Physics-Informed Neural ODEs (PINODE)

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Reduced-Order Models

Schematics, terminology, notation

Variations of ROMs

Linear, nonlinear, citations

Physics-Informed Loss

Definition of Physics-informed ML.
Derivation of PI loss through chain rule.
Problem with evaluating RHS of differential equations.
Interpretation with cross-borrowing strength.

Physics-Informed Koopman Networks

Linear latent dynamics
Paper
Not a rom so not suitable for downstream tasks.

Physics-Informed Neural ODEs (PINODE)

Nonlinearity in latent space - require a lot of data - picky to initialization - good interpolation bad extrapolation

PINODE Results on Burgers

Add PI loss => Fixes most of the issues (example with Burgers) Points learned - Inform the model about unseen conditions Paper reference

PINODE Active

> PIKN: "we use it and it works" > PINODE: "this is how you need to use it right" > PINODE-Active: can we use it right automatically?
Loop scheme

PINODE Active Results

Best result (Burgers)

PINODE-CS

Application of the above Loss and setup

PINODE-CS Results

Results on Burgers Maybe results on a harder problem

References

References: