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# Rapid Inverse Parameter Inference Using Physics-Informed Neural Network

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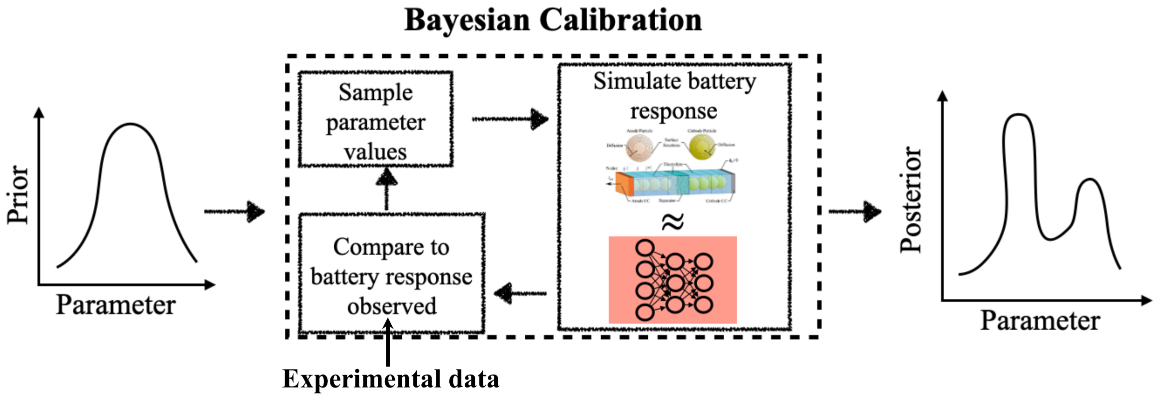
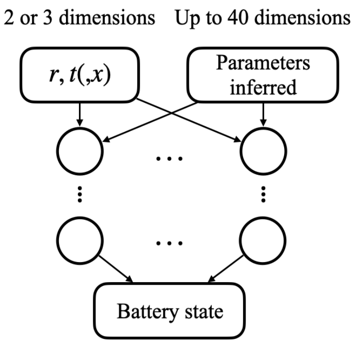
## Uncertainty-aware parameter inference

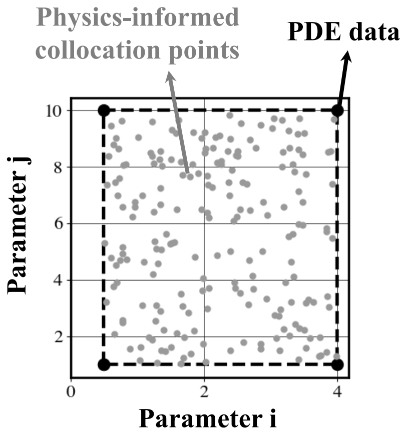
Bayesian parameter inference accounts for uncertainties (experimental noise, sparse observation, model inaccuracy)

A surrogate model is needed to replace expensive physics-based models.




## Data-driven surrogate in a data-poor regime

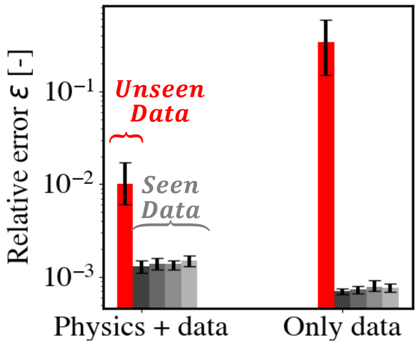



The surrogate's input is high-dimensional and cannot solely rely on synthetic PDE data.

## Physics-informed surrogate in the low-data limit

Paper




Physics-informed training ensures accurate predictions where synthetic data is not available

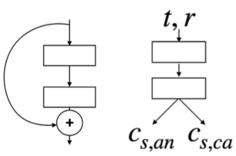
Using synthetic data is preferable if it is available

## Physics-informed surrogate in the zero-data limit

Paper

Code

**Highest-performing architectures**



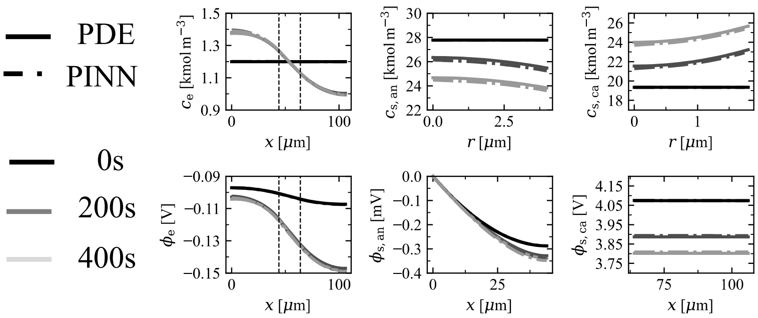

**Multifidelity training**

P2D surrogate = SPM surrogate + correction surrogate

**Enforce secondary conservation**

$$\int \mathrm{j}\, \mathrm{dx} = \frac{\pm \mathrm{I}}{\mathrm{A}}$$

$$\frac{\mathrm{d}}{\mathrm{dt}} \int \varepsilon_e c_e = 0$$




## Computational speed-up

| Model | Forward simulations for MCMC | MCMC computational time |
|---|---|---|
| SPM PDE | 30 s | 12.6 $\times 10^6$s |
| PINN SPM surrogate | 314 $\mu$s | 44 s |
| P2D PDE | 360 s | 151.2 $\times 10^6$s |
| PINN P2D surrogate | 364 $\mu$s | 51 s |

$10^5 - 10^6$ Speed-up for Bayesian inference tasks

## Next steps

1) Calibration against experimental data

2) Extension to other relevant operating modes (Constant voltage, Constant Power, dynamic current)

3) Further calibration acceleration by reducing the inferred parameter space

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