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Data-driven emulation of planetary-scale collisions

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Image credit: Lynette Cook for Gemini Observatory/AURA



Mercury's large core

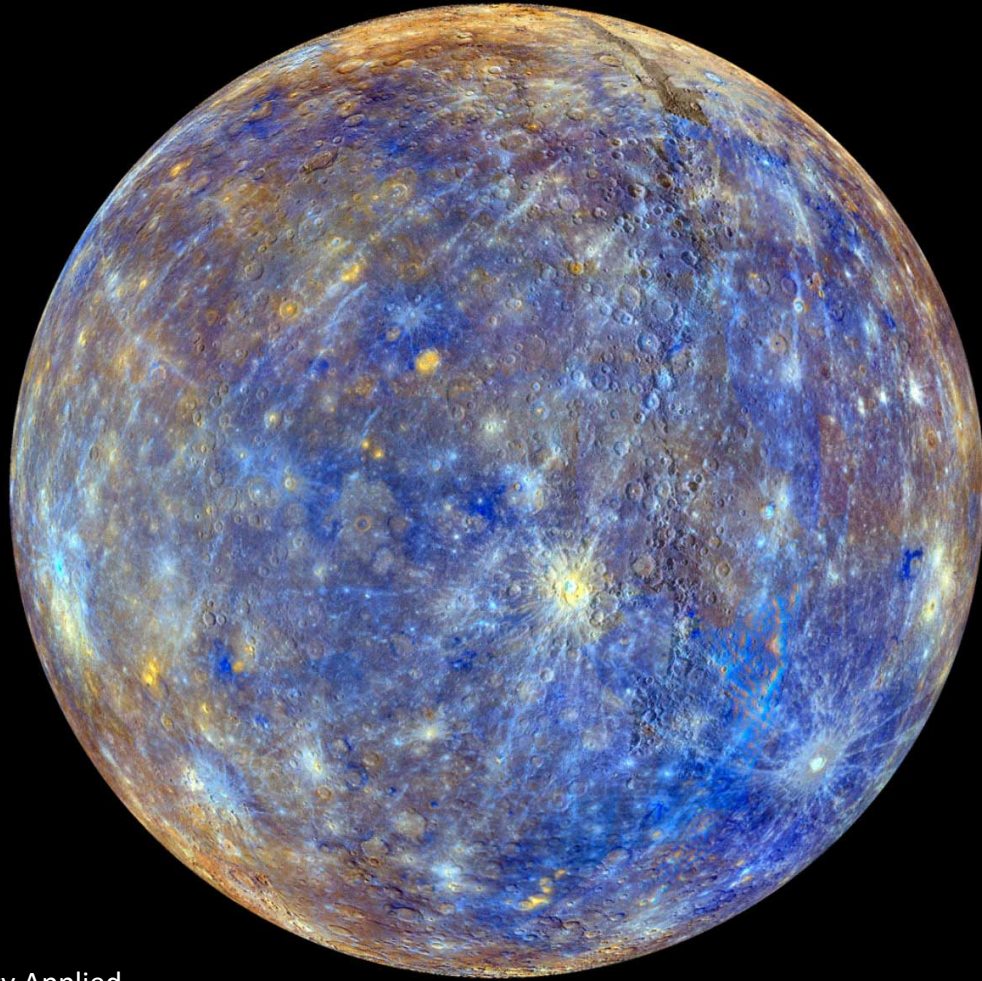


Image credit: NASA / Johns Hopkins University Applied
Physics Laboratory / Carnegie Institution of Washington

Reference: Chau et al. (2018)

Origin of the Moon

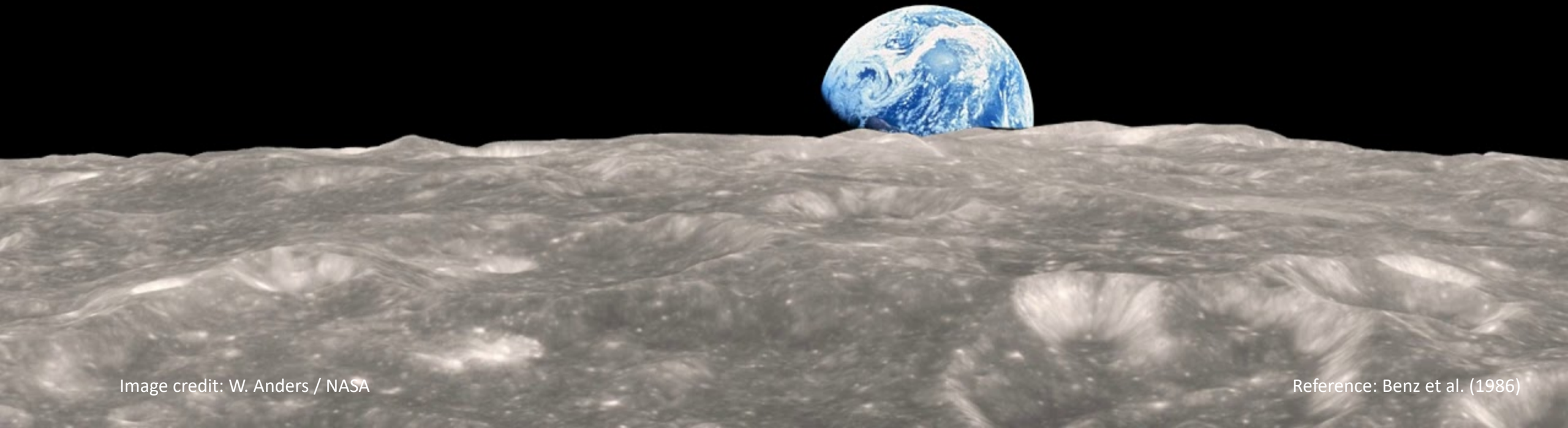
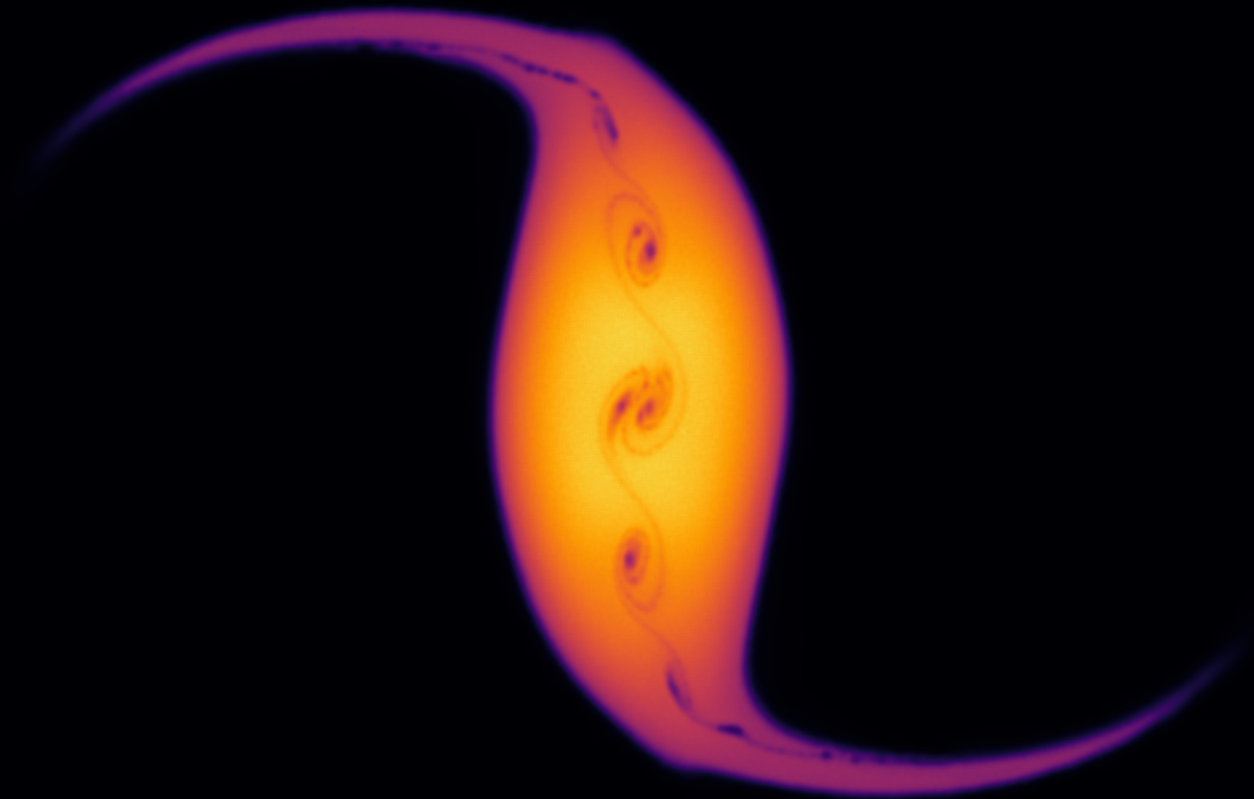


