Google Case Competition
Adaptive Staffing Intelligence

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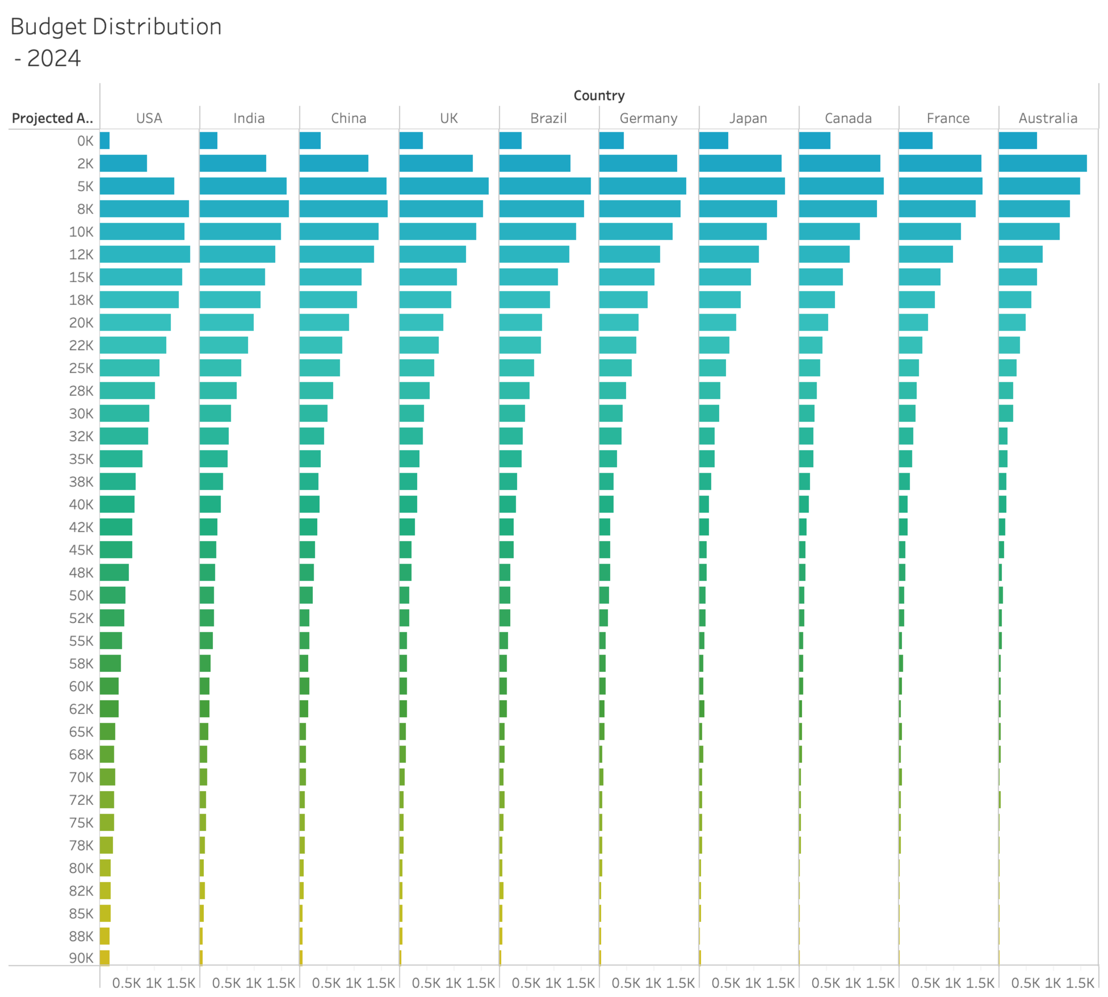
Problem Statement

