Toronto Ferry Ticket Demand Forecasting using SARIMA and Prophet with MLOps Integration (DVC & MLflow)

This project demonstrates a complete time series forecasting workflow using SARIMA and Prophet. It includes preprocessing, exploratory analysis, model fitting, and forecasting for a 30-day horizon. The pipeline is modular, reproducible, and designed for extensibility.

Project structure

```
sarima-prophet-mlflow-dvc-pipeline/
├── .dvc/                                            # DVC configuration
├── .venv/                                           # Virtual environment
├── data/
│   ├── raw/
│   │   └── TorontoIslandFerryTicketCount.csv
│   └── processed/
│       └── daily_tickets_2022_25.parquet
├── models/
│   ├── sarima_model.pkl
│   └── prophet_model.pkl
├── notebooks/
│   ├── exploratory_analysis.ipynb
│   ├── sarima_exploration.ipynb
│   └── prophet_exploration.ipynb
├── output/
│   ├── plots/
│   └── results/
│       ├── sarima_cv_results.csv
│       └── prophet_cv_results.csv
├── scripts/
│   ├── __init__.py
│   ├── sarima_model.py
│   └── prophet_model.py
├── utils/
│   ├── __init__.py
│   ├── evaluate_forecast.py
│   └── mlflow_logger.py
├── .env
├── requirements.txt
└── README.md
```

Toronto Ferry Ticket Sales Redemption Data

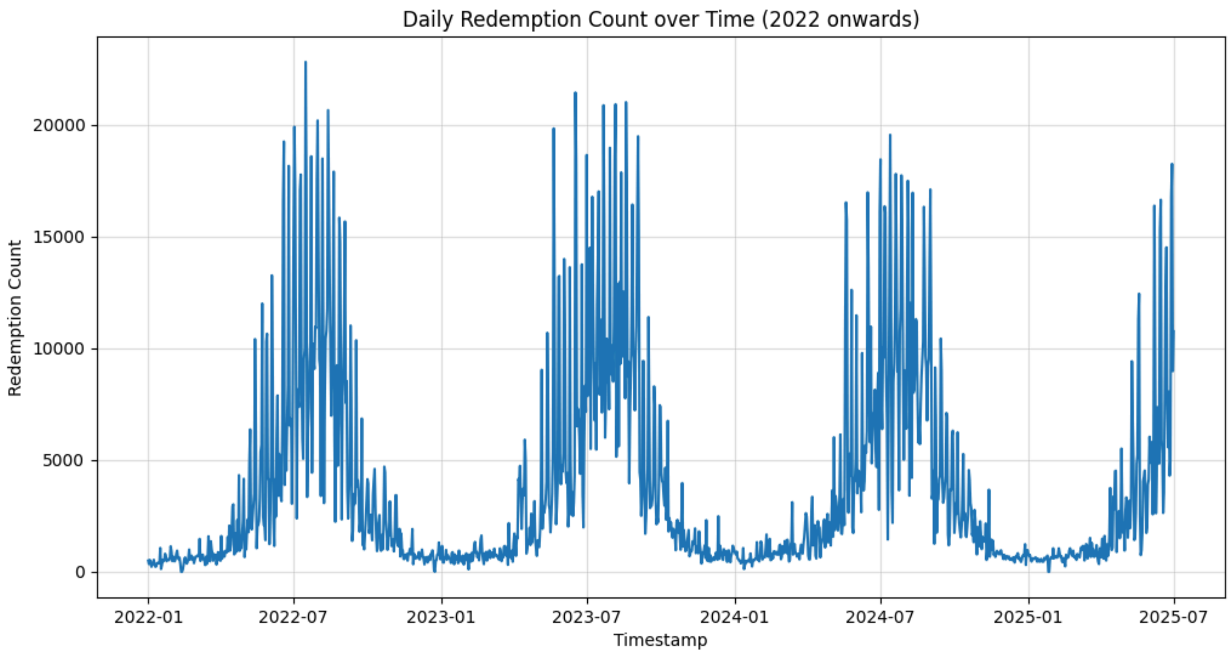


Figure: Daily redemption count from 2022 onwards.

