UNSW AUSTRALIA
Canberra

Never Stand Still

School of Engineering and Information Technology

Informative Optimal Collision Avoidance Maneuvers using Deep Neural Networks

Rasit Abay, Melrose Brown and Russell Boyce

Date: 09/11/2018

ADFA
AUSTRALIAN DEFENCE FORCE ACADEMY

Introduction

- Active collision avoidance is an effective way to avoid dangerous encounters between space objects.
- There are three optimization problems to be solved to compute the optimal collision avoidance maneuver (excluding brute-force methods).
  - The location of the maneuver in orbit
  - The direction of the maneuver
  - The magnitude of the maneuver
- It is compute-intensive to solve numerical optimization problems, and most methods require good initial estimates of the solution (Two-point boundary problem).

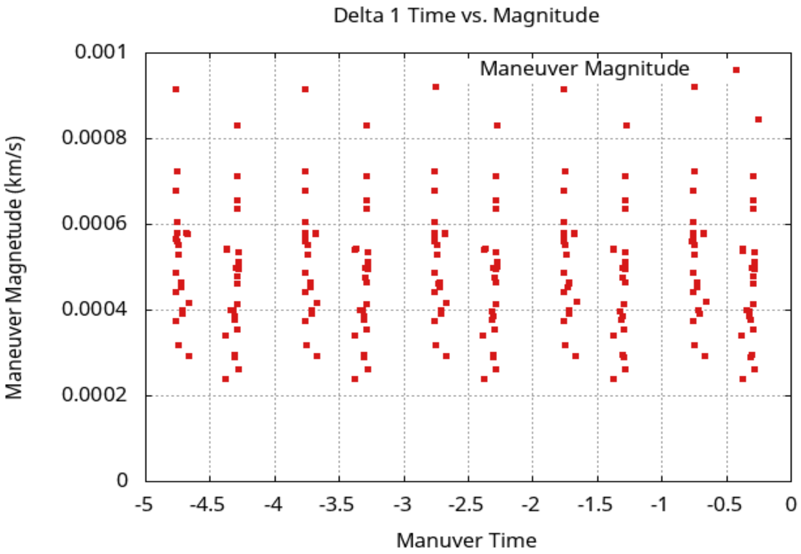
Background

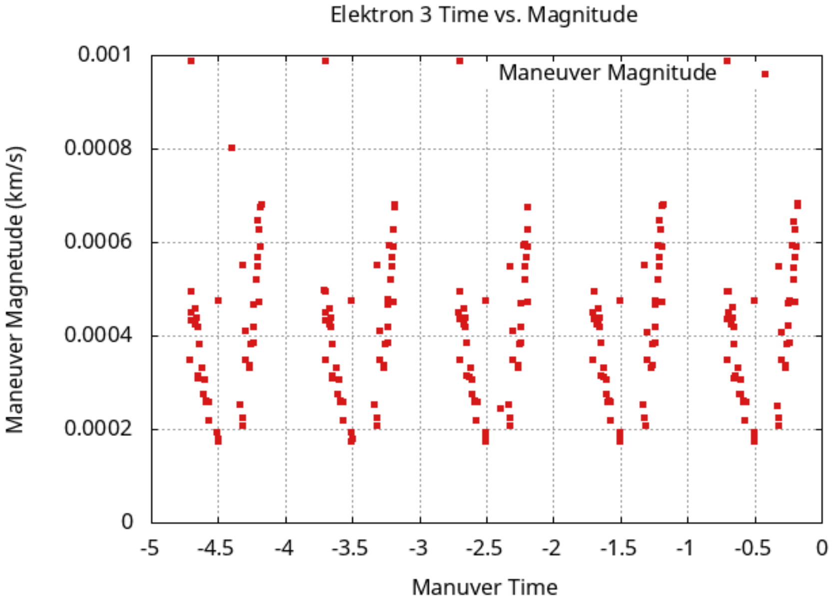
- An open source collision avoidance tool is currently being developed.
  - 6DoF dynamics (gravitational forces are computed by Orekit)
  - BRDF models (Ashkmin-Premoze)
  - Facet-based object modeling
- The tool can use numerical and analytical orbit propagation methods to compute optimal maneuvers by defining the problem as TPBVP.
  - However, the optimal maneuver location on orbit needs to be searched, and this is computed intensive.
- Monte-Carlo method to compute the optimal maneuvers with high fidelity orbit propagator is also being implemented to the collision avoidance tool.
  - It reduces the computation time drastically to provide a reasonable initial estimate of the optimal maneuver location on the orbit.

