IE 501 : Project

Food Waste Optimization for Hostel Mess/Hotels

Project Members :

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Motivation

In our bustling hostel mess, we confront a mounting challenge day by day - an escalating issue of food waste. It's a problem that not only impacts our daily operations but also raises questions about sustainability and resource utilization. Each uneaten plate of food represents not just a waste of nourishment but also a squandered opportunity to make a difference. It's a call to action, a challenge that demands our innovative solutions. By harnessing the power of linear programming techniques, we can not only reduce food waste but also contribute to a more sustainable future.

Description of Problem

The hostel mess at our institution currently faces a significant challenge - a daily food waste problem that amounts to approximately 60-70 kilograms of uneaten food, despite catering to around 400 people. This issue not only results in the inefficient use of resources but also has financial implications. To address this problem, we propose a Food Waste Optimization project that aims to reduce food waste while ensuring that the nutritional needs and preferences of our hostel residents are met.

Key Objectives

1. Minimize Food Waste: The primary objective of this project is to significantly reduce the daily food waste currently averaging between 60-70 kilograms, without compromising the quality of meals.

2. Meet Nutritional Needs: Ensure that all residents have access to balanced and nutritious meals that cater to different dietary requirements, including vegetarian and non-vegetarian options.

3. Cost Reduction: Reduce the overall cost of food production and minimize the financial losses incurred due to food wastage.

Tentative Solution Methodology:

1. Data Collection and Analysis: Collect and analyze historical data on food consumption, meal preferences, and waste patterns to identify areas where optimization is most needed.
2. Menu Planning Optimization: Use linear programming techniques to optimize the menu planning process, considering factors such as ingredient availability, portion sizes, and the preferences of hostel residents.
3. Resource Allocation: Optimize resource allocation for food procurement, preparation, and storage to reduce food spoilage.

Linear Programming Formulation for Food Waste Optimization

Decision Variables:

$$x_i : \text{Quantity of food item } i \text{ prepared for current day meal for all } i$$

Parameters:

D_j : Total Daily demand for food items on jth day considering all residents
C_i : Cost of preparing one unit of food item i for all i
W_j : Total Wastage (in kilograms) of food items on jth day
Q_j : Quantity (in kilograms) of food items on jth day prepared
D_{ji} : Daily demand for food item i on jth day observed
$D_{predicted}$: Total Demand quantity predicted for current day
w_i Wastage coefficient of food item i, i.e. wastage per quantity of i produced
B : Budget per day

So we have

$$D_j = Q_j - W_j$$

w_i can be calculated using liking factor and nutrition value of food item. **Objective Function:**

$$\text{Minimize } \sum_i w_i \cdot x_i$$

Constraints:
1. Demand Constraints:

$$x_i \geq \min_j(D_{ji}) \quad \text{for all } i$$

The constraint $x_i \geq \min_j(D_{ji})$ ensures that the quantity prepared for item i is at least as much as the minimum observed demand across all days j.
2. Non-negativity Constraints:

$$x_i \geq 0 \quad \text{for all } i$$

3. Total food quantity Lower bound:

$$\sum_i x_i \geq \text{D\_predicted} + \text{Standard Deviation of}(D_j)$$

This constraint ensures that if one food item is finished, individuals can still consume the remaining items to avoid hunger.

4. Budget Constraint: The budget constraint:

$$\sum_i x_i \cdot c_i \leq B$$

Demand Prediction

Kernel Density Estimation (KDE) is a non-parametric method used to estimate the probability density function of a dataset. In the context of predicting demand, KDE analyzes historical demand data to estimate the probability distribution of demand for specific days.

To predict demand for a particular day in a week using KDE:

1. **Data Preparation:** Gather historical demand data for the past 7-8 weeks, organized by days of the week. Create a dataset where each row represents a day and its observed demand over past weeks.

2. **KDE Modeling:** Apply KDE separately for each day of the week using historical demand data. Fit a KDE model to each day's demand data to estimate its probability density function.

3. **Prediction:** Given new demand data for a specific day, input it into the corresponding KDE model for that day of the week. Use the KDE model to estimate the probability density function of demand for the specific day.

4. **Demand Estimation:** Compute metrics like mean, median, or mode of the estimated distribution to obtain the predicted demand for the specific day. Alternatively, sample from the distribution to generate demand scenarios or percentiles for a range of potential demand values.

