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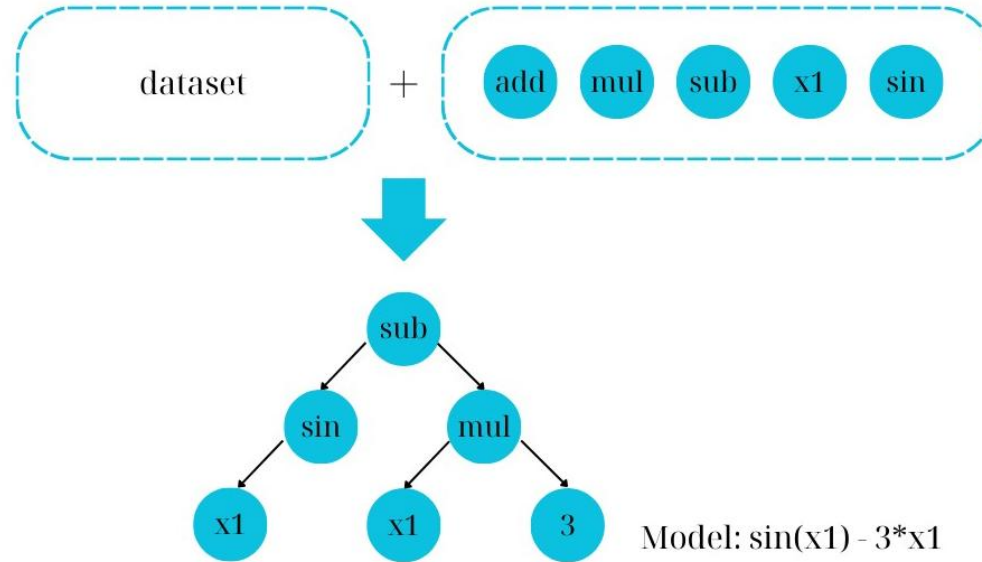
Symbolic Regression-Based Models for Hyperelastic Material

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Symbolic regression



Problem statement

Tasks:

- ▶ generate synthetic data based on the hyperelastic material in a way that can be typically obtained from experiment. The dataset has 3 variables: time, strain values, stress values;
- ▶ conduct a series of comparative calculations to study different accuracy metrics;
- ▶ test the same metrics for two variants of input data: one hysteresis loop and two.

Problem statement

$$W = C_1(\bar{I}_1 - 3) + C_2(\bar{I}_2 - 3) \quad (1)$$

where C_1 and C_2 are empirically determined material constants, and \bar{I}_1 and \bar{I}_2 are the first and second invariant of Finger tensor (the inverse of the left Cauchy-Green tensor).

$$\sigma_{uniax} = 2 \left(\lambda^2 - \frac{1}{\lambda} \right) \left[C_{10} + \frac{C_{01}}{\lambda} \right] \quad (2)$$

where C_{10} and C_{01} are material parameters.

Technical stack

- ▶ gplearn
- ▶ Deep Symbolic Optimization (DSO)
- ▶ PySR
- ▶ symreg
- ▶ QLattice
- ▶ Operon

Hyperparameters

1. Functional of quality that is formulated from the sense of metrics that is used.
2. A policy optimizer, which is an algorithm for optimizing the parameters.
3. Token optimization options.

Error metrics

$$E_1 = -\frac{1}{N} \sum_{i=1}^N \log \left(1 + \left| \frac{\Delta x_i}{\Delta y_i} - \frac{\delta x_i}{\delta y_i} \right| \right)$$

where N is the number of data points, $\frac{\Delta x_i}{\Delta y_i}$ is an implicit derivative estimated from the data, and $\frac{\delta x_i}{\delta y_i}$ is the implicit derivative derived from the candidate implicit equation.

$$E_2 = \frac{1}{1 + \frac{1}{\sigma_y} \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - f(X_i))^2}}$$

where n – dataset size, f – possible approximation function, (X,y) – given dataset, σ_y – standard deviation of the target values.

Input data

- ▶ Function set: ["add", "sub", "mul", "div", "n2"]
- ▶ Number of samples 500000 and 1000000
- ▶ Constants required for data generation:

$$E = 5, \varepsilon_0 = 3.8, \eta = 0.2, C10 = 1.4, C01 = -0.3.$$

- ▶ 1000 iterations

Application of symbolic regression to the approximation of hyperelastic behavior (one loop)

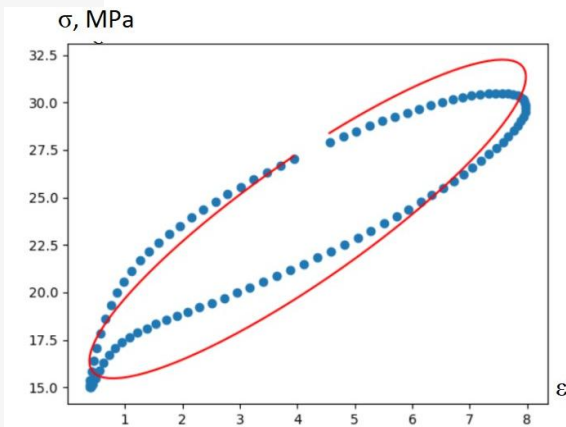


Fig. 1. Approximation using E2 metric without constants search for one hysteresis loop
 $R = 0.7901$