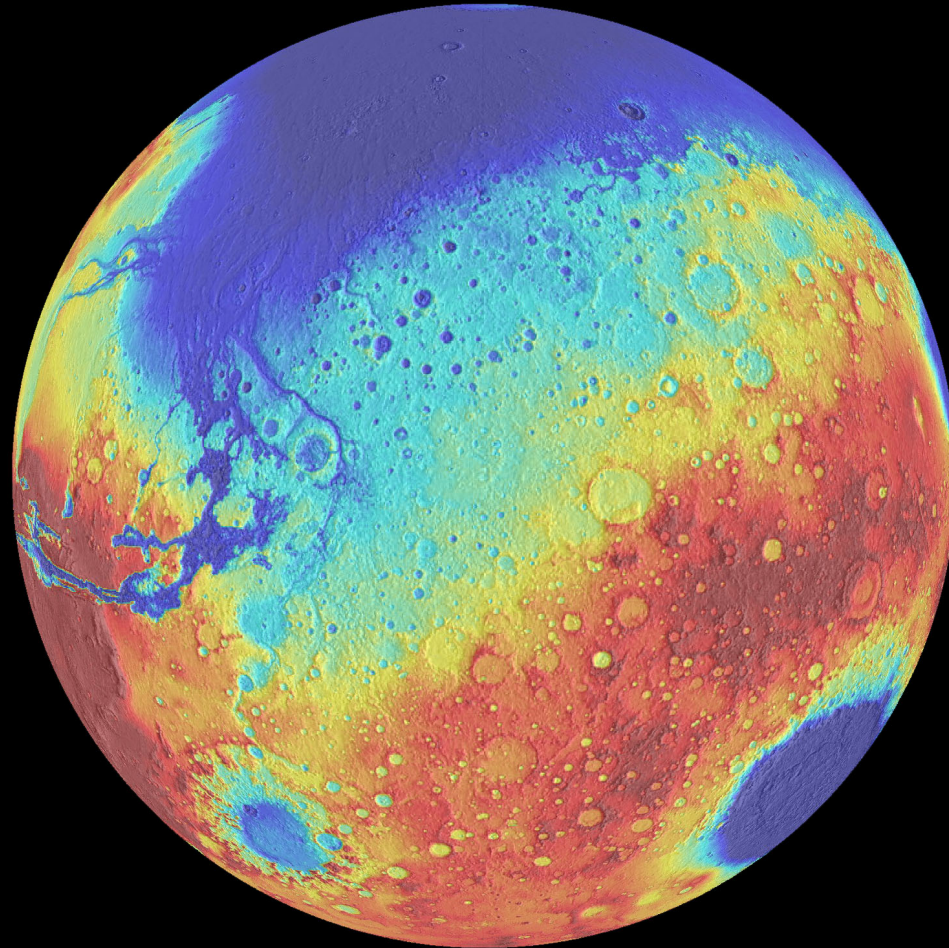
Image credit: W. Anders / NASA

Reference: Benz et al. (1986)

