

# Supplementary Material for “Subcategory-aware Convolutional Neural Networks for Object Proposals and Detection”

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## 1. Additional Qualitative Results

We present additional qualitative examples obtained from our detection framework on the KITTI detection benchmark [2] and the PASCAL3D+ dataset [8] in this supplementary material.

For car in KITTI and the 12 rigid categories in PASCAL3D+, we use 3D Voxel Patterns (3DVPs) [7] as subcategories in our region proposal network and our detection network. For pedestrian and cyclist in KITTI, we cluster objects according to their orientations to obtain their subcategories. After detecting the objects with bounding boxes, we transfer the segmentation masks from 3DVPs (i.e., segmentation mask of the cluster center in each 3DVP) to the detected objects according to the subcategory classification results. As a result, our method is able to segment the detected objects. Using the provided camera matrices in KITTI, we are able to back-project the detected objects into 3D, so as to localize them in the 3D space. Fig. 1, Fig. 2, Fig. 3 and Fig. 4 present 2D detection and 3D localization results on the KITTI test set, where object detections with scores larger than 0.5 are shown. Fig. 5 and Fig. 6 present detection results on the PASCAL3D+ test set, where object detections with scores larger than 0.7 are shown.

## 2. Running Time

We implemented our detection framework in Caffe [3], and conducted experiments in the environment with an Intel Xeon GPU 2.8GHz and a NVIDIA GeForce GTX TITAN X Graphics Card. Table 1 presents the running time of our detection framework on KITTI and PASCAL (PASCAL3D+ and PASCAL VOC 2007). For region proposal, we generated around 2,000 regions per image on the three datasets. Since we used more image scales on KITTI than PASCAL and the size of KITTI images is also larger, it takes 2.3 seconds to process one KITTI image, while 1.2 seconds is needed to process one PASCAL image in our experimental setting. We also present the running time of Faster R-CNN [5] in Table 1 for comparison.

|                     | Region Proposal | Detection | Total |
|---------------------|-----------------|-----------|-------|
| Ours                |                 |           |       |
| KITTI (AlexNet [4]) | 1.5s            | 0.8s      | 2.3s  |
| PASCAL (VGG16 [6])  | 0.8s            | 0.4s      | 1.2s  |
| Faster R-CNN [5]    |                 |           |       |
| KITTI (AlexNet [4]) | 1.1s            | 0.9s      | 2.0s  |
| PASCAL (VGG16 [6])  | 0.3s            | 0.4s      | 0.7s  |

Table 1. Running time of our detection framework on KITTI [2] and PASCAL (PASCAL3D+ [8] and PASCAL VOC 2007 [1]).

## References

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Car  Pedestrian  Cyclist 



Figure 1. 2D detection and 3D localization results on the KITTI test set. Detections with scores larger than 0.5 are shown. Blue regions in the images are the estimated occluded areas.

