Quantifying Context Bias in Domain Adaptation for Object Detection

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Abstract

Domain adaptation for object detection (DAOD) has become essential to counter performance degradation caused by distribution shifts between training and deployment domains. However, a critical factor influencing DAOD—context bias resulting from learned foreground-background (FG–BG) associations—has remained underexplored. In this work, we present the first comprehensive empirical and causal analysis specifically targeting context bias in DAOD. We address three key questions regarding FG–BG associations in object detection: (a) are FG–BG associations encoded during the training, (b) is there a causal relationship between FG–BG associations and detection performance, and (c) is there an effect of FG–BG association on DAOD. To examine how models capture FG–BG associations, we analyze class-wise and feature-wise performance degradation using background masking and feature perturbation, measured via change in accuracy (defined as drop rate). To explore the causal role of FG–BG associations, we apply do-calculus on FG–BG pairs guided by class activation mapping (CAM). To quantify the causal influence of FG–BG associations across domains, we propose a novel metric—Domain Association Gradient—defined as the ratio of drop rate to maximum mean discrepancy (MMD). Through systematic experiments involving background masking, feature-level perturbations, and CAM, we reveal that convolution-based object detection models encode FG–BG associations. These associations substantially impact detection performance, particularly under domain shifts where background information significantly diverges. Our results demonstrate that context bias not only exists but also causally undermines the generalization capabilities of object detection models across domains. Furthermore, we validate these findings across multiple models and datasets, including state-of-the-art architectures such as ALDI++. This study highlights the necessity of addressing context bias explicitly in DAOD frameworks, providing insights that pave the way for developing more robust and generalizable object detection systems.

1 Introduction

Domain adaptation for object detection (DAOD) has been studied extensively to enable object detectors to perform well on datasets with distribution shifts from the training data (Kay et al., 2024; Chen et al., 2022; Deng et al., 2021; Hoyer et al., 2023; Li et al., 2022b; Koh et al., 2021; Kalluri et al., 2023). It is well known that there is an entanglement between background and foreground features in object detection, leading to a phenomenon called context bias in DAOD (Torralba & Efros, 2011; Divvala et al., 2009; Khosla et al., 2012; Zhang et al., 2024; Choi et al., 2012; Shetty et al., 2019). Here, significant differences in background features between the source and target domains can cause a notable decline in the quality and number of detections, even when the foreground features remain unchanged. Recent studies in image classification (Li et al., 2023; Aniraj et al., 2023) and segmentation (Zhu et al., 2024; Chen et al., 2021; Dreyer et al., 2023) have attempted to mitigate context bias by minimizing this association. Oliva & Torralba (2007) demonstrated that context bias could result in the corruption of foreground objects by contextually correlated backgrounds, substantially degrading detection quality. However, there has been no prior work specifically analyzing the impact of context bias in DAOD. This work aims to address this gap.

In the realm of human cognition, the brain can accurately and instantly recognize foreground-background (FG–BG) associations without extensive training (Papale et al., 2018). Several studies, including Zhang et al. (2023); Poort et al. (2016); Papale et al. (2018); Huang et al. (2020), have investigated the processes of background suppression and foreground representation to understand the scene and temporal dynamics of foreground and background modulation in the brain. These insights can be applied to the field of computer vision for DAOD through a comprehensive analysis of the representation of FG–BG associations.

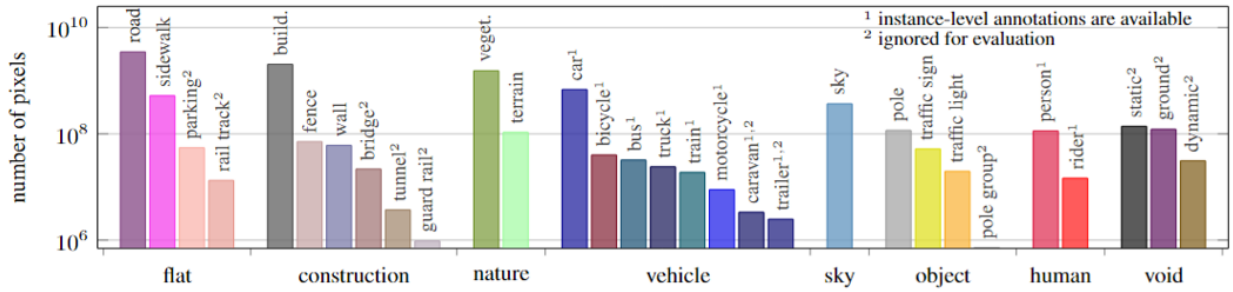


Figure 1: The proportion of background pixels in Cityscapes (Cordts et al., 2016) are the highest of all classes. The image is from Cityscapes publication.

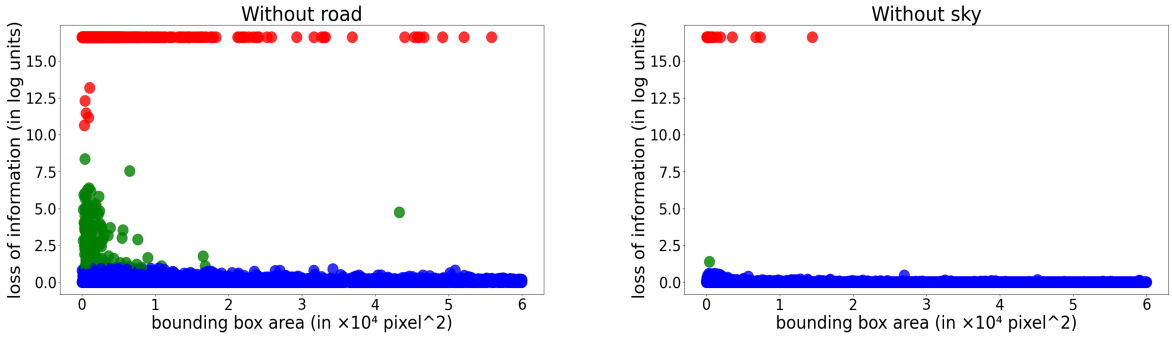


Figure 2: **Loss of information as a function of the bounding box area of the object.** The left-hand figure shows the suppression of "road" while the right-hand figure shows the suppression of "sky". The dots are grouped into three clusters - red indicates missed detections (maximum information loss), green indicates partial matches (significant loss). Blue dots indicate no change. The label of "road" is more associated with "car" than "sky".

1.1 Our observations on context bias

To motivate our problem, we first look at the proportion of background features in autonomous driving datasets, as an example. For the Cityscapes dataset (Cordts et al., 2016), the number of pixels from built-up features (such as "road" and "sidewalk") is much greater than that of foreground objects (see Fig. 1). Based on semantic segmentation outcomes (Alonso et al., 2021; Wang et al., 2020; Erisen, 2024), "road" has the highest accuracy and lowest variability. As a motivating experiment, we aim to quantify the change in performance as a function of the background masking for a real dataset. We use the second layer ($res2.2$) of the ResNet-50 backbone in the Detectron2 (Wu et al., 2019), trained on the Cityscapes dataset, for object detection. We hypothesize that $res2.2$ effectively balances low and high-level features on FG–BG. The loss of information is computed when activated features for the specific background regions are set to zero, using semantic labels as a function of the ground-truth bounding-box area of the foreground objects. We define performance drop ΔIoU as $0 \leq \Delta IoU \leq 1$ and the amount of loss of information as the negative log of the complement of ΔIoU ($-log(\Delta IoU)$), which computes the change of intersection over union (IoU) with background masking. Figure 2 shows the performance drop of the removal of "road" as opposed to "sky".

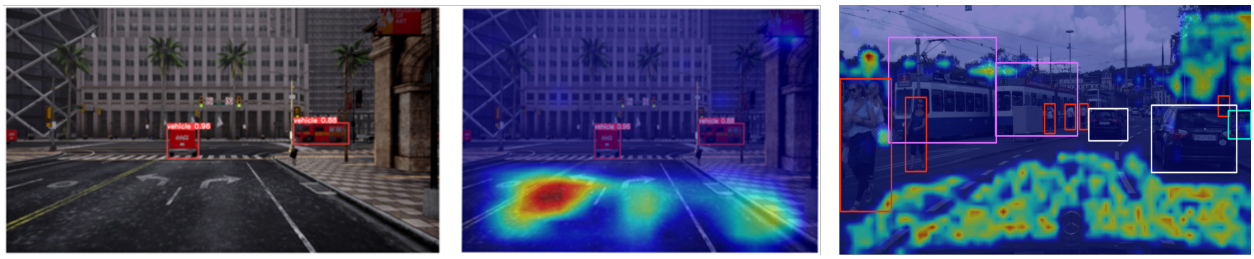


Figure 3: The left figure shows 2D inference of CARLA dataset using YOLOv4 model while the center figure shows the CAM attention map of the inference using EigenCAM (Muhammad & Yeasin, 2020). The right figure is EigenCAM result of YOLOv11 trained on Cityscapes. Road and vegetation are significantly enhanced.

We find that the loss of information is much higher with the "road" suppressed than for "sky", which means that "road" has more contextual association with "car", particularly when the "car" size is small.

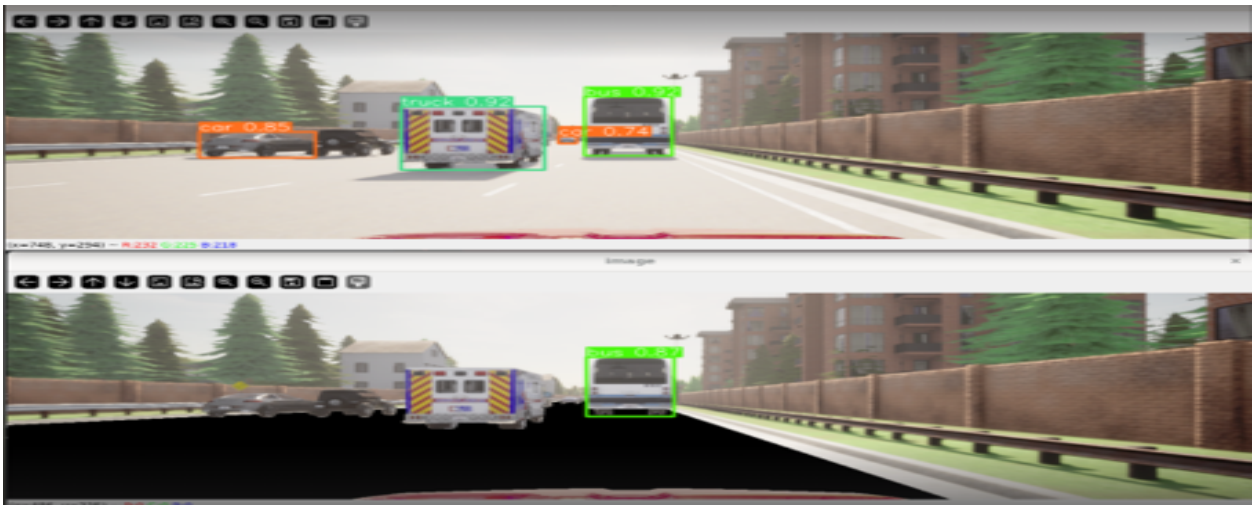


Figure 4: Masking the road on CARLA image and generating inference using YOLOv8 model - the top figure shows that 3 out of 4 vehicles get detected correctly, while in the bottom figure with road masking, only one vehicle is detected.