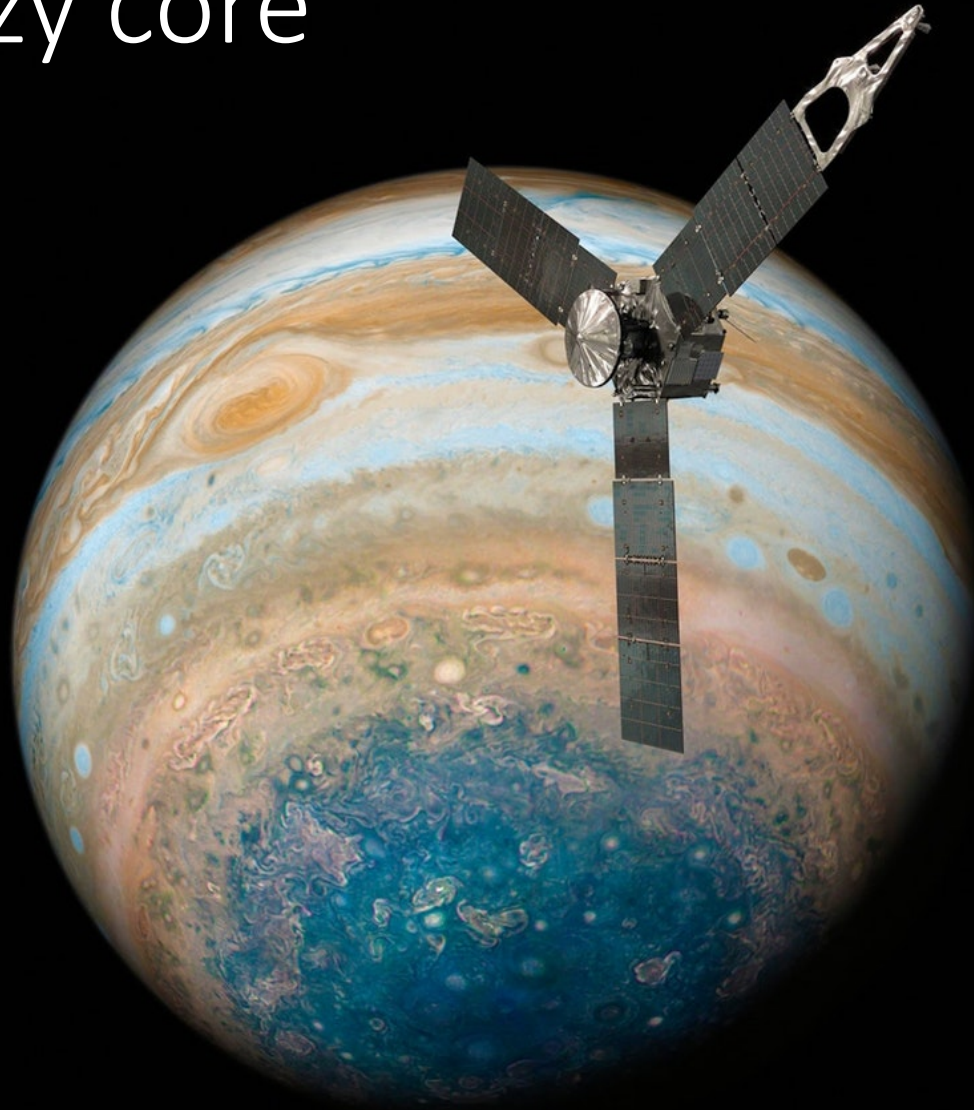
Origin of the Moon



Martian hemispheric dichotomy



Jupiter's fuzzy core



Uranus' tilted axis

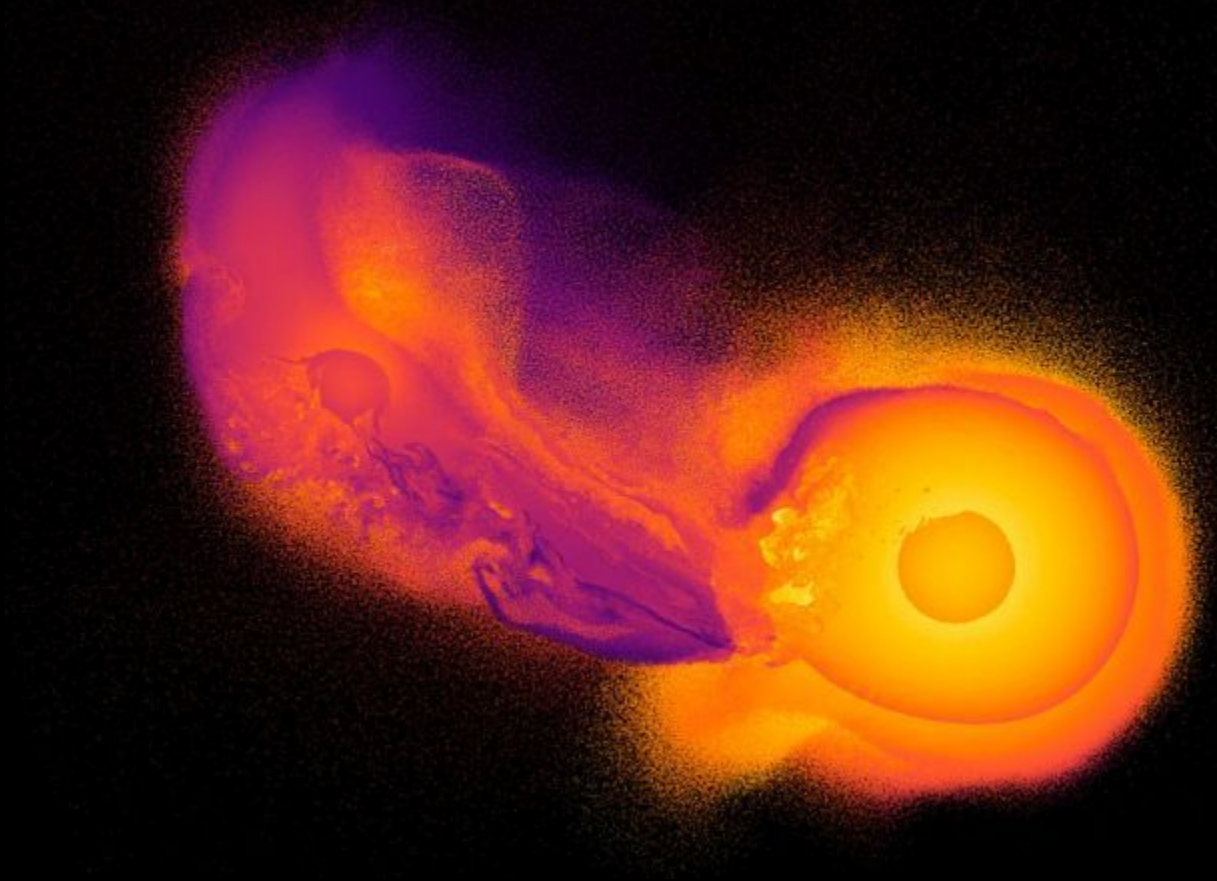
“We’re finally figuring out how Uranus ended up its side.”



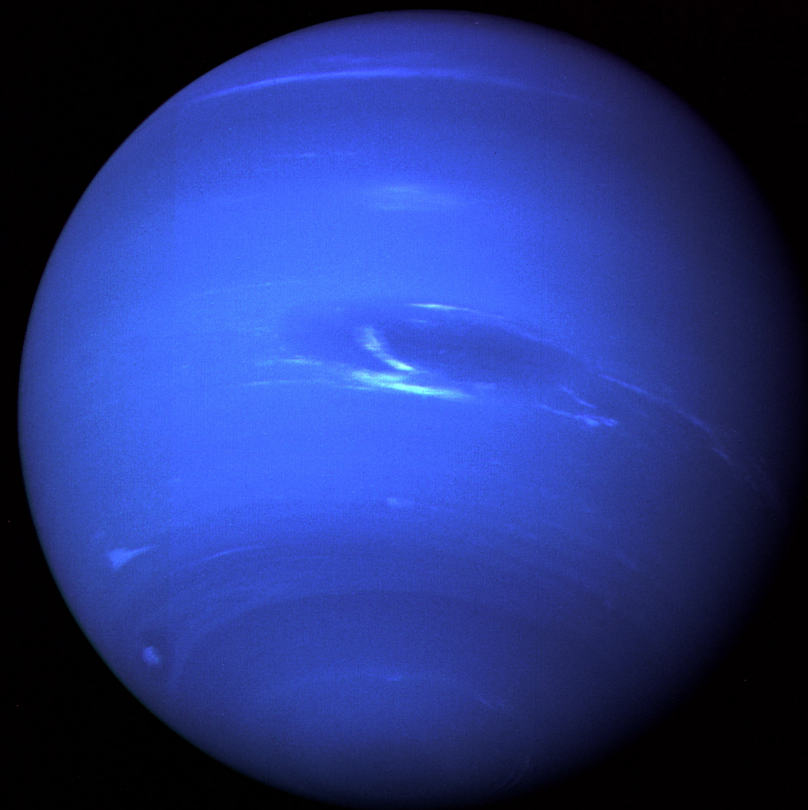
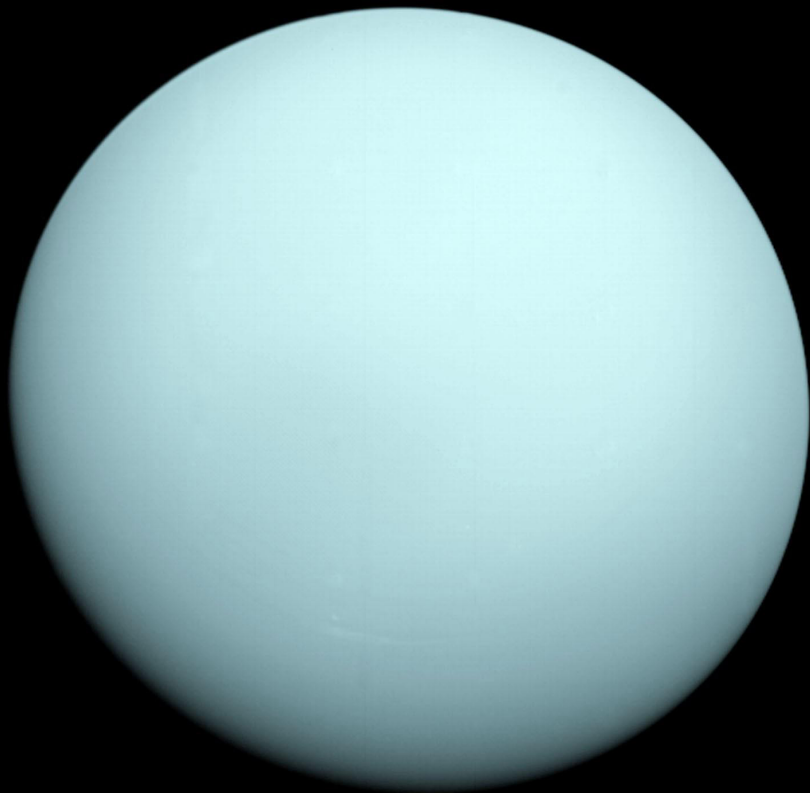
“Something big crashed into Uranus and changed it forever.”

“Uranus was slammed by an object twice the size of Earth.”

Uranus' tilted axis



Ice giant dichotomy



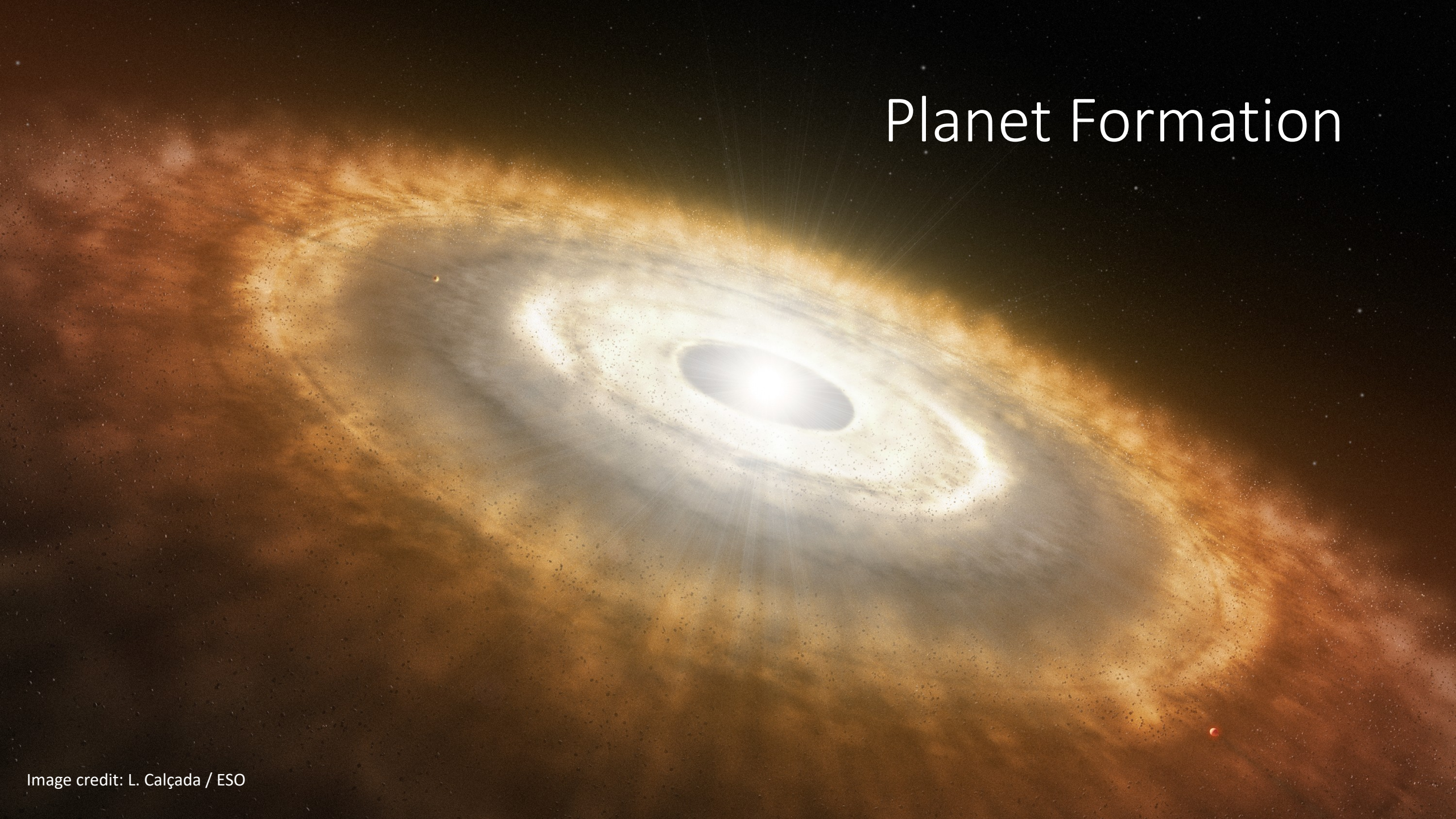
Origin of Pluto-Charon



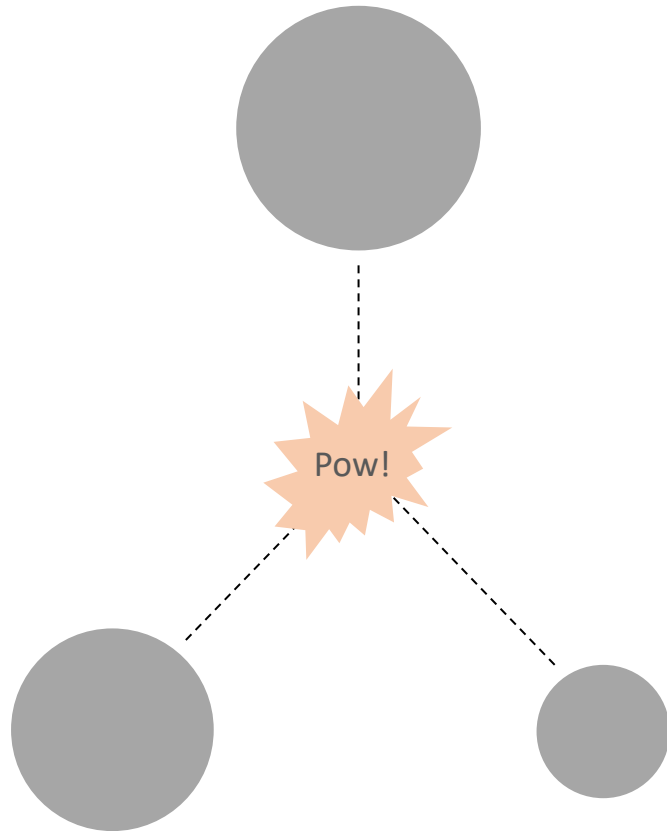
Image credit: NASA / Johns Hopkins University Applied
Physics Laboratory / Southwest Research Institute

Reference: Kegerreis et al. (2019)

Planet Formation



Planet Formation

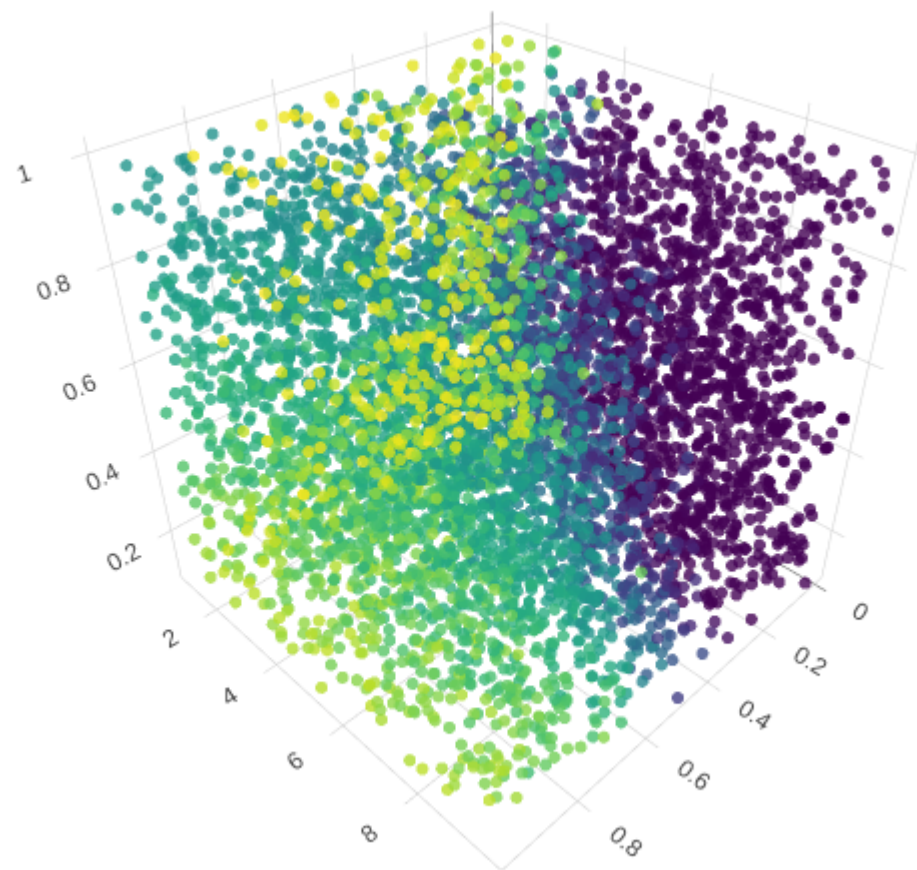


Why machine learning?

