

# Physics Informed Neural Networks for solving Partial Differential Equations

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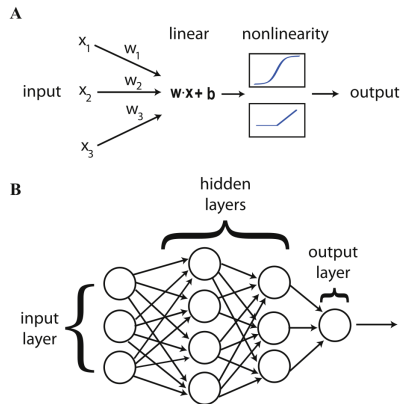
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# Introduction

- ❑ **Machine Learning(ML)** is a sub-field of Artificial Intelligence.
- ❑ ML has a goal to develop algorithms that can learn from data automatically.
- ❑ **Artificial Neural Network(ANN), Neural Network(NN), or Neural Net** is a model of Machine Learning which is inspired by **neurons in the human brain**.
- ❑ **Physics Informed Neural Network(PINN)** is an application of ANN for solving Problems in physics.

# Artificial Neural Network

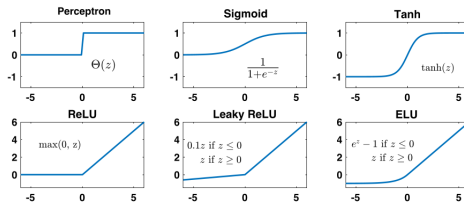
- ❑ The primary component of an ANN is '**stylized neurons**'.
- ❑ A neuron consists of a **linear transformation** followed by a **non-linear activation function**. There are different types of Non-linear activation functions like Perceptrons, Sigmoid, Tanh, ReLU, ELU, etc.
- ❑ ANN consists of such neurons stacked in layers. A deep Neural Network(DNN) has more than two hidden layers.



**Figure:** structure of Neural Network  
(Source: P. Mehta, M. Bukov, C.-H. Wang et al. / Physics Reports 810 (2019) 1–124)

# Artificial Neural Network

- ❑ **Universal Approximation Theorem:** A neural network with single hidden layer can approximate any continuous, multi-input/multi-output function with arbitrary accuracy.

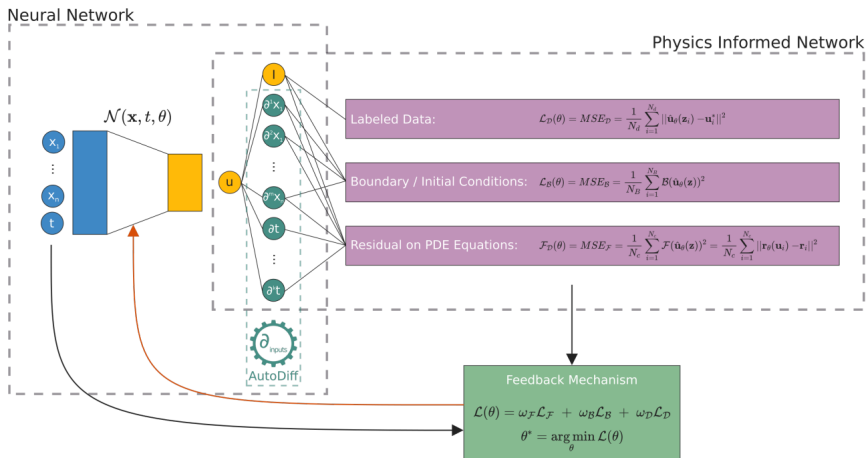


**Figure:** Some Non-linear Activation Functions (Source: P. Mehta, M. Bukov, C.-H. Wang et al. / Physics Reports 810 (2019) 1–124)

# Physics Informed Neural Network

- ❑ **Physics Informed Neural Network(PINN)** is a technique which uses Neural Network as a solution of a Partial Differential Equation.
- ❑ PINN approximates PDE solutions by minimizing a loss function that reflects the PDE, Boundary condition, Initial Condition, constraints etc.
- ❑ PINN has four parts
  1. Neural Network Architecture
  2. Auto Differentiation
  3. Loss Function
  4. Optimizer

# PINN Building Blocks



**Figure:** Building Block of PINN (source: Scientific Machine Learning through Physics-Informed Neural Networks, S Cuomo, V S di Cola, F Giampaolo, G Rozza, M Raissi, F Piccialli arXiv:2201.05624 )