- Yearly seasonality - winter low and summer high
- Weekly seasonality - weekend high
- Presence of spikes on summer days

Basic Statistics

- The mean ticket count is approximately 3,700, while the median (50th percentile) is around 1,600, indicating a right-skewed distribution. This suggests that a few extreme high values are pulling the mean above the median.
- A high standard deviation of 4,440 tickets reflects a wide dispersion in daily ticket sales, pointing to substantial variability across days.

Log-transformation for variance stability and first-difference to remove trend and make the series stationary

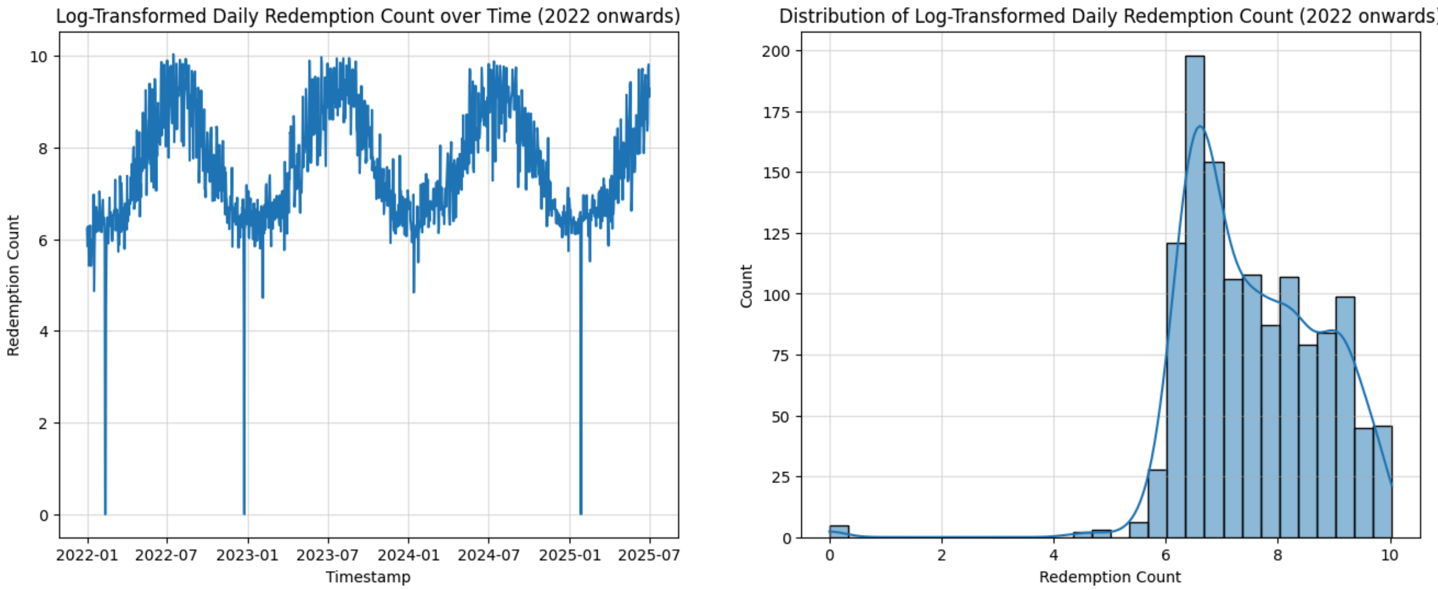


*Figure: log-transformed daily redemption stabilizes the variance.

