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Using physics to enhance machine learning models: The "Toy Model" Concept

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Many engineering systems are complex enough that it is either impossible to model them accurately with known physics, or computationally exorbitant to do so, or both. Machine learning is commonly employed to model and optimize such systems. In this talk I will present one method to increase the robustness and range of machine learning predictions of such systems. The central idea is to transform the feature space into a more fundamental space of 'toy variables' that are generated by physical models. The physics might be imprecise or incomplete, but the primary role of the toy variables is to simplify the learning task. In some cases, the toy variables might lower dimensionality or allow extrapolation. An example application is diesel engine calibration, which involves optimization of many operating parameters to minimize fuel consumption while meeting emission constraints. The performance of empirical engine emission models can be significantly improved by using system-level physics-based models to transform the feature space from the raw parameter space to a more fundamental space involving in-cylinder phenomena. Additional Toy Model examples of aerodynamic forces on a spinning baseball and turbine efficiency will be presented. All of the above examples involve systems where the known physics cannot be described precisely by a set of equations. System-level models with bold approximations are usually used. Some ideas for using the known physics of such systems with LSTM models will be presented in the context of recently acquired datasets for pulsating flow, acoustic data and heat transfer data.