

# Health Aware meal recommendations using Contextual Multi -Armed Bandits

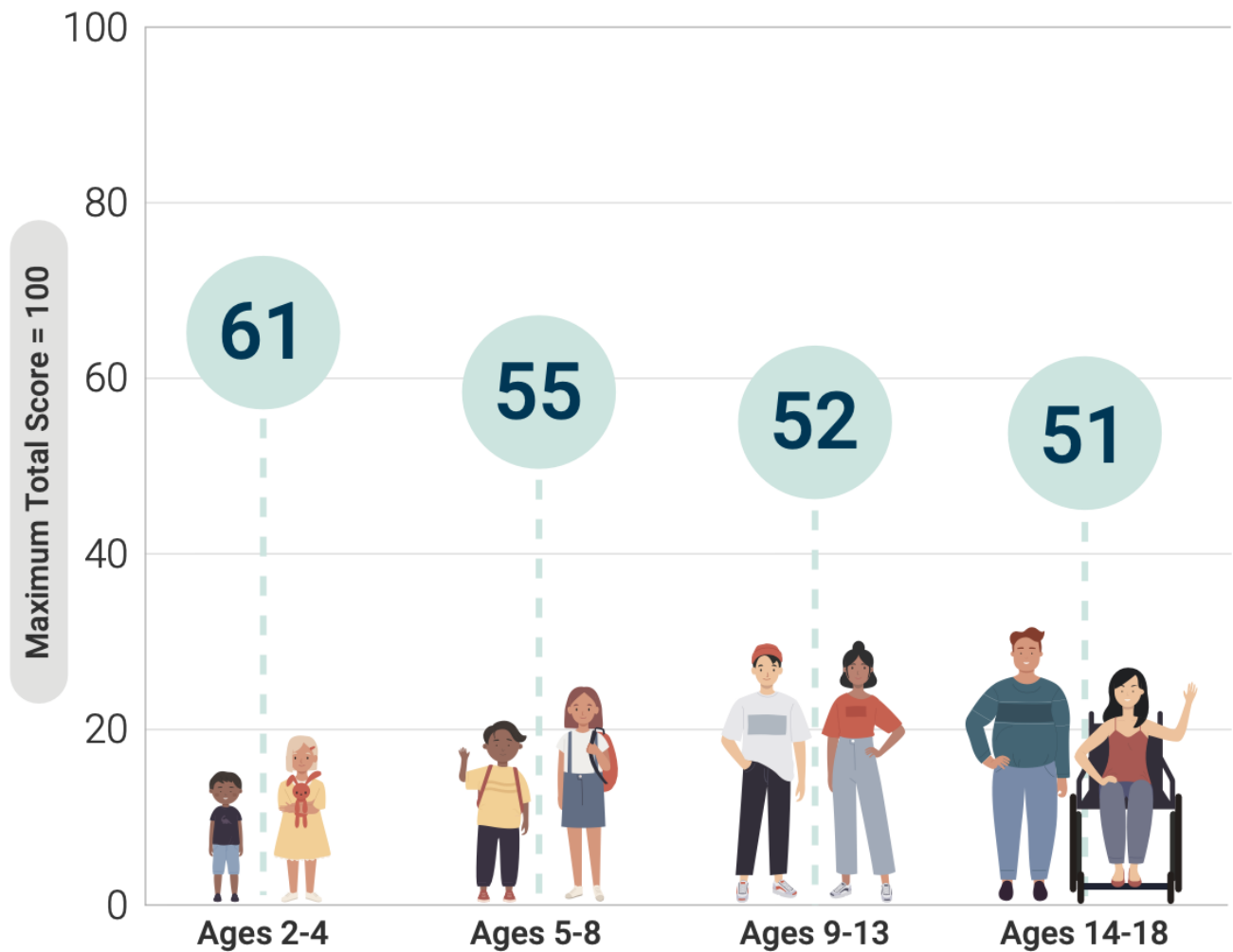
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# Healthy Eating Index Scores Across Childhood and Adolescence



**Data Source:** Analysis of What We Eat in America, NHANES 2015-2016, ages 2 through 18, day 1 dietary intake, weighted.