Can machine learning models provide of the optimal maneuver location?

Background

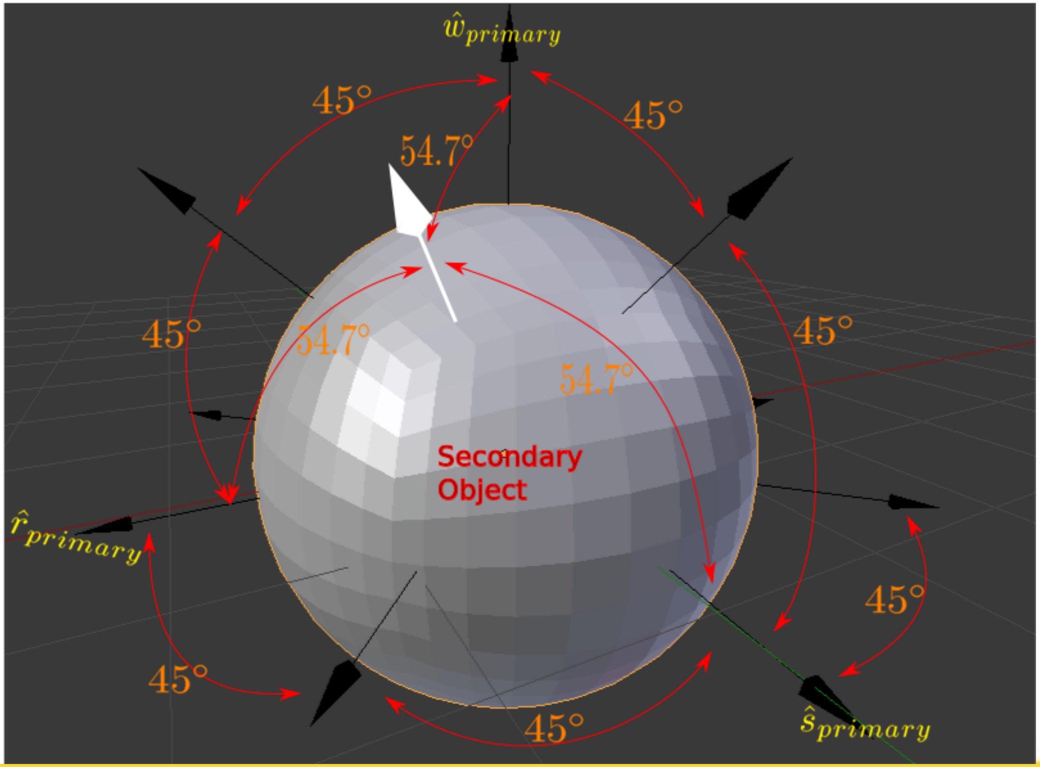
- Universal approximation theory states that any closed and bounded function, if there exists such function can be approximated by neural networks.
- Neural networks can determine smooth and nonlinear decision boundaries better (Tree-based models can determine the box-like decision boundaries).





Assumptions and Limitations

- Fixed object (spheres) sizes (2m and 0.2m) and covariance matrices (10m and 100m) are used.
- The relative position is assumed to be 10 m at close approach.
- The probability of collision threshold is selected as 1e-9.



Methods

- This work uses publicly available TLEs, and SGP4 for computing optimal maneuver direction, maneuver location in orbit and maneuver magnitude, and they are used for training fully-connected neural network model.

$$P_c = \frac{1}{\sqrt{(2\pi)^3 |C_c|}} \int_V e^{\left(-\frac{1}{2}(\Delta r_{ca} + \delta r_{ca})^T C_c^{-1} (\Delta r_{ca} + \delta r_{ca})\right)}$$

$$\begin{aligned} M &= (\Delta r_{ca} + \mathcal{J}\delta v_{mt})^T C_c^{-1} (\Delta r_{ca} + \mathcal{J}\delta v_{mt}) \\ &= \Delta r_{ca}^T C_c^{-1} \Delta r_{ca} + \Delta r_{ca}^T C_c^{-1} \mathcal{J} \delta v_{mt} \\ &+ \delta v_{mt}^T \mathcal{J}^T C_c^{-1} \Delta r_{ca} + \delta v_{mt}^T \mathcal{J}^T C_c^{-1} \mathcal{J} \delta v_{mt} \end{aligned}$$

$$\mathcal{L} = M + \lambda(\Delta v_{ca} \mathcal{J} \delta v_{mt})$$

Constraint enables the primary object to move sideways at the close approach time.