First differencing of log-transformed series

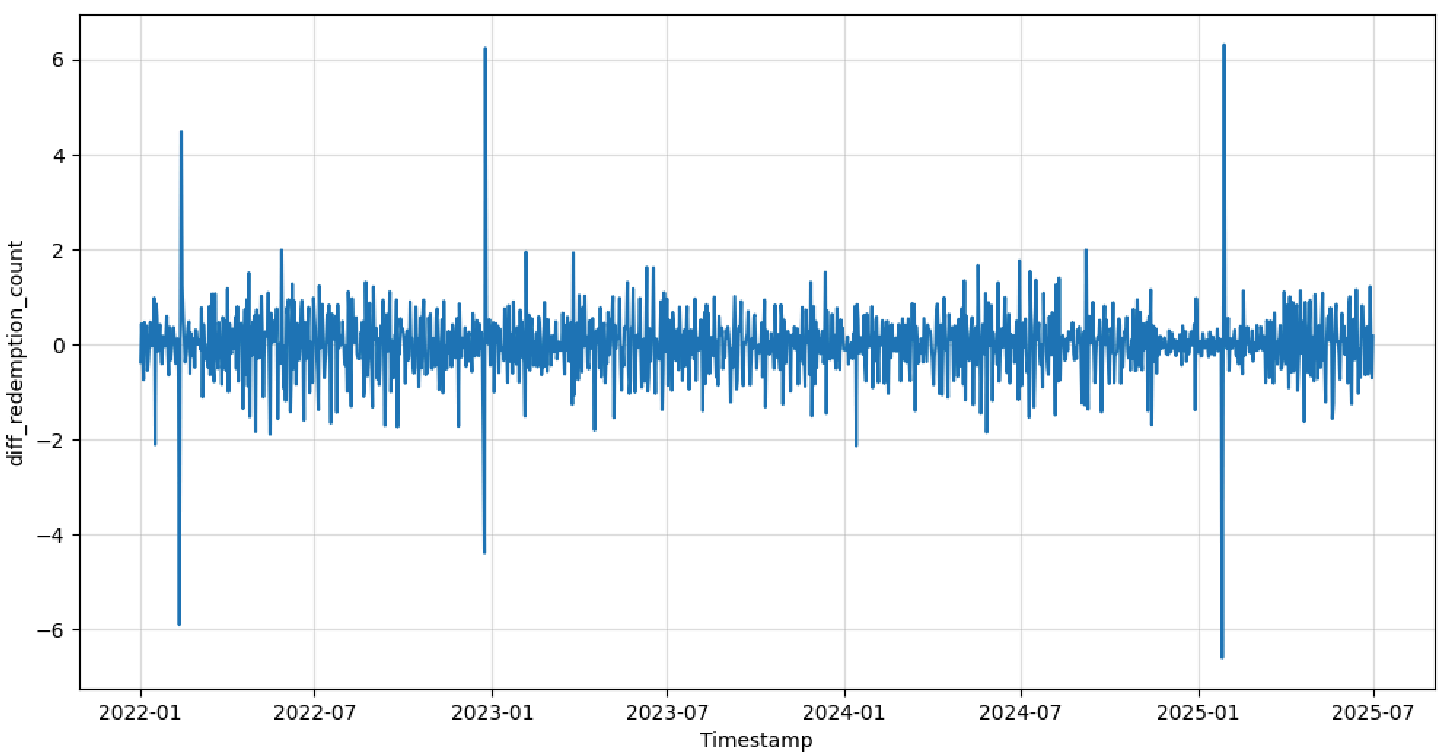


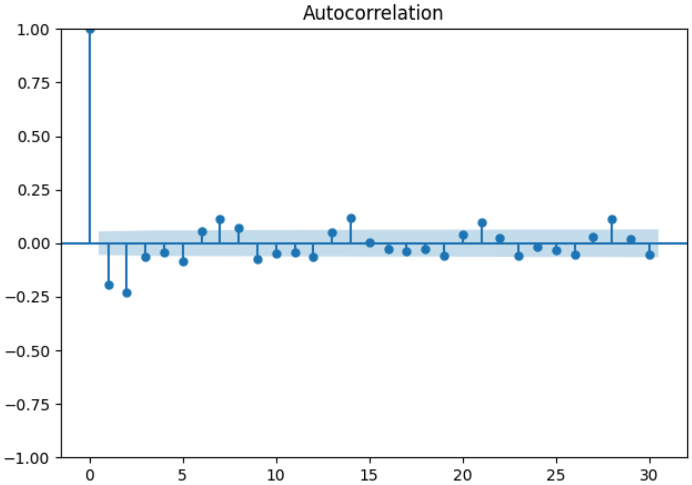
Figure: We see that the series mean is zero, with almost stable variance and sudden spikes

