



Physics Informed Neural Networks – for Identification and Forecasting of Chaotic Dynamics

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Introduction

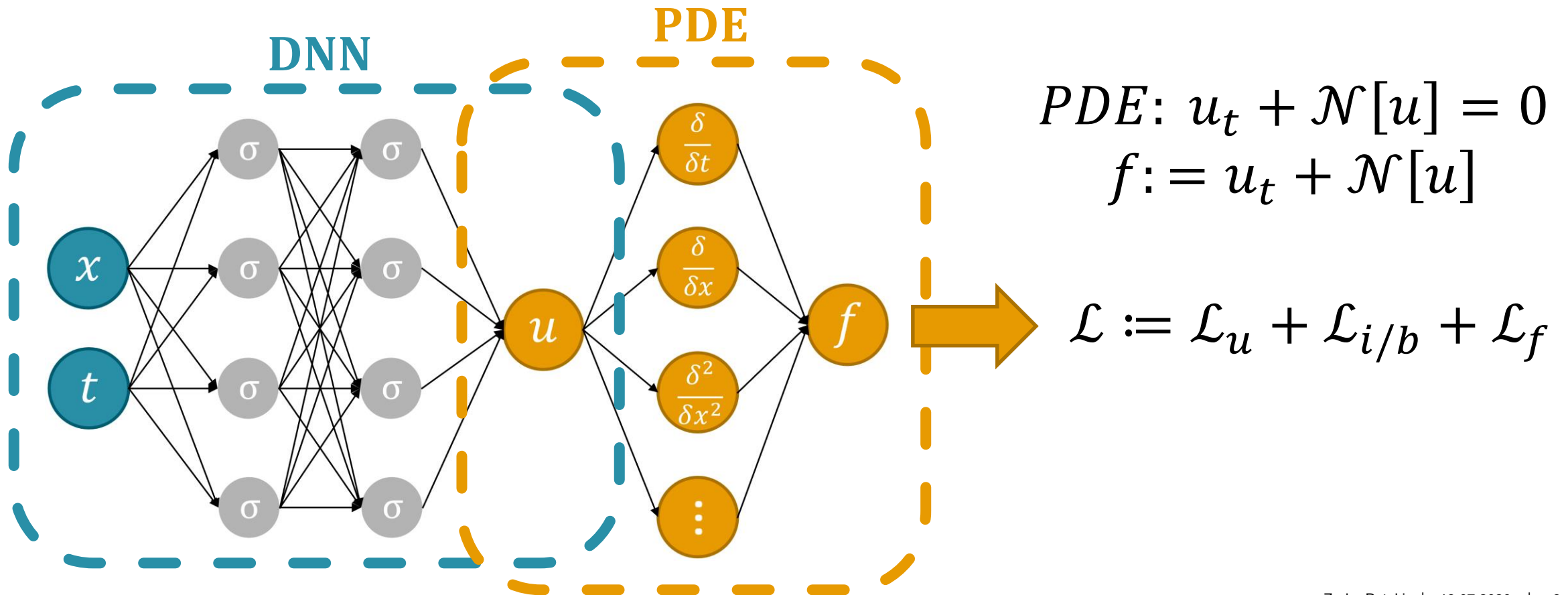
- Chaotic dynamics in nature



https://en.wikipedia.org/wiki/Chaos_theory

Introduction

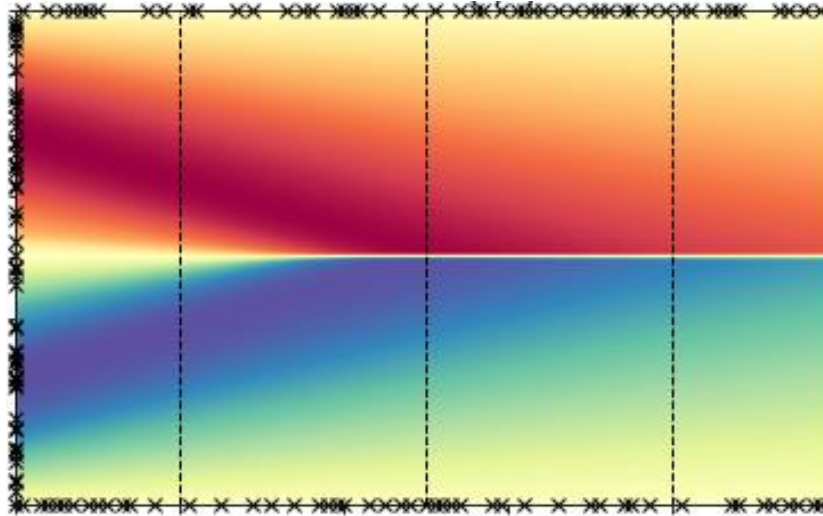
- Why physics informed neural networks?



