

Physics-informed neural networks

What is a PINN

- NN constraints by physical laws
Instead of fitting the input-output relationship **empirically**, the PINN learning is **guided by physics**.
- Utilize the NN's representation power (a universal function approximator)
- Derivatives of $u(x,t)$ w.r.t x and t can be calculated analytically because $u(x,t)$ is exact!

Example of solving PDEs: Diffusion equation

$$\frac{\partial u}{\partial t} = a \frac{\partial^2 u}{\partial x^2}$$

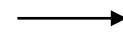
1st order derivative in time t

2nd order derivatives in space x

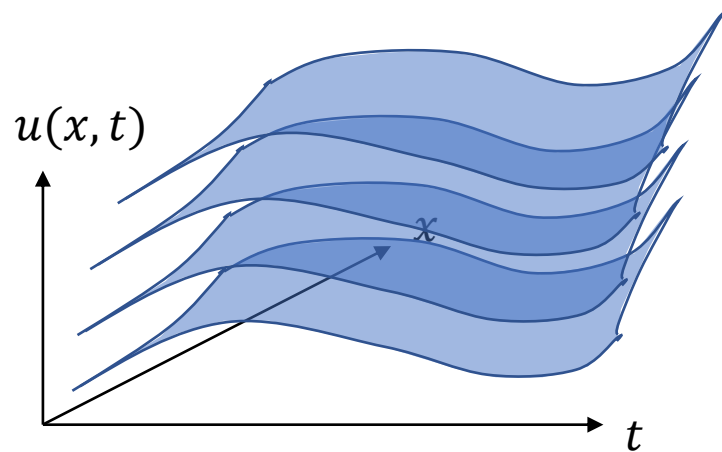


1 initial condition

2 boundary conditions



GOAL: solve for $u(x, t)$



Need to give boundary and initial conditions to properly find a unique surface $u(x, t)$

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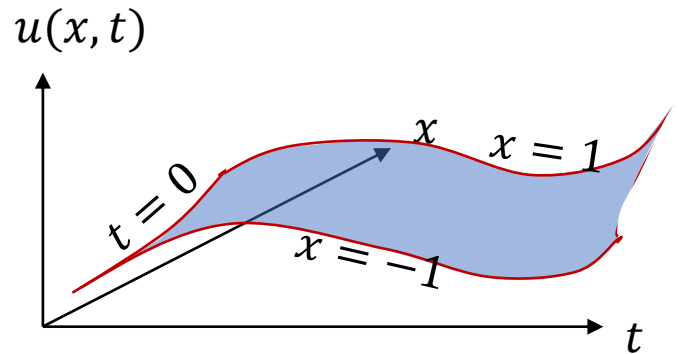


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GOAL: solve for $u(x, t)$



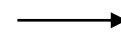
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Example of solving PDEs: Diffusion equation

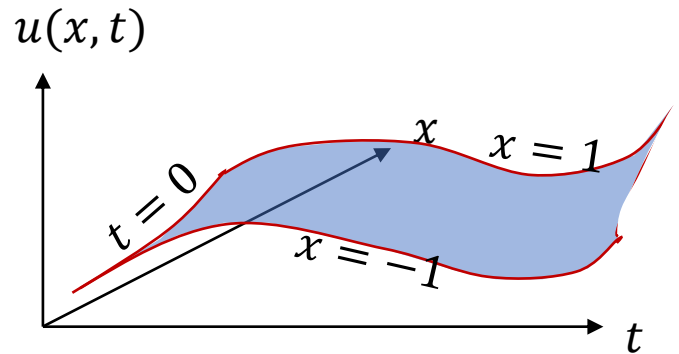
$$\frac{\partial u}{\partial t} = a \frac{\partial^2 u}{\partial x^2}$$

Initial condition: $u(t = 0, x) = f(x)$

Boundary conditions: $u(t, x = -1) = u(t, x = 1) = 0$



GOAL: solve for $u(x, t)$



Need to give boundary and initial conditions to properly find a unique surface $u(x, t)$

Solve it numerically

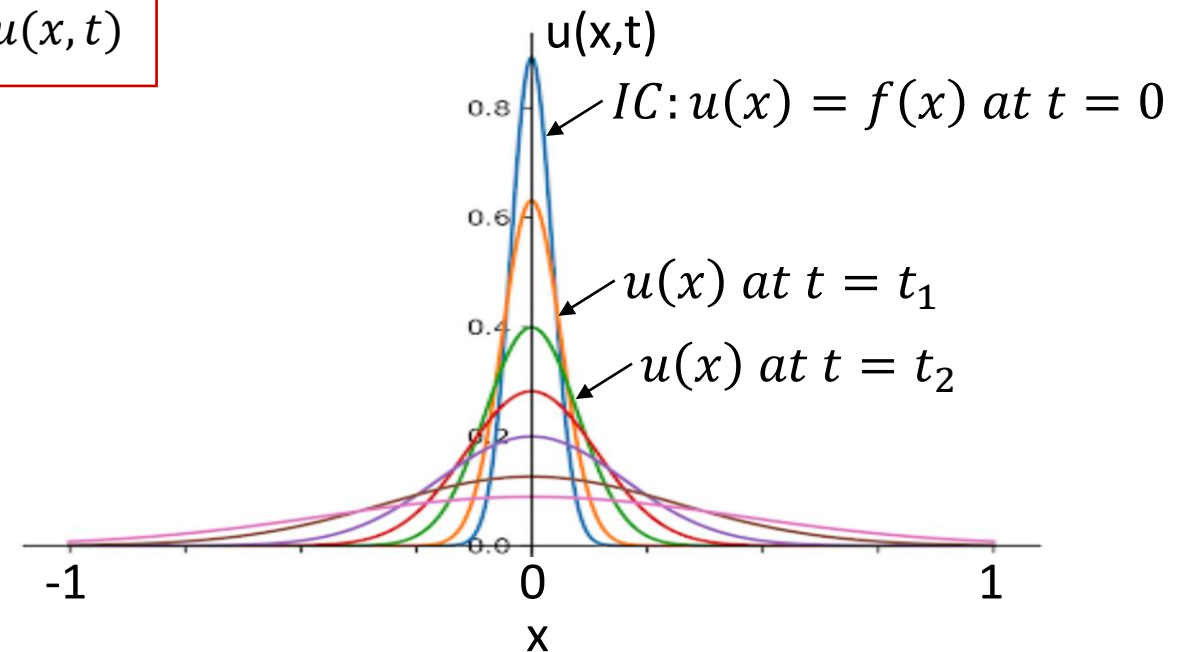
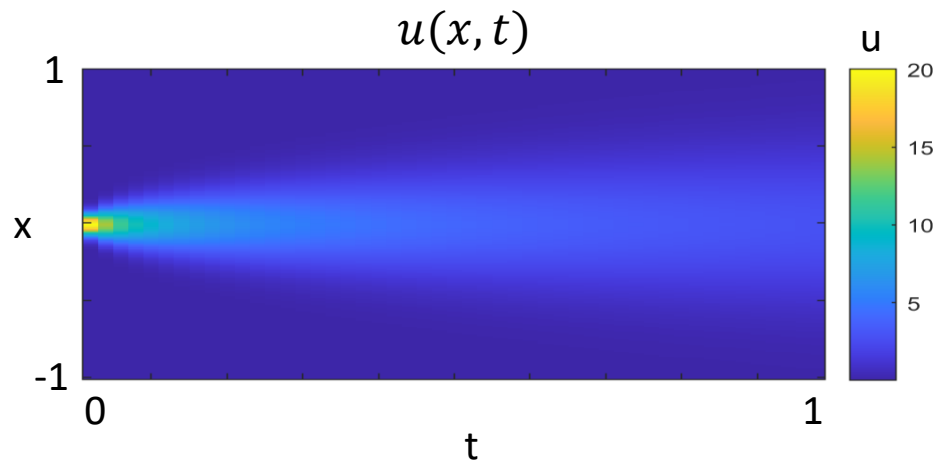
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→ *GOAL: solve for $u(x, t)$*