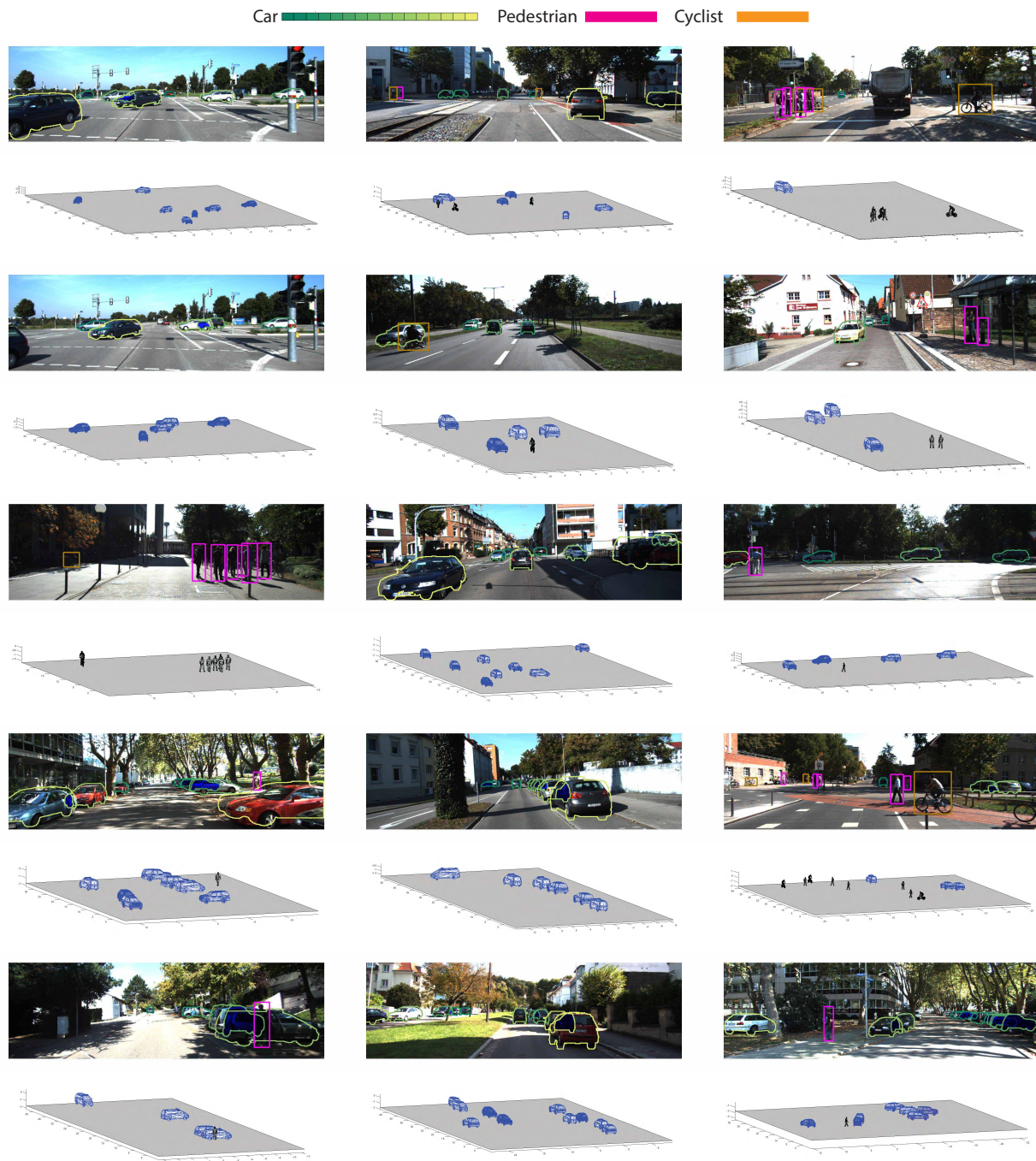














Figure 2. 2D detection and 3D localization results on the KITTI test set. Detections with scores larger than 0.5 are shown. Blue regions in the images are the estimated occluded areas.



Figure 3. 2D detection and 3D localization results on the KITTI test set. Detections with scores larger than 0.5 are shown. Blue regions in the images are the estimated occluded areas.



Figure 4. 2D detection and 3D localization results on the KITTI test set. Detections with scores larger than 0.5 are shown. Blue regions in the images are the estimated occluded areas.

aeroplane  bicycle  boat  bottle  bus  car  chair   
 diningtable  motorbike  sofa  train  tvmonitor 

