Accelerated Root Finding for the DART Inverse Test Using Machine Learning Decision Trees

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The DART Inverse Test

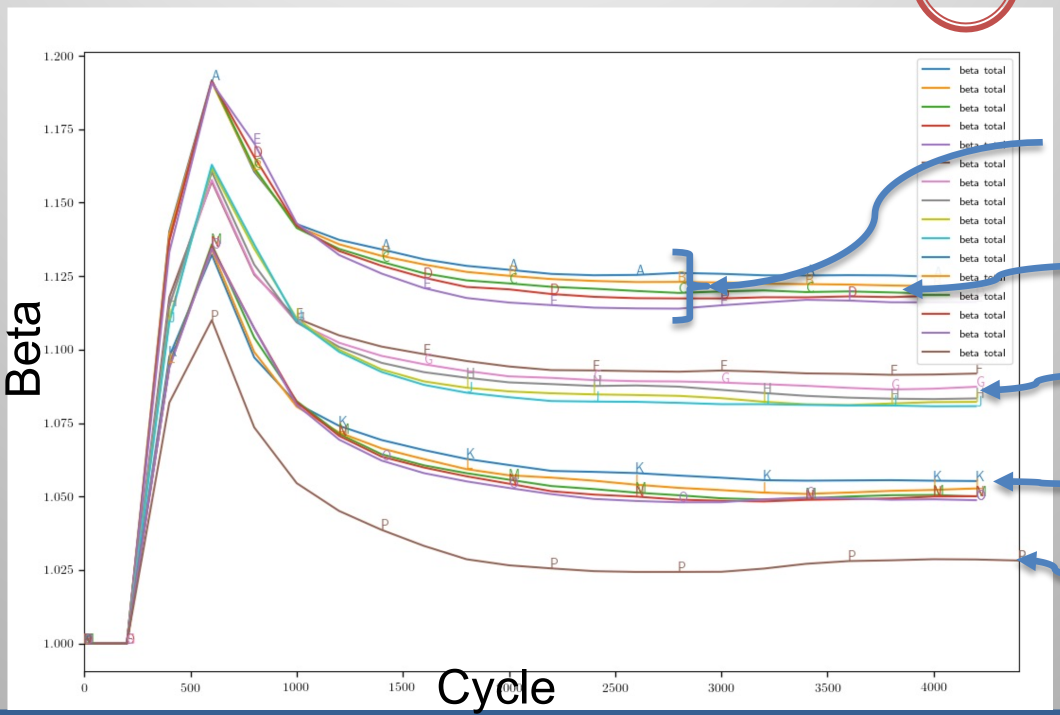
- Triaxial, rocky body
  - Uniform, constant density
  - No porosity
- Spherical impactor mass = 570 kg
  - Impactor momentum = $3.42\text{E}11 \text{ g cm/s}$
  - No impact angle (head on)
- Vary the yield strength and density parameters to drive to $\Delta v = 0.115 \text{ cm/s}$

3D Calculations

- SPH with Tillotson EOS
  - No damage model
    - — Damage in all cases pushed beta much too high for this exercise
- Monolithic material (no boulder-like inclusions)
- 10cm resolution at impact site
- Assuming no information about total mass (or density) of Dimorphos – fixing only the triaxial dimensions (volume)

