Noisy Inliers Make Great Outliers:
Out-of-Distribution Object Detection with Noisy Synthetic Outliers

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Abstract

Many high-performing works on out-of-distribution (OOD) detection use real or synthetically generated outlier data to regularise model confidence; however, they often require retraining of the base network or specialised model architectures. Our work demonstrates that Noisy Inliers Make Great Outliers (NIMGO) in the challenging field of OOD object detection. We hypothesise that synthetic outliers need only be minimally perturbed variants of the in-distribution (ID) data in order to train a discriminator to identify OOD samples — without expensive retraining of the base network. To test our hypothesis, we generate a synthetic outlier set by applying an additive-noise perturbation to ID samples at the image or bounding-box level. An auxiliary feature monitoring multilayer perceptron (MLP) is then trained to detect OOD feature representations using the perturbed ID samples as a proxy. During testing, we demonstrate that the auxiliary MLP distinguishes ID samples from OOD samples at a state-of-the-art level, reducing the false positive rate by more than 20% (absolute) over the previous state-of-the-art on the OpenImages dataset. Extensive additional ablations provide empirical evidence in support of our hypothesis.

1. Introduction

Deep Neural Networks produce state-of-the-art performance across a variety of tasks when deployed under in-distribution settings in which the deployment-time data encountered closely matches that seen at training. However, in the real world, samples that do not belong to the training distribution are encountered. Upon encountering these out-of-distribution (OOD) samples, these deep networks tend to fail silently and produce overconfident outputs on erroneous predictions. Overall these failures are hard to detect and recover from. When considered under the light of safety-critical applications such as self-driving vehicles and medical robotics, the possibility of silent failures related to OOD samples presents a severe risk that must be addressed before the wide-spread adoption of these systems.

In outlier-based OOD detection methods rely on the availability of an additional outlier dataset containing samples directly taken from the OOD set or an

Figure 1: Overview of our proposed NIMGO framework. Feature maps are extracted from the backbone of a pre-trained object detector and localised to object-specific regions using the predicted bounding boxes. Pre-deployment, an auxiliary MLP is trained to distinguish the feature vectors of normal ID detections (blue) from ID detections with added noise (orange). At test time, the pipeline for the training samples is repeated (blue) for all test samples with the auxiliary MLP producing OOD detections scores for each object in a test image. Illustrative input images are drawn from the BDD100K.

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In summary, our core contributions are the following:

1. We demonstrate that noisy outliers produce downstream performance more effective than outliers created by recent state-of-the-art methods without the need for expensive retraining of the base network.

2. We expand deep feature based OOD detection from classification to object detection by utilising object-specific features from the backbone of an object detector network.

3. Our proposed NIMGO architecture improves upon the state-of-the-art in OOD object detection, significantly reducing the number of false positives in a wide range of settings.

4. Through our ablations we demonstrate that perturbation-based outliers generated by additive noise are more effective than comparable transforms, and that strong performance can be achieved with a wide range of noise magnitudes.

We release a publicly available code repository at: [released upon publication].

2. Related Works

Conventional approaches to OOD detection incorporate the use of deep features [42, 50, 4, 44] or the outputs of the model [16, 15, 11, 8, 57]. However, these methods often fall short of outlier-based detectors, highlighting the importance of being able to generate synthetic outliers that are as effective as real outliers. In this section we identify the core contributions in the four areas that most overlap with ours: i) Many works utilise pre-processed real outlier data to regularise the confidence estimates of a model. ii) When real outlier data is unavailable, synthetic outlier data can be created using generative models at the cost of increased training. iii) Avoiding the costs of generator-based outliers, perturbations of the ID set can be used to produce similar benefits. iv) Many outlier synthesis methods are restricted to classification and segmentation, leaving a gap in object detection.