We train a YOLOv4 detection model (Bochkovskiy et al., 2020) on a sample CARLA (Dosovitskiy et al., 2017) dataset collected under sunny conditions and provide inference on a separate CARLA dataset collected under cloudy conditions. We find that the model focuses on the road in front of the vehicles rather than the vehicles themselves (see Fig. 3) using class activation mapping (CAM). Additionally, to capture whether the same issue arises across different types of models, we perform an analogous experiment where we transform the road pixels by masking them and find that the YOLOv8 model is unable to detect most of the vehicles otherwise detected in the normal image (see Fig. 4). This outcome suggests that convolution-based neural network models may have implicitly learned to associate vehicles with road environments, leading to poor performance in detecting vehicles when a different background is present.

In order to understand the spread of feature patterns across domains, we plot the foreground and background feature distributions of different domains using UMAP (McInnes et al., 2018). Figure 5 presents the visualization of the foreground and background features from different domains in 2D. We use the features of "car" at the 5th ResNet layer ($res.5.2$) from different data distributions. We assume that $res.5.2$ captures high-level features of FG and BG. The interesting finding is the differences in background alignment across the comparisons. It is immediately apparent that as the target domain shifts away from the source domain, the background becomes more separable than the foreground. For the Cityscapes training (CST)

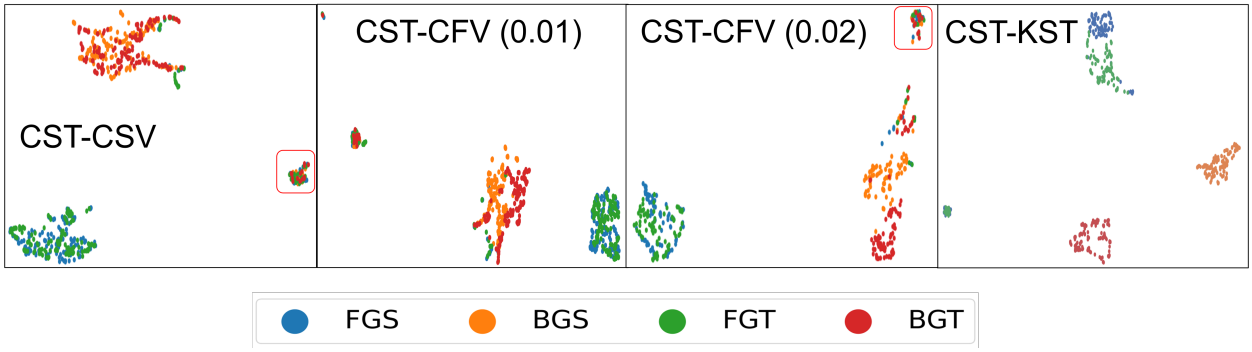


Figure 5: **UMAP feature embedding results.** "CST" is Cityscapes train, "CSV" is Cityscapes validation, "CFV (0.0X)" are Cityscapes foggy validation with different parameters for fogginess. "KST" means KITTI semantic train. We used the "car" label, as it is the most common category across the datasets. "FGS" is foreground in the source domain, and "BGS" is background in the source domain. "FGT" and "BGT" are foreground and background in the target domain. Similar colors should be intertwined, indicating similar feature distribution.

and validation (CSV) datasets, foreground and background features are distinguishable from each other but appear intermingled between the source and target domains. In the CST-CFV panel, foreground features remain clustered together while the background features are separable but overlapping. We see an extreme case in the CST-KST where the foreground features between CST and KST are next to each other but are non-overlapping, while the background features are very distant from each other. The feature extraction process is illustrated in the Method section 3.

Prior studies (Choi et al., 2012; Torralba, 2003) have researched context bias for object detection and classification. The studies have pointed out that relying only on local features (foreground features in our case) has limitations, including degraded quality due to noise and ambiguity in the target search space. They extend the likelihood to incorporate context information surrounding the foreground, thereby enhancing object classification and detection by providing a stronger conditional probability, as in Equation 1. The conditional probability of the object (O) given the features (f) is given as:

$$P(O|f) = P(O|F, B) = \frac{P(F|O, B)P(O|B)}{P(F|B)} \tag{1}$$

where F and B denote the foreground and background features, respectively. However, it does not address DAOD issues like sim-to-real transfer and the root causes of FG–BG associations during training and inference remain unclear, especially given the causal relationships imposed post-detection.

The challenge with using a convolutional neural network (CNN) under the assumption of an identical and independent distribution (i.i.d) to estimate likelihood is the inability to explicitly teach the model to learn each factor in a specific order (Schölkopf et al., 2021; Agrawal et al., 2019). In other words, it means that the parameters of a CNN can differ depending on how it is trained, as in equation 2. The modeling can also be interpreted as:

$$P(O|f) = P(O|B, F) = \frac{P(B|O, F)P(O|F)}{P(B|F)} \tag{2}$$

In CNNs, likelihood estimation is the process of finding the mean of a distribution with proper priors, which requires more samples to accurately estimate the true mean. This aligns with the principle that a more extensive and refined dataset, achieved through data augmentation, is crucial for better performance (Taylor & Nitschke, 2018). However, such datasets typically do not account for FG–BG associations, which are subtle to capture during data collection. In summary, FG–BG associations can disrupt the trained

estimation process for each probability estimate, leading to performance degradation in target domains due to these broken associations.

From these observations and hypotheses, our fundamental questions are as follows:

Q1. Are FG–BG associations being inadvertently learned during the training process?

Deep learning identifies latent patterns that optimize objective functions, typically by maximizing data likelihood. During the feature extraction process, models may learn spurious or unexpected features if such features improve predictive performance without any understanding of causality by following the previous reasoning (Bishop, 2006; Goodfellow et al., 2016; MacKay, 2003; Murphy, 2012). This underscores the importance of incorporating causal reasoning into deep learning frameworks to improve robustness and generalization (Schölkopf et al., 2021). From our motivation (see Fig. 2, 3, and 4), we conduct two experiments for Q1 by performing class-wise and feature-wise background removal.

These experiments are designed to capture the existence of FG–BG associations under fair conditions. From these findings about FG–BG associations, we pose the following question: **To what extent do FG–BG associations affect model accuracy?** To address this, we conduct a series of experiments aimed at capturing, representing, and quantifying the impact of FG–BG associations across domains, leading into the next set of questions (Q2 and Q3).

Q2. Is there a causal relationship between FG–BG associations and object detection?

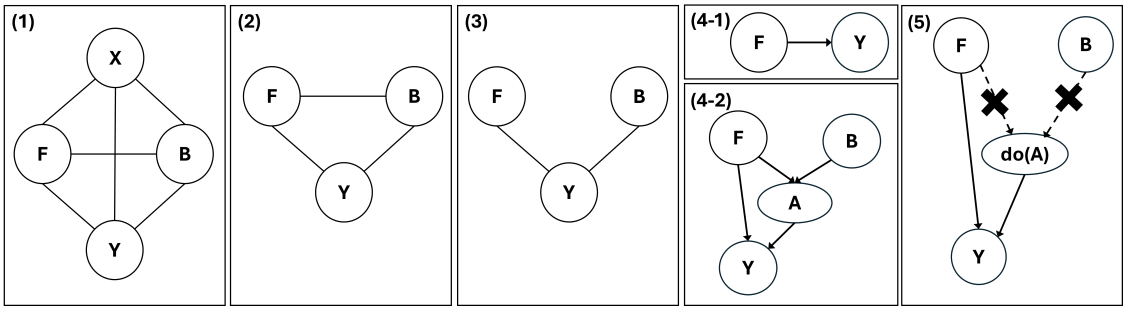


Figure 6: **Identification process to generate a causal graph.** (1) is the first step from a complete undirected graph where "X" is an image, "F" is foreground, "B" is background, and "Y" is an outcome. "X" is removed because the object detection model will engineer on the input. So it generates (2). (3) is induced because "F" and "B" are independent. (4-1) is the optimal factor graph we derive that the outcome is solely related to "F". (4-2) indicates we captured from preliminary experiments (see Introduction 1). "A" indicates FG–BG associations. (5) is the factor graph with do-calculus to quantify the causal effect of "A" on "Y". By applying the backdoor adjustment, we can quantify the causal effect.

We employ graph-based causal analysis to investigate the causal effect of FG–BG associations on object detection performance. As illustrated in Figure 6, a causal model is constructed using the PC algorithm (Glymour et al., 2019) to infer causal relationships within the object detection pipeline. In the context of a graphical causal model (F →Y ←B), it represents the joint distribution P(Y, F, B), which can be decomposed as either $P(Y|F,B)P(F|B)P(B)$ or $P(Y|F,B)P(B|F)P(F)$ (see the panel (3) in Figure 6, Equation 1 and 2). This is a spurious factor leading to FG–BG associations in CNN training. Causal identification further enables through intervention analysis (do-calculus). The causal effect of FG–BG associations (A) on object detection performance (Y) can be expressed as $P(Y|\text{do}(A)) = \sum_F P(Y|A,F), P(F)$, following the backdoor adjustment formula. This effect can be quantified by the expected difference $\mathbb{E}[Y|A=0,F] - \mathbb{E}[Y|A=1,F]$, which captures the impact of FG–BG association (A) on detection outcomes (Y), conditioned on contextual features (F) (see Fig. 6). To this end, we design an experiment through intervention via CAM and instance masks. By combining CAM with ground-truth instance masks, we perform do-calculus interventions incurring backdoor adjustment to model the causal influence of FG–BG associations on object detection

accuracy. The combination of CAM and instance masks control activated background regions for each instance with different thresholds.

Q3. What is the impact of FG–BG associations on DAOD and how can the effect be quantified?

