Hochschule
Bonn-Rhein-Sieg
University of Applied Sciences

German
Research Center
for Artificial
Intelligence

Bonn-Aachen
International Center for
Information Technology

Benchmarking Out-of-Distribution Detection in 2D Object Detection

Thesis Defense

February 19, 2022

Jaswanth Bandlamudi

Supervisors

Prof. Dr. Paul G Plöger
Prof. Dr. Nico Hochgeschwender
Prof. Dr. Matias Valdenegro Toro
M.Sc. Octavio Arriaga

Introduction

- Deep Neural Networks, current State-Of-The-Art (SOTA) performers in
  - Classification
  - Object Detection
  - Segmentation
- Trained with *closed world assumption*, test data $\sim$ train data
- Deployed in open world $\Longrightarrow$ Out-of-Distribution(OOD) examples
- Applications
  - Product recommendations, recoverable
  - Time series prediction, partially reversible
  - Autonomous driving / Medical diagnosis, irreversiable and catastrophic

Out-of-Distribution (OOD) detection (1/3)

- What is OOD data ?
  - Data that is outside the semantic space formed by the images used for training
  - Input with objects which are not used in training but have features closer to the object of interest.

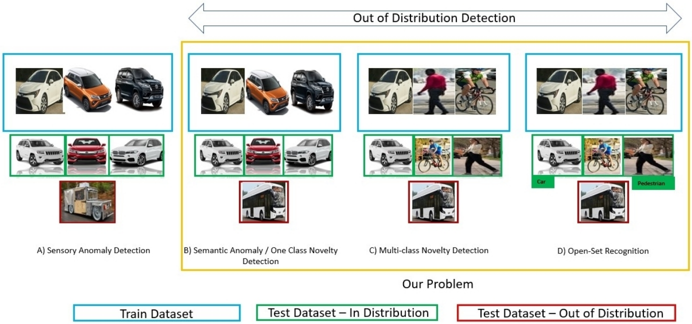

Figure 1: Class differentiation in generalized OOD detection framework

Out-of-Distribution (OOD) detection(2/3)

Different types of OOD data

- Data from a different domain
- Data with poor quality of features
- Data with inputs that are neither used nor prominent in the training data

Out-of-Distribution (OOD) detection(3/3)

Current Object Detection model performance on OOD data

(a) False Positive detection

(b) False Negative detection

Figure 2: Examples of failures in object dedtection

OOD detector - Expectations

- Produce a ***Novelty Score (NS)***.
- NS can be a distance metric, a class-dependent probabilistic value, an entropy value, or a descriptive statistic value
- OOD detection can be posed as a binary classification problem.

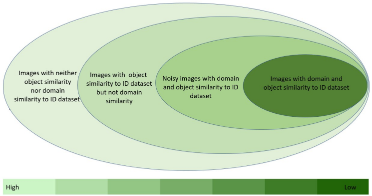

Figure 3: Expected behavior of NS from OOD detector.

$$X = \begin{cases} \text{ID}, & \text{if } NS \geq \delta \\ \text{OOD}, & \text{otherwise} \end{cases} \tag{1}$$

Previous works

Table 1: Previous works on OOD detection

Method	Works Proposed
Metric based methods	Devries and Taylor [2018], Oberdiek et al. [2018], Hendrycks et al. [2018] , Lee et al. [2018]
Inconsistency based methods	Liang et al. [2017]
Generative methods	Hendrycks and Gimpel [2017], Ren et al. [2019], Van Den Oord et al. [2016]
Uncertainty based methods	Malinin and Gales [2018], Lakshminarayanan et al. [2017], Van Amersfoort et al. [2020]

- Works only for classification problem
- Not directly adaptable to object detection problem

Methodology

In this work

- Single-Shot Detector (SSD) is used to solve the object detection problem.
- For OOD detection we decided to use
  1. Max-Softmax score based OOD detection
  2. ODIN
  3. Mahalanobis distance based OOD detection
  4. Uncertainty based OOD detection
     - Bayesian Neural Network
     - Sub-Ensemble
- A new benchmark dataset **Out of Distribution for Object Detection** (OD^2) dataset

References (1/2)

Terrance Devries and Graham W Taylor. Learning Confidence for Out-of-Distribution Detection in Neural Networks. 2018.

Philipp Oberdiek, Matthias Rottmann, and Hanno Gottschalk. Classification uncertainty of deep neural networks based on gradient information. In **Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)**, volume 11081 LNAI, pages 113–125, 2018. ISBN 9783319999777.

Dan Hendrycks, Mantas Mazeika, and Thomas Dietterich. Deep anomaly detection with outlier exposure. In **arXiv**, 2018.

Kimin Lee, Kibok Lee, Honglak Lee, and Jinwoo Shin. A simple unified framework for detecting out-of-distribution samples and adversarial attacks. Technical report, 2018.

Shiyu Liang, Yixuan Li, and Rayadurgam Srikant. Enhancing the reliability of out-of-distribution image detection in neural networks. **arXiv preprint arXiv:1706.02690**, 2017.

Dan Hendrycks and Kevin Gimpel. A baseline for detecting misclassified and out-of-distribution examples in neural networks. In **5th International Conference on Learning Representations, ICLR 2017 - Conference Track Proceedings**, 2017. ISBN 1610.02136v3.

References (2/2)

Jie Ren, Peter J. Liu, Emily Fertig, Jasper Snoek, Ryan Poplin, Mark A. DePristo, Joshua V. Dillon, and Balaji Lakshminarayanan. Likelihood ratios for out-of-distribution detection. In **arXiv**, 2019.

Aäron Van Den Oord, Nal Kalchbrenner, Oriol Vinyals, Lasse Espeholt, Alex Graves, and Koray Kavukcuoglu. Conditional image generation with PixelCNN decoders. In **Advances in Neural Information Processing Systems**, pages 4797–4805, 2016.

Andrey Malinin and Mark Gales. Predictive uncertainty estimation via prior networks. In **Advances in Neural Information Processing Systems**, volume 2018-December, pages 7047–7058, 2018.

Balaji Lakshminarayanan, Alexander Pritzel, and Charles Blundell. Simple and scalable predictive uncertainty estimation using deep ensembles. In **Advances in Neural Information Processing Systems**, volume 2017-December, pages 6403–6414, 2017.

Joost Van Amersfoort, Lewis Smith, Yee Whye Teh, and Yarin Gal. Simple and scalable epistemic uncertainty estimation using a single deep deterministic neural network. Technical report, 2020.