

3D Common Corruptions and Data Augmentation

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<https://3dcommoncorruptions.epfl.ch/>

Abstract

We introduce a set of image transformations that can be used as **corruptions** to evaluate the robustness of models as well as **data augmentation** mechanisms for training neural networks. The primary distinction of the proposed transformations is that, unlike existing approaches such as Common Corruptions [27], the geometry of the scene is incorporated in the transformations – thus leading to corruptions that are more likely to occur in the real world. We also introduce a set of **semantic** corruptions (e.g. natural object occlusions. See Fig. 1).

We show these transformations are ‘efficient’ (can be computed on-the-fly), ‘extendable’ (can be applied on most image datasets), expose vulnerability of existing models, and can effectively make models more robust when employed as ‘3D data augmentation’ mechanisms. The evaluations on several tasks and datasets suggest incorporating 3D information into benchmarking and training opens up a promising direction for robustness research.

1. Introduction

Computer vision models deployed in the real world will encounter naturally occurring distribution shifts from their training data. These shifts range from lower-level distortions, such as motion blur and illumination changes, to semantic ones, like object occlusion. Each of them represents a possible failure mode of a model and has been frequently shown to result in profoundly unreliable predictions [15, 23, 27, 31, 66]. Thus, a systematic testing of vulnerabilities to these shifts is critical before deploying these models in the real world.

This work presents a set of distribution shifts in order to test models’ robustness. In contrast to previously proposed shifts which perform uniform 2D modifications over the image, such as Common Corruptions (2DCC) [27], our shifts incorporate 3D information to generate corruptions that are consistent with the scene geometry. This leads to shifts that are more likely to occur in the real world (See Fig. 1). The resulting set includes 20 corruptions, each representing a

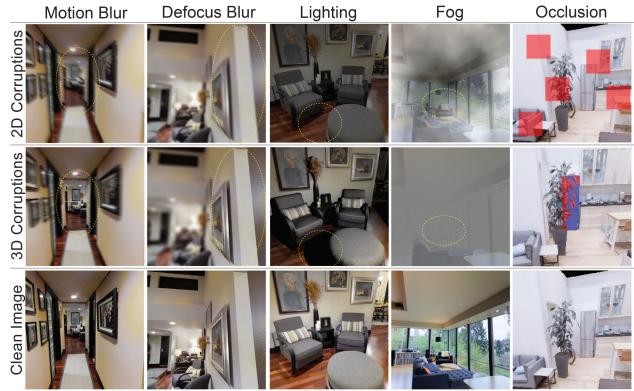


Figure 1. Using 3D information to generate real-world corruptions. The top row shows sample 2D corruptions applied uniformly over the image, e.g. as in Common Corruptions [27], disregarding 3D information. This leads to corruptions that are unlikely to happen in the real world, e.g. having the same motion blur over the entire image irrespective of the distance to camera (top left). Middle row shows their 3D counterparts from 3D Common Corruptions (3DCC). The circled regions highlight the effect of incorporating 3D information. More specifically, in 3DCC, **1. motion blur** has a *motion parallax* effect where objects further away from the camera seem to move less, **2. defocus blur** has a *depth of field* effect, akin to a large aperture effect in real cameras, where certain regions of the image can be selected to be in focus, **3. lighting** takes the scene geometry into account when illuminating the scene and casts shadows on objects, **4. fog** gets denser further away from the camera, **5. occlusions** of a target object, e.g. fridge (blue mask), are created by changing the camera’s viewpoint and having its view *naturally obscured by another object*, e.g. the plant (red mask). This is in contrast to its 2D counterpart that randomly discards patches [13]. See the [project page](#) for a video version of the figure.

distribution shift from training data, which we denote as *3D Common Corruptions* (3DCC). 3DCC addresses several aspects of the real world, such as camera motion, weather, occlusions, depth of field, and lighting. Figure 2 provides an overview of all corruptions. As shown in Fig. 1, the corruptions in 3DCC are more diverse and realistic compared to 2D-only approaches.

We show in Sec. 5 that the performance of the methods aiming to improve robustness, including those with diverse data augmentation, reduce drastically under 3DCC. Furthermore, we observe that the robustness issues exposed by 3DCC well correlate with corruptions generated via photorealistic synthesis. Thus, 3DCC can serve as a challeng-

