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<tr><th>authors</th><td>Andreas Sedlmeier
Thomas Gabor
Thomy Phan
Lenz Belzner
Claudia Linnhoff-Popien</td></tr>
<tr><th>title</th><td>Uncertainty-Based Out-of-Distribution Classification in Deep Reinforcement Learning</td></tr>
<tr><th>publication_date</th><td>2019-12-31 00:00:00</td></tr>
<tr><th>source</th><td>SupportedSources.INTERNET_ARCHIVE</td></tr>
<tr><th>journal</th><td></td></tr>
<tr><th>volume</th><td></td></tr>
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<tr><th>urls</th><td>https://web.archive.org/web/20200904171514/https://arxiv.org/pdf/2001.00496v1.pdf</td></tr>
<tr><th>id</th><td>id4228853893268313996</td></tr>
<tr><th>abstract</th><td>Robustness to out-of-distribution (OOD) data is an important goal in building reliable machine learning systems. Especially in autonomous systems, wrong predictions for OOD inputs can cause safety critical situations. As a first step towards a solution, we consider the problem of detecting such data in a value-based deep reinforcement learning (RL) setting. Modelling this problem as a one-class classification problem, we propose a framework for uncertainty-based OOD classification: UBOOD. It is based on the effect that an agent's epistemic uncertainty is reduced for situations encountered during training (in-distribution), and thus lower than for unencountered (OOD) situations. Being agnostic towards the approach used for estimating epistemic uncertainty, combinations with different uncertainty estimation methods, e.g. approximate Bayesian inference methods or ensembling techniques are possible. We further present a first viable solution for calculating a dynamic classification threshold, based on the uncertainty distribution of the training data. Evaluation shows that the framework produces reliable classification results when combined with ensemble-based estimators, while the combination with concrete dropout-based estimators fails to reliably detect OOD situations. In summary, UBOOD presents a viable approach for OOD classification in deep RL settings by leveraging the epistemic uncertainty of the agent's value function.</td></tr>
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<tr><th>title</th><td>Uncertainty-Based Out-of-Distribution Detection in Deep Reinforcement Learning</td></tr>
<tr><th>publication_date</th><td>2019-01-08 00:00:00</td></tr>
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<tr><th>id</th><td>id-185732030543801788</td></tr>
<tr><th>abstract</th><td>We consider the problem of detecting out-of-distribution (OOD) samples in deep reinforcement learning. In a value based reinforcement learning setting, we propose to use uncertainty estimation techniques directly on the agent's value estimating neural network to detect OOD samples. The focus of our work lies in analyzing the suitability of approximate Bayesian inference methods and related ensembling techniques that generate uncertainty estimates. Although prior work has shown that dropout-based variational inference techniques and bootstrap-based approaches can be used to model epistemic uncertainty, the suitability for detecting OOD samples in deep reinforcement learning remains an open question. Our results show that uncertainty estimation can be used to differentiate in- from out-of-distribution samples. Over the complete training process of the reinforcement learning agents, bootstrap-based approaches tend to produce more reliable epistemic uncertainty estimates, when compared to dropout-based approaches.</td></tr>
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