This method allows forecasting demand based on past observations, providing insights into potential demand patterns and variability for effective planning.

The GitHub link for the code is as follows:
https://github.com/SuperSat001/Food-Waste-Optimization-IE501

```python
from pulp import *

prob = LpProblem("Minimize Food Wastage", LpMinimize)

# Decision Variables
num_items = 3  # Number of food items
x = {i: LpVariable(f"x_{i}", lowBound=0) for i in range(1, num_items +
    1)}

D_predicted = 50
D_j = {1: 40, 2: 35, 3: 45}  # Total Daily demand for food items on
    each day
C = {1: 2, 2: 3, 3: 2.5}  # Cost of preparing one unit of food item i
    for all i
W_j = {1: 5, 2: 8, 3: 6}  # Total Wastage (in kilograms) of food items
    on each day
Q_j = {1: 60, 2: 50, 3: 55}  # Quantity (in kilograms) of food items on
     each day prepared
D_ji = {1: {1: 10, 2: 15, 3: 12},  # Daily demand for food item i on
    each day observed
         2: {1: 8, 2: 10, 3: 12},
         3: {1: 12, 2: 13, 3: 10}}
w = {1: 0.1, 2: 0.08, 3: 0.12}  # Wastage coefficient of food item i
B = 10000  # Budget per day

# Objective Function
prob += lpSum(w[i] * x[i] for i in range(1, num_items + 1))

# Constraints
for i in range(1, num_items + 1):
    prob += x[i] >= min(D_ji[i].values())  # Demand Constraints

prob += lpSum(x.values()) >= D_predicted + 5  # Total food quantity
    Lower bound (example standard deviation = 5)

prob += lpSum(x[i] * C[i] for i in range(1, num_items + 1)) <= B  #
    Budget Constraint

prob.solve()

for v in prob.variables():
    print(f"{v.name} = {abs(v.varValue)}")

print(f"Total Wastage: {value(prob.objective)}")
```

Listing 1: Code for linear programming

```python
from sklearn.neighbors import KernelDensity
import numpy as np

demand_data = [30, 25, 28, 35, 40, 32, 27, 31]

demand_data = np.array(demand_data).reshape(-1, 1)

kde = KernelDensity(bandwidth=2.0, kernel='gaussian')
kde.fit(demand_data)

# New data for prediction (e.g., demand observed for a new Monday)
new_demand_data = np.array([27, 29, 33]).reshape(-1, 1)  # Example new
    demand data

log_density = kde.score_samples(new_demand_data)
density = np.exp(log_density)

most_likely_demand = new_demand_data[np.argmax(density)]
print("Predicted demand (most likely value):", most_likely_demand)
```

Listing 2: Code to predict demand using Kernel density estimation

DATE	breakfast	lunch	tiffin	DInner						
22/8	10.1	30.47	8.5	30.32			85	122	55	140
23/8	7.46	30.67	9.22	26.34			89	145	70	138
24/8	24.95	29.14	11.7	32.96			84	130	73	145
25/8	11.5	20.4	9.5	27.72			93	128	65	120
26/8	7.46	34.06	12.5	28.56			90	144	82	135
27/8	12.47	28.26	14.3	30.5			102	138	60	120
28/8	10.22	24.93	14.8	24.75			91	136	68	130
29/8	8.97	17.8	16.08	23.44			85	122	55	140
30/8	14.68	34.32	10.77	23.44			89	145	70	138
31/8	9.07	22.71	12.78	27.76			84	130	73	145
1/9	12.76	18.52	13.18	25.2			93	128	65	120
2/9	10.63	23.67	8.794	25.84			90	144	82	135
3/9	8.52	26.65	14.33	24.21			102	138	60	120
4/9	13.46	28.19	13.75	26.84			91	136	68	130
5/9	20.001	26	12.92	31.65			85	122	55	140
6/9	28.959	23.28	18.49	16.44			89	145	70	138
7/9	12.24	24.87	11	27.15			84	130	73	145
8/9	8.97	20.5	9.8	23.5			93	128	65	120
9/9	9.8	36.5	8.1	10.7			90	144	82	135
10/9	10.1	25.4	0	0			102	138	60	120
11/9	8.205	22.45	12.72	23.26			91	136	68	130
12/9	10.3	18.47	18.74	17.67			85	122	55	140
13/9	7.6	17.55	13.74	22.76			89	145	70	138
14/9	11.76	17.5	14.85	12.77			84	130	73	145
15/9	10.63	27.72	16.11	28.61			93	128	65	120
16/9	8.54	18.64	12.17	22.705			90	144	82	135
17/9	10.44	16.74	18.79	18.99			102	138	60	120
18/9	9.55	8.604	16.7	23.88			91	136	68	130
19/9	11.43	18.745	13.72	19.92			85	122	55	140
20/9	9.45	16.225	14.5	18.28			89	145	70	138
21/9	10.35	18	13.65	17.825			84	130	73	145
22/9	8.65	16.34	14.75	19.36			93	128	65	120
23/9	7.6	15.45	8.3	18.7			90	144	82	135

