



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

Thesis Defense

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1. Introduction

2. Problem Overview

3. Solution

4. Previous works

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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, irreversible and catastrophic



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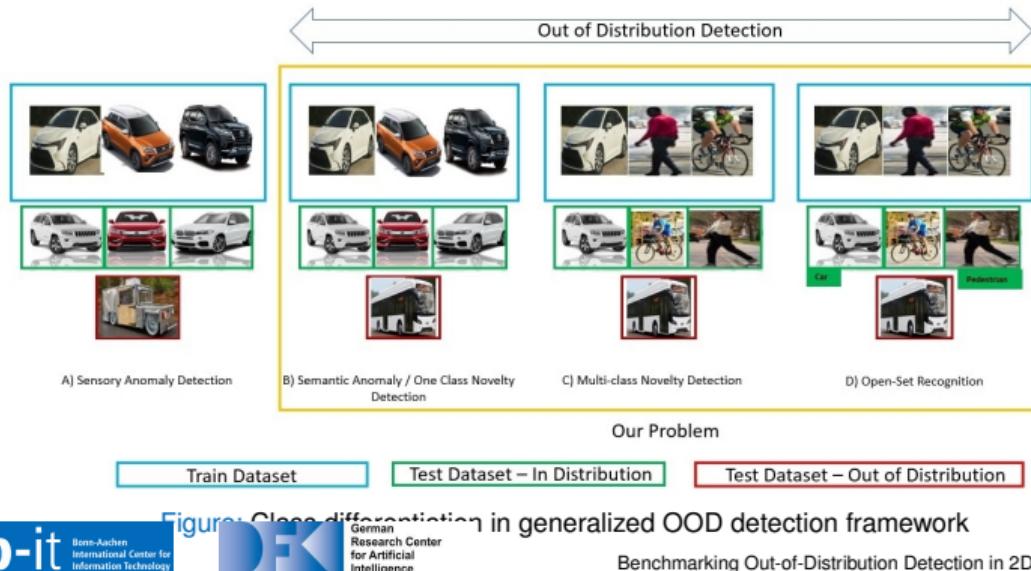
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Out-of-Distribution (OOD) detection (1/3)

- 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.



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 detection



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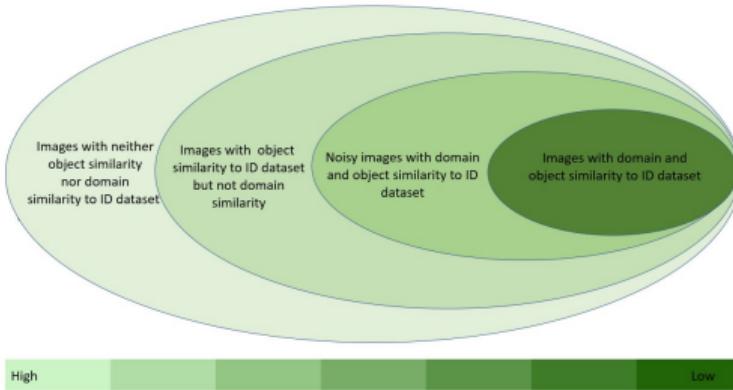
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OOD detector - Expectations

- 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.



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



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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



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OD² 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)

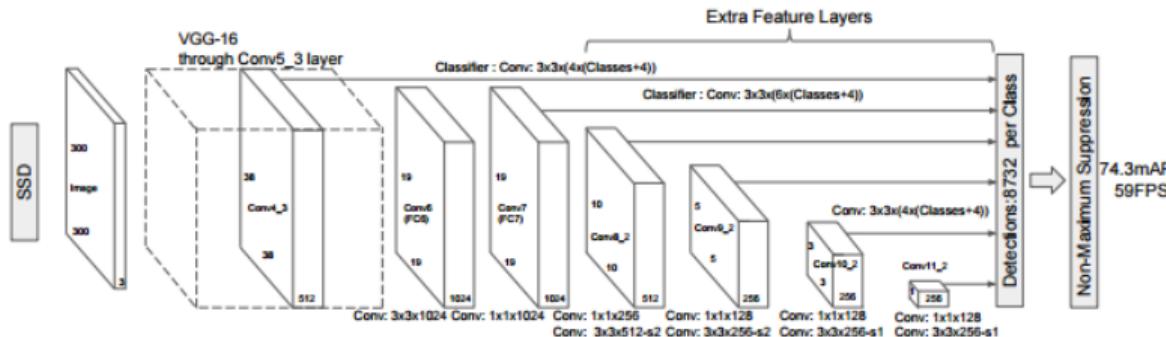


Figure: SSD framework proposed by Liu et al. [2016, p. 24].

- 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_{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 (1/6)

- Max-Softmax

Maximum value of softmax scores are used as novelty score

$$s(\mathbf{x}^*) = \max_c P(y_c | \mathbf{x}^*; \mathcal{D}) \quad (2)$$

- ODIN

$$\tilde{\mathbf{x}} = \mathbf{x} - \epsilon \text{sign}(-\nabla_{\mathbf{x}} \log S_{\hat{y}}(\mathbf{x}; T)) \quad (3)$$

$$S_i(\mathbf{x}; T) = \frac{\exp(f_i(\mathbf{x})/T)}{\sum_{j=1}^N \exp(f_j(\mathbf{x})/T)} \quad (4)$$

- ϵ is the perturbation magnitude
- T is the Temperature



OOD methods (2/6)

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

$$M(x) = \max_c - (f(x) - \hat{\mu}_c)^T \hat{\Sigma}^{-1} (f(x) - \hat{\mu}_c) \quad (5)$$

