Supplementary Material for DeepVoting: A Robust and Explainable Deep Network for Semantic Part Detection under Partial Occlusion

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Since there are no real-world semantic part datasets with different occlusion levels, we randomly choose several images with partial occlusion and/or truncation from MS COCO [1] 2014val. We run DeepVoting on these images and plot the detection heatmap (yellow for high scores and blue for low scores). Note that no ground-truth annotations are available.





Figure 1: Detecting *wheels* of *cars*. The left rear *wheel* of the left *car* is partially occluded by a chair, and the right *wheels* of the right *car* are occluded by the same chair and the left car.





Figure 2: Detecting *wheels* of a *bike*. The rear *wheel* is occluded by a blue bag.

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Figure 3: Detecting *license plates* of a *car*. The *license plate* is occluded by a woman.





Figure 4: Detecting *side windows* of a *car*. The rear *side window* is truncated.



Figure 5: Detecting *headlights* of a *car*. The *headlight* is both occluded and truncated.





Figure 6: Detecting wheels of a motorbike. Most of the wheels are occluded by the legs of two men.





Figure 7: Detecting *headlights* of a car. The headlight is occluded by the head of a man.

In these heatmaps, we can see strong responses in the area of occluded semantic parts. These heatmaps are then used to generate bounding boxes for the target part, followed by bounding box regression and non-maximum suppression.

References

 T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. L. Zitnick. Microsoft coco: Common objects in context. In *European conference on computer vision*, pages 740–755. Springer, 2014. 1