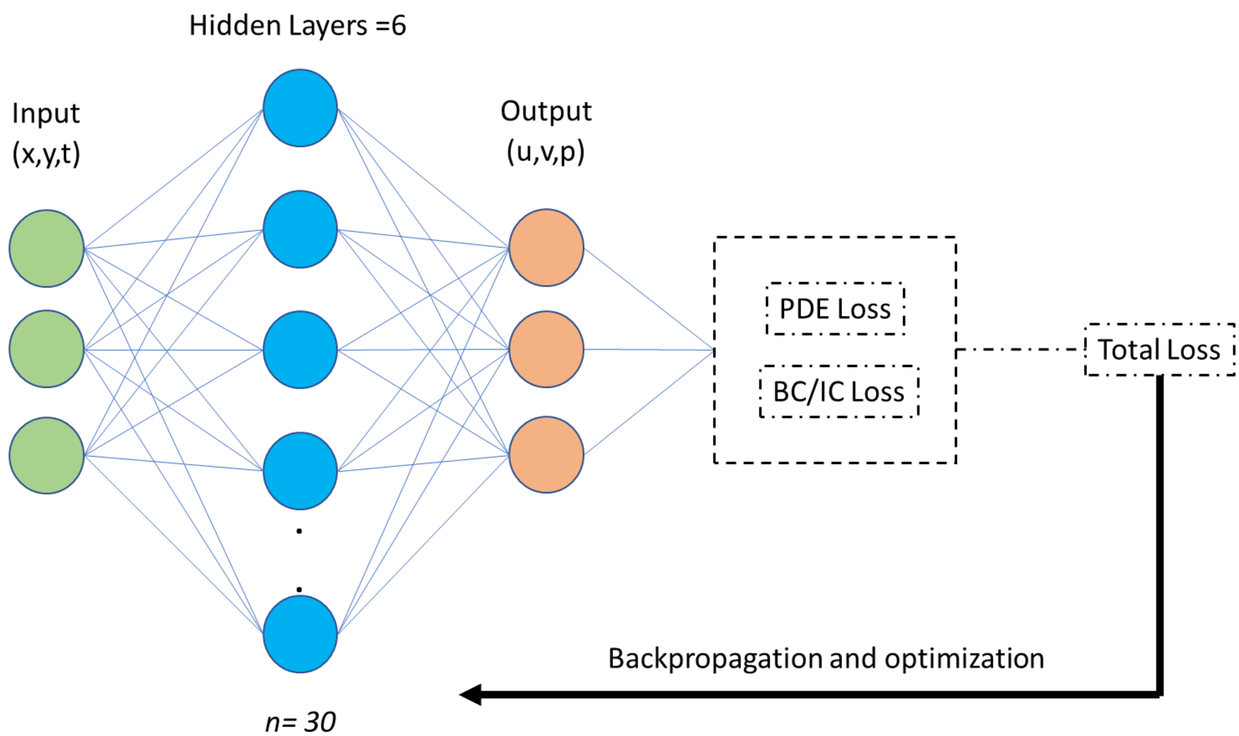
Introduction:

Due to the huge growth in of advanced applications in machine learning and deep learning in different scientific and industrial sectors, many methods have more popular in recent years as more computational power and efficiency is needed to solve such problems. Deep learning has become one of the booming methods to solve partial differential equations for many applications. Though applicable to solve a lot of problems involving PDEs, it suffers a lot from accuracy or computational time depending on the complexity of the problem. In this project, we explore physics informed neural networks which are deep neural networks that honor the physical laws involved in the problem by incorporating governing physical equations. Instead of purely data driven neural network solution, PINNs add another term in the minimization of the loss function to ensure the consistency of the neural network solution with the physical laws.

Methodology:

Similar to conventional neural network methods, the architecture of PINNs takes an input, passes it through hidden layers, and produces an output. In our case, our PINN architecture takes (x, y, t) and our inputs, passes it through 6 hidden layers, and outputs (u, v, p). Then it calculates the total loss term composed of PDE losses, Boundary condition losses, and Initial condition losses. To optimize the results, it uses an Adam optimizer to minimize the cost function through gradient descent. The gradient values are obtained by backpropagation. The neural network keeps iterating through the whole process until the it reaches the epoch threshold.


Hidden Layers =6
Input
(x,y,t)
Output
(u,v,p)
PDE Loss
BC/IC Loss
Total Loss
Backpropagation and optimization
n= 30