SAND2021-8779PE

Machine Learning for Plasticity and Continuum Damage Models

Genetic Programming with Symbolic Regression

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The Need for Reliability in Extreme Environments

- Weapons systems need to perform reliably in a wide range of environments
- Several potential points of failure:
  - Mechanical
  - Electrical
- **What can we do to make the future better?**
- Present focus: ductile mechanical failure

(a)

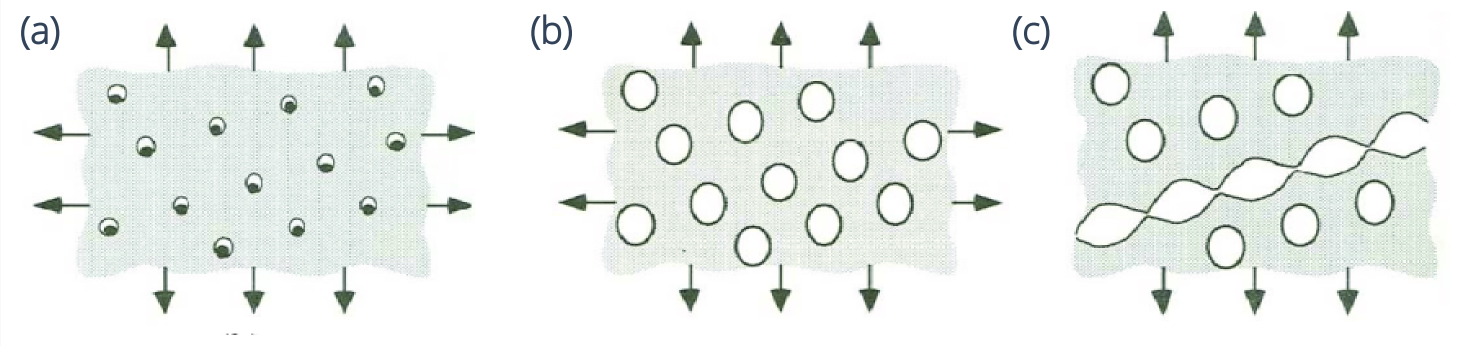
(b)

Figure: (a) A sounding rocket, testing how technologies will fare in flight (SAND2018-11495V).

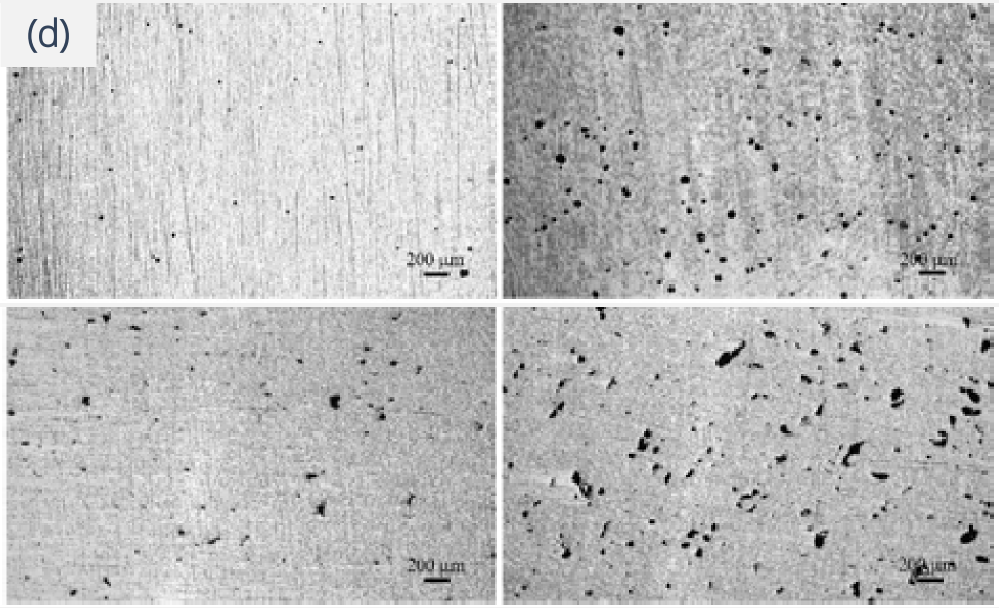
(b) Simulation of a vehicle accident during materials transport (SAND2018-13982V).

