of calories after protein and fat have been accounted for. For individuals with very high levels of body fat, protein and fat intake levels should be calculated based upon lean body mass. Finally, we recommend levels of sodium, fiber, sugar, and cholesterol based upon USDA recommendations.

²² (Calculate TDEE - Daily Calorie Requirements, n.d.)

Decision Support System Interface



Model Limitation

To solve integer LP problems, NEOS solvers use the Branch and Bound method. Our model has a mix of integer and binary decision variables, thus the total number of iterations to solve the problem increases drastically, as we will have a huge branch-and-bound tree. For our model, we encountered the “out of memory” issue when adding the food variety constraint. By introducing such a limit, we are promoting the relaxed problems to have fractional solutions. When the dataset size is large, it may exceed the memory of the solver, so we will not be able to reach the optimal solution. One solution can be to obtain food variety in one restaurant, instead of 10 restaurants, or use alternate constraints to meet the same requirements.

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