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Object Detection Accuracy (mAP) Cheat Sheet

6 Freebies to Help You Increase the Performance of Your Object Detection Models



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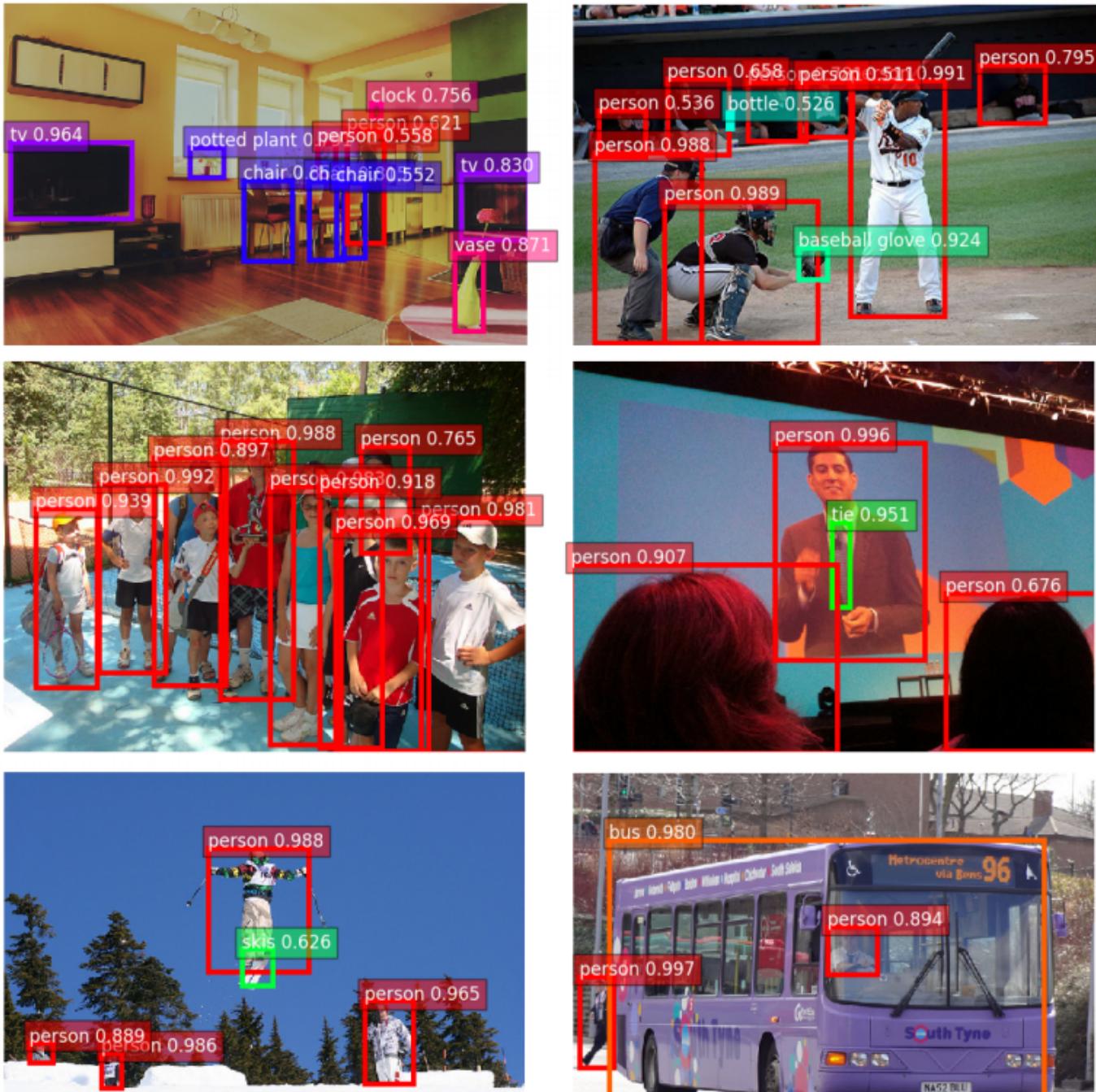
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Object detection is one of those machine learning (ML) applications that have garnered increasing attention from the general AI community. Lying in the middle of contemporary computer vision applications including motion recognition, image classification, biometrics, autonomous cars, forensics, real-world robotics to name but a few, its crystal clear that both AI researchers and engineers alike will be camping on this trend for a long time.

