# EML WEBINAR

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WEDNESDAY, 15 JULY 2026
10 AM BOSTON, 10 PM BEIJING
4 PM PARIS, 3 PM LONDON


# MIGUEL BESSA

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## DISENTANGLING UNCERTAINTY IN AI FOR ENGINEERING

Neural networks are usually trained for deterministic predictions. Methods that do quantify uncertainty conflate two distinct sources: the model's ignorance where data is sparse (epistemic), and the irreducible noise in the data-generating process (aleatoric). Disentangling them is essential — epistemic uncertainty tells us where to acquire more data; aleatoric uncertainty tells us what variability we must design around. Yet recent benchmarks show that no existing method reliably disentangles the two in practice [Mucsányi et al., 2024]. This talk presents Variance estimation Bayesian Neural Networks (VeBNNs), recently accepted at ICML 2026, which resolve this through a three-step cooperative training strategy: a deterministic mean network, a variance network trained on residuals via a Gamma likelihood, and Bayesian inference with the aleatoric variance held fixed. The method is architecture-agnostic and demonstrated across UCI regression, ResNet-34 image regression under distribution shift, and a new plasticity constitutive model learning problem — possibly the first open dataset with known ground-truth aleatoric uncertainty. I will close with the design of recycled polypropylene/polyethylene blends, where batch variability spans orders of magnitude in failure strain. Uncertainty-aware inverse optimization with VeBNN yields blends that are most reliable, not most extreme. The next step, which we are pursuing, is principled Bayesian optimization on top of VeBNN. The same principle reaches further: into uncertainty at foundation-model scale, where networks are trained as point estimates of intractable posteriors, and into gating in agentic systems, where calibrated distributions may matter more than confidence scores.

**Miguel Bessa** is an Associate Professor of Engineering at Brown University, where he develops methods in artificial intelligence and computational mechanics to solve frontier engineering problems. His contributions include being one of the earliest to introduce data-driven methods in computational mechanics, the co-development of self-consistent clustering analysis (SCA), uncertainty-aware design with new Bayesian methods, and the foundations of neural topology optimization — with applications spanning supercompressible metamaterials, nanomechanical resonators with quality factors above one billion at room temperature, lightsails for interstellar propulsion, and sustainable polymer composite design. Bessa received a PhD from Northwestern University (2016) as a Fulbright scholar, held a postdoctoral position at Caltech (2017), and was Assistant and then Associate Professor at TU Delft before joining Brown in 2022. His group is a strong proponent of open-source software (github.com/bessagroup).

Discussion leader: **Kaushik Bhattacharya**, California Institute of Technology

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