cases	doc_1	doc_2	decision	id
			DUPLICATES	127

doc_1	
authors	• Sedlmeier, A. • Gabor, T. • Phan, T. • Belzner, L. • Linnhoff-Popien, C.
title	Uncertainty-based Out-of-Distribution Classification in Deep Reinforcement Learning
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source	SupportedSources.CROSSREF
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doi	10.5220/0008949905220529
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id	id7019467509828881948
abstract	
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doc_2	
authors	• Andreas Sedlmeier • Thomas Gabor • Thomy Phan • Lenz Belzner • Claudia Linnhoff-Popien
title	Uncertainty-Based Out-of-Distribution Classification in Deep Reinforcement Learning
publication_date	2019-12-31 00:00:00
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urls	• https://web.archive.org/web/20200904171514/https://arxiv.org/pdf/2001.00496v1.pdf
id	id4228853893268313996
abstract	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.
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