# Solving Burgers' Equation

- I have solved **Burgers' Equation**

$$\frac{\partial u}{\partial t} + u \frac{\partial u}{\partial x} = \nu \frac{\partial^2 u}{\partial x^2} \quad x \in [-1, 1], \quad t \in [0, 1]$$

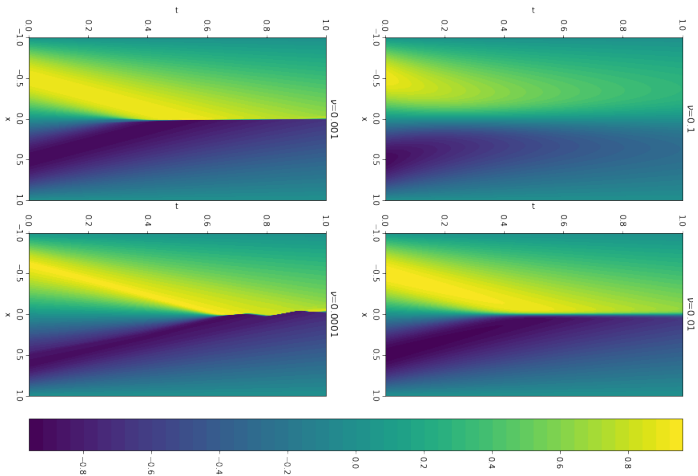
- Dirichlet boundary conditions and initial conditions are

$$u(-1, t) = u(1, t) = 0, \quad u(x, 0) = -\sin \pi x.$$

- I have solved for four values of viscosity  
( $\nu = 0.1, 0.01, 0.001, 0.0001$ )



# Results for Burgers' Equation



**Figure:** Solution plots of Burgers' Equation

# Solving Heat Equation

- ❑ I have solved **1d Heat Equation**

$$\frac{\partial u}{\partial t} = \alpha \frac{\partial^2 u}{\partial x^2}, \quad x \in [0, 1], \quad t \in [0, 1]$$

- ❑ Dirichlet boundary conditions:

$$u(0, t) = u(1, t) = 0$$

- ❑ I have solved for two initial conditions

- ❑ Sinusoidal initial condition( taking  $\alpha = 0.4$ )

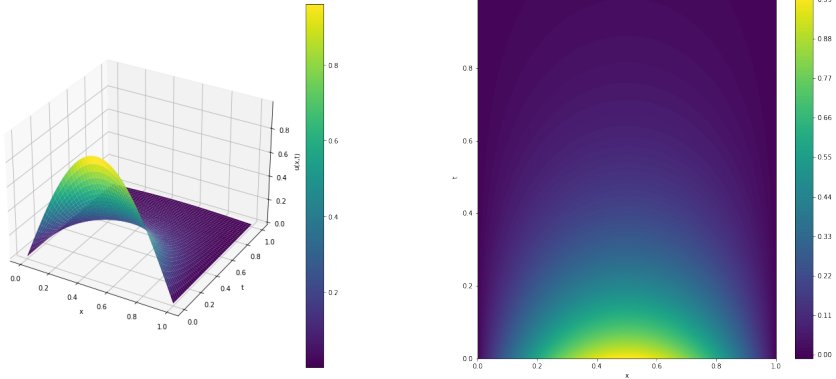
$$u(x, 0) = \sin \pi x$$

- ❑ Dirac Delta initial condition( taking  $\alpha = 0.008$ )

$$u(x, 0) = \delta\left(x - \frac{L}{2}\right)$$

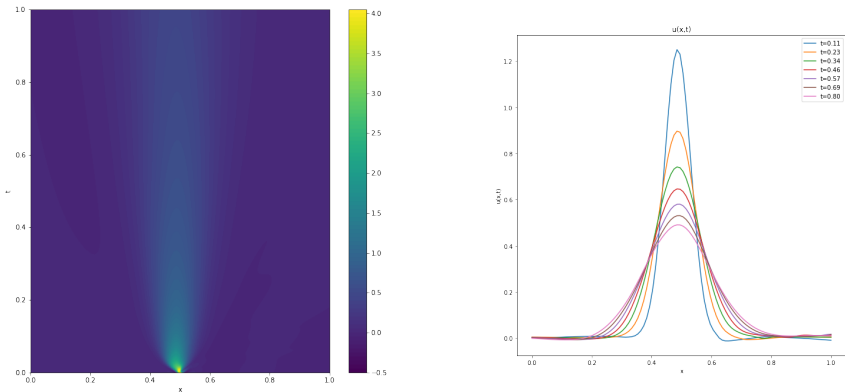
Where length of the rod =  $L = 1$ . I have generated Dirac function by using Gaussian distribution with variance very less than one.