While the causal association with detection outcomes (Y) learned in source domains typically remains stable, the conditional distribution $P(Y|A)$ may shift due to background distribution changes. This can weaken the causal strength in target domains, resulting in performance degradation. We quantify this effect using the Domain Association Gradient (*Gradient* in the rest of the paper), which captures the impact of FG–BG associations by combining intertwined features within and across domains. We note that prior domain adaptation research emphasizes FG feature alignment exclusively (e.g., domain discriminator (Zhou et al., 2023) and moment matching (Peng et al., 2019)), and thus our effort is to highlight the gap in the literature. In the causal graph in Fig. 6, we denote FG-BG associations by A and detection performance by Y. The causal effect of A on Y like Average Treatment Effect (ATE (Naimi & Whitcomb, 2023)) can then be given by the interventional contrast as

$$ATE = \mathbb{E}\big[Y \mid do(A=1),\ F\big] - \mathbb{E}\big[Y \mid do(A=0),\ F\big] \tag{3}$$

where $A = 1$ corresponds to the presence of the observed FG-BG associations and $A = 0$ denotes the intervention that destroys this association. In practice, we estimate this effect using the drop rate (ΔY), which is the decrease in detection accuracy when we intervene on the background and disrupt FG–BG associations while keeping the foreground object unchanged. Therefore, the drop rate can be seen as an empirical approximation of the average causal effect of A on Y.

While the drop rate shows how much performance shifts under an intervention on A, it does not quantify changes in association. To disentangle these two factors, we use an MMD-based term that measures the magnitude of the feature distribution shift between associated and non-associated features across inter- and cross-domain contexts. Specifically, the combination of $\Delta MMD \approx MMD(\texttt{f2b}) + MMD(\texttt{b2f}) - MMD(\texttt{f2f}) - MMD(\texttt{b2b})$ captures how much foreground (f) and background (b) features diverge when the association is broken, compared to within-context variation (`f2f` and `b2b`). In other words, cross-context feature comparisons, such as `f2b` and `b2f`, are expected to yield higher MMD values than within-context comparisons, such as `f2f` and `b2b`, because the latter reflect similar contextual structures. However, if FG-BG associations significantly influence object detection, the MMD of cross-context features is smaller than when the associations are absent, yet it remains larger than within-context comparisons. A small value indicates that features capture strong FG-BG associations and a large value implies that features capture weak associations. The Domain Association Gradient is then defined as the equation 4.

$$\text{Gradient} \approx \frac{\text{change in outcome } (\Delta Y)}{\text{association magnitude } (\Delta MMD)}. \tag{4}$$

The numerator measures the interventional change in the outcome, while the denominator, ΔMMD, quantifies the magnitude of FG-BG associations. Intuitively, if a FG-BG association is strong, the denominator is small and the numerator is large, resulting in high *Gradient*. Conversely, when the association is weak, the *Gradient* value is low. This makes the *Gradient* name literal: it's a rate of change of performance w.r.t. a measure of FG-BG associations. Our experimental procedure is described in detail in Section 3.

1.2 Contributions

Our main contributions are as follows:

- We highlight a crucial gap, suggesting that considering alleviation of context bias is essential for enhancing the generalization and robustness of models across various environments by quantifying its effect. None of the current approaches investigate how context bias can manifest across various domains. We examine the issue of DAOD in relation to context bias.
- We analyze FG–BG associations and the causal relationship through the drop rate and do-calculus. Additionally, we employ distance-based metrics to measure the association between foreground and background under domain shifts.

- We also propose an additional metric, *Gradient*, to quantify context bias in the source and target domains. To our knowledge, this is the first work to quantify this phenomenon.

- We provide a novel and practical research perspective by framing context bias as a critical factor in cross-domain object detection. Our study follows a logical progression from empirical observation to theoretical analysis, followed by quantitative and qualitative evaluations resulting in convincing evidence that FG–BG associations significantly affect domain adaptation performance.

2 Related Work

2.1 FG–BG Associations and Context Bias

There have been a number of studies aimed at improving performance in tasks such as classification, object recognition, and object localization, researching background influence (Xiao et al., 2020; Liang et al., 2023; Zhang et al., 2007; Ribeiro et al., 2016; Zhu et al., 2016; Rosenfeld et al., 2018; Barbu et al., 2019; Sagawa et al., 2019) and context bias (Torralba & Efros, 2011; Khosla et al., 2012; Choi et al., 2012; Shetty et al., 2019). Xiao et al. (2020) and Zhu et al. (2016) studied the effect of background on classification accuracy by modifying images with different combinations of foreground and background. Choi et al. (2012) proposed a graphical model that constructed FG–BG associations using conditional probability, serving as a methodological inspiration for us. Several studies have addressed context bias using techniques such as data augmentation to generate out-of-distribution samples in the background, a combination of naturally unmatched backgrounds and foregrounds (e.g., an elephant in a room), and applying background removal during training. Torralba (2003) demonstrated that background effects can be factorized into object priming, focus of attention, and scale selection by modeling the FG–BG associations in a probabilistic model. Liang et al. (2023) studied background influence using fashion datasets (Jia et al., 2020; Takagi et al., 2017). These studies (Zhai et al., 2024; Wu et al., 2022) localized foreground objects more effectively than CAM-based algorithms, without bounding box information and with only classification labels. These prior works focused on context bias within the same domain and used datasets with smaller variations, such as centered objects or single objects. Thus, we found that there remains a gap in understanding how context bias affects DAOD.

2.2 Domain Adaptation for Object Detection

Different variations of DAOD methods have been proposed using feature alignment, synthetic images, and self-training or self-distillation. Feature alignment finds transformations between source and target domains to reduce distribution shifts with adversarial training (He & Zhang, 2019; Chen et al., 2021; Ganin et al., 2016; Zhu et al., 2019). It can be helpful to extract common latent features from different domains. Progressive Domain Adaptation for Object Detection (Hsu et al., 2020) synthesized a new dataset by using CycleGAN (Zhu et al., 2017), which enables bridging domain gaps, and Self-Adversarial Disentangling for Specific Domain Adaptation (Zhou et al., 2023) achieved 45.2 mAP on the Cityscapes to Cityscapes foggy dataset using synthetic images. Gong et al. (2022) utilized transformers to focus on aligning features across backbone and decoder networks. However, combining multiple sources into a single dataset and performing single-source domain adaptation for feature alignment does not guarantee better performance compared to using the best individual source domain (Zhao et al., 2020).

Self-training uses a teacher model to predict pseudo-labels in target domains to gradually understand domain shift (Caron et al., 2021; Pham et al., 2022; Cai et al., 2019; Chen et al., 2022; Cao et al., 2023). MIC (Hoyer et al., 2023) employed masked images in the teacher-student model, and MRT (Zhao et al., 2023) proposed a modified masked-based retraining approach for the teacher-student model. Kay et al. (2024) performed alignment and distillation to enforce invariance across domains to reduce feature discrepancies.

Finding common features from multiple domains is critical for DAOD. They have demonstrated that foreground features in the latent space can be aligned using dimension-reduction methods such as UMAP (McInnes et al., 2018) and t-SNE (Van der Maaten & Hinton, 2008). These studies did not address how to manage context bias when adapting across different domains. Instead, they proposed and validated their

methods within the DAOD framework using accuracy metrics. Thus, we focus on analyzing the root causes of domain discrepancy in object detection both qualitatively and quantitatively.

3 Method

The following abbreviations are used throughout this paper to refer to the datasets and models in Table 1:

Table 1: Dataset and model abbreviations

Abbreviation	Meaning
CST	Cityscapes Train
CSV/ CFV / CRV	Cityscapes Validation / Foggy / Rainy
KST	KITTI Semantic Train
BG-20K	Background 20K Dataset
VKC / VKF / VKM / VKO / VKR / VKS	Virtual KITTI Clone / Fog / Morning / Virtual KITTI Overcast / Rain / Sunset
ALDI++	ResNet-50 FPN with ALDI++ best
Res	ResNet-50 FPN
Eff	EfficientNet-B0 FPN
Yo	YOLOv11

3.1 Models

We employ ResNet-50 ("Res") and EfficientNet-B0 ("Eff") as backbones for FPN models implemented in Detectron2, as well as YOLOv11 ("Yo") (Khanam & Hussain, 2024), an anchor-free detection model. "Res" represents a backbone dominantly used in different architectures. "Eff" is chosen for its lightweight architecture. Additionally, we include the state-of-the-art DAOD method ALDI++ with a ResNet-50 backbone to evaluate its effectiveness in mitigating FG–BG associations.

3.2 Datasets

We use multiple datasets for training and evaluation, including Cityscapes, KITTI Semantic, and various subsets of Virtual KITTI. Additionally, BG-20K, a collection of 20,000 images containing non-salient objects, is utilized to generate randomized background images. The Cityscapes and "KST" sets share 8 foreground and 11 background object categories. The Virtual KITTI subsets contain 3 foreground and 10 background object classes.

The dataset sizes are as follows:

- **Cityscapes**: 2,950 training images, 500 validation images, 1,500 foggy validation images, and 1,188 rainy validation images.
- **KITTI Semantic Train**: 200 images.
- **Virtual KITTI Semantic**: 2,126 images across 6 simulated weather conditions. This dataset is synthetic and based on object tracking in diverse environments.

3.3 Training and Tests

We train "Res" and "Eff" on the "CST", "KST", and "VKC" datasets. "Yo" is trained with the same conditions using the Ultralytics framework. ALDI++ was trained on ("KST", "CSV") and ("VKC", "VKF") as source and target domain pairs, respectively. We use pre-trained ALDI++ model from the official repository without additional training on Cityscapes. For training, we use a learning rate of 0.02 for "Res", with input resolutions of 1024×2048 for Cityscapes and 375×1242 for KITTI-related datasets. For "Eff", we use 1024×1024 resolution for Cityscapes and the same KITTI resolution, with a learning rate of 0.01. All models

use identical data augmentation: resizing and cropping, color jitter, and horizontal flipping. Each model is trained with a batch size of 8. Training ran for approximately 100 epochs for ALDI++, "Res" and "Yo", and 200 epochs for "Eff". During evaluation, we use 1024×2048 images for Cityscapes-related datasets and 375×1242 for KITTI-related datasets on models except "Yo". "Yo" is trained and evaluated on 512x1024 and 320x1024 image resolutions respectively. The best model checkpoint is selected based on the highest mean Average Precision with 0.5 IoU threshold (mAP@50) from a DAOD perspective. For example, "Res" achieves a mAP@50 of 67.758 on the Cityscapes validation set and 54.617 on the "CFV" at epoch 7799, and 67.597 and 57.131 at epoch 7999, respectively. We select the model from epoch 7999 for subsequent experiments. For "KST", the model with the highest performance on "CFV" is chosen. For "VKC", we select the model with the highest mAP@50 on "VKF", which represents the largest domain shift among the Virtual KITTI variants. All models except "Yo" are trained using the standard loss functions provided by Detectron2 and Ultralytics is utilized for "Yo". Training is conducted using an NVIDIA RTX A4500 GPU.