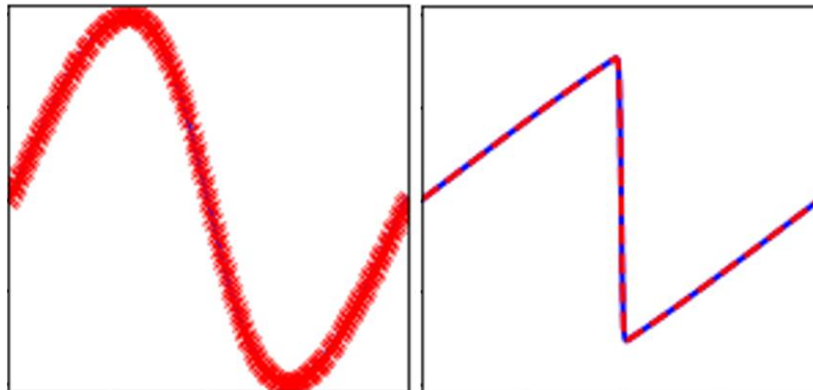
Goal of Thesis

Inference

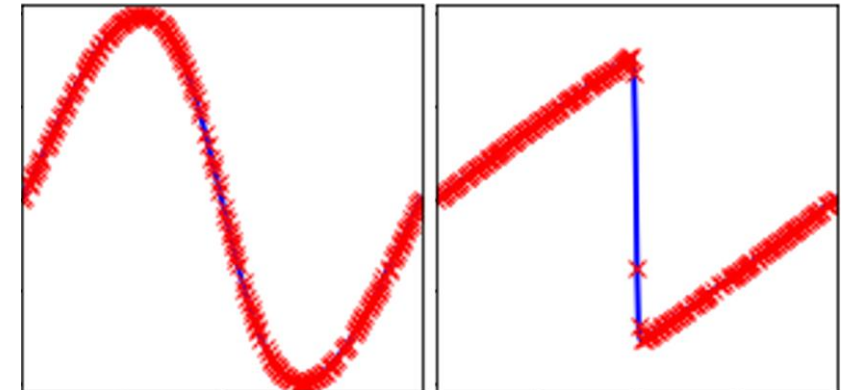
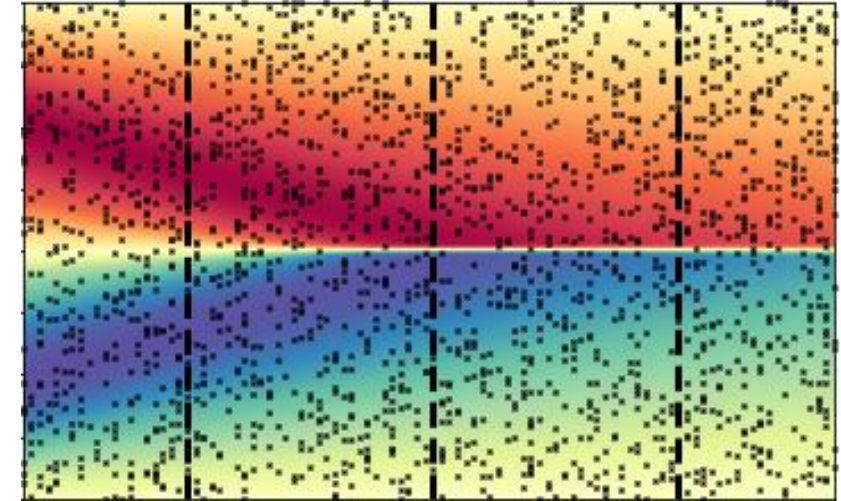
Continuous-time



