Engineering Risk Analysis Group
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# Uncertainty-Aware Data-Driven Models for Reliable Industrial Asset Monitoring under Distribution Shift

## Motivation and Objectives

In safety-critical engineering systems, ensuring the trustworthiness of a model is a fundamental requirement. When deploying data-driven models for industrial asset monitoring, it is crucial to rigorously quantify the uncertainty associated with each decision. A model that makes high-confidence errors can lead to catastrophic failures or unnecessary maintenance costs. This challenge is exacerbated in industrial environments by distribution shift. Changes in operating conditions often cause standard models to become overconfident on out-of-distribution data.

The objective of this thesis is to develop reliable neural networks that integrate robust Uncertainty Quantification (UQ) with domain adaptation capabilities. We will investigate methods to prevent model overconfidence during operational shifts, ensuring that the system can either adapt to new environments or explicitly flag low-confidence predictions when it encounters unseen scenarios. The proposed framework will be validated on relevant industrial tasks to demonstrate its ability to enhance safety and decision-making utility.

## Methodology

- Literature Review: Review state-of-the-art techniques in Uncertainty Quantification (e.g., Bayesian Neural Networks, Ensembles) and their intersection with domain adaptation.
- Method Development: We will develop the data-driven framework that prioritizes reliability:

Uncertainty Estimation: Implement probabilistic methods (e.g., Monte Carlo Dropout, Deep Ensembles) to distinguish between aleatoric uncertainty and epistemic uncertainty.

Robust Learning: Integrate adaptation mechanisms to align features or learn invariant representations.

- Validation and Case Studies: The performance of the developed methods will be evaluated on benchmark datasets or industrial case studies. Potential options include: Regression task: using battery data to estimate state-of-health. Classification task: using wind turbine data to detect faults.
- Comparison: We will compare the proposed approach against deterministic baselines to quantify improvements.

## Requirements

- Background: Good understanding of Machine Learning concepts.
- Technical Skills: Proficiency in Python and frameworks (PyTorch). Familiarity with probabilistic modeling or statistics is beneficial.
- Interests: Curiosity for reliable AI, focusing on robustness and safety in engineering systems.

**Starting date:** Flexible, as soon as possible

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## References

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2. Zhuang, F., Qi, Z., Duan, K., Xi, D., Zhu, Y., Zhu, H., Xiong, H., & He, Q. (2021). A Comprehensive Survey on Transfer Learning. *Proceedings of the IEEE*, 109(1), 43-76.
3. Han, T., Wang, Z., & Meng, H. (2022). End-to-end capacity estimation of Lithium-ion batteries with an enhanced long short-term memory network considering domain adaptation. *Journal of Power Sources*, 520, 230823.