3.4 Q1 - Exp1. Class-wise Background Removal Experiments in Image Space

The initial experiment evaluates the effect of background variation by performing inference on foreground objects placed over random background images fixed across different domains. Foreground regions are preserved and composited with backgrounds randomly sampled from the BG-20K dataset (see Figure 12 in Appendix A.1). The same sequence of background images is applied consistently across domains, thereby reducing the learned association between foreground and background. To ensure statistical validity, the experiment is repeated six times using different random sequences of background selections. Algorithm 1 describes the experiment process. The results, summarized using the mAP@50 metric and standard deviation, are presented in Table 4.

Algorithm 1: Class-wise Background Removal Experiments in Image Space

Input:

- FG: Set of foreground object instances
- $BG-20K$: Set of 20,000 random background images
- D: Set of target domains for inference

Output: Mean and standard deviation of mAP@50 across 6 repeated trials

```
foreach domain d ∈ D do
    foreach foreground object f ∈ FG do
        Randomly sample a fixed set of background images BG_i ⊂ BG_20K;
        Synthesize image I_{f,d} by placing f onto a background from BG_i;
    Apply the trained model to all synthesized images {I_{f,d}} for domain d;
    Measure detection performance using mAP@50;
Compute mean and standard deviation of mAP@50 across all six trials;
```

3.5 Q1-Exp2. Feature-wise Background Removal Experiments in Feature Space

The second experiment investigates feature-wise FG–BG associations by selectively suppressing specific background labels in the feature space during inference. Using ground-truth semantic annotations, a particular background class (e.g., "road") is removed in repeated inference runs. This is achieved by zeroing out activation values in the corresponding background regions at shallow network layers: $res2.2$ in "Res" and ALDI++, *backbone.bottom_up._blocks*.0 in "Eff", and *model*.1 in "Yo". Due to the hierarchical nature of deep learning models, targeted suppression weakens FG–BG associations for the removed background label, potentially affecting detection performance. To evaluate this effect, we measure the number of detections from unmodified models and compare them to detections after modification. The drop rate, calculated for each FG–BG class pair, reflects the sensitivity of foreground object detection to the presence of specific background labels.

Definition of detection drop: A detection is counted as dropped under either of the following conditions:

1. The predicted class changes due to background label removal.
2. The loss of information we defined is greater than 1.0, which means IoU with ground truth significantly decreases (less than 0.1 IoU).
3. The prediction matches a different ground-truth object not originally considered a true positive.

Importantly, drop rates are computed only for true positive cases. To ensure statistical rigor, the process is repeated six times. Since drop rate distributions does not satisfy normality assumptions, we employ the Wilcoxon signed-rank test (Woolson, 2005) to assess statistical significance. Algorithm 2 describes the experiment process.

Algorithm 2: Feature-wise Background Removal Experiments in Feature Space

Input:

- FG: Set of foreground object instances
- BG: Set of background regions with semantic labels
- L_{remove}: Background label to be removed (e.g., "road")
- M: Deep learning models (e.g., "Res")

Output: Drop rate statistics for each FG–BG pair and Wilcoxon test results

```
for i = 1 to 6 do
    foreach model m ∈ M do
        foreach image x with semantic ground truth do
            Perform standard inference on x with model m, store number of detections D_std;
            Remove BG activated pixels in shallow feature maps corresponding to label
              L_remove (e.g., res2.2 for "Res");
            Perform modified inference on x, store number of detections D_mod;
            Compute detection drop ΔD = D_std − D_mod for each FG–BG pair;
    Store all ΔD values for statistical analysis;
Aggregate drop rates for each FG–BG pair across all trials;
Conduct Wilcoxon signed-rank test to assess significance of drop rate distributions;
```

3.5.1 Q2-Exp1. FG–BG Association with Respect to Activated Background Region

Using CAM masks with varying thresholds, we measure the mAP@50 drop rate to investigate the causal influence of activated background regions on object detection performance. Smooth-GradCAM++ (Omeiza et al., 2019) generates contextually meaningful instance masks by gradient backward on each object's score with 0.85 confidence threshold. The CAM masks are binarized by applying threshold values that decrease by 0.1 with each bin increase. The extent of the activated background region is controlled by the chosen threshold, while the masked foreground region remains fixed throughout the experiment, regardless of background variation. Through statistical analysis, the causality of association and accuracy is demonstrated. Algorithm 3 describes the experiment process. Figure 7 illustrates the contextual masks depending on different layers and bins. We define the hit ratio as the ratio of foreground and background pixels captured by CAM in the activation maps, normalized by the number of ground truth pixels from the instance masks. "FG mean" is the number of pixels hit by CAM and the ground truth of the instance mask. "BG mean" is the activated background region over the number of foreground pixels. We average all instances' hit ratios to compute the "FG mean" and "BG mean.". It indicates CAM captures properly contextual information for each instance. Definition of associated and non-associated is in Section 3.6.1.

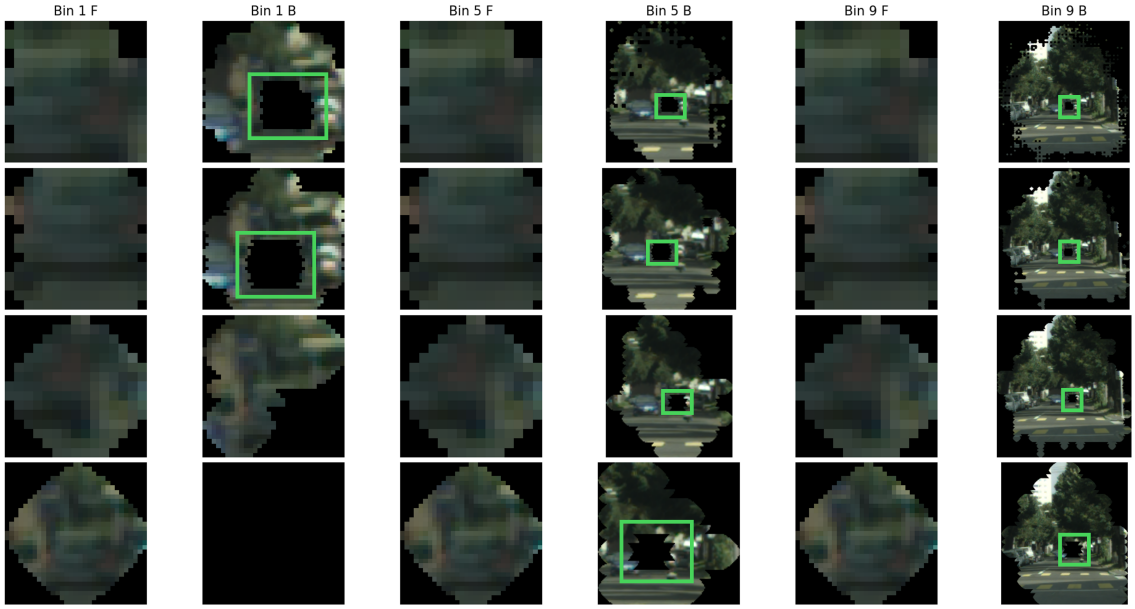


Figure 7: **"Res" foreground and background images using CAM and instance masks.** Each column corresponds to bins 1, 5, and 9 with foreground and background orders. Each row is a different layer. The green bounding boxes highlight where the foreground object gets located. Foreground regions are maintained across layers. The image blurriness is due to scaling.

Algorithm 3: Causality Analysis via Smooth-GradCAM++ Mask Thresholding

Input:

- FG: Set of foreground object instances with 0.85 confidence threshold
- x: Input image
- T: Set of CAM thresholds (e.g., maximum of activation value to $1e^{-9}$ in 0.1 decrements)

Output: Drop rates under different CAM thresholds

foreach *foreground instance* $f \in FG$ **do**
  Generate Smooth-GradCAM++ map H_f using prediction confidence of f from image x;
  foreach *threshold* $t \in T$ **do**
    Binarized CAM mask: $M_f^{(t)} = \mathbb{1}(H_f \geq t)$;
    (Note: foreground region remains fixed; only background area changes);
    Remove partial BG activations in shallow feature maps corresponding to the Masks (e.g., $res2.2$ for "Res") and compute detection result D_{mod};
    Compute drop rate: $\Delta D_t = D_{std} - D_{mod}$ where D_{std} is detection without CAM masking;
Aggregate drop rates and hit ratios across all instances;
Analyze drop rate trend across thresholds to infer FG–BG causality;

3.6 Q3-Exp1 and Exp2. Quantification the Causal Effect on DAOD

The results from our experiments confirm the existence and causal effect of FG–BG associations. However, these findings do not directly quantify their influence on DAOD. To address this, we introduce a new metric, Domain Association Gradient (referred to as *Gradient*), which measures performance perturbation in response to the strength of FG-BG associations. For the association strength, we add the MMD between

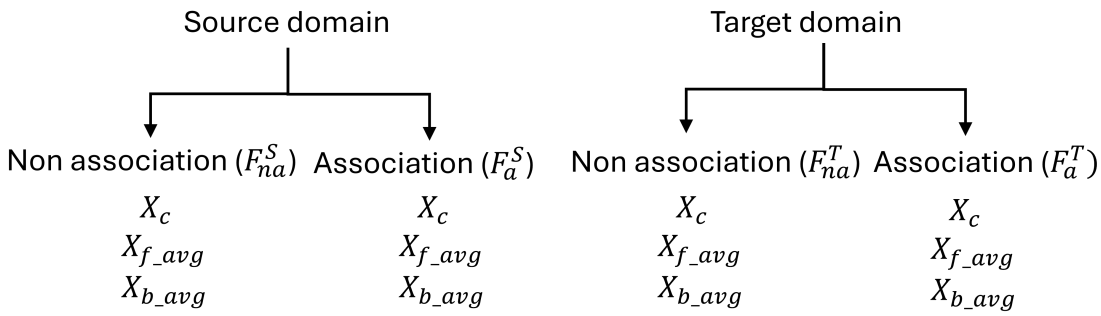


Figure 8: **Feature extraction graph.** We extract features from all true positives with different FG–BG pairs. The process to generate each feature is described in Algorithm 4.

FG and BG (f2b and b2f) and subtract the MMD within FG and within BG (f2f and b2b). Figure 8 illustrates the feature extraction breakdown. For each domain (D), we can separate the features into association (F_a^D) and non-association features (F_{na}^D). These features can then be further broken down into CAM-activated features (X_c), 2D pooled averaged FG features within X_c (X_{f_avg}) and 2D pooled averaged BG features within X_c (X_{b_avg}) using instance masks to make FG and BG separable. The detailed process to extract each feature from FG and BG of different domains (e.g. X_c, X_{f_avg}, X_{b_avg}) is described in Section 3.6.1.