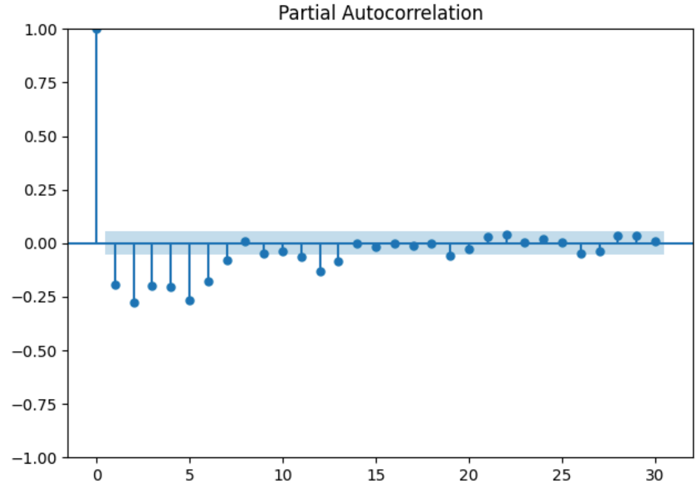
One-step differencing of log-transformed time-series

- Log transformation stabilizes the variance and reduce the impact of spikes

- one-step differencing now removes the trend, making the time-series stationary.
- one-step differencing represents the relative changes or growth rate in redemption counts from one day to the next.
- it centers around zero with occasional spkies and dips

ACF and PACF plots





Auto-correlation and Partial Auto-correlation of 1-step differencing of log-transformed time series

- PACF suggests significant auto-correlation at lag 1, 2, 3, 4, 5 and 6. After that the correlation dies. We can try with AR(p) p from 1 to 6 and see the BIC
- ACF suggests signification relationships at lag 1 and 2. q could be 1 or 12

Augmented Dickey-Fuller test

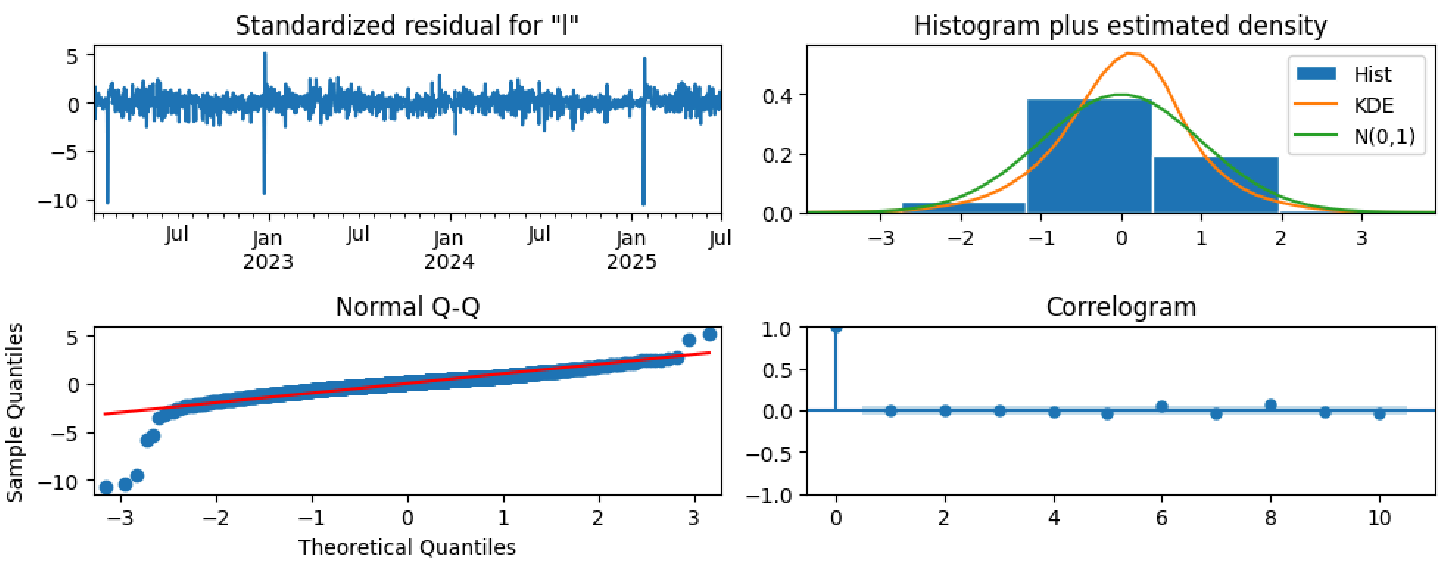
```
from statsmodels.tsa.stattools import adfuller
import pandas as pd

# Run the test
result = adfuller(data_diff['diff_redemption_count'].dropna())

# Organize results
adf_output = {
    'ADF Statistic': result[0],
    'p-value': result[1],
    'Number of Lags Used': result[2],
    'Number of Observations Used': result[3],
    'Critical Values': result[4],
    'IC Best (AIC)': result[5]
}

# Display as DataFrame
adf_df = pd.DataFrame.from_dict(adf_output, orient='index', columns=['Value'])
print(adf_df)
```

```
                                                               Value
ADF Statistic                                             -16.285116
p-value                                                          0.0
Number of Lags Used                                               12
Number of Observations Used                                     1264
Critical Values                      {'1%': -3.4355, '5%': -2.8638}
IC Best (AIC)                                            2274.831503
```