Solved numerically

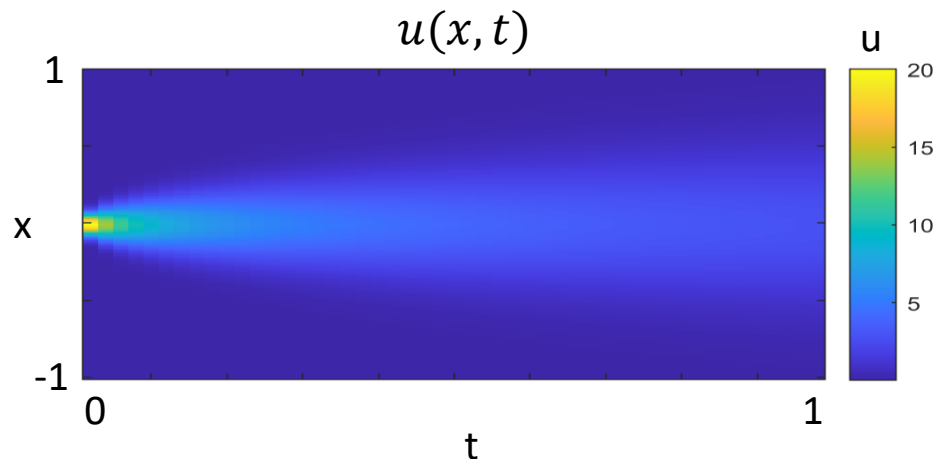


What do we need if we want to find $u(x,t)$ with a NN?

1. Learn u empirically with data

NN can fit any smooth and continuous functions!

Give some sample data points and fit the surface $u(x,t)$



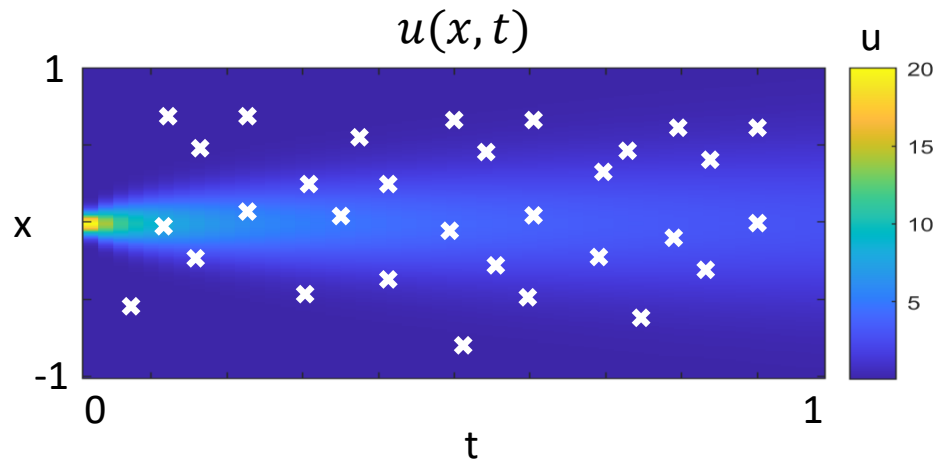
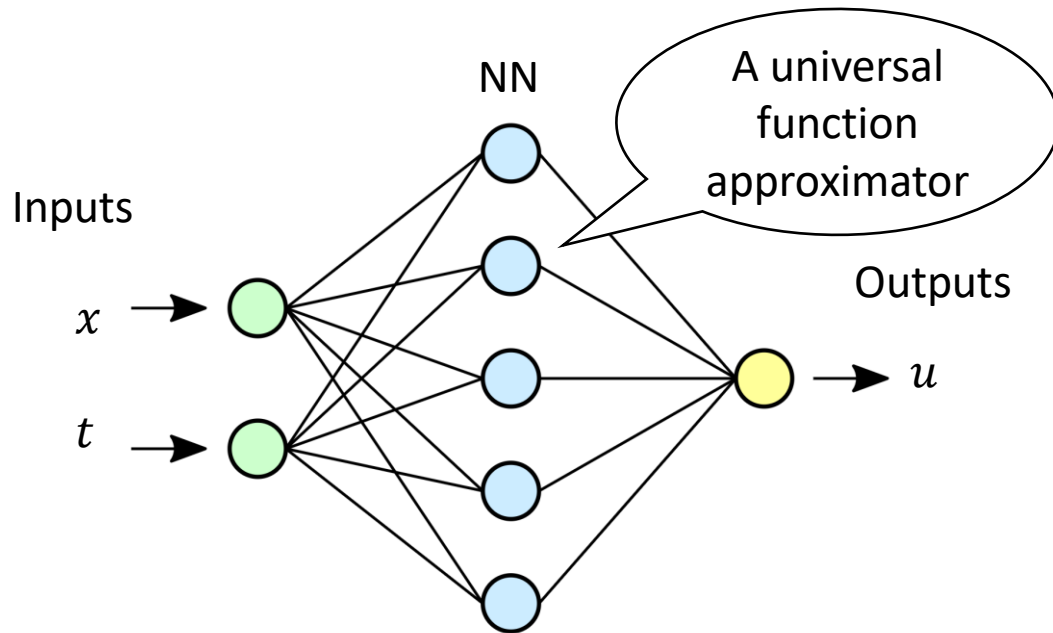
2. Learn u with physics equation + ICs + BCs

$$\frac{\partial u}{\partial t} = a \frac{\partial^2 u}{\partial x^2}$$

Initial condition: $u(t=0, x) = f(x)$

Boundary conditions: $u(t, x=-1) = u(t, x=1) = 0$

Learn u empirically



Training data (ground truth):

input: $t_i, x_i, \quad i = 1 \dots N$
output: $u_i, \quad i = 1 \dots N$

NN Prediction:

input: $t_i, x_i, \quad i = 1 \dots N$
output: $u_{pred}(t_i, x_i), \quad i = 1 \dots N$

What would be the loss function?

