Exploring data-driven modeling of boundary layer transition

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Prediction of laminar-turbulent transition in boundary layer flows is an important component of predicting the aerodynamic performance of a number of aerospace configurations. According to the CFD Vision 2030 [1], transition modeling represents a critical area in CFD simulation capability that will remain a pacing item for the foreseeable future. The fact that transition can take place via either one of a myriad possible paths adds to the challenges in reliable transition predictions, despite a limited knowledge of the relevant input parameters. In the low disturbance environments typical of flight applications, transition is often initiated by small amplitude disturbances in the form of linear instability waves of the laminar boundary layer. These disturbances amplify linearly at first and eventually undergo a sequence of nonlinear interactions that result in transition to turbulence. Because the nonlinear phase is rather rapid, the amplification of boundary layer instabilities is governed by the linear stability theory over a majority of the distance leading up to the onset of transition. Semi-empirical transition correlations based on the linear stability theory have been successful in explaining the observed trends in transition location within a broad class of flows. However, the application of stability theory is highly non-robust and often requires a significant domain expertise. Recent work at the NASA Langley Research Center has been aimed at bridging the gap between physics based transition analyses such as those based on linear stability theory and practical applications that require transition prediction by users that may not be well versed in transition physics. The applications of deep learning have been at the center of these efforts. This presentation will focus on the progress achieved thus far, highlighting the applications of neural networks to selected transition scenarios across a range of Mach numbers and flow configuration, as well as the lessons learned and remaining challenges with respect to the selection of training data and neural networks architectures, hyperparameter tuning, and the physical insights distilled from the otherwise black-box models.

1. Slotnick, J., Khodadoust, A., Alonso, J., Darmofal, D., Gropp, W., Lurie, E., and Mavriplis, D., "CFD Vision 2030 Study: A Path to Revolutionary Computational Aerosciences," NASA CR-2014-218178, Langley Research Center, March 2014. doi:2060/20140003093