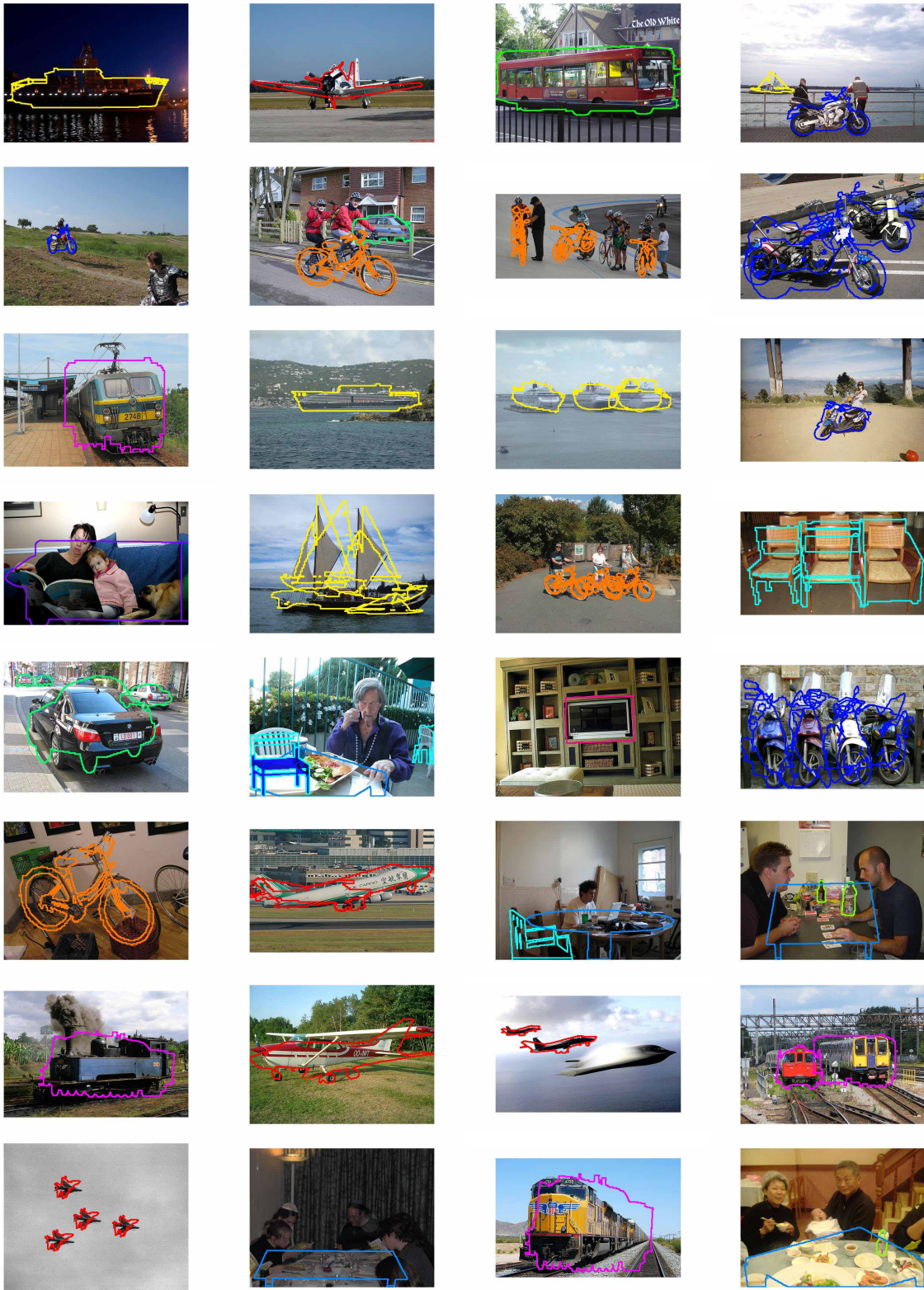


Figure 5. 2D detection results on the PASCAL3D+ test set. Detections with scores larger than 0.7 are shown.

aeroplane █ bicycle █ boat █ bottle █ bus █ car █ chair █  
 diningtable █ motorbike █ sofa █ train █ tvmonitor █

