Business Agent Dynamic Staffing System

Yihan Zhou

2025/2

Problem Formulation & Goal

Efficient Support & Enhanced Customer Satisfaction:

- Ensure advertisers receive timely, high-quality support to minimize waiting times, improve customer satisfaction, and boost ad revenue.

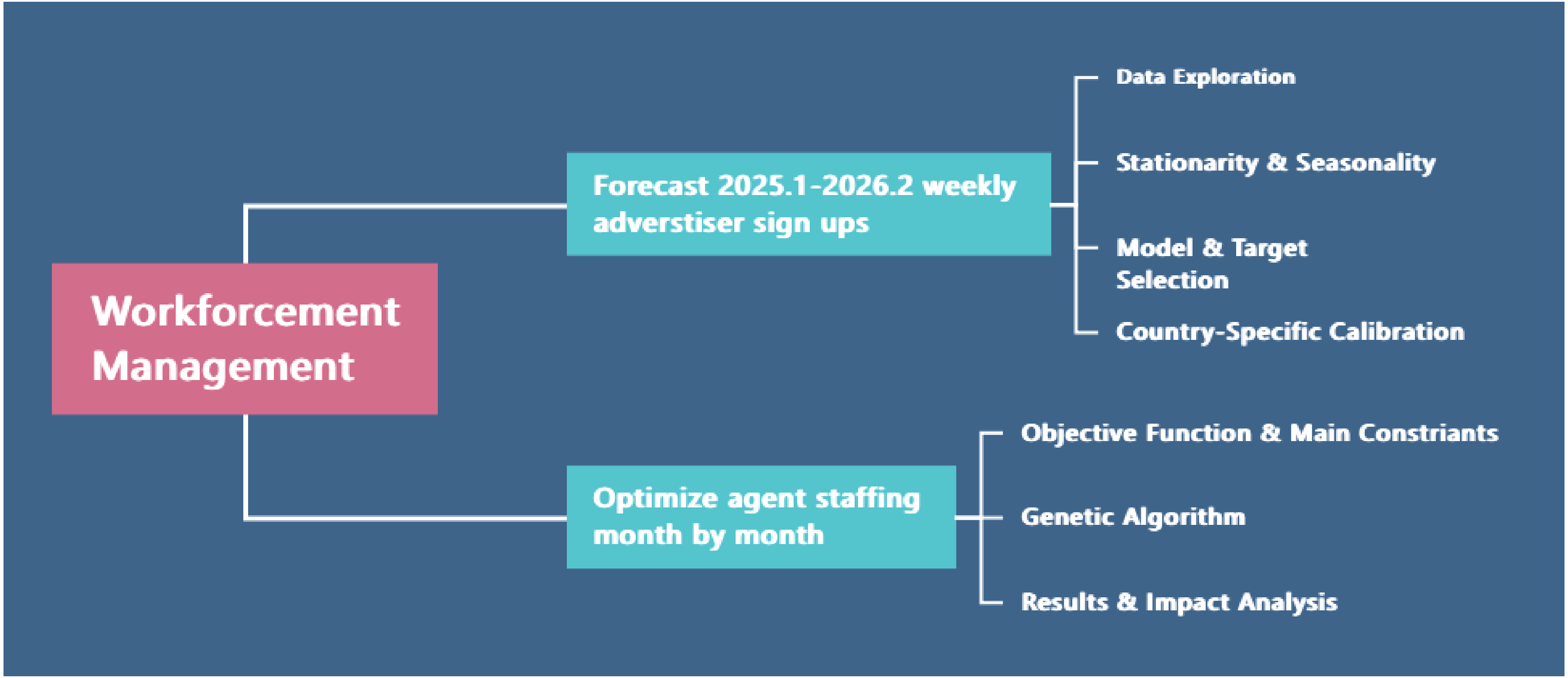
Maximized Cost Efficiency:

- Balance agent salaries, hiring/firing costs, and potential lost revenue from unmet demand, thereby reducing resource waste and maximizing ROI.