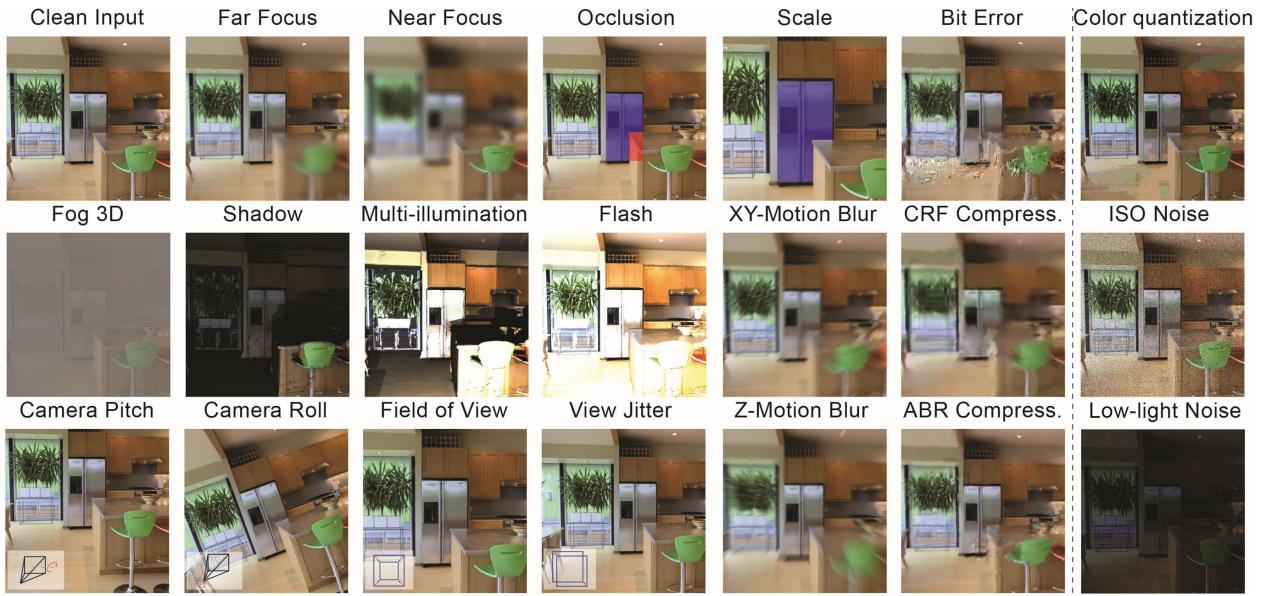


Figure 2. The new corruptions. We propose a diverse set of new corruption operations ranging from defocusing (near/far focus) to lighting changes and 3D-semantic ones, e.g. object occlusion. These corruptions are all *automatically generated, efficient* to compute, and can be applied to *most datasets* (Sec. 3.3). We show that they expose vulnerabilities in models (Sec. 5.2.1) and are a good approximation of realistic corruptions (Sec. 5.2.3). A subset of the corruptions marked in the last column are novel and commonly faced in the real world, but are not 3D based. We include them in our benchmark. For occlusion and scale corruptions, the blue and red masks denote the amodal visible and occluded parts of an object, e.g. the fridge.

ing testbed for real-world corruptions, especially those that depend on scene geometry.

Motivated by this, our framework also introduces new *3D data augmentations*. They take the scene geometry into account, as opposed to 2D augmentations, thus enabling models to build invariances against more realistic corruptions. We show in Sec. 5.3 that they significantly boost model robustness against such corruptions, including the ones that cannot be addressed by the 2D augmentations.

The proposed corruptions are *generated programmatically with exposed parameters*, enabling fine-grained analysis of robustness, e.g. by continuously increasing the 3D motion blur. They are *efficient* to compute and can be computed on-the-fly during training as data augmentation with a small increase in computational cost. They are also *extendable*, i.e. they can be applied to standard vision datasets, e.g. ImageNet [12], that do not come with 3D labels.

2. Related Work

This work presents a data-focused approach [51, 62] to robustness. We give an overview of some of the related topics within the constraints of space.

Robustness benchmarks based on corruptions: Several studies have proposed robustness benchmarks to understand the vulnerability of models to corruptions. A popular benchmark, Common Corruptions (2DCC) [27], generates synthetic corruptions on real images that expose sensitivities of image recognition models. It led to a series of works either creating new corruptions or applying similar corruptions on other datasets for different

tasks [7, 32, 42, 44, 65, 78]. In contrast to these works, 3DCC modifies real images *using 3D information* to generate realistic corruptions. The resulting images are both perceptually different and expose different failure modes in model predictions compared to their 2D counterparts (See Fig. 1 and 8). Other works create and capture the corruptions in the real world, e.g. ObjectNet [3]. Although being realistic, it requires significant manual effort and is not extendable. A more scalable approach is to use computer graphics based 3D simulators to generate corrupted data [37] which can lead to generalization concerns. 3DCC aims to generate corruptions *as close to the real world* as possible while staying *scalable*.

Robustness analysis works use *existing* benchmarks to probe the robustness of different methods, e.g. data augmentation or self-supervised training, under several distribution shifts. Recent works investigated the relation between synthetic and natural distribution shifts [14, 26, 43, 67] and effectiveness of architectural advancements [5, 47, 63]. We select several popular methods to show that 3DCC can serve as a challenging benchmark (Fig. 6 and 7).

Improving robustness: Numerous methods have been proposed to improve model robustness such as data augmentation with corrupted data [22, 39, 40, 59], texture changes [24, 26], image compositions [80, 82] and transformations [29, 79]. While these methods can generalize to some unseen examples, performance gains are non-uniform [22, 60]. Other methods include self-training [74], pre-training [28, 49], architectural changes [5, 63], and diverse ensembling [33, 50, 76, 77]. Here we instead adopt a data-focused approach to robustness by **i.** providing a