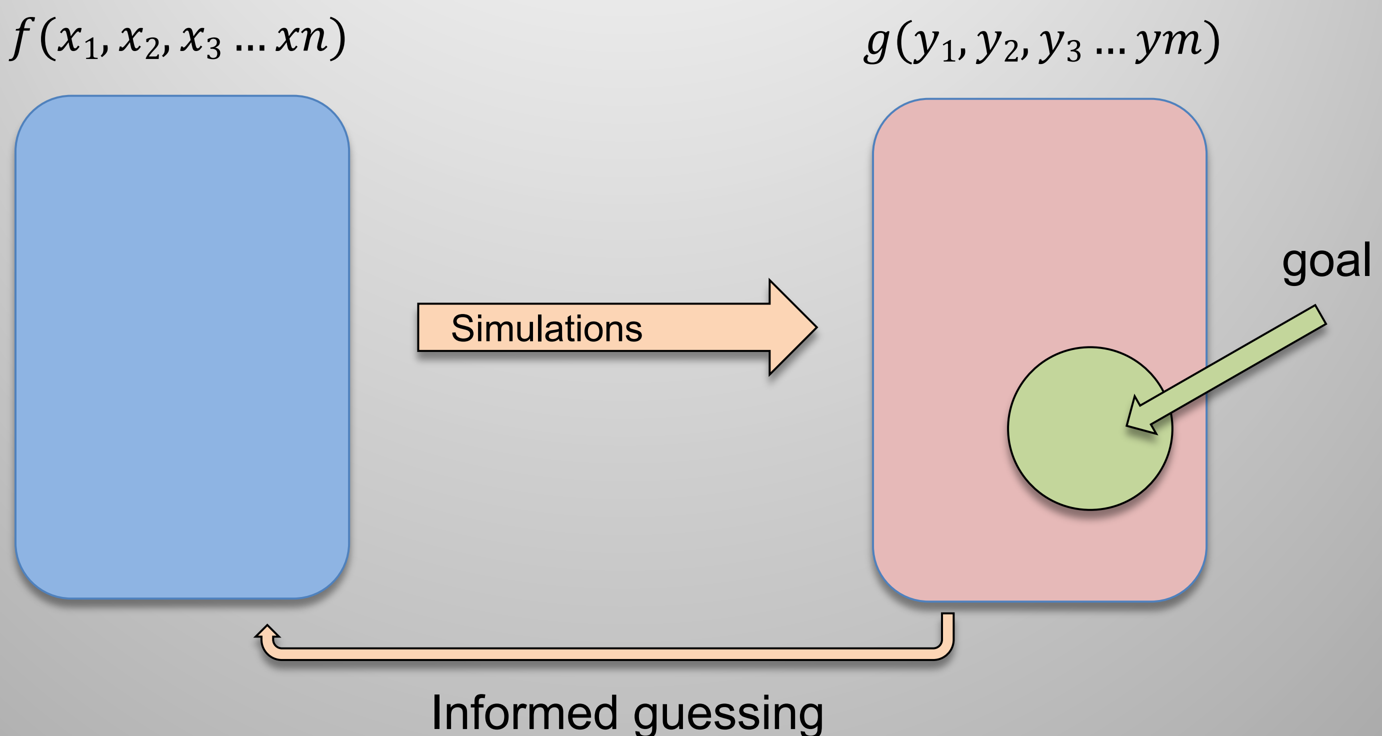
The Simulation Outputs Group Into Families

- Varying density and yield strength together results in families of Δv or β, grouped by the choice of maximum yield stress. $Y_i = Y_0 + \frac{\mu_i P}{1+\mu_i P/(Y_m - Y_0)}$



Inverse Problems are Typically Time-Consuming

- Repeated guessing and checking or running thousands of simulations and hoping for a "hit"