Operational Flexibility & Scalability:

- Dynamically adjust staffing levels based on daily registration fluctuations so that rapidly responding to high-demand periods while controlling costs to enhance overall operational adaptability.

Data & Methods Overview



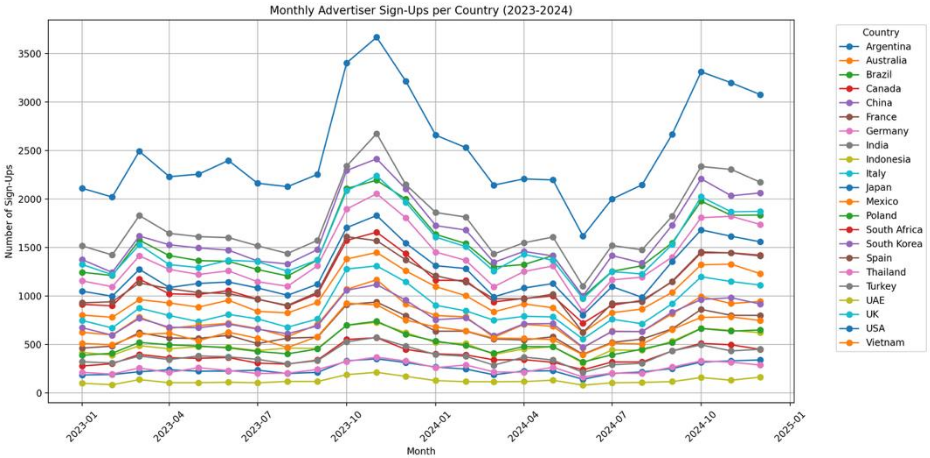
Forecast Model

Forecast Model

Data Exploration → Stationarity & Seasonality → Model & Target Selection → Country-Specific Calibration

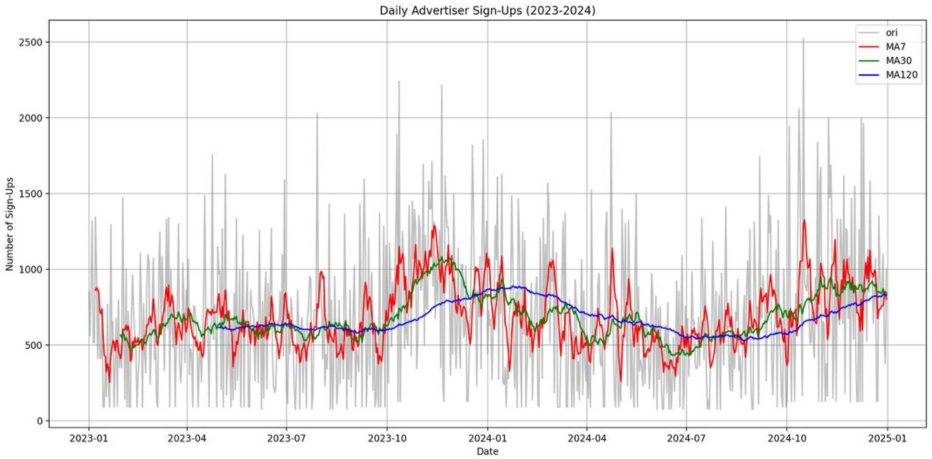
Data Aggregation and Trend Analysis

- Aggregate daily sign-ups across cities
- Observed **similar monthly trends across countries**



Time Series Analysis on Daily Sign-up Trends

- Combined daily sign-ups from all cities
- MA7, MA30, and MA120: **smooth short-term fluctuations** and reveal underlying patterns