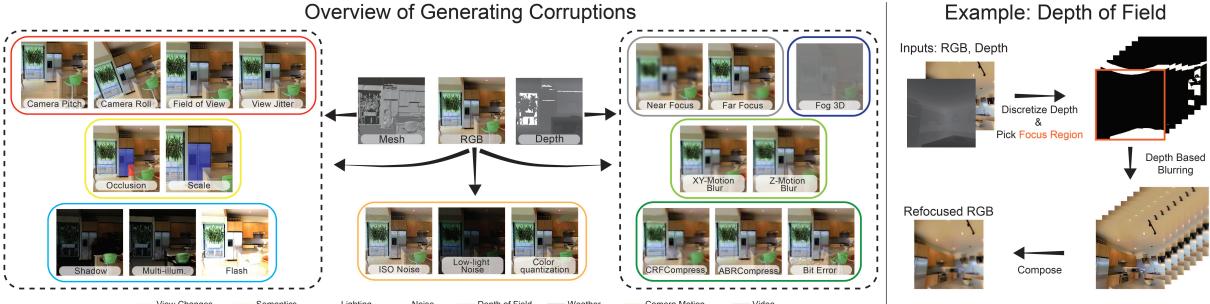


Figure 3. Left: We show the *inputs* needed to create each of our corruptions, e.g. the 3D information such as depth, and RGB image. These corruptions have also been grouped (in solid colored lines) according to their *corruption types*. For example, to create the distortions in the dashed box in the right, one only needs the RGB image and its corresponding depth. For the ones in the left dashed box, 3D mesh is required. Note that one can create *view changes* corruptions also from panoramic images if available, without a mesh. **Right:** As an example, we show an overview of generating depth of field effect *efficiently*. The scene is first split into multiple layers by discretizing scene depth. Next, a region is chosen to be kept in focus (here it is the region closest to the camera). We then compute the corresponding blur levels for each layer according to their distance from the focus region, using a pinhole camera model. The final refocused image is obtained by compositing blurred image layers.

large set of realistic distribution shifts and **ii.** introducing new 3D data augmentation that improves robustness against real-world corruptions (Sec. 5.3).

Photorealistic image synthesis involves techniques to generate realistic images. Some of these techniques have been recently used to create corruption data. These techniques are generally specific to a single real-world corruption. Examples include adverse weather conditions [19, 30, 61, 68, 69], motion blur [6, 48], depth of field [4, 17, 52, 70, 71], lighting [25, 75], and noise [21, 73]. They may be used for purely artistic purposes or to create training data. Some of our 3D transformations are instantiations of these methods, with the downstream goal of testing and improving model robustness in a unified framework with a wide set of corruptions.

Image restoration aims to undo the corruption in the image using classical signal processing techniques [18, 20, 34, 41] or learning-based approaches [1, 8, 45, 46, 56, 83, 84]. We differ from these works by generating corrupted data, rather than removing it, to use them for benchmarking or data augmentation. Thus, in the latter, we train with these corrupted data to encourage the model to be invariant to corruptions, as opposed to training the model to remove the corruptions as a pre-processing step.

Adversarial corruptions add imperceptible *worst-case* shifts to the input to fool a model [11, 35, 40, 66]. Most of the failure cases of models in the real world are not the result of adversarial corruptions but rather *naturally occurring distribution shifts*. Thus, our focus in this paper is to generate corruptions that are likely to occur in the real world.

3. Generating 3D Common Corruptions

3.1. Corruption Types

We define different corruption types, namely *depth of field*, *camera motion*, *lighting*, *video*, *weather*, *view changes*, *semantics*, and *noise*, resulting in 20 corruptions

in 3DCC. Most of the corruptions require an RGB image and scene depth, while some needs 3D mesh (See Fig. 3). We use a set of methods leveraging 3D synthesis techniques or image formation models to generate different corruption types, as explained in more detail below. Further details are provided in the [supplementary](#).

Depth of field corruptions create refocused images. They keep a part of the image in focus while blurring the rest. We consider a layered approach [4, 17] that splits the scene into multiple layers. For each layer, the corresponding blur level is computed using the pinhole camera model. The blurred layers are then composited with alpha blending. Figure 3 (right) shows an overview of the process. We generate *near focus* and *far focus* corruptions by randomly changing the focus region to the near or far part of the scene.

Camera motion creates blurry images due to camera movement during exposure. To generate this effect, we first transform the input image into a point cloud using the depth information. Then, we define a trajectory (camera motion) and render novel views along this trajectory. As the point cloud was generated from a single RGB image, it has incomplete information about the scene when the camera moves. Thus, the rendered views will have disocclusion artifacts. To alleviate this, we apply an inpainting method from [48]. The generated views are then combined to obtain parallax-consistent motion blur. We define *XY-motion blur* and *Z-motion blur* when the main camera motion is along the image XY-plane or Z-axis, respectively.

Lighting corruptions change scene illumination by adding new light sources and modifying the original illumination. We use Blender [10] to place these new light sources and compute the corresponding illumination for a given viewpoint in the 3D mesh. For the *flash* corruption, a light source is placed at the camera’s location, while for *shadow* corruption, it is placed at random diverse locations outside the camera frustum. Likewise, for *multi-illumination* corruption, we compute the illumination from a set of random light

sources with different locations and luminosities.

Video corruptions arise during the processing and streaming of videos. Using the scene 3D, we create a video using multiple frames *from a single image* by defining a trajectory, similar to motion blur. Inspired by [78], we generate *average bit rate (ABR)* and *constant rate factor (CRF)* as H.265 codec compression artifacts, and *bit error* to capture corruptions induced by imperfect video transmission channel. After applying the corruptions over the video, we pick a single frame as the final corrupted image.