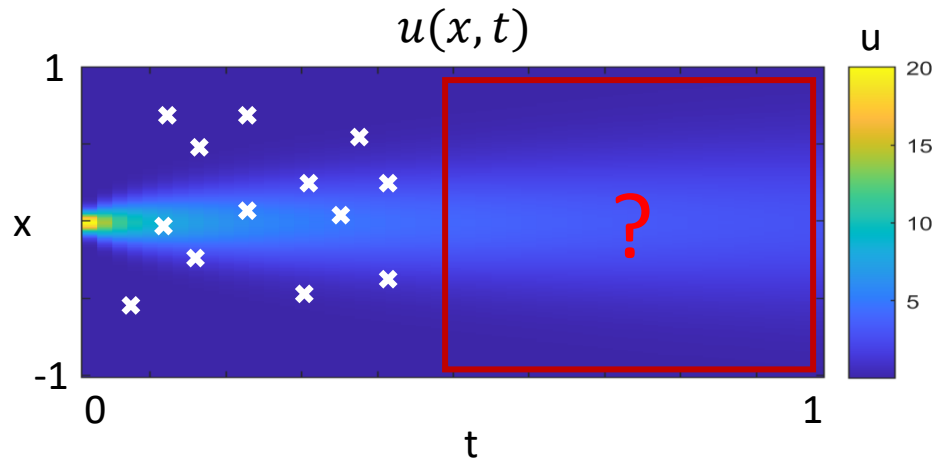
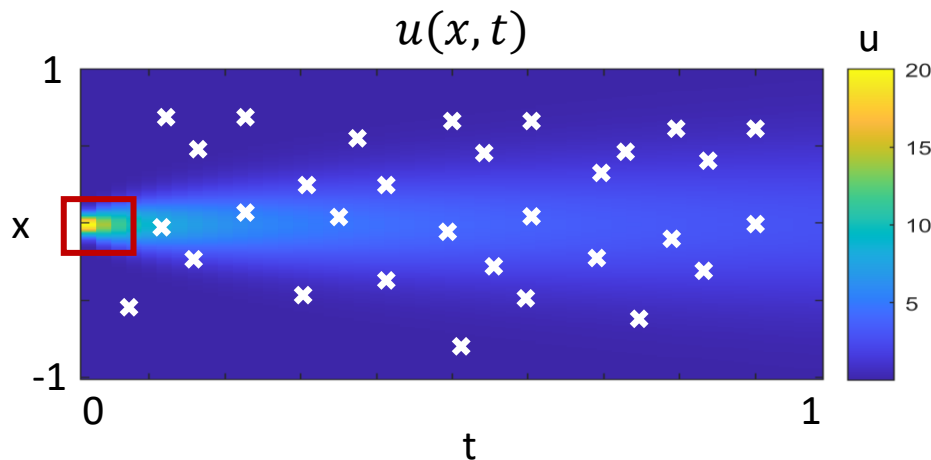
Data loss:

$$\text{minimize} \quad \frac{1}{N} \sum_i^N |u_i - u_{pred}(t_i, x_i)|^2$$

GOAL: Find NN that minimizes the difference between ground truth and prediction (the loss function)

Problems of empirical learning

- NN will need lots of u training data to well approximate $u(x,t)$.
- The learnt $u(x,t)$ cannot be generalized to new t and x domains!



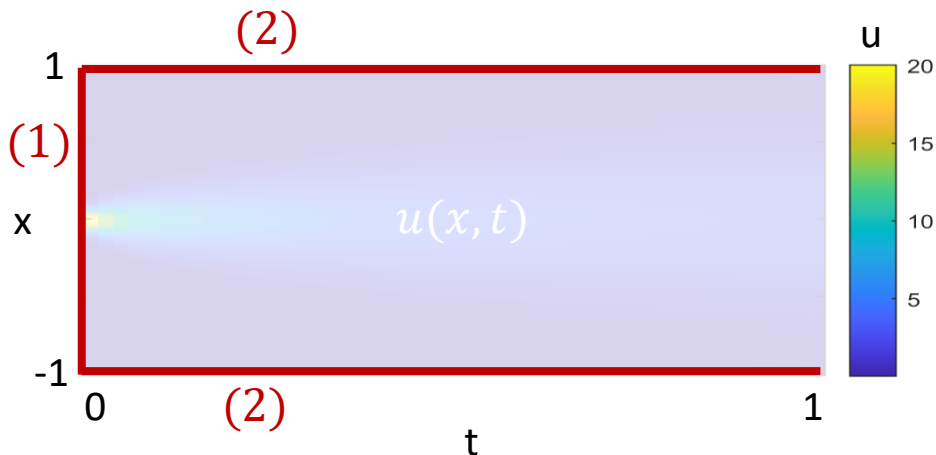
Problems of empirical learning

- NN will need lots of u training data to well approximate $u(x,t)$.
- The learnt $u(x,t)$ cannot be generalized to new t and x domains!
- Can we use **physical constraints** to reduce the training data needed to make NN approximate $u(x,t)$?
- Can we use **physical constraints** to help NN generalize to new t and x domains?

Learn u with physics equation + ICs + BCs

$$(3) \frac{\partial u}{\partial t} = a \frac{\partial^2 u}{\partial x^2} \quad \begin{array}{l} (1) \text{ Initial condition: } u(t=0, x) = f(x) \\ (2) \text{ Boundary conditions: } u(t, x=-1) = u(t, x=1) = 0 \end{array}$$