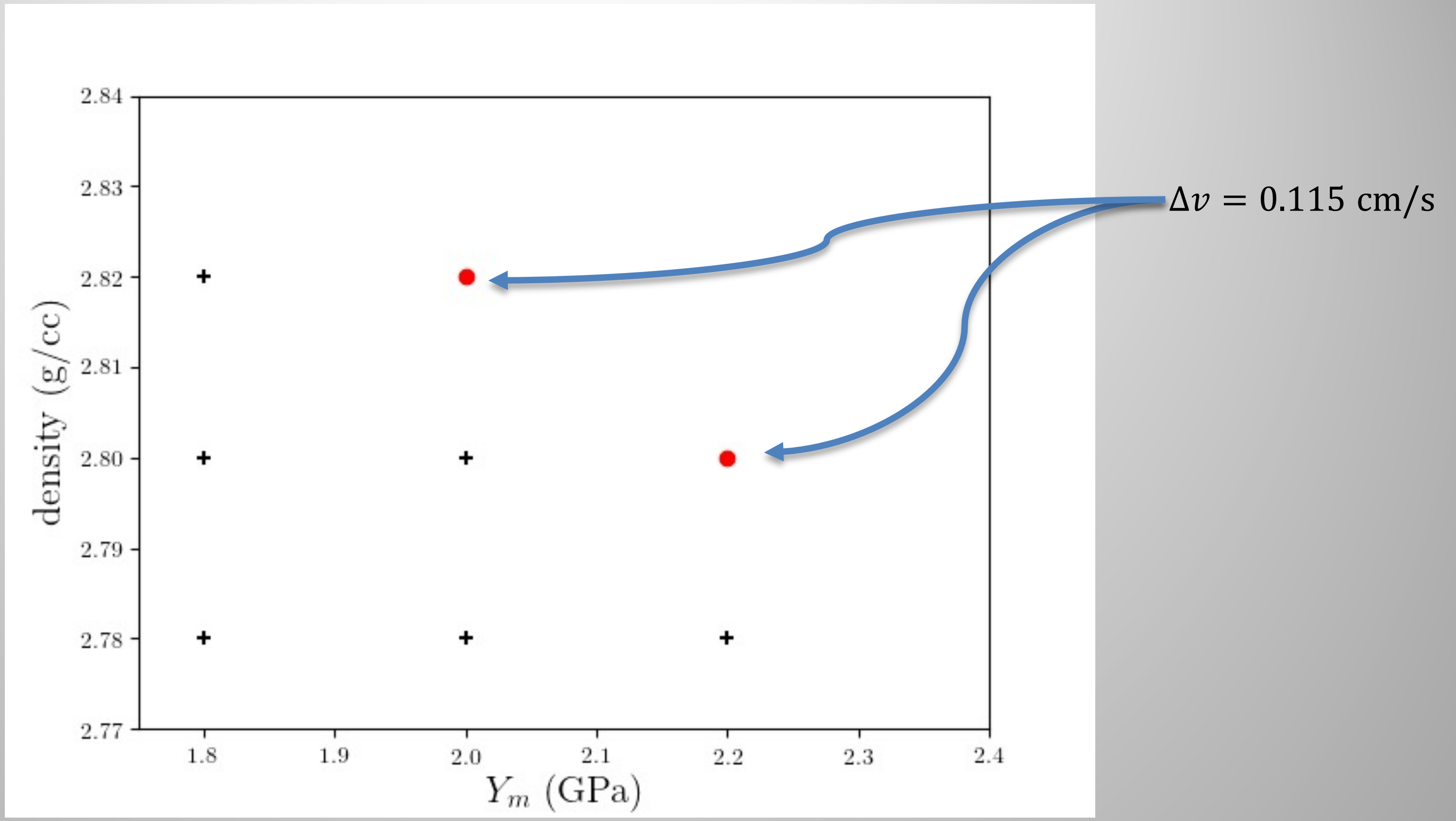
Decision Tree Regressor

- Most popular fast, supervised machine learning algorithm
- Non-parametric
  - Makes no assumptions about the parametric form of the output functor (good)
  - Generally requires large datasets to be accurate (bad)
- Steerable (good)
- Naïve (bad)

