Deep Learning for Magnetic Field Extrapolation

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All solar activities happening in solar atmosphere are manipulated by its magnetic field. Thus, magnetogram has been regarding as the most reliable evidence to diagnose solar activities. However, only photospheric magnetograms can be directly measured, while the broad chromosphere and coronal layers which are more closely associated with solar bursts, such as solar flare and CME, cannot be measured directly. Traditionally, we employ numerical simulation methods to compute solar coronal magnetogram. For example, we leverage classical magnetic field extrapolation to compute solar coronal magnetogram from observed photospheric magnetogram. However, magnetic field extrapolation has strict limitations due to the requirement of boundary conditions. In addition, it has high computational complexity due to the griding of the magnetic field space.

Deep learning provides a powerful tool for processing a variety of complex tasks, including resolving partial differential equation (PDE). Physics-informed neural network (PINN) [1] has been well known in many "AI for science" fields. It can embed the knowledge of any physical laws that govern a given data-set in the learning process. The magnetic field extrapolation concerns a well-known Maxwell's equations, which is formulated as

$$(\nabla \times B) \times B = \vec{0}, in\ \Omega, \tag{1}$$

$$\nabla \cdot B = 0, in\ \Omega, \tag{2}$$

$$B = B_0, in\ \partial\Omega. \tag{3}$$

The solution of these three equations can be approximated by using neural network since universal approximation theorem exists [2][3]. Suppose $B^{NN}(x, y, z)$ is the network, our objective is to train the network so that $B^{NN}(x, y, z) \approx B(x, y, z)$.

Thus, a simple multilayer perceptron (MLP) as shown in Figure 1 is proposed to provide $B^{NN}(x, y, z)$ which is then optimized so that the equations (1)-(3) are minimized. It should be pointed that the most advantage of the proposed model is grid-free. It randomly samples the magnetic field space to seek the best approximation of $B^{NN}(x, y, z) \approx B(x, y, z)$. In our model, two hidden layers are used in the MLP. The reconstructed magnetic field can be validated by the numerical solution of the well-known B. C Low 1990 [4] which is shown in Figure 2 in contrast to the reconstructed one using the MLP. It cannot distinguish the numerical solution and the reconstructed one.

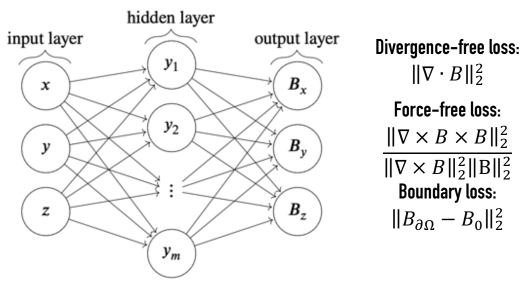

Figure 1. The schematic diagram of the MLP

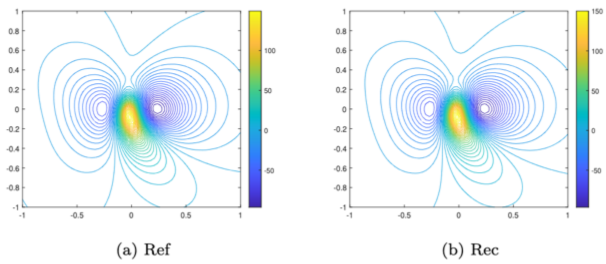

Figure 2. The reconstructed magnetic field *Bx* at (*x*, *y*, 0) plane using the MLP.

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