Ductile Mechanical Failure is Accelerated in Porous Materials

- Void nucleation (a), growth (b), and coalescence (c) lead to ductile fracture.
- (d) Example of defects (pores) present in metal components formed by selective laser melting and electron beam melting.



Adapted from Das et al. 2013.



Adapted from Gong et al. 2015.

[1] Das et al. 2013, Procedia Engineering 55, doi:10.1016/j.proeng.2013.03.332

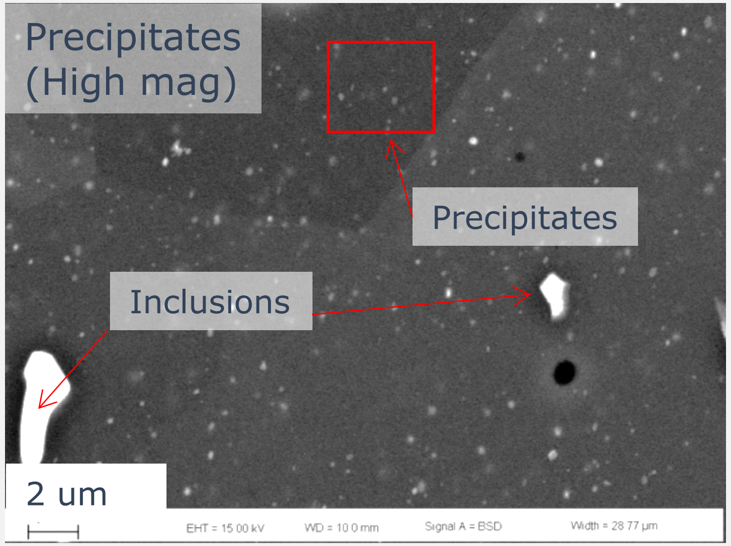
[2] Kim and Moylan 2016, NIST Advanced Manufacturing Series 100-16, https://doi.org/10.6028/NIST.AMS.100-16

[3] Gong et al. 2015, Materials & Design 86:545-554.

Existing Models of Damage are Insufficient

- Want to model and predict failure for accurate engineering analysis
- Established models of continuum damage have many (often unrealistic) assumptions
  - Spherical (self-similar) void growth
  - Perfect plasticity
  - Rate and temperature-independent
  - Isotropic, homogenous matrix
- Real materials are complex!

(a)



(b)

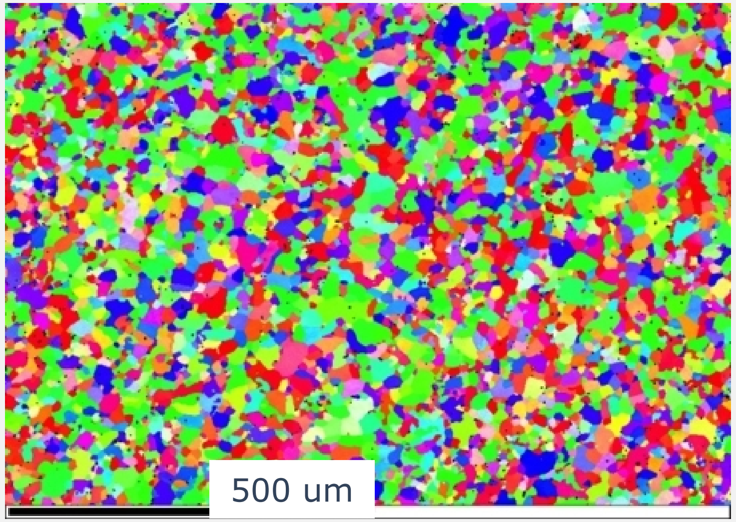


Figure: (a) SEM images showing multiple phases that conspire to nucleate damage, (b) Electron backscatter diffraction (EBSD) describing crystallographic orientation.