Forecast Model

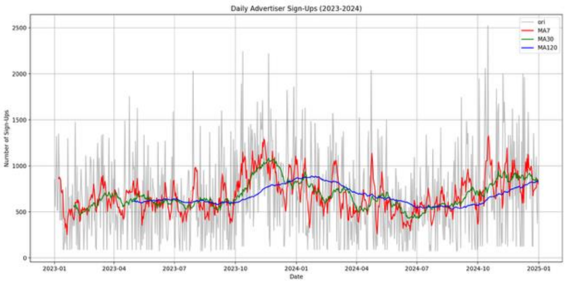
Data Exploration → **Stationarity & Seasonality** → Model & Target Selection → Country-Specific Calibration

Stationarity (ADF Test)

- ADF Statistic: -4.9483
- P-Value: 2.80e-05
- **Time series is stationary**

Seasonal Decomposition

- Periods = **7**/ **30** /**120**
- **Weekly & Monthly seasonality**



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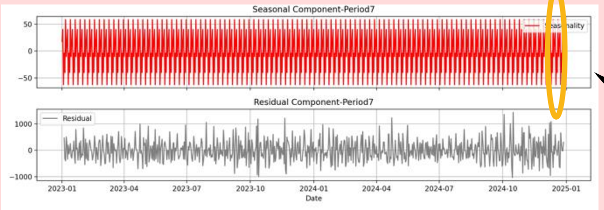

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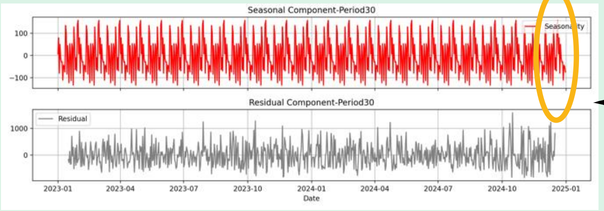

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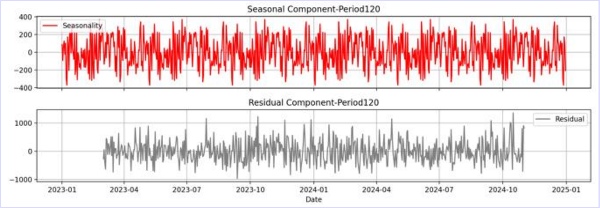
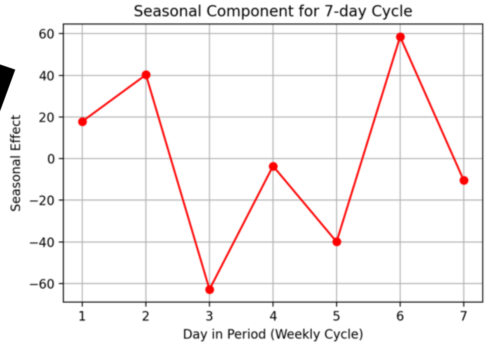
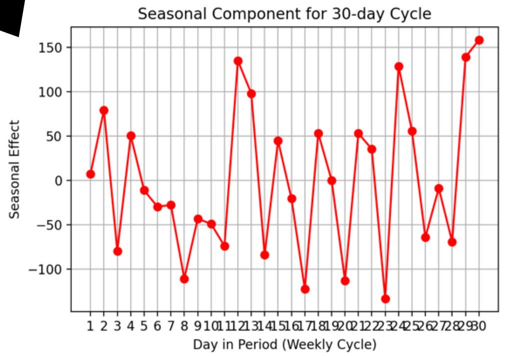