- p-value = 0 suggestes that the data does not provide enough evidence in favor of the null hypothesis that the time series has a unit root - the series is non-staionary.
- So we reject the Null Hypothesis that the series is non-stationary.
- 1-step differencing of log-transformation has made the seties stationary.

Apply SARIMA (2,1,2)× (1,0,1,7) model on log-transformed redemption tickets

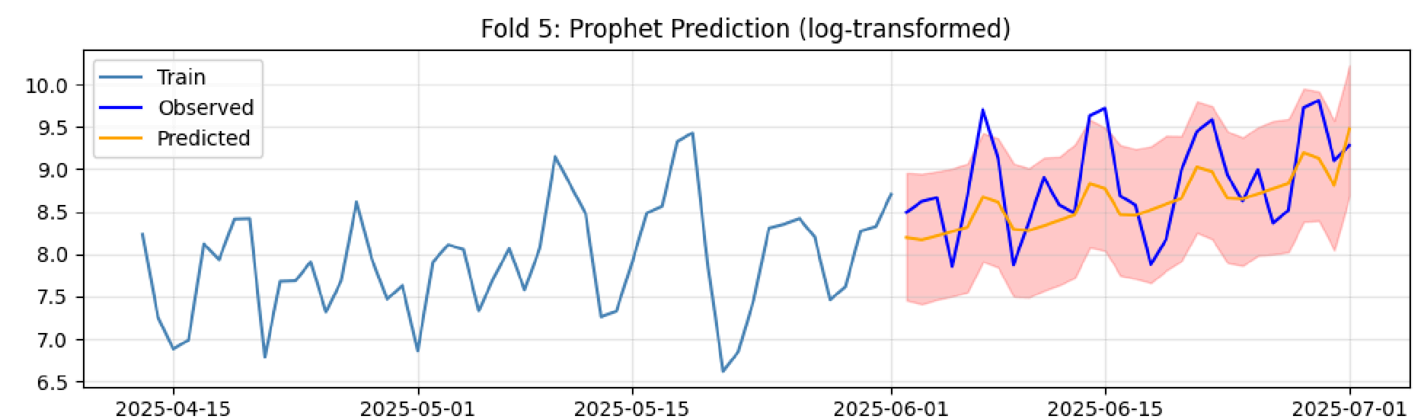
```
sarima_model = SARIMAX(
    y,
    order=(2,1,2),
    seasonal_order=(1,0,1,7),
    enforce_stationarity=False,
    enforce_invertibility=False
)
final_res = sarima_model.fit(disp=False)

forecast_steps = 30 # 7
future_index = pd.date_range(start=y.index[-1] + pd.Timedelta(days=1), periods=forecast_steps, freq='D')
forecast = final_res.forecast(steps=forecast_steps)
forecasted_object = final_res.get_forecast(steps=forecast_steps)
mean_forecast = forecasted_object.predicted_mean
confint = forecasted_object.conf_int()

forecast = pd.Series(forecast, index=future_index)
```

