MACHINE LEARNING DESIGN THINKING FOR FLUID MODELS

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Abstract—Machine learning and particularly algorithms based on artificial neural networks establishes a field of research lying at the intersection of different disciplines such as mathematics, statistics, computer science, and neuroscience. This approach is characterized by the utilization of algorithms to extract knowledge from large and heterogeneous data sets. A neural network technique is played to implement machine learning or to design intelligent machines for constructing mathematical models that can perform various complicated tasks. The set of machine learning algorithms have modernized and structured for fluid flows. It is helped to develop flow modeling and improvement techniques using neural networks the biologically impressed algorithms, current lines of mechanics research, and industrial applications

Keywords—Machine Learning, Neural Networks, Artificial intelligence, Fluid flow models, Modeling Techniques.

1. Introduction

Fluid mechanics is traditionally handled massive amounts of information from experiments, field measurements, and large-scale numerical simulations. Big data technology is vibrant to solve mechanical environment problems over the last decade because of high-performance computing architectures and advances in experimental measurement capabilities. Over the past 50 years, many advancement techniques are developed to handle data of fluid flows, starting from advanced algorithms for processing and compression, to databases of flow fields. However, the analysis of mechanics data is relied, to a large extent, on domain expertise, statistical analysis, and heuristic algorithms. a huge amount of information is today widespread across scientific disciplines, and gaining insight and actionable information from them has become a replacement mode of scientific inquiry also as an advertisement opportunity.

Our generation is experiencing an unprecedented confluence of 1) vast and increasing volumes of information, 2) advances in computational hardware and reduced costs for computation, data storage, and transfer, 3) powerful algorithms, 4) an abundance of open-source software and benchmark problems, and 5) significant and ongoing investment by the industry on data-driven problem-solving. These advances have, in turn, fueled renewed interest and progress within the field of machine learning. Machine learning provides a modular and agile modeling framework that will be tailored to deal with many challenges in mechanics, like reduced-order modeling, experimental processing, shape optimization, turbulence closure, and control. As scientific inquiry increasingly shifts from first principles to data-driven approaches, we may draw a parallel between current efforts in machine learning with the event of numerical methods within the 1940s and 1950s to resolve the equations of fluid dynamics. mechanics stands to learn from learning algorithms and in return present challenges that will further advance these algorithms to enhance human understanding and engineering intuition. Additionally to outlining successes, we emphasize the importance of understanding how learning algorithms work and when these methods succeed or fail. it’s important to balance excitement about the capabilities of machine learning with the truth that its application to mechanics is an open and challenging field. during this context, we also highlight the advantage of incorporating domain knowledge about mechanics into learning algorithms. We envision that the mechanics community can contribute to advances in machine learning like the advances in numerical methods within the last century..

2. Ease of Use

A. MACHINE LEARNING

Learning is also a method throughout that association of events with consequences is completed. So primarily learning is also the simplest way to substantiate the cause and impact principle. The science of coming up with the intelligent machine is declared as machine learning and additionally the tool accustomed style such an intelligent machine is neural networks. A neural network could think of as a black-box that provides some desired output for the given input.

In distinction to most standard learning strategies, which are thought-about exploitation shallow-structured learning architectures, deep learning refers to machine learning techniques that use supervised and/or unattended methods to mechanically learn hierarchical representations in deep architectures for classification. Galvanized by
biological observations on human brain mechanisms for the process of natural signals, deep learning has attracted a lot of attention from the academic community in recent years due to its progressive performance in several analysis domains. Deep learning has also been effectively connected in trade things that exploit the expansive volume of advanced info. Firms like Google, Apple, and Facebook, World Health Organization collect and analyze large amounts of data every day, are sharply pushing forward deep learning connected projects. As an example, Apple's Siri, the virtual personal assistant in iPhones, offers an honest variety of services together with weather reports, sport news, answers to user's queries, and reminders, etc. by utilizing deep learning and a lot of and a lot of information collected by Apple services. Google applies deep learning algorithms to huge chunks of messy information obtained from the online for Google's translator.

Deep learning is currently a greatly dynamic examination territory in machine learning. Deep learning refers to a class of Machine learning techniques as shown in Fig.1, wherever several layers of information process stages in graded architectures are exploited for unsupervised feature learning and pattern classification. It's within the intersections among the analysis areas of a neural network, graphical modeling, optimization, pattern recognition, and signal processing.

Figure 1. Shows correlation between artificial intelligence, Machine learning and deep learning

B. MACHINE LEARNING IN FLUID DYNAMICS

Fluid dynamics present challenges that dissent from those tackled in several applications of machine learning, like image recognition and advertising. In fluid flows, it's usually necessary to precisely quantify the underlying physical mechanisms, therefore, analyzing them. moreover, fluids flow entail complicated, multi-scale phenomena whose understanding associate degreed management stay to an outsize extent unresolved. Unsteady flow fields need algorithms capable of addressing nonlinearities and multiple spatiotemporal scales which cannot be a gift in well-liked machine learning algorithms. additionally, several outstanding applications of machine learning, like taking part in video games, believe cheap system evaluations associate degreed a complete categorization of the strategy that has to be learned, this can be not the case in fluids, wherever experiments may even be troublesome to repeat or automatize and wherever simulations might need large scale supercomputers operative for extended periods of it slow.