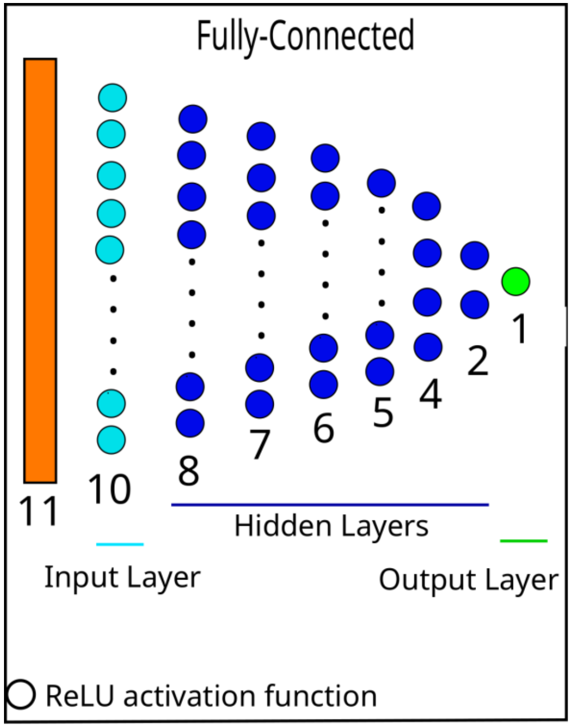
$$\begin{bmatrix} \delta v_{mt} \\ \lambda \end{bmatrix}_{4x1} = \begin{bmatrix} 2\mathcal{J}^T C_c^{-1} \mathcal{J} & \Delta v_{ca} \mathcal{J} \\ \Delta v_{ca} \mathcal{J} & 0 \end{bmatrix}^{-1}_{4x4} \begin{bmatrix} -2\mathcal{J}^T C_c^{-1} \Delta r_{ca} \\ 0 \end{bmatrix}_{4x1}$$

ADFA AUSTRALIAN DEFENCE FORCE ACADEMY

UNSW AUSTRALIA Canberra

Methods

- Fully-connected neural networks are trained with orbits of 6 different space objects (Planet CubeSats) over one year (a TLE per day).
  - The training data include 94900 samples.
  - Keplerian orbital elements at close approach and collision geometry are used as features while optimal maneuver location on orbit is target variables.
  - The versatility of neural networks with additional data (transfer learning).

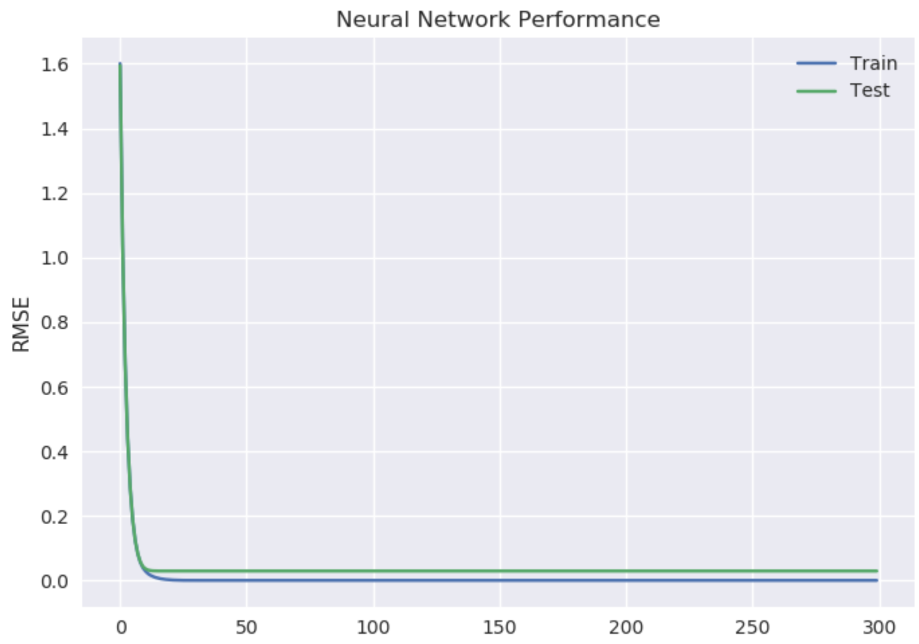


Input data are standardized $$z_s = \frac{x - \mu_{(x)}}{\sigma_{(x)}}$$

Parameters	Values
Learning Rate	1e-4
Optimizer	Adam
Beta1	9e-6
Beta2	999e-6
Decay	1e-7
Epoch Number	300