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

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



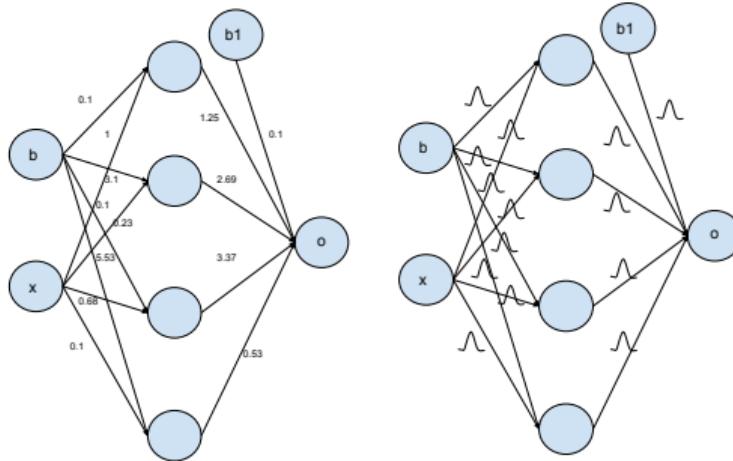
OOD methods (3/6)

- Uncertainty based OOD detection
 - quantifies trustworthiness in the model output
 - » epistemic uncertainty, higher in areas of low data density.
 - » aleatoric uncertainty, labelling and measurement noise
 - OOD data is implicitly modeled by epistemic uncertainty
 - To quantify epistemic uncertainty, we used
 - » Bayesian Neural Network.
 - » Deep Sub-Ensembles



OOD methods (4/6)

— Bayesian Neural Network

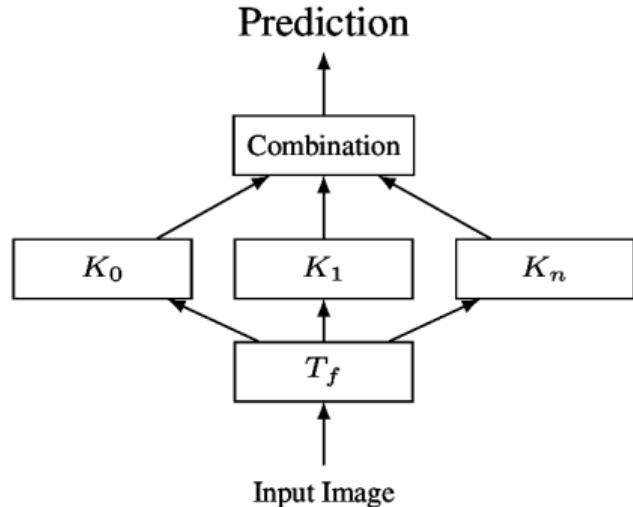


- » Bayesian Flipout layers [Wen et al., 2018]
- » Reparameterization trick for training [Kingma et al., 2015]
- » Prior $P(w) \sim N(0, 1)$
- » multiple forward passes for uncertainty quantification



OOD methods (5/6)

– Sub-Ensemble Network



- » Model is divided into Trunk and Task layers
- » Trunk layers have 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 (6/6)

- Novelty Score

Entropy

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

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

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



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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

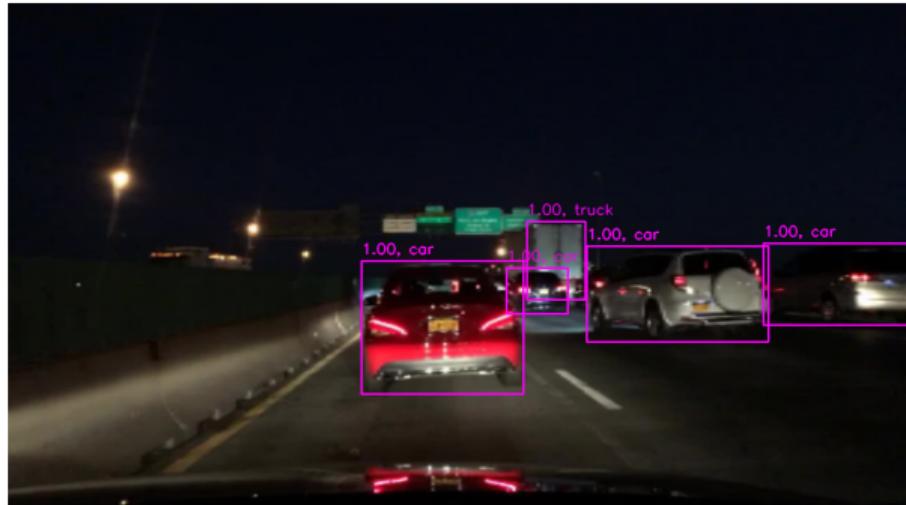


Figure: Positively matched vanilla prior boxes with ground truth boxes.

- 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

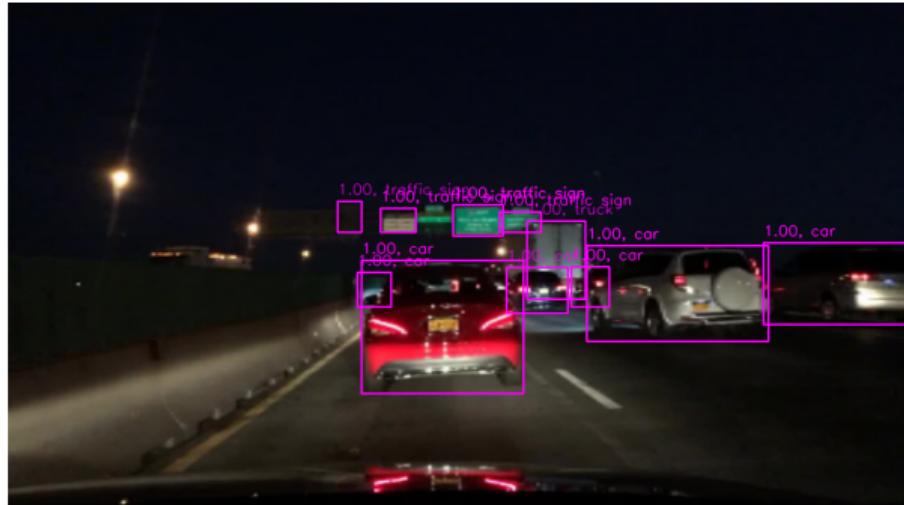


Figure: Positively matched tuned prior boxes with ground truth boxes..