Outlier-based OOD Detection Some prior works [25, 19, 56, 29, 17, 36, 1] seek to extrapolate characteristics of the testing OOD set from an available set of real outlier data constructed from either the testing OOD set or an entirely separate dataset. These methods often present significant performance improvements over comparative methods as having prior knowledge over the OOD samples allows for targeted calibration of OOD detectors. However, the use of these outlier sets is inherently problematic; if the real outlier set does not accurately represent the OOD samples encountered at test time, substantial drops in performance are observed [44]. In practice, acquiring a real outlier set that is guaranteed to be representative of all OOD samples encountered at deployment time is infeasible due to the near-infinite set of potential events/objects that can be encountered. By contrast to these works, we do not require the presence of a real outlier set, instead synthesising outliers by directly applying perturbations to the ID set.

Generator-based Outliers When real outlier data is unavailable, some works attempt to replicate the performance of outlier-based detectors via the generation of synthetic outlier data. Early work [24] proposed a Generative Adversarial Network (GAN) [10] architecture, training a generative model that created low ID density samples in the image space. Further work expanded on this approach to train a specific reject class [48, 49] or to encourage uniform predictions on overconfident OOD samples [43]. Scaling input-
based generative models becomes complex as the fidelity of images increases, as such, feature-based generative methods have been proposed for novelty detection [41] and OOD object detection [6]. Rather than explicit outliers, methods proposed for semantic segmentation [31, 28] detect discrepancies in generated images when given intentionally erroneously labelled segmentation maps. The generator-based approaches discussed above commonly rely on specialised network architectures or require retraining of the base network, making them infeasible under settings where they rely on large models pretrained on equivalently as big datasets. As an example, the OpenOOD benchmark [52] does not currently include methods that require retraining on the ImageNet [40] dataset. In contrast, we avoid the additional computational costs associated with retraining and specialised architectures by obtaining feature vectors for perturbed ID samples as synthetic outliers on a pre-trained network.

**In-Distribution Perturbations** It is not always feasible to prescribe specialised training regimes or architectures for OOD challenges; when these methods are unavailable, perturbations of the known data can be utilised for OOD detection purposes. As some of the earliest work in OOD detection, ODIN [26] proposed to add small input perturbations based on adversarial noise designed to increased the softmax scores for given inputs. Generalised ODIN [18] refined the perturbations from [26] proposing a pipeline for automated hyperparameter selection, but required retraining of the base network. Training with adversarial input samples was shown to improve generalisation to a wide array of test-time input perturbations [54]. Pixel-wise perturbations were proposed in [37] constructing a pipeline of random pixel mutations to generate synthetic outliers for pixel-wise likelihood calculations. This pipeline was then expanded upon in [4] proposing a modified mutation scheme of random pixel permutation for the purposes of training an auxiliary feature monitoring MLP. Related works have used noisy ID data to generate ID representations that are then used for score-matching to detect OOD samples [20]. Perturbation-based outliers present an important avenue for generating synthetic outliers, however, the application of all the aforementioned methods is restricted solely to the classification domain with image- or pixel-level transforms considered. By contrast to these previous works, our proposed NIMGO detector expands the use of perturbation-based outlier synthesis methods to object detection, addressing the challenges of scaling to a more complex domain whilst making no requirements over specialised model architecture or expensive retraining of the base network.

**OOD-Adjacent Object Detection** Applications of OOD detection methods to object detection is a new field, however, existing works in related domains introduce avenues for research. Akin to OOD detection, open-set error detection [2] commonly relies on the outputs of the final layer of the object detector network [33, 20]. In a similar vein, recent works have sought to explain failures in deep object detectors by analysing the sensitivity of individual components to unique errors [32] and the influence of the datasets [31]. Related works in failure monitoring make use of auxiliary networks trained on backbone object detector features [35, 34]. Comparatively few works [6, 5] have explicitly addressed the problem of OOD object detection, with the current methods addressing the task still requiring explicit retraining of the base network [53]. In this work, we propose to integrate the success from related fields in object detection to OOD detection expanding upon the currently small body of work in the field.

