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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 $\Longrightarrow$ 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.

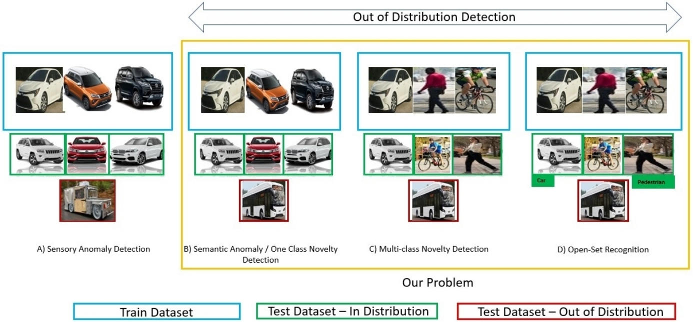


Figure: Class differentiation in generalized OOD detection framework

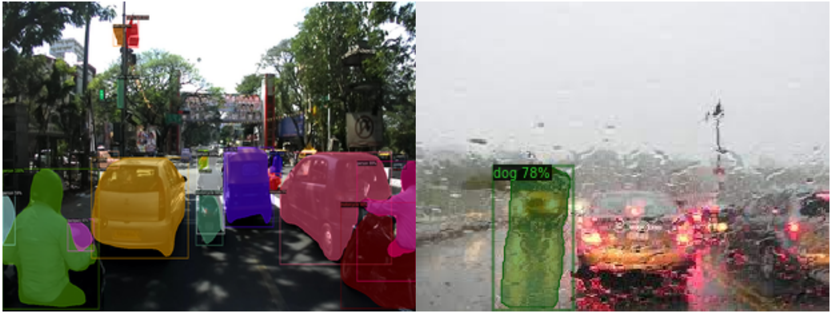
Out-of-Distribution (OOD) detection(2/3)

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

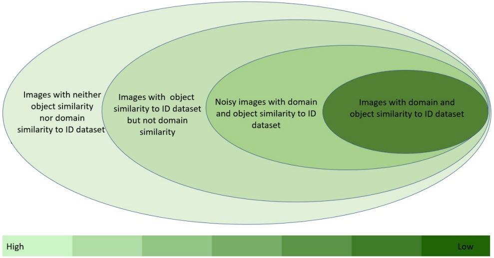


(a) (b)

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.



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

Fig ... ehav

1. Introduction

2. Problem Overview

3. Solution

4. Previous works

5. Methodology

6. Results

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 [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

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)

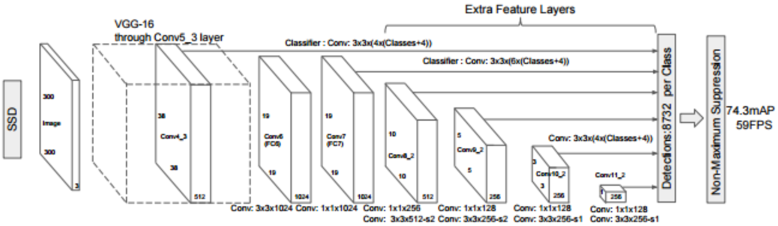


Figure: SSD framework proposed by Liu et al. [2016, p. 24].

- 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,
  - $IoU^{groundtruth}_{defaultbox}$ > 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
- Top 200 detections are considered

OOD methods (1/5)

- Max-Softmax

  Maximum value of softmax scores are used as novelty score

$$s\left(\mathbf{x}^*\right) = \max_c P\left(y_c \mid \mathbf{x}^*; \mathcal{D}\right) \tag{2}$$

- ODIN

$$\tilde{\boldsymbol{x}} = \boldsymbol{x} - \epsilon \operatorname{sign}\left(-\nabla_{\boldsymbol{x}} \log S_{\hat{y}}(\boldsymbol{x}; T)\right) \tag{3}$$

$$S_i(\boldsymbol{x}; T) = \frac{\exp\left(f_i(\boldsymbol{x})/T\right)}{\sum_{j=1}^{N} \exp\left(f_j(\boldsymbol{x})/T\right)} \tag{4}$$