- improved performance



OOD Detection - MaxSoftmax

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

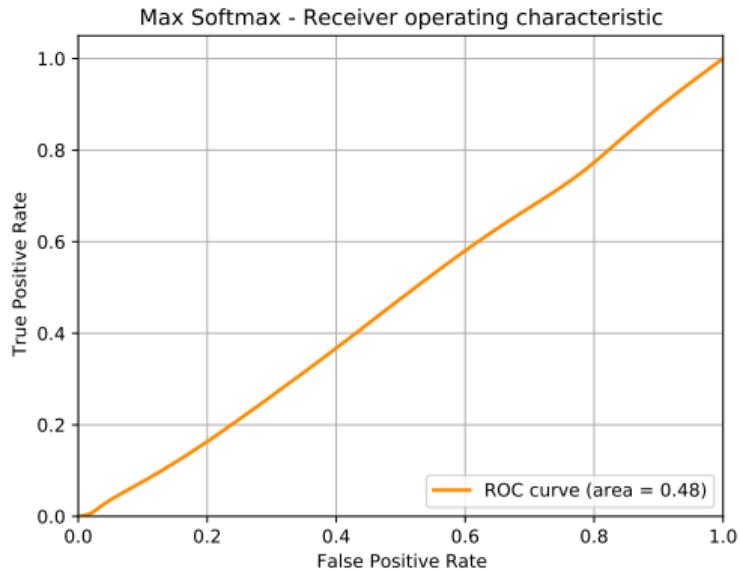


Figure: AUROC curve for OOD detection using softmax scores.



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: magnitude=0.2, Temperature=10



Figure: magnitude=0.005, Temperature=100



Figure: magnitude=0.005, Temperature=10

- 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

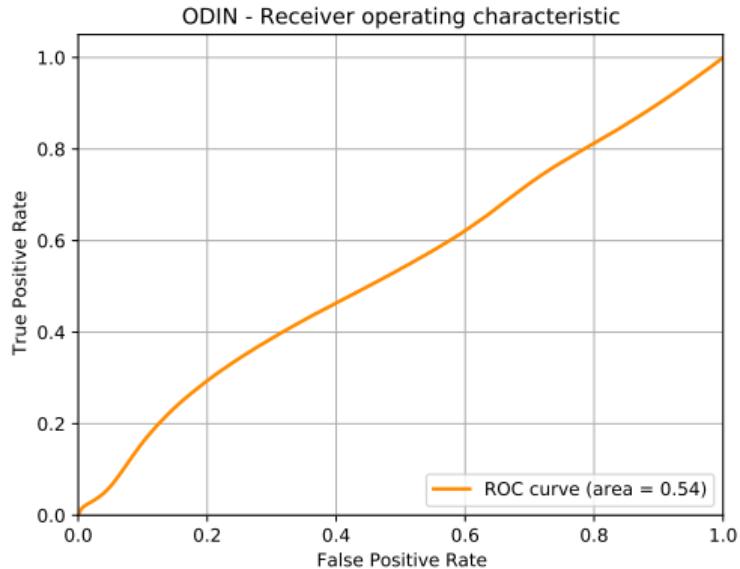


Figure: AUROC curve for OOD detection using softmax scores after applying ODIN



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

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



Figure: Class masked images to extract class specific mean and covariance



UQ models - Performance (1/6)

Layers highlighted in green are chosen as

- Flipout layers to model Bayesian-SSD
- Task network to model Sub-Ensemble SSD

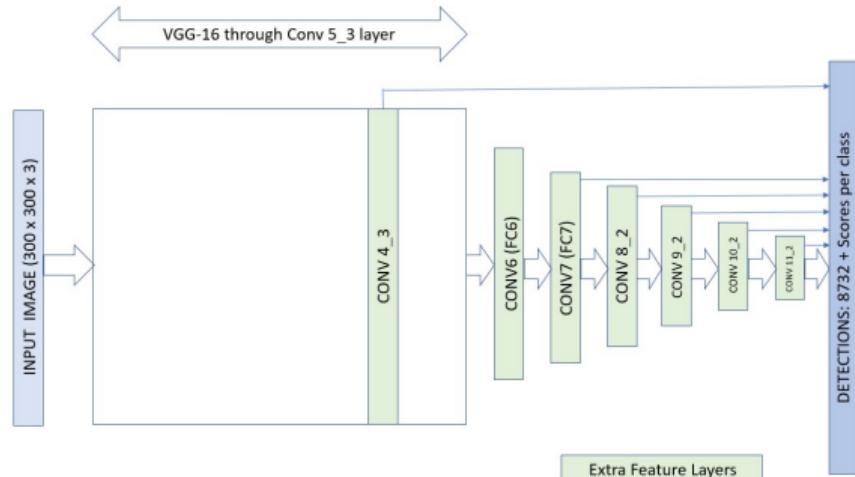


Figure: modified SSD for uncertainty quantification



UQ models - Performance (2/6)

- Bayesian SSD model

Table: AP values for various classes using tuned Prior boxes

Class	score
Pedestrian	0.172
Rider	0.149
Car	0.476
Truck	0.4
Bus	0.401
Motorcycle	0.196
Bicycle	0.232
Traffic Sign	0.184
Mean	0.276

