# Physics-informed neural networks

### Pause and Ponder

- 3. What activation function should I choose when using 1 hidden layer NN to approximate functions?
  - E.g. A pulse function  $\rightarrow$  use tanh, sigmoid rather than sin, cos

4. Where should I place the collocation points?

Nabian et al., 2021: Sampling the collocation points according to a distribution proportional to the loss function will improve the convergence behavior of the PINNs training.

### Empirical learning vs PINN

Empirical learning

Need training data of  $u_i(x_i, t_i)$  to approximate u(x, t)

#### PINN

Only need training data (or knowledge) at IC, BC. u(x,t) within the x,t domain can be predicted without training data within the domain (just like a PDE solver)

- Application 1: Prediction of solution for a well-posed problem (this is what a traditional numerical solver can do)
  - Given an eqn + BC + IC and parameters  $\lambda$ , what's the model prediction?
- Application 2: Prediction of solution when data is available within the domain but not at the IC, BC (difficult for a traditional numerical solver!)
   Given an eqn and parameters λ, what's the model prediction best describes the data?
- Application 3: Data-driven discovery of unknown parameters (difficult for a traditional numerical solver!)

What are the parameters  $\lambda$  that best describe the data and the eqn?

## E.g., Nonlinear Schrodinger equation

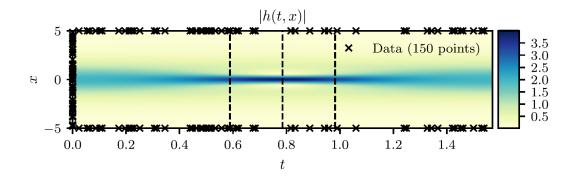
#### Problem statement

$$ih_t + 0.5h_{xx} + |h|^2 h = 0$$
,  $x \in [-5, 5]$ ,  $t \in [0, \pi/2]$ ,

*IC*:  $h(0, x) = 2 \operatorname{sech}(x)$ ,

BC: h(t, -5) = h(t, 5),

$$h_X(t, -5) = h_X(t, 5),$$



#### **Training data (from ground truth):**

$$\{x_0^i, h_0^i\}_{i=1}^{N_0}$$

#### **Collocation points:**

$$\{t_b^i\}_{i=1}^{N_b} \quad \{t_f^i, x_f^i\}_{i=1}^{N_f}$$

#### **Physics equations:**

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

#### Loss function:

$$MSE_{0} = \frac{1}{N_{0}} \sum_{i=1}^{N_{0}} |h(0, \mathbf{x}_{0}^{i}) - \mathbf{h}_{0}^{i}|^{2}, \quad \textbf{(1) IC}$$

$$MSE_{b} = \frac{1}{N_{b}} \sum_{i=1}^{N_{b}} \left( |h^{i}(t_{b}^{i}, -5) - h^{i}(t_{b}^{i}, 5)|^{2} + |h_{x}^{i}(t_{b}^{i}, -5) - h_{x}^{i}(t_{b}^{i}, 5)|^{2} \right)$$

$$\textbf{(2) BC}$$

$$MSE_f = \frac{1}{N_f} \sum_{i=1}^{N_f} |f(t_f^i, x_f^i)|^2$$
. (3) Eqn

### E.g., Nonlinear Schrodinger equation

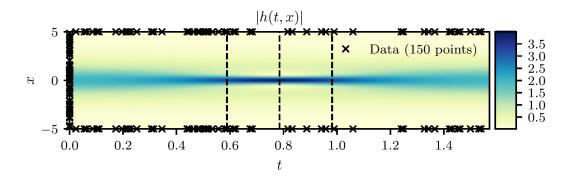
#### Problem statement

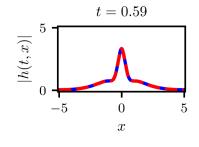
$$ih_t + 0.5h_{xx} + |h|^2 h = 0, \quad x \in [-5, 5], \quad t \in [0, \pi/2],$$

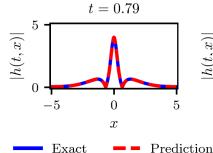
*IC*:  $h(0, x) = 2 \operatorname{sech}(x)$ ,

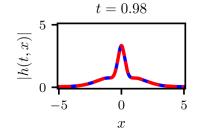
BC: h(t, -5) = h(t, 5),

$$h_X(t, -5) = h_X(t, 5),$$









#### **Trick**

$$h = u + iv$$

eqn becomes

$$i(u+iv)_t + 0.5(u_{xx}+iv_{xx}) + (u^2+v^2)(u+iv) = 0$$

IC:  $u + iv(0, x) = 2\operatorname{sech}(x)$ 

BC: 
$$u(t,-5) = u(t,-5)$$
,  $v(t,-5) = v(t,-5)$   
 $u_x(t,-5) = u_x(t,-5)$ ,  $v_x(t,-5) = v_x(t,-5)$ 

**NN input:** x,t

**NN output:** u,v

NN architecture: 5 layers 100 neurons per layer

**Data points:** 50 pts at t=0 (2sech(x))

Collocation points: 50 pts at x=5, x=-5,

20000 pts within the domain

### Schrodinger equation coding exercise

• TF1.14

layers = [2, 100, 100, 100, 100, 2]

Iterations: 2000

