**Motivation**

Adapting a source-trained detector to an unlabelled target domain.

**Challenges of UDA in object detection:**
- Distribution mismatch across domains.
- Error accumulation (i.e., false positives as pseudo-labels) during self-training.
- No target annotations.
- Calibration: model detection thresholds across domains may differ due to domain gap.

**Our Approach**

Self-supervision with challenging composite images.

- **What is DACA?** An UDA approach that composes target images via random augmentations (only during training phase) and leverages self-training to adapt the model to the target domain.
- **Why are the images challenging?** Because they stem from random augmentations, yet they present new-to-learn knowledge for the detector.

**Step 1: Detect**

Draw pseudo-detections from the target image.

**Step 2: Augment**

Random augmentations of the most confident target region (i.e., average confidence of all the detections) target loss increments knowledge towards the target $\ell = \ell_S + \ell_T$.

**Step 3: Compose**

Combine the generated augmentations into a composite image.

**Step 4: Adapt**

Backpropagate total loss. Source loss maintains source knowledge whilst target loss increments knowledge towards the target $\ell = \ell_S + \ell_T$.

**Results**

DACA is superior to SOTA in two adaptation scenarios.

**Adaptation scenarios & datasets:**
- Weather: Cityscapes → Foggy Cityscapes
- Cross-camera: KITTI → Cityscapes
- Synthetic2Real: Sim10K → Cityscapes

**Qualitative results:**
- Detection performance (AP) for the Car class.
- Detection performance (AP) for the C - F adaptation benchmark.

**Ablations:**
- List of augmentations
- Effect of transformations
- Effect of grid layout

**References:**

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