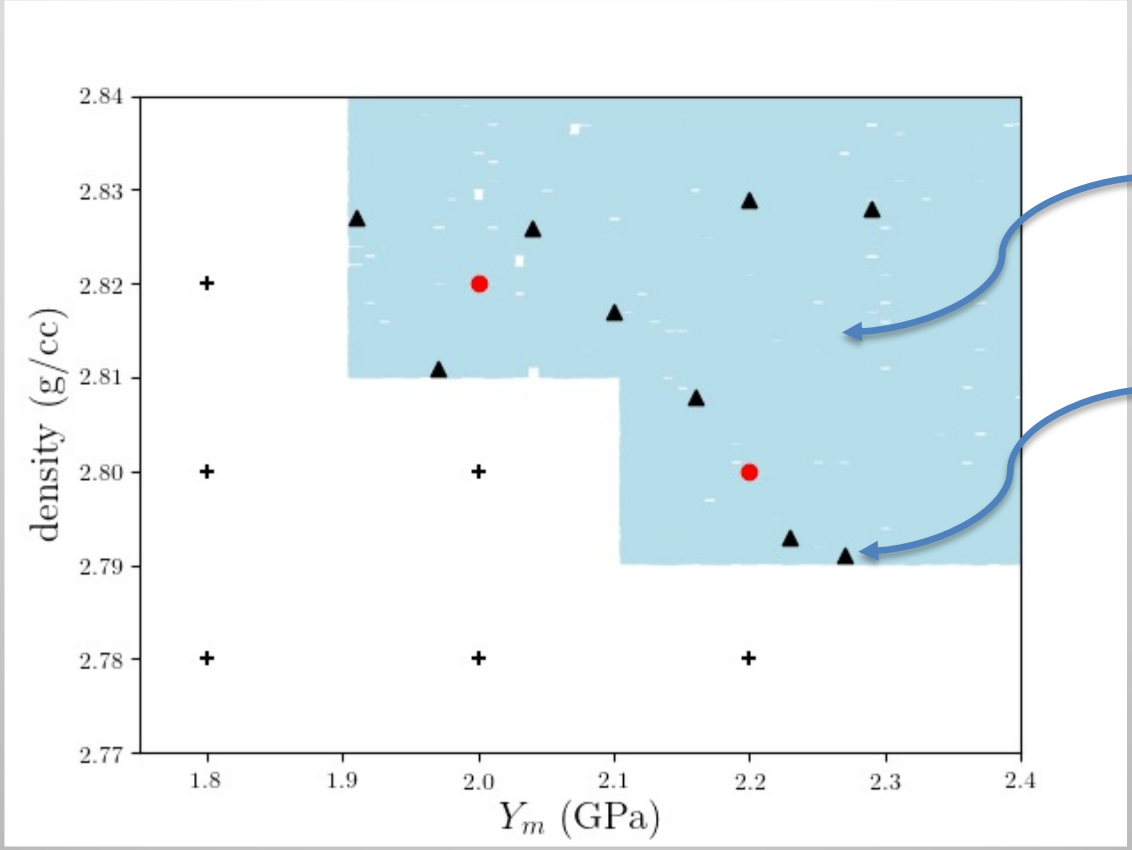
Is this Overkill?

- Future trials may involve many more input and output parameters
  - Difficult for humans to find trends
  - Easy for computers
- Computer cycles are cheap – Human cycles are not