Approach: Machine Learning/Artificial Intelligence

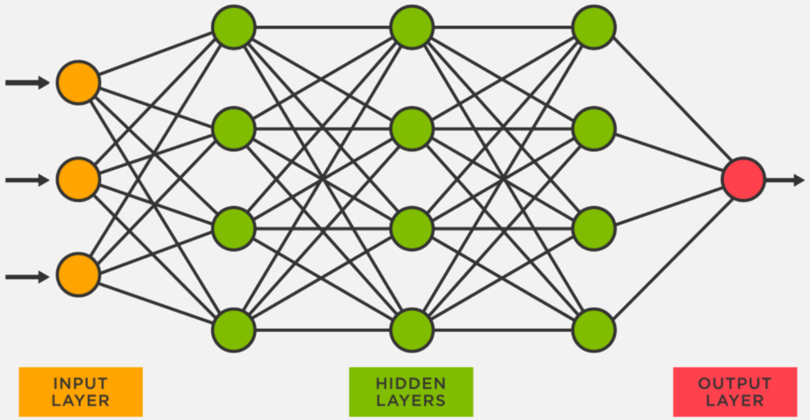
Generate Training Data → Train ML Model → Find Best-Fit Expressions → Determine Optimal Solution

Want to improve physical accuracy and maintain interpretability!

Neural network: "black box"

vs.

Genetic programming with symbolic regression: interpretable algebraic expressions

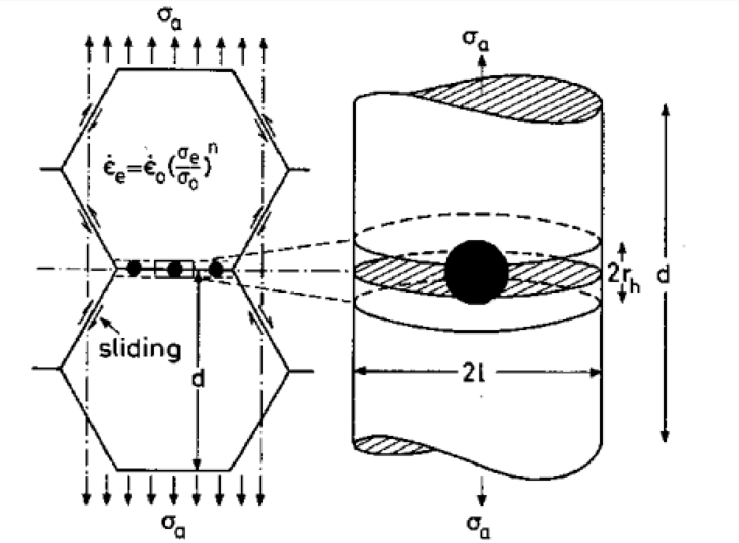


$$-X_1\left(X_1 + {X_0}^2 X_3\left(0.9534(X_0 + X_2 - \cosh(X_0) + \frac{\cosh(X_0)}{X_1}) + {X_0}^2\right)\right)$$