The intuition is that if a strong FG–BG association is learned, the MMD between features that preserve this association should be small, due to shared contextual dependencies. Besides, the drop rate should be large with a strong FG–BG association. Consequently, the *Gradient* value that is computed using these features should be larger than those derived from features lacking FG–BG associations. We calculate *Gradient* values for each FG–BG pair using the drop rate and analyze their patterns using the equations 5. Only FG–BG pairs with statistically significant drop rate differences identified in Experiment 3.5 are included in this analysis. Based on our hypothesis, we expect Gradient^S to exceed Gradient^T, as models trained on the source domain tend to capture stronger FG–BG associations. Each superscript (S and T) denotes the source and target domain, respectively.

$$\text{Gradient}^{\text{S}} = \frac{\text{Source domain drop rate}}{\text{f2b}^{\text{S}} + \text{b2f}^{\text{S}} - \text{f2f}^{\text{S}} - \text{b2b}^{\text{S}}}, \quad \text{Gradient}^{\text{T}} = \frac{\text{Target domain drop rate}}{\text{f2b}^{\text{T}} + \text{b2f}^{\text{T}} - \text{f2f}^{\text{T}} - \text{b2b}^{\text{T}}} \tag{5}$$

Equation 6 defines how various feature combinations, drawn from different contexts, are used in computing this metric. Specifically, cross-context feature comparisons, such as `f2b` and `b2f`, are expected to yield higher MMD values than within-context comparisons like `f2f` and `b2b`, since the latter reflect similar contextual structures.

$$\begin{aligned}
\text{f2f}^{\text{S}} &= \text{MMD}(X_{f_avg} \in F_{na}^S,\, X_{f_avg} \in F_a^S) & \text{f2f}^{\text{T}} &= \text{MMD}(X_{f_avg} \in F_{na}^T,\, X_{f_avg} \in F_a^T) \\
\text{f2b}^{\text{S}} &= \text{MMD}(X_{f_avg} \in F_{na}^S,\, X_{b_avg} \in F_a^S) & \text{f2b}^{\text{T}} &= \text{MMD}(X_{f_avg} \in F_{na}^T,\, X_{b_avg} \in F_a^T) \\
\text{b2f}^{\text{S}} &= \text{MMD}(X_{b_avg} \in F_{na}^S,\, X_{f_avg} \in F_a^S) & \text{b2f}^{\text{T}} &= \text{MMD}(X_{b_avg} \in F_{na}^T,\, X_{f_avg} \in F_a^T) \\
\text{b2b}^{\text{S}} &= \text{MMD}(X_{b_avg} \in F_{na}^S,\, X_{b_avg} \in F_a^S) & \text{b2b}^{\text{T}} &= \text{MMD}(X_{b_avg} \in F_{na}^T,\, X_{b_avg} \in F_a^T)
\end{aligned} \tag{6}$$

Furthermore, we conduct a focused analysis on `f2b` and `b2f` MMD values for both associated and non-associated features across domains using equation 7 and 8. We compute the sum of these values and compare them using pairwise T-test (O'Mahony, 2017) after Shapiro-Wilk test (Shapiro & Wilk, 1965).

$$\begin{aligned}
f2b_{asso} &= \text{MMD}(X_{f_avg} \in F_a^S,\, X_{b_avg} \in F_a^T) & f2b_{no-asso} &= \text{MMD}(X_{f_avg} \in F_{na}^S,\, X_{b_avg} \in F_{na}^T) \\
b2f_{asso} &= \text{MMD}(X_{b_avg} \in F_a^S,\, X_{f_avg} \in F_a^T) & b2f_{no-asso} &= \text{MMD}(X_{b_avg} \in F_{na}^S,\, X_{f_avg} \in F_{na}^T)
\end{aligned} \tag{7}$$

$$\text{sum}_{\text{a-a}} = \text{f2b}_{\text{asso}} + \text{b2f}_{\text{asso}} \qquad \text{sum}_{\text{na-na}} = \text{f2b}_{\text{no-asso}} + \text{b2f}_{\text{no-asso}} \tag{8}$$

A higher sum_{na-na} than sum_{a-a} indicates that FG–BG association persists across domains and may influence DAOD performance when the model unintentionally leverages such cross-domain dependencies during inference. In other words, if the FG-BG association does not have an impact across DAOD, then sum_{na-na} and sum_{a-a} should not show a statistical difference. We randomly sample non-associated features to correspond to the number of associated features. We divide all datasets into two groups. The first group includes Cityscapes-related datasets with "KST" and the second group contains only the Virtual KITTI-related dataset due to unmatched label configurations.

3.6.1 Associated Features and Non-associated Features Extraction

With the drop rate experiment (Algorithm 3) as pre-processing, we define associated features when the extracted features of each instance are not detected without background context. In other words, it indicates the features encode association between FG–BG. Conversely, non-associated features indicate that FG–BG association is not included in the extracted feature. We extract features and cluster them per FG–BG pair. We use four layers per model to extract features at different scales. For "Res" and ALDI++, we use $res2.2, res3.3, res4.5, res5.2$ and for "Eff", we use *backbone.block*.0, 1, 3, and 5. From each domain, we save associated features and non-associated features. Algorithm 4 describes steps to process foreground-related features and background-related features. Table 2 defines F_a^D and F_{na}^D, meaning FG–BG associated features and FG–BG non-associated features from each domain D.

Algorithm 4: Feature Extraction from CAM and Ground Truth Instance Mask

Input:

- C: CAM mask from Algorithm 3.
- G: Ground truth instance binary mask
- A: Activation maps from different layers (e.g. $res2.2, res3.3, res4.5$, and $res5.2$ for "Res")

Output: X_c, X_{f_avg}, X_{b_avg}

Compute features X from CAM mask C;
    $X = A \cdot \mathbb{1}(C = 1)$;
Compute Normalized features X_c from X;
    X_c =Normalize(X);
Separate normalized features using ground truth mask G:
    X_{f_avg} = Adaptive pool 2d($X_c \cdot \mathbb{1}(G = 1)$);
    X_{b_avg} = Adaptive pool 2d($X_c \cdot \mathbb{1}(G = 0)$);

Table 2: **Definition of FG–BG associated features and non-associated features at each domain D.** "1" means BG removal is performed and detection fails for BG removal and Detection, respectively. "0" indicates BG removal is not applied and the success of detection.

		Detection	
		0	**1**
BG removal	**1**	When "road" is removed, detection fails → car feature with association (F_a^D)	Without "road", detection succeeds → car feature without association (F_{na}^D)
	0	False Negative. Unknown association impact on prediction.	True Positive. No association impact on prediction.

4 Experiments

Q1. Are FG–BG associations being inadvertently learned during the training process?

Model Evaluation

We evaluated the trained models using the mAP@50 metric. Table 3 summarizes the evaluation results. Among models trained on the Cityscapes dataset, ALDI++ outperformed others on Cityscapes-related datasets and "KST", likely due to longer training epochs on target domain and the use of multiple domain datasets via DAOD algorithms. Although "Yo" achieved strong performance on "CST", its domain adaptation capability was weaker than that of the baseline "Res". "Eff" consistently showed the lowest performance on both Cityscapes and "KST" but outperformed "Yo" on "KST". For models trained on "KST", ALDI++ outperformed other models, while "Eff" and "Yo" showed significantly worse results. The "KST" dataset, with only 200 images, introduced a domain shift that limited generalization to larger datasets. Consequently, "Res" and "Yo" also exhibited weakened performance due to insufficient data. With VKC-trained models, "Res" and "Yo" demonstrated reasonable domain generalization compared to "Eff". However, on the "VKF" validation set, "Yo"'s performance dropped significantly relative to "Res", despite its overall strong results on other datasets. "Eff" also experienced a notable performance decline on "VKF". ALDI++ demonstrated the effectiveness of domain generalization methods.

Table 3: **Model evaluation across different training and validation sets.** "-" is not measurable because of unmatched class category.

Dataset	Cityscapes Train				KST Train				VKC Train			
	Res	Eff	Yo	ALDI++	Res	Eff	Yo	ALDI++	Res	Eff	Yo	ALDI++
CST	79.14	41.12	**88.26**	87.97	-	-	-	-	-	-	-	-
CSV	67.59	42.90	59.56	**70.08**	43.23	2.74	21.69	**51.09**	-	-	-	-
CFV	57.13	20.58	44.49	**67.45**	35.48	0.61	12.53	**43.62**	-	-	-	-
CRV	58.65	23.18	48.77	**69.78**	37.42	0.86	17.57	**47.82**	-	-	-	-
KST	46.25	28.92	23.91	**47.96**	86.17	10.42	21.53	**92.44**	-	-	-	-
VKC	-	-	-	-	-	-	-	-	81.67	50.09	**85.99**	81.96
VKF	-	-	-	-	-	-	-	-	61.14	5.80	34.27	**72.60**
VKM	-	-	-	-	-	-	-	-	79.72	29.52	79.55	**80.27**
VKO	-	-	-	-	-	-	-	-	75.14	30.41	**81.93**	78.58
VKR	-	-	-	-	-	-	-	-	71.66	25.53	75.93	**78.36**
VKS	-	-	-	-	-	-	-	-	76.02	26.18	**78.65**	77.59

Q1-Exp1. Class-wise Background Removal Experiments in Image Space

This experiment evaluated the role of FG–BG associations by replacing background regions with non-salient object images while preserving foreground objects. We measured mAP@50 over six repetitions using randomly generated images. Table 4 presents the mean and standard deviation across the six evaluation runs. Models trained on Cityscapes showed substantial performance drops compared to their original evaluation. Notably, ALDI++ exhibited greater degradation than "Res" on "KST", suggesting that ALDI++ strongly relies on FG–BG associations learned from both source and target domains. Similarly, models trained on "KST" and "VKC" also experienced considerable performance declines, indicating that FG–BG associations were learned during training and utilized during inference.

Q1-Exp2. Feature-wise Background Removal Experiments in Feature Space

In addition to background perturbation in image space, we performed background removal in feature space in Table 5. Specifically, we zeroed out activated background regions in the shallow layers of each model architecture, preventing background information from propagating to deeper layers. This effectively disables the FG–BG association during inference. The Cityscapes-related datasets and "KST" contain 88 distinct FG–BG combinations, while the Virtual KITTI datasets include 30 combinations. We report only the combinations that resulted in a statistically significant performance drop of at least 8%. Note that additional combinations exhibited smaller drops and are not included in the table. Figure 9 illustrates the example

Table 4: **Mean ± standard deviation of mAP@50 across synthetic datasets and models trained on Cityscapes, "KST", and "VKC".** The bolded values are the highest mAP@50 for each train dataset-model pair.

