<table>
<tr><th rowspan="2">cases</th><th>doc_1</th><th>doc_2</th><th>decision</th><th>id</th></tr>
<tr><td>
<table>
<tr><th>authors</th><td>Robin B. Chan
Matthias Rottmann
Hanno Gottschalk</td></tr>
<tr><th>title</th><td>Entropy Maximization and Meta Classification for Out-of-Distribution Detection in Semantic Segmentation</td></tr>
<tr><th>publication_date</th><td>2021-10-01 00:00:00</td></tr>
<tr><th>source</th><td>SupportedSources.OPENALEX</td></tr>
<tr><th>journal</th><td>arXiv (Cornell University)</td></tr>
<tr><th>volume</th><td></td></tr>
<tr><th>doi</th><td>10.1109/iccv48922.2021.00508</td></tr>
<tr><th>urls</th><td>https://openalex.org/W3112906266
https://doi.org/10.1109/iccv48922.2021.00508
http://arxiv.org/pdf/2012.06575</td></tr>
<tr><th>id</th><td>id-7924627670073505000</td></tr>
<tr><th>abstract</th><td></td></tr>
<tr><th>versions</th><td></td></tr>
</table>
</td><td>
<table>
<tr><th>authors</th><td>Robin Chan
Matthias Rottmann
Hanno Gottschalk</td></tr>
<tr><th>title</th><td>Entropy Maximization and Meta Classification for Out-Of-Distribution Detection in Semantic Segmentation</td></tr>
<tr><th>publication_date</th><td>2021-07-27 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>
<tr><th>doi</th><td></td></tr>
<tr><th>urls</th><td>https://web.archive.org/web/20210730170902/https://arxiv.org/pdf/2012.06575v2.pdf</td></tr>
<tr><th>id</th><td>id-8904738483363938247</td></tr>
<tr><th>abstract</th><td>Deep neural networks (DNNs) for the semantic segmentation of images are usually trained to operate on a predefined closed set of object classes. This is in contrast to the "open world" setting where DNNs are envisioned to be deployed to. From a functional safety point of view, the ability to detect so-called "out-of-distribution" (OoD) samples, i.e., objects outside of a DNN's semantic space, is crucial for many applications such as automated driving. A natural baseline approach to OoD detection is to threshold on the pixel-wise softmax entropy. We present a two-step procedure that significantly improves that approach. Firstly, we utilize samples from the COCO dataset as OoD proxy and introduce a second training objective to maximize the softmax entropy on these samples. Starting from pretrained semantic segmentation networks we re-train a number of DNNs on different in-distribution datasets and consistently observe improved OoD detection performance when evaluating on completely disjoint OoD datasets. Secondly, we perform a transparent post-processing step to discard false positive OoD samples by so-called "meta classification". To this end, we apply linear models to a set of hand-crafted metrics derived from the DNN's softmax probabilities. In our experiments we consistently observe a clear additional gain in OoD detection performance, cutting down the number of detection errors by up to 52% when comparing the best baseline with our results. We achieve this improvement sacrificing only marginally in original segmentation performance. Therefore, our method contributes to safer DNNs with more reliable overall system performance.</td></tr>
<tr><th>versions</th><td></td></tr>
</table>
</td><td>DUPLICATES</td><td>115</td></tr>
</table>