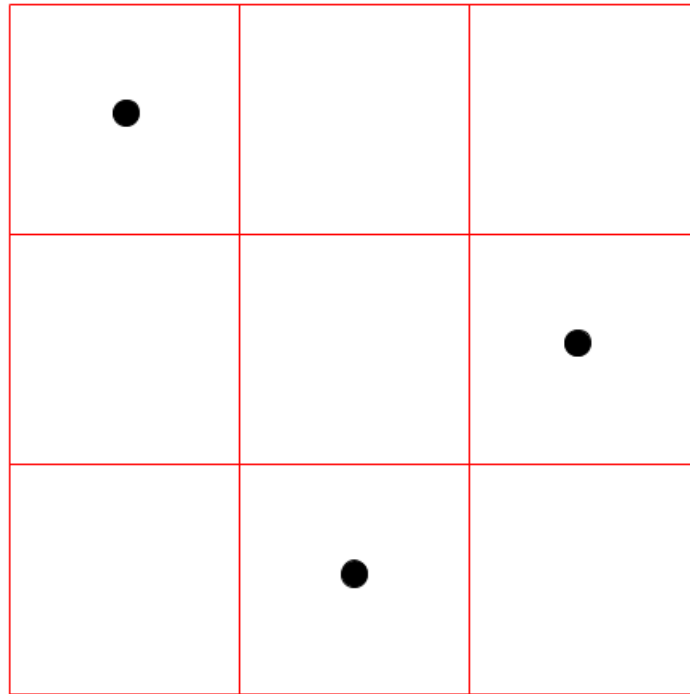
- Collisions are important for planet formation
- Simulations are expensive, parameter space is high dimensional
- Analytic and semi-analytic approaches aren't getting the job done
- Needs to generalize to any quantifiable property
- Must be usable “on-the-fly” (i.e., in N-body simulations)
- Should provide us with physical insights
- Would be nice if models obey physics

Data | Collision Dataset

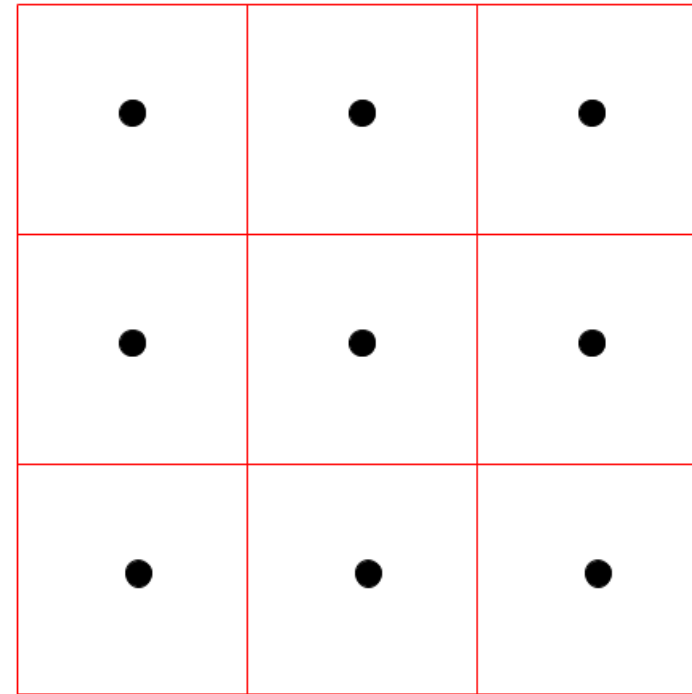
- 10,700 simulations of collisions
- Smoothed-particle hydrodynamics run on Piz Daint supercomputer
- Latin hypercube sample (LHS) with adaptive response surface method
- LHS10K, LHS500, LHS200
- Available on Dryad repository:
<https://doi.org/10.5061/dryad.j6q573n94>