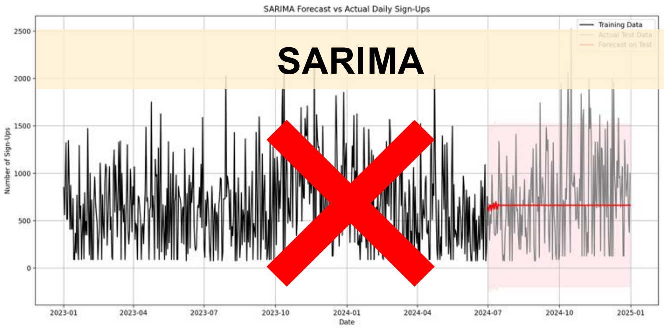


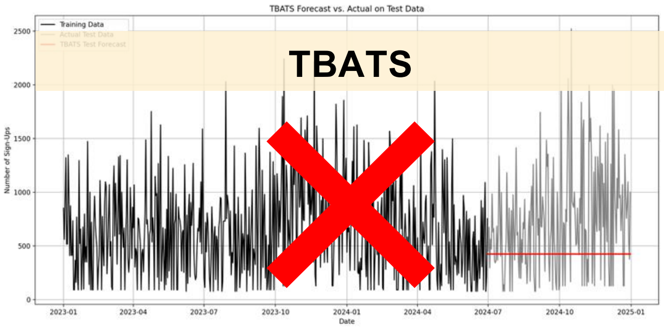


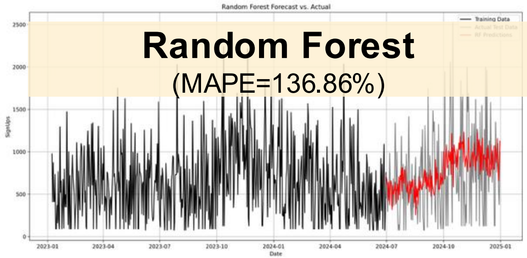
Forecast Model

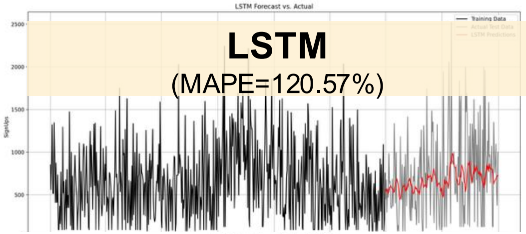
Data Exploration → Stationarity & Seasonality → **Model & Target Selection** → Country-Specific Calibration

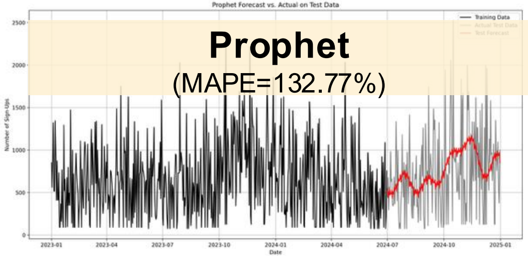
Training: Before 2024.6.31 | Testing: After 2024.7.1











Why Prophet?

*Built on a **decomposable time series model:***

- Multiple Seasonality: weekly & yearly
- Trend Changepoints: automatic detection
- Custom Components: add holiday factors

Terrible MAPE?

MAPE: Mean Average Percentage Error

<10%	The model is highly accurate
10% - 20%	The model is good
>50%	The model is **falsely predicted**

Predict MA7 Instead!

Why a 7-day Moving Average?

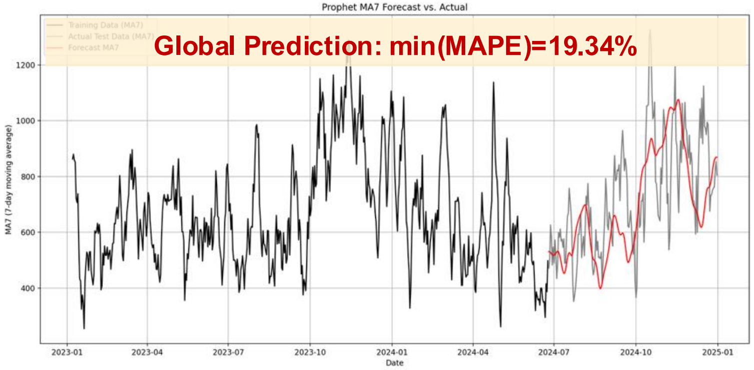
- Smooth Outliers
- Highlights Trends
- Better Model Stability

Forecast Model

Data Exploration → Stationarity & Seasonality → Model & Target Selection → **Country-Specific Calibration**