### 3. Noisy Inliers as Synthetic Outliers

We propose the Noisy Inliers Make Great Outliers (NIMGO) OOD detector, a powerful method for generating and utilising synthetic outliers in OOD object detection. We base NIMGO on prior work in perturbation-based outlier synthesis [4, 37, 26] for image classification and expand upon these works by addressing the challenging task of OOD object detection and considering additional transforms in this new context. NIMGO detects OOD samples by training an auxiliary MLP to discriminate between ID samples and synthetic outliers formed from noisy ID samples. The core idea behind NIMGO is to encourage the auxiliary MLP to learn a tight bound around the ID samples seen during training by utilising an outlier set that is generated by adding minimal perturbations to the ID set. During deployment, the auxiliary MLP predicts an OOD score $\hat{y}_{d}$ per detection $d$ based on the deviations of test-time samples.

**Object Detection Challenges** The use of deep features for detecting OOD samples under the image-level classification setting is ubiquitous [50, 4, 42]. However, OOD object detection presents unique characteristics that make the task more challenging. Specifically, we observe that in object detection extracted feature maps from the backbone of the network correspond to the image as a whole, not individual object instances. This makes the object detection task challenging since backbone features cannot directly be utilised for object-level OOD detection. The easiest solution to these issues is to apply the OOD detectors to the layers of the network that deal with object-specific features, i.e., the fully connected layers of a Faster-RCNN [38] detector. However, this solution restricts deep feature-based methods to a subset of the layers when these methods require access to multi-scale features from across the network [50, 4, 42]. We propose to leverage the backbone features of the object detector by taking inspiration from the Faster-RCNN [38] architecture, extracting object-level features out of the backbone by pooling features over proposed regions of interest.
Preliminaries We use a pre-trained object detector network \( f \) that takes an input image \( x \) and produces a set of \( D \) predicted bounding boxes \( f(x) = \{b_1, ..., b_D\} \). We additionally extract a set of \( L \) feature maps \( \{M_1, ..., M_L\} \) from the backbone of the object detector network for each input image \( f(x) = \{b_1, ..., b_D, M_1, ..., M_L\} \), where \( L \) is the number of layers where features are being extracted from.

Feature Extraction For each bounding box \( b_d \) where \( d \in \{1, ..., D\} \) and feature map \( M_l \) where \( l \in \{1, ..., L\} \), we extract object-specific feature maps \( \{O_{1,1}, ..., O_{1,D}, O_{2,1}, ..., O_{2,D}, ..., O_{L,D}\} \). The extraction of object-specific features is done by taking cropped regions of each feature map \( M_l \) defined by each of the proposed bounding boxes \( b_d \). The object-specific feature maps \( O_{l,d} \) are then reduced to a vector representation \( p_{l,d} \) via a bilinear interpolation operation along the spatial axis. Finally, the pooled feature vectors \( p_{l,d} \) are concatenated layer-wise to form a single object-specific vector \( q_d \) with a length equal to the sum of number of channels \( c \) for each layer:

\[ |q_d| = \sum_i c_i. \]

Outlier Synthesis We follow previous works [4, 37] and generate synthetic outliers by perturbing ID samples. To this end, we define a function \( g(x) \) that returns the input image with a perturbation applied \( x^o = g(x) \). However, when considering input perturbations in the object detection setting, it is not enough to consider image-level transforms alone as with previous works [4, 37]. Instead, we optionally allow for the transformation to be applied to only the predicted bounding boxes \( b_d \) from the original image \( x \). For NIMGO we make use of an additive noise transformation function \( g(x) \). We ablate parameters of this transformation in Section 4.4 and compare performance against other input perturbations in Section 4.5.