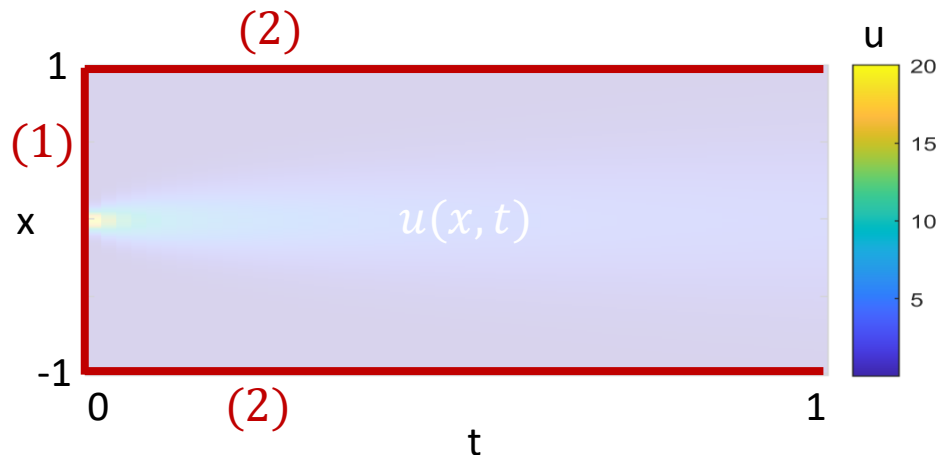
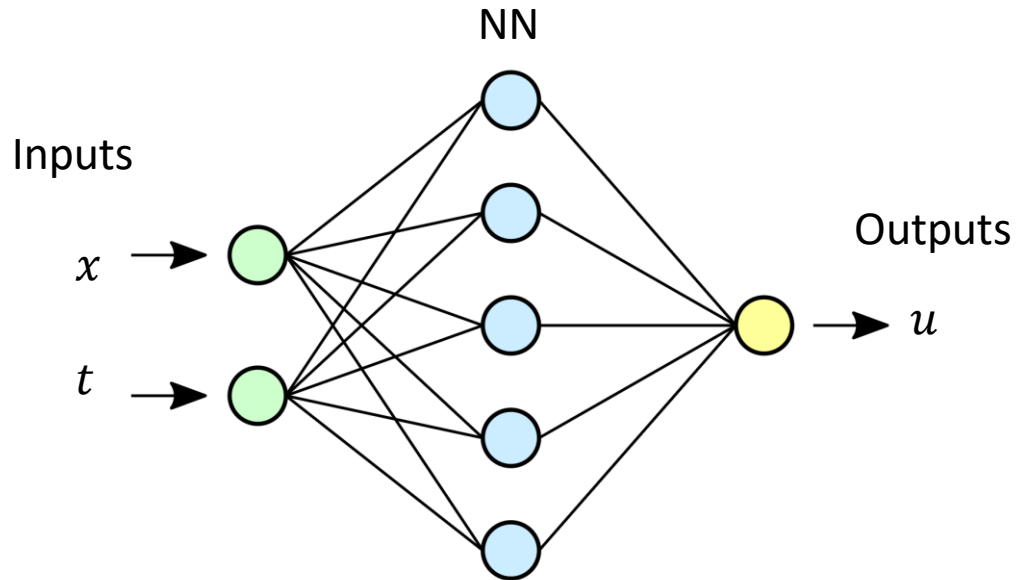
→ GOAL: solve for $u(x, t)$



Mathematically, the information we need to get $u(x, t)$ is **(1) ICs + (2) BCs + (3) physics equation**.

Instead of traditional numerical solver, can we use a NN to predict $u(x, t)$ using **(1), (2), (3)**?

Learn u with physics equation + ICs + BCs



Use NN to search for a surface that satisfies
(1) ICs + (2) BCs + (3) physics equation.

1. Initial $NN(x, t) = u(x, t)$. x, t are inputs, u is output
2. For a NN, all derivatives of u w.r.t x and t can be calculated analytically because $u(x, t)$ is exact!

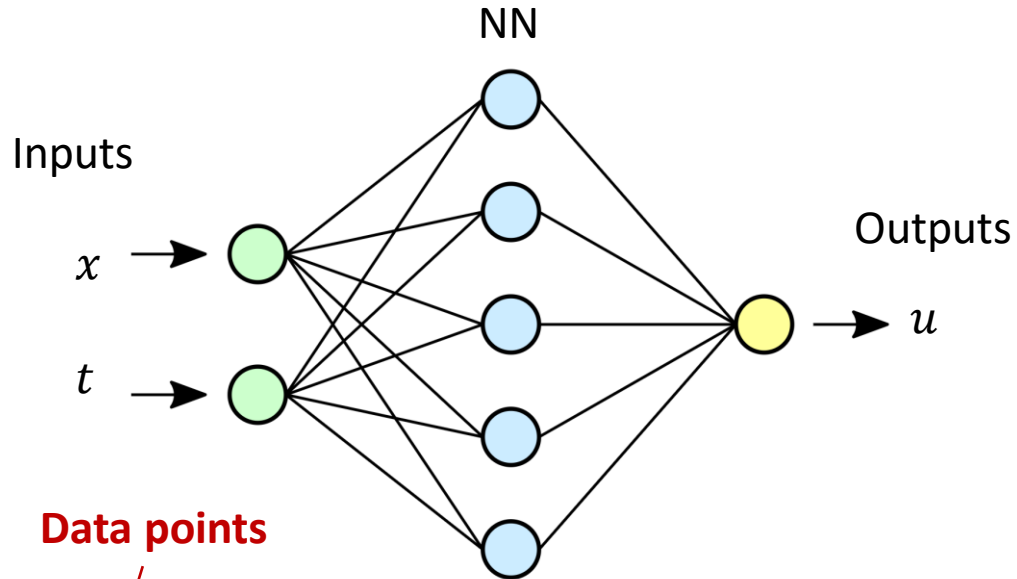
3. We can calculate $\frac{\partial u}{\partial t}, \frac{\partial^2 u}{\partial x^2}$

4. In the cost function, minimize $\left[\frac{\partial u}{\partial t} - a \frac{\partial^2 u}{\partial x^2} \right]^2$

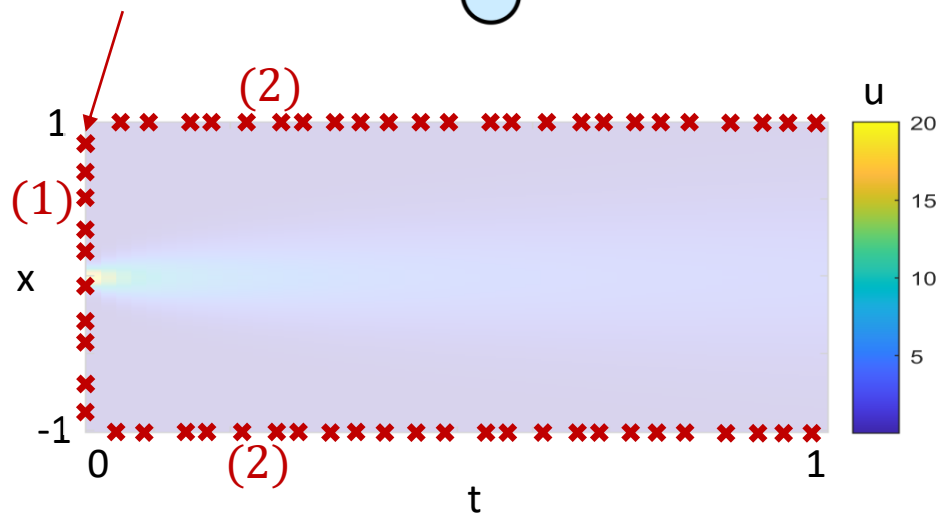
Turn the problem into an optimization problem!