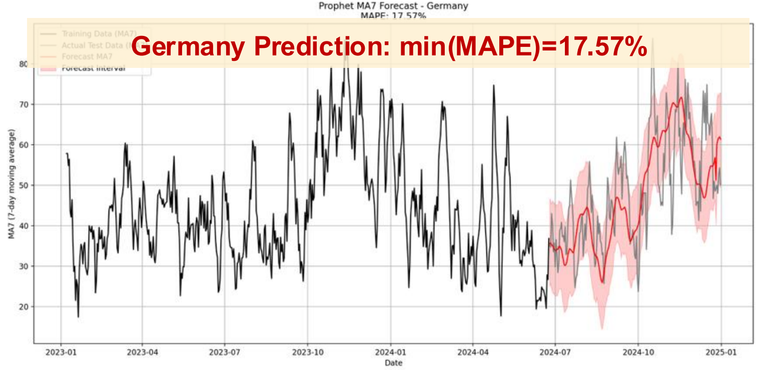
Global tuning to set baseline parameters

- **Data:** daily sign-ups from all cities
- **Seasonality:** **weekly & yearly + customized monthly**
- **Trend Flexibility:** **low sensitivity to trend changes**
  changepoint_prior_scale=0.02
  changepoint_range=0.8
- **Seasonality Controls:**
  seasonality_prior_scale=0.18 - ***Moderate amplitude***
  seasonality_mode='additive'– ***Add linearly to the trend***



Grid search for country-level adjustments

- **Objective:** Optimize forecasting models for each country
- **Refined Parameter Grid:** **narrow grid around baseline parameters**
  changepoint_prior_scale ±0.005
  seasonality_prior_scale ±0.02
  changepoint_range ±0.05
- **Enhancements:** Add **country-specific holiday seasonality**
- **Iterative Process:** **Loop adjustments** until MAPE stabilizes



Forecast Model

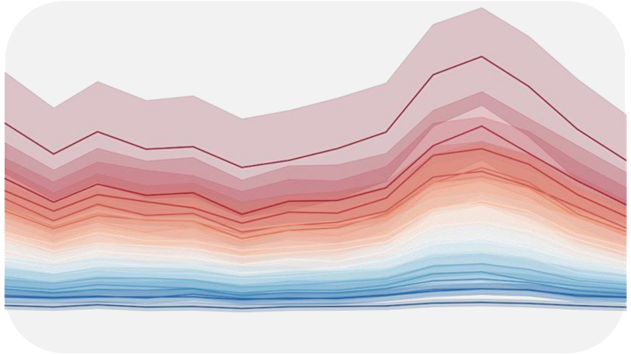
Data Exploration → Stationarity & Seasonality → Model & Target Selection → Country-Specific Calibration