- "Going too far is half the fun of getting nowhere."
  - Bill Griffith

An Initial Scan of the Parameter Space Already Found Two Successes



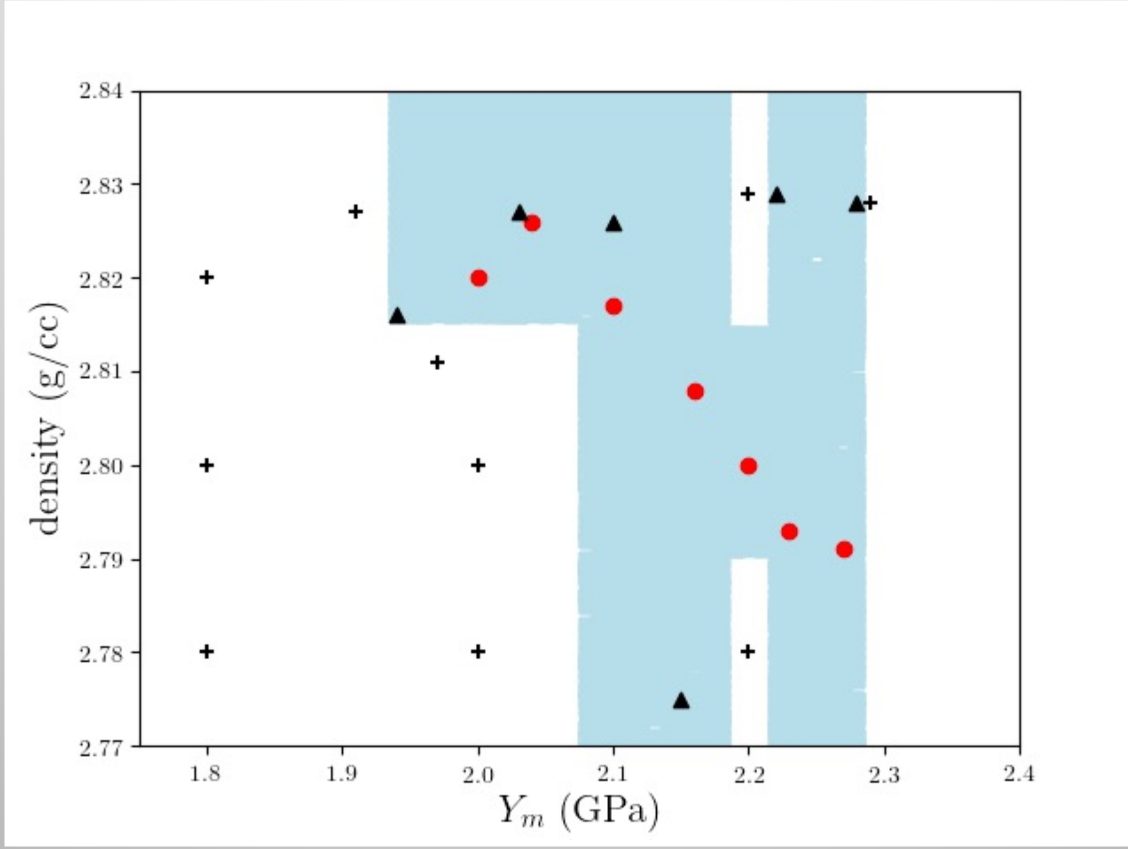
ML Algorithm Chooses the Next Parameter Set From the Prediction Space



