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cases	**authors**: Postels, Janis; Segu, Mattia; Sieber, Luca; Sun, Tao; Tombari, Federico; Van Gool, Luc; Yu, Fisher **title**: On the Practicality of Deterministic Epistemic Uncertainty **publication_date**: 2022-07-05 00:00:00 **source**: SupportedSources.CORE **journal**: **volume**: **doi**: None **urls**: http://arxiv.org/abs/2107.00649 **id**: id7745130642074932596 **abstract**: A set of novel approaches for estimating epistemic uncertainty in deep neural networks with a single forward pass has recently emerged as a valid alternative to Bayesian Neural Networks. On the premise of informative representations, these deterministic uncertainty methods (DUMs) achieve strong performance on detecting out-of-distribution (OOD) data while adding negligible computational costs at inference time. However, it remains unclear whether DUMs are well calibrated and can seamlessly scale to real-world applications - both prerequisites for their practical deployment. To this end, we first provide a taxonomy of DUMs, and evaluate their calibration under continuous distributional shifts. Then, we extend them to semantic segmentation. We find that, while DUMs scale to realistic vision tasks and perform well on OOD detection, the practicality of current methods is undermined by poor calibration under distributional shifts.Comment: International Conference on Machine Learning 202 **versions**:	**authors**: Federico Tombari; Fisher Yu; Luc van Gool; Luca Sieber; Tao Sun; Mattia Segu; Janis Postels **title**: On the Practicality of Deterministic Epistemic Uncertainty **publication_date**: 2021-07-01 00:00:00 **source**: SupportedSources.PAPERS_WITH_CODE **journal**: **volume**: **doi**: **urls**: https://arxiv.org/pdf/2107.00649v3.pdf; https://github.com/google/uncertainty-baselines; https://openreview.net/pdf?id=W3-hiLnUYl **id**: id3797114930759664951 **abstract**: A set of novel approaches for estimating epistemic uncertainty in deep neural networks with a single forward pass has recently emerged as a valid alternative to Bayesian Neural Networks. On the premise of informative representations, these deterministic uncertainty methods (DUMs) achieve strong performance on detecting out-of-distribution (OOD) data while adding negligible computational costs at inference time. However, it remains unclear whether DUMs are well calibrated and can seamlessly scale to real-world applications - both prerequisites for their practical deployment. To this end, we first provide a taxonomy of DUMs, and evaluate their calibration under continuous distributional shifts. Then, we extend them to semantic segmentation. We find that, while DUMs scale to realistic vision tasks and perform well on OOD detection, the practicality of current methods is undermined by poor calibration under distributional shifts. **versions**:	DUPLICATES	99