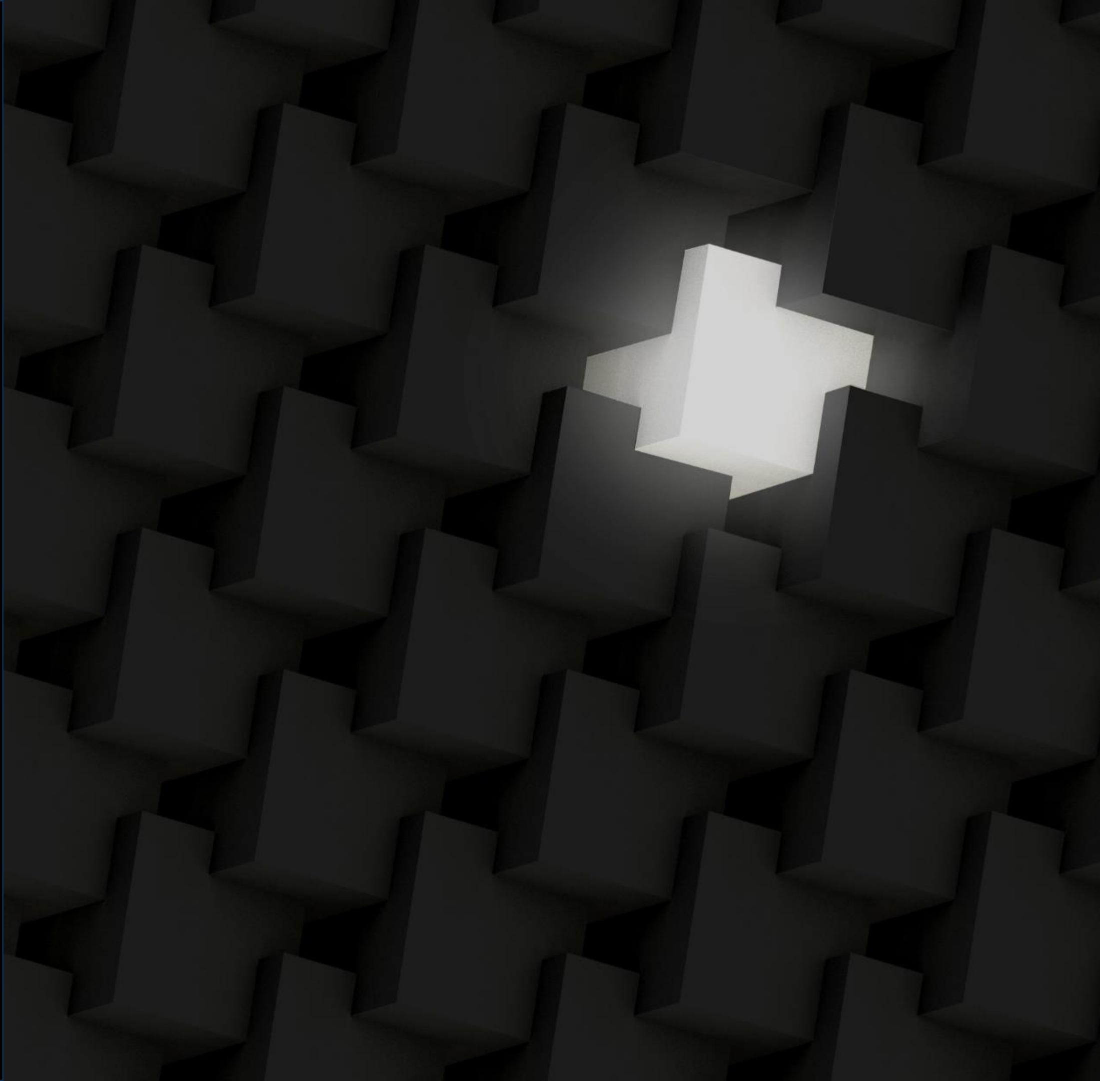
Carnegie Mellon University
Software Engineering Institute