Weather corruptions degrade visibility by obscuring parts of the scene due to disturbances in the medium. We define a single corruption and denote it as *fog 3D* to differentiate it from the fog corruption in 2DCC. We use the standard optical model for fog [19, 61, 69]:

$$\mathbf{I}(\mathbf{x}) = \mathbf{R}(\mathbf{x})\mathbf{t}(\mathbf{x}) + \mathbf{A}(1 - \mathbf{t}(\mathbf{x})), \quad (1)$$

where $\mathbf{I}(\mathbf{x})$ is the resulting foggy image at pixel x , $\mathbf{R}(\mathbf{x})$ is the clean image, \mathbf{A} is atmospheric light, and $\mathbf{t}(\mathbf{x})$ is the transmission function describing the amount of light that reaches the camera. When the medium is homogeneous, the transmission depends on the distance from the camera, $\mathbf{t}(\mathbf{x}) = \exp(-\beta d(\mathbf{x}))$ where $d(\mathbf{x})$ is the scene depth and β is the attenuation coefficient controlling the fog thickness.

View changes are due to variations in the camera extrinsics and focal length. Our framework enables rendering RGB images conditioned on several changes, such as *field of view*, *camera roll* and *camera pitch*, using Blender. This enables us to analyze the sensitivity of models to various view changes in a controlled manner. We also generate images with *view jitter* that can be used to analyze if models predictions flicker with slight changes in viewpoint.

Semantics: In addition to view changes, we also render images by selecting an object in the scene and changing its occlusion level and scale. In *occlusion* corruption, we generate views of an object occluded by other objects. This is in contrast to random 2D masking of pixels to create an unnatural occlusion effect that is irrespective of image content, e.g. as in [13, 47] (See Fig. 1). Occlusion rate can be controlled to probe model robustness against occlusion changes. Similarly, in *scale* corruption, we render views of an object with varying distances from the camera location. Note that the corruptions require a mesh with semantic annotations, and are generated automatically, similar to [2]. This is in contrast to [3] which requires tedious manual effort. The objects can be selected by randomly picking a point in the scene or using the semantic annotations.

Noise corruptions arise from imperfect camera sensors. We introduce new noise corruptions that do not exist in the previous 2DCC benchmark. For *low-light noise*, we decreased the pixel intensities and added Poisson-Gaussian distributed noise to reflect the low-light imaging setting [21]. *ISO noise* also follows a Poisson-Gaussian distribution, with a fixed photon noise (modeled by a Poisson), and varying electronic noise (modeled by a Gaussian). We also included



Figure 4. **Visualizations of 3DCC with increasing shift intensities.** **Top:** Increasing the shift intensity results in larger blur, less illumination, and denser fog. **Bottom:** The object becomes more occluded or shrinks in size using *calculated viewpoint changes*. The blue mask denotes the amodal visible parts of the fridge/couch, and the red mask is the occluded part. The leftmost column shows the clean images. Visuals for all corruptions for all shift intensities are shown in the [supplementary](#).

color quantization as another corruption that reduces the bit depth of the RGB image. Only this subset of our corruptions is not based on 3D information.

3.2. Starter 3D Common Corruptions Dataset

We release the full open source code of our pipeline, which enables using the implemented corruptions on any dataset. As a starter dataset, we applied the corruptions on 16k Taskonomy [81] test images. For all the corruptions except the ones in *view changes* and *semantics* which change the scene, we follow the protocol in 2DCC and define 5 shift intensities, resulting in approximately 1 million corrupted images ($16k \times 14 \times 5$). Directly applying the methods to generate corruptions results in uncalibrated shift intensities with respect to 2DCC. Thus, to enable aligned comparison with 2DCC on a more uniform intensity change, we perform a calibration step. For the corruptions with a direct counterpart in 2DCC, e.g. motion blur, we set the corruption level in 3DCC such that for each shift intensity in 2DCC, the average SSIM [72] values over all images is the same in both benchmarks. For the corruptions that do not have a counterpart in 2DCC, we adjust the distortion parameters to increase shift intensity while staying in a similar SSIM range as the others. For *view changes* and *semantics*, we render 32k images with smoothly changing parameters, e.g. roll angle, using the Replica [64] dataset. Figure 4 shows example corruptions with different shift intensities.

3.3. Applying 3DCC to standard vision datasets

While we employed datasets with full scene geometry information such as Taskonomy [81], 3DCC can also be applied to standard datasets without 3D information. We exemplify this on ImageNet [12] and COCO [38] validation

sets by leveraging depth predictions from the MiDaS [54] model, a state-of-the-art depth estimator. Figure 5 shows example images with *near focus*, *far focus*, and *fog 3D* corruptions. Generated images are physically plausible, demonstrating that 3DCC can be used for other datasets by the community to generate a diverse set of image corruptions. In Sec. 5.2.4, we quantitatively demonstrate the effectiveness of using predicted depth to generate 3DCC.

