SkyTraceX: A Real-Time Short-Horizon Aircraft Trajectory Prediction System Using Gradient Boosted Telemetry Models

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Abstract

Predicting short-horizon aircraft trajectories is a critical component of modern aviation visualization and anomaly detection systems. In this paper, we introduce SkyTraceX, a lightweight machine learning pipeline designed to forecast aircraft spatial coordinates up to 60 seconds ahead using structured ADS-B telemetry data. Our framework leverages a LightGBM gradient boosting regression model trained on kinematic motion continuity features extracted from sequential flight observations. To enable near-real-time deployment, the system architecture combines sliding-window feature extraction with a Redis inference cache and PostgreSQL telemetry storage. Experimental evaluation using open-source ADS-B telemetry demonstrates that SkyTraceX significantly improves prediction accuracy. Specifically, the system reduces Mean Absolute Error (MAE) by up to 34% compared to standard constant-velocity extrapolation baselines while maintaining the low latency required for real-time aviation intelligence applications.

1 Introduction

Short-horizon aircraft trajectory prediction is a foundational element for airspace visualization, anomaly detection, and predictive flight intelligence systems [1]. Historically, trajectory estimation has relied heavily on physics-based extrapolation methods or external third-party trajectory prediction APIs. While these approaches provide a functional baseline, they often struggle to capture nonlinear motion transitions such as sudden heading or altitude changes and may introduce unwanted infrastructure dependencies.

Recently, structured telemetry-based machine learning approaches have emerged as efficient alternatives. These methods enable robust trajectory estimation without the computational overhead associated with sequence-learning architectures such as LSTMs or Transformers [**?**]. Tree-based gradient boosting models, in particular, perform well for short-horizon prediction tasks because they capture nonlinear relationships between kinematic variables while maintaining low inference latency.

This paper presents the architecture and evaluation of SkyTraceX, a telemetry-driven machine learning system optimized for real-time aircraft trajectory prediction using gradient boosted regression techniques.

2 Related Work

Aircraft trajectory prediction methods can generally be grouped into four major categories: physics-based motion extrapolation models, statistical regression approaches, tree-based machine learning prediction models, and deep learning sequence modeling architectures.

Physics-based models such as constant-velocity or constant-turn-rate extrapolation provide fast estimation but lack robustness during turning or altitude transition phases [?]. Deep learning sequence architectures such as attention-based trajectory prediction models improve long-horizon prediction performance but introduce computational overhead unsuitable for low-latency inference environments [?]. Gradient boosting regression models represent a practical middle-ground solution capable of capturing nonlinear motion continuity while preserving deployment efficiency in structured telemetry environments.

3 Telemetry Dataset

The SkyTraceX trajectory prediction pipeline utilizes structured ADS-B telemetry observations aggregated from publicly available aircraft tracking streams, primarily leveraging the OpenSky Network [1] and ADS-B Exchange [5].

The dataset contains approximately 300,000 structured telemetry samples collected from commercial flights operating within the Western India regional airspace over a 30-day observation window. Sequential telemetry windows were constructed using sliding-window motion continuity modeling across consecutive aircraft state observations.

Telemetry samples containing incomplete state vectors or timestamp discontinuities were filtered during preprocessing.

Each telemetry record includes:

- Latitude and Longitude
- Altitude
- Velocity and Heading
- Vertical rate
- Timestamp

4 Feature Engineering

To support short-horizon trajectory continuity modeling, a 10-second sliding-window was utilized to extract derived motion features:

- **Delta Coordinates:** Δ latitude and Δ longitude
- **Velocity Gradient Estimation:** Rate of change in airspeed
- **Heading Stability Indicators:** Heading variance
- **Temporal Motion Continuity Features**

5 Model Architecture

The prediction pipeline employs a LightGBM gradient boosting regression framework optimized for structured telemetry feature modeling [4]. The model predicts aircraft spatial coordinates 15, 30, and 60 seconds ahead.

Hyperparameters selected via grid-search optimization:

- Learning rate: 0.05
- Number of estimators: 300

- Maximum depth: 8
- Feature fraction: 0.9
- Bagging fraction: 0.8

6 Baseline Comparison

To evaluate predictive effectiveness, the proposed model was compared against a constant-velocity extrapolation baseline derived from instantaneous motion vectors:

$$lat_{t+\Delta t} = lat_t + v\cos(\theta)\Delta t$$

$$lon_{t+\Delta t} = lon_t + v\sin(\theta)\Delta t$$

7 Evaluation Metrics

Trajectory prediction performance was evaluated using standard regression error metrics.

7.1 Mean Absolute Error and Root Mean Square Error

Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) measure positional deviation and sensitivity to prediction outliers.

7.2 Great-Circle Distance Error

Prediction accuracy was evaluated using great-circle distance error computed via the Haversine formulation:

$$d = 2r\arcsin\left(\sqrt{\sin^2\left(\frac{\Delta\phi}{2}\right) + \cos(\phi_1)\cos(\phi_2)\sin^2\left(\frac{\Delta\lambda}{2}\right)}\right)$$

8 Experimental Results

SkyTraceX consistently outperformed constant-velocity baselines across all evaluated prediction horizons.

Table 1: Trajectory Prediction Error Comparison (meters)

Prediction Horizon	Baseline MAE	Baseline RMSE	SkyTraceX MAE	SkyTraceX RMSE
15 seconds	120.4	145.2	**85.1**	**102.3**
30 seconds	250.8	310.5	**180.6**	**215.8**
60 seconds	580.2	710.4	**395.4**	**480.1**

9 Deployment Architecture

The SkyTraceX prediction pipeline operates within a scalable aviation analytics infrastructure consisting of:

- Redis inference caching layer enabling low-latency prediction retrieval

- PostgreSQL telemetry storage supporting historical trajectory archiving
- Sliding-window preprocessing pipeline supporting real-time feature extraction
- Five-second telemetry polling optimisation balancing latency and computational cost

10 Discussion and Future Work

Future improvements include:

- Flight-phase-aware trajectory modelling
- Extended prediction horizon benchmarking
- Uncertainty-aware trajectory estimation
- Integration with trajectory intent inference modules

11 Conclusion

We presented SkyTraceX, a telemetry-driven prediction system optimized for short-horizon aircraft trajectory forecasting. By utilizing gradient boosted regression, the proposed approach provides an efficient alternative to traditional physics-based models and computationally intensive deep learning architectures. The results demonstrate that structured machine learning pipelines can deliver accurate real-time trajectory predictions with minimal infrastructure overhead, making them suitable for modern aviation intelligence platforms.

References

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