RESEARCH REVIEW 2020

Knowing When You Don’t Know: Engineering AI Systems in an Uncertain World

Eric Heim



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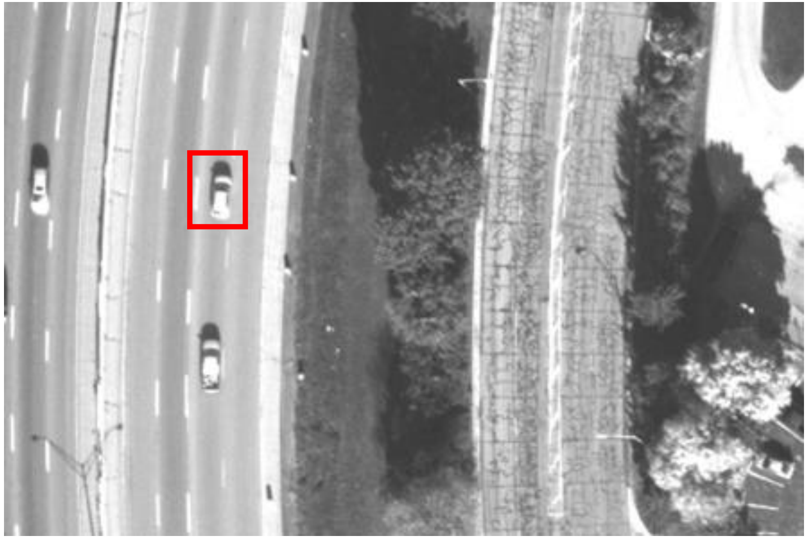
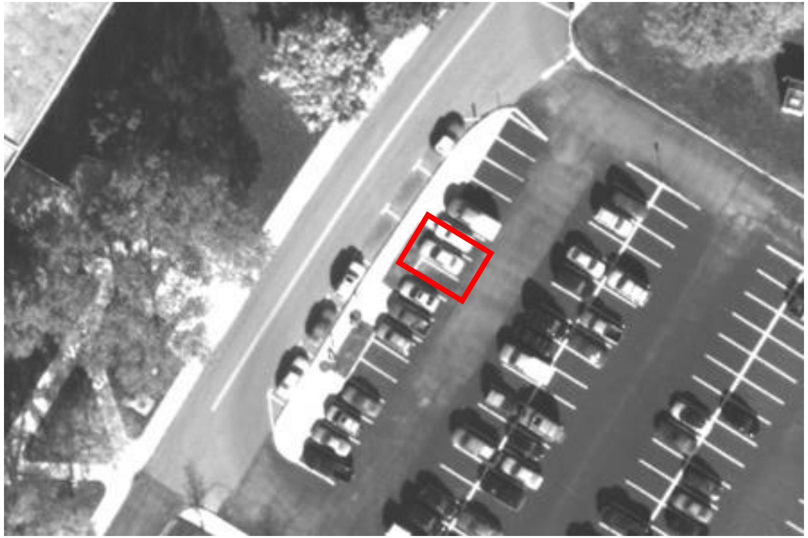
Why Uncertainty Matters