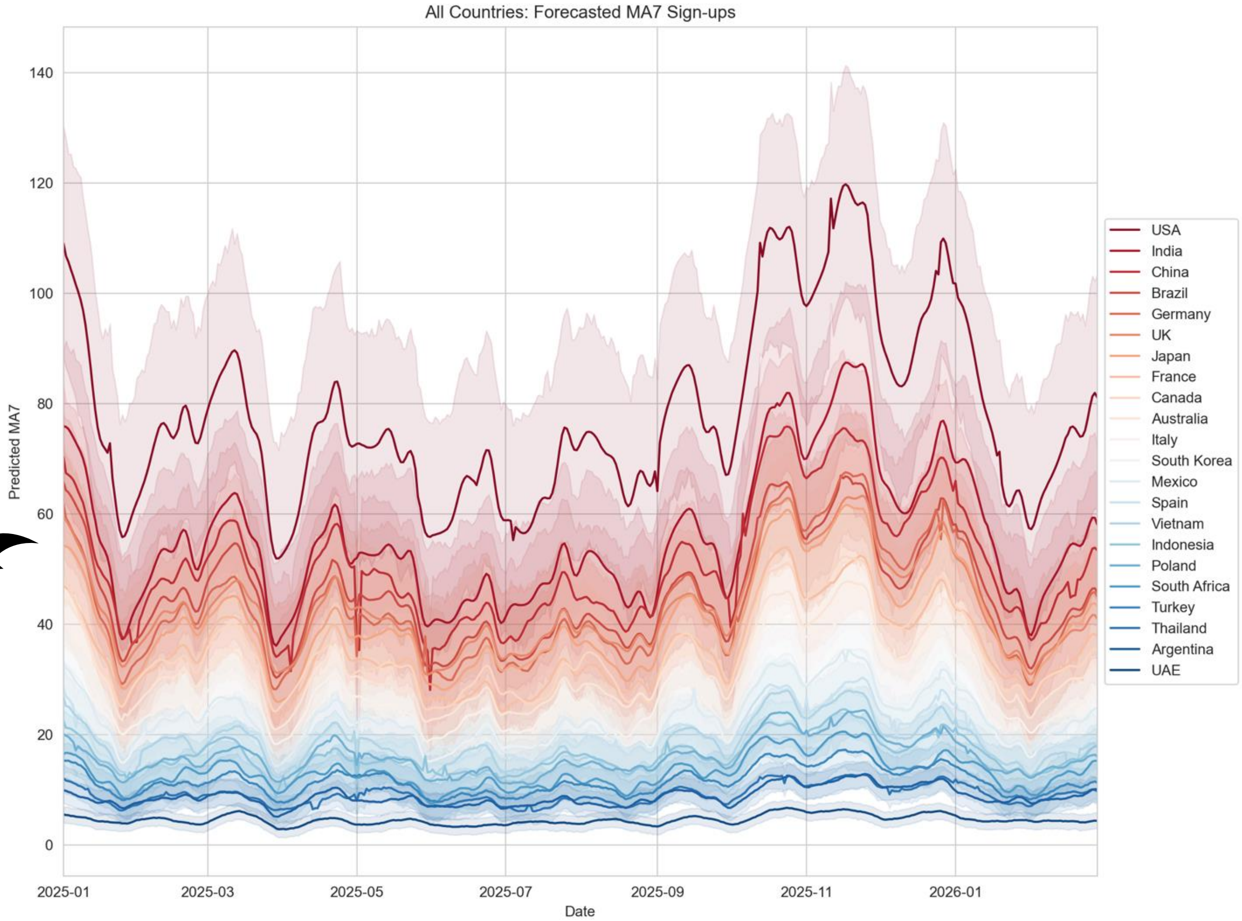
Summary and Results

- **Parameter Summary Table**

Country	changepoint_prior_scale	seasonality_prior_scale	changepoint_range	seasonality_mode	MAPE
Argentina	0.005	0.08	0.9	additive	0.214
Australia	0.02	0.1	0.9	multiplicative	0.195
Brazil	0.02	0.1	0.9	multiplicative	0.200
Canada	0.02	0.1	0.9	multiplicative	0.192
China	0.02	0.12	0.8	multiplicative	0.188
France	0.02	0.1	0.9	multiplicative	0.191
Germany	0.02	0.12	0.8	additive	0.176
India	0.02	0.1	0.9	multiplicative	0.192
Indonesia	0.02	0.12	0.85	multiplicative	0.181
Italy	0.01	0.16	0.8	multiplicative	0.187
Japan	0.02	0.1	0.8	multiplicative	0.181
Mexico	0.02	0.06	0.8	multiplicative	0.197
Poland	0.02	0.1	0.85	multiplicative	0.195
South Africa	0.015	0.1	0.85	multiplicative	0.195
South Korea	0.015	0.14	0.8	multiplicative	0.202
Spain	0.02	0.18	0.8	multiplicative	0.185
Thailand	0.01	0.12	0.8	additive	0.196
Turkey	0.01	0.1	0.9	multiplicative	0.200
UAE	0.005	0.16	0.85	additive	0.237
UK	0.001	0.12	0.85	multiplicative	0.195
USA	0.02	0.1	0.9	multiplicative	0.197
Vietnam	0.025	0.1	0.7	additive	0.226

