## Appendix A

## De-duplication Experiments

A dataset with 300 M images is almost guaranteed to contain images that overlap with the validation set of target tasks. In fact, we find that even for ImageNet, there are 890 out of 50 K validation images have near-duplicate images in the training.

We use visual embeddings to measure similarities and identify duplicate or near-duplicate images. The embeddings are based on deep learning features. We find there are 5536 out of 50 K images in ImageNet validation set, 1648 out of 8 K images in COCO minival*, 201 out of 4952 images in Pascal VOC 2007 test set, and 84 out of 1449 images in Pascal VOC 2012 validation set that have near duplicates in JFT-300M. We rerun several experiments by removing near-duplicate images from validation sets and then comparing performance between baselines and learned models. We observe no significant differences in trends. Table 1, 2 and 3 show that the duplicate images have minimal impact on performance for all experiments.

|  | Original |  | De-duplication |  |
| :--- | :---: | :---: | :---: | :---: |
|  | Top-1 Acc. | Top-5 Acc. | Top-1 Acc. | Top-5 Acc. |
| MSRA checkpoint | 76.4 | 92.9 | 76.4 | 92.9 |
| Random initialization | 77.5 | 93.9 | 77.5 | 93.8 |
| Fine-tune from JFT-300M | 79.2 | 94.7 | 79.3 | 94.7 |

Table 1. Top-1 and top-5 classification accuracy on ImageNet validation set, before and after de-duplication. Single model and single crop are used.

|  | Original |  | De-duplication <br>  mAP@0.5 |  |
| :--- | :---: | :---: | :---: | :---: | | mAP@[0.5,0.95] | mAP@0.5 | mAP@[0.5,0.95] |  |  |
| :--- | :---: | :---: | :---: | :---: |
| ImageNet | 54.0 | 34.5 | 54.0 | 34.6 |
| 300M | 57.1 | 36.8 | 56.8 | 36.7 |
| ImageNet+300M | 58.2 | 37.8 | 58.2 | 37.7 |

Table 2. mAP@ 0.5 and mAP@[0.5, 0.95$]$ for object detection performance on COCO minival*, before and after de-duplication.

|  | VOC07 Detection <br> Original |  | De-duplication | VOC12 |
| :--- | :---: | :---: | :---: | :---: | Segmentation | Original |
| :--- | De-duplication

Table 3. Object detection and semantic segmentation performance on Pascal VOC, before and after deduplication. (Left) Object detection mAP@ 0.5 on Pascal VOC 2007 test set. (Right) Semantic segmentation mIOU on Pascal VOC 2012 validation set.

We do not conduct de-duplication experiments of COCO testdev dataset for object detection and pose estimation as their groundtruth annotations are not publicly available.

## Appendix B

## Detailed and Per-category Results: Object Detection

In this section, we present detailed and per-category object detection results for Table 2 (Section 5.2) from the main submission, evaluated on the COCO test-dev split. In Table 4, we report detailed AP and AR results using different initializations. In Table 7, we provide per-category AP and AP@. 5 results.

|  | AP | AP@.5 | AP@.75 | AP(S) | AP(M) | AP(L) | AR | AR@.5 | AR@. 75 | AR(S) | AR(M) | AR(L) |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| ImageNet | 34.3 | 53.6 | 36.9 | 15.1 | 37.4 | 48.5 | 30.2 | 47.3 | 49.7 | 26.0 | 54.6 | 68.6 |
| 300M | 36.7 | 56.9 | 39.5 | 17.1 | 40.0 | 50.7 | 31.5 | 49.3 | 51.9 | 28.6 | 56.9 | 70.4 |
| ImageNet+300M | 37.4 | 58.0 | 40.1 | 17.5 | 41.1 | 51.2 | 31.8 | 49.8 | 52.4 | 29.0 | 57.7 | 70.5 |

Table 4. Object detection performance on COCO test-dev split using different model initializations.