24/9	10.33	19.02	7.54	15.6			102	138	60	120
25/9	1.5	22.82	3.6	10			91	136	68	130
26/9	4.1	10	7	3			85	122	55	140
27/9	6.5	9.6	4.7	10			89	145	70	138
28/9	5.2	9.5	6.2	10.1			84	130	73	145
29/9	7	14	13.8	13.8			93	128	65	120
30/9	4.7	11.8	9.5	11.7			90	144	82	135
1/10	4.72	9.8	10.2	14.34			102	138	60	120
2/10	9.72	13.78	6.27	14.34			91	136	68	130
3/10	9.74	14.72	7.32	12.4			85	122	55	140
4/10	7.4	57.28	0	0			89	145	70	138
5/10	5.14	14.23	8.71	20.701			84	130	73	145
6/10	9.85	19.341	7.68	18.41			93	128	65	120
7/10	5.6	18.53	8.56	11.77			90	144	82	135
8/10	8.2	16.52	9.4	17.7			102	138	60	120
9/10	7.55	14.48	6.2	13.07			91	136	68	130
10/10	7.155	15.43	9.2	17.83			85	122	55	140
11/10	15.25	24.23	11.31	18.8			89	145	70	138
12/10	13.26	20.71	13.98	23.69			84	130	73	145
13/10	15.25	24.23	11.311	18.08			93	128	65	120
14/10	6.15	17.33	9.4	17.8			90	144	82	135
15/10	8.1	13.75	7.5	15.75			102	138	60	120
16/10	9.2	13.74	9.28	18.23			91	136	68	130
17/10	8.21	14.3	7.7	18.22			85	122	55	140
18/10	9.23	13.7	11.6	16.23			89	145	70	138
19/10	9.7	11.605	5.2	18.24			84	130	73	145
20/10	8.2	15.45	8.12	16.52			93	128	65	120
21/10	7.522	17.12	7.45	13.212			90	144	82	135
22/10	8.42	16.536	9.224	15.66			102	138	60	120
average	9.834225806	20.20332258	10.95348333	19.62071667						
	wated	amount			demand	per day				

				22/8	74.9	91.53	46.5	109.68		
				23/8	81.54	114.33	60.78	111.66		
				24/8	59.05	100.86	61.3	112.04		
				25/8	81.5	107.6	55.5	92.28		
				26/8	82.54	109.94	69.5	106.44		
				27/8	89.53	109.74	45.7	89.5		
				28/8	80.78	111.07	53.2	105.25		
				29/8	76.03	104.2	38.92	116.56		
				30/8	74.32	110.68	59.23	114.56		
				31/8	74.93	107.29	60.22	117.24		
				1/9	80.24	109.48	51.82	94.8		
				2/9	79.37	120.33	73.206	109.16		
				3/9	93.48	111.35	45.67	95.79		
				4/9	77.54	107.81	54.25	103.16		
				5/9	64.999	96	42.08	108.35		
				6/9	60.041	121.72	51.51	121.56		
				7/9	71.76	105.13	62	117.85		
				8/9	84.03	107.5	55.2	96.5		
				9/9	80.2	107.5	73.9	124.3		
				10/9	91.9	112.6	0	0		
				11/9	82.795	113.55	55.28	106.74		
				12/9	74.7	103.53	36.26	122.33		
				13/9	81.4	127.45	56.26	115.24		
				14/9	72.24	112.5	58.15	132.23		
				15/9	82.37	100.28	48.89	91.39		
				16/9	81.46	125.36	69.83	112.295		
				17/9	91.56	121.26	41.21	101.01		
				18/9	81.45	127.396	51.3	106.12		
				19/9	73.57	103.255	41.28	120.08		
				20/9	79.55	128.775	55.5	119.72		
				21/9	73.65	112	59.35	127.175		
				22/9	84.35	111.66	50.25	100.64		
				23/9	82.4	128.55	73.7	116.3		