Cityscapes Trained

Dataset + BG	Res	Eff	Yo	ALDI++
CSV	44.5 ± 6.1	10.02 ± 6.4	32.78 ± 0.6	**47.96** ± 6.3
CFV	34.6 ± 10.6	8.99 ± 4.5	15.70 ± 0.3	**43.17** ± 9.8
CRV	29.1 ± 4.4	14.24 ± 8.4	17.37 ± 0.3	**38.18** ± 5.1
KST	**41.4** ± 4.4	25.33 ± 6.4	19.92 ± 1.4	33.98 ± 6.7

KST Trained

Dataset + BG	Res	Eff	Yo	ALDI++
CSV	19.2 ± 5.2	0.16 ± 0.1	21.34 ± 0.3	**23.01** ± 0.7
CFV	17.0 ± 5.8	0.22 ± 0.1	10.35 ± 0.1	**24.55** ± 0.1
CRV	13.6 ± 3.4	2.25 ± 2.1	14.29 ± 0.1	**35.29** ± 0.7

VKC Trained

Dataset + BG	Res	Eff	Yo	ALDI++
VKF	38.7 ± 10.7	1.17 ± 0.5	14.61 ± 0.5	**51.04** ± 0.5
VKM	61.8 ± 5.1	11.44 ± 6.4	35.26 ± 0.6	**64.17** ± 0.3
VKO	60.0 ± 4.7	10.70 ± 5.5	33.66 ± 0.4	**64.44** ± 0.5
VKR	58.4 ± 3.5	7.99 ± 3.5	27.56 ± 0.4	**59.81** ± 0.4
VKS	59.8 ± 6.5	12.92 ± 4.6	35.93 ± 0.8	**64.26** ± 0.2

of significant performance drop on "CST" with "Res" model. It indicates that the models learned notable FG–BG associations during training, which can cause performance degradation.

Table 5: **The number of FG–BG pairs statistically significant different across models**. Only FG–BG pairs more than 8% drop rate are denoted. The bold values indicate stronger FG–BG associations for each model across the respective datasets.

	Res	**ALDI++**	**Eff**	**Yo**
CST	14/88	**18/88**	15/88	12/88
CSV	7/88	**17/88**	7/88	3/88
CFV	13/88	**20/88**	11/88	7/88
CRV	15/88	**21/88**	12/88	6/88
KST	2/88	2/88	**4/88**	2/88
VKC	8/30	7/30	**9/30**	4/30
VKF	**7/30**	**7/30**	4/30	2/30
VKM	**9/30**	7/30	7/30	3/30
VKO	**9/30**	7/30	8/30	3/30
VKR	7/30	**9/30**	**9/30**	6/30
VKS	8/30	8/30	**9/30**	4/30

Q2. Is there a causal relationship between FG–BG associations and object detection?

In the previous section, we validated the existence of FG–BG associations. To further investigate this phenomenon, we computed CAM masks for each object and analyzed background-region-based associations. To explore the causal relationship, we applied the do-calculus using CAM-derived masks and ground-truth instance masks. We also note that "Yo" contains non-differentiable non-maximum suppression (NMS), which prevents us from using gradient-based CAM to capture specific objects' contextual masks. Thus, we are unable to answer the Q2 and Q3 experiments using this particular model.

Q2-Exp1. FG–BG Association with Respect to Activated Background Regions

With do-calculus, we computed the mean of the drop rate of all classes per bin. While foreground regions were maintained regardless of bin (see Fig. 7 and Table 6), the drop rate significantly increased with bin 1, which has a small amount of activated background (see Table 7). The drop rate converged toward 0 when enlarging the background region, which means the objects were detected correctly. Through the experiment, we confirmed a causal relationship between FG–BG associations and outcomes, as the accuracy of foreground objects changed notably across bins, particularly across from bin 1 to bin 5.

Table 6: **Definition of FG–BG associated features and non-associated features for each domain D.** The FG mean of 1.0 indicates that all foreground pixels are captured by the CAM. The BG mean represents the ratio of captured background pixels to the total number of foreground pixels, reflecting the extent of background activation relative to the foreground.

Layer	Hit ratio			
	Associated		Non-associated	
	FG mean	BG mean	FG mean	BG mean
$res2.2$	1.0	14.81	1.0	20.04
$res3.3$	1.0	14.33	1.0	18.79
$res4.5$	1.0	12.66	1.0	27.2
$res5.2$	1.0	21.0	1.0	12.33

Table 7: **Drop rate per bin.** 5 numbers in each cell are bin 1, 3, 5, 7, and 9 ("B"). The lower means fewer or no drop rates were measured. The bolded values highlight the significant performance drop.

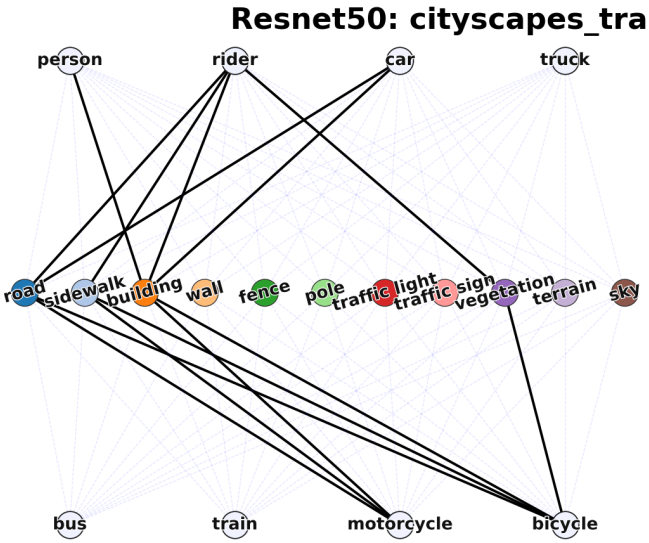
	Res					**ALDI++**					**Eff**				
	B1	B3	B5	B7	B9	B1	B3	B5	B7	B9	B1	B3	B5	B7	B9
CST	**0.65**	0.14	0.02	0.01	0.00	**0.66**	0.18	0.02	0.00	0.00	**0.74**	0.31	0.25	0.26	0.18
CSV	**0.62**	0.10	0.02	0.00	0.00	**0.64**	0.11	0.01	0.00	0.00	**0.71**	0.18	0.14	0.13	0.10
CFV	**0.67**	0.12	0.03	0.00	0.00	**0.68**	0.10	0.02	0.01	0.00	**0.79**	0.19	0.09	0.11	0.11
CRV	**0.67**	0.27	0.07	0.02	0.01	**0.64**	0.20	0.05	0.01	0.01	**0.65**	0.12	0.06	0.07	0.09
KST	**0.84**	0.53	0.22	0.01	0.00	**0.70**	0.31	0.00	0.02	0.02	**0.82**	0.71	0.36	0.69	0.68
VKC	**0.57**	0.08	0.02	0.00	0.00	**0.33**	0.03	0.01	0.00	0.00	**0.71**	0.19	0.07	0.04	0.03
VKF	**0.75**	0.37	0.12	0.04	0.01	**0.42**	0.05	0.02	0.01	0.00	**0.92**	0.15	0.04	0.05	0.02
VKM	**0.63**	0.10	0.03	0.00	0.00	**0.42**	0.05	0.02	0.01	0.00	**0.77**	0.25	0.11	0.06	0.05
VKO	**0.56**	0.11	0.03	0.00	0.00	**0.33**	0.05	0.02	0.00	0.00	**0.76**	0.23	0.05	0.03	0.05
VKR	**0.62**	0.13	0.04	0.01	0.00	**0.33**	0.05	0.02	0.00	0.00	**0.80**	0.26	0.11	0.08	0.07
VKS	**0.64**	0.16	0.07	0.02	0.01	**0.34**	0.05	0.02	0.00	0.00	**0.77**	0.21	0.06	0.03	0.03

Q3. What is the impact of FG–BG associations on DAOD and how can the effect be quantified?

We computed *Gradient* values and analyzed the MMDs between associated and non-associated features across different domains. This allowed us to quantify the impact of FG–BG associations on domain shifts.

Q3-Exp1. Domain Association Gradient

To validate our hypothesis that $Gradient^S$ should be higher than $Gradient^T$ due to learned FG–BG associations, we categorized the comparisons into three cases: **(1) $Gradient^S$ significantly higher than $Gradient^T$, (2) $Gradient^S$ significantly lower than $Gradient^T$**, and **(3) no statistically significant difference.** Table 8 summarizes the results. Overall, the findings support our hypothesis. However, ALDI++ showed opposite results on the CST-CSV pair, possibly due to DAOD training strategy using target domain information (CFV). In the Virtual KITTI-related datasets, particularly for "Eff", some results contradicted expectations. This may be attributed to strong spatial and temporal correlations inherent in the dataset, which is derived from object-tracking video sequences, or to biases introduced by a small number



BG	FG	Drop rate
building	person	0.22
road	rider	0.21
sidewalk	bicycle	0.21
building	bicycle	0.20
building	rider	0.19
building	motorcycle	0.18
road	bicycle	0.18
road	motorcycle	0.16
sidewalk	motorcycle	0.16
sidewalk	rider	0.14
vegetation	rider	0.12
building	car	0.11
road	car	0.10
vegetation	bicycle	0.09

Figure 9: **Feature-wise drop rates of "Res" on "CST".** Bold edges indicate statistically significant difference on the FG–BG pair. The table on the right in the figure illustrates the drop rate in decreasing order.

of detections and drops. These results elaborate quantification of class-wise causal effects in DAOD. Figure 10 presents the results of the *Gradient* comparisons as box plots to present the visual comparison.

Table 8: *Gradient* **comparison across different domains.** Each number's denominator is the number of FG–BG association in common across two domains. Cases 1, 2 and 3 are given as C1, C2 and C3. The bolded values represent the dominant case for each dataset-model pair.