Physics-informed NN

Training data (ground truth):



Data points

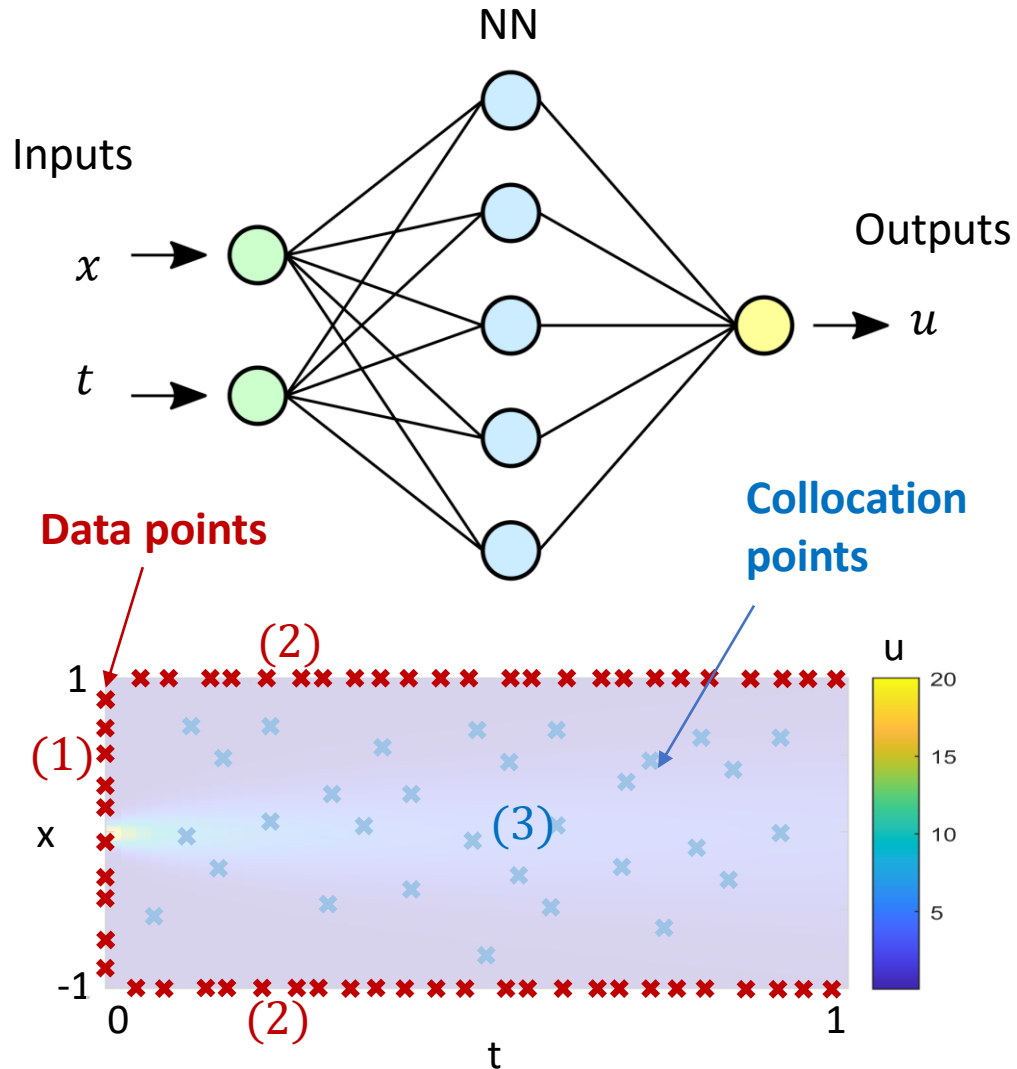


What would be the loss function?

$$\begin{aligned} \text{minimize } & \frac{1}{N} \sum_i |u_0^i - u_{pred}(t=0, x_i)|^2 \quad (1) \text{ IC} \\ \text{minimize } & \frac{1}{M} \sum_j |u_{lb}^j - u_{pred}(t_j, x=-1)|^2 \\ & + \frac{1}{M} \sum_j |u_{ub}^j - u_{pred}(t_j, x=1)|^2 \quad (2) \text{ BC} \end{aligned}$$

GOAL: Find NN that minimizes the loss function

Physics-informed NN



Q: How to incorporate physics equation in the loss function?

$$(3) \quad \frac{\partial u}{\partial t} = a \frac{\partial^2 u}{\partial x^2} \longrightarrow \frac{\partial u}{\partial t} - a \frac{\partial^2 u}{\partial x^2} = 0$$

Recall: $NN(x,t) = u(x,t)$ is a smooth, analytical function
 $\frac{\partial u}{\partial t}, \frac{\partial^2 u}{\partial x^2}$ can be directly calculated at the collocation points.

What would be the loss function?

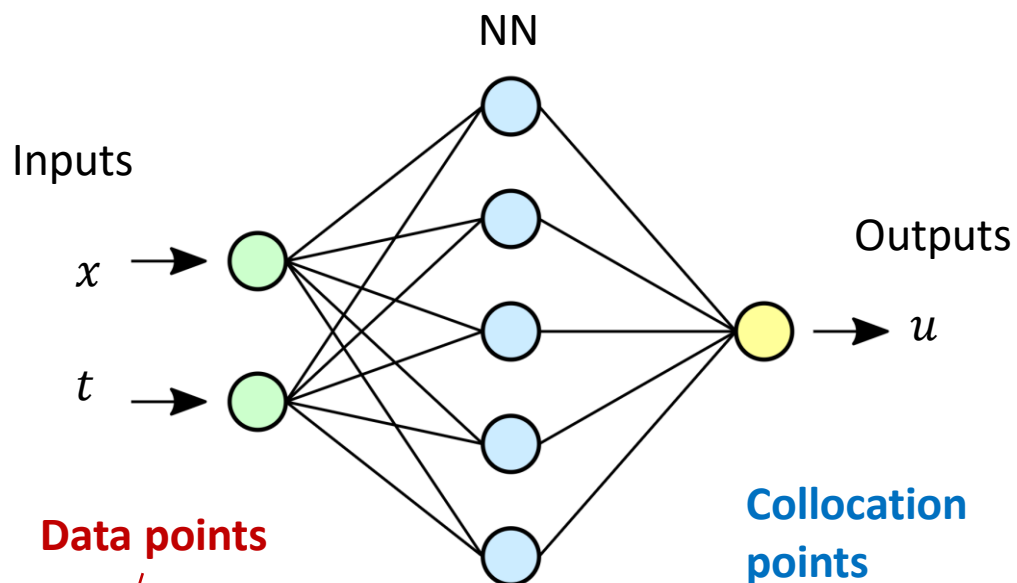
Equation loss:

$$\text{minimize} \quad \frac{1}{N_f} \sum_k \left| \frac{\partial u_{pred}^k}{\partial t} - a \frac{\partial^2 u_{pred}^k}{\partial x^2} \right|^2 \quad (3) \text{ Eqn}$$