Training and Testing To discriminate between ID and OOD samples, we instantiate an auxiliary feature monitoring MLP \( f_{\beta} \) that accepts the pooled feature vectors \( q_d \) as inputs and produces a resultant OOD score for the detection \( \hat{y}_d = f_{\beta}(q_d) \). During training of the auxiliary MLP, for each image in the training set, we repeat the feature extraction process obtaining the object-specific pooled feature vectors \( q_d \) and corresponding bounding boxes \( b_d \). Next, the input image \( x \) is perturbed using the transformation function \( x^o = g(x) \) and the feature extraction process is repeated using the outlier image \( x^o \) paired with the predicted bounding boxes from the original unperturbed image \( b_d \), returning the outlier pooled feature vectors \( q_d^o \).

In practice, the pooled feature vectors \( q_d \) and \( q_d^o \) only need to be obtained once and compared directly for subsequent training, removing the need for excessive inference passes of the base network. The auxiliary MLP is trained to distinguish the clean ID pooled feature vectors \( q_d \) from the noisy feature vectors \( q_d^o \). During testing, the auxiliary MLP is used to generate an OOD detection score \( \hat{y}_d = f_{\beta}(q_d) \) in the range of \( \hat{y} \in [0, 1] \) for each detection.

4. Experiments

We conduct a series of experiments to demonstrate the efficacy of using noisy ID data as a synthetic outlier dataset for the training of the discriminator MLP. We first describe our experimental setup in Section 4.1 and detail the implementation of NIMGO in Section 4.2. We then evaluate on the challenging task of OOD object detection in Section 4.3 comparing to the state-of-the-art on several ID and OOD set combinations. Finally, we ablate the critical components of our method, specifically, we ablate the sensitivity of the auxiliary MLP to the noise magnitude in Section 4.4 and demonstrate the unique effectiveness of noisy inliers compared to alternative transforms in Section 4.5.

4.1. Experimental Setup

We follow the evaluation protocol defined by [6] with the accompanying benchmark repository.

Datasets We make use of the predefined ID/OOD splits for the object detection task defined in [6]. The two ID datasets are constructed from predefined subsets of the popular PASCAL–VOC [7] and Berkley DeepDrive-100K [55] (BDD100K) datasets. For the OOD datasets, subset versions of the MS-COCO [27] and OpenImages [22] datasets are provided where classes that appear in the custom ID datasets are removed.

Evaluation Metrics We consider the standard AUROC and FPR95 metrics defined in the evaluation protocol [6] and extensively used across the classification literature [57] [26] [50] [42]. AUROC: The Area Under The Receiver Operating Characteristic curve (AUROC) is defined by the area under the ROC curve with true positive rate (TPR) on the y-axis and false positive rate (FPR) on the x-axis; higher is better. An AUROC score of 50% indicates a method that is as effective as random guessing. FPR95 reports the false positive rate when the true positive rate reaches 95%; lower is better. For real world deployment, a binary classifier based on a threshold of the confidence scores determines if a detection is ID or OOD; under these conditions FPR95 provides better insight into how an OOD detector will perform. We note that under the evaluation protocol [6] detections from the ID set are the positive class and OOD detections the negative class; OOD detections scores can be inverted to accommodate swapping of the labels. Our NIMGO OOD detector is a post-hoc addition to a pre-trained network and does not affect the on-task performance of the base model under the average precision (AP) metric. Since NIMGO does not affect the AP metric, we do not report it, as in [6].

Baselines We compare against the following state-of-the-art methods: MSP [16], ODIN [26], Mahalanobis Dis-
Figure 2: Box-level examples of the transformations applied to ID samples to generate synthetic outliers, image-level variants apply the specified transform to the whole image. Original image is from BDD100K [55]. (a) Original image with predicted bounding boxes from the Faster-RCNN [38] object detector; object-specific features for all transforms are extracted from within the bounding box regions. (b) Setting pixels to a solid colour as in the Black and White transforms. (c) Additive noise transforms as in the Uniform and Normal noise transforms. (d) Pasting of the objects into a new ID scene selected randomly from the ID set; objects are not moved from their original position. (e) Modified variant of the transform proposed in [4]; i.e., randomly permuting the order of pixels within the bounding box. (f) Swapping the objects with the content from another region in the image.