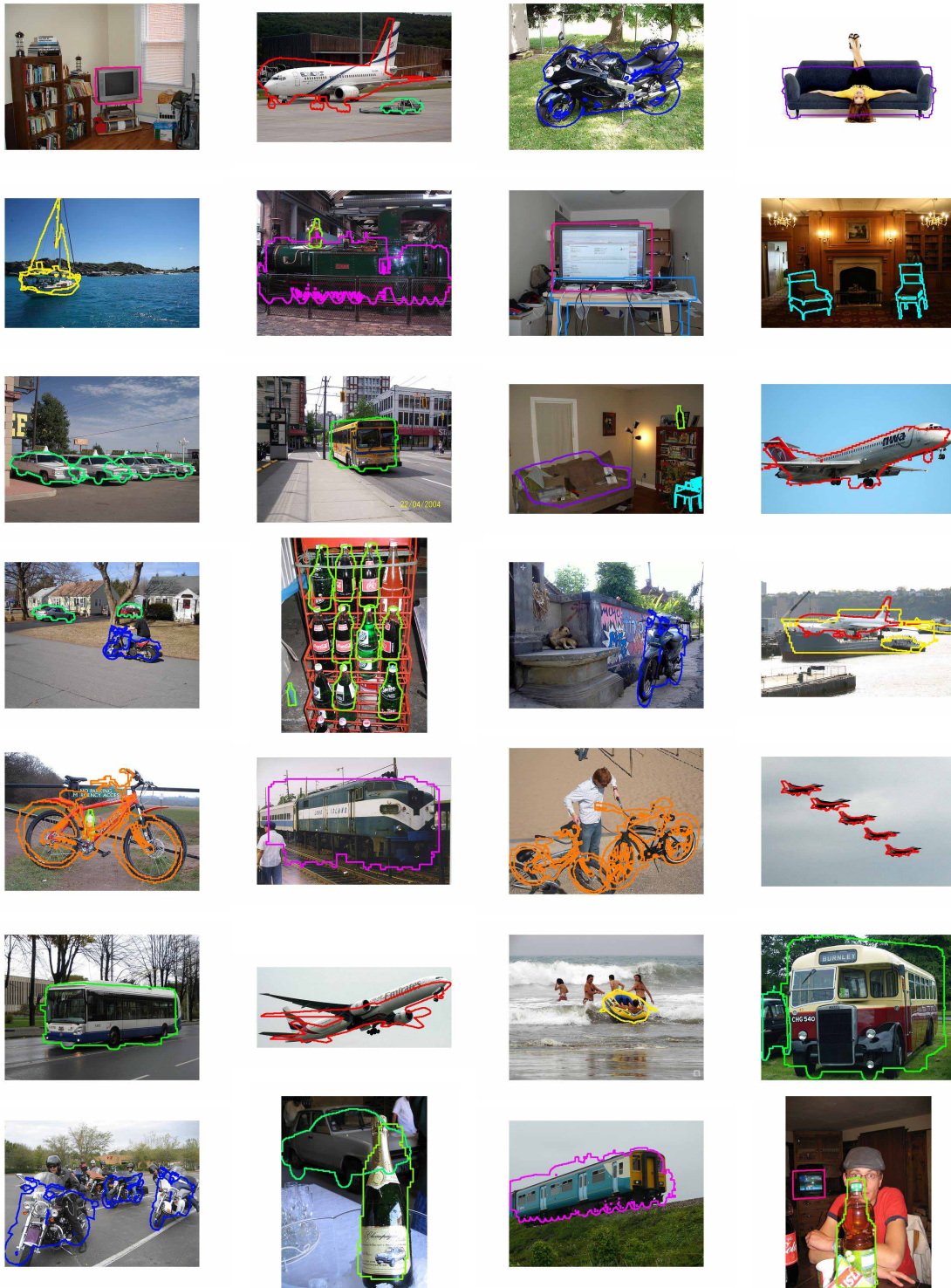


Figure 6. 2D detection results on the PASCAL3D+ test set. Detections with scores larger than 0.7 are shown.