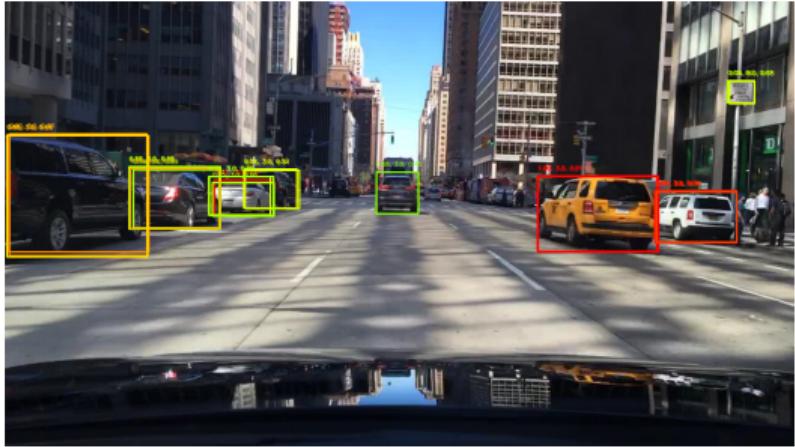
- Sub-Ensemble SSD model

Table: AP values for various classes using tuned Prior boxes

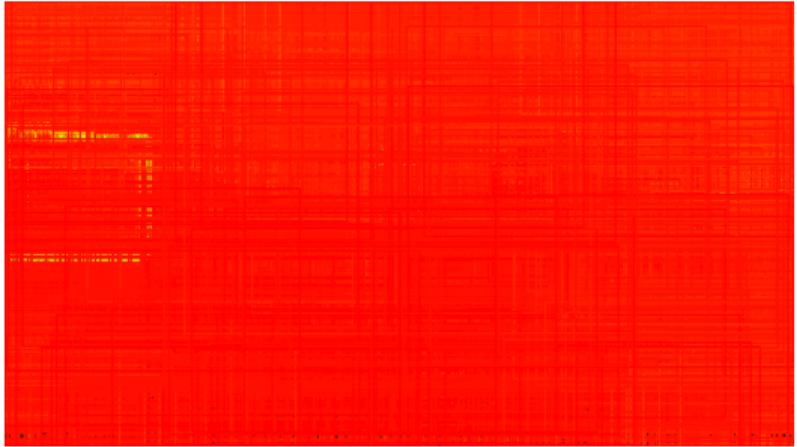
Class	score
Pedestrian	0.167
Rider	0.144
Car	0.47
Truck	0.393
Bus	0.396
Motorcycle	0.181
Bicycle	0.211
Traffic Sign	0.171
Mean	0.267



UQ models - Performance (3/6)



(a) Detections with variances represented as ellipses



(b) Visualizing all 8732 boxes regressed by SSD300

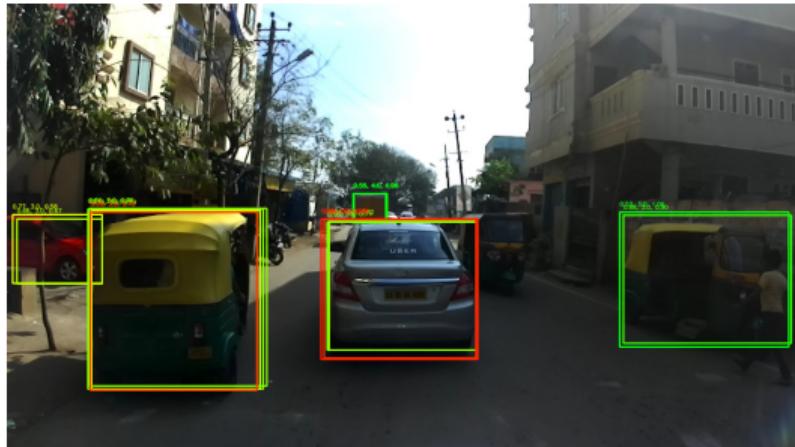


(c) Colormap

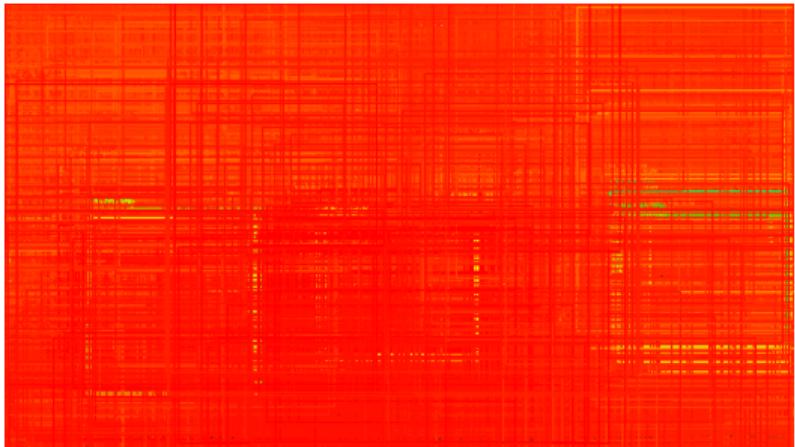
Figure: Inference of Bayesian-SSD300 model on a sample image from BDD



UQ models - Performance (4/6)



