ENHANCING PUBLIC HEALTH: LEVERAGING MULTI-ARMED BANDIT FOR VACCINATION OUTREACH

"Empowering Health, One Arm at a Time"


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BACKGROUND

- Extremely low current vaccination rate via SMS outreach
- Large volume of messages via traditional A/B testing
- Traditional A/B testing lacks the contextual and interpretability

SOLUTION

- Create personalized SMS campaign with different verbiages by developing **multi-armed bandits (MAB) models**
- Measure **the uplift in performance** to enhance efficiency and cost-effectiveness in experimentation
- To utilize the effectiveness of **contextual MAB** in incorporating different factors to derive actionable interoperable insights

IMPACT

$ 1 M → $ 12M

Projected Cost savings per campaign — Cost savings per annum

85% Decrease in message overload

Better Adaptivity & Interpretable Results using contextual MAB

5% Increase in flu vaccination rates across all features

Millions of patients Get vaccinated with boosted engagements & enhanced loyalty

Dataset Overview

- 1000+ FEATURES
- 100M PATIENTS
- 7 TYPES OF VACCINES

TYPE OF DATA USED

- 2022 Vaccine Measurement Data
- Patient Data like Age, Gender, Income
- Prescription Pickup Record Table
- 10 Verbiages: Value, Cost, Safety, etc

Synthetic Data

Marketing research on verbiage preference → Estimate vaccination rate for verbiage → Stratify sample eligible/ segment patients → Create counterfactuals for each patient for each verbiage

Age	V1	V2	V3	V4
>65	0	1	0	0
35-65	0	0	0	0
<35	0	1	0	1
35-65	0	0	0	0

Data Preprocessing

Feature Engineering

Created synthetic response data for new veribages

Clustering Techniques

Identified the right features for the contextual MAB

Exploratory Data Analysis

Helped in determining the focused vaccine for MAB

MODEL 1: SEGMENTED MAB

Synthetic Response Data → Cluster selected

01 Put eligible patients into pre-defined clusters

02 ACTION : Initialize and subsequently send a verbiage to patients per cluster

- Epsilon-Greedy Algo
- Thompson Sampling → Time Distribution

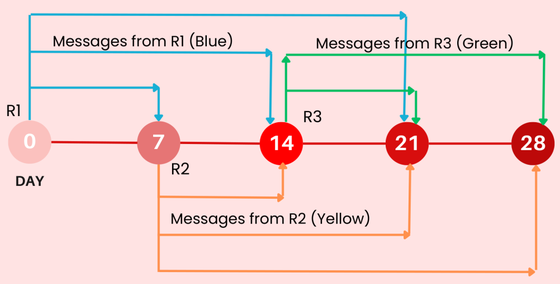
Age Group: 35-65

03 REWARD: Update rewards for that verbiage based on patient's vaccination response

Explore for knowledge from earlier rounds and exploit using the current feedback

Thompson Sampling with Time Distribution

We update the beta distribution weekly for a faster signal change for the MAB



Different colours highlight the Messages from a particular round

MODEL 2: CONTEXTUAL BANDIT

VISION

Explore for knowledge and exploit current knowledge simultaneously

Contextual Bandits: Given a Context → Choose an Action → Observe reward (update models)

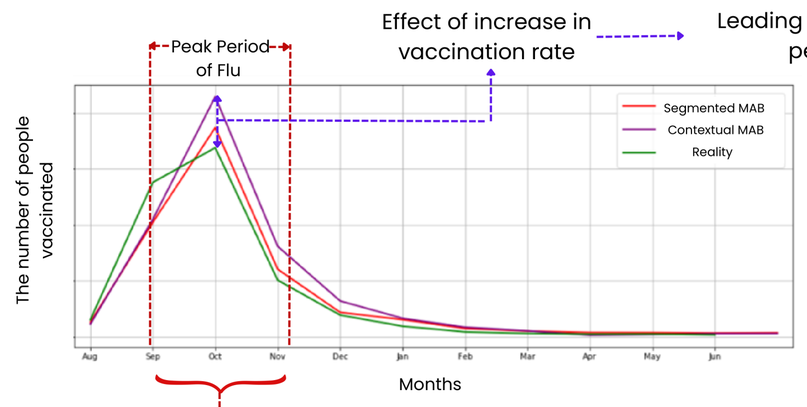
Goal: To maximize the rewards (Flu vaccination rate)

Context : Patient features → AGE, INCOME

Action/Arm: Text messages with different verbiages → Model: Thompson Sampling

ADAPTIVITY OF MAB

Effect of increase in vaccination rate → Leading to increase in millions of people vaccinated



Unlike A/B testing, MAB efficiently leverages peak periods of flu campaigns, leading to escalated vaccination rates. → Faster convergence with less volume of messages

% Increase in Vaccination rates compared to A/B testing

Feature: Age	Epsilon-Greedy Algo	Thompson Sampling
>65	1.33%	3.68%
35-65	2.42%	6.71%
<35	0.38%	0.00%
Overall	1.78%	4.39%

A/B TESTING VS MAB

Case of Segmented MAB based on Age

Thompson Sampling is performing better in more cases and requires 1/4th volume of messages compred to A/B testin

CONTEXTUAL BANDIT PERFORMANCE

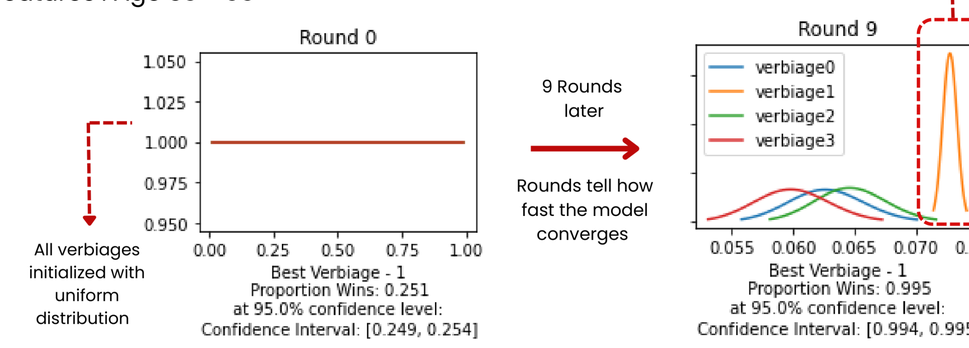
Model: Contextual MAB
Features : Age, Income

4.61% Improvement in vaccination rate across all features

Proportion Wins :

The **Proportion Wins** is computed as the proportion of times where the best arm outperforms other arms using Monte Carlo simulations.

Model: Segmented MAB-Thompson Sampling
Features : Age 35 - 65



Proportion Wins:

Features : Age 35 - 65, Income Above 70k