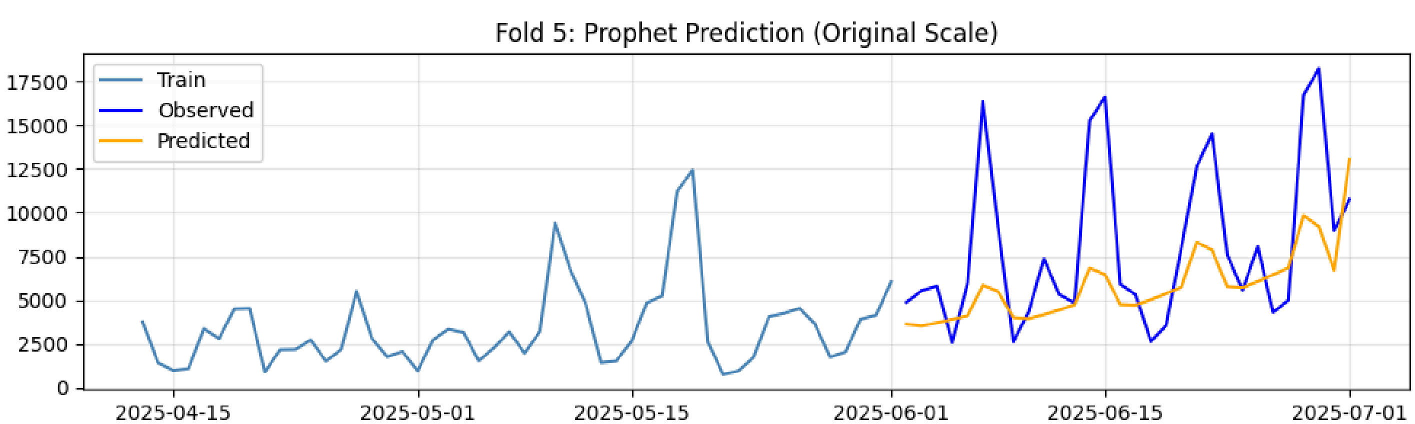


- Residuals are approximately normal, but not perfect. Mild departure from normality, especially in the extremes. This is acceptable for forecasting, though you might consider a robustness check if prediction intervals are critical.
- The spike at lag 1 (Correlogram) suggests some autocorrelation remains, which means the model might be slightly underfitting short-term dynamics.
- SARIMA(2,1,2)(1,0,1,7) model is reasonably well-specified.

Prophet Modeling with TimeSeriesSplit Cross-Validation

```
# TimeSeriesSplit with 7-day test windows to simulate weekly forecasting
tscv = TimeSeriesSplit(n_splits=n_splits, test_size=forecast_horizon)

for fold, (train_idx, test_idx) in enumerate(tscv.split(df)):

    train_df = df.iloc[train_idx]
    test_df = df.iloc[test_idx]

    model = Prophet(
        growth='linear',
        yearly_seasonality=True,
        weekly_seasonality=True,
        daily_seasonality=False,
        holidays=holiday_df
    )
    model.fit(train_df)

    future = model.make_future_dataframe(periods=len(test_df), freq='D')
    forecast = model.predict(future)
    # forecast_test = forecast.set_index('ds').loc[test_df['ds'].values]
    forecast_test = forecast.set_index('ds').reindex(test_df['ds'])

    evaluation_metric_dict = evaluate_forecast(test_df['y'], forecast_test['yhat'])
```





Model Evalution: SARIMA vs Prophet (30-day forecast)

A comparison table below showing **SARIMA vs Prophet** on original scale metrics, with **% improvement** of Prophet over SARIMA for each fold:

📊 Fold-wise Comparison with % Improvement

Fold	SARIMA MAE	Prophet MAE	% MAE ↓	SARIMA RMSE	Prophet RMSE	% RMSE ↓	SARIMA SMAPE	Prophet SMAPE	% SMAPE ↓
1	473.04	213.04	**54.98%**	507.79	246.57	**51.44%**	101.30	33.55	**66.88%**
2	265.57	267.11	**-0.58%**	322.59	371.62	**-15.20%**	31.37	30.14	**3.89%**
3	1273.46	819.95	**35.61%**	1770.19	1164.53	**34.23%**	72.41	41.31	**42.94%**
4	1984.88	1531.90	**22.78%**	3091.61	2152.43	**30.37%**	50.77	41.67	**17.91%**
5	4368.85	3167.34	**27.47%**	5954.60	4324.06	**27.42%**	59.20	39.96	**32.52%**

> **% Improvement = ((SARIMA − Prophet) / SARIMA) × 100**

Aggregated Summary (Mean across folds)