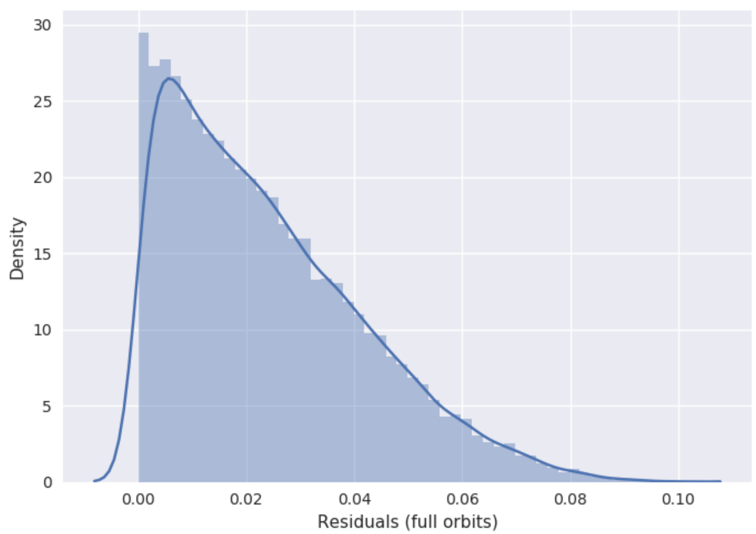
Results and Discussions

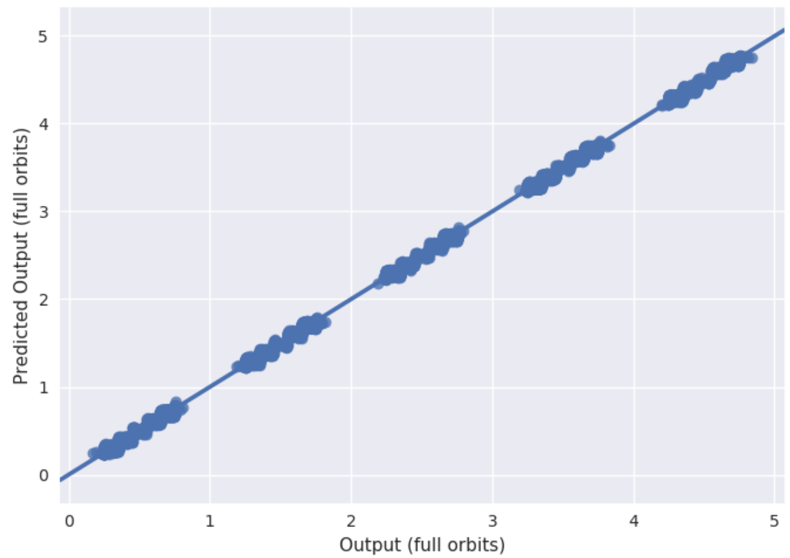
- Train/test performance of the neural networks show high variance, and this indicates the model has difficulty in generalization.
  - Additional data can provide better bias-variance tradeoff.
  - Combining different machine learning models can lead to better performance.
  - Feature preprocessing and generation can improve performance.



Results and Discussions

❖ The residual and regression plots show that it is feasible to approximate the function by neural networks that map orbital characteristics and collision geometry to the optimal location to conduct the maneuver to avoid a dangerous encounter.





Conclusions and Future Work

- The optimal maneuver location in the orbit to avoid collision can be predicted by deep neural networks, and this will reduce the computation time.
- The training process indicates that the variance is high, and a better bias-variance trade-off can be achieved by introducing more data.
- All publicly available TLEs will be used to approximate the function that can map orbital characteristics and collision geometry to the optimal maneuver location on orbit in the future study.
- The feasibility of approximating a function to predict optimal maneuver direction using machine learning will be investigated in the future study.

Thank you

- Questions ?