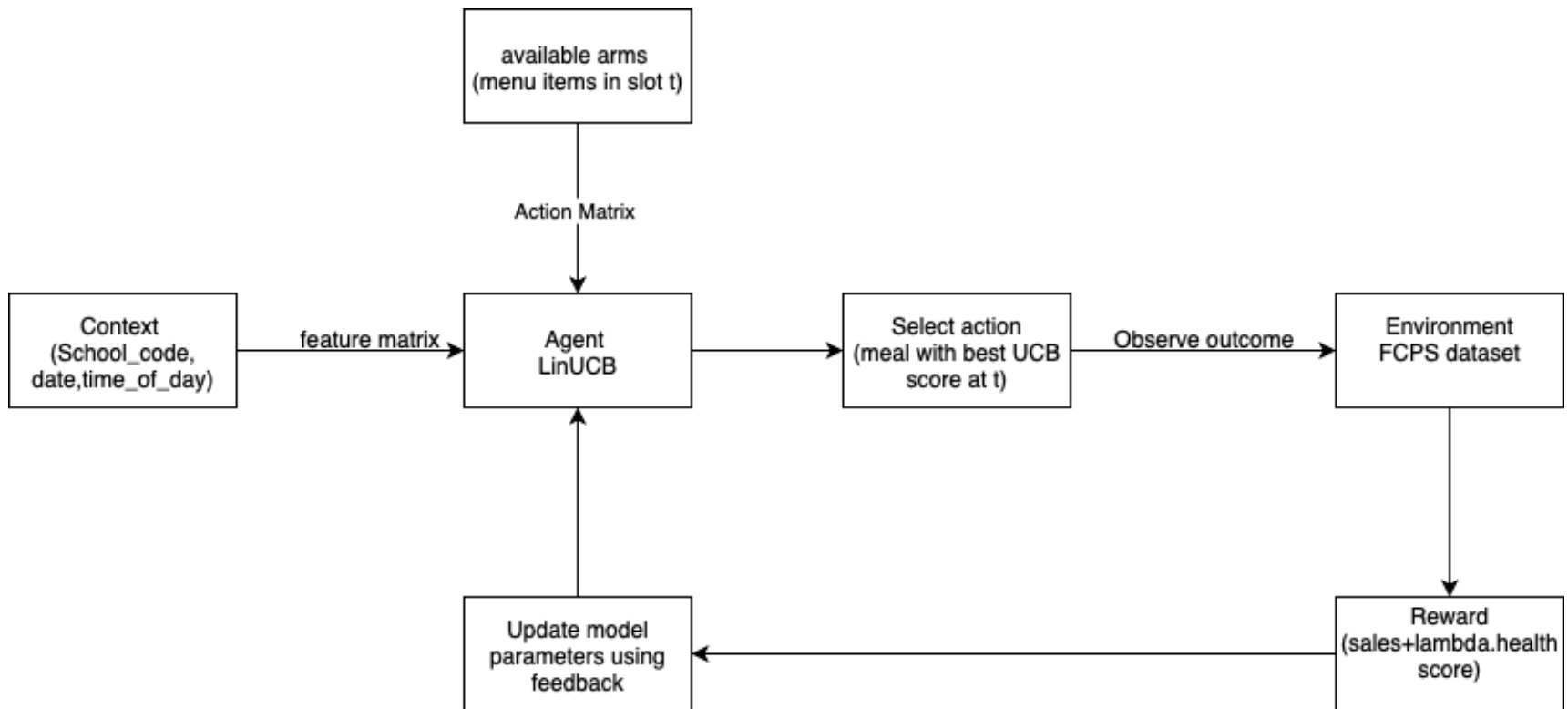
# Motivation

- As seen in the earlier slide, there is a clear need for healthier meals for children and adolescents.
- What if every school meal could be both *what kids love to eat* and *what keeps them healthy*?
- Goal: Build a **school meal recommendation system** for student satisfaction that **maximizes both popularity and healthiness**.
- Objective: Learn **adaptive, data-driven meal recommendations** that balance **taste and nutrition**.
- Approach :Contextual Multi -Armed Bandits (CMAB) for decision optimization

