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Navid Azizan Ruhi
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<tr><th>publication_date</th><td>2021-02-24 00:00:00</td></tr>
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https://github.com/StanfordASL/SCOD</td></tr>
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<tr><th>abstract</th><td>In order to safely deploy Deep Neural Networks (DNNs) within the perception pipelines of real-time decision making systems, there is a need for safeguards that can detect out-of-training-distribution (OoD) inputs both efficiently and accurately. Building on recent work leveraging the local curvature of DNNs to reason about epistemic uncertainty, we propose Sketching Curvature of OoD Detection (SCOD), an architecture-agnostic framework for equipping any trained DNN with a task-relevant epistemic uncertainty estimate. Offline, given a trained model and its training data, SCOD employs tools from matrix sketching to tractably compute a low-rank approximation of the Fisher information matrix, which characterizes which directions in the weight space are most influential on the predictions over the training data. Online, we estimate uncertainty by measuring how much perturbations orthogonal to these directions can alter predictions at a new test input. We apply SCOD to pre-trained networks of varying architectures on several tasks, ranging from regression to classification. We demonstrate that SCOD achieves comparable or better OoD detection performance with lower computational burden relative to existing baselines.</td></tr>
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