4. 3D Data Augmentation

While benchmarking uses corrupted images as *test data*, one can also use them as augmentations of *training data* to build invariances towards these corruptions. This is the case for us since, unlike 2DCC, 3DCC is designed to capture corruptions that are more likely to appear in the real world, hence it has a sensible augmentation value as well. Thus, in addition to benchmarking robustness using 3DCC, our framework can also be viewed as new data augmentation strategies that take the 3D scene geometry into account. We augment with the following corruption types in our experiments: *depth of field*, *camera motion*, and *lighting*. The augmentations can be efficiently generated on-the-fly during training using parallel implementations. For example, the depth of field augmentations take 0.87 seconds (wall clock time) on a single V100 GPU for a batch size of 128 images with 224×224 resolution. For comparison, applying 2D defocus blur requires 0.54 seconds, on average. It is also possible to precompute certain selected parts of the augmentation process, e.g. the illuminations for lighting augmentations, to increase efficiency. We incorporated these mechanisms in our implementation. We show in Sec. 5.3 that these augmentations can significantly improve robustness against real-world distortions.

5. Experiments

We perform evaluations to demonstrate that 3DCC can expose vulnerabilities in models (Sec. 5.2.1) that are not captured by 2DCC (Sec. 5.2.2). The generated corruptions are similar to expensive realistic synthetic ones (Sec. 5.2.3) and are applicable to datasets without 3D information (Sec. 5.2.4). Finally, the proposed 3D data augmentation improves robustness qualitatively and quantitatively (Sec. 5.3). Please see the [project page](#) for more extensive qualitative results.

5.1. Preliminaries

Evaluation Tasks: 3DCC can be applied to any dataset, irrespective of the target task, e.g. dense regression or low-dimensional classification. Here we mainly experiment with surface normals and depth estimation as target tasks widely employed by the community. We note that the robustness of models solving such tasks is underexplored compared to classification tasks (See [supplementary](#) for results on classification). To evaluate robustness, we compute

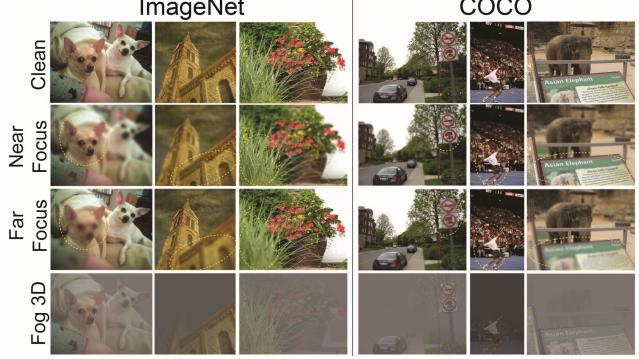


Figure 5. **3DCC can be applied to most datasets**, even those that do not come with 3D information. Several query images from the ImageNet [12] and COCO [38] dataset are shown with *near focus*, *far focus* and *fog 3D* corruptions applied. Notice how the objects in the circled regions go from sharp to blurry depending on the focus region and scene geometry. To get the depth information needed to create these corruptions, predictions from MiDaS [54] model is used. This gives a good enough approximation to generate realistic corruptions (as we will quantify in Sec. 5.2.4).

the ℓ_1 error between predicted and ground truth images.

Training Details: We train UNet [58] and DPT [53] models on Taskonomy [81] using learning rate 5×10^{-4} and weight decay 2×10^{-6} . We optimize the likelihood loss with Laplacian prior using AMSGrad [55], following [77]. Unless specified, all the models use the same UNet backbone (e.g. Fig. 6). We also experiment with DPT models trained on Omnidata [17] that mixes a diverse set of training datasets. Following [17], we train with learning rate 1×10^{-5} , weight decay 2×10^{-6} with angular & ℓ_1 losses.

Robustness mechanisms evaluated: We evaluate several popular data augmentation strategies: DeepAugment [26], style augmentation [24], and adversarial training [35]. We also include Cross-Domain Ensembles (X-DE) [77] that has been recently shown to improve robustness to corruptions by creating diverse ensemble components via input transformations. We refer to the [supplementary](#) for training details. Finally, we train a model with augmentation with corruptions from 2DCC [27] (2DCC augmentation), and another model with 3D data augmentation on top of that (2DCC + 3D augmentation).

5.2. 3D Common Corruptions Benchmark

5.2.1 3DCC can expose vulnerabilities

We perform a benchmarking of the existing models against 3DCC to understand their vulnerabilities. However, we note that our main contribution is not the performed analyses but the benchmark itself. The state-of-the-art models may change over time and 3DCC aims to identify the robustness trends, similar to other benchmarks.

Effect of robustness mechanisms: Figure 6 shows the average performance of different robustness mechanisms on 3DCC for surface normals and depth estimation tasks. These mechanisms improved the performance over the baseline but are still far from the performance on clean data.

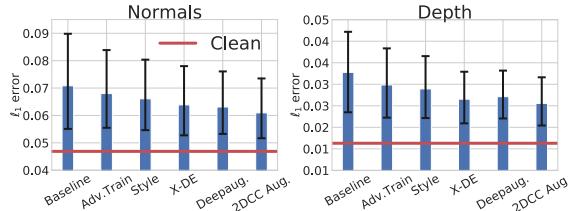


Figure 6. Existing robustness mechanisms are found to be insufficient for addressing real-world corruptions approximated by 3DCC. Performance of models with different robustness mechanisms under 3DCC for surface normals (left) and depth (right) estimation tasks are shown. All models here are UNets and are trained with Taskonomy data. Each bar shows the ℓ_1 error averaged over all 3DCC corruptions (lower is better). The black error bars show the error at the lowest and highest shift intensity. The red line denotes the performance of the baseline model on clean (uncorrupted) data. This denotes that existing robustness mechanisms, including those with diverse augmentations, perform poorly under 3DCC.

