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Using deep learning methods to predict the evolution of unstable flame fronts

This study investigates the possibility of using Neural Networks to simulate the leading edge of a propagating flame in a one-dimensional channel

The past few decades have seen significant advances in the academic field of Machine Learning and are today being applied in everything from self-driving cars to predicting the stock market.

Another application of machine learning is to predict the time advancement of a partial differential equation. One of the problems with using deep learning to simulate the evolution of flame fronts due to diffusive-thermal instabilities is that a chaotic partial differential equation is used to model them. A chaotic equation implies that small changes to the initial state of the flame front leads to significant and seemingly random changes to the flame fronts' evolution. Therefore, it has been considered close to impossible to predict the long-term development of the flame front.

This study shows that two different state-of-the-art methods are not only able to learn and accurately predict relatively long-term time series of the development of the flame front. But also to capture the long-term characteristic behaviours. Furthermore, the study shows that with minor modifications to these techniques, it is possible to create methods which can be trained for multiple values of a parameter defining the system containing the flame front. Whereas with the unmodified versions, one instance of the method (also called network) could only be trained for a single value of the same parameter. This means that the modified network takes into account the value of this parameter when making the prediction.

The case studied can be described as a flame fronts propagation due to diffusive-thermal instabilities in a one-dimensional channel. These flame fronts can be modelled through a partial differential equation named "Kuramoto-Sivashinsky equation". Numerically approximating the time-advancement of the system for a given initial condition showed that the channel width of the system greatly affects the characteristics of the flame fronts' evolution. The fundamental goal of the study is to generate a database of long time series of solutions to this equation. With these solutions, the network is trained to predict the evolution of the flame front from any initial condition within the domain. In the case of the modified version of the methods, the channel width is the varying parameter.

There are many reasons why it is advantageous to approximate the time-advancement of partial differential equations using Machine Learning methods. One of these advantages is the time aspect. Consider a case where a company wants to simulate the airflow over an airfoil. It can take days, if not weeks, to numerically solve the problem for complex cases. If you instead use a pre-trained machine learning network, this simulation time can be reduced to a fraction of that time. This study aims to contribute to the research within this field of machine learning, especially for the case of the parameter-dependent network, which is not well-researched yet.