We ablate the following set of transforms to evaluate the effectiveness of noisy ID samples: setting pixel values to black or white, pixel order permutation [4] (Pixel Permute), additive noise normally or uniformly distributed (Noise), randomly moving objects within image (Move Boxes) and pasting objects from the ID training set into random images (Context Change). Visual examples of these transforms are provided in Figure 2.

4.2. Implementation

Base Network Architecture Following the evaluation protocol defined in [6], we implement the Faster-RCNN [38] detector with a ResNet-50 [14] backbone using the Detectron2 library [5]. Of the compared methods, Generalized ODIN [18], CSI [46], GAN-Synthesis [24] and Virtual Outlier Synthesis (VOS) [6] all require the base model to be retrained with a custom loss objective, for all other comparison methods a standard pretrained network is used. For fair comparison, we split evaluation between post-hoc OOD detection methods and those that require retraining of the base network.

Feature Extraction During feature extraction, hooks are applied to all Conv2d layers present within the ResNet-50 backbone of the Faster-RCNN base model. Retrieval of object-specific features \( p_{l,d} \) is done using the ROIAlign [13] operation with the predicted bounding boxes \( b \), with appropriate spatial scaling factors, pooling the features down to a channels length \( c_l \) vector per layer \( l \). Across the entirety of the network, 64 Conv2d layers are hooked into, resulting in a 28879 length pooled feature vector \( q_d \) per detected object \( d \) to be fed into our auxiliary MLP.

MLP Architecture The auxiliary MLP is constructed as a 3-layer fully connected MLP with a single output neuron fed into a Sigmoid activation with a dropout connection before the final layer. The input size for each fully connected layer is progressively halved, with rounding, resulting in input sizes of [28879, 14439, 7219]. The MLP, initialised with Xavier initialisation [9], is trained for 10 epochs using the SGD optimiser with a learning rate of 0.001, momentum of 0.9, dropout rate of 50% and batch size of 32 images.²

Noise Implementation For the additive noise transformation functions, we sample the noise from two distributions, either uniformly distributed, \( x \sim U(-0.5 \cdot \alpha_w, 0.5 \cdot \alpha_w) \), (Uniform) or a normally distributed \( x \sim N(0, \alpha_w^2) \) (Normal). Both noise schedules are parameterised by a scalar

²The size of each individual batch for the MLP is determined by the number of predicted boxes within the 32 images.
Post-hoc OOD Detectors

Table 1: OOD detection results comparing NIMGO to state-of-the-art post-hoc OOD detectors. Comparison metrics are FPR95 and AUROC, directional arrows indicate if higher (↑) or lower (↓) values indicate better performance. Best results are shown in red and bold, second best results are shown in orange. In both the PASCAL-VOC and BDD100K settings, NIMGO provides significant improvements of greater than 30% in the FPR95 metric when OpenImages is the OOD set with the image-level noise model. Across the majority of metrics and benchmark permutations, NIMGO sets a new state-of-the-art in OOD object detection.

| In-Distribution Dataset | Method | FPR95↓ | AUROC↑ |
|-------------------------|--------|--------|--------|
|                        | MSP [15] | 70.99 | 73.13 |
|                        | ODIN [26] | 59.82 | 63.14 |
|                        | Mahalanobis [25] | 96.46 | 96.27 |
|                        | Energy Score [20] | 56.89 | 58.69 |
|                        | Gram Matrices [42] | 62.75 | 67.42 |
| PASCAL-VOC             | NIMGO (ours) (Uniform, Box, $\alpha_{w} = 50$) | 47.22 | 82.87 |
|                        | NIMGO (ours) (Uniform, Image, $\alpha_{w} = 50$) | 51.39 | 88.15 |
|                        | MSP [15] | 80.94 | 79.04 |
|                        | ODIN [26] | 62.85 | 58.92 |
|                        | Mahalanobis [25] | 57.66 | 60.16 |
|                        | Energy Score [29] | 60.06 | 54.97 |
|                        | Gram Matrices [42] | 60.93 | 77.55 |
| Berkley DeepDrive-100K | NIMGO (ours) (Uniform, Box, $\alpha_{w} = 100$) | 58.17 | 80.97 |
|                        | NIMGO (ours) (Uniform, Image, $\alpha_{w} = 100$) | 44.60 | 82.38 |