This suggests that 3DCC exposes robustness issues and can serve as a challenging testbed for models. The 2DCC augmentation model returns slightly lower ℓ_1 error, indicating that diverse 2D data augmentation only partially helps against 3D corruptions.

Effect of dataset and architecture: We provide a detailed breakdown of performance against 3DCC in Fig. 7. We first observe that baseline UNet and DPT models trained on Taskonomy have similar performance, especially on the view change corruptions. By training with larger and more diverse data with Omnidata, the DPT performance improves. Similar observations were made on vision transformers for classification [5, 16]. This improvement is notable with view change corruptions, while for the other corruptions, there is a decrease in error from 0.069 to 0.061. This suggests that combining architectural advancements with diverse and large training data can play an important role in robustness against 3DCC. Furthermore, when combined with 3D augmentations, they improve robustness to real-world corruptions (Sec. 5.3).

5.2.2 Redundancy of corruptions in 3DCC and 2DCC

In Fig. 1, a qualitative comparison was made between 3DCC and 2DCC. The former generates more realistic corruptions while the latter does not take scene 3D into account and applies uniform modifications over the image. In Fig. 8, we aim to quantify the similarity between 3DCC and 2DCC. On the left of Fig. 8, we compute the correlations of ℓ_1 errors between clean and corrupted predictions made by the baseline model for a subset of corruptions (full set is in [supplementary](#)). 3DCC incurs less correlations both intra-benchmark as well as against 2DCC (Mean correlations are 0.32 for 2DCC-2DCC, 0.28 for 3DCC-3DCC, and 0.30 for 2DCC-3DCC). Similar conclusions are obtained for depth estimation (in the [supplementary](#)). In the right, we provide the same analysis on the RGB domain by computing the ℓ_1 error between clean and corrupted images, again suggesting that 3DCC yields lower correlations.

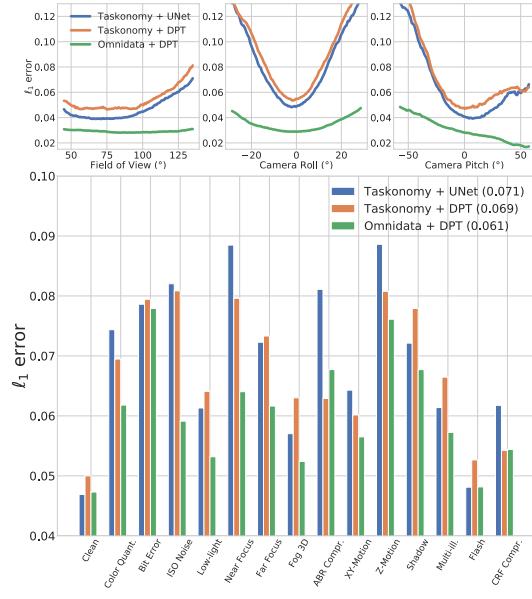


Figure 7. Detailed breakdown of performance on 3DCC. The benchmark can expose trends and models’ sensitivity to a wide range of corruptions. We show this by training models on either Taskonomy [81] or Omnidata [17] and with either a UNet [58] or DPT [53] architecture. The average ℓ_1 error over all shift intensities for each corruption is shown (lower is better). **Top:** We observe that Taskonomy models are more susceptible to changes in field of view, camera roll, and pitch compared to Omnidata trained model, which is consistent with their methods. **Bottom:** The numbers in the legend are the average performance over all the corruptions. We can see that all the models are sensitive to 3D corruptions, e.g. *z-motion blur* and *shadow*. Overall, training with large diverse data, e.g. Omnidata, and using DPT is observed to notably improve performance.

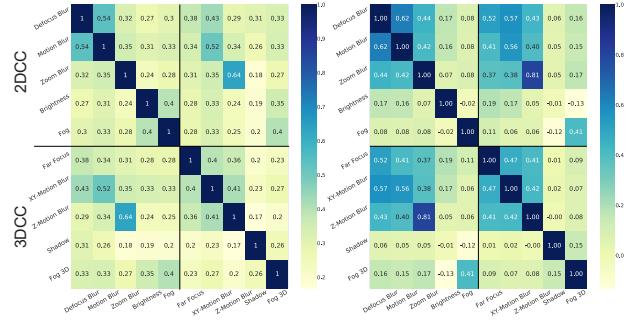


Figure 8. Redundancy among corruptions. We quantified the pairwise similarity of a subset of corruptions from 2DCC and 3DCC by computing their correlations in the ℓ_1 errors of the surface normals predictions (left) and RGB images (right). 3DCC incurs less correlations both intra-benchmark as well as against 2DCC. Thus, 3DCC has a diverse set of corruptions and these corruptions do not have a significant overlap with 2DCC. Using depth as target task yields similar conclusions (full affinity matrices are provided in the [supplementary](#)).