24/9	91.67	118.98	52.46	104.4
25/9	89.5	113.18	64.4	120
26/9	80.9	112	48	137
27/9	82.5	135.4	65.3	128
28/9	78.8	120.5	66.8	134.9
29/9	86	114	51.2	106.2
30/9	85.3	132.2	72.5	123.3
1/10	97.28	128.2	49.8	105.66
2/10	81.28	122.22	61.73	115.66
3/10	75.26	107.28	47.68	127.6
4/10	81.6	87.72	0	0
5/10	78.86	115.77	64.29	124.299
6/10	83.15	108.659	57.32	101.59
7/10	84.4	125.47	73.44	123.23
8/10	93.8	121.48	50.6	102.3
9/10	83.45	121.52	61.8	116.93
10/10	77.845	106.57	45.8	122.17
11/10	73.75	120.77	58.69	119.2
12/10	70.74	109.29	59.02	121.31
13/10	77.75	103.77	53.689	101.92
14/10	83.85	126.67	72.6	117.2
15/10	93.9	124.25	52.5	104.25
16/10	81.8	122.26	58.72	111.77
17/10	76.79	107.7	47.3	121.78
18/10	79.77	131.3	58.4	121.77
19/10	74.3	118.395	67.8	126.76
20/10	84.8	112.55	56.88	103.48
21/10	82.478	126.88	74.55	121.788
22/10	93.58	121.464	50.776	104.34
average	80.73029032	114.4902258	54.86759677	109.4638226

DATE	breakfast	lunch	tiffin	DInner
22/8	10.1	30.47	8.5	30.32
23/8	7.46	30.67	9.22	26.34
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26/8	7.46	34.06	12.5	28.56
27/8	12.47	28.26	14.3	30.5
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7/9	12.24	24.87	11	27.15
8/9	8.97	20.5	9.8	23.5
9/9	9.8	36.5	8.1	10.7
10/9	10.1	25.4	0	0
11/9	8.205	22.45	12.72	23.26
12/9	10.3	18.47	18.74	17.67
13/9	7.6	17.55	13.74	22.76
14/9	11.76	17.5	14.85	12.77
15/9	10.63	27.72	16.11	28.61
16/9	8.54	18.64	12.17	22.705
17/9	10.44	16.74	18.79	18.99
18/9	9.55	8.604	16.7	23.88
19/9	11.43	18.745	13.72	19.92

20/9	9.45	16.225	14.5	18.28
21/9	10.35	18	13.65	17.825
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23/9	7.6	15.45	8.3	18.7
24/9	10.33	19.02	7.54	15.6
25/9	1.5	22.82	3.6	10
26/9	4.1	10	7	3
27/9	6.5	9.6	4.7	10
28/9	5.2	9.5	6.2	10.1
29/9	7	14	13.8	13.8
30/9	4.7	11.8	9.5	11.7
1/10	4.72	9.8	10.2	14.34
2/10	9.72	13.78	6.27	14.34
3/10	9.74	14.72	7.32	12.4
4/10	7.4	57.28	0	0
5/10	5.14	14.23	8.71	20.701
6/10	9.85	19.341	7.68	18.41
7/10	5.6	18.53	8.56	11.77
8/10	8.2	16.52	9.4	17.7
9/10	7.55	14.48	6.2	13.07
10/10	7.155	15.43	9.2	17.83
11/10	15.25	24.23	11.31	18.8
12/10	13.26	20.71	13.98	23.69
13/10	15.25	24.23	11.311	18.08
14/10	6.15	17.33	9.4	17.8
15/10	8.1	13.75	7.5	15.75
16/10	9.2	13.74	9.28	18.23
17/10	8.21	14.3	7.7	18.22
18/10	9.23	13.7	11.6	16.23
19/10	9.7	11.605	5.2	18.24

20/10	8.2	15.45	8.12	16.52
21/10	7.522	17.12	7.45	13.212
22/10	8.42	16.536	9.224	15.66
average	9.834225806	20.20332258	10.95348333	19.62071667
	wated	amount		