$\alpha_{w}$ which is a predefined magnitude multiplier. During comparisons in Section 4.3, details on the noise schedule are defined in brackets in the form of (distribution, target, weight), e.g. (Normal, Box, $\alpha_{w} = 10$) corresponds to additive noise sampled according to $x \sim N(0, 100)$ and applied exclusively to the predicted bounding boxes. We ablate the effect of the parameter $\alpha_{w}$ in Section 4.4.

4.3. Results and Discussion

Post-hoc Detectors Table 1 compares the results of our NIMGO OOD detector to the current state-of-the-art in post-hoc OOD object detection. In general, Table 1 demonstrates the effectiveness of NIMGO as it sets a new state-of-the-art across a number of benchmark permutations.

Across the board, we observe that the majority of best or second best results belong to NIMGO. Specifically, we observe that in the PASCAL-VOC setting, NIMGO sets a new state-of-the-art for all metrics except AUROC in the MS-COCO setting. Under the BDD100K setting, the image-level noise model sets a new state-of-the-art across all dataset and metric permutations barring one, and the box-level noise model outperforms all other methods except Mahalanobis [25] when MS-COCO is the OOD set. In the OpenImages as OOD setting, the image-level noise model provides an absolute reduction in FPR95 of 31.72% in the BDD100K setting and 31.16% in the PASCAL-VOC setting, more than halving the previous state-of-the-art. Even when considering the box-level noise model, we still see significant improvements over the next best detector [29] of 58.69% → 30.57% (ours) in the PASCAL-VOC setting and 54.97% → 40.3% (ours) in the BDD100K setting.

Retraining Detectors Comparisons between NIMGO and the current state-of-the-art OOD detectors that require retraining of the base network are shown in Table 2. We emphasise that in this comparison NIMGO is disadvantaged compared to all other methods, as NIMGO does not utilise nor require any form of specialised architecture or retraining of the network.

Similarly to the comparisons with the post-hoc OOD detectors, we observe strong performance from NIMGO across a wide breadth of the dataset permutations. When OpenImages is the target OOD set, we see an over 20% absolute drop in the FPR95 from both of the noise schedules, with the image-level noise nearly halving the previous state-of-the-art from 51.33% to 27.53% whilst providing marginal improvements to the state-of-the-art in the AUROC metric. Similar to PASCAL-VOC, the biggest performance improvements are observed when the OpenImages dataset is OOD with the image-level model reducing the FPR95 by over 10% by comparison to the state-of-the-art. When MS-COCO is the OOD distribution, we still observe strong performance on the FPR95 metric with the box-level noise improving over the previous state-of-the-art when PASCAL-VOC is ID set and the image-level noise outperforming all baselines except VOS in both the ID settings. In summary, NIMGO, which does not require retrain-
ing or a specific network architecture, either outperforms or performs on-par with OOD detectors that do require retraining.

**General Trends** We note that the primary improvements of our proposed NIMGO in Tables 1 and 2 are reflected as reductions in the FPR95 metric, indicating that NIMGO reaches 95% TPR faster than comparative methods. We attribute this behaviour to the high similarity between the ID set (positive class) and the synthetic outlier set. During training, the auxiliary MLP is forced to learn a tight bound surrounding the ID training data resulting in very low OOD scores on test data that is similar to the training data, namely, the ID testing data.

**4.4. Noise Magnitude Ablation**

Figure 3 ablates the sensitivity of the auxiliary MLP to varying values of the noise magnitude $\alpha_w$ when PASCAL-VOC is the ID set and OpenImages is the OOD set. In general, the performance curves reported match expectations where we observe initial low relative performance, due to a lack of discriminative features between the ID training and synthetic outlier set, that improves up to a peak and is followed by a drop in performance as the weighting parameter $\alpha_w$ becomes too large. Critically, we make the observation that Figure 3 demonstrates that only extremely high values of $\alpha_w \in [150, 200]$ result in substantial enough degradations in performance to increase the false positive rate to a level comparable to the previous state-of-the-art [6] at 51.33%.

