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

Thesis Defense

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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 $\implies$ 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.

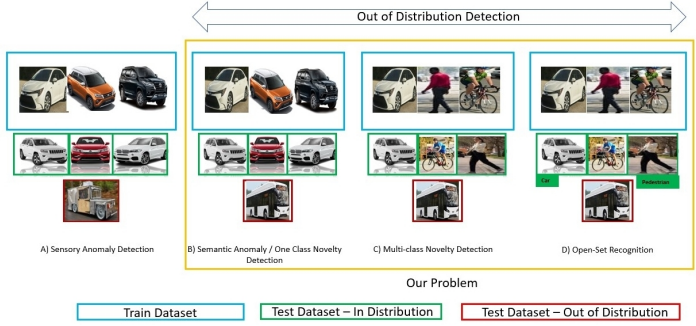

Figure: Class differentiation in generalized OOD detection framework

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) (b)

Figure: 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.

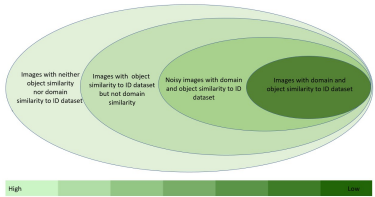

Figure: Expected behavior of OOD detector.

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

Previous works

Table: 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 [2017a], 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

- Proposed new benchmark dataset **Out of Distribution for Object Detection** (OD^2) dataset
- 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 [Hendrycks and Gimpel, 2017b]
  2. ODIN [Liang et al., 2017]
  3. Mahalanobis distance based OOD detection [Lee et al., 2018]
  4. Uncertainty based OOD detection [Malinin and Gales, 2018, Lakshminarayanan et al., 2017]
     - » Bayesian Neural Network
     - » Sub-Ensemble

OD^2 Dataset

Table: Table showing various type of images to address the OOD cases

Purpose	Dataset Source	Classes	Novelty Score Behavior	Task
In-Distribution	BDD100K [Yu et al., 2020]	Pedestrian, Rider, Car, Truck, Bus, Motorcycle, Bicycle, Traffic sign	Low Novelty score	Object detector performance
Low light and bad image quality	BDD100K (non-clear weather) and Climate-GAN [Schmidt et al., 2021] generated Smog images	Pedestrian, Rider, Car, Truck, Bus, Motorcycle, Bicycle, Traffic sign	Medium Novelty Score	Detector Robustness
Classes with semantic-variance	IDD [Varma et al., 2019]	Trucks, Motorcycles, Traffic Sign	High Novelty Score	OOD detection
Novel Classes	IDD	Auto-Rickshaws	High Novelty Score	Multi class novelty detection
Out-of-Domain images	Climate-GAN generated Flood and Fire images	Pedestrian, Rider, Car, Truck, Bus, Motorcycle, Bicycle, Traffic sign	High Novelty Score	Out-Of-Domain detection

Single Shot multi-box Detector (SSD) model (1/2)

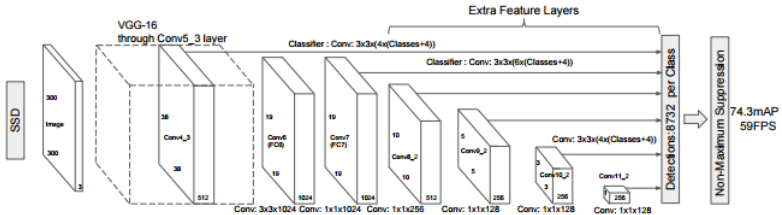

Figure: SSD framework proposed by Liu et al. [2016, p. 24].

- Single network for detection and classification
- No Fully-Connected layers
- Low input resolution

Single Shot multi-box Detector (SSD) model (2/2)

- Default boxes
- Matching strategy is used,
  - $IoU_{defaultbox}^{groundtruth}$ > 0.5
  - overlapped objects and simple learning
- Processing of features from multiple layers
  - Deep feature maps
  - Shallow feature maps

- Loss

$$L(x, c, l, g) = \frac{1}{N} \left(L_{\text{conf}}(x, c) + \alpha L_{\text{loc}}(x, l, g) \right)$$

  - L_{conf} is Softmax Loss
  - L_{loc} is Smooth L_1 Loss
- Filter boxes with low confidence and NMS with 0.45 IOU
- Take top 200 detections

SSD Object Detection Results

Figure: Matched prior boxes and ground truth boxes

Table: Average Precision values using SSD300 model with and without tuned prior boxes

	Agents								
Models	**Pedestrian**	**Rider**	**Car**	**Truck**	**Bus**	**Motorcycle**	**Bicycle**	**Traffic Sign**	**mean**
SSD300	0.006	0.004	0.095	0.083	0.15	0.045	0.092	0.001	0.059
SSD300 - Tuned	0.165	0.135	0.470	0.239	0.389	0.163	0.213	0.186	0.265

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