- **Prediction Results:** 2025.1–2026.2
- **Summed into monthly sign-ups**





Optimization Model

Optimization Model

Goal

Every Monday in 2025, an optimization process determines agent staffing levels for next several weeks

The model considers staffing costs, hiring/firing expenses, and lost revenue from unmet demand

Objective: Maximize net profit

Problem Formulation

Objective Function:

$$\max\left(\sum_{t=0}^{T}\sum_{i=0}^{V_t} 0.135 b_i - \sum_{t=0}^{T}(s_t + h_t + L_t)\right)$$

Key Variables:

- T = optimization horizon
- V_t = forecasted demand volume at time t
- b_i= budget of demand i
  (concave truncated distribution, given the minimum eligibility)
- s_t = staffing cost at t
  (salary per unit of labor per time period)
- h_t = hiring/firing cost at t
  (1 month salary per hired agent)
- L_t = lost revenue from unserviceable demand at t, minimized by redistributing demand within 60-day windows

Optimization Model

Main Constraints

- **Idle unit constraint ->** Less than current staffing level minus the ongoing demands
- **Backlog constraint ->** 60 days removal
- **Staffing adjustment granularity constraint ->** Staffing adjustments, hiring/firing units in multiples of 10)

Key Assumptions

- **Labor Efficiency**
  A small frictional loss (~5%) is assumed, so each agent effectively works at 95% capacity.
  Staffing and workload balancing can thus be treated separately, with fractional agent units (1/10 of an agent) assignable independently.
- **Reliable Foresight:** Demand forecasts for the next 60 days are assumed accurate, with near-zero mean residual.
- **Advertiser Prioritization:** High-budget advertisers are always given priority for agent assignment.
- **Concave Budget Distribution:** The predicted budgets follow a concave pattern, influencing how revenue potential scales with spending.
- **Uplift Distribution:** Its specific shape is less critical due to the Central Limit Theorem smoothing out variations.

Optimization Model

How to minimize L_t given staffing level

Double Queue Approach to Minimize Lost Quantity

- **Unserviceable Orders U_t:** Defined by orders waiting over 60 days in backlog
- **Queue:** Either represents stable staffing capacity or represents accumulated backlogs
- **Formula:** $U_t = \sum_{k=-60}^{t} \alpha_k \, v_k$ with $\sum_{k=t-60}^{t} \alpha_k = 1$
  Distribute new "lost" orders proportionally across the 60-day window to reduce losses.

Minimizing Sum of Budget given Quantity

- **Concavity of Revenue Loss:** Probability function $P(B|B > c_i)$ of budget is concave, implying concave revenue loss for unserviceable orders each day
- **Proportional Distribution:** Allocate the lost orders U_t proportionally to the daily volume v_k within the expansion window
- **Outcome:** This strategy minimizes overall backlog and reduces total concave revenue loss

Optimization Model

Adjustable Settings For Application

- Trained given every agent was full and evenly distributed in 60 day period
- Actual frictional cost model replacing min(1,5% current level)
- Destroy all backlog demands at the end of the finite horizon

Solution: Genetic Algorithm (GA)

📌 **Algorithm Steps**:

🔷 **Step 1**: Forecast demand & initialize staffing levels.

🔷 **Step 2**: Perform GA optimization (**Selection, Crossover, Mutation**).

Each individual holds the information of the change for each week (e.g. -1, -2, 0, … +1, …)

🔷 **Step 3**: Deploy the optimal staffing plan every Monday.