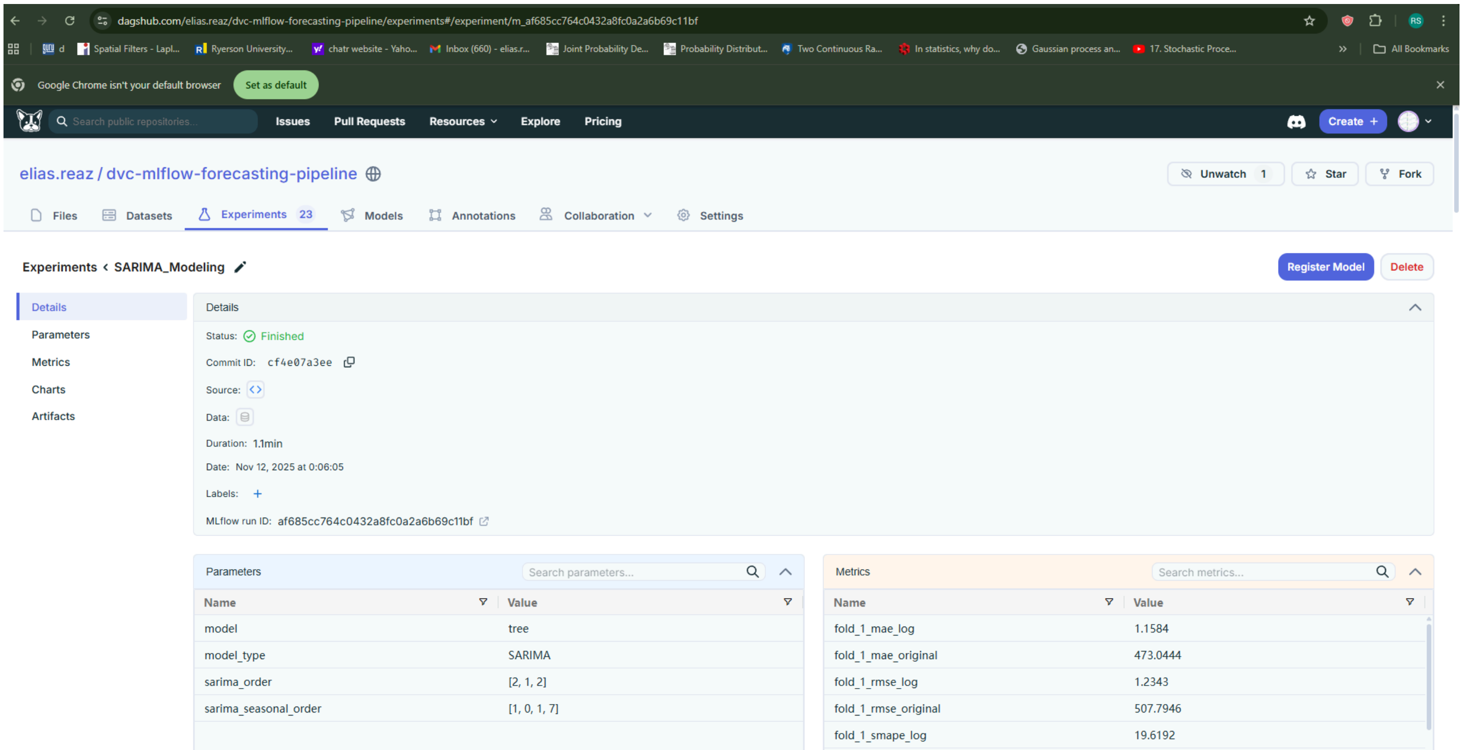
Metric	SARIMA	Prophet	% Improvement
MAE	1873.16	1199.47	**35.95%**
RMSE	2329.76	1251.85	**46.27%**
SMAPE	62.81	37.33	**40.58%**

Insights

- Prophet consistently outperforms SARIMA in Fold 1, 3, 4, and 5, with substantial gains in SMAPE and RMSE.
- Fold 2 is an anomaly where SARIMA slightly edges Prophet in MAE and RMSE.
- Prophet achieves ~36% lower MAE, ~46% lower RMSE, and ~41% lower SMAPE on average. If you're selecting a model for forecasting, Prophet appears to generalize better across varied error metrics.
- Overall, **Prophet** shows **stronger generalization** capturinng both trend and seasonality and **lower error** across all metrics.

MLflow Integration with DagsHub

This project uses MLflow for experiment tracking, model management, and reproducibility, fully integrated with DagsHub's hosted MLflow server.



https://dagshub.com/elias.reaz/dvc-mlflow-forecasting-pipeline/experiments