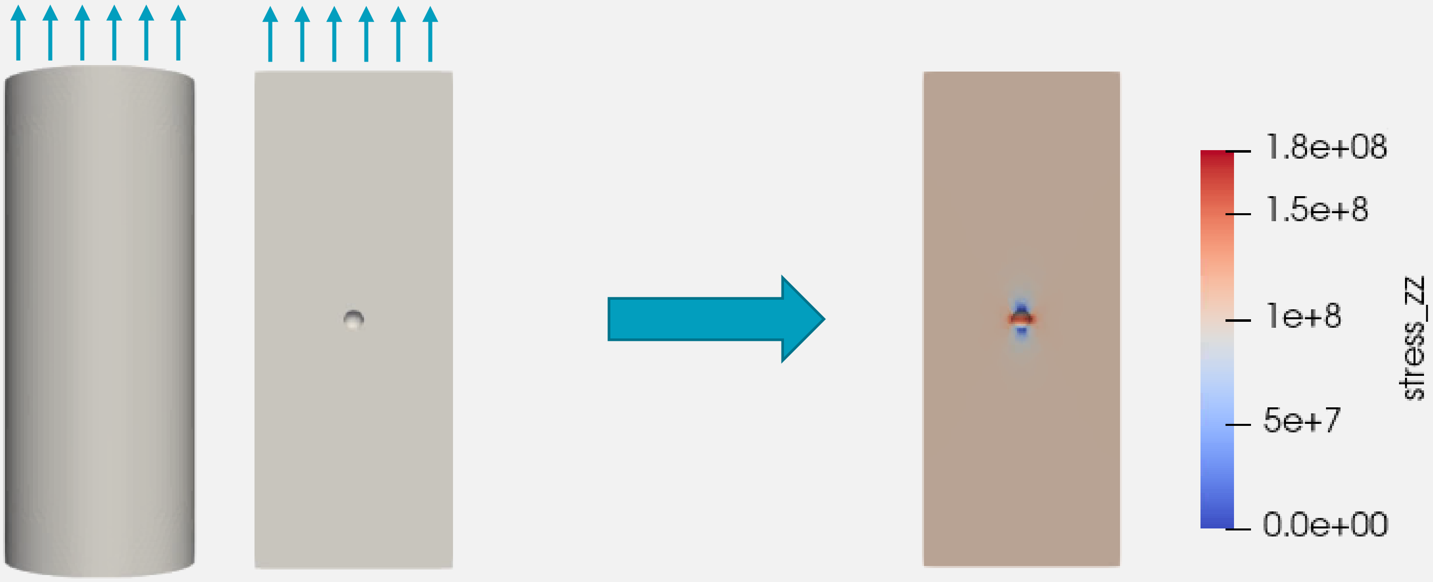
X_0-Hydrostatic stress
X_1-Von mises stress
X_2-Lode angle
X_3-Void volume fraction

Training Data Generation

- Training data generated via a series of finite element simulations using the Cocks-Ashby model of void growth
- Hydrostatic stress, von Mises equivalent stress, void volume fraction



Voids growing on grain boundary in power-law creeping solid



Genetic Programming with Symbolic Regression (GPSR)

Genetic Programming (GP): Evolution of computer programs

Symbolic Regression (SR): Searching space of mathematical functions

Fitness: Measure of how well model matches data

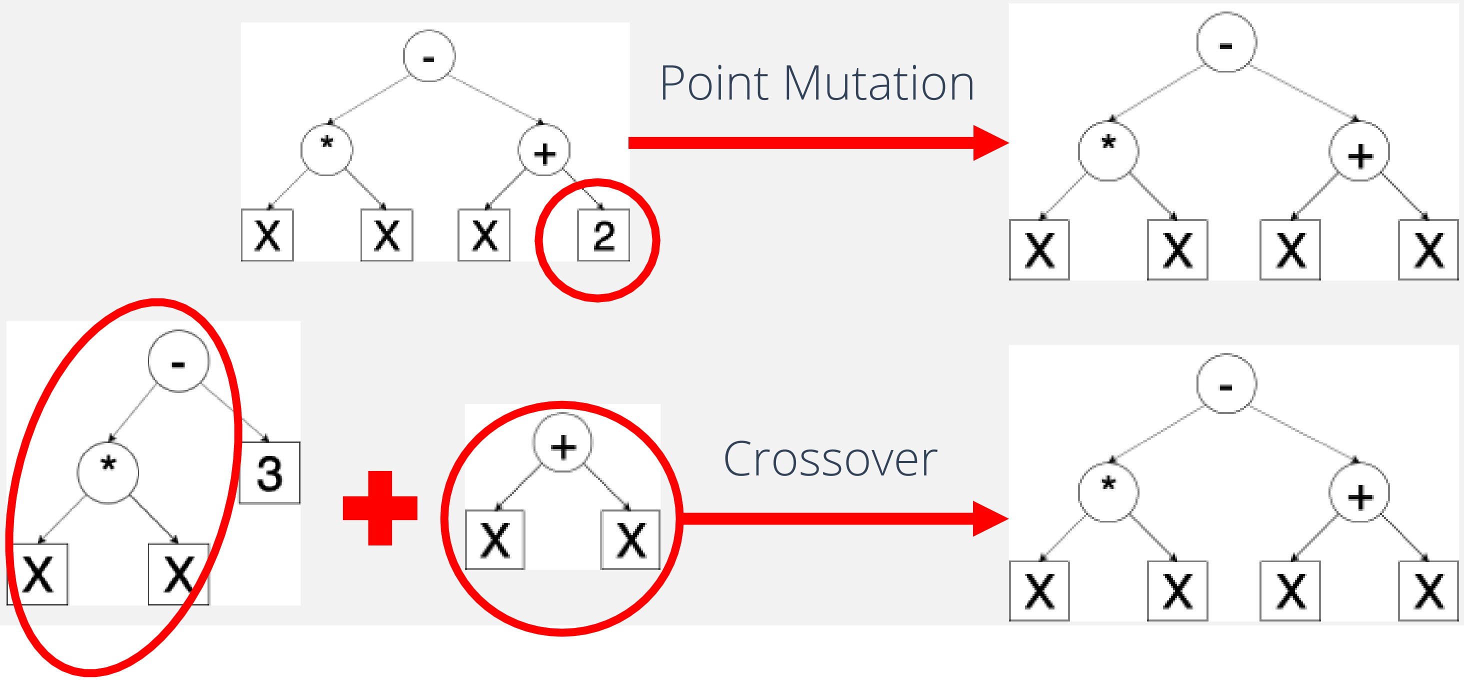
- Models represented as trees
- Limited number of mathematical operations
- New models generated via mutations