  - ϵ is the perturbation magnitude
  - T is the Temperature

OOD methods (2/5)

- Mahalanobis distance based OOD detection
  assuming intermediate layer features follow class-conditional Gaussian distributions with tied covariances

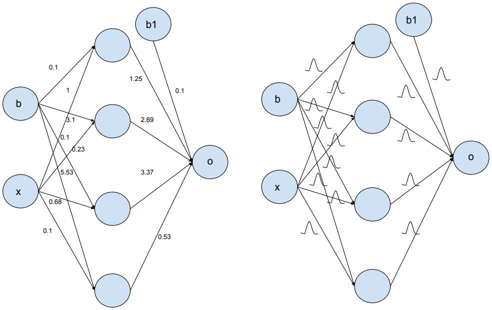
$$M(x) = \max_{c} -(f(x) - \hat{\mu}_c)^T \hat{\Sigma}^{-1} (f(x) - \hat{\mu}_c) \tag{5}$$

$$\hat{\mu}_c = \frac{1}{N_c} \sum_{i:y_c=c} f(x_i)$$

$$\hat{\Sigma} = \frac{1}{N} \sum_{c} \sum_{i:y_c=c} (f(x_i) - \hat{\mu}_c)(f(x_i) - \hat{\mu}_c)^T$$

OOD methods (3/5)

- Uncertainty based OOD detection
  - Bayesian Neural Network



» Bayesian Flipout layers [Wen et al., 2018]

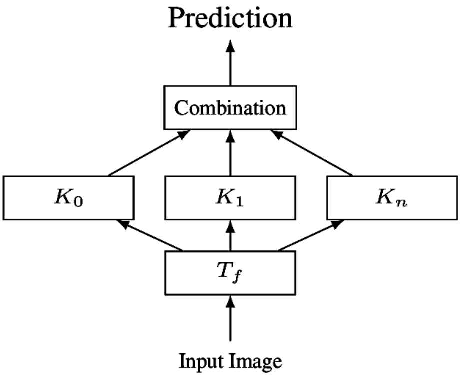
» Reparameterization trick for training [Kingma et al., 2015]

» Prior $P(w) \sim N(0, 1)$

» multiple forward passes for uncertainty quantification

OOD methods (4/5)

– Sub-Ensemble Network



- Model is divided into Trunk and Task layers
- Trunk layers has best performing weights restored and cannot be trained
- Task layers are randomly initialized and re-trained
- Random initialization of layers creates ensemble model.

OOD methods (5/5)

– Novelty Score

Entropy

$$\text{Entropy} = -\sum_{i=1}^{C} P\left(c_i \mid \mathbf{x}^*; \mathcal{D}\right) \ln P\left(c_i \mid \mathbf{x}^*; \mathcal{D}\right) \tag{6}$$

Box deviation is the square root of the trace of the covariance matrix $C(x^*)$.

$$C\left(\mathbf{x}^*\right) = \frac{1}{N} \sum_{i=1}^{N} \hat{\mathbf{v}}_{\mathbf{x}^*}^{i} \hat{\mathbf{v}}_{\mathbf{x}^*}^{i\,T} - \mathbf{I}_{\mathbf{x}^*} \mathbf{I}_{\mathbf{x}^*}^{T} \tag{7}$$

SSD Object Detection Results (1/2)

Table: AP values for various classes using vanilla-SSD Prior boxes

Class	score
Pedestrian	0.006
Rider	0.004
Car	0.095
Truck	0.083
Bus	0.15
Motorcycle	0.045
Bicycle	0.092
Traffic Sign	0.001
Mean	0.059

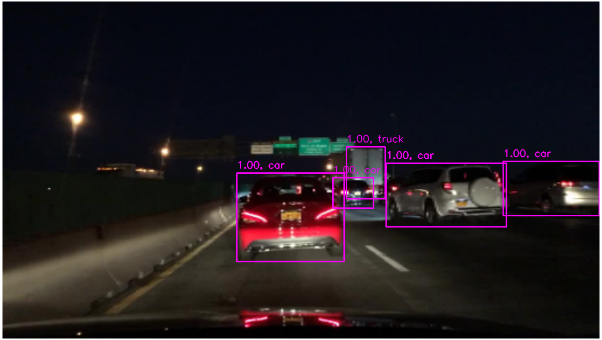


Figure: SSD framework proposed by Liu et al. [2016, p. 24].