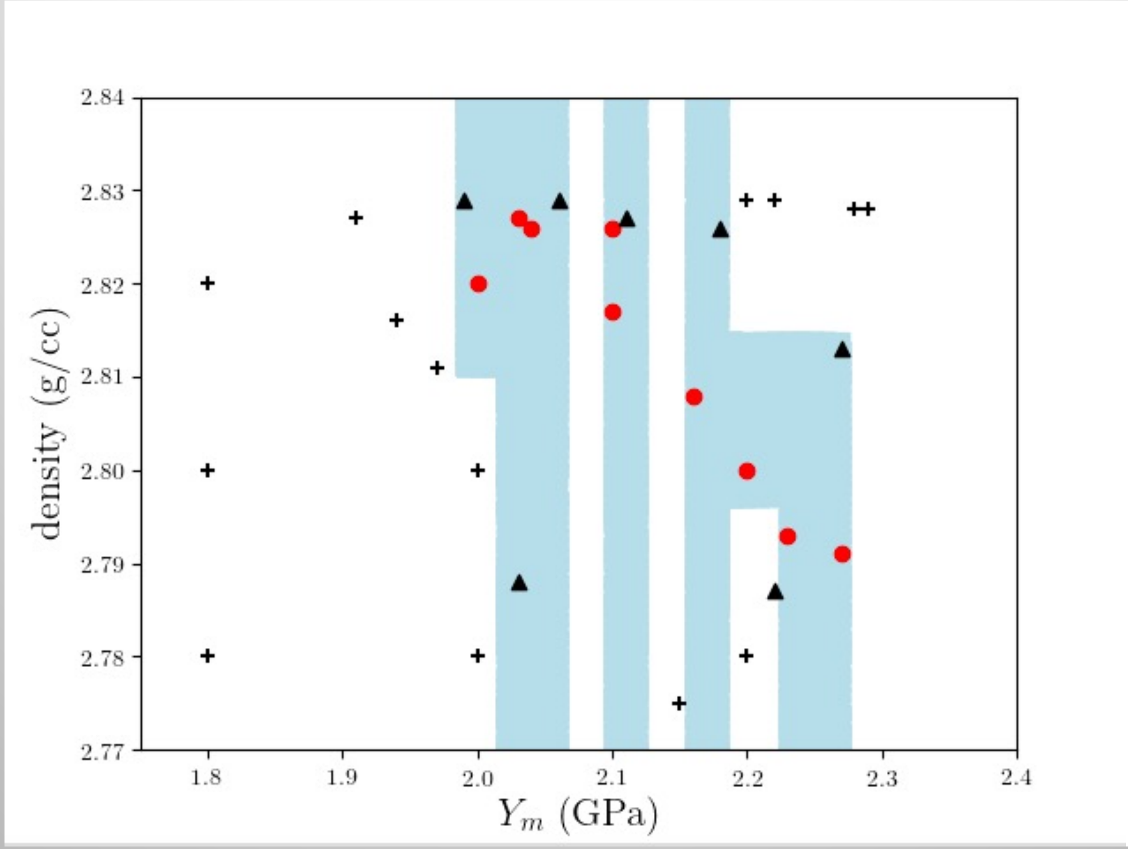
Prediction space

Mitchell's Best Sampling choice

ML Algorithm Refines the Prediction Space and Chooses More Samples

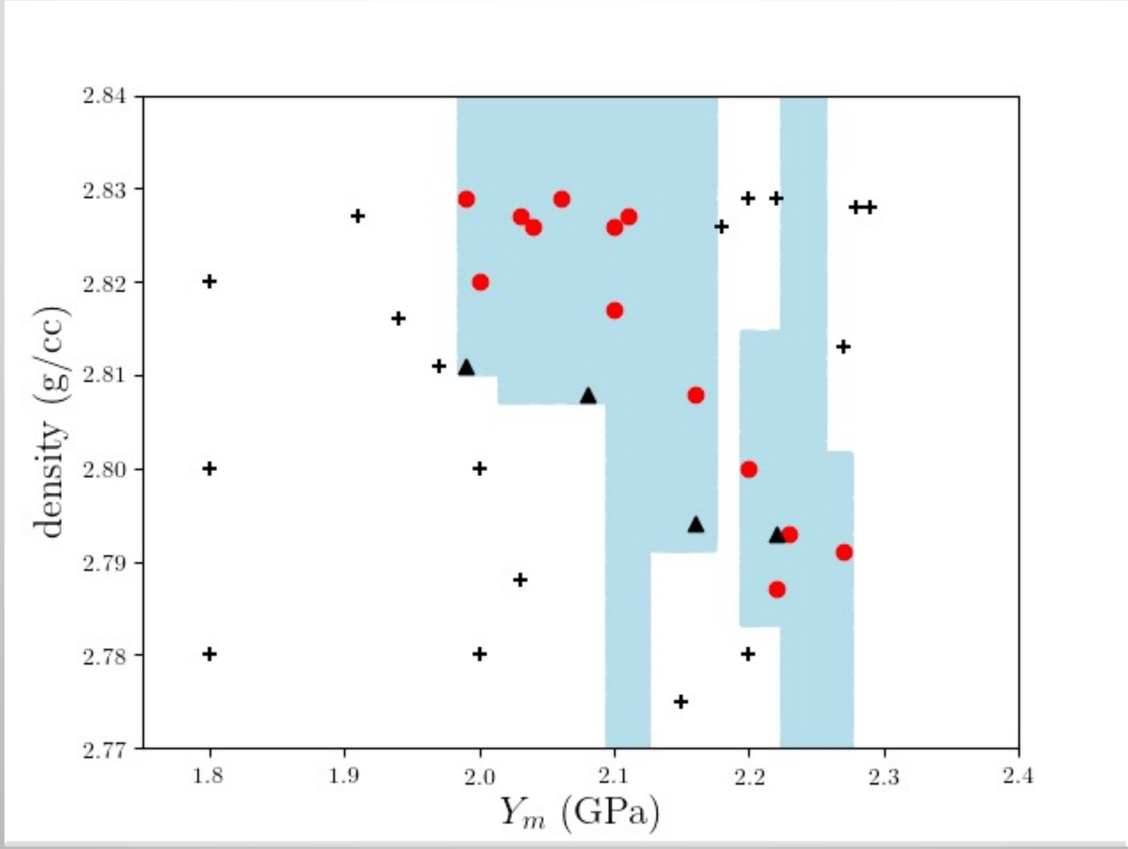


Enhance…



2.84
2.83
2.82
2.81
2.80
2.79
2.78
2.77
density (g/cc)
1.8
1.9
2.0
2.1
2.2
2.3
2.4
Y_m (GPa)

Enhance!!!