Data | Latin Hypercube Sampling

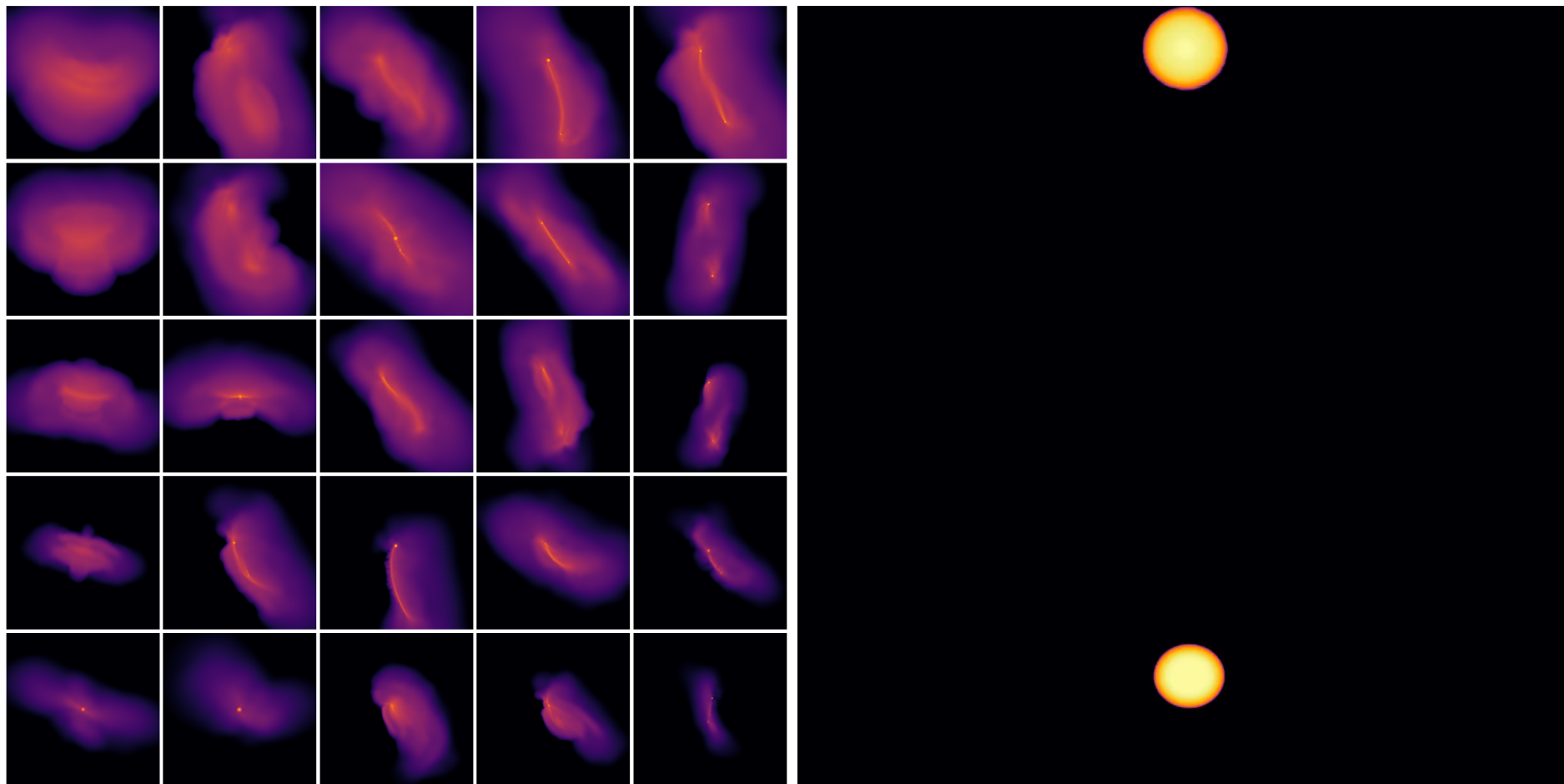


Latin Hypercube Sampling

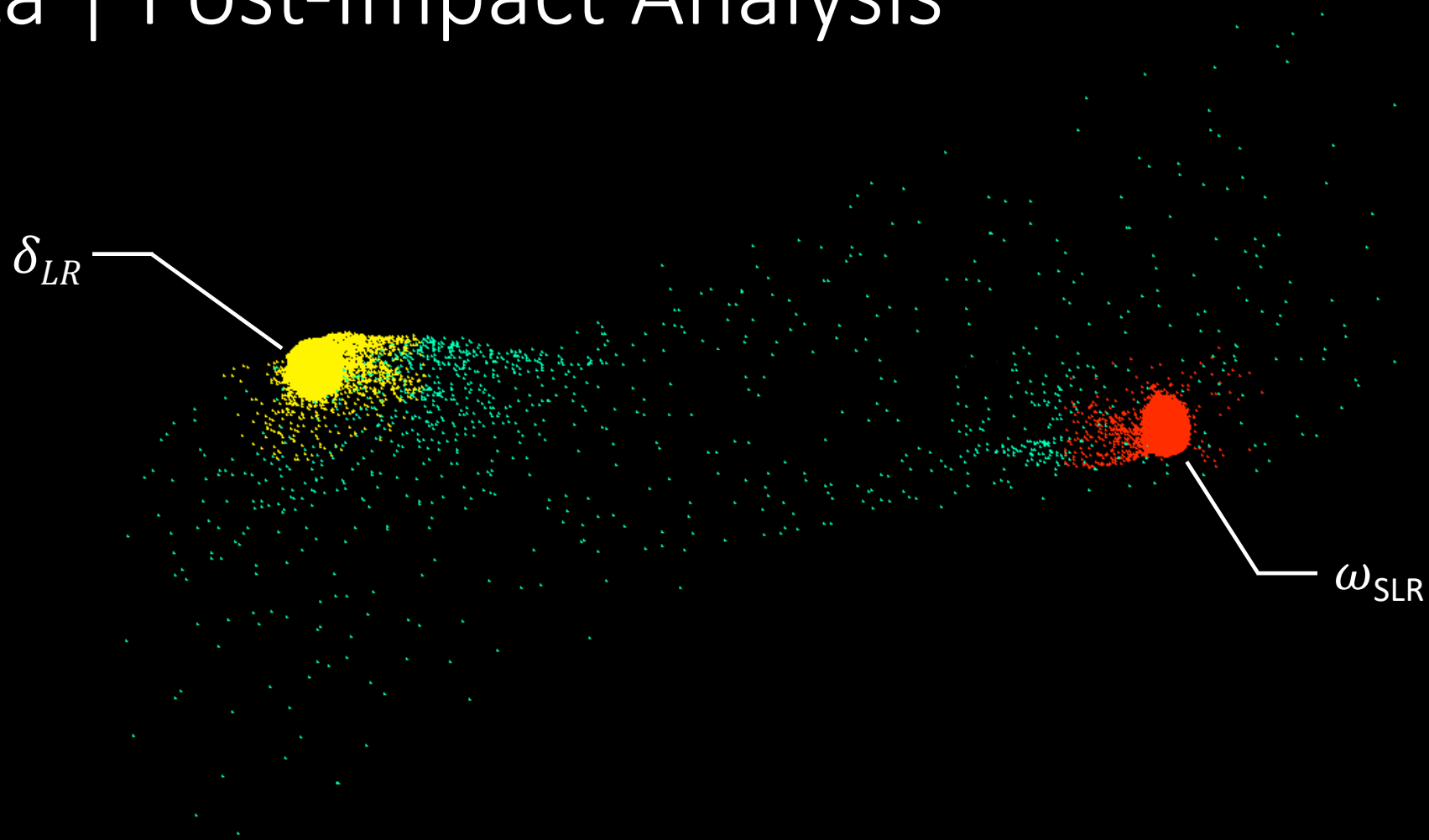


Standard Stratified Sampling

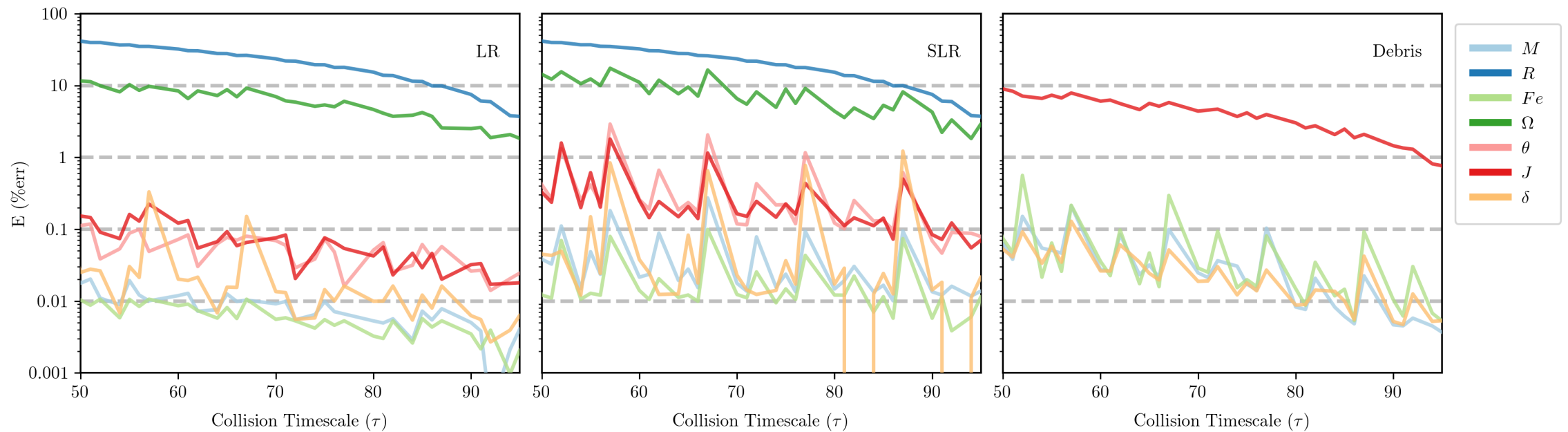
Data | Simulations



Data | Post-Impact Analysis



Data | Post-Impact Convergence



Methods | Collision models

- Perfectly inelastic merger (PIM)
- Impact-erosion model (IEM)
- Fragmentation model (EDACM)
- Polynomial chaos expansion (PCE)
- Gaussian processes (GP)
- Multi-layer perceptrons (MLP)
- XGBoost (XGB)

Analytic & semi-analytic

Data-driven (ML and UQ)