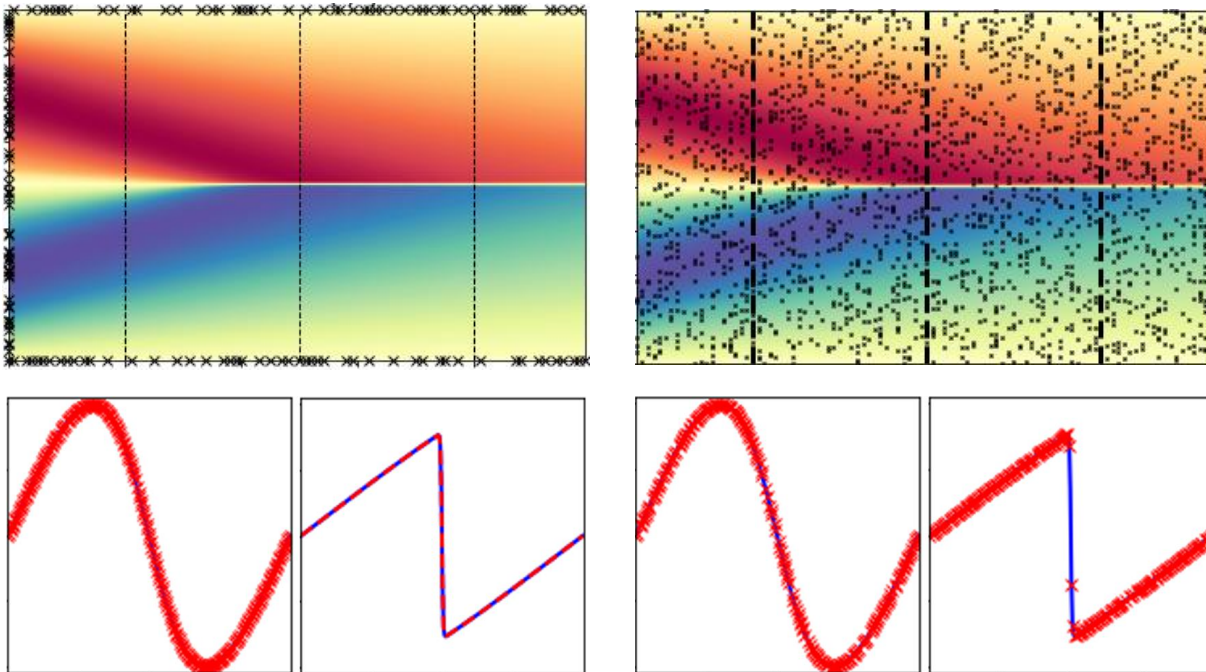
Discrete-time



Identification



Goal of Thesis

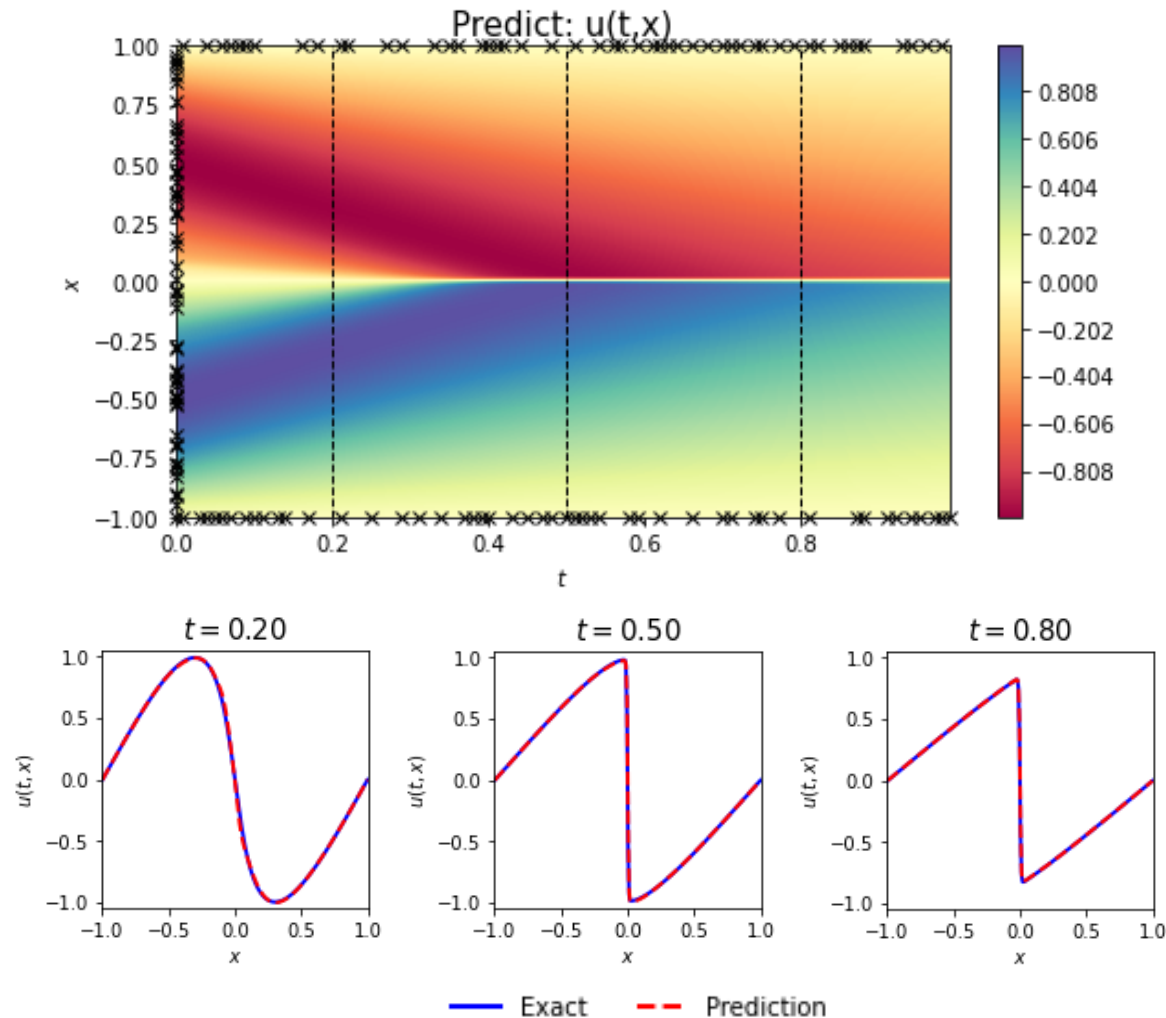


Apply to more complex examples

