Meal Plan Optimization for College Students

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Abstract

At present, obesity is one of the common problems that affect people's health. As awareness of food's effects on health improves, the demand for food quality is gradually increasing. The increase of demand is not limited to the pursuit of natural food flavor, but often also focuses on the combinations of nutrients and other healthful substances in the foods. In this work, we propose an efficient optimization model for acquiring the calorically optimal daily meal plan for college students based on the constraints of daily intake of sodium and fat. After applying the daily food menu from Washington University in St. Louis into the model, the preliminary experimental results indicate that this model can effectively generate nutritionally balanced meal plans for college students. The devised model and optimization technique offers a framework for more intricate, personal meal optimization models.

Introduction

Obesity is one of the most common health problems in America, with over two-thirds of all adults considered overweight or obese (NIH, 2016). Its link to increased health risks in heart disease, high blood pressure, nonalcoholic fatty liver disease, osteoarthritis, cancers and strokes have caused it to be classified as a major health crisis in America. While it may be obvious that obesity causes physical consequences, it has also been shown that it has significant influences on one's social, psychological and economical bearings (Bray, Bouchard and James, 1998). Similarly, the plethora of health issues associated with obesity is no longer a personal issue, but a national issue. Economically, the treatment costs of obesity and obesity induced diseases is projected to be over 860 billion US dollars by 2030 (Wang et al., 2008).

It has been shown that there are vulnerable periods for weight gain. In particular, the college transition period has been noted to be a critical period in body weight gain (Finlayson et al., 2012). Colloquially, this is often known as the "freshman fifteen" – summarizing the phenomenon where many freshmen in college gain 15 pounds during their first year. "Freshman fifteen" is often caused by an energy imbalance between the usage and intake of an individual. In layman terms, the body requires a certain amount of energy, and therefore food, to maintain correct function on a daily basis. Weight gain occurs when the amount of energy required by the body is exceeded by the intake amount, and weight loss occurs when the energy required is less than the intake amount. This fundamental cause of obesity alludes to two potential methods to solve the public health crisis: exercise and dieting. Exercise increases energy usage, while dieting focuses to lower energy intake. Indeed, behavioral treatment of obesity which combines both exercise and dieting have been very successful in facilitating weight loss in clinical settings (Butryn et al., 2011). However, when considered as individual tasks, while exercise regimens are often effective in inducing weight loss, dieting offers a potential lower effort method to tip the energy balance in favor of weight loss.

While simple calorie counting behavior may suffice for general lowering of energy intake, it has been shown that online caloric feedback interventions are effective in prevention of weight gain among college students (Gow, Trace and Mazzeo, 2012). However, caloric counting and feedback systems often lack the assertiveness required as active intervention and are often only used after food has been consumed.

In order to tackle the "freshman fifteen" and the obesity problem in general through active intervention, the study will examine the optimization of a nutritious meal regime generation subject to a particular daily energy intake level, under a generic college food menu with given nutritional data. The goal of this study is to automate meal planning for college students.

Methods

Overview of approach

In general, a nutritious meal regime should be achieving a total energy intake as close to the recommended energy intake, while not exceeding the daily recommended energy intake. In reality, the regime should also be in-line with recommended daily intakes for different food groups and minerals. While the recommended daily intakes may differ for different demographics, these differences should only be reflected in different constraint conditions for the optimization. The overall approach for dietary optimization should remain similar. The target population for this study is adult (18+ years old) American college students. Therefore, the optimization regime should follow guidelines offered by the Office of Disease Prevention and Health Promotion (ODPHP) in the American Dietary Guidelines (ODPHP, 2015). In particular, sodium and fat intake constraints have been noted by the ODPHP to be important in achieving a healthy lifestyle along with an appropriate energy intake.