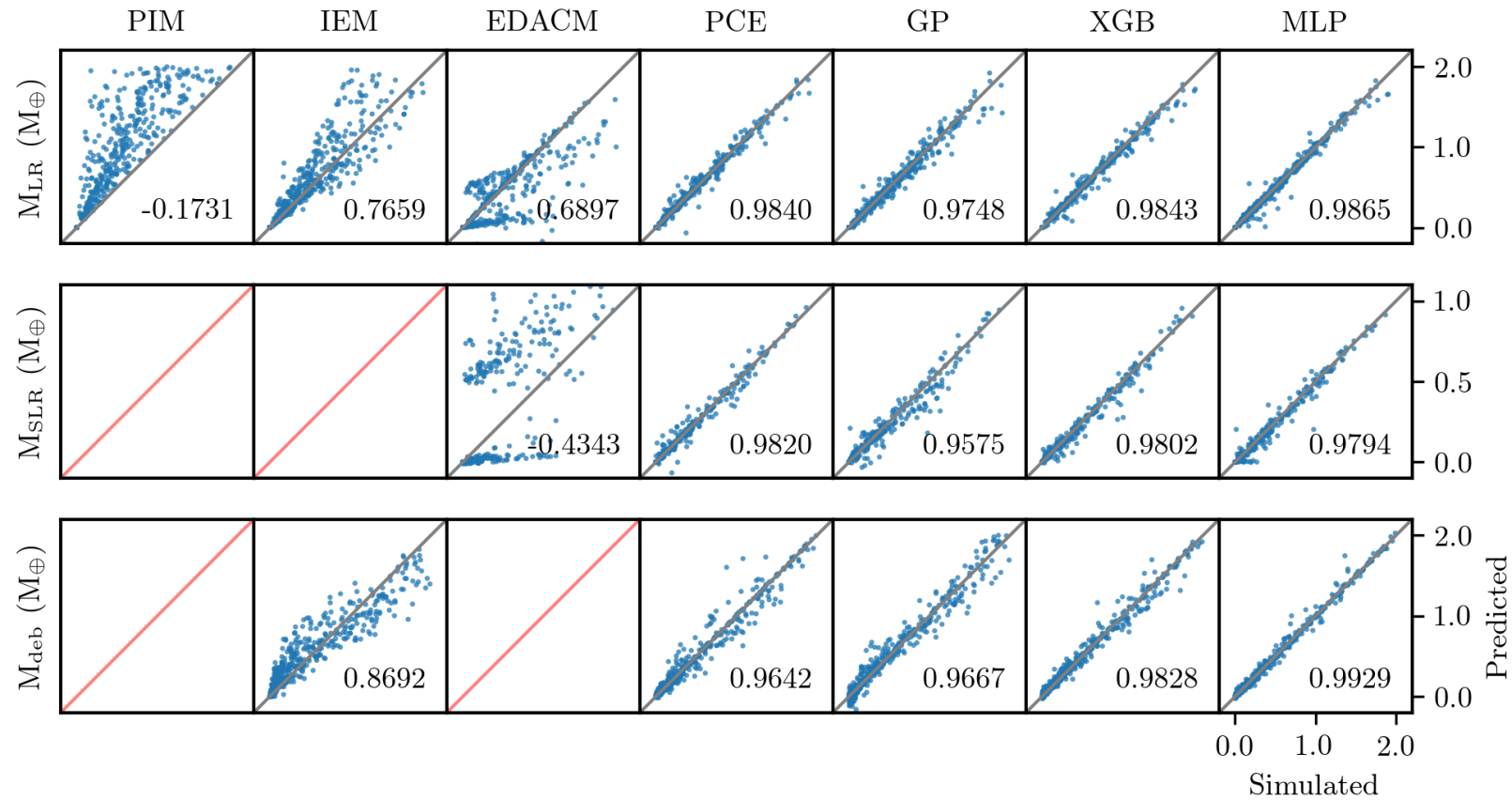
Methods | Training Pipeline

- One emulator per post-impact property (single-target regression)
- GP, MLP, PCE, and XGB
- Train on LHS10K
- Hyperparameter optimization with hyperopt / UQLab
 - 80/20 train/test split
 - 5-fold cross-validation
- Validate on LHS500
- Sensitivity analysis (Sobol' index)

Results | Predictions



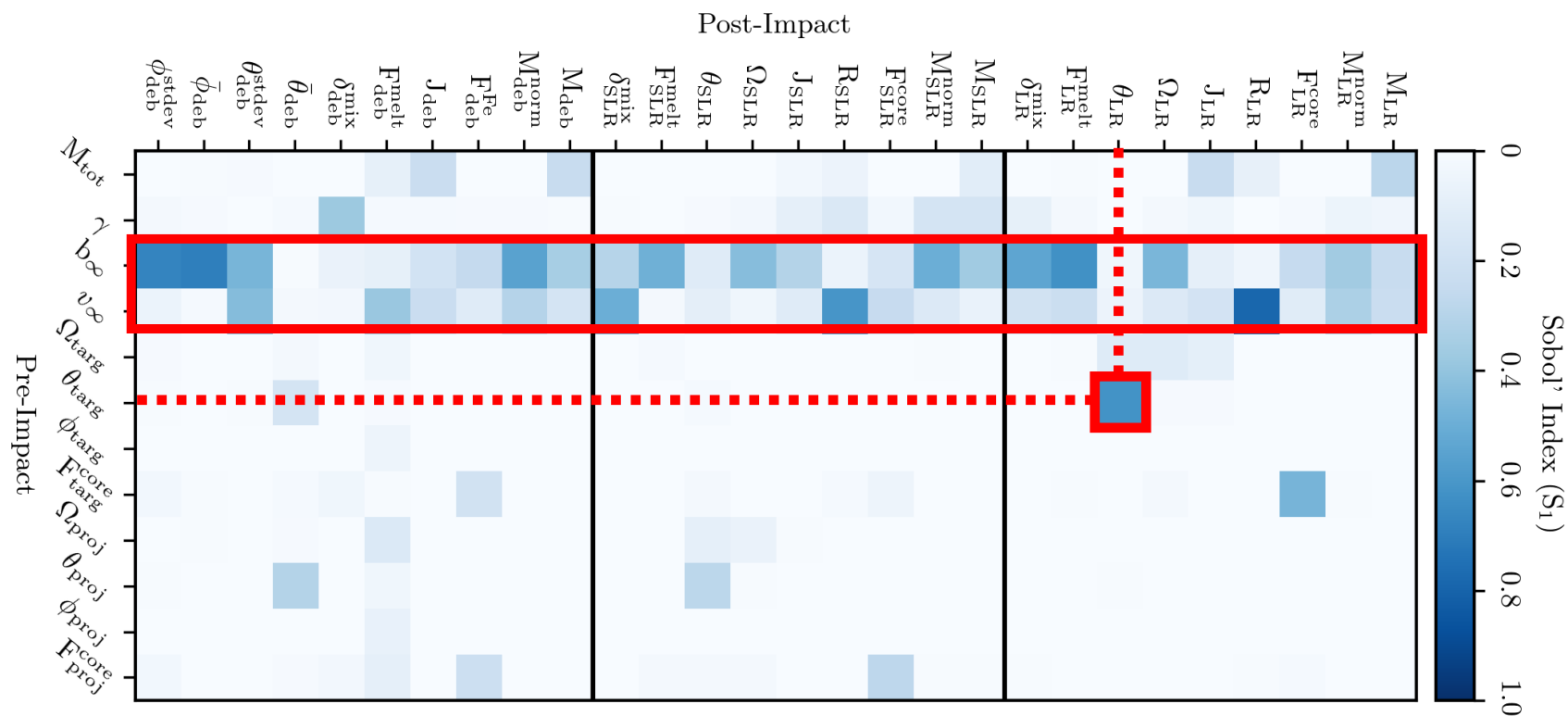
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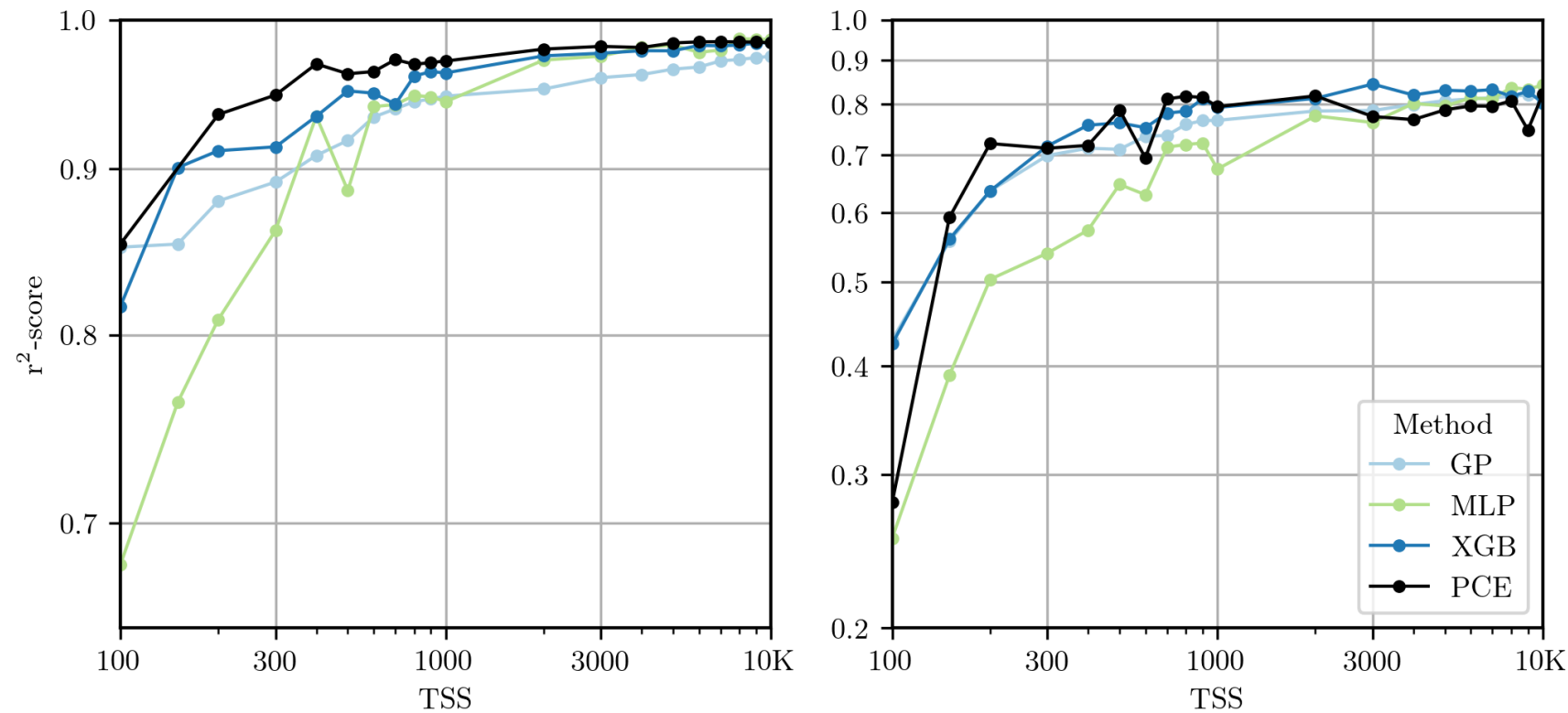
Results | Sensitivity Analysis



