Frameworks for DCE with gradient based optimisation

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Physics Informed Machine Learning



Data



ML Framework for Engineering Classical physics



ML Framework for Engineering Classical physics + machine learning



ML Framework for Engineering Optimise controls



Optimisation Framework AutoDiff with PyTorch

- Analytical derivatives: chain rule as code runs
- Complex models
- Gradient-based optimisation
- Probabilistic models by re-parameterisation trick





Opportunities for DCE Physics informed neural net: Solve PDEs with NN

- Solve for all possible parameters
- Include data
- Design NN architecture to satisfy physical laws
- Can NNs always find good solutions?
- Uncertainty propagation through PDE
- Model calibration

$$\mathcal{L} = w_{\text{data}} \mathcal{L}_{\text{data}} + w_{\text{PDE}} \mathcal{L}_{\text{PDE}}$$



Opportunities for DCE Application to Digital twins

- Develop or extend a python package
 - Specifically for digital twins
 - Real-time data
 - Probabilistic or deterministic models and NN



Demonstrator Ideas In Mineral Processing



Theory Adapt physics informed neural nets to grains

- NN for grain kinematics (as opposed to PDEs)
 - Grain specific loss function
- Inverse problem: what is the physical law or material?
 - E.g. geotechnical: porosity, permeability, strength
 - E.g. transient response



Applications Predict flow features

- Energy efficiency of mineral processing equipment
- Particle Mixers
- Powder "flowability"
- Granular wear and tear



Rock + slurry. Sinnott, 2017, Minerals Engineering (data 61)

Rotating drum



z = controls e.g. rotating speed

Rotating drum Optimise milling efficiency

- 1. Input: grain size, geometry, ...
- 2. Train NN to results of DEM. Predict: kinematics and/or energy

[Option: Bayesian Variational Inference]

- Add sensors as inputs
- 3. Optimise energy required by autodiff through NN - with gradients



z = controls e.g. rotating speed