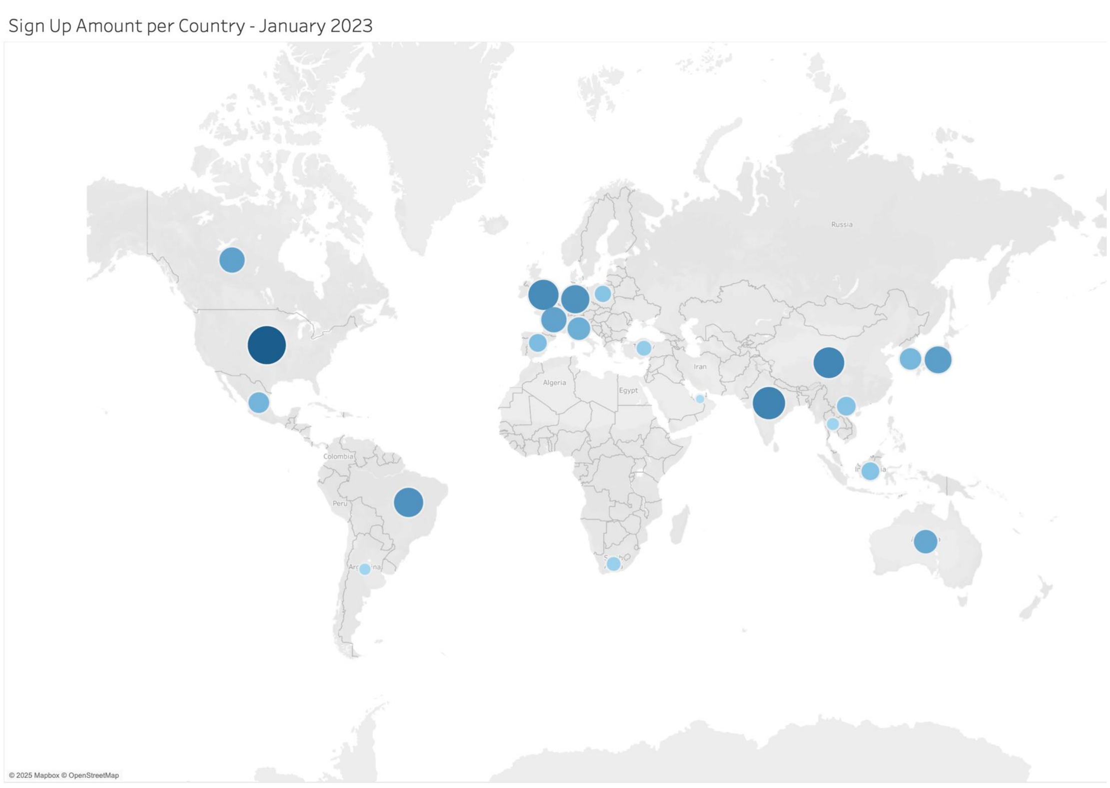
Given a historical dataset from advertisers around the world, we were tasked with developing a dynamic month-by-month staffing plan that ensured that eligible businesses that advertise on Google could access support from Ads Experts.

> “Agent staffing is managed locally in each country [...]. Each agent can handle up to 10 advertisers at any time, but the unpredictable daily influx of new accounts makes staffing optimization a challenge. Overstaffing leads to idle capacity and reduced ROI, while understaffing delays advertiser support and reduces incremental revenue.”