Comparing the uniform and normally distributed noise schedules in Figure 3b we observe that the normally distributed noise peaks in performance at lower values of $\alpha_w$ compared to uniformly distributed noise. This behaviour is expected due to the uniformly distributed noise having a bounded and linear relationship with $\alpha_w$, $x \sim U(-0.5 \cdot \alpha_w, 0.5 \cdot \alpha_w)$ while the normally distribution noise has an unbounded squared relationship with $\alpha_w$, $x \sim N(0, \alpha_w^2)$. From Figure 3b we can approximate the best $\alpha_w$ parameter as $\alpha_w \in [50, 60]$ for uniformly distributed noise and $\alpha_w \in [20, 30]$ for normally distributed noise.

**4.5. Alternative Transforms**

We compare the efficacy of noisy inliers as synthetic outliers to other perturbation-based synthetic outlier transformations in Table 3 using the AUROC metric. Within Table 3 we observe a high degree of variance across the performance of differing transformations. We discuss this behaviour below, identifying characteristics of individual transforms that potentially degrade their performance.

We observe high-level behaviours that assist in explaining the relative performance of each transformation in Table 3. All variants of the Solid Colour transformations perform poorly, strongly indicating that mapping to a single output is too simple of a representation for the outlier set.

| In-Distribution Dataset | Method | FPR95↑ | AUROC↑ |
|-------------------------|--------|--------|--------|
| PASCAL-VOCS             | Generalized ODIN [18] | 59.57 / 70.28 | 83.12 / 79.23 |
|                         | CSI [46] | 59.91 / 57.41 | 81.83 / 82.95 |
|                         | GAN-Synthesis [24] | 60.93 / 59.97 | 83.67 / 82.67 |
|                         | VOS-ResNet50 [6] | 47.53 / 51.33 | 88.70 / 85.23 |
|                         | NIMGO (ours) (Uniform, Box, $\alpha_w = 50$) | 47.22 / 30.57 | 82.87 / 88.15 |
|                         | NIMGO (ours) (Uniform, Image, $\alpha_w = 50$) | 51.39 / 27.53 | 77.91 / 87.97 |
| Berkley DeepDrive-100K  | Generalized ODIN [18] | 57.27 / 50.17 | 85.22 / 87.18 |
|                         | CSI [46] | 47.10 / 37.06 | 84.09 / 87.99 |
|                         | GAN-Synthesis [24] | 57.03 / 50.61 | 78.82 / 81.25 |
|                         | VOS-ResNet50 [6] | 44.27 / 35.54 | 86.87 / 88.52 |
|                         | NIMGO (ours) (Uniform, Box, $\alpha_w = 100$) | 58.17 / 40.30 | 80.97 / 87.49 |
|                         | NIMGO (ours) (Uniform, Image, $\alpha_w = 100$) | 44.60 / 23.25 | 82.38 / 90.94 |

Table 2: OOD detection results comparing NIMGO to state-of-the-art OOD detectors that require retraining of the base network or specialised architectures to achieve their results. We note that even under this setting, NIMGO does not require retraining to attain the stated performance. Comparison metrics are FPR95 and AUROC, directional arrows indicate if higher (↑) or lower (↓) values indicate better performance. Best results are shown in red and bold, second best results are shown in orange. In the PASCAL-VOC setting we see that NIMGO provides significant performance improvements with the OpenImages OOD set, with over 20% improvements in the FPR95 metric compared to current state-of-the-art, and strong performance on the MS-COCO OOD set setting a new state-of-the-art for FPR95. In the BDD100K setting we observe that NIMGO with image-level noise provides similarly significant improvements when OpenImages is the OOD set with a decrease in FPR95 of over ~10% compared to current state-of-the-art.
Figure 3: Performance of the MLP discriminator reported as the average over the box- and image-level noise schedules as the weighting factor $\alpha_w$ is varied. ID set is PASCAL-VOC with OpenImages as OOD. (a) Comparison under the FPR95 metric, lower is better. (b) Comparison under the AUROC metric, higher is better. As expected, we observe a drop in performance at both high and low values of the weighting factor $\alpha_w$ due to the noise constituting most of the signal to the MLP at high values and a lack of learning signal for the MLP at low values.