- Nonlinear Schrodinger equation
- Kuramoto-Sivashinsky equation

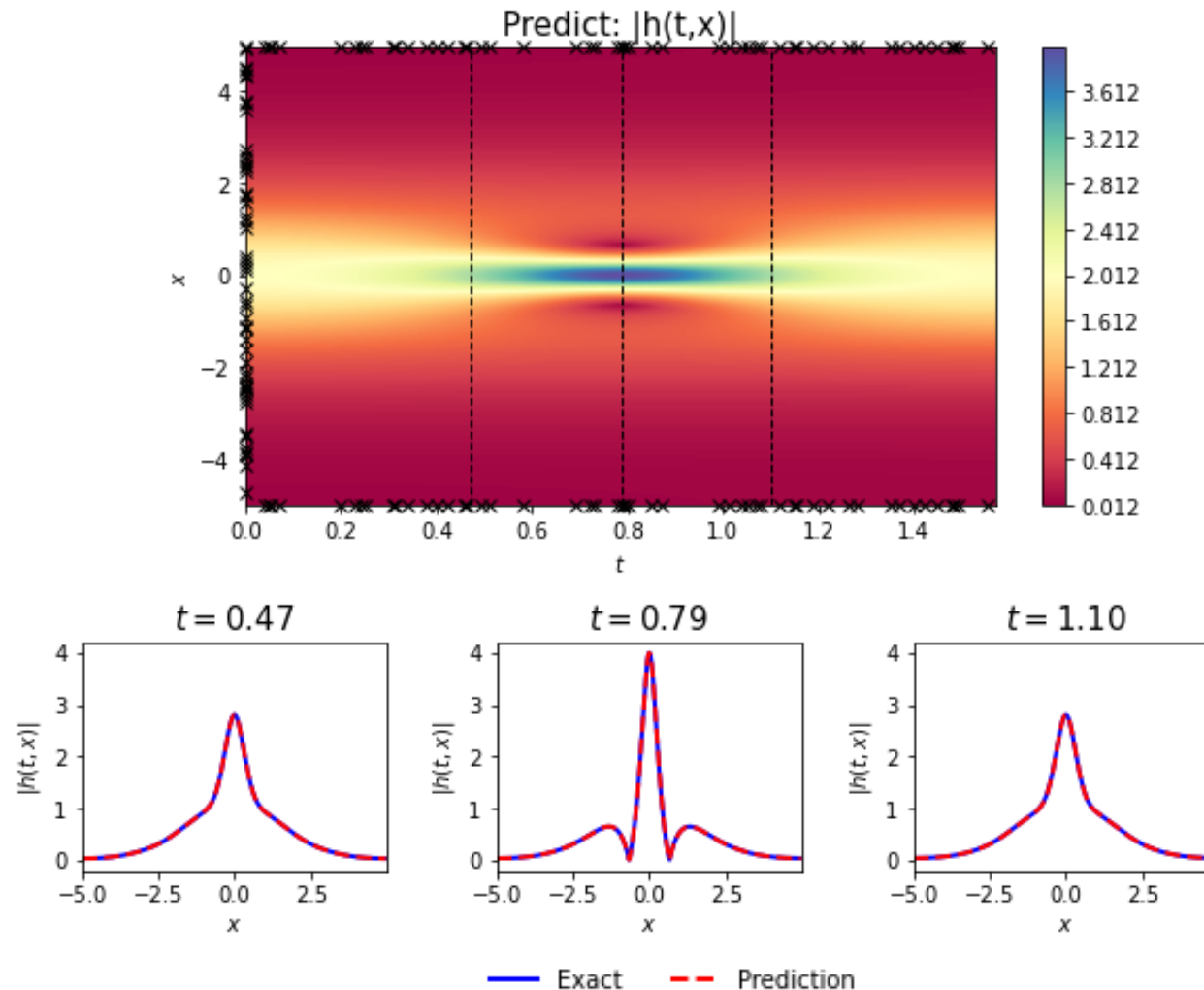
Continuous-time Inference – The Burgers equation

