3D Common Corruptions and Data Augmentation

1. Problem
- Neural networks are not robust when deployed in the real world.
- They are vulnerable to non-adversarial image corruptions.

2. Realistic 3D Corruptions
- Common Corruptions [1] are 2D based (applied uniformly).
  Hence, they could be unrealistic.
- We incorporate scene geometry and real world properties to generate 3D corruptions that are more realistic.

3. All 3D Common Corruptions (3DCC)
- 3DCC has a diverse set of corruptions which:
  1. can be used for benchmarking to test robustness
  2. or as data augmentation to improve robustness.
- They are extendable to datasets without 3D labels, e.g. ImageNet & COCO.
- They can also be generated efficiently.

4. Benchmarking with 3D Common Corruptions
- 3DCC provides a challenging testbed to identify model failures:
  - This includes a new set of semantic based corruptions, e.g. occlusions.

5. Data Augmentation with 3D Common Corruptions
- Augmenting training data with 3DCC significantly improves robustness.

6. Applying 3DCC to Standard Vision Datasets
- 3DCC can also be applied to standard datasets without 3D information.
  - We introduce the ImageNet-3DCC (now also in RobustBench [4]).
  - To do this, we used the depth predictions from a SOTA depth estimator [3].
    - This gives a good approximation to generate realistic corruptions.

References:
[2] OASIS: A large-scale dataset for single image 3D in the wild. Chen et al. CVPR 2020