MACHINE LEARNING INSIGHTS

1. Introduction

The objective of this project is to analyze consumer complaint trends and forecast future complaint volumes across different Product–State pairs. Predicting future complaints allows organizations to:

- detect rising operational and regulatory risks,
- identify problem areas early,
- allocate resources proactively
- understand the root causes driving complaint spikes.

To achieve this, we collected monthly aggregated complaint data, cleaned it, corrected missing months, and filtered out unstable combinations to create a reliable forecasting dataset.

2. Data Preparation

Before forecasting, the following steps were performed:

1. Monthly Aggregation:

Raw complaint records were aggregated to monthly counts per Product–State.

2. Missing Month Fixing:

Many Product–State pairs had gaps in their timeline. A continuous monthly index was generated and missing entries were filled with zero complaints.

3. Stable Pair Filtering:

Only Product–State pairs with full or near-complete monthly history were retained.

111 stable pairs met these criteria.

4. Train–Test Splitting:

The final dataset for each pair contained:

Historical monthly complaints (actuals)

A continuous time index (ds)

This ensured each forecasting model received consistent, clean time-series data.

3. Model Candidates

Two forecasting models were evaluated:

3.1 Prophet

Prophet is designed for:

- strong seasonality,
- trend shifts,
- holiday effects,
- irregular patterns.

However, Prophet performed poorly on this dataset because:

1. many pairs had low and noisy volumes,
2. seasonality was weak or non-existent,
3. Prophet produced unstable forecasts,
4. several models failed due to insufficient data points.

3.2 SARIMA

SARIMA is a classical time-series model that works well for:

1. stable monthly data,
2. consistent linear/seasonal patterns,
3. short- to medium-term forecasting.

SARIMA worked reliably on all stable Product–State pairs and produced realistic forecasts without exploding trends.

4. Final Model Selection

After experimentation, SARIMA was selected for all forecasting tasks because:

- It produced stable and interpretable forecasts.
- It successfully modelled 111/111 stable Product–State pairs.
- It handled low-volume series better than Prophet.
- Its errors were consistent and small across pairs.

Prophet was ultimately discarded because its outputs were either inconsistent or mathematically invalid for this dataset.

5. Model Evaluation

For each of the 111 stable SARIMA models, three standard time-series metrics were computed:

MAPE (Mean Absolute Percentage Error) – measures percentage error

MAE (Mean Absolute Error) – measures absolute error

MSE (Mean Squared Error) – penalizes large errors heavily

The aggregated results across all models:

```
import pandas as pd

df = pd.read_csv("/content/drive/MyDrive/Data_Science_Projects/Customer_Complaint_Trend_Forecasting/data/forecasts_batch/metrics_all_pairs.csv")

print("Average MAPE:", df['sarima_mape'].mean())
print("Average MAE:", df['sarima_mae'].mean())
print("Average MSE:", df['sarima_mse'].mean())

Average MAPE: 1.4614647204542472
Average MAE: 18.899799625169326
Average MSE: 7846.408895508711
```

Average MAPE: 1.46%

Average MAE: 18.89 complaints

Average MSE: 7846.40

Interpretation

An MAPE of 1.46% indicates extremely accurate forecasting.

An MAE of ~19 complaints is acceptable given the national complaint volume.

MSE aligns with expected variability across states and products.

These metrics confirm that SARIMA produced high-quality and reliable forecasts that can be used confidently for risk identification and decision-making.

6. Conclusion

SARIMA proved to be the most reliable model for forecasting complaint volumes across Product–State pairs. Forecast outputs were stable, realistic, and consistent across all 111 valid combinations. These forecasts were later used to perform:

- identification of risky Product–State pairs,
- comparison of historical vs predicted complaint volumes,
- root-cause analysis for rising combinations
- visualization dashboards in Tableau and Python.

This forecasting pipeline now supports proactive monitoring of complaint trends and offers actionable insights for regulatory and operational teams.