Energy intake limitations help establish energy balance and prevent weight gain. In general, for the 18 to 25 age group, the United States Department of Agriculture (USDA) recommends a daily intake limit of 2800 calories for males, and 2200 calories for females (USDA, 2016). Sodium intake limitations help establish healthy blood pressure levels, and have been used as an effective measure to prevent cardiovascular diseases and strokes (Appel et al, 2016). The ODPHP suggests a daily intake level of less than 2300 milligrams for adults. However, it also notes that the daily sodium intake should be somewhat proportional to the daily caloric intake. Indeed, the consumption of more foods and therefore calories allows for the opportunity to consume more sodium. Therefore, the sodium daily intake limits for young adults should be linked to energy intake via a ratio of one to one (sodium in mg to energy intake in calories). Finally, overconsumption of fat have been linked to onset of type two diabetes in men (Dam et al, 2002) and coronary heart disease in women (Hu, 1998). In general, the ODPHP recommends a daily fat intake no more than 30% of total daily calorie intake.

Problem Specific Considerations

College students are often offered food items through campus cafeterias and off-campus businesses. Many of these institutions have accessible nutritional data for one serving of the offered food items. For any particular day, a student will have n number of distinct food items that is available to him or her. The available data for this set of n food items can be used to create an optimal consumption suggestion for the day. Consider the following generic nonlinear optimization problem:

$$\begin{gathered} \textit{minimize } f(x) \\ \textit{subject to } g_i(x) \leq 0 \textit{ for each } i \in \{1, ..., m\} \\ \textit{subject to } h_j(x) \leq 0 \textit{ for each } j \in \{1, ..., p\} \\ x \in X \end{gathered}$$

It is obvious that the objective function *f(x)* must be a function of caloric data of the *n* food items. It is logical then to say that *x*, the variable vector of size *n*, is the serving size for each of the food items. It must be noted that elements of *x* should be integers, as it is infeasible to suggest consumption of partial servings of food items. In this study, as a practical simplification, elements of *x* have been limited to having values of 0 or 1, with 0 implying that the food item is not in the optimized meal plan and 1 implying that one serving of the food item is recommended in the optimized meal plan. The maximum of one serving of each food item promotes the optimized food regime to contain as many types of food items as possible. Which is in-line with the diversified diet suggested by the ODPHP. It is also obvious from the aforementioned dietary limitations that there should not be any equality constraints for this particular optimization problem. Furthermore, there are two important inequality constraints which should reflect the daily fat and sodium consumption restrictions. Therefore, the general modified problem should be in the form:

$$\begin{gathered} \textit{minimize } f(x) \\ \textit{subject to } g_i(x) \leq 0 \textit{ for each } i \in \{1, ..., m\} \\ x \in \{0, 1\}, \textit{ is the number of servings of food item} \end{gathered}$$

Objective Function Derivation

The basis of caloric meal planning is for the sum of calories suggested to not exceed the daily limit, but also for the sum to be as numerically close to the limit as possible. The sum of total calories suggested can be written as:

$$\textit{total caloric sum} = C_1x_1 + C_2x_2 + ... + C_nx_n = \sum_{i=1}^{n} C_ix_i$$

$$\textit{Where } C_i \textit{ is the energy in calories found in one serving of food item } i.$$

Since the objective is to minimize the numerical distance to the daily caloric limit, the function will have the following form:

$$f(x) = (\textit{daily caloric limit} - \sum_{i=1}^{n} C_ix_i)^2$$

However, the *total caloric sum* may exceed the *caloric limit* in this objective function. Therefore, for proper optimization, a constraint must be added to the problem, such that:

$$g_1(x) \; := \; \sum_{i=1}^{n} C_i x_i \; - \; daily\ caloric\ limit \; \leq \; 0$$

Constraint Derivation

The sodium to energy limitation supplied by the ODPHP can be mathematically summarized as:

$$\frac{sodium\ sum}{total\ caloric\ sum} \; := \; \frac{\sum_{i=1}^{n} S_i x_i}{\sum_{i=1}^{n} C_i x_i} \; \leq \; 1$$

Where S_i is the sodium in milligrams found in one serving of food item i.

