FCPS - Waste Cost Management

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The Challenge: Food Waste in School Nutrition

Understanding the Scale

Our analysis covers **188,856 meal production records** from **187 Fairfax County Public Schools**

The average leftover rate sits at **18.4%**, though the median is notably lower at 5%.

Current menu planning remains **manual and static**

~$29K worth of food discarded across 187 schools — a significant opportunity for adaptive, data-driven menu optimization.

Project Goals

Data-Driven Framework

Analyze meal production, serving, and waste trends across all 187 schools

Pattern Recognition

Identify high-waste menu items and their contextual factors including school_name , day of week, meal type, and production cost.

01

Implement Contextual Bandits

Deploy LinUCB algorithms to recommend optimal meal combinations based on real-world performance data.

02

Continuous Learning

Update recommendations based on school and waste feedback from each service period.

03

Sustainable Planning

Support FCPS sustainability goals to reduce $29K in waste identified in sample data.

Understanding LinUCB

What is LinUCB?

Linear Upper Confidence Bound (LinUCB) is a contextual bandit algorithm designed for adaptive decision-making in uncertain environments.

It elegantly balances two critical objectives:

- **Exploration:** Testing new options to gather learning data
- **Exploitation:** Selecting options with proven performance

The Core Formula

$r = \theta^T x + \varepsilon$

- **r** = expected reward (success, satisfaction, performance)
- **x** = feature vector (contextual characteristics)
- **θ** = model parameters learned over time
- **ε** = prediction error

LinUCB in Action: FCPS Meal Optimization

System Architecture

Arms

Each unique dish is an "arm" the model can choose.

Rounds

A "round" is a day, school, and meal type combination.

Key Context Features

- Planned_Total, Served_Total
- Production_Cost_Total, Discarded_Cost, Left_Over_Cost
- DayOfMonth, Month
- One-hot encoded Meal_Type categories

The model continuously tracks diagnostic metrics including **reward, regret, uncertainty, θ-change (Δθ)**, and **exploration ratio** to monitor its balance of exploration versus exploitation.

Building the X Matrix: Example Round

Consider a round: Breakfast at "GWU" on October 22, 2025, where only "Apple" and "Banana" were served.

- **Available dishes:** "Apple" and "Banana" feature vectors (e.g., [100, 80, 1]) are included.
- **Unavailable dishes:** For dishes like "Chicken" or "Salad" not served in this round, zero-vector placeholders ([0, 0, 0]) are created.

This approach ensures consistent matrix dimensionality across all rounds, clearly indicating which arms were available for selection in each context.

LinUCB Decision Flow: Step-by-Step

1

Initialization

A (identity matrix), **b=0** for each arm (dish).

2

Arm Selection

The arm (dish) with the **highest p_i (upper confidence bound)** is chosen. This selection balances known performance with exploration of new options.

3

Reward Computation

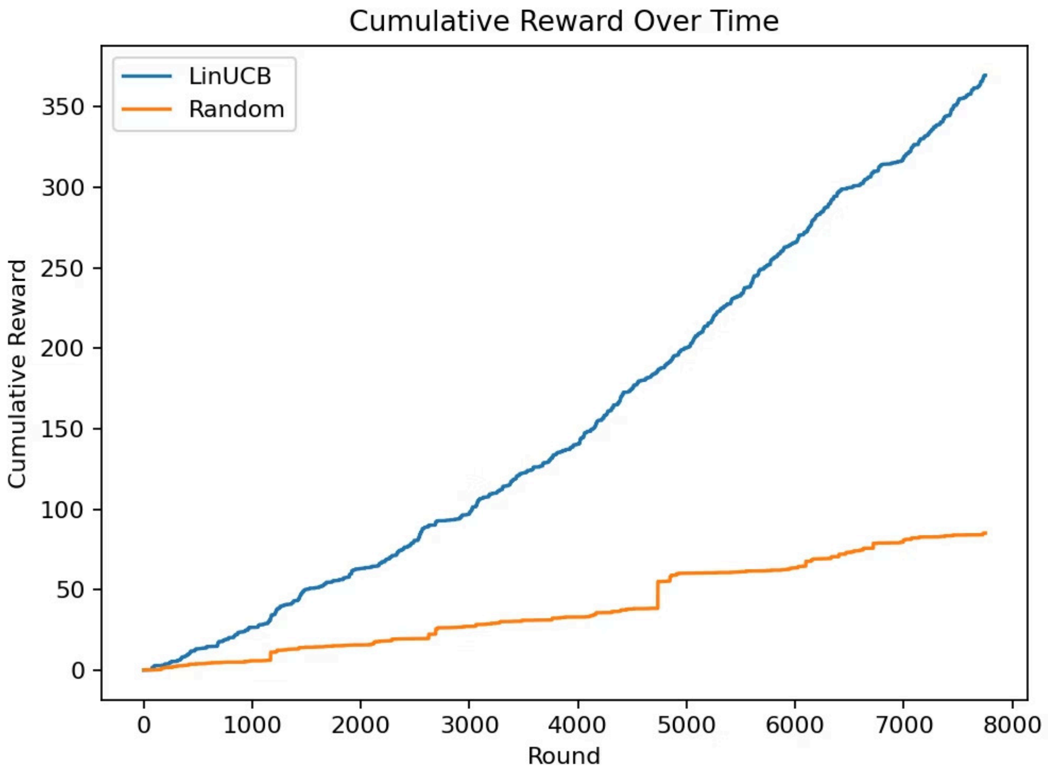
Served / Planned

4

Model Update

After observing the reward, the model parameters are refined

Performance: Cumulative Reward Over Time



Key Findings & Impact

4x Performance Gain: LinUCB achieved 369.57 cumulative reward vs. 90.44 random baseline

Real-World Data Handling: Successfully processed 321 unique dishes from messy operational dataset

Rapid Convergence: Model stabilized quickly with sharp uncertainty reduction in early rounds

Thank you