$$u_t + uu_x - (0.01/\pi)u_{xx} = 0$$



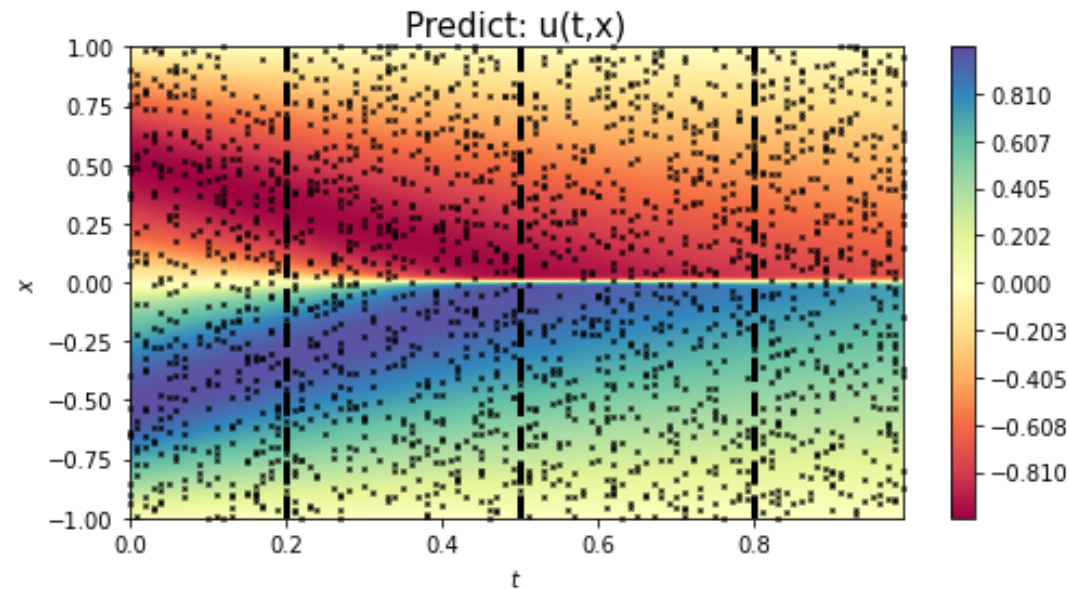
→ The Nonlinear Schrödinger equation

$$ih_t + 0.5h_{xx} + |h|^2h = 0$$



Continuous-time Identification – The Burgers Equation

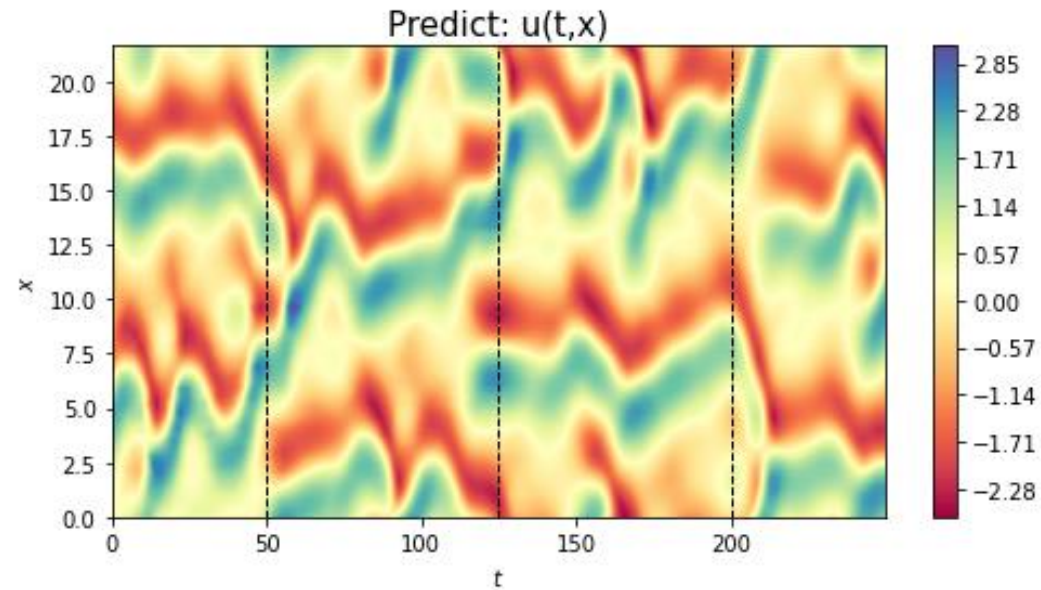
$$u_t + \lambda_1 \cdot uu_x - \lambda_2 \cdot u_{xx} = 0$$