Exploratory Data Analysis

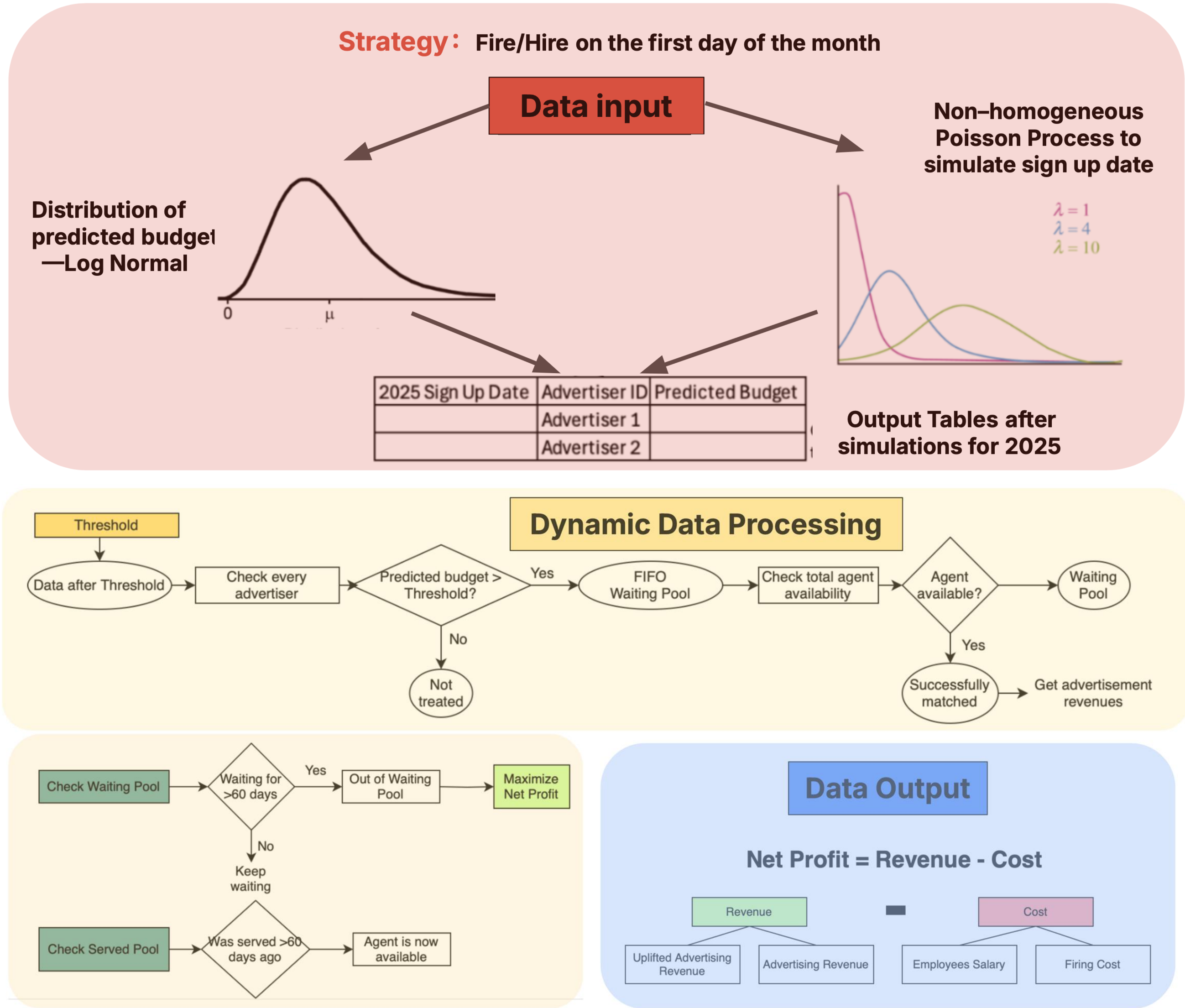


The previous graph shows that the budget distribution for the top 10 countries by budget in 2024 follows a Lognormal distribution, an observation that is going to be useful for our analysis. The results were similar for 2023. Additionally, the U.S. has the higher number of advertiser sign ups, as revealed by the following graph.



Optimal Model

We created a Semi-Markov Decision Process, which is a technique to model situations where you make decisions, but the time between decisions isn’t fixed. The following diagram explains our strategy to address our problem, which is hiring and firing personnel on the first of the month.



The problem had the following constraints, which we then modeled mathematically:

- Google projects an advertiser’s annual budget upon sign-up.
- If the budget exceeds a country-specific threshold, the advertiser is eligible for support. They then enter a waiting pool.
- If agent capacity is available, an advertiser is assigned an agent.
- If no capacity is available, the advertiser waits for up to 60 days.
- If unassigned after 60 days, the advertiser is removed from pool.
- Each agent can manage up to 10 advertisers at a time.
- All agents start 2025 with no assigned advertisers.
- Advertisers graduate after 60 days of support
- New agents require 1 month of ramp-up before being available.
- Firing an agent requires 1 month’s notice and incurs a cost of 40% of their annual salary.

1.State Space

$$S_t = (A_t, W_t, S_t, R_t, C_t, H_{t-1}, F_{t-1})$$

where:

- A_t = Number of available agents
- W_t = Number of advertisers in the waiting pool
- S_t = Number of advertisers currently assigned
- R_t = Cumulative revenue
- C_t = Cumulative cost (salary + firing penalty)
- H_{t-1}, F_{t-1} = Hiring & firing decisions from the previous month

2.Action Space

$$A_t \in \{-30, -20, -10, 0, 10, 20, 30\}$$

Hiring Delay: H_t takes **1 month** to be effective:

$$A_{t+2} = A_{t+1} + H_t$$

Firing Delay: F_t takes **1 month notice**:

$$A_{t+1} = A_t - F_t$$

3.State Transition Dynamics

Advertiser Sign-Up Process:

$$W_t = W_{t-1} + \text{New Sign-Ups}$$

Agent-Advertiser Assignment:

$$S_t = S_{t-1} + \min(W_t, 10 \times A_t)$$

$$W_t = W_t - \min(W_t, 10 \times A_t)$$

Advertiser Graduation (After 60 Days):

$$S_t = S_t - \text{Graduated Advertisers}$$

4.Objective Function

Maximize total **net profit** over 12 months:

$$J = \sum_{t=1}^{12} R_t - C_t$$

where:

- **Revenue Function:**

$$R_t = \sum S_t \times E[\text{Uplifted Budget}]$$

- **Cost Function:**

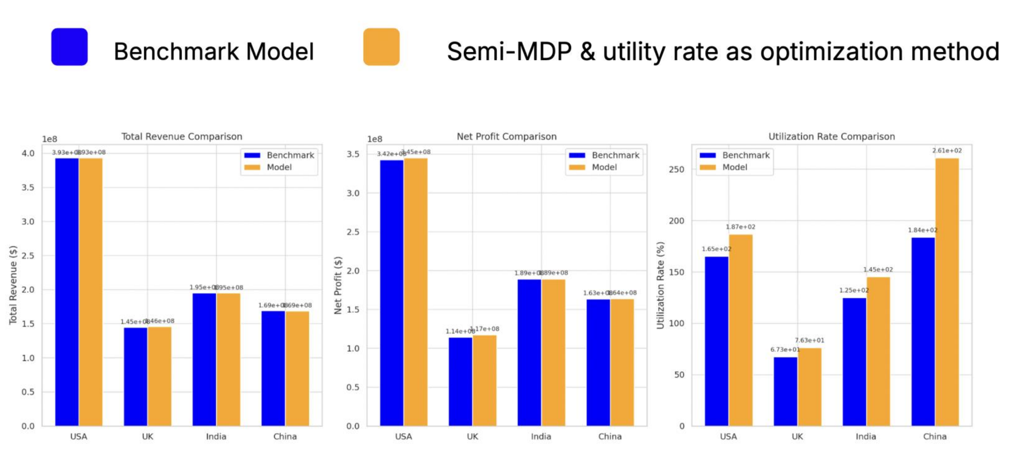
$$C_t = A_t \times \frac{\text{Salary}}{12} + F_t \times 0.4 \times \text{Salary}$$

Model Comparison

We originally compared the following models. However, we found out that only one was suitable for this context.

Model	Suitable Scenarios	Suitable or Not?
MILP (Mixed Integer Linear Programming)	Well-defined, **static** problems with known constraints.Best for **one-time staffing optimization**.	❌ **Not suitable.**
MDP (Markov Decision Process)	**Short-term decision-making** where all information is observable.Good for structured, **sequential** decision problems.	❌ **Not suitable.**
Semi-MDP (Semi-Markov Decision Process)	Problems with **delayed actions** (e.g., hiring takes 1 month).Works well for **medium-term optimization.**	✅ **Suitable.**
POMDP (Partially Observable MDP)	**Highly uncertain environments** with hidden information. Best for **real-world dynamic staffing** with incomplete data.	❌ **Too complex.**

We ended up implementing three models:
Benchmark Model(No Hiring or Firing), **Semi-MDP** & utility rate as optimization method and **Semi-MDP & DQN (Deep Q-Network).** However, we didn’t have enough computing power to finish the latter.



$1,293,332 higher than Second model for USA!

HIgher than Benchmark’ net profit:
USA: $2,718,676.86
UK: $3,109,699.53
India: $150,586.55
China: $287,660.28

For sensitivity analysis, three market extremes were simulated. The results were:

1. Although users of Google's newly launched products may not adapt to them at the beginning, the sign-up rate for advertisers would recover eventually.
2. Google rolled out a marketing strategy that suddenly led to a huge increase in users. Q4 sign up is doubled.
3. The market will pick up in 2025, with the number of sign-ups increasing by 50% every month throughout the year.

Final results

If we had the opportunity to use more resources for this project, we would have compared and implemented the Semi-MDP and DQN model, which has more benefits such as self-improvement and adaptability.

We would also like to see the effect of implementing a 3 or 6 months pilot program in a mid-sized market (e.g., UK or Canada), monitoring performance metrics, in order to refine the model.

A recommendation for stakeholders is to integrate machine learning-based demand forecasting to predict advertiser sign-ups and adjust hiring before demand spikes.