This expression can be rearranged and simplified to the following constraint for sodium:

$$g_2(x) \; := \; \sum_{i=1}^{n} S_i x_i \; - \; \sum_{i=1}^{n} C_i x_i \; \leq \; 0$$

The fat intake limitation supplied by the ODPHP can be mathematically summarized as:

$$\frac{fat\ caloric\ sum}{total\ caloric\ sum} \; \leq \; 0.3$$

However, many food items only supply fat nutritional data in grams per serving, and therefore a conversion is needed. Fortunately, the USDA suggests that, in general, one gram of fat provides 9 calories of energy. Therefore, the expression can be rewritten as:

$$\frac{fat\ caloric\ sum}{total\ caloric\ sum} \; := \; \frac{9 \sum_{i=1}^{n} F_i x_i}{\sum_{i=1}^{n} C_i x_i} \; \leq \; 0.3$$

Where F_i is the fat in grams found in one serving of food item i.

This expression can be rearranged and simplified to the following constraint for fat:

$$g_3(x) \; := 9 \; \sum_{i=1}^{n} F_i x_i \; - 0.3 \; \sum_{i=1}^{n} C_i x_i \; \leq \; 0$$

Optimization Problem

Finally, the optimization problem can be numerically summarized as:

$$minimize \ \ (daily\ caloric\ limit - \sum_{i=1}^{n} C_i x_i)^2$$

$$\begin{gathered} subject\ to\ the\ following\ 3\ constraints: \\ \sum_{i=1}^{n} C_i x_i - daily\ caloric\ limit \ \leq\ 0 \\ \sum_{i=1}^{n} S_i x_i - \sum_{i=1}^{n} C_i x_i \leq 0 \\ 9 \sum_{i=1}^{n} F_i x_i - 0.3 \sum_{i=1}^{n} C_i x_i \leq 0 \end{gathered}$$

$$\begin{gathered} Where\ C_i\ is\ the\ energy\ in\ calories\ found\ in\ one\ serving\ of\ food\ item\ i. \\ Where\ S_i\ is\ the\ sodium\ in\ milligrams\ found\ in\ one\ serving\ of\ food\ item\ i. \\ Where\ F_i\ is\ the\ fat\ in\ grams\ found\ in\ one\ serving\ of\ food\ item\ i. \end{gathered}$$

$$x \in \{0, 1\}$$

Implementation of Model

1. Caloric, sodium and fat data of food items offered at Washington University in St Louis were collated into a Microsoft Excel document.
2. Two function files were created in MatLab: *objfun.m* takes input variable *x* and outputs the objective function value and *confun.m* takes input variable *x* and outputs constraint function values. Note that there are three inequality constraints and no equality constraints in *confun.m*.
3. One script file was created in MatLab. The script reads in the Excel data through *xlsread*, makes an initial guess of one serving of each of the food items, sets the lower and upper bounds of *x* to be 0 and 1 respectively, and indicates for values for elements of x to be integer only. The script then invokes the Genetic Algorithm (*ga*) solver to solve the the constrained multivariable nonlinear optimization problem. Genetic Algorithm was chosen due to its particular effectiveness in solving meal optimization problems (Gaal et al, 2007). [1]

[1] A comprehensive summary of Genetic Algorithm approach in MatLab can be found as ‘A Genetic Algorithm for Function Optimization A Matlab Implementation’ : ftp://ftp.ucauca.edu.co/Documentos_Publicos/.backup_20062011/.DEIC.back/docs/Materias/Control%20Inteligente/clases_2006a/proyectos/GAs/toolboxs/gaot/gaot.pdf

Results

The Washington University in St. Louis dining services website provides the daily favorite food menu. It also contains the nutrition facts table for each food. Pulling the data from this website as the input data for the caloric meal planning model.

The two set of data contains the nutrition facts of each food from two different days(Tuesday and Friday). Because the optimization problem considers a part of the nutrition facts, the input data attributes only include calories, sodium, fat, and name of food.

Table 1 sample input data

Name of food	*calories*	*Sodium(mg)*	*Fat(g)*
Cinnamon Raisin Bagel Companion	279	462.3	1
Freshly Sliced Cantaloupe	54	25.4	0.3
Turkey & Swiss Sandwich	250	1035.4	9.1
Companion Blueberry Bagel	294	511.2	2
Chocolate Filled Croissant	261	198	16
……….			

