REALISTIC ON-THE-FLY OUTCOMES OF PLANETARY COLLISIONS: BRINGING MACHINE LEARNING TO N-BODY SIMULATIONS Alexandre Emsenhuber (1), Saverio Cambioni (1), Erik Asphaug (1), Travis S. J. Gabriel (2), Stephen R. Schwartz (1) and Roberto Furfaro (3)
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Introduction. Grazing collisions between planetary bodies usually do not always lead to the accretion of the projectile; these hit-and-run collisions (HRCs) act as strong close encounters with specific properties: 1) some mass exchange occurs, and 2) the relative velocity of the two bodies is decreased [1]. HRCs hence results in two main remnants, along with a relatively small mass of escaping debris. Furthermore, they occur roughly half the time across a range of dynamical scenarios [2, 3]. 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 [4], the efficiency of material mixing between bodies coming from different regions of the system, and the ensemble of these effects may influence the delivery of volatiles throughout the solar system [5].

Methods. 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 entire range of impact angles θ_coll.

First we reanalyze the SPH simulations to retrieve additional information that is required for the orbital fitting. This is coupled with a mass-radius relationship for the bodies that can also be used for the bodies' physical radius in the N-bodies. This ensures that the collision properties derived from the N-body simulations are consistent with the underlying SPH simulations. We refer to [3] for more details on the methodology.

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 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 two ensembles of Neural Networks (NNs). The first is able to predict the masses of the largest remnant given as $\xi_\mathrm{L} = (M_\mathrm{L} - M_\mathrm{T})/M_\mathrm{P}$, and the second largest, given as $\xi_\mathrm{S} = M_\mathrm{S}/M_\mathrm{P} - 1$, for HRCs. The second NN provides three parameters which allow to properly determine the relative orbit of the two HRCs remnants: 1) the scaled orbital energy, to retrieve the velocity change; 2) the impact parameter, for the shape of the orbit; and 3) the shift of the longitude of the pericenter, for the angle of deflection.

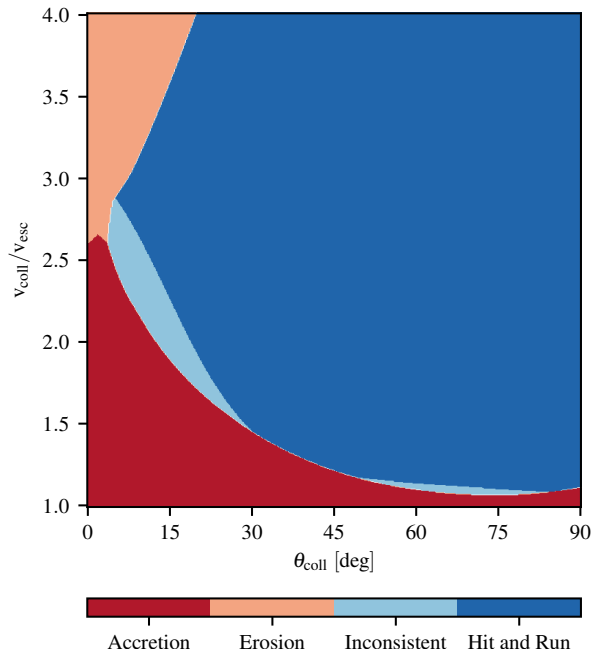

Figure 1: Decision boundaries for the classifier, coupled check with the orbital energy NN as function of the impact angle and velocity, for a target mass $M_\mathrm{T} = 0.1\,\mathrm{M}_\oplus$ and projectile mass ratio $\gamma = 0.7$.

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 93% at testing. The neural networks have mean square error lower than 3×10^{-2} and regression index above 96% at testing. Figure 1 shows the decision boundaries for the classifier, coupled with the orbital energy from the second NN (as consistency check). The light blue region is where the two algorithms give different answers, with the classifier providing HRC while

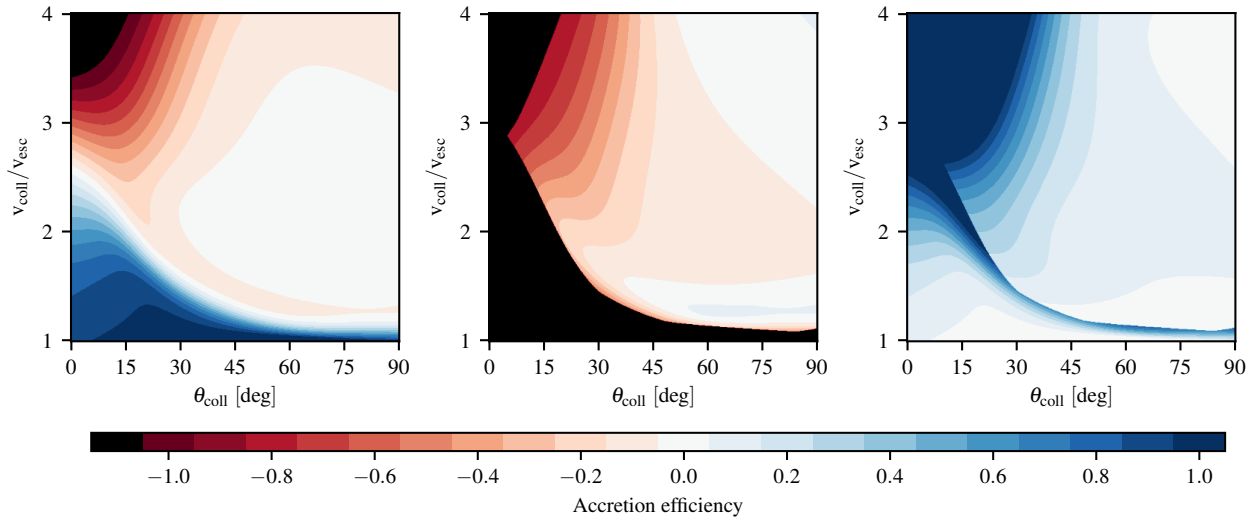

Figure 2: Mass of the largest (*left*), second (*center*) remnants, and debris (*right*) given in terms of the accretion efficiency (see text) as function of the impact angle and velocity, for a target mass $M_T = 0.1\,M_\oplus$ and $\gamma = M_P/M_T = 0.7$. The black region shows the regime where a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

the NN provides a negative value for the orbital energy, meaning that the orbit is bound. The size of this region is small, and close to the transition between the accretion (or erosion) and HRC regimes. As a result, although the two answers above are different, they are close to each other. That is, despite their different methodologies, the two different algorithms produce relatively similar results.

Figure 2 shows two maps of mass of the two largest remnants and the debris ($\xi_D = -(\xi_L + \xi_S)$) 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 in the HRC regime from Figure 1. The map of the mass the largest remnant is quite similar to our previous result in [6]. 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).

Outlook. The algorithm presented here described in full in [3] and available at https://github.com/aemsenhuber/collresolve. When applying this to the formation of the solar system's terrestrial planets (similar to [4]), we find that the number of collisions is almost doubled, and some bodies survived the formation of the major planets despite having undergone multiple successive collisions as the projectile with those. About half of the initial mass is converted into debris. The systems that are formed using the realistic collision approach show a greater diversity of planets than in the control runs where perfect merging is assumed, both in terms of size and composition.

Future work. 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. Also, we aim to perform N-body simulations taking into account the debris and variable core mass fraction.

References

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