KI DELTA LEARNING
Scalable AI for Automated Driving

Unsupervised Domain Adaptation for Object Detection in varying Camera Mounting Positions

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WP 2.3

Sensors

Use-Case in Delta Learning

Decreasing the domain gap, produced when detecting objects from a different camera mounting height/orientation. Knowledge transfer for object detection in a new camera position, without access to ground truth annotations for the new data. This saves the effort and time utilized in data labelling.

Task: 2D Object Detection
Method: Unsupervised domain adaption using adversarial domain discrimination.

Technical Problem

- Object Detection networks generalize well for the given task, provided a significant amount of labeled data is available for supervision during training.
- For the same task, test performance of the trained network on an unseen data distribution is often degraded.
- For example, experiments in Table 1 show mAP, mAR for a network trained on images from Domain A (Fig 1, left). Performance of the network reduces by upto ~50% on Domain B (Fig 1, right).
- Key take-away: Neural networks also learn the nuances of data distribution

Figure 1: Argoverse dataset images. Left: Roof-mounted camera, facing front in the direction of driving. Right: Roof-mounted camera facing in rear-right direction.

Technical Solution

- To prevent the network from learning domain specific features, a discriminator network (*D*) is added to the detector model.
- Discriminator network uses the feature representation of original images learned by the feature extractor (*F*) and classifies them into either of two domains.
- The duo forms an adversarial network, with *F* aiming for deterministic features and *D* aiming for optimal domain loss.
- Expected Result: Network converges to a deterministic feature representation that is common to both domains.

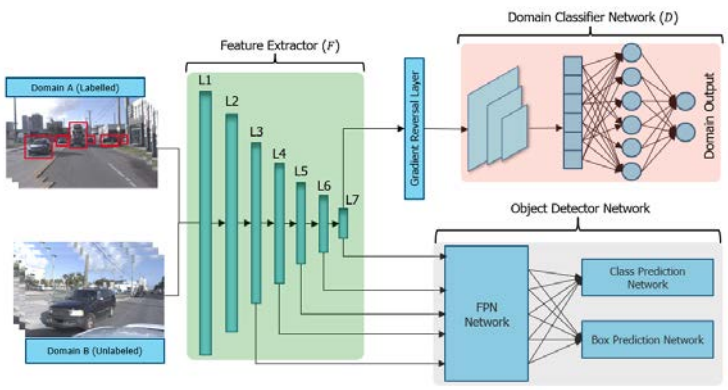

Figure 2: Adversarial Object Detector Network: Green-shaded region represents the feature extractor network (F), red-shaded region represents the domain classifier network, gray-shaded region represents the object classifier and regression network.

Evaluation

- Experiments to be performed on 3 datasets: ZF Internal, Argoverse & Waymo.
- Domain gap is significantly large in ZF dataset as compared to Argoverse (refer Table 1).
- Hypothesis: Shift in camera height contributes to a large domain gap. To be verified with Waymo Open dataset.
- Next step: Evaluate performance of the adversarial network on target domain.

Dataset (Domain Shift)	Category	mAP Domain A	mAP Domain B	% Drop in mAP	mAR Domain A	mAR Domain B	% Drop in mAR
ZF (Orientation + Height)	Overall	0.1614	0.0758	53.04 %	0.3142	0.2238	28.77 %
	Car	0.7441	0.4332	41.78 %	0.8028	0.5664	29.45 %
Argoverse (Orientation)	Pedestrian	0.2289	0.2264	1.09 %	0.408	0.394	3.43 %
	Car	0.4325	0.3779	12.62 %	0.5689	0.5276	7.26 %

Table 1: Experimental results on ZF and Argoverse dataset: mAP and mAR are computed for total class list and individual classes for Domain A and Domain B.

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Partners

External partners

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