	Res			**ALDI++**			**Eff**		
	C1	C2	C3	C1	C2	C3	C1	C2	C3
CST - CSV	**4/5**	0/5	1/5	4/10	**6/10**	0/10	**3/7**	**3/7**	1/7
CST - CFV	**11/11**	0/11	0/11	**15/15**	0/15	0/15	**7/11**	2/11	2/11
CST - CRV	**10/11**	1/11	0/11	**8/10**	2/10	0/10	**7/10**	3/10	0/10
CST - KST	**1/1**	0/1	0/1	**1/1**	0/1	0/1	**2/3**	1/3	0/3
VKC - VKF	**5/5**	0/5	0/5	**4/4**	0/4	0/4	**1/2**	**1/2**	0/2
VKC - VKM	**5/7**	2/7	0/7	**4/4**	0/4	0/4	1/5	**4/5**	0/5
VKC - VKO	**4/7**	3/7	0/7	**4/4**	0/4	0/4	1/5	**4/5**	0/5
VKC - VKR	**6/6**	0/6	0/6	**5/5**	0/5	0/5	1/5	**4/5**	0/5
VKC - VKS	2/6	**4/6**	0/6	**4/5**	1/5	0/5	1/5	**4/5**	0/5

Q3-Exp2. Associated and Non-associated Features

To understand the class- and feature-wise impact across different domains, we compared the gap between the MMD of associated features and that of non-associated features. Similar to previous *Gradient* analysis, we categorized the comparisons into three cases: **(1) The summation of MMD of `f2b` and `b2f` in associated features significantly lower than that of non-associated features (2) The summation of MMDs of `f2b` and `b2f` for associated features significantly higher than that of non-associated features**, and **(3) no statistically significant difference.** Overall, associated features sharing the same FG–BG association across domains exhibited lower MMD than non-associated features, indicating stronger FG–BG association consistency in cross-domain. However, "Eff" showed reversed outcomes on the CST-CRV and CST-KST pairs. This may be due to a limited number of detections, resulting in insufficient feature representations or overall poor model performance. Table 12 presents the results, while Figure 11 depicts

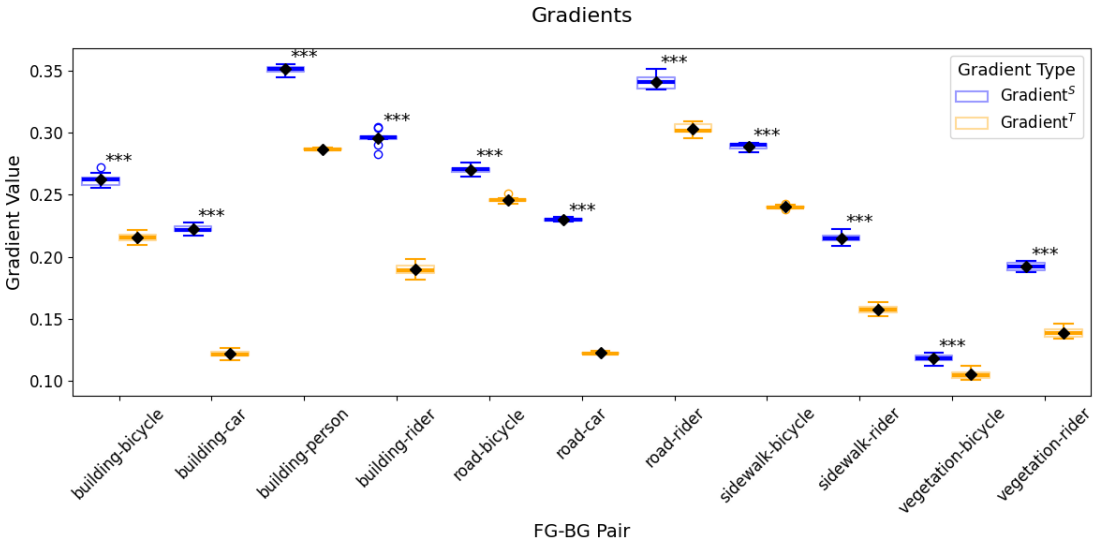


Figure 10: ***Gradient^S* and *Gradient^T* comparison of "Res" model with "CST" and "CFV"**. The number of "*" indicates the level of statistical significance of a p-value.

the results of associated and non-associated feature comparison, with statistical analysis annotated in the box plots.

Table 9: **Associated and non-associated features comparison across different domains.** Each number's denominator is the number of FG–BG association in common across two domains. Cases 1, 2 and 3 are given as C1, C2 and C3. "-" is not measurable statistically. The bolded values represent the dominant case for each dataset-model pair.

	Res			**ALDI++**			**Eff**		
	C1	C2	C3	C1	C2	C3	C1	C2	C3
CST - CSV	**5/5**	0/5	0/5	**9/10**	0/10	1/10	**3/7**	2/7	2/7
CST - CFV	**11/11**	0/11	0/11	**9/15**	6/15	0/15	**6/11**	5/11	0/11
CST - CRV	**8/11**	3/11	0/11	**7/10**	3/10	0/10	2/10	**6/10**	2/10
CST - KST	**1/1**	0/1	0/1	**1/1**	0/1	0/1	0/3	**2/3**	1/3
VKC - VKF	**2/5**	1/5	**2/5**	**4/4**	0/4	0/4	**2/2**	0/2	0/2
VKC - VKM	**4/7**	2/7	1/7	**4/4**	0/4	0/4	**3/5**	1/5	1/5
VKC - VKO	**5/7**	2/7	0/7	**4/4**	0/4	0/4	**4/5**	1/5	1/5
VKC - VKR	**4/6**	1/6	1/6	**5/5**	0/5	0/5	**4/5**	1/5	0/5
VKC - VKS	**5/6**	1/6	0/6	**5/5**	0/5	0/5	**3/5**	1/5	1/5

5 Discussion and Conclusion

In this work, we present a comprehensive empirical and theoretical investigation into the role of context bias in DAOD. While context bias has previously been studied in classification and segmentation tasks, our work is the first to formally identify, quantify, and causally analyze this phenomenon within the context of DAOD.

Our findings show that modern object detection models frequently rely on FG–BG associations that often do not generalize well across domains. Through systematic background masking and feature-level perturbations, we demonstrate that removing or altering background information can lead to substantial drops in detection performance even when the foreground remains intact. These effects are consistent across various model

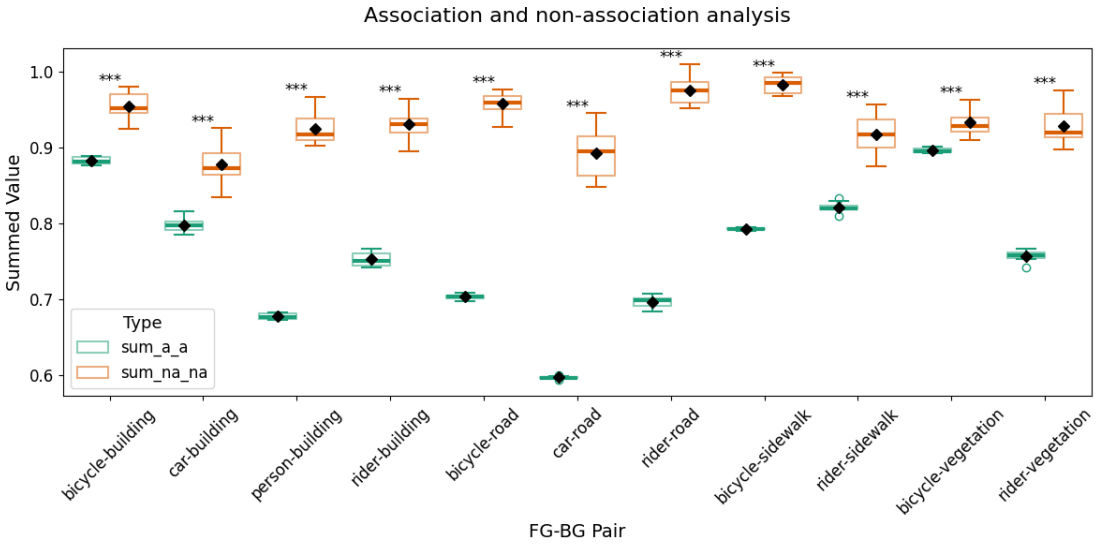


Figure 11: **MMD of associated features and non-associated comparison of "Res" model with "CST" and "CFV"**. The number of "*" indicates the level of statistical significance of a p-value.

architectures and domain pairs, including ALDI++, a state-of-the-art DAOD model on the Cityscapes dataset.

Furthermore, we present that FG–BG associations are not only empirically observable but also causally linked to detection outcomes. Using a combination of do-calculus, Smooth-GradCAM++, and layer-wise feature analysis, we construct and validate a causal model that quantifies the influence of context bias. We introduce a novel metric and find that domain shifts exacerbate performance disparities when models rely on FG–BG associations.

In the Appendix (Section A.3), we provide additional clarifications of our experimental results. Specifically, we include (i) a fixed color background replacement experiment analyzed from a counterfactual perspective, (ii) ViTDet (Li et al., 2022a) attention maps and drop rates under background replacement in image space, and (iii) *Gradient*, and a comparison of associated versus non-associated features, using a Radial Basis Function (RBF) kernel. Together, these supplementary analyses help address several open questions and limitations of our main experiments.

Limitations

Despite the strength of our analysis, we acknowledge that extracting foreground and background features separately across large datasets is computationally expensive. This limits the scalability of some of the proposed methods. Some outliers may be due to class imbalance in foreground objects across datasets. For example, "car" and "person" are dominant but other foreground objects are rare. There are also certain neural network architectures, such as in "Yo", that prevent us from computing the CAM masks and deriving the FG and BG activation features. Thus, while our method is robust, it is only applicable to architectures that support gradient-based CAM methods.

Future Work

Importantly, our results suggest that current DAOD methods may unintentionally reintroduce context bias from the target domain. This highlights a new dimension of the domain adaptation problem and points to the need for bias-aware adaptation strategies that explicitly consider FG–BG association. Our focus in this work is to show that robust DAOD requires dissociating FG from BG to maintain performance even in divergent domains. The FG–BG association may act as a spurious or beneficial factor, depending on the

stage of the pipeline. During the feature extraction process (primarily handled by the backbone network), if the features become entangled, this can lead to significant performance drops or complete failure to identify known FG. However, once the FG has been identified, it helps to provide BG cues to determine whether such an association is viable. For example, a car being in "sky" can account for cases where we want to identify the car and then flag the association between the car and "sky" as unusual.

Since entanglement occurs during feature aggregation, we believe it is due to the pooling mechanism, which aggregates features without regard for object boundaries. To mitigate the entanglement between FG and BG features, we believe that the pooling steps may be redesigned for DAOD. Therefore, building a mask for the object boundary is crucial before the feature extraction process. However, that leads to a chicken-and-egg problem. We are actively exploring several potential remedies, including mask-based pooling to emphasize foreground regions, EM-based mask generation, and graph-matching techniques. We believe these approaches can mitigate the identified performance drops, and we plan to extend our study in this direction in future work.