https://github.com/nasa/bingo

$= {}^2 - (\; + 2)$

$= {}^2 - 3$

$= \; + $



$= {}^2 - 2$

$= {}^2 - 2$

Current Effort: Running GPSR

- Sample output expressions from the Gurson model of continuum damage
- Limited number of mathematical operations (+, –, x)

Best-fit solution

Fitness: 0.3406
Complexity: 38

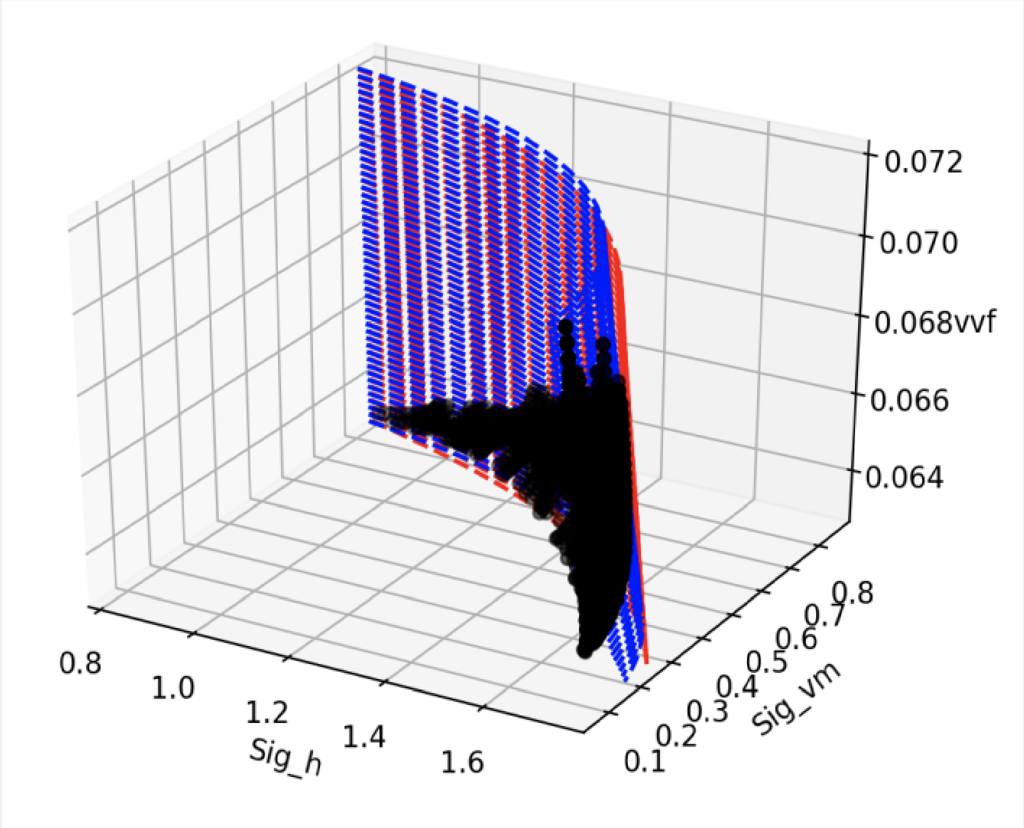
$$((X_0-2X_1-X_2+3.743+(X_2-X_1)^2)(X_2-(X_2-X_1)^2))(X_2-X_1)-(((X_2-X_1)^2(X_2)+X_0))(4.844)+X_2-((X_0-X_2+2X_1)((X_2-X_1)^2(X_2)+X_1-(((X_2-X_1)^2(X_2)-X_0)^2((X_2+X_1)(X_2-X_1)^2(X_0-X_1+(X_2-X_1)^2-(X_2+X_1)(X_2-X_1)^4)))+2X_2-X_0-X_1))$$