(a) Detections with variances represented as ellipses

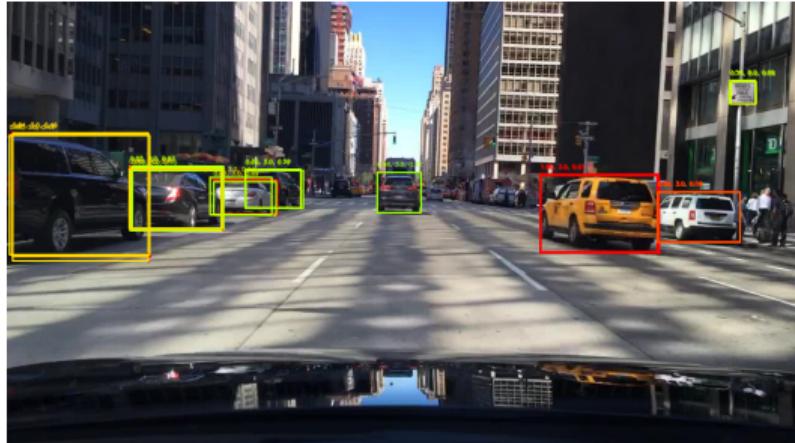


(b) Visualizing all 8732 boxes regressed by SSD300

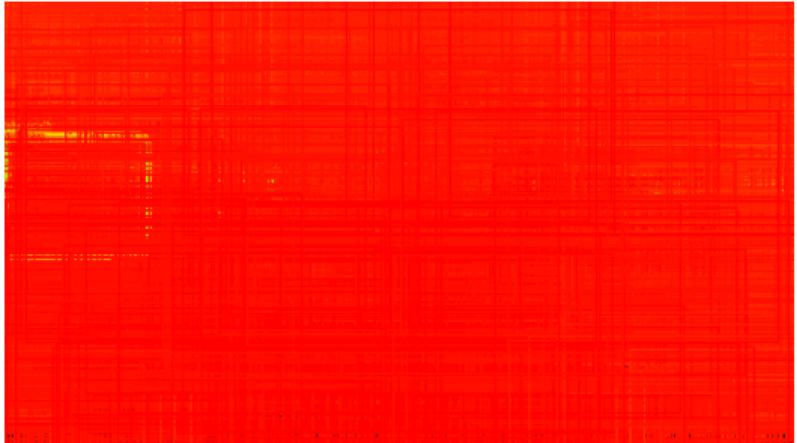
Figure: Inference of Bayesian-SSD300 model on a sample image from BDD



UQ models - Performance (5/6)



(a) Detections with variances represented as ellipses

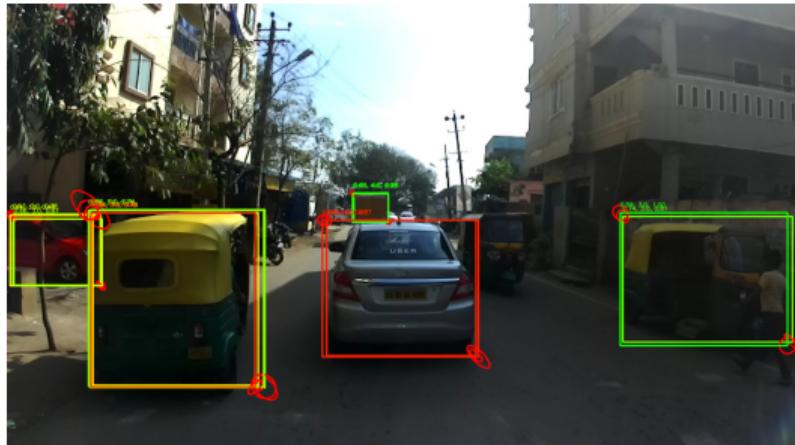


(b) Visualizing all 8732 boxes regressed by SSD300

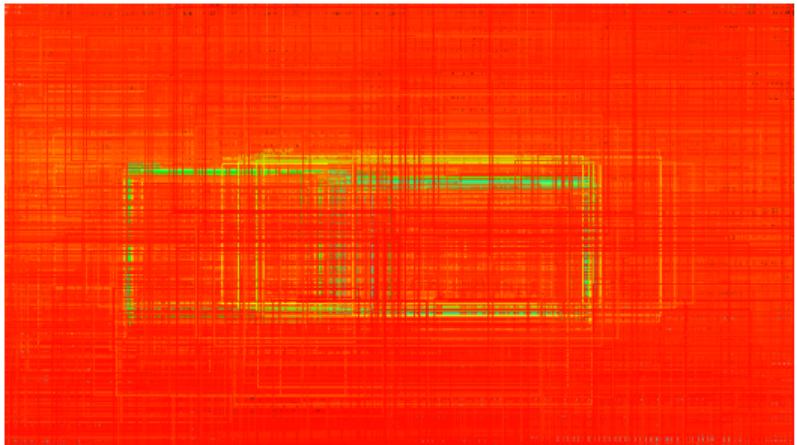
Figure: Inference of Bayesian-SSD300 model on a sample image from BDD



UQ models - Performance (6/6)



(a) Detections with variances represented as ellipses

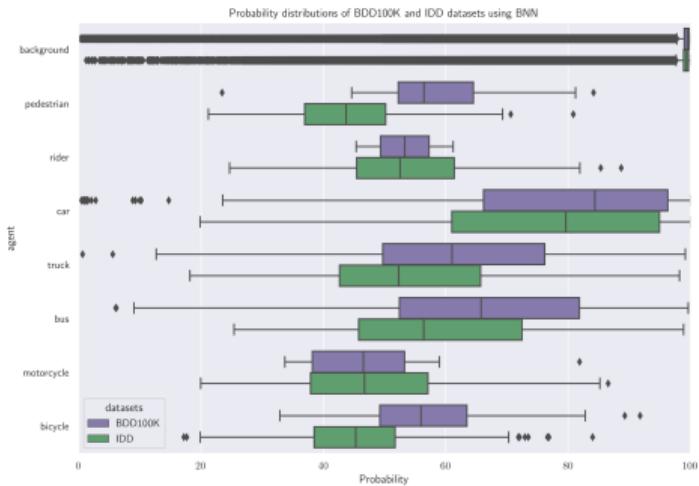


(b) Visualizing all 8732 boxes regressed by SSD300

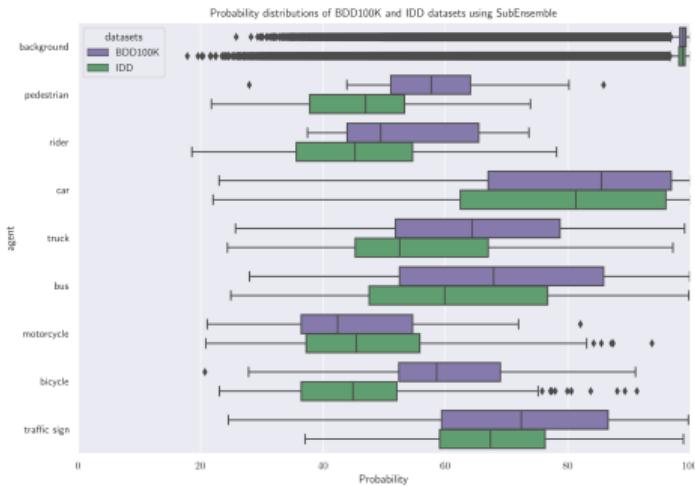
Figure: Inference of Bayesian-SSD300 model on a sample image from BDD



UQ models - OOD Detection (1/7)



(a) Detections with variances represented as ellipses

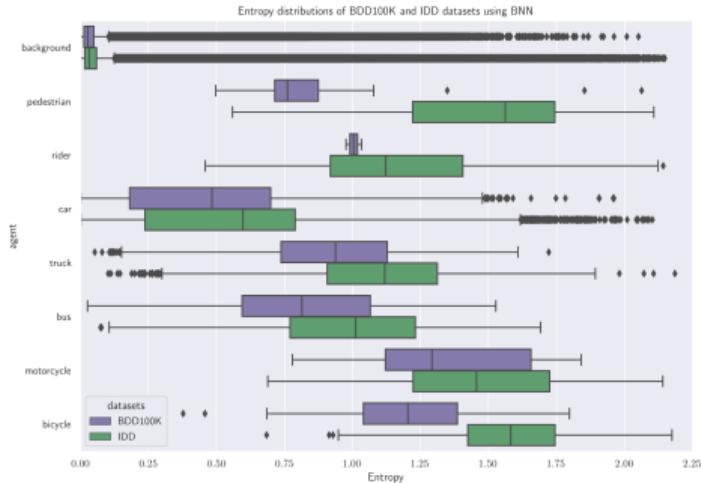


(b) Visualizing all 8732 boxes regressed by SSD300

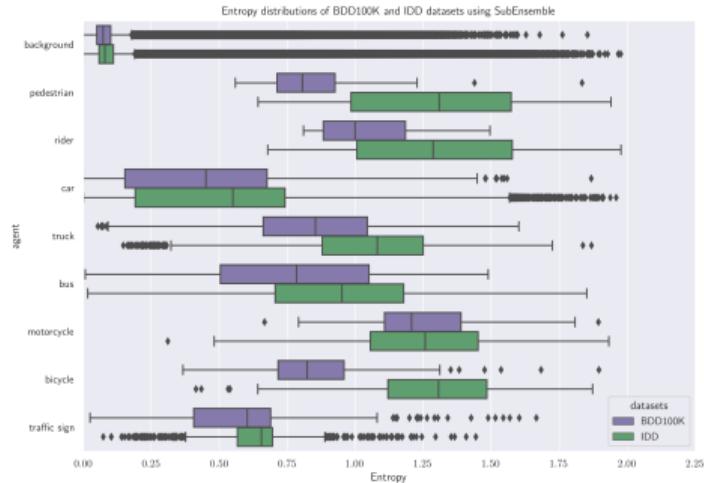
Figure: Inference of Bayesian-SSD300 model on a sample image from BDD



UQ models - OOD Detection (2/7)



(a) Detections with variances represented as ellipses

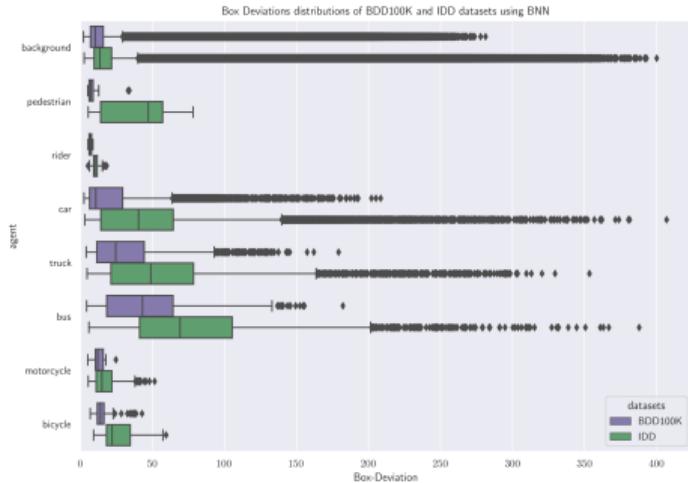


(b) Visualizing all 8732 boxes regressed by SSD300

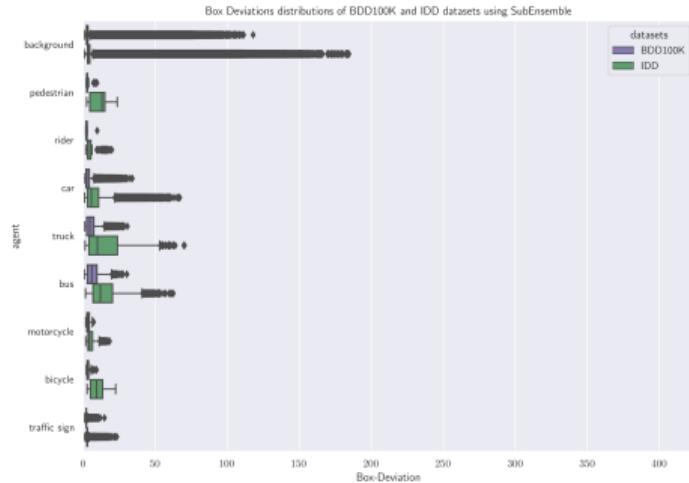
Figure: Inference of Bayesian-SSD300 model on a sample image from BDD