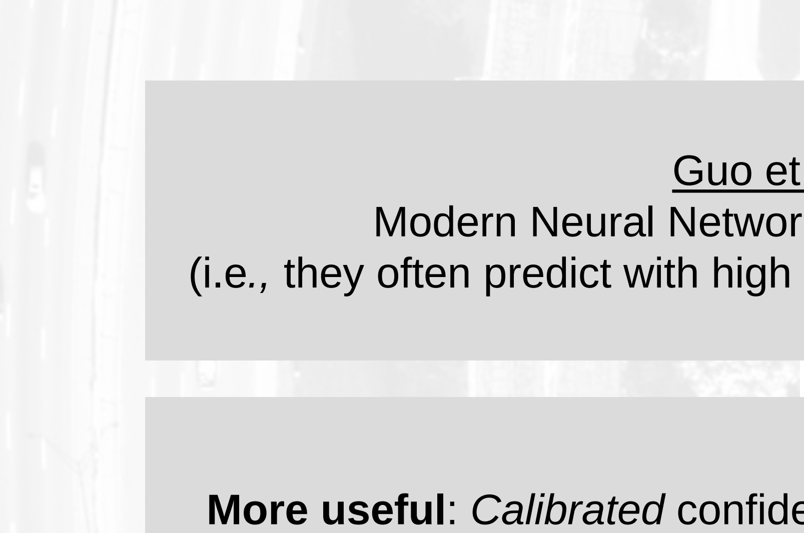
0.9773 Confident

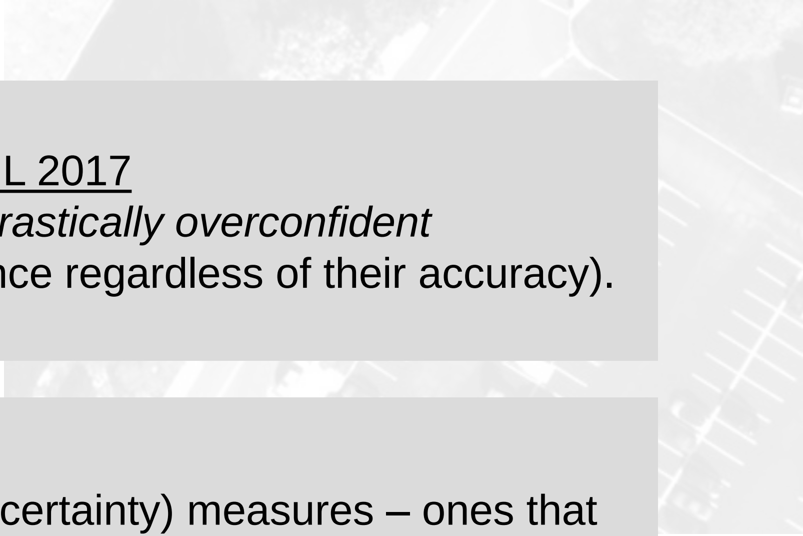


0.9834 Confident

Images from the Cars Overhead with Context Data Set (https://gdo152.llnl.gov/cowc/), Lawrence Livermore National Laboratory

Why Uncertainty Matters





Guo et al.; ICML 2017

Modern Neural Networks are *drastically overconfident*
(i.e., they often predict with high confidence regardless of their accuracy).

More useful: *Calibrated* confidence (uncertainty) measures – ones that indicate how likely it is that the model will produce correct inferences.

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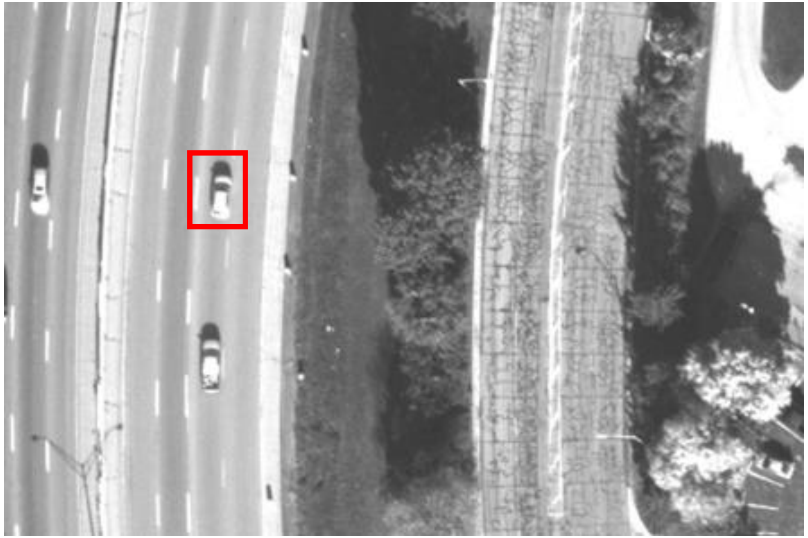
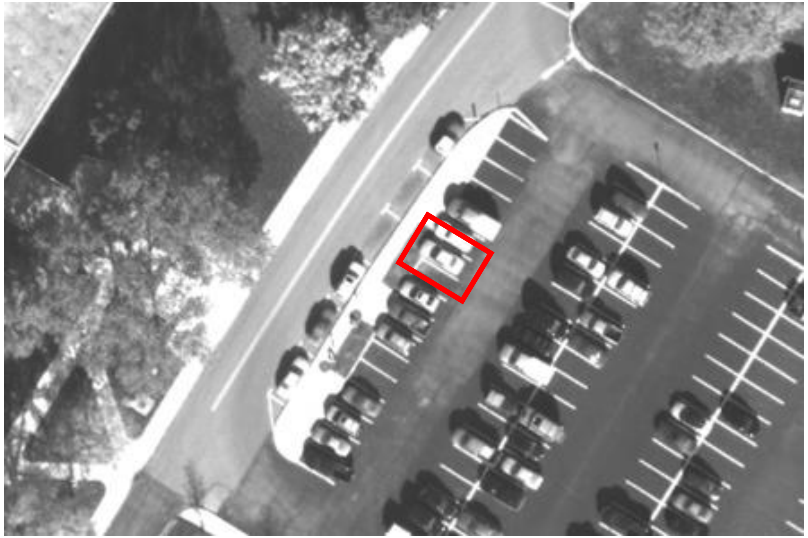
Why Uncertainty Matters



