Bayesian Aerothermal Sensor Assessments: Averaging, Transfer Learning, and Anomaly Detection

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In many cases, the uncertainties in engine performance metrics are far greater than the benefits afforded by highly constrained design optimisation loops. Thus, a valid line of inquiry is how we may reduce the uncertainties in engine performance metrics. To compute a 1D pressure or temperature at an axial station, practitioners have area averaged radially and circumferentially located sensor data and broken down the uncertainty into systematic and random — utilising the analysis of Coleman and Steele.

In this talk I present some of our work that questions many of these assumptions and other concerns. Our solution is a Bayesian spatial model that tries to interpolate sparse engine measurements with a physics-based probabilistic approach. Averages — both area and mass — are easily computed as 1D probability density functions. Uncertainties owing to limited spatial sampling and finite measurement precision are straightforward consequences of the law of total covariance.

We extend our spatial model across multiple axial measurement planes — and across engines — via inductive transfer learning. This permits us to quantify how similar certain engines are, and to leverage engines with more sensors to better understand engines with fewer sensors. This once again can yield greater confidence in 1D performance values.

Time permitting, I will also present how our Bayesian framework can be used for spatial anomaly detection — leveraging ideas from the field of optimal transport. This is very useful for identifying faulty sensors and anomalous aerothermal behaviour.