- Target: $u_t + uu_x - (0.01 / \pi)u_{xx} = 0$
- Prediction: $u_t + 0.97 \cdot uu_x - (0.015 / \pi)u_{xx} = 0$

→ The Kuramoto-Sivashinsky Equation

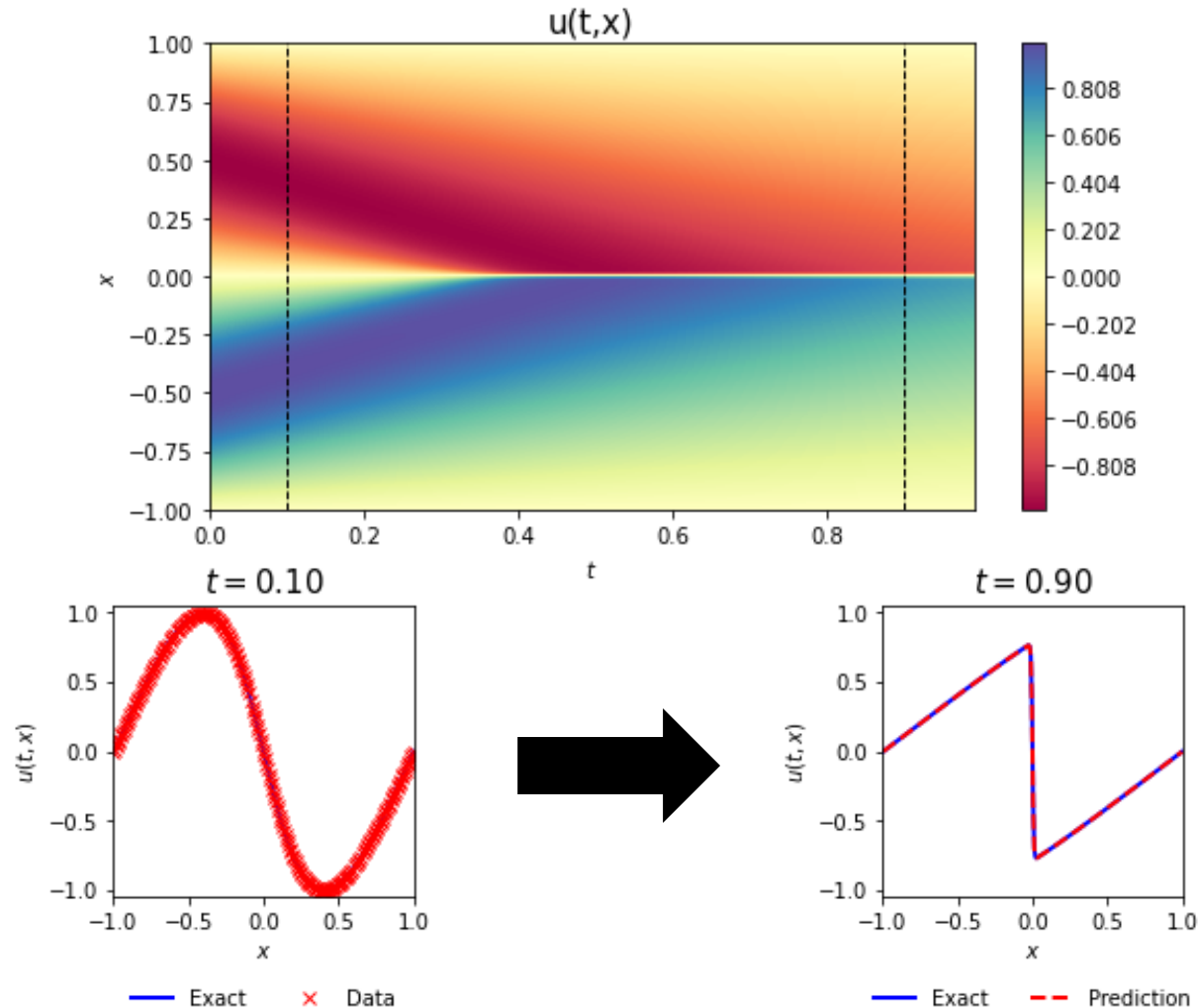
$$u_t + \lambda_1 \cdot uu_x + \lambda_2 \cdot u_{xx} + \lambda_3 \cdot u_{xxxx} = 0$$



