THE DEFLECTOR SELECTOR: A MACHINE LEARNING FRAMEWORK FOR PRIORITIZING DEFLECTION TECHNOLOGY DEVELOPMENT.
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Introduction: Impacts on the Earth by natural Solar System objects (i.e., asteroids and comets) can pose a significant threat to human lives and infrastructure. Several ground- and space-based observing campaigns have been dedicated to detecting and tracking Near Earth Asteroids, but research concerning the best methods for deflecting a hazardous asteroid impactor once it has been detected is still in the theoretical stages.

Several technologies have been proposed for impactor deflection, including nuclear explosives, kinetic impactors, and gravity tractors. However, none of these technologies has been developed and fully tested in space. Developing and testing every proposed deflection technology is currently prohibitively expensive. However, if humanity waits until a clear impact threat is detected to select which technologies to use, there may not be time to develop and deploy the chosen deflection technique before the impact. Determining now which technologies are most likely to be useful would allow policy and funding decision-makers to effectively prioritize a subset of the proposed deflection technologies.

Theoretical studies of the various proposed deflection technologies have focused either on modeling the capabilities of a single technology, or comparing the abilities of the different technologies to address specific impact scenarios. No comprehensive study comparing the effectiveness of the various proposed technologies on deflecting the likely hazardous object population has been published.

We have developed a model to map the distribution of parameters of a hypothetical impactor population to the set of technologies that can deflect these objects. Our model, the Deflector Selector, is designed to address the following question:

1. Which deflection method has the highest likelihood of deflecting the broadest range of possible impactors?
2. Which impactor characteristics is the choice of deflection method most sensitive to?
3. Which areas of the impactor parameter space are not covered by current deflection technologies?

Framework: The Deflector Selector model consists of a machine learning algorithm that takes as its input the characteristics of a hazardous object (e.g., orbital parameters, size, etc.) and outputs the deflection technologies capable of deflecting the object. To train the algorithm, we produced a set of training data using orbital integrations to simulate the application of a change in velocity, \( \Delta V \), to deflect a hazardous object, and a literature search of deflection technologies to calculate which technologies could apply that \( \Delta V \), given the object’s size.

Orbital Simulations. We performed simulations of asteroid deflections using an N-body integrator that included the gravitational effects of Jupiter, Venus, and Mars, as well as the Sun and th Earth. We first generated a population of Earth-impacting orbits by rotating the orbits of all known Apollo and Aten objects in space such that the objects’ orbits intersected the Earth’s, then integrating the orbits of the objects and the planets backwards in time from the moment of collision to time \( t = -15 \text{ yr} \). When run forward in time, the objects are guaranteed to collide with the Earth at \( t = 0 \text{ yr} \).

We then simulated the instantaneous application of a deflection technology (such as a nuclear explosive or a kinetic impactor) to an impacting object by adding a random \( \Delta V \) to the object’s velocity in the direction of its motion at a random lead time before Earth impact. For each of 8,000 impactor orbits, we ran 200 instantaneous deflection simulations. We also simulated the application of slow-push rather than instantaneous technologies, such as gravity tractors, but applying a \( \Delta V/\text{year} \) at every timestep of the integration. We ran 100 slow-push deflection simulations for each impactor orbit.

![Figure 1: Summary of the instantaneous deflection orbital simulations.](image)
Figure 1 summarizes the results, showing the percentage of simulations that resulted in a successful deflection for every combination of lead time and ΔV applied. As expected, larger ΔV values increase the proportion of successful deflections, and the magnitude of the ΔV required to increase this success rate increases sharply for decreasing lead times.

**Technology Specifications.** Our orbital simulations can only reveal which values of ΔV are required to deflect an incoming hazardous object, given its orbit and a lead time. To map these ΔVs to the proposed deflection technologies, we conducted a literature search in order to calculate the ΔV values that each technology can apply, given the object’s mass. We considered the three most plausible technologies: nuclear explosives, kinetic impactors, and gravity tractors. For each technology, we calculated the required ΔV to achieve a success rate of 100% for a given lead time, using the results from our orbital simulations. We then used deflection technology studies to estimate whether each technology could apply such a ΔV, given an impactor diameter and assuming a constant density of 3 g/cm³.

Our results are summarized in Figure 2, which shows the predicted success rate of each of the three technologies on our simulated impactor orbits, given the object’s size and the lead time between technology application and Earth impact.

**Machine Learning.** The purpose of the orbital simulations and technology capability estimates described above was to develop a set of training data to feed to a machine learning algorithm. Once the machine learning algorithm is trained to predict the success probability of each technology given a hazardous impactor’s size and orbit, we can then run the algorithm on a realistic simulated population of impactors to predict which technology is most likely to be effective in the event that an object is detected on a collision course with the Earth.

We used a machine learning algorithm known as a decision tree, which has the benefit of calculating the relative importance of the various parameters (object size, orbital elements, etc.) in deciding whether a technology would be successful or not.

**Results:** To test the training data pipeline and our decision tree algorithm, we used the extremely simplified population of simulated impactors created from Aten and Apollo orbits. Our orbital simulations and technology calculations produced a data set in which each point consisted of the object’s size, semi-major axis, eccentricity, and inclination, the lead time, and a β parameter representing the object’s internal strength, and four corresponding labels representing whether the detection was successful, and whether each of the three technologies was capable of applying the deflection. We trained the algorithm on 80% of the data and then used the remaining 20% as validation to test the algorithm’s accuracy. We performed this cross-validation technique ten times, each time randomly selecting 80% of the data set for training and 20% for validation. The measured accuracy of the trained algorithm was ~98%, indicating that this data set is well-suited for classification using the decision tree method.

**Future Work:** Based on our very simple simulated impactor population, the Deflector Selector decision tree predicted that nuclear explosives are the most likely to be effective in deflecting a hazardous impactor. Now that the model is complete, our next steps will be to refine the model to reduce the number of assumptions involved, consider additional technologies and object parameters, and use a more realistic simulated population of potential impactors. Our first priority will be to estimate more realistic lead times as a function of the hazardous object’s orbit. We anticipate that our model will be a valuable tool for researchers in planetary science and technology development, and ultimately for policy and research funding decision-makers.

![Figure 2: Predicted success rate of each technology, given the impacting object’s diameter and the lead time.](image-url)