UQ models - OOD Detection (3/7)



(a) Detections with variances represented as ellipses



(b) Visualizing all 8732 boxes regressed by SSD300

Figure: Inference of Bayesian-SSD300 model on a sample image from BDD



UQ models - OOD Detection (4/7)

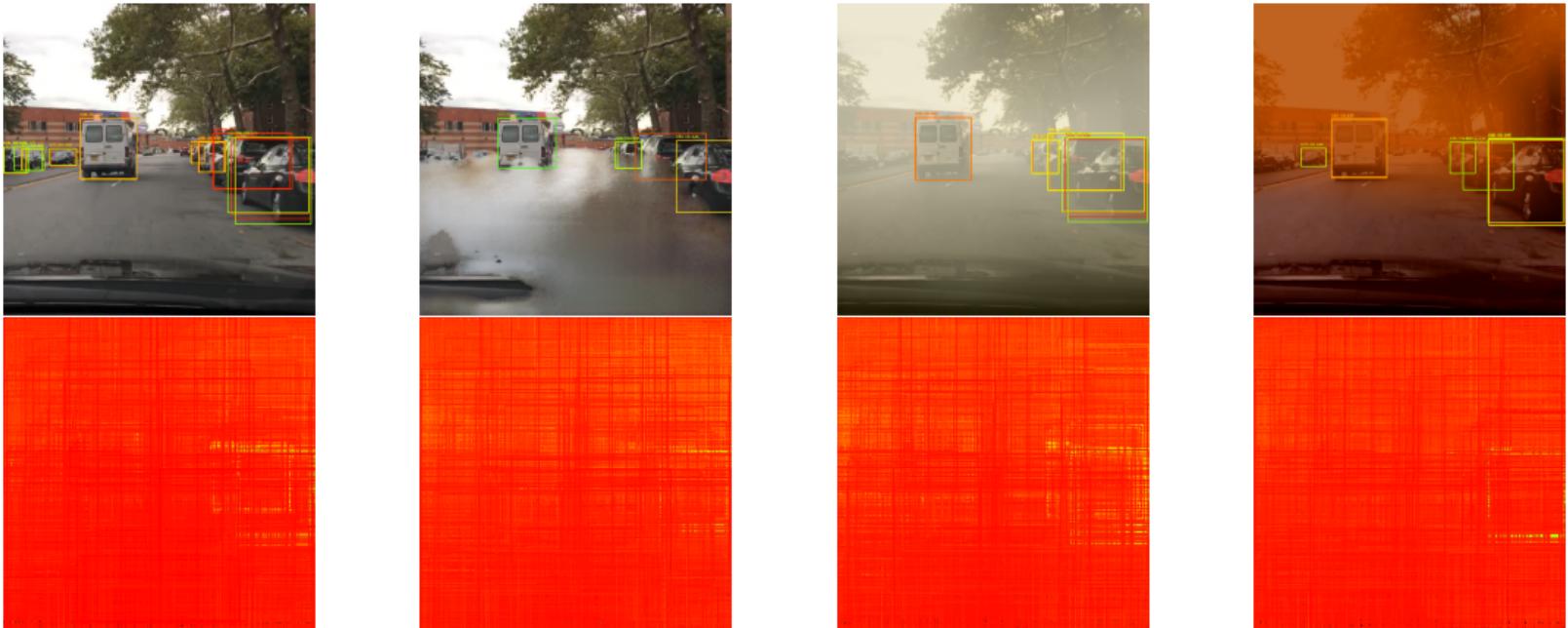
Table: Previous works on OOD detection

Models	Metrics	Agents									
		Background	Pedestrian	Rider	Car	Truck	Bus	Motorcycle	Bicycle	Traffic Sign	Mean
Bayesian-SSD300	Probability	0.45	0.14	0.75	0.45	0.37	0.38	0.49	0.23	-	0.45
	Entropy	0.56	0.88	0.59	0.59	0.67	0.64	0.6	0.84	-	0.56
	Box_deviation	0.64	0.93	0.82	0.76	0.69	0.7	0.62	0.85	-	0.64
Sub-Ensemble SSD300	Probability	0.44	0.21	0.34	0.46	0.34	0.4	0.53	0.19	0.41	0.44
	Entropy	0.56	0.86	0.72	0.58	0.71	0.62	0.51	0.88	0.62	0.56
	Box_deviation	0.76	0.95	0.84	0.79	0.74	0.75	0.71	0.94	0.88	0.75

- metrics struggled in classifying background class between ID and OOD data.
- Box deviation performed well in detecting OOD.
- performance is similar in Car, Truck, Bus, and Rider



UQ models - OOD Detection (5/7)