- Target: $u_t + uu_x + u_{xx} + u_{xxxx} = 0$
- Prediction: $u_t + 0.093 \cdot uu_x - 0.055 \cdot u_{xx} - 0.001 \cdot u_{xxxx} = 0$

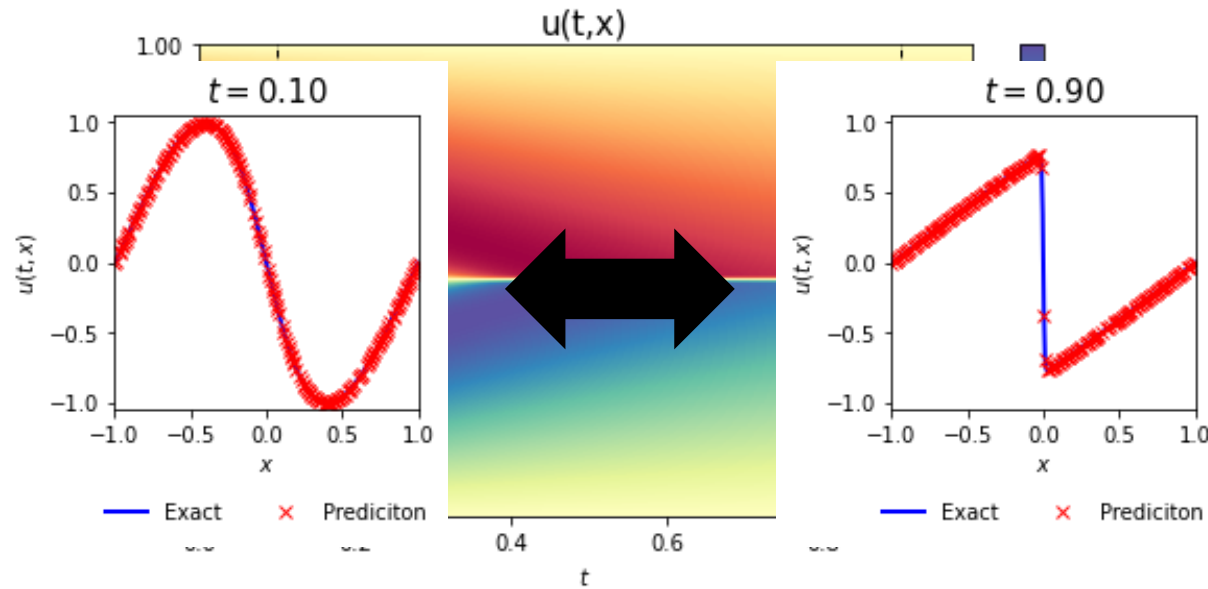
Discrete-time Inference – The Burgers Equation