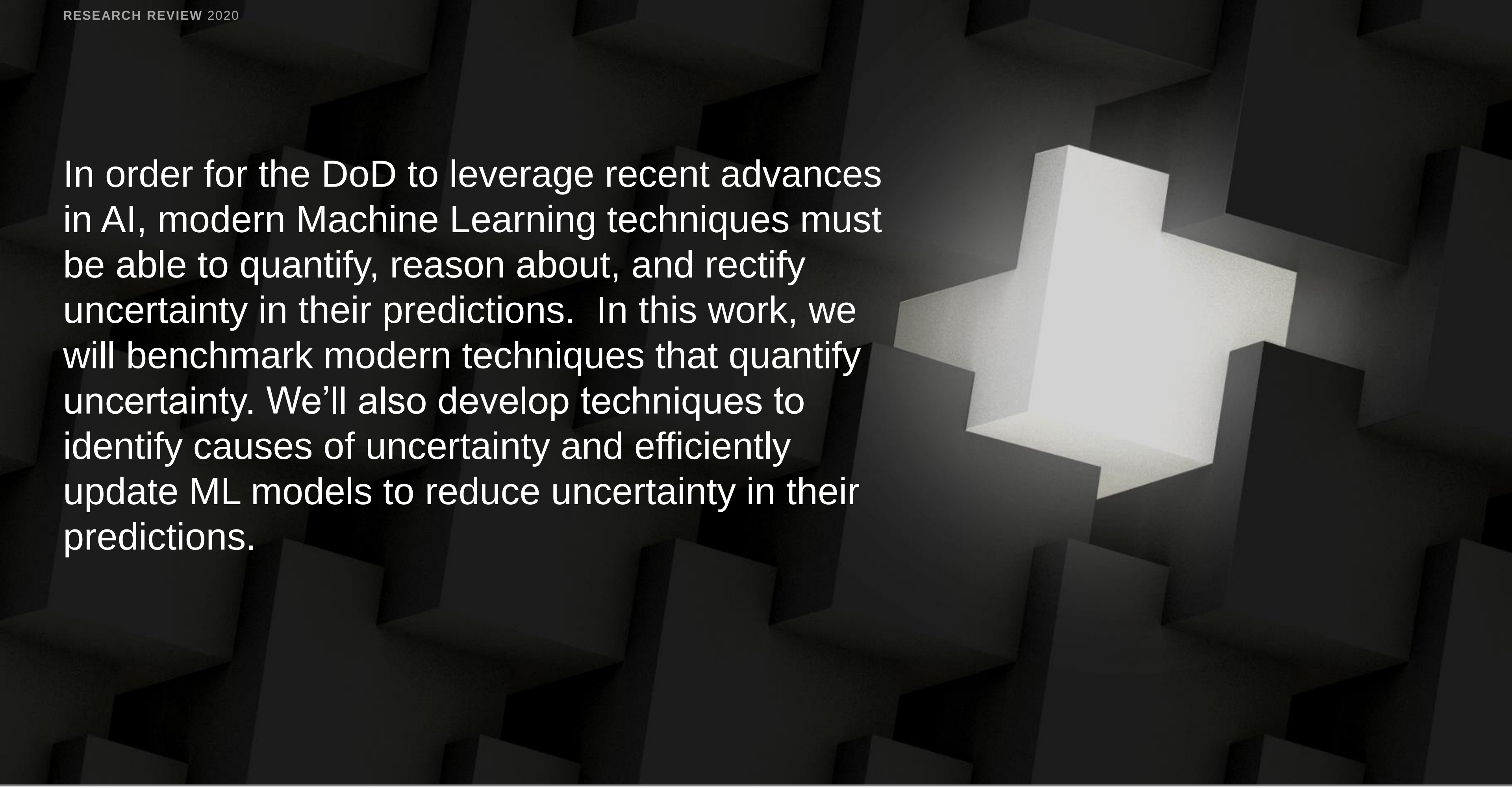
0.2463 Confident



0.9834 Confident

Calibrated uncertainty allows humans to compare inferences

Images from the Cars Overhead with Context Data Set (https://gdo152.llnl.gov/cowc/), Lawrence Livermore National Laboratory



In order for the DoD to leverage recent advances in AI, modern Machine Learning techniques must be able to quantify, reason about, and rectify uncertainty in their predictions. In this work, we will benchmark modern techniques that quantify uncertainty. We’ll also develop techniques to identify causes of uncertainty and efficiently update ML models to reduce uncertainty in their predictions.

Quantifying Uncertainty

Quantify – How do techniques for quantifying uncertainty in predictions practically perform?

Multiple, different approaches to quantifying uncertainty

- *Post-training Calibration* (Nieini, et al, AAAI 2015) (Guo et al., ICML 2017) (Hein et al., CVPR 2019)
- *Bayesian Neural Networks* (Blundell et al., ICML 2016)(Gal and Ghahramani, ICML 2016)
- *Deep Ensembles* (Lakshminarayanan et al., NeurIPS 2017)(Andrey et al., NeurIPS 2018)

We will compare these methods in terms of their computational runtime, data efficiency, and ability to accurately quantify uncertainty.