Performance of BNN on BDD100K weather dataset

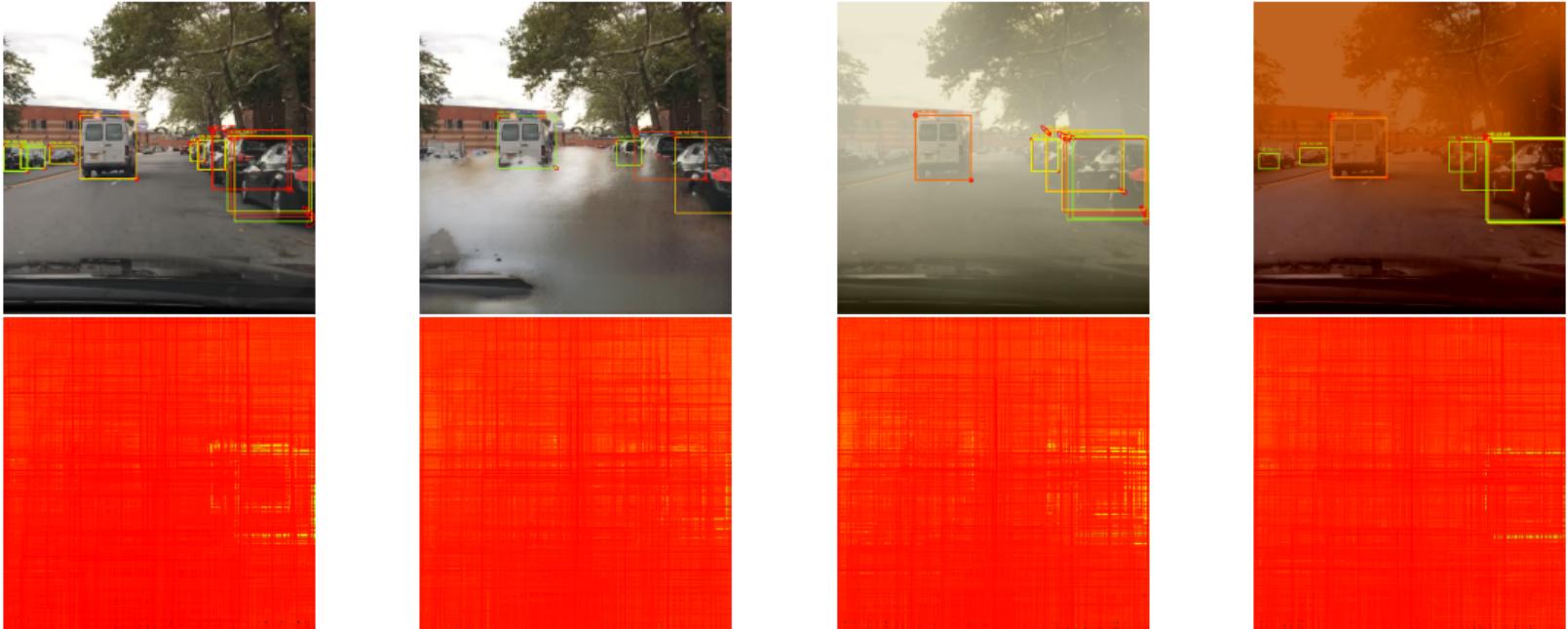


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UQ models - OOD Detection (6/7)



Performance of Sub-Ensembles on BDD100K weather dataset



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UQ models - OOD Detection (7/7)

Table: Uncertainty quantification metrics calculated using Bayesian and Sub-Ensemble versions of SSD300 model

		Bayesian SSD300	Sub-Ensemble SSD300
Flood	Probability	0.43	0.5
	Entropy	0.57	0.5
Smog	Box Deviation	0.46	0.5
	Probability	0.43	0.5
	Entropy	0.57	0.5
	Box Deviation	0.44	0.5
Wild Fire	Probability	0.51	0.53
	Entropy	0.49	0.46
	Box Deviation	0.49	0.46

- change in weather the object detection performance has deteriorated especially in the case of flood images.
- scores suggest that using uncertainty quantification methods performed almost similar to an unbiased random classifier.
- uncertainty quantification methods not being able to detect skewed datasets complies with the results reported by Ovadia et al. [2019]



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Contributions (1/2)

- Proposed a new benchmark dataset called Out-of-Distribution detection for Object Detection (OD^2) dataset
- Max Softmax, ODIN, Mahalanobis distance based OOD detector, and uncertainty based OOD detector are modelled.
- Single Shot multi-box Object Detector (SSD300) is trained on BDD100K dataset and tuned the prior boxes
- we observed that ODIN outperformed the Max-Softmax based OOD detectors, could not successfully model Mahalanobis distance-based OOD detector.
- BNN based and a Sub-Ensemble model of SSD object detector network are modelled and trained.



Contributions (2/2)

- We used entropy to quantify uncertainty in the classification head of object detector and box deviation to quantify uncertainty in the regression head of object detectors.
- We performed extensive experimentation on all the three available OOD detectors for object detection purposes. We also performed studies on the class-specific behavior of the uncertainty quantification metrics.



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Observations (1/1)

- object detector performance is dependent on the prior knowledge of the dataset.
- Deep learning-based object detectors struggle when deployed in open environments.
- The OOD detection methods proposed for classification did not directly transfer their performance into the task of object detection.
- Sub-Ensemble-based uncertainty quantification with box deviation as a metric out-performed all other methods in OOD detection.
- Entropy struggled in detecting samples that are ambiguous due to their semantic appearance.
- The OOD detection methods proposed in this work did not work as expected on the BDD100K-Weather data in the *OD²* benchmarking dataset.



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Future-work (1/1)

- An object detector without the usage of background class would be useful for improved OOD performance.
- Exploring the effects of uncertainty calibration methods Guo et al. [2017] on OOD detection is still an open-ended question.
- Combining Entropy and Box-Deviation to obtain a single novelty score might result in a better representation of OOD detection ability.
- Disentangling of Predictive uncertainty.
- Though we believe a strong benchmark in the form of OD^2 dataset is proposed, we believe it can be further modified and extended to include more class-agnostic tasks.



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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.

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