Physics-informed Neural Network: principles and case studies

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Machine learning, especially deep learning, have gained attention on a variety of fields nowadays due to their significant capability to handle the complex and nonlinear properties through nonlinear hyperspace transformation. However, data-driven methods heavily rely on sufficient training data, which becomes challenging to obtain under various conditions at industrial applications, leading to data shortages and imbalances. To address these challenges, physics-informed neural networks (PINNs) have emerged as a solution, incorporating the known physical principles into deep neural network at training phase. PINNs are constructed by enforcing governing equation of any physical laws as regularizers in the loss function, ensuring that outputs adhere to the prescribed physical laws, even in regions with sparse or no data. In order to explain the fascinating features of PINNs, this study not only explains the basic principles of PINNs, including mathematical foundations, and structures, over conventional neural networks but also introduces various methods to apply PINNs. Furthermore, this study demonstrates the integrated framework of multiphysics-informed neural network (MPINN) for prognosis and health management (PHM) applications, focusing on the complex mechatronic systems. The MPINN framework confirms its effectiveness using an electric motor system as an illustrative example. Notably, the MPINN achieves accurate and efficient multidimensional response predictions for mechatronic systems, even with limited data.