Detecting Cause of Uncertainty

Detect – How do we detect why a deployed model became uncertain in its predictions?

These are two (of potentially many) causes for model performance degradation:

1. Data set shift – The distribution of data changes from that on which the model was trained.

   Our approach: Explicit detection of data set shift (Rabanaser, Gunnemann, and Lipton, NeurIPS 2019)

2. Emergence of novel classes – Never-before-seen categories of observations emerge in the deployment environment.

   Our approach: Open-World Models (Cortes, et al., COLT 2016) (Rudd et al., TPMI 2017) (Oza et al., CVPR 2019)

We will develop techniques to identify what causes a model to degrade in its certainty.

Rectifying Uncertainty in ML Models

Rectify – Once uncertainty is detected and quantified, how do we make models more confident in uncertain cases in the future?

One option is to label the offending instances and then retrain the model.

Challenges

1. Labeling all potentially offending instances can be human intensive.

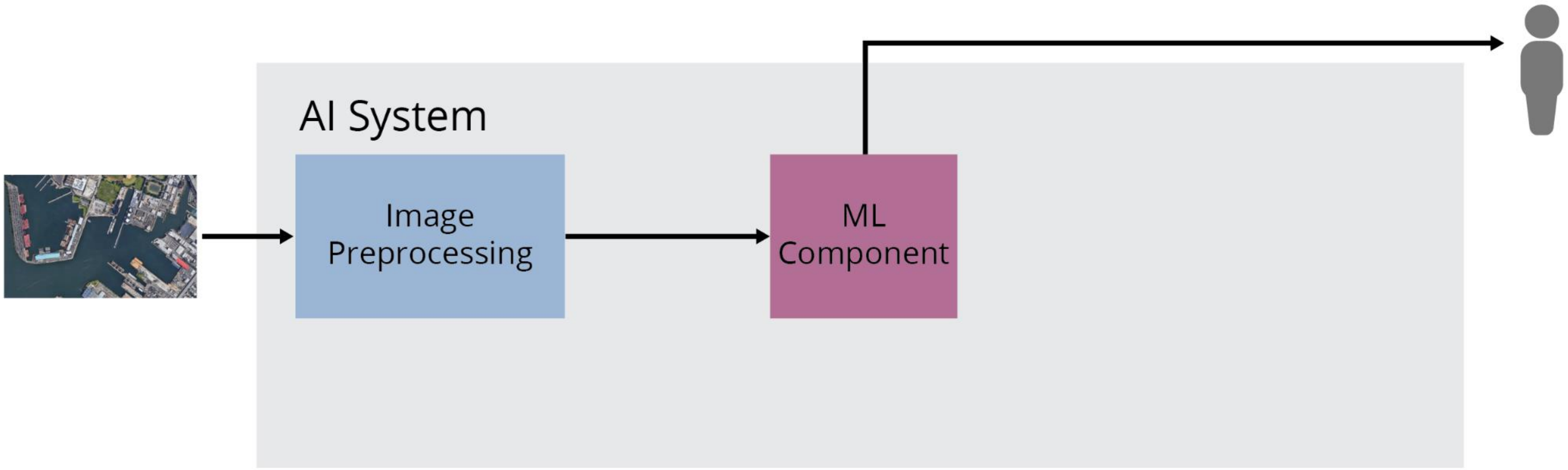
   Our Approach: Active Learning (Settles, 1995)