$$u_t + uu_x - (0.01/\pi)u_{xx} = 0$$



Discrete-time Identification – The Burgers Equation

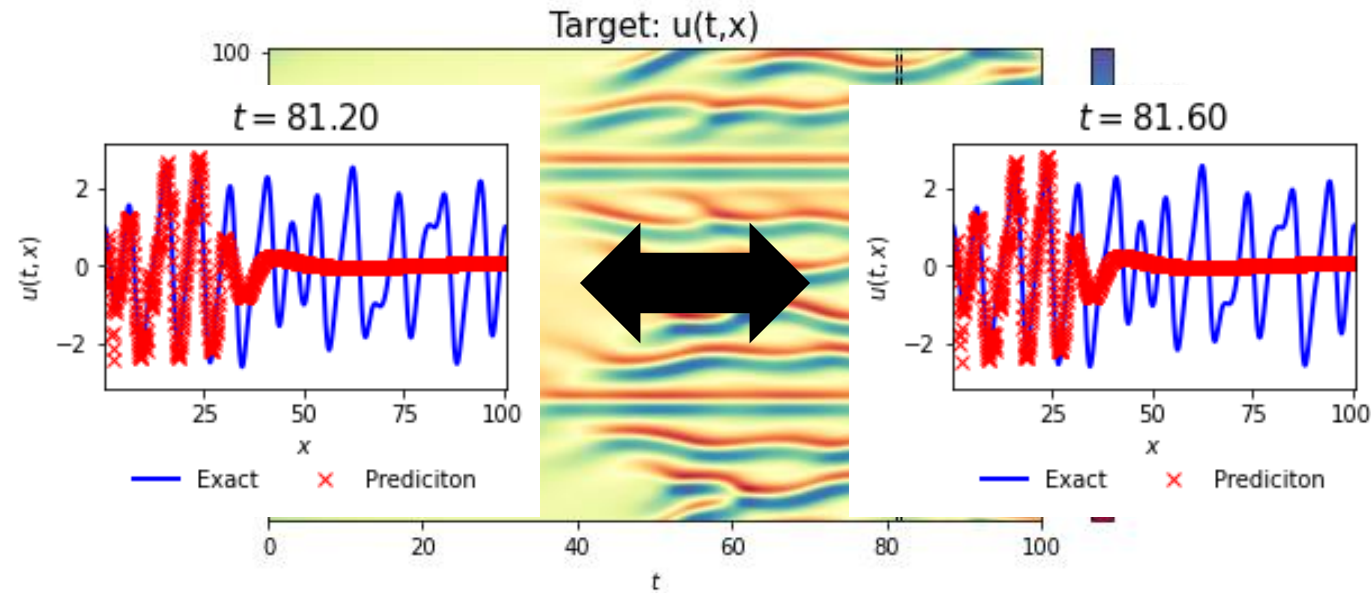
$$u_t + \lambda_1 \cdot uu_x - \lambda_2 \cdot u_{xx} = 0$$



- Target: $u_t + uu_x - (0.01 / \pi)u_{xx} = 0$
- Prediction: $u_t + 0.9998 \cdot uu_x - (0.012 / \pi)u_{xx} = 0$

→ The Kuramoto-Sivashinsky Equation

$$u_t + \lambda_1 \cdot uu_x + \lambda_2 \cdot u_{xx} + \lambda_3 \cdot u_{xxxx} = 0$$



- Target: $u_t + uu_x + u_{xx} + u_{xxxx} = 0$
- Prediction: $u_t + 0.059 \cdot uu_x + 0.001 \cdot u_{xx} - 2.2 \cdot 10^{-7} \cdot u_{xxxx} = 0$

Summary and Outlook

- Physics informed neural networks (PINNs) could solve problems with minimal amounts of data
- The frameworks could be applied to different problems involving different partial differential equations (PDEs)
- However, they struggled to solve problems involving higher order PDEs
 - Implementing PINNs in examples where chaotic dynamics are present will require more research



Thank you for your interest & attention!

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