Alternative solution

Fitness: 0.3512
Complexity: 20

$$X_0^3X_2(X_1-X_2)(X_2-X_1)(X_1-X_0)(2X_1-X_2)-(X_1-2X_0+X_2+X_0X_2(X_1-X_2)^2)$$

Comparison of data to model output

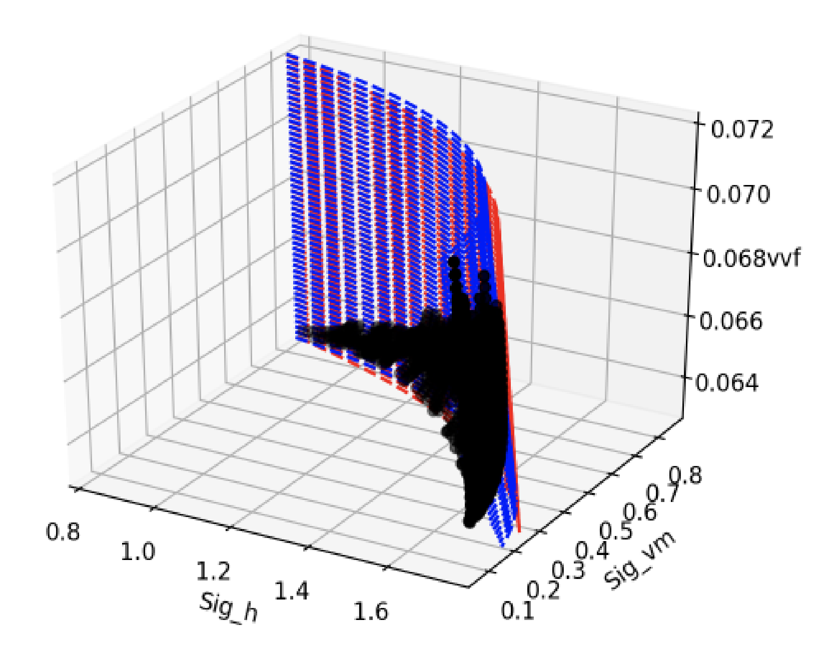


X_0-Hydrostatic stress
X_1-Von mises stress
X_2-Lode angle
X_3-Void volume fraction

Black = FE data
Blue = Gurson Model
Red = GPSR Model

Summary and Future Directions

- GPSR technique: highly tunable, able to generate accurate mathematical models
- Efficacy of GPSR approach demonstrated by collaborators at University of Utah
- Current effort:
  - Improve the fitness of expressions generated for Cocks-Ashby model
  - Demonstrate the validity of all assumptions
- Future work:
  - More complex microstructure, geometry
  - Varied loading




thank you