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researchers, on the other hand, concentrating their efforts on improving the performance of object detection neural networks.

This guide explores proven universal approaches that researchers in the object detection field can apply to boost model performance across different network structures with up to 5 percent without increasing computational costs in any way. Researchers most definitely need to explore these tweaks and consider applying them in object detection training for increased performance.



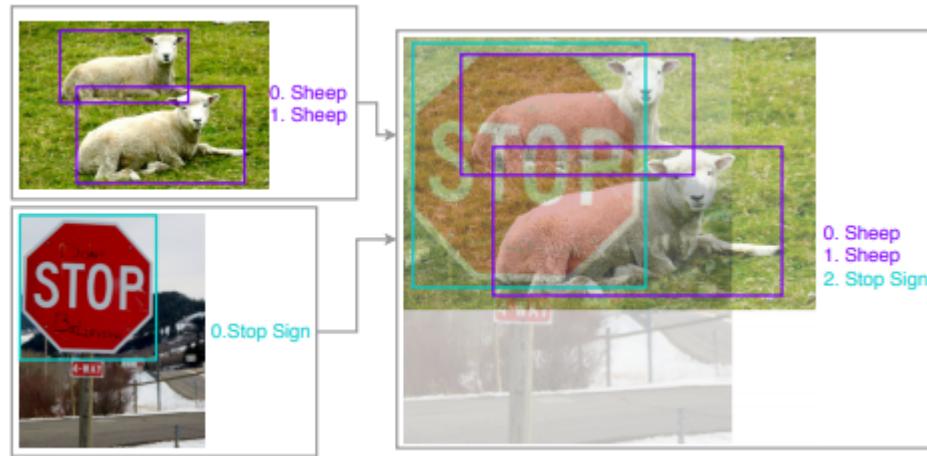
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Visually Coherent Image Mix-up for Object Detection (+3.55% mAP Boost)

The methodology has already been proven to be successful in lessening adversarial fears in network classification after testing it on COCO 2017 and PASCAL datasets with YOLOv3 models.



The difference here is that researchers introduce occlusions and spatial signal perturbations that are common in natural image presentation, in particular, the use of geometry preserved placements for image mix-up to avoid distorted images during initial training iterations. They also go for a beta distribution with more visually coherent ratios including $a \geq 1$ and $b \geq 1$ instead of following conventional image classification which achieves actual model performance improvements.



These performance freebees come directly from a research paper I found while building my weekly AI research newsletter AI Scholar. Keep up to date and be the first to learn about these and more by signing up today

Classification Head Label Smoothening (+2.16% mAP Boost)

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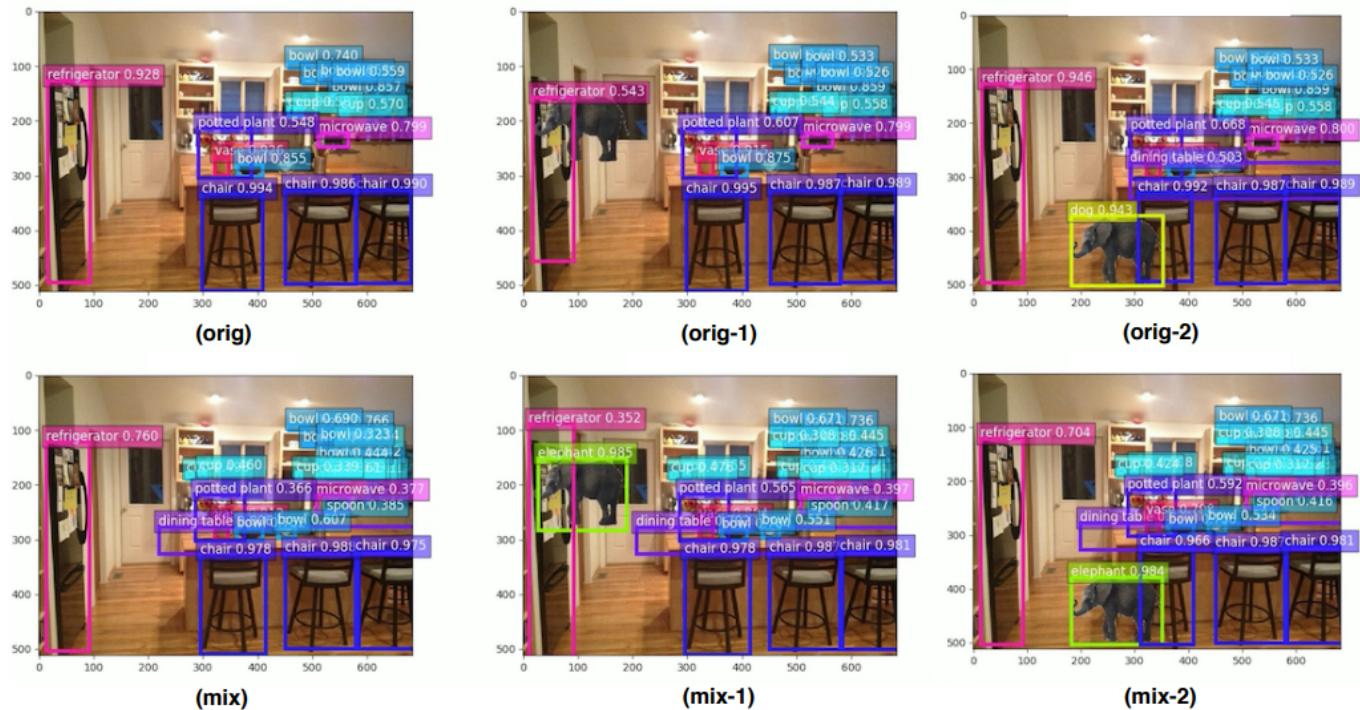
can result to over-fitting. One possible solution to this is to relax our confidence on the labels. For instance, we can slightly lower the loss target values from 1 to, say, 0.9. And naturally, we increase the target value of 0 for the others slightly as such. This idea is called label smoothing. Consult this for more information.