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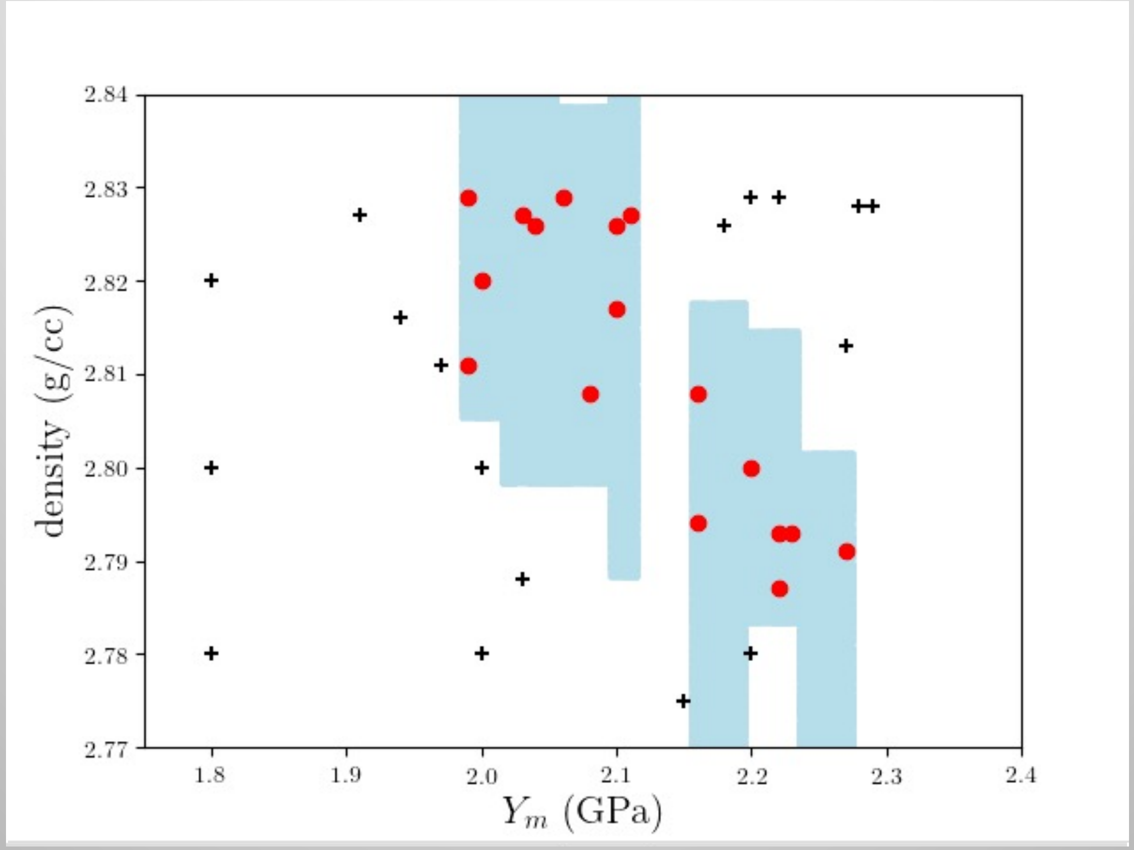
Several Candidate Parameter Sets Found in Short Order



Key judgments from the Exercise

- The synthetic observations are most consistent with a uniform, non-porous, single-density body with $\rho \approx 2.79 - 2.83$ g/cc and $Y_m \approx 2.3 - 2.0$ GPa.

- Including any damage model would require tuning the damage parameters to something akin to no damage, or tuning the density and yield strength to something very unlike rock.

- We did not assess the effects of porosity as this would not drive the Δv results in a helpful direction. Additionally, guidance from the Red Team briefing suggested bulk densities that are inconsistent with porous granite. It is still possible for a highly porous, metallic body to result in a similar Δv.

Major Caveats / Things to Try Next

- ρ and Y_m alone are probably not a sufficient input parameter set
  - A *curve* of possible input choices yield the same output
  - Y_0 and porosity could also drive the decision tree
  - Lack of damage model is simplifying, but unrealistic
- Δv need not be the only output parameter
  - Crater size
  - Velocity dispersion of the debris
  - Flavor profile of the caramelized debris…
- I made no mention of the error analysis
  - And I'm not going to

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