We believe our work opens a novel research direction in DAOD by emphasizing the need to go beyond feature alignment and focus on understanding and mitigating causal biases introduced by background context. Future work may explore efficient integration of bias-awareness into end-to-end training pipelines and investigate connections between FG–BG associations and broader issues such as spurious correlations and fairness in DAOD.

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A Appendix

A.1 BG-20K synthetic image example

Figure 12 shows an example of superimposing the foreground objects with a random background image from the BG-20K dataset.

Figure 12: **Example of synthetic image.** We visualize the annotated bounding boxes for foreground objects.

A.2 Additional BG replacement experiments with simple changes

We conducted fixed BG replacement to ensure a diverse and unbiased distribution of conditions. Specifically, we experimented with different solid background colors and noise-added backgrounds. While we did not perform a detailed statistical analysis, we observed noticeable variations in accuracy across these settings. Our experimental design was therefore structured to progress from simple perturbations to more controlled and feasible analyses, yielding more generalizable and practical results. Figure 13 illustrates the outcome.

A.3 ViTDeT experiments

Transformer-based detectors can strengthen our experiment, but it is difficult to apply the same process due to their architecture. They reorganize spatial information through a pose-embedding step, which introduces obstacles to tracking spatial information and removes background while capturing foreground-background-related features. So we performed simple experiments using VitDet (Li et al., 2022a). Gradient-based CAM is not suitable; we applied Ablation CAM (Ramaswamy et al., 2020) like method and measured the attention map for each object. For example, we zeroed out for each token for a “car” and computed the weight of the token as the difference Intersection over Union (IoU) between the original bounding box and the new bounding box. If a current target car is not detected after removing the token’s activation, the token’s weight will be 1.0. We visualize an attention map based on the computed weights and the normalized activation map (see Fig. 14).

Because the ViT-based model uses global attention, the map often activates across the entire image. After suppressing the top 20% of the highest responses, the “road” and “buildings” remain prominently highlighted.

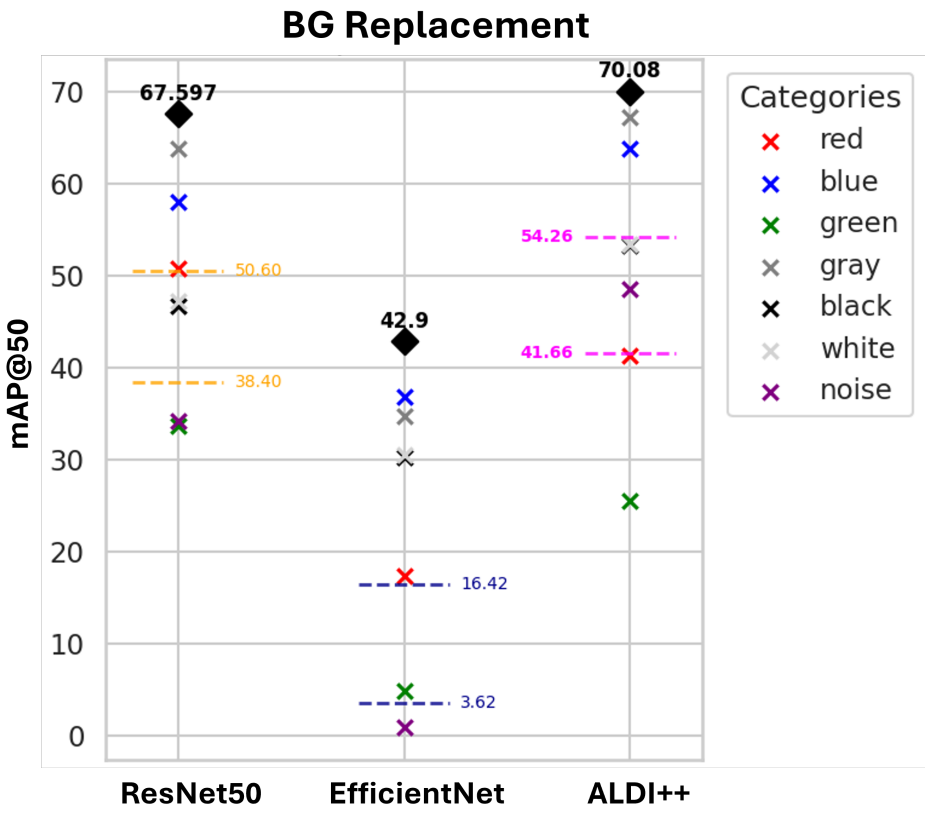

Figure 13: The black diamonds are mAP@50 of each model on the Cityscapes train set. The different categories ("x") mean types of background (e.g., changed in red). The dashed lines represent the range of random BG experiments we performed. Each number on the figure is mAP@50.

Figure 14: **Left panel**: An attention map (white) is overlaid on the RGB input, with the green box marking the target object. **Right panel**: Attention map with thresholding values. The red bounding box is the same target object.

Besides, we measured the drop rate of mAP@50 by removing background region in image space. Table 10 demonstrates the drop rate results on Cityscapes and Virtual KITTI datasets. Still, it expresses significant drops on BG labels. An interesting finding is that the drop rate rarely increases on a few labels, such as "traffic sign" and "traffic light". Due to its global attention feature, it may exhibit different FG–BG

Table 10: Per-background Δ mAP@50 for Cityscapes and Virtual KITTI. mAP@50 on "CSV" is 74.82 and on "VKC" is 79.42. It shows a significant drop even with "CST", which was the training set.

	road	sidewalk	building	wall	fence	pole	traffic light	traffic sign	vegetation	terrain	sky
CFV	-16.22	-15.62	-9.88	-1.43	-1.52	-4.92	-0.75	-0.98	-7.80	-3.25	-0.79
CRV	-14.45	-11.13	-10.21	-0.52	-0.39	-3.19	-0.04	-0.71	-5.93	-1.23	-0.04
CST	-8.75	-10.94	-6.04	-0.50	-0.96	-2.34	-0.03	-0.35	-5.03	-1.83	-0.22
CSV	-10.15	-10.51	-4.78	-0.63	-0.69	-3.22	-0.22	-0.39	-5.02	-1.95	-0.34
KST	-4.77	-7.01	-1.01	-0.95	-0.52	-2.96	+1.58	+0.11	-7.07	-6.29	-1.29

	terrain	sky	tree	vegetation	building	road	guardRail	traffic sign	traffic light	pole
VKC	-1.44	-0.93	-1.60	-0.54	-0.78	-0.96	-0.11	-0.38	+0.00	-0.11
VKF	-10.29	-7.05	-12.11	-8.86	-4.47	-7.57	-5.60	-2.36	+0.10	-0.80
VKM	-1.04	-1.88	-3.89	-0.08	-1.17	-1.33	-0.07	-0.34	-0.01	-0.23
VKR	-3.08	-0.40	-2.91	-3.17	-2.08	-2.48	-0.65	-1.31	+0.00	-0.59
VKO	-0.88	-1.10	+1.12	-1.25	+0.96	-3.02	+0.45	-0.36	-0.11	+0.86
VKS	-2.25	-1.76	-3.80	-0.56	-1.20	-1.56	-0.21	-0.59	-0.06	-0.13

associations. It could be potentially token-wise, but globally. However, this investigation falls beyond our current scope and we aim to analyze transformer-based detectors in future work.

A.4 MMD with different kernel results

Different from the multiscale kernel used, we utilize RBF kernel to compute MMD. The number of pairs with statistically significant differences differs slightly from the main results, but the findings support the same overall conclusions.

Table 11: *Gradient* **comparison across different domains with RBF kernel** Each number's denominator is the number of FG–BG associations in common across two domains. Cases 1, 2, and 3 are given as C1, C2, and C3. The bolded values represent the dominant case for each dataset-model pair. $*$ indicates that it differs from the result in the main text.

	Res			**ALDI++**			**Eff**		
	C1	C2	C3	C1	C2	C3	C1	C2	C3
CST - CSV	**2/5**$*$	1/5	**2/5**$*$	4/10	**6/10**	0/10	**3/7**	**3/7**	1/7
CST - CFV	**11/11**	0/11	0/11	**15/15**	0/15	0/15	**8/11**$*$	2/11	1/11$*$
CST - CRV	**10/11**	1/11	0/11	**8/10**	2/10	0/10	**6/10**	4/10	0/10
CST - KST	**1/1**	0/1	0/1	**1/1**	0/1	0/1	**2/3**	1/3	0/3
VKC - VKF	**5/5**	0/5	0/5	**4/4**	0/4	0/4	**2/2c**	0/2	0/2
VKC - VKM	**5/7**	2/7	0/7	**4/4**	0/4	0/4	1/5	**4/5**	0/5
VKC - VKO	**3/7**$*$	**3/7**$*$	1/7$*$	**4/4**	0/4	0/4	1/5	**3/5**$*$	1/5$*$
VKC - VKR	**6/6**	0/6	0/6	**5/5**	0/5	0/5	2/5$*$	**3/5**$*$	0/5
VKC - VKS	**4/6**$*$	0/6$*$	1/6$*$	**4/5**	1/5	0/5	1/5	**4/5**	0/5

Table 12: **Associated and non-associated features comparison across different domains with RBF kernel.** Each number's denominator is the number of associations in common across two domains. Cases 1, 2, and 3 are given as C1, C2, and C3. "-" is not measurable statistically. The bolded values represent the dominant case for each dataset-model pair. $*$ indicates that it differs from the result in the main text.

	Res			**ALDI++**			**Eff**		
	C1	C2	C3	C1	C2	C3	C1	C2	C3
CST - CSV	**5/5**	0/5	0/5	**9/10**	0/10	1/10	**3/7**	2/7	2/7
CST - CFV	**11/11**	0/11	0/11	**9/15**	6/15	0/15	**6/11**	5/11	0/11
CST - CRV	**8/11**$*$	1/11$*$	2/11$*$	**7/10**	3/10	0/10	2/10	**6/10**	2/10
CST - KST	**1/1**	0/1	0/1	**1/1**	0/1	0/1	0/3	**2/3**	1/3
VKC - VKF	**3/5**$*$	1/5	1/5$*$	**4/4**	0/4	0/4	**2/2**	0/2	0/2
VKC - VKM	**4/7**	2/7	1/7	**4/4**	0/4	0/4	**3/5**	1/5	1/5
VKC - VKO	**4/7**$*$	2/7	1/7$*$	**4/4**	0/4	0/4	**4/5**	1/5	1/5
VKC - VKR	**4/6**	1/6	1/6	**4/5**$*$	1/5$*$	0/5	**4/5**	1/5	0/5
VKC - VKS	**5/6**	1/6	0/6	**4/5**$*$	1/5$*$	0/5	**3/5**	1/5	1/5