Machine learning has additionally become instrumental in artificial intelligence, and algorithms like reinforcement learning area unit used habitually in autonomous driving and flight. Whereas several robots operate in fluids, it seems that the subtleties of fluid dynamics don't seem to be presenting a major concern in their style. Mechanics from Living Organisms to Machines. We believe, that the deeper understanding and exploitation of mechanics can become vital within the style of robotic devices, once their energy consumption and dependability in complicated flow environments become a priority. Within the context of flow management, actively or passively manipulating flow dynamics for associate degree engineering objective might modification the character of the system, creating predictions, and supported knowledge of uncontrolled systems, impossible. Though fluid knowledge is large in some dimensions, like spatial resolution, it ought to be thin in others; e.g., it ought to be overpriced to perform constant quantity studies. Moreover, the fluids knowledge are usually extremely heterogeneous, requiring special care once selecting the type of learning machine. Additionally, several fluid systems area unit non-stationary, and even for stationary flows, it's about to be prohibitively overpriced to induce statistically converged results. Fluid dynamics are central to transportation, health, and defense systems, and it is, therefore, essential that machine learning solutions are explicable, interpretable, and generalizable. Moreover, it's usually necessary to provide guarantees on performance, which is presently rare. Indeed, there's a poignant lack of convergence results, analysis, and guarantees in several machine learning algorithms. it's additionally necessary to deem whether or not the model area unit about to be used for interpolation at intervals a parameter regime or for extrapolation, which is significantly tougher. Finally, we tend to emphasize the importance of cross-validation on withheld information sets to stop overfitting in machine learning.

C. NEURAL NETWORK

The power and adaptability of neural networks emanate from their standard structure supported by the somatic cell as a central building component, a caricature of the somatic cells within the human brain every neuron receives associate degree
input, processes it through associate activation operate, associated produces an output. Multiple neurons are often combined into totally different structures that mirror information concerning the matter and therefore the kind of information. Feed-forward networks are among the foremost common structures, and that they are composed of layers of neurons, wherever a weighted output from one layer is that the input to successive layer. Neural network architectures have an associate input layer that receives the information and an output layer that produces a prediction. Nonlinear improvement ways, like the back-propagation area unit wont to determine the network weights to reduce the error between the prediction and tagged training information. Deep neural networks involve multiple layers and varied sorts of nonlinear activation functions. Once the activation functions are expressed in terms of convolution kernels, a strong category of networks emerges, specifically convolution neural networks, with nice success in image and pattern recognition.

D. NEURAL NETWORK MODELING

Over the last three decades, neural networks are used to model dynamic systems and mechanics problems. Early examples embrace the utilization of Neural Networks to be told the solutions of standard and partial differential equations. We tend to note that the potential of this work has not been explored and in recent years there are more advances together with separate and continuous in time networks. We tend to note conjointly the likelihood of using these strategies to uncover latent variables and cut back the number of constant studies usually related to partial differential equations. Neural networks also are oftentimes used in system identification techniques, like NARMAX, that are usually used to model fluid systems. In mechanics, neural networks were widely used to model heat transfer, turbulent flows, and different issues in physical science. Recurrent Neural Network with Long Short Term Memory is revolutionary for speech recognition, and that they are thought of as one in every of the landmark successes of computing. they're presently and different issues in physical science. Recurrent Neural Network with Long Short Term Memory is revolutionary for speech recognition, and that they are thought of as one in every of the landmark successes of computing. they're presently and different issues in physical science.

Similarly, neural network models are vulnerable to overfitting, and care should be taken to cross-validate models on a sufficiently chosen test set; Finally, it's necessary to expressly incorporate physical properties like symmetries, constraints, and preserved quantities.

3. CONCLUSION

Fluid mechanics subjects historically involved with huge knowledge with enormous applications. For many years it is used machine learning to know, predict, optimize, and manage flows. Currently, machine learning capabilities are progressing at associate degree unprecedented rate, and mechanics is commencing to tap into the complete potential of those powerful strategies. However deep learning can undoubtedly become an important powerful tool in many aspects of flow modeling, not all machine learning is deep learning. It is vital to contemplate many factors once selecting strategies, together with the standard and amount of information, the required inputs and outputs, the value perform to be optimized, whether or not or not the task involves interpolation or extrapolation, and the way vital it's for models to be interpretable. Flow control is experimented to cross-validate machine-learned models, otherwise, results are also vulnerable to over fitting. It is furthermore important to develop and adapt machine learning algorithms that don't seem to be solely physics hip however additionally physics consistent, a serious outstanding challenge in artificial intelligence. This merging might give solutions to several long-sought issues and new hope for governing mechanisms in fluid dynamics.

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