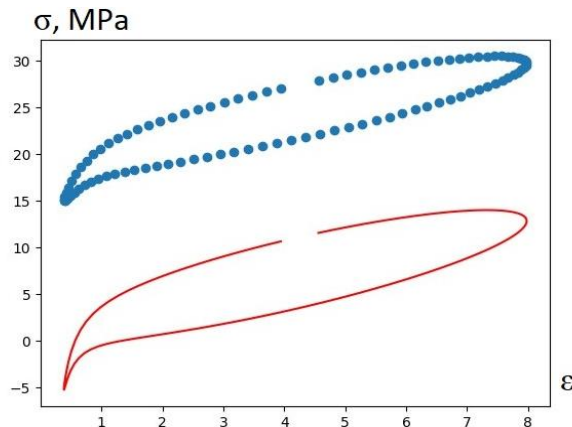


Fig. 2. Approximation using E1 metric without constants search for one hysteresis loop
 $R = 0.7712$

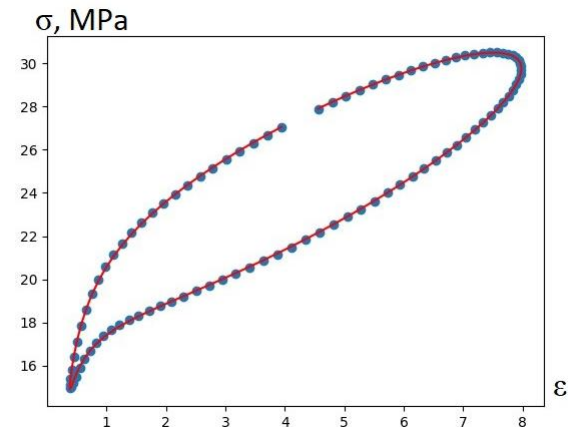


Fig. 3. Approximation using E1 metric with constants search for one hysteresis loop
 $R = 0.9126$

Application of symbolic regression to the approximation of hyperelastic behavior (two loops)

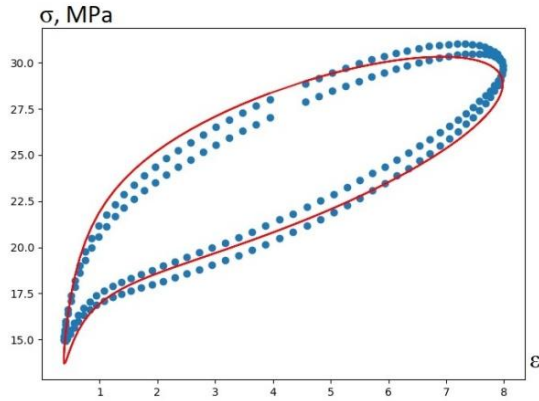


Fig. 4. Approximation using E2
metric without constants
search
 $R = 0.7817$

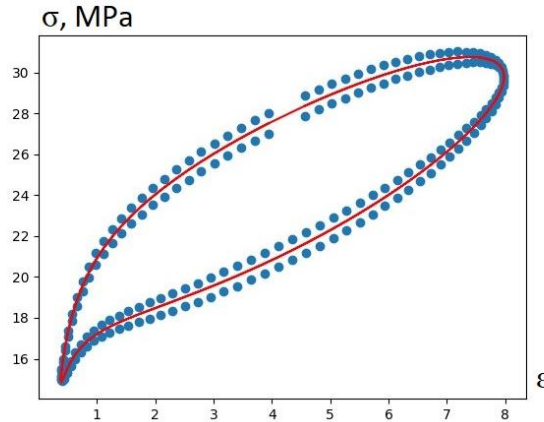


Fig. 5. Approximation using E2
metric with constants search
 $R = 0.7817$

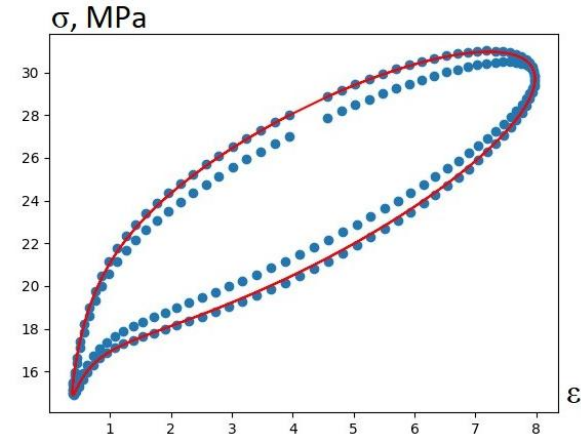


Fig. 6. Approximation using E1
metric with constants search
for 2 hysteresis loops
 $R = 0.8617$

Conclusions

- ▶ We investigated an error metric based on implicit derivatives (E_2) alongside the standard inverse normalized root mean squared error ($NRMSE$, E_1).
- ▶ SR successfully captured the qualitative trends of the material behavior (R-squared up to 0.86), the novel E_1 metric did not consistently outperform the established E_2 metric. However, E_1 offered a visually better fit in specific scenarios (single hysteresis loop without constant search).

Thank you for your attention!



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Accuracy of models in different configurations

	Without const search	With const search
E_1 and 1 loop	$R = 0.7712$	$R = 0.9126$
E_2 and 1 loop	$R = 0.7901$	$R = 0.9933$
E_1 and 2 loops	$R = 0.7817$	$R = 0.8617$
E_2 and 2 loops	$R = 0.8674$	$R = 0.9356$