DS223 - Marketing Analytics

Group Project

Problem Definition

Group 7

09.11.2025

Problem Definition

1. Problem Area

The selected problem area for the group project of Marketing Analytics course, is Pricing Strategy and Product Testing within Marketing Analytics.
Pricing plays a crucial role in determining a product's market success. However, many businesses struggle to determine the optimal price point for their products, especially during the early stages of product introduction. Traditional methods such as surveys or static A/B testing often fail to adapt to changing consumer behavior and result in lost revenue opportunities.

2. Preliminary Research

In today's digital environment, businesses have access to real-time user interaction data from online platforms. Yet, most companies still rely on static A/B pricing tests, which divide users evenly among price options and wait until a large sample size is reached to determine a winner. This approach is inefficient, slow, and does not utilize data adaptively.

Recent research and industry applications suggest that multi-armed bandit algorithms, such as Thompson Sampling, can make pricing tests more dynamic and intelligent. These algorithms continuously learn from incoming data and automatically adjust which price options to show more frequently, accelerating decision-making and maximizing conversions. Moreover, recent studies have highlighted the benefits of adaptive learning approaches in dynamic pricing contexts. For example, algorithms capable of updating strategies in response to observed demand have been shown to significantly improve revenue outcomes(Qu, 2024).

Recent studies have also demonstrated the limitations of traditional A/B testing, which allocates equal traffic to all variants and delays decision-making. According to Kumar S. (2023), multi-armed bandit algorithms such as Thompson Sampling, UCB, and Epsilon-Greedy provide a more adaptive framework by continuously updating allocation

based on real-time feedback. His findings show that Thompson Sampling achieves higher cumulative rewards, lower regret, and better scalability in dynamic environments compared to other approaches. This supports our project's use of Thompson Sampling as the core method for optimizing product pricing tests.

3. Specific Problem

Businesses lack a data-driven, adaptive framework that enables them to efficiently test and identify the best price for a product based on real-time consumer behavior.
The specific problem we aim to address is:

> *How can companies dynamically test multiple price points for a product and automatically adapt to customer responses to find the optimal price?*

4. Solution with Methodology

Data Collection

The proposed system will collect user interaction data from experimental product pages, including:

- Impressions (how many users saw each price)
- Clicks or purchases (conversion behavior)
- Time of interaction

These data points will feed directly into the learning algorithm.

Analytical Techniques

We will apply Thompson Sampling, a probabilistic multi-armed bandit method, to dynamically allocate traffic among different price variants. The approach will use:

1. Bernoulli Thompson Sampling for conversion-focused metrics (binary outcomes such as purchase/no purchase).
2. Normal (Gaussian) Thompson Sampling for revenue-focused metrics (continuous outcomes such as purchase amount or total revenue per user).

Implementation Plan

- Create a web-based platform where companies can upload products and define several price variants (e.g., three price points).
- Randomly assign visitors to different variants initially.
- Track user interactions in real time and store them in a database.
- Run the Thompson Sampling model periodically to update which price option receives more exposure.
- Display analytics dashboards for marketers to monitor results (conversion rates, revenue, algorithm learning curve).

5. Expected Outcomes

By implementing this system, companies can:

- Identify optimal pricing faster and with fewer user samples.
- Increase conversion rates and overall revenue.
- Reduce the inefficiencies and delays of static A/B testing.
- Make data-driven pricing decisions supported by live customer feedback.

6. Evaluation Metrics

The effectiveness of the proposed solution will be assessed using the following Key Performance Indicators:

- Revenue Uplift: the total increase in sales achieved by faster convergence to the optimal pricing strategy.
- Regret Minimization: the reduction in potential revenue lost during the pricing test compared to an ideal strategy.
- Model Efficiency: the number of iterations or time steps required to identify the best-performing price option.

References

Kumar, S. (2023). *Multi-Armed Bandit Algorithms in A/B Testing: Comparing the Performance of Various Multi-Armed Bandit Algorithms in the Context of A/B Testing. Journal of Mathematical & Computer Applications*, 2(2), 1–4. https://doi.org/10.47363/JMCA/2023(2)159

Qu, J. (2024). *Survey of dynamic pricing based on multi-armed bandit algorithms*. Applied and Computational Engineering, 37(1), 160–165. https://doi.org/10.54254/2755-2721/37/20230497