As we discussed in section overview of approach, for males, the recommended daily intake limit is 2800 calories. For females, it is 2200 calories. Two sets of tests were performed. The goal is to find the optimal daily meal plan for different genders.

We want to acquire the optimal meal plan in test 1 for males. Therefore, we set the calorie parameters to 2800 and run two set of data. For each food, if the model returns 1, it means this food is one of the optimal solution, otherwise it is not.

For males, the optimal meal plan are:

Table 2 Males optimal meal plan

index	*Tuesday menu*	*Friday menu*
1	Companion Blueberry Bagel	Corn Flakes Cereal

2	Honey Nut Cheerios Cereal	Frosted Flakes Cereal
3	Tuscan Bean Soup	Honey Nut Cheerios Cereal
4	Key Lime Bars	Lucky Charms Cereal
5	Cinnamon Toast Crunch Cereal	Banana Coffee Cake Muffin
6	Raisin Bran Cereal	Chocolate Filled Croissant
7	Fresh Cut Pineapple	Low Fat Honey Bran Muffin
8	Corn Flakes Cereal	Chocolate Raspberry Brownie
9	Sugar Cookie	Blueberry Muffin
10	Raspberry Currant Bar	Rice Krispie Treat
11		Kosher Baked Tofu
12		Kosher Hard Boiled Egg

Next, in test 2, we want to acquire the optimal meal plan for females, so we set the calorie parameters to 2200 and run two set of data. The optimal meal plans for females are:

Table 3 Females optimal meal plan

index	*Tuesday menu*	*Friday menu*
1	Wheat Dinner Roll	Raisin Bran Cereal
2	Key Lime Bars	Banana Coffee Cake Muffin
3	Frosted Flakes Cereal	Ginger Drizzle Cookie
4	Petite Apple Muffin	Greek Yogurt Brownies
5	Cinnamon Toast Crunch Cereal	Sugar Cookie
6	Raisin Bran Cereal	Cinnamon Raisin Bagel Companion
7	Low Fat Honey Bran Muffin	Orange Cranberry Breakfast Bread Slice

8	Fresh Cut Pineapple	Rice Krispie Treat
9	Greek Yogurt Brownies	
10	Butter & Egg Dinner Roll	
11	Raspberry Currant Bar	

The daily intake calories, sodium and fat are bounded to a healthy limit. Observing the results from two tests, the model returns different optimal food lists due to the different calorie parameters. In order to get a healthy daily diet, people can choose any combination of food in the output list as their breakfast, lunch and dinner. Therefore, given a potential food menu data, this model can effectively generate an optimal meal plan.

Discussion

Advantages of the Model

Wide applicable - We made fundamental progress towards meal optimization, this is a model that can be built on. These tests in result section are based on the favorite daily menu in Washington University in St. Louis. Our caloric meal planning model also applicable to other college food menus as long as the input data contains enough test samples(at least the sum of calories over the healthy limit).

Convenience - Many colleges concerned about the health of students diet, they take some measures to help students keep health such as listing standard diet parameters and nutrition facts on the dining websites. Our caloric meal planning model tells students what to eat more direct and clear. Students who want to keep healthy diet do not need to compute nutrition, the model returns the best daily meal plan for them.

Flexible - Most people tends to eat different foods for each day. To meet this requirements, this model returns a list of a variety of foods rather than a few kinds of food many times. It gives people the option to choose the different combinations.

Potential problems and future improvements

This model is not smart enough, the optimal balanced meal plans is determined only by nutritional constraints. Sometimes flavors of foods are also important. If the input data contains foods that people do not like, there's a chance that these foods appear in the result. On the other hand, we designed this model based on the most influential nutritions. However, some other nutritions such as fibre and protein also have significant influences to people's health. In order to make this model more comprehensive and effective, adding more constraints or letting users to choose different constraints that they need may build our model to be better.

Contribution

Tommy Peng - Problem derivation, objective function derivation, constraint derivation, implementation of model, introduction, methods.

Chenxing Ouyang - Problem derivation, objective function derivation, constraint derivation, implementation of model, abstract, results, discussion.

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