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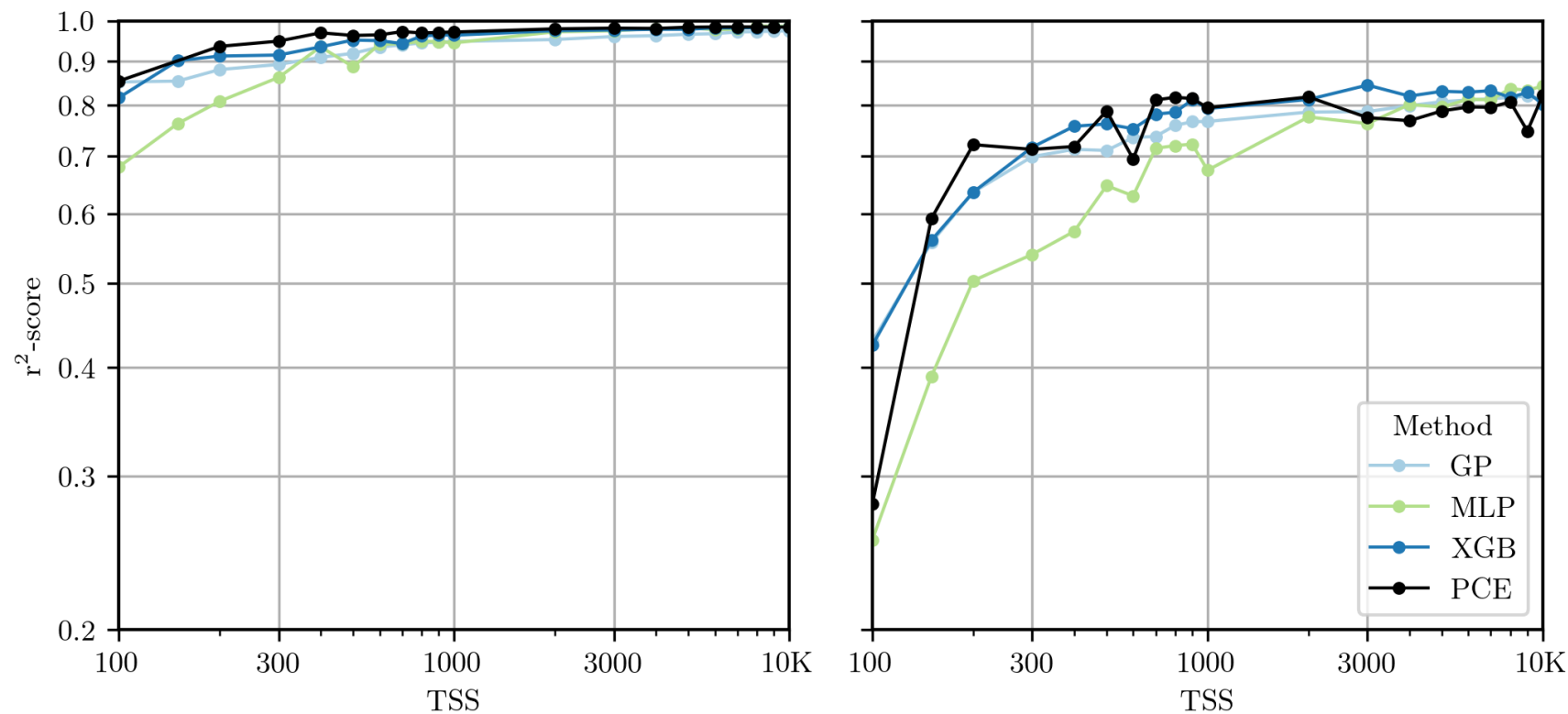


Results | Dataset Requirements





Results | Dataset Requirements



Work to be done...

- Training Data
 - Expand the collision parameter space
 - Higher-resolution simulations
 - New equations of state
- Models
 - Physical self-consistency
 - Multi-target regression for conserved quantities
 - Advanced techniques (e.g., ensemble methods)
 - Implement into N-body integrators

Thanks!

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PlanetS



SWISS NATIONAL SCIENCE FOUNDATION

- Pre-print on arXiv from tomorrow!
- Simulations available on Dryad:
<https://doi.org/10.5061/dryad.j6q573n94>
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