Fantastic Git on label smoothing with experiments

Data Pre-processing (Mixed Results)

For object detection preprocessing it is critical to take extra caution guards as detection networks are sensitive to geometrical transformations. Some proven data augmentation methods include:

- Random geometry transformation for random cropping (with constraints), random expansion, random horizontal flip and random resize (with random interpolation).
- Random color jittering for brightness, hue, saturation, and contrast



Training Scheduler Revamping (+1.44% mAP Boost)

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model iterations. For a Faster-RCNN, for example, the default step learning rate schedule aims at reducing the learning rate by 0.1 ratio at 60k iterations. Likewise, YOLOv3 uses the same ratio to lessen learning rate at 40k and 45k iterations.

The downside of the step scheduler in state-of-the-art object detectors is a sharp learning rate transition which may result in optimizer re-stabilization for subsequent iterations.

A better approach would involve training with:

- **Cosine scheduler** — scales the learning rate according to the value of cosine function on 0 to pi. It starts by slowly reducing the learning rate, and quickly reducing it halfway to finally achieve a tiny slope which further reduces the learning rate to 0.
- **Warm up scheduler** — aims to avoid gradient explosion during the initial model training iterations.



Cosine scheduler suffers less from plateau phenomenon and has been proven to outperform step scheduler. Applying both of these schedulers can help you achieve

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Synchronized Batch Normalization (+0.56% mAP Boost)

It's true that batch normalization implementation on multiple devices (GPUs) is fast and doesn't increase communication overheads. But, it reduces the batch size and alters statistics during computation which hurts model performance. The solution for this lies in synchronized batch normalization. The evaluation of synchronized batch normalization with YOLOv3 has been done to show the impacts of comparatively smaller batch-size on GPUs.

Random Shapes Training for Single-stage ODN (+0.98% mAP Boost)

To curb memory limitations and enable simpler batching, many single-stage object detection are trained with fixed shapes. Natural images come in a variety of unfixed shapes. To deal with the problem of overfitting that can be caused by training with fixed images and to improve the generalization of network predictions, the best approach is to implement a random shapes model training.

If you thought these performance hacks were useful you would find my article Deep Learning Performance Cheat Sheet useful

In Summary



To compare and validate the incremental improvements for the object detection tweaks, YOLOv3, and Faster R-CNN were used to represent single and multiple stages pipeline on COCO and PASCAL VOC datasets. The proposed freebies enhanced Faster-RCNN models by approximately 1.1% to 1.7% absolute mean AP over prevailing state-of-the-art

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For researchers who are driving the object detection field, this is free lunch that is up for grabs. Method code and pre-trained weights can be accessed here

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