5.2.3 Soundness: 3DCC vs Expensive Synthesis

3DCC aims to expose a model’s vulnerabilities to certain real-world corruptions. This requires the corruptions generated by 3DCC to be similar to real corrupted data. As generating such labeled data is expensive and scarcely avail-

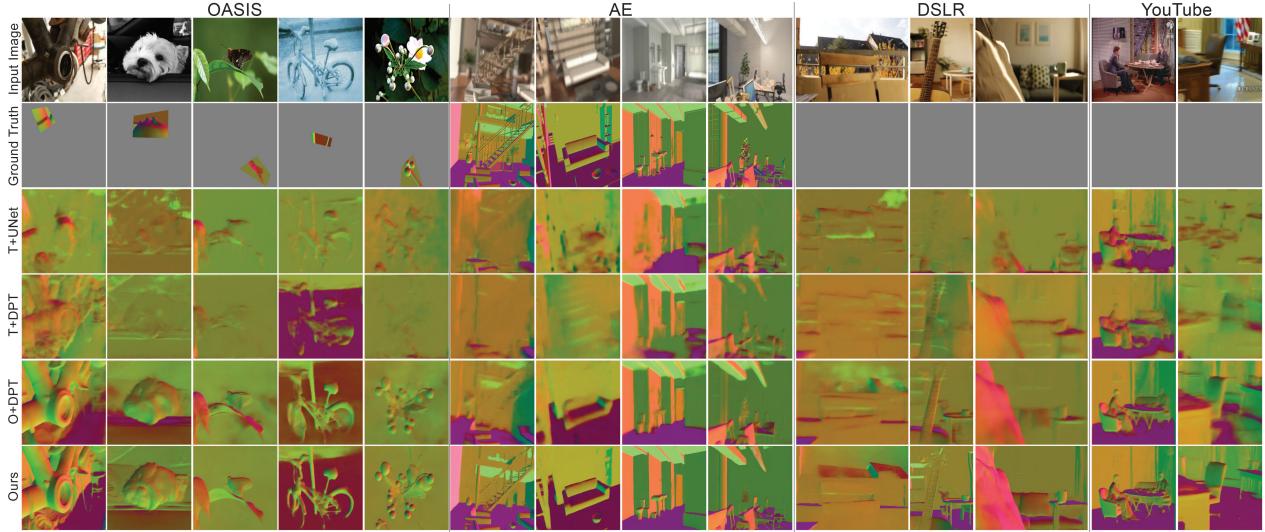


Figure 9. **Qualitative results of learning with 3D data augmentation** on random queries from OASIS [9], AE (Sec. 5.2.3), manually collected DSLR data, and in-the-wild YouTube videos for surface normals. The ground truth is gray when it is not available, e.g. for YouTube. The predictions in the last row (ours) are from the O+DPT+2DCC+3D model. They are noticeably sharper and more accurate. See the [project page](#) and [supplementary](#) for more results.

able, as a proxy evaluation, we instead compare the realism of 3DCC to synthesis made by Adobe After Effects (AE) which is a commercial product to generate high-quality photorealistic data and often relies on expensive and manual processes. To achieve this, we use the Hypersim [57] dataset that comes with high-resolution z-depth labels. We then generated 200 images that are near- and far-focused using 3DCC and AE. Figure 10 shows sample generated images from both approaches that are perceptually similar. Next, we computed the prediction errors of a baseline normal model when the input is from 3DCC or AE. The scatter plot of ℓ_1 errors are given in Fig. 11 and demonstrates a strong correlation, 0.80, between the two approaches. For calibration and control, we also provide the scatter plots for some corruptions from 2DCC to show the significance of correlations. They have significantly lower correlations with AE, indicating the depth of field effect created via 3DCC matches AE generated data reasonably well.

5.2.4 Effectiveness of applying 3DCC to other datasets

We showed qualitatively in Fig. 5 that 3DCC can be applied to standard vision datasets like ImageNet [12] and COCO [38] by leveraging predicted depth from a state-of-the-art model from MiDaS [54]. Here, we quantitatively show the impact of using predicted depth instead of ground truth. For this, we use the Replica [64] dataset that comes with ground truth depth labels. We then generated 1280 corrupted images using ground truth depth and predicted depth from MiDaS [54] *without fine-tuning on Replica*. Figure 12 shows the trends on three corruptions from 3DCC generated using ground truth and predicted depth. The trends are similar and the correlation of errors is strong (0.79). This



Figure 10. **Visual comparisons of 3DCC and expensive After Effects (AE) generated depth of field effect** on query images from Hypersim. 3DCC generated corruptions are visually similar to those from AE.

suggests that the predicted depth can be effectively used to apply 3DCC to other datasets, and the performance is expected to improve with better depth predictions. See the [supplementary](#) for more analysis and quantitative evaluations on ImageNet which suggests that 3DCC can be informative during model development by exposing nonlinear trends and vulnerabilities that are not captured by 2DCC.

5.3. 3D data augmentation to improve robustness

We demonstrate the effectiveness of the proposed augmentations qualitatively and quantitatively. We evaluate UNet and DPT models trained on Taskonomy (T+UNet, T+DPT) and DPT trained on Omnidata (O+DPT) to see the effect of training dataset and model architecture. The training procedure is as described in Sec. 5.1. For the other models, we initialize from O+DPT model and train with 2DCC augmentations (O+DPT+2DCC) and 3D augmentations on top of that (O+DPT+2DCC+3D), i.e. our proposed model.