GOAL: Find NN that minimizes the loss function

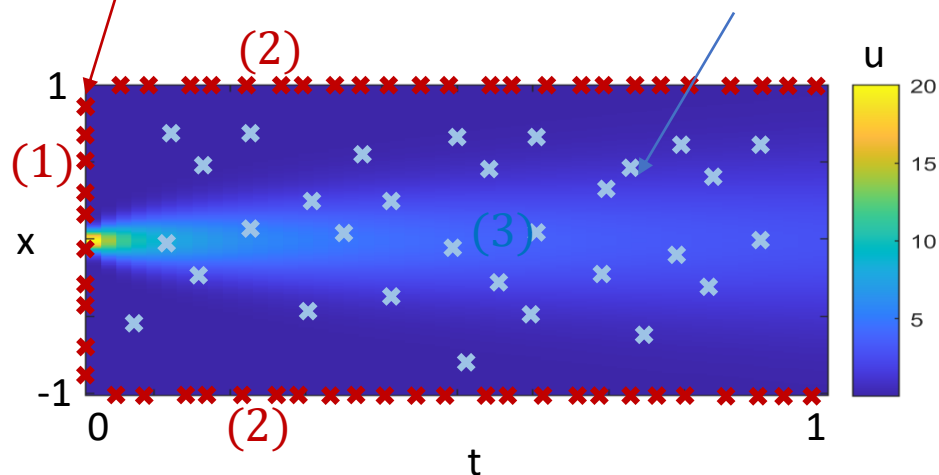
→ solving for $u(x,t)$ satisfying (1) ICs + (2) BCs + (3) Eqn

Physics-informed NN



Data points

Collocation points



Given a partial differential equation of a general form:

$$u_t + \mathcal{N}[u] = 0, \quad x \in \Omega, \quad t \in [0, T]$$

where $\mathcal{N}[\cdot]$ is a nonlinear differential operator.

Define equation residue f as

$$f := u_t + \mathcal{N}[u]$$

Cost function: (MSE: mean squared error)

$$MSE = \underbrace{MSE_u}_{\text{Data loss}} + \underbrace{MSE_f}_{\text{Equation loss}},$$

$$\frac{1}{N_u} \sum_{i=1}^{N_u} |u(t_u^i, x_u^i) - \hat{u}^i|^2,$$

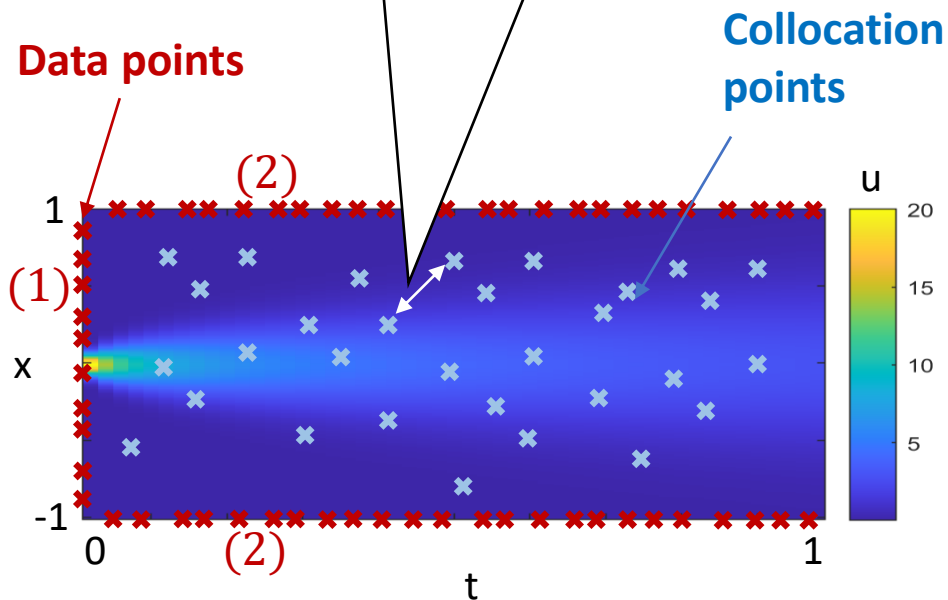
Data points

Equation loss

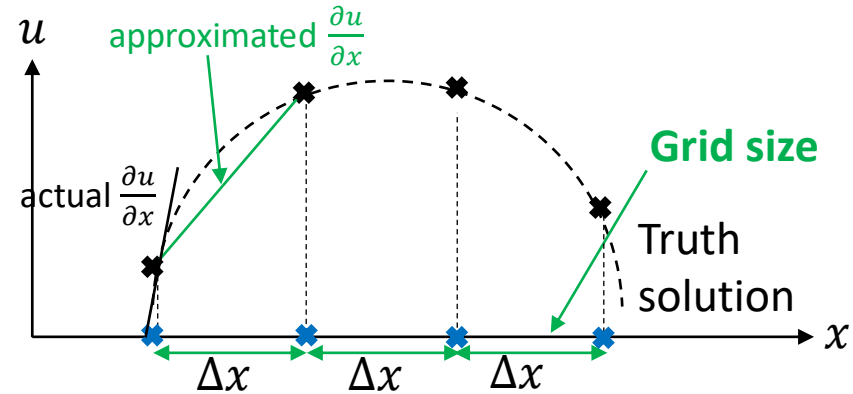
$$\frac{1}{N_f} \sum_{i=1}^{N_f} |f(t_f^i, x_f^i)|^2,$$

Collocation points

Q: Wouldn't $\frac{\partial u}{\partial x}$ be poorly approximated between the collocation points that are far apart?



