| | doc_1 | doc_2 | decision | id |
|---|---|---|---|---|
| cases | see doc_1 table below | see doc_2 table below | NOT DUPLICATES | 196 |

**doc_1**

| | |
|---|---|
| authors | David MacÃªdo; Tsang Ing Ren; Cleber Zanchettin; Adriano L. I. Oliveira; Teresa Ludermir |
| title | Entropic Out-of-Distribution Detection: Seamless Detection of Unknown Examples |
| publication_date | 2021-08-04 00:00:00 |
| source | SupportedSources.INTERNET_ARCHIVE |
| journal | |
| volume | |
| doi | |
| urls | https://web.archive.org/web/20210810034140/https://arxiv.org/pdf/2006.04005v3.pdf |
| id | id5285811626360868691 |
| abstract | In this paper, we argue that the unsatisfactory out-of-distribution (OOD) detection performance of neural networks is mainly due to the SoftMax loss anisotropy and propensity to produce low entropy probability distributions in disagreement with the principle of maximum entropy. Current out-of-distribution (OOD) detection approaches usually do not directly fix the SoftMax loss drawbacks, but rather build techniques to circumvent it. Unfortunately, those methods usually produce undesired side effects (e.g., classification accuracy drop, additional hyperparameters, slower inferences, and collecting extra data). In the opposite direction, we propose replacing SoftMax loss with a novel loss function that does not suffer from the mentioned weaknesses. The proposed IsoMax loss is isotropic (exclusively distance-based) and provides high entropy posterior probability distributions. Replacing the SoftMax loss by IsoMax loss requires no model or training changes. Additionally, the models trained with IsoMax loss produce as fast and energy-efficient inferences as those trained using SoftMax loss. Moreover, no classification accuracy drop is observed. The proposed method does not rely on outlier/background data, hyperparameter tuning, temperature calibration, feature extraction, metric learning, adversarial training, ensemble procedures, or generative models. Our experiments showed that IsoMax loss works as a seamless SoftMax loss drop-in replacement that significantly improves neural networks' OOD detection performance. Hence, it may be used as a baseline OOD detection approach to be combined with current or future OOD detection techniques to achieve even higher results. |
| versions | |

**doc_2**

| | |
|---|---|
| authors | David MacÃªdo; Tsang Ing Ren; Cleber Zanchettin; Adriano L. I. Oliveira; Teresa Ludermir |
| title | Entropic Out-of-Distribution Detection |
| publication_date | 2021-05-24 00:00:00 |
| source | SupportedSources.INTERNET_ARCHIVE |
| journal | |
| volume | |
| doi | |
| urls | https://web.archive.org/web/20201205011648/https://arxiv.org/pdf/1908.05569v11.pdf |
| id | id5122796610781899051 |
| abstract | Out-of-distribution (OOD) detection approaches usually present special requirements (e.g., hyperparameter validation, collection of outlier data) and produce side effects (e.g., classification accuracy drop, slower energy-inefficient inferences). We argue that these issues are a consequence of the SoftMax loss anisotropy and disagreement with the maximum entropy principle. Thus, we propose the IsoMax loss and the entropic score. The seamless drop-in replacement of the SoftMax loss by IsoMax loss requires neither additional data collection nor hyperparameter validation. The trained models do not exhibit classification accuracy drop and produce fast energy-efficient inferences. Moreover, our experiments show that training neural networks with IsoMax loss significantly improves their OOD detection performance. The IsoMax loss exhibits state-of-the-art performance under the mentioned conditions (fast energy-efficient inference, no classification accuracy drop, no collection of outlier data, and no hyperparameter validation), which we call the seamless OOD detection task. In future work, current OOD detection methods may replace the SoftMax loss with the IsoMax loss to improve their performance on the commonly studied non-seamless OOD detection problem. |
| versions | |