2. Retraining, validating and redeploying a model can be time intensive.

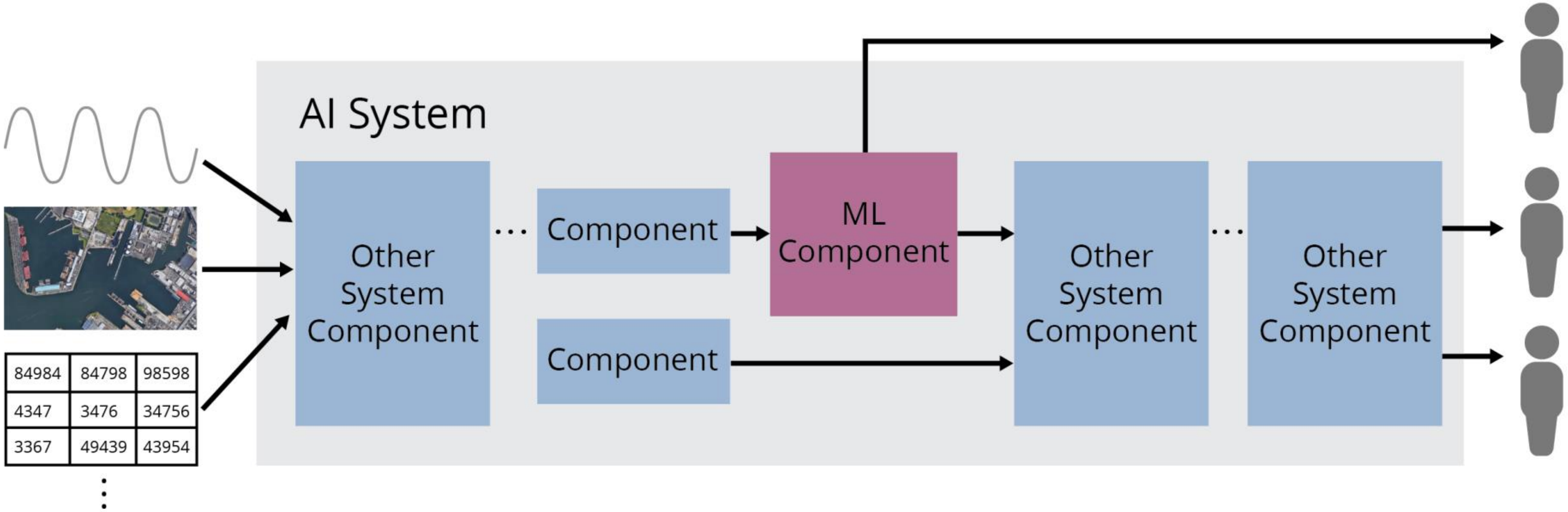
   Our Approach: Develop best practices for V&V on ML models; Online Learning where possible (Bottou, 1998)

We will develop techniques to efficiently update models to provide more certainty in their predictions, once uncertainty is quantified and the source is identified.