# Results for Heat Equation



**Figure:** Plots of solution of Heat equation for periodic initial function

# Results for Heat Equation



**Figure:** Plots of solution of Heat equation for Dirac delta initial function

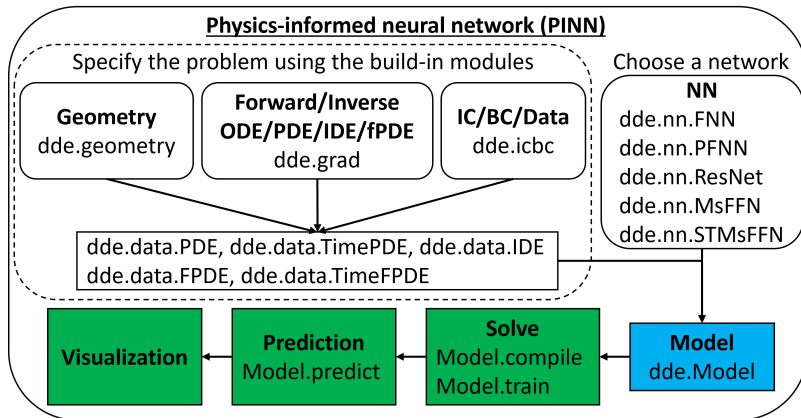
# Advantages of PINN

- ❑ A trained PINN can predict the values on the simulation grid of **different resolutions** without being retrained.
- ❑ PINN uses **automatic differentiation** to compute required derivatives which is superior to numerical or symbolical differentiation.
- ❑ Besides using experimental data, PINN uses the underlying physics during the network training. So
  - ❑ If the **size of the data is small**, it can give an accurate solution.
  - ❑ It can predict a precise value if the **boundary conditions are not provided**, and there is sufficient data.

# References

1. Scientific Machine Learning through Physics-Informed Neural Networks: Where we are and What's next.-Salvatore Cuomo1 , Vincenzo Schiano Di Cola, Fabio Giampaolo , Gianluigi Rozza , Maziar Raissi and Francesco Piccialli
2. Lu, Lu and Meng, Xuhui and Mao, Zhiping and Karniadakis, George Em, DeepXDE: A deep learning library for solving differential equations
3. P. Mehta, M. Bukov, C.-H. Wang et al. / Physics Reports 810 (2019) 1–124)
4. Physics Informed Deep Learning (Part I): Data-driven Solutions of Nonlinear Partial Differential Equations-Maziar Raissi, Paris Perdikaris and George Em Karniadakis

# DeepXDE



**Figure:** Implementation of PINN by DeepXDE (source:Lu, Lu and Meng, Xuhui and Mao, Zhiping and Karniadakis, George Em, DeepXDE: A deep learning library for solving differential equations)

# Training data for Burgers' equation

Network=[2,50,50,50,1], activation = 'tanh'

$\nu$	Optimizer	Training time (sec-ond)	final train loss
0.1	L-BFGS	128.997	$2.05 \times 10^{-06}$
0.01	L-BFGS	214.848	$4.50 \times 10^{-06}$
0.001	adam(lr=0.001) + L-BFGS	1417.553	$2.05 \times 10^{-06}$
0.0001	adam(lr=0.001) + L-BFGS	1166.165	$2.89 \times 10^{-02}$

**Table:** Training times and final losses for different viscosity



# Training data for heat equation

Network = [2,20,20,20,1], activation = 'tanh'

Initial function	Optimizer	Training time (second)	final train loss
Periodic	adam(lr=0.001) + L-BFGS	145.807	$6.72 \times 10^{-07}$
Dirac delta	adam(lr=0.001) + L-BFGS	145.332	$3.60 \times 10^{-02}$

**Table:** Training times and final losses for different initial function

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