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Realistic On-the-fly Outcomes of Planetary Collisions: Bringing Machine Learning to N-body simulations

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Abstract

Giant impacts result almost half the time in hit-and-run collisions (HRCs), where most of the impactor continues downrange in a deflected orbit. Here we present an update of our data-driven methodology [1] that can be applied to *N*-body simulations to predict the resulting mass and orbit of the two main remnants from a HRC.

1. Introduction

Grazing collisions usually do not always lead to the accretion of the projectile; they act as strong close encounters with specific properties: 1) some mass exchange occurs, and 2) the relative velocity of the two bodies in decreased [2]. This kind of collision hence results in two main remnants, along with a relative small mass of escaping debris. *N*-body models of terrestrial planet formation thus need to properly handle this kind of collision. This ensures a realistic accounting of the number of collisions each body suffered, the time scale needed for the formation of the system [3], the efficiency of material mixing between bodies coming from different regions of the system, and the delivery of volatiles [4].

2. Methodology

We use machine learning to streamline a set of about 800 Smoothed Particle Hydrodynamics (SPH) simulations of giant impacts into fast predictors that can quickly model collisions on-the-fly during N-body studies. Our simulation span a range of target mass (M_T) between 10^{-2} and $1\,\mathrm{M}_\oplus$, projectile mass fraction $\gamma = M_\mathrm{P}/M_\mathrm{T}$ between 0.2 and 0.7, scaled impact velocity $v_\mathrm{coll}/v_\mathrm{esc}$ between 1 and 4 and the whole range of impact angles θ_coll. We refer to [1] for more details on the methodology.

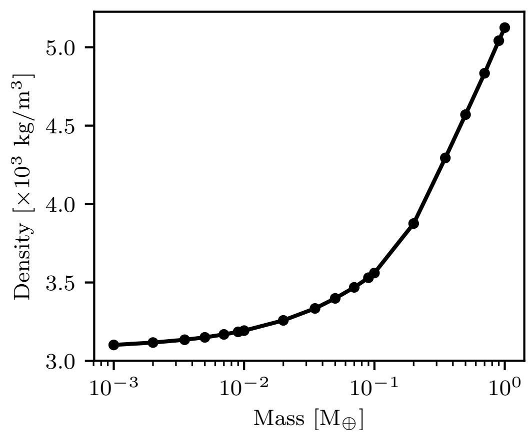

Figure 1: Bulk density as function of the mass.

First, we derive a mass-radius relationship from the initial body profiles which is used for both the analysis and detection criterion during the *N*-body modelling. The extracted bulk density as function of mass is provided in Figure 1. This ensures that the collision properties derived from the *N*-body simulations are consistent with the underlying SPH simulations.

We then train, validate and test a multi-class Support Vector Machine (SVM) able to discriminate between different types of collisions: accretion (single significant remnant whose mass is greater than the target), erosion (single remnant but whose mass is less than the target), and Hit-and-run collisions (HRC, two large remnants). Accretionary and erosive scenarios are cases in which we cannot fit a relative orbit of the second largest remnant, which is instead fit for Hit-and-run surviving projectiles.

Finally, we train, validate and test an ensemble of Neural Networks (NNs) able to predict the following quantities: 1) mass of the largest remnant, given as $\xi_\mathrm{L} = (M_\mathrm{L} - M_\mathrm{T})/M_\mathrm{P}$, 2) mass of the second remnant, given as $\xi_\mathrm{S} = M_\mathrm{S}/M_\mathrm{P} - 1$; 3) relative orbit of an un-

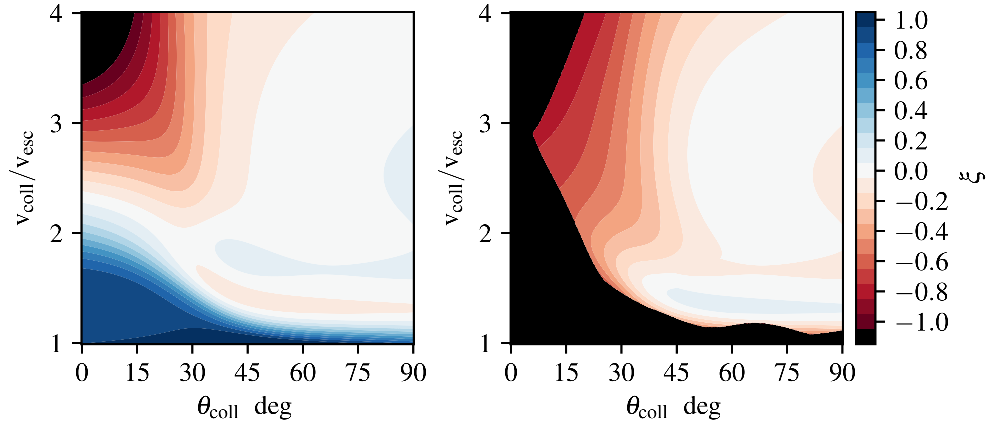

Figure 2: Mass of the largest (*left*) and second (*right*) remnants given in terms of the accretion efficiency (see text) as function of the impact angle and velocity, for a target mass $M_T = 0.1\,M_\oplus$ and $\gamma = M_P/M_T = 0.7$. The black region shows the regime where a single significant remnant is found.

bounded surviving hit-and-run projectile through three parameters: 3a) the scaled orbital energy (which relates to the semi-major axis); 3b) the impact parameter (which relates to the eccentricity); and 3c) the shift of the longitude of the pericentre. The last three parameters allow to properly determine the relative orbit of the two HRCs remnants, including the velocity change and the angle of deflection.

3 Results

The performance of the machine learning tools are evaluated in terms in how well their predictions correlate with the correspondent values of the "parent" SPH simulations. The classifier of types of collision reaches an accuracy above 95% at testing. The neural networks have mean square error lower than 4×10^{-2} and regression index above 99% at testing.

Figure 2 shows two maps of mass of the largest and second largest remnants as predicted by the neural network and classifier. Among the four impact properties (M_T, $\gamma = M_P/M_T$, θ_{coll}, v_{coll}/v_{esc}), we keep the target and projectile masses as constants and vary the other parameters. While a largest remnant can be always identified (Figure 2, left panel), the second remnant mass is only defined when both the classifier identifies an HRC and the orbital energy ε is positive (as consistency check). The map of the mass the largest remnant is quite similar to our previous result in [1]. For the mass of the second remnant, it remains similar to the mass of the projectile, except in regions close to the transition with the erosion regime (steep angle and high velocity).

4. Future work

The developed machine learning tools allow to accurately and quickly simulate giant impact collisions during N-body evolution of planetary system. The predictors mimics their "parent" SPH simulations, but run in a fraction of a second, thus enabling on-the-fly modelling. The tools will be soon released in form of a code library that can be easily integrated in N-body codes such as `REBOUND` or `mercury`.

We plan to extend the set of underlying simulations to improve both the classifier and NN in the region of high uncertainty and provide a better prescription for the transition between the Graze-and-merge collision (GMC) regime and HRC.

References

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