Uncertainty in AI Systems: An AI Engineering Perspective



Uncertainty in AI Systems: An AI Engineering Perspective

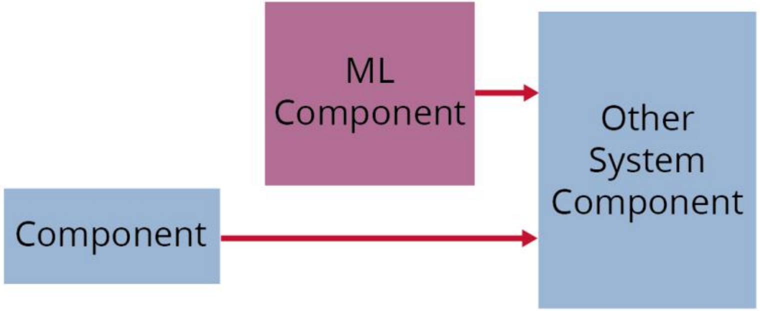


84984	84798	98598
4347	3476	34756
3367	49439	43954

⋮

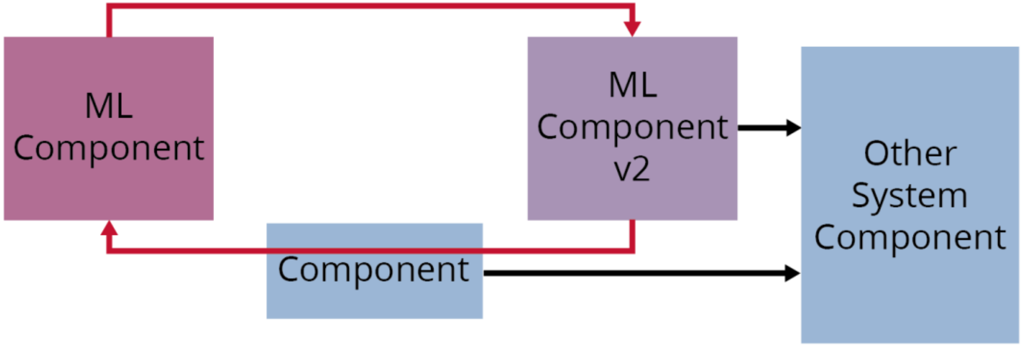
Uncertainty in AI Systems: An AI Engineering Perspective

Calibrated uncertainty from ML components can inform downstream AI system components that their inferences may not be correct and should use contingencies, i.e., **Robustness**.



Uncertainty in AI Systems: An AI Engineering Perspective

Detecting and Rectifying uncertainty enables **best practices** for iterating on ML models to be developed, providing rigor to the process of maintaining ML models.



Mission Statement and Team

In order for the DoD to leverage recent advances in AI, modern Machine Learning techniques must be able to quantify, reason about, and rectify uncertainty in their predictions. In this work, we will benchmark modern techniques that **quantify uncertainty**, develop techniques to **identify causes of uncertainty**, and efficiently **update ML models to reduce uncertainty** in their predictions.

Through this work, the DoD will be able to engineer AI systems that are more robust, and can be more reliably developed and maintained.

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Tepper/MLD

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MLD

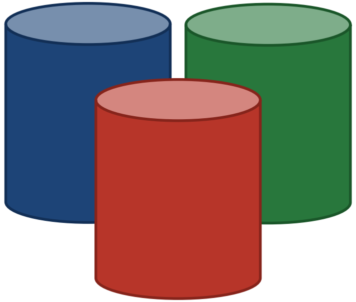
How can we work together?

An important part of this work is making sure we develop techniques to manage uncertainty in a manner that maps to the **needs of real-world DoD missions**.

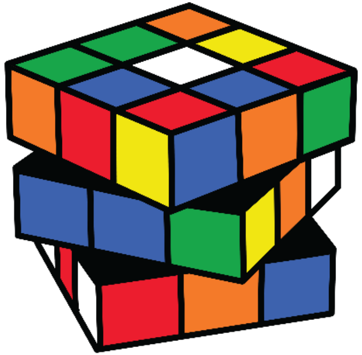
We want to partner with DoD collaborators to ensure we are doing so.

If you have…

Domain Expertise



Mission-Relevant Data



Real-World Problem

…we would love to work with you! (info@sei.cmu.edu)