By contrast, the Change Context transform does not directly affect the predicted objects themselves making it difficult for the MLP to discriminate ID from outlier. We observe that the performance of the Move Boxes transformations is consistent with ablations shown in previous works [6] on the performance of high-probability background proposals as outliers. The Pixel Permute transform does directly affect the predicted objects as hoped, but destroys low-level feature information which would still be expected to appear in realistic OOD objects. To summarise, the addition of noise to ID samples serves as the most powerful synthetic outlier set with an approximately 8% performance gap between the best of the noise transforms compared to the non-noise transforms on MS-COCO.

5. Limitations

**Aleatoric Uncertainty** During deployment, particularly in robotics applications, additional aleatoric uncertainty [21] is often introduced through imperfect sensor readings and natural variability in deployment conditions. Under these conditions, the additional noise can cause the

| Transform                  | MS-COCO | OpenImages |
|----------------------------|---------|------------|
| Black (Box)                | 43.71   | 44.20      |
| Black (Image)              | 48.99   | 51.52      |
| Change Context             | 52.47   | 49.32      |
| White (Image)              | 55.57   | 49.51      |
| White (Box)                | 54.93   | 56.98      |
| Pixel Permute (Image)      | 67.89   | 76.19      |
| Move Boxes                 | 74.15   | 78.57      |
| Pixel Permute (Box)        | 74.47   | 85.19      |
| Noise (Normal, Box, $\alpha_w = 20$) | 77.25 | 87.19 |
| Noise (Uniform, Image, $\alpha_w = 50$) | 77.91 | 87.97 |
| Noise (Normal, Image, $\alpha_w = 20$) | 82.21 | 88.43 |
| Noise (Uniform, Box, $\alpha_w = 50$) | 82.87 | 88.15 |

Table 3: Comparison of the effectiveness of alternative ID transforms for training the discriminator MLP. Comparison metric is AUROC, higher is better. Best results are shown in **red and bold**, second best results are shown in orange. For relevant transforms, whether the transform is applied to the entire image or just the predicted bounding boxes is defined in brackets. The use of noisy ID detections as synthetic outliers consistently outperforms synthetic outliers generated by alternative transformations.

ID testing set to overlap with our outlier set. As such, noisy ID samples may be erroneously labelled as OOD at a higher rate than the results reported in Tables 1 and 2. We note that the core of this issue relates back to capture bias [47], where training and testing datasets are intentionally curated to only contain low-noise and non-ambiguous samples which is known to cause problems in models generalising to real-world deployment [12]. Inclusion of difficult samples that are ambiguously labelled or intentionally noisy would help alleviate the capture bias problem by allowing direct tuning on deployment-like conditions.

6. Conclusion

This paper presents the notion that noisy ID samples make powerful synthetic outliers for the task of OOD detection. We demonstrate the effectiveness of our synthetic outliers by comparing to current state-of-the-art in OOD object detection, setting a new state-of-the-art across a number of benchmark permutations without the need for expensive retraining of the network. We present a hypothesis with supporting empirical evidence as to the surprising power of noisy inliers as synthetic outliers. We identify and discuss the limitations of our method, making note of challenges that affect the wider OOD detection challenge with suggestions for adaptations. In this paper, we consider additive noise as our ID transformation function, however, there is a near endless set of potential perturbations that could be more effective than noise, opening future research directions into custom transformations.
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