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Computational Heat Transfer and Data-Driven Inverse Modelling Using Neural Networks (Deep Learning)

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Abstract

Deep learning approaches are used to study the feasibility of solving inverse problems with linear and non-linear behaviour. The boundary conditions in inverse issues are defined by sparse measurements of a variable such as velocity or temperature. Although this is mathematically tractable for basic issues, complex problems can be tremendously difficult. To address the non-linear and complicated effects, a brute force technique was utilised to get an approximate solution through trial and error. Machine learning techniques may now make it possible to model inverse situations more quickly and accurately. We propose a synthesis of computational mechanics and machine learning to illustrate that machine learning can be utilised to solve inverse problems. To establish a database, the forward problems must be solved first. The machine learning algorithms are then trained using this database. From assumed measurements, the trained algorithm is utilised to establish the problem's boundary conditions.

Keywords: Computational; Machine learning; Deep learning

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Introduction

Within the engineering and scientific communities, inverse modelling is a crucial topic. The inverse problem, which arises in the modelling of engineering systems, is distinct from the forward (direct) problem in several aspects. The forward issue is practically well posed, and a numerical assessment of the solution can be done with any specified computation accuracy and specified boundary conditions. The inverse problem, on the other hand, is concerned with estimating an unknown boundary using measurements (observations) made from within the domain geometry. Ill-posedness, which is characterised by instability and non-uniqueness of the solution, is a practical challenge encountered in the application of inverse modelling for parameter estimation [1]. In a linear thermal conduction model, the temperature field behaviour is undoubtedly a single, unique solution of Laplacian's equation.

With established temperature boundary conditions, a numerical evaluation of that solution can be performed with any specified precision of calculation. In contrast to direct problems, inverse problem solutions are not unique, and optimisation is usually required to produce findings within a small range of uncertainty. Some heuristic approaches for solving inverse problems and picking regularisation parameters [2] are formalised in this situation in terms of their ability to handle ill-posed (unstable) problems. The aim behind such formal approaches is to reformulate the inverse problem in terms of an approximation well-posed problem using some sort of regularisation (stabilisation) technique. A heuristic method's goal is to produce a solution in a reasonable amount of time that is adequate for solving the problem at hand.

This solution may not be the best of all the solutions to this problem, but it is still useful because it does not take an inordinate amount of time to find. It's worth noting that a brute-force method to the inverse problem can be used to find a solution [3]. When dealing with thousands of parameters, however, the computational cost of brute-force methods makes them unsuitable for application. In the past, trial and error learning has been the primary way of data analysis in decision issues; however this strategy becomes impractical when datasets are vast. Machine Learning (ML) is a potentially more efficient and accurate approach to the problem since it proposes innovative alternatives to analysing massive amounts of previous data to create forward-looking predictive models.

Over the years, machine learning has piqued people's curiosity, and it is now a standard tool in many fields of study. The main benefit of machine learning is that it allows computers to self-learn and predict trends using operational algorithms. This characteristic allows the computer to be continuously trained, the training dataset to be expanded and more accurate results to be obtained over time as a result of data accumulation and the development of quick and efficient algorithms [4]. The ability to interpret data without being explicitly programmed is the key difference between ML and conventionally programmed artificial intelligence (AI) algorithms.

This means that an engineer is not required to provide machine instructions on how to handle different types of data records. Instead, a machine uses input data to define these rules. As a result, it is clear that algorithm research and selection are the most significant aspects of ML overall. Deep Learning (DL), a subset of machine learning, is a relatively new technique that employs numerous layers to extract higher-level features from raw data.

The vast amounts of available training data and the much enhanced processing power that allows the training of deep neural networks are the key reasons behind DL. DL is about "deeper" neural networks that provide a hierarchical representation of the data, as opposed to typical ML methods. Whether it's a linear or non-linear relationship, deep learning finds the necessary mathematical adjustment to turn the input into the output [5]. For linear/non-linear heat conduction, convection–conduction, and natural convection problems, the effectiveness of a Machine Learning (ML) approach for solving inverse problems has been described. By comparing statistical assessment criteria like accuracy and loss on in/out of sample data, the correctness of the algorithms was verified. When comparing the training and testing sets for almost all of the case studies in this study, no significant variations in performance were discovered.

Conclusion

The difficulty of finding the optimum solution for a non-linear ill-posed problem, as well as the theory that underpins it, is significantly less established than the theory that underpins linear problems. We are avoiding non-uniqueness solutions in this work by presuming that the boundary conditions are known. Using a combination of unsupervised learning and probability distribution, on the other hand, is an approach for having a unique solution. For further validation and deeper understanding of Neural Networks (NN) concepts in computational mechanics, an inverse modelling ML technique is studied for steady-state thermal convection–conduction and natural convection issues (from simple to more complex physical systems).

References

1. Zienkiewicz OC, Taylor RL, Nithiarasu P (2013) The Finite Element Method for Fluid Dynamics, seventh edn. Elsevier 2013.
2. Hughes TJR (2012) The Finite Element Method: Linear Static and Dynamic Finite Element Analysis Courier Corporation.
3. Owen AB, Prieur C (2017) On shapley value for measuring importance of dependent inputs, SIAM/ASA J Uncertain Quantif 5 (1) 986-1002.
4. Lundberg SM, Lee SI (2017) A unified approach to interpreting model predictions. Advances in Neural Information Processing Systems 30, 4765–4774
5. LeCun Y, Bengio Y, Hinton G (2015) Deep learning. Nature 52, 436–444.