Qualitative evaluations: We consider **i.** OASIS [9], **ii.**

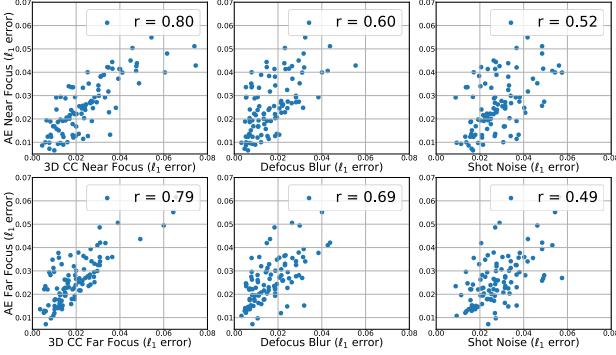


Figure 11. Corruptions of 3DCC are similar to expensive realistic synthetic ones while being cheaper to generate. Scatter plots of ℓ_1 errors from the baseline model predictions on 3DCC against those created by Adobe After Effects (AE). The correlation between 3DCC near (far) focus and those from AE near (far) focus is the *strongest* (numbers are in the legend of left column). We also added the most similar corruption from 2DCC (defocus blur) for comparison, yielding weaker correlations (middle). Shot noise (right) is a *control baseline*, i.e. a randomly selected corruption, to calibrate the significance of the correlation measure.

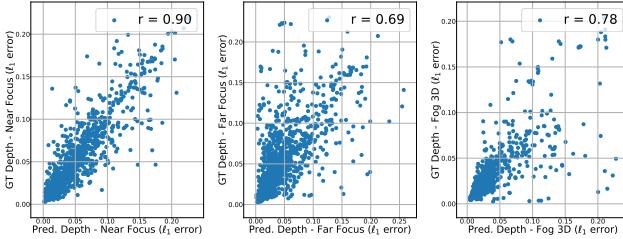


Figure 12. Effectiveness of applying 3DCC without ground truth depth. Three corruptions from 3DCC are generated using depth predictions from MiDaS [54] model on unseen Replica data. Scatter plots show the ℓ_1 errors from the baseline model when corruptions are generated using the predicted depth (x-axis) or the ground truth (y-axis). The trends are similar between two corrupted data results, suggesting the predicted depth is an effective approximation to generate 3DCC. See the [supplementary](#) for more tests including control baselines.

AE corrupted data from Sec. 5.2.3, **iii.** manually collected DSLR data, and **iv.** in-the-wild YouTube videos. Figure 9 shows that predictions made by the proposed model are significantly more robust compared to baselines. We also recommend watching the clips on the [project page](#).

Quantitative evaluations: In Table 1, we compute errors made by the models on 2DCC, 3DCC, AE, and OASIS [9] data (no fine-tuning). Again, the proposed model yields lower errors across datasets showing the effectiveness of augmentations. Note that robustness against corrupted data is improved *without sacrificing performance on in-the-wild clean data*, i.e. OASIS.

6. Conclusion and Limitations

We introduce a framework to test and improve model robustness against real-world distribution shifts, particularly those centered around 3D. Experiments demonstrate that the proposed 3D Common Corruptions is a challenging

Model Benchmark	T+UNet	T+DPT	O+DPT	O+DPT+2DCC	O+DPT+2DCC+3D (Ours)
2DCC [27] (ℓ_1 error)	8.15	7.47	6.43	5.78	5.32
3DCC (ℓ_1 error)	7.08	6.89	6.13	5.94	5.42
AE (Sec. 5.2.3) (ℓ_1 error)	12.86	12.39	7.84	6.50	4.94
OASIS [9] (angular error)	30.49	32.13	24.42	23.67	24.65

Table 1. Effectiveness of 3D augmentations quantified using different benchmarks. ℓ_1 errors are multiplied by 100 for readability. Our model yields lower errors across the benchmarks. 2DCC and 3DCC are applied on the same Taskonomy test images. More results are given in [supplementary](#). Evaluations on OASIS sometimes show a large variance due to its sparse ground truth.

benchmark that exposes model vulnerabilities under real-world plausible corruptions. Furthermore, the proposed data augmentation leads to more robust predictions compared to baselines. We believe this work opens up a promising direction in robustness research by showing the usefulness of 3D corruptions in benchmarking and training. Below we briefly discuss some of the limitations:

3D quality: 3DCC is upper-bounded by the quality of 3D data. The current 3DCC is an imperfect but useful *approximation* of real-world 3D corruptions, as we showed. The fidelity is expected to improve with higher resolution sensory data and better depth prediction models.

Non-exhaustive set: Our set of 3D corruptions and augmentations are *not exhaustive*. They instead serve as a starter set for researchers to experiment with. The framework can be employed to generate more domain-specific distribution shifts with minimal manual effort.

Large-scale evaluation: While we evaluate some recent robustness approaches in our analyses, our main goal was to show that 3DCC successfully exposes vulnerabilities. Thus, performing a comprehensive robustness analysis is beyond the scope of this work. We encourage researchers to test their models against our corruptions.

Balancing the benchmark: We did not explicitly balance the corruption types in our benchmark, e.g. having the same number of noise and blur distortions. Our work can further benefit from weighting strategies trying to calibrate average performance on corruption benchmarks, such as [36].

Use cases of augmentations: While we focus on robustness, investigating their usefulness on other applications, e.g. self-supervised learning, could be worthwhile.

Evaluation tasks: We experiment with dense regression tasks. However, 3DCC can be applied to different tasks, including classification and other semantic ones. Investigating failure cases of semantic models against, e.g. on smoothly changing occlusion rates, using our framework could provide useful insights.

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