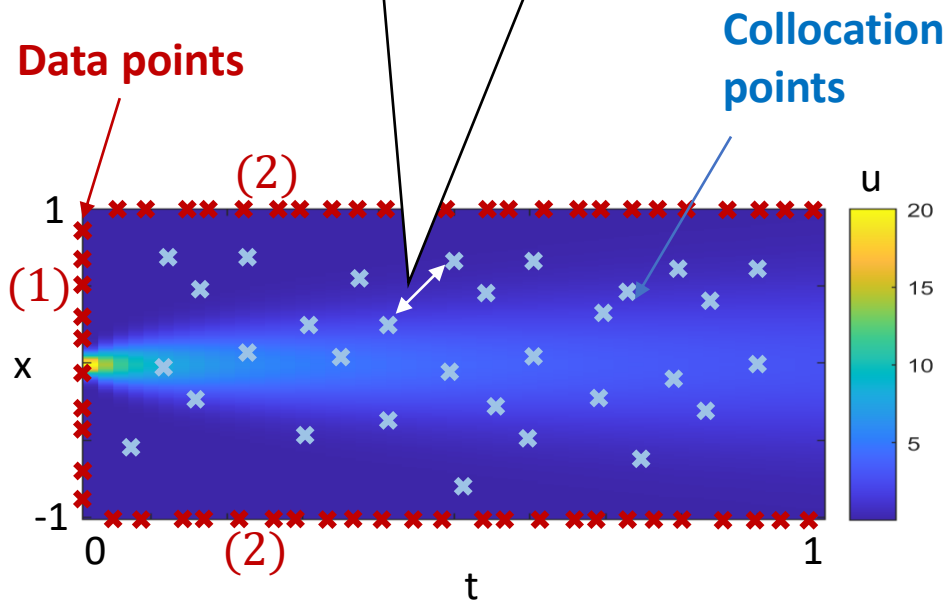
Finite difference: $\frac{\partial u}{\partial x} \approx \frac{u(x + \Delta x e_1) - u(x)}{\Delta x}$



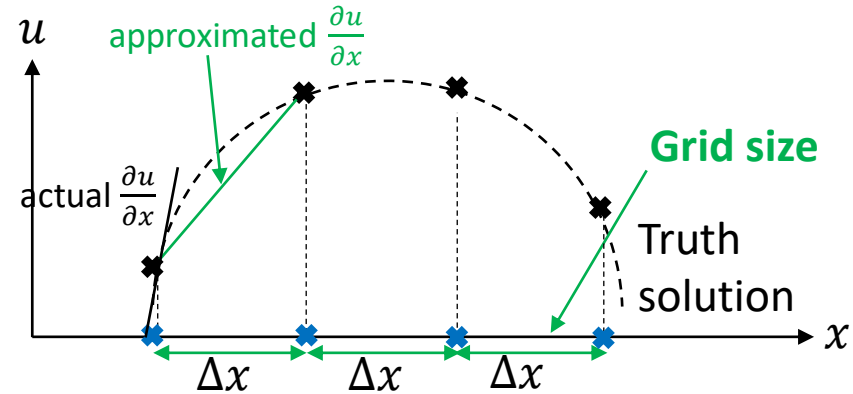
Drawbacks:

1. Truncation error: Δx needs to be sufficiently small
2. If we calculate derivatives of $u(x, t)$ w.r.t. $e_1, e_2, e_3 \dots e_n$, it requires $O(n)$ evaluations

Q: Wouldn't $\frac{\partial u}{\partial x}$ be poorly approximated between the collocation points that are far apart?

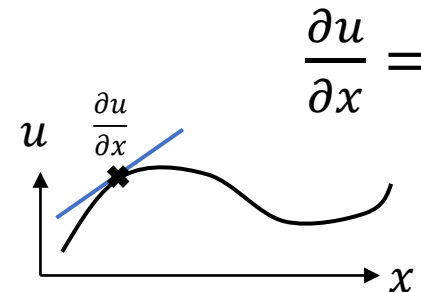


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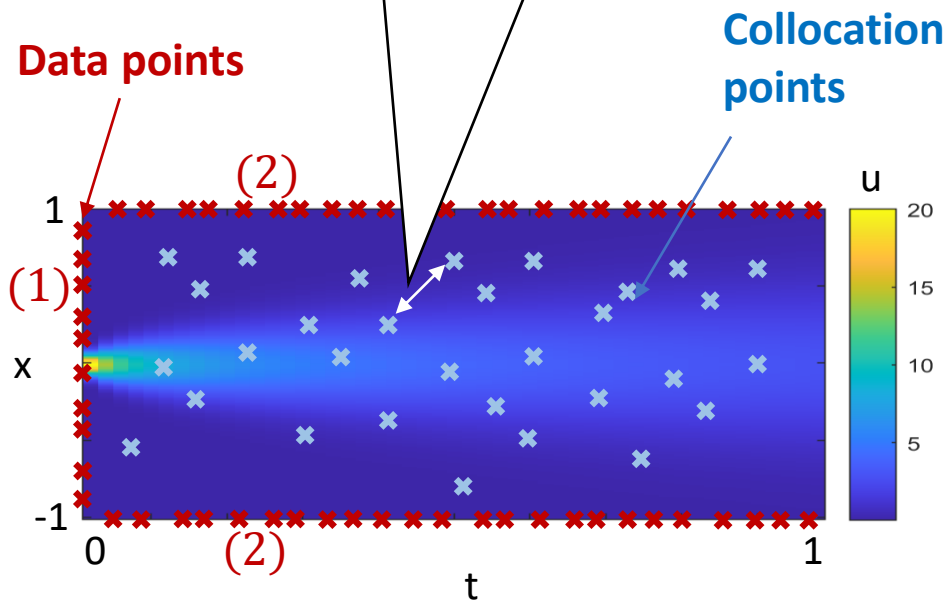


Automatic differentiation: differentiate NN output with respect to their input coordinates.

e.g. $\text{NN}(x) = u = \sigma(w_2 \sigma(w_1 x + b_1) + b_2)$,

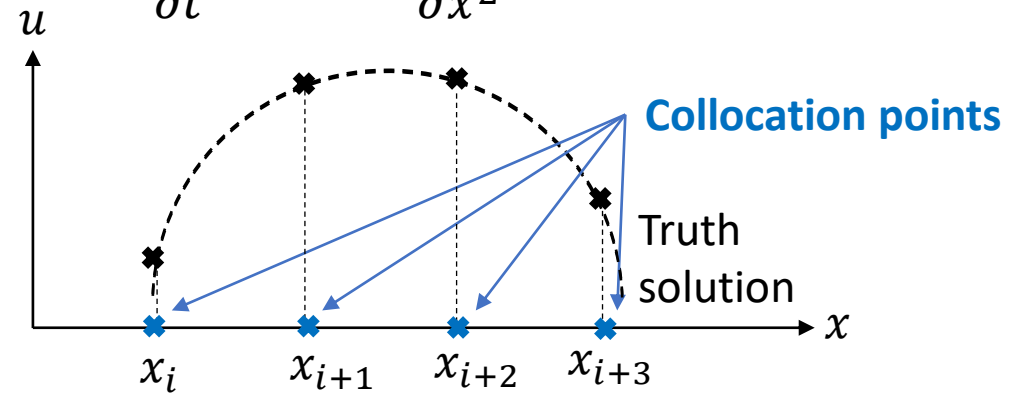


Q: Wouldn't $\frac{\partial u}{\partial x}$ be poorly approximated between the collocation points that are far apart?