Optimization Model

Optimization heuristics for faster convergence

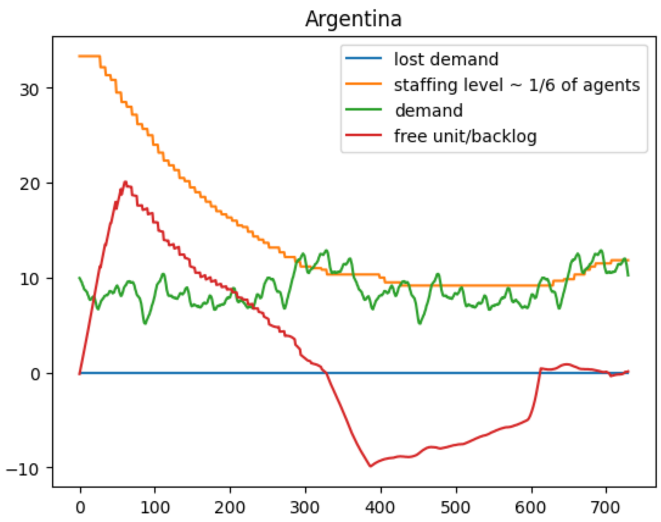
- Merge suboptimal patterns like -1, 0, +1 for three weeks

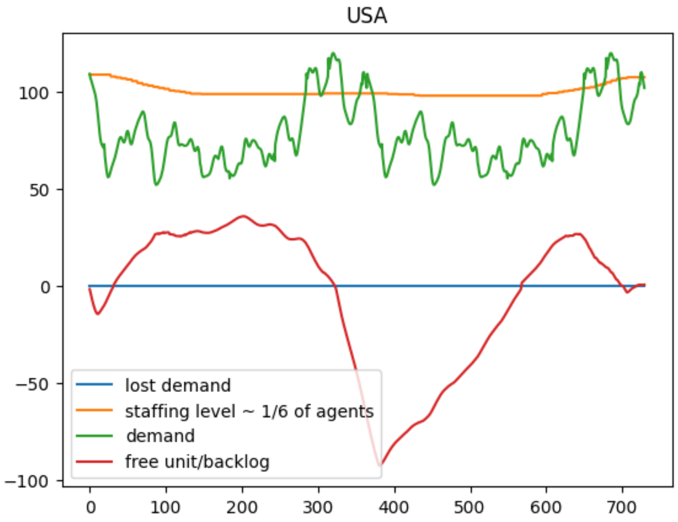
Hiring/Firing Constraints:

- **Max hiring per week:** 10 agents (cost: 1 month salary) for smooth optimization.
- **Max firing per week**: **10 agents** (cost: 4 month salary) **for smooth optimization**
- **Cannot hire and fire in the same week due to apparent suboptimality**

Result & Impact Analysis

Result & Impact Analysis – Example Countries





Relatively high budget

```
Possible Revenue: 2,645,752$

Revenue Loss: 0$                (-0%)
Salary Cost: 4,212,527$         (-159%)

Net Profit: -1,566,774$         (-59%)
```

- Excessive initial staffs causing significant loss

```
Possible Revenue: 230,530,706$

Revenue Loss: 0$                (-0%)
Salary Cost: 95,880,724$        (-41%)

Net Profit:  134,649,981$       (+59%)
```

- Reasonable initial level gives a decent gross profit rate

Result & Impact Analysis

📌 Advantages

✅ Running the model with lower and upper bound of CI shows adequately **low sensitivity with mostly <10%** change in the next 8 decisions

✅ Minimizes lost revenue L_t + hiring/firing costs h_t

✅ Takes future demand into account, avoiding short-sightedness

✅ Can be ran periodically given each week's new market input

📌 Disadvantages:

❌ Could lose a small amount of precision with unknown performance of workload balancing algorithm with respect to staffing changes

❌ Uses finite horizon optimization given by the dataset to approximate for an infinite horizon case, causing boundary effects. Partially solve by having double horizon input than output and disallowing utilization of backlog towards the end

Conclusion & Future Work

📌 Summary:

GA **dynamically optimizes** agent staffing.

It **adapts to market fluctuations**, improving **net revenue**.

📌 Future Optimizations:

GA can use adaptive learning rate w.r.t. country baseline

Reinforcement Learning (RL) for smarter adjustments.

More advanced demand forecasting models (e.g., LSTM).