# CMAB Framework Overview

- Context: school, time\_of\_day, day\_of\_week.
- Action: meal (item\_id).
- Reward: total\_meals\_served +  $\lambda \times \text{health\_score}$ .
- Focus: Balancing exploration and exploitation.

# CMAB Flow for FCPS



# Nutrition Data Extraction

- Reverse engineered LINQ connect API system using browser dev tools monitoring
- Found key endpoints for menu items
- Scope of extraction : full academic year coverage with all meal types and categories for all 187 FCPS institutions

# Sales Dataset (FCPS)

- FCPS meal sales dataset: includes schools, timestamps, and meal details.
- Context variables: school, time, day, seasonality.
- Action variables: 160+ meal items (arms).

# System design overview

- Modules:
  1. `utils/env.py` → Simulates the FCPS environment
  2. `model.py` → Implements LinUCB bandit model
  3. `main.py` → Trains and evaluates the system
- Data Flow: Dataset → Environment → Model → Results



# Environment Design (env.py)

- `load_data()`: Loads FCPS preprocessed CSV data.
- `build_item_mapping`: map a unique index to all 160 items and use it subsequently
- `build_feature_matrix()`: Returns contextual feature matrix.
- `build_action_matrix()`: Defines available meal actions per timestep.
- `health_scores()`: Provides healthiness scores for each meal.

# LinUCB Algorithm (model.py)

- Equation:  $\hat{y}_a = \theta_a^T x_t + \alpha \sqrt{x_t^T A_a^{-1} x_t}$
- Balances exploration (uncertainty) and exploitation (expected reward).
- Each meal (arm) has its own  $A_a$  (covariance) and  $b_a$  (reward) matrices.
- Algorithm Steps:
  - 1. Estimate reward using context features
  - 2. Add confidence bound (exploration term)
  - 3. Choose action with highest upper bound
  - 4. Update model with observed reward

# Training & Update Mechanism

- `train()`: Iteratively selects meals, observes rewards, updates model.
- `action()`: Chooses arm maximizing upper confidence bound.
- `update()`: Updates  $A_a$  and  $b_a$  using observed reward.
- `reset()` & `save()`: Manage experiment lifecycle and persistence.

# Reward Design & Health Factor ( $\lambda$ )

- $\text{Reward} = \text{total\_meals\_served} + \lambda \times \text{healthiness\_score}$ .
- $\lambda$  tunes the trade-off between popularity and nutrition.
- Larger  $\lambda \rightarrow$  healthier meals favored

# Evaluation Metrics (metrics.py)

- Regret: Difference between optimal and chosen reward.
- Cumulative Reward: Tracks long-term performance.
- Plots used for comparing exploration strategies.
- Example: Cumulative Reward vs Time.

# Benchmarking Experiments (benchmark.py)

- Tested multiple  $\lambda$  values for reward balancing.
- Compared LinUCB vs baseline (random, popularity-based).
- Saved results via `bench_results_to_csv()`.
- Metrics: Mean cumulative reward, total regret, and recommendation stability.

# Results Visualization (plot.py)

- `plot_top_meals()`: Shows most recommended items.
- `plot_recommendations()`: Trends over time or by context.
- Example visuals: Heatmaps, bar charts, and cumulative reward plots.

# Key Findings



# Future Work

- • Extend to full RL (state transitions, delayed rewards).
- • Implement Thompson Sampling or Neural Bandits.
- • Integrate model with real-time FCPS meal systems.

# Thank You / Q&A

- Questions or feedback welcome!