PINN: searches for a curve that satisfies

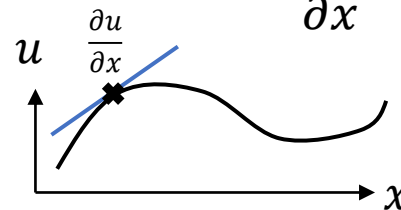
$$\frac{\partial u(x_i)}{\partial t} - a \frac{\partial^2 u(x_i)}{\partial x^2} \approx 0 \text{ at the collocation pts}$$



Automatic differentiation: differentiate NN output with respect to their input coordinates.

e.g. $\text{NN}(x) = u = \sigma(w_2 \sigma(w_1 x + b_1) + b_2)$,

$$\frac{\partial u}{\partial x} = \sigma'(z_2) w_2 \sigma'(z_1) w_1$$

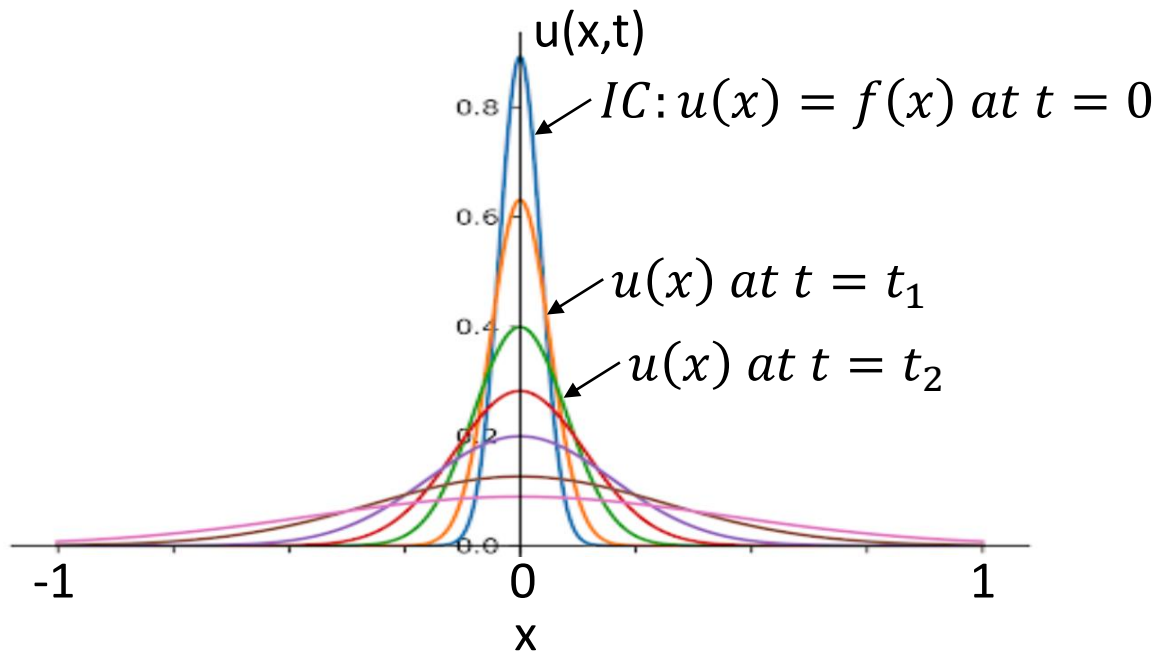


Comparison

$$(3) \frac{\partial u}{\partial t} = a \frac{\partial^2 u}{\partial x^2}$$

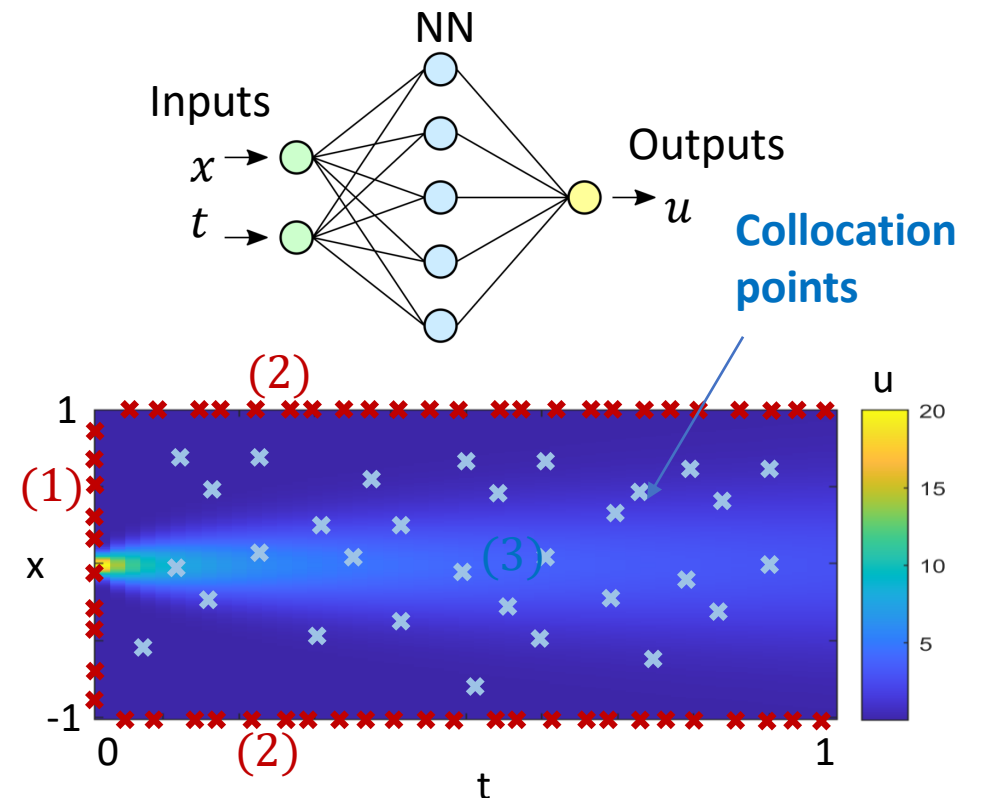
(1) Initial condition: $u(t = 0, x) = f(x)$
(2) Boundary conditions: $u(t, x = -1) = u(t, x = 1) = 0$

Finite-difference methods: Starting with IC, calculate discretized spatial derivative, updating the solution with a discretized timestep.



PINN:

Search for a surface that satisfies physics constraints (equation + ICs + BCs).



Pause and Ponder

1. What would happen if we tune the weights between eqn and data loss?

$$MSE = \underbrace{\alpha MSE_u}_{\text{Data loss}} + \underbrace{\gamma MSE_f}_{\text{Equation loss}}$$

2. What would happen to PINN if we use ReLU activation function?