Machine-Learning Enhanced Orbit Propagation: Improving Low Earth Orbit Prediction Using TLE and GPS Data

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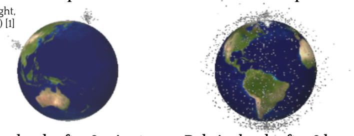
Background Information

- Earth's orbit has become increasingly crowded with satellites and orbital debris since 1957
- There are around 34,000 trackable debris objects (greater or equal to 10 cm) in orbit
- Debris is dangerous since it can cause collisions with active satellites or other debris
- Collisions can trigger a "chain reaction" effect, since one crash makes new debris fields

Debis Cloud Dispersion After a Collision (Example Timeline)

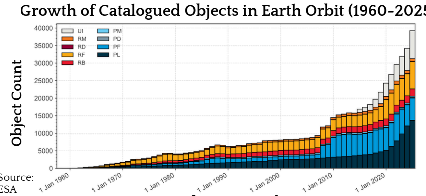
Source: Wright, David (2009) [1]



Debris clouds after 9 minutes **Debris clouds after 3 hours**

- Accurate orbit prediction is essential for Space Situational Awareness (SSA)
- SGP4 propagation is the standard method for predicting orbits using public catalog data
  - Residual error grows over time in LEO space due to simplifications and drag/solar activity affects
  - High-accuracy tracking data is expensive/time-consuming to collect continuously

Growth of Catalogued Objects in Earth Orbit (1960-2025)



Source: ESA (2025) [2]

Research Question & Goals

Research Question:
Can a supervised machine learning (ML) correction model reduce multi-day LEO propagation prediction error compared to standard SGP4 propagation?

Long-Term Goals:

- Apply the ML model to spacecraft of different sizes and trajectories (ex. Swarm A/B/C) to test the effectiveness of the model under different conditions
- Apply the ML model to orbital debris without a known GPS truth

Methodology

1) Data Collection

- 26 weekly "TLE packets" of CASSIOPE satellite
- CASSIOPE GPS truth data
- Space-weather (Kp, F10.7) aligned by time

2) Baseline Propagation

- Use SGP4 to propagate each TLE packet forward 2 weeks
- Convert to ITRF at each epoch

3) Computing Residual Error

- Match SGP4 baseline epochs to GPS truth data epochs
- Residual error = |truth-SGP4| (km)

4) Build ML Dataset

- Align features by same time/epoch
- Features: Baseline states (SGP4), space weather, time since epoch

5) Train ML Model on Residuals

- Use Neural Network ML to predict residual components given input data features
- Training using 20 TLE packets

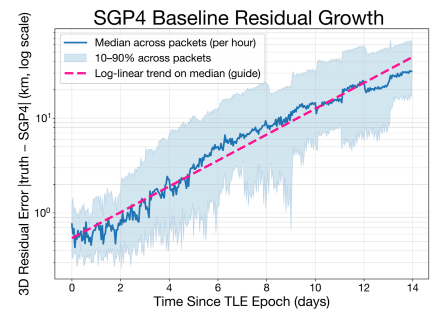
6) Apply Time-Gated Correction

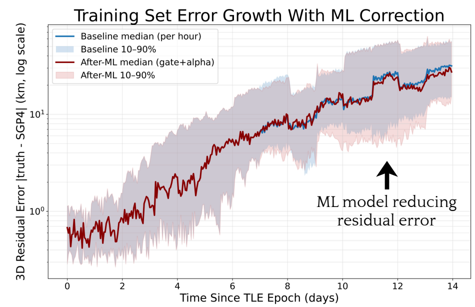
- corrected = SGP4 – a(t) * c_pred
- a(t) = 0 until day 7
- a(t) = 1 after day 7
- Goal: stabilize early and correct later

7) ML Validation + Results

- Validate ML model on 6 unseen TLE packets
- Compare baseline SGP4 propagation error to after-ML error

Results





- Baseline SGP4 shows clear error growth in LEO over time
  - Residual error increasing from sub-km levels to tens of km after 14 days

- 7–14 day improvements (ML correction):
- p50 (median): 6.64 km → 6.50 km
- p90 (high error): 25.08 km → 24.81 km
- p99 (worst outliers): 29.57 km → 30.02 km

Analysis & Conclusions

- ML correction was applied using **time-gating** (no ML influence from 0–7 days, correction active in 7–14 days) to keep early predictions stable where SGP4 is already more reliable
- SGP4 error growth in LEO was confirmed using 2-week propagations (reinforces why assisted correction is necessary)
- With time-gated correction, ML model produced measurable improvement in 7-14 day window (reducing typical and high-end error), while keeping 0-7 day outputs unchanged
- Limitations: worst-case outliers (p99) slightly worsened, showing the importance of outlier-aware training
- Overall, results support the main research goal

Significance

- Earth's orbit is increasingly crowded with space objects, and collisions can create large debris fields
- ML correction that can learn the repeatable error patterns of SGP4 can reduce LEO uncertainty and risk for satellites
- AI has the potential to make SSA better and safer

Future Work

- Expanding training dataset for the ML model
- Switching coordinate system for residuals and ML correction
- Validating ML model on other satellites (Swarm A/B/C, etc.)
- Validating ML model on debris that only has catalog data and no GPS truth

Acknowledgements

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Use of AI: Generative AI (ChatGPT by OpenAI) was used as a writing/coding assistant (brainstorming and debugging). Project coding and results analysis were performed and verified by the author.

References:

[1] D. Wright, "Colliding Satellites: Consequences and Implications," Union of Concerned Scientists, Feb. 26, 2009. [Online]. Available: https://www.ucs.org/sites/default/files/2019-10/SatelliteCollision-2-12-09.pdf
[2] ESA Space Debris Office, "ESA'S ANNUAL SPACE ENVIRONMENT REPORT," Mar. 31, 2025. [Online]. Available: https://www.sdo.esoc.esa.int/environment_report/Space_Environment_Report_latest.pdf