- Poor performance, can be improved by tuning

SSD Object Detection Results (2/2)

Table: AP values for various classes using tuned Prior boxes

Class	**score**
Pedestrian	0.165
Rider	0.135
Car	0.479
Truck	0.389
Bus	0.389
Motorcycle	0.163
Bicycle	0.213
Traffic Sign	0.186
Mean	0.265

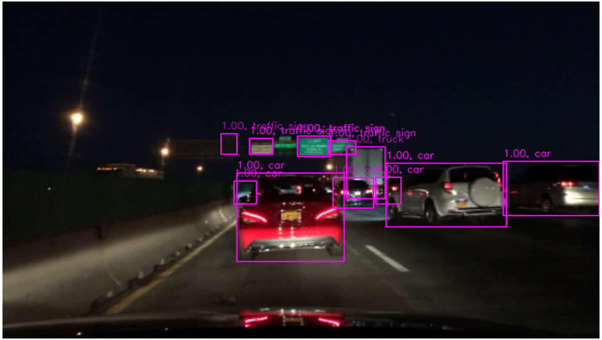


Figure: SSD framework proposed by Liu et al. [2016, p. 24].

- improved performance

OOD Detection - MaxSoftmax

- ROC score of 48 %
- poorer than un-biased random classifier
- complex scenarios, class overlap

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

OOD Detection - ODIN (1/2)

- gradient of loss w.r.t input image is calculated and scaled by a perturbation magnitude.
- input image is modified by subtracting the perturbation.


Figure: Block diagram of a 1st order system.


Figure: Step response of a 1st order system.


Figure: Step response of a 1st order system.

- hyperparameters are tuned using a fraction of test images sampled from IDD dataset
- Perturbation Magnitude 0.2 and Temperature of 1000

OOD Detection - ODIN (2/2)

- ROC score of 54 %
- improvement over max-softmax method
- effect of perturbation is not observed in smaller objects

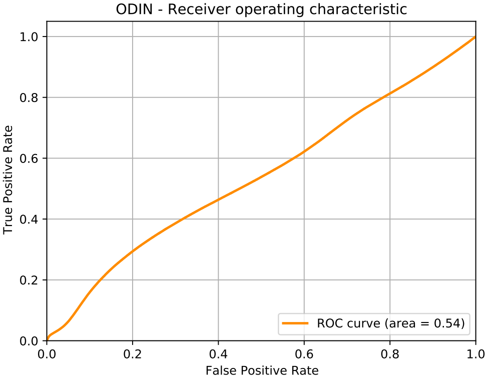


Figure: SSD framework proposed by Liu et al. [2016, p. 24].

OOD Detection - Mahalanobis distance (1/1)

- class-wise mean vectors of each class and a tied covariance matrix using the features from the penultimate layer
- images with other classes masked out by the mean of the image

  - penultimate layer of the SSD is of shape (78588×1)
  - the covariance matrix is of shape (78588×78588)
  - calculating it is not possible with available resources.

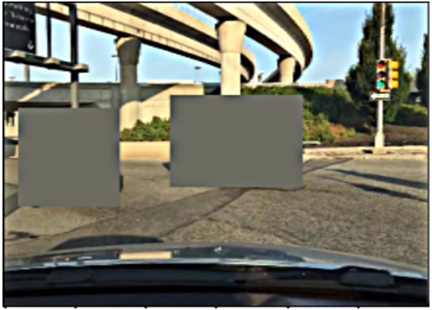


Figure: SSD framework proposed by Liu et al. [2016, p. 24].

OOD Detection - Bayesian SSD object detector (1/1)

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