## Per-category Results: Semantic Segmentation

In Table 5, we report quantitative results on the VOC 2012 segmentation validation set for all classes (refer to Figure 5 (left), Section 5.3 in the main submission). Results are reported for different initializations. We observe more than 7 point improvement for categories like boat and horse.

| Initialization | mIOU | bg | aero | bike | bird | boat | bottle | bus | car | cat | chair | cow | table | dog | horse | mbike | persn | plant | sheep | sofa | train | tv |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| ImageNet | 73.6 | 93.2 | 88.9 | 40.1 | 87.3 | 65.0 | 78.8 | 89.9 | 84.3 | 88.8 | 37.2 | 81.6 | 49.3 | 84.1 | 78.9 | 79.3 | 83.3 | 57.7 | 82.0 | 41.7 | 80.3 | 73.1 |
| 300M | 75.3 | 93.7 | 89.8 | 40.1 | 89.8 | 70.6 | 78.5 | 89.9 | 86.1 | 92.0 | 36.9 | 80.9 | 52.8 | 87.6 | 82.4 | 80.8 | 84.3 | 61.7 | 84.4 | 44.8 | 80.9 | 72.6 |
| ImageNet+300M | 76.5 | 94.8 | 90.4 | 41.6 | 89.1 | 73.1 | 80.4 | 92.3 | 86.7 | 92.0 | 39.6 | 82.7 | 52.7 | 86.2 | 86.1 | 83.6 | 85.7 | 61.5 | 83.9 | 45.3 | 84.6 | 73.6 |

Table 5. Per-class semantic segmentation performance on PASCAL VOC 2012 validation set.

## Detailed Results: Human Pose Estimation

In Table 6, we present all AP and AR results for the performance reported in Table 7 (Section 5.4) in the main submission.

|  | AP | AP@.5 | AP@.75 | AP(M) | AP(L) | AR | AR@.5 | AR@.75 | AR(M) | AR(L) |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| CMU Pose [3] | 61.8 | 84.9 | 67.5 | 57.1 | 68.2 | 66.5 | 87.2 | 71.8 | 60.6 | 74.6 |
| ImageNet [26] | 62.4 | 84.0 | 68.5 | 59.1 | 68.1 | 66.7 | 86.6 | 72.0 | 60.8 | 74.9 |
| 300M | 64.8 | 85.8 | 71.5 | 62.2 | 70.3 | 69.4 | 88.4 | 75.2 | 63.9 | 77.0 |
| ImageNet+300M | 64.4 | 85.7 | 70.7 | 61.8 | 69.8 | 69.1 | 88.2 | 74.8 | 63.7 | 76.6 |

Table 6 . Human pose estimation performance on the COCO test-dev split.

Table 7. Per-class object detection performance on COCO test-dev split using different model initializations.

| Initialization $\rightarrow$ | ImageNet |  | 300M |  | ImageNet +300 M |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | AP@. 5 | AP | AP@. 5 | AP | AP@. 5 | AP |
| person | 71.5 | 47.7 | 73.1 | 49.8 | 72.7 | 49.9 |
| bicycle | 48.9 | 26.4 | 54.9 | 30.0 | 52.7 | 29.9 |
| car | 55.7 | 34.7 | 58.3 | 36.9 | 59.3 | 37.1 |
| motorcycle | 56.5 | 36.7 | 61.6 | 40.5 | 59.9 | 39.6 |
| airplane | 67.9 | 52.0 | 70.1 | 55.0 | 70.4 | 54.7 |
| bus | 77.7 | 62.5 | 79.5 | 64.6 | 79.0 | 64.2 |
| train | 66.8 | 59.2 | 69.7 | 62.8 | 69.7 | 62.1 |
| truck | 46.3 | 29.9 | 49.7 | 33.0 | 52.2 | 34.5 |
| boat | 30.6 | 19.4 | 32.5 | 22.1 | 32.1 | 22.3 |
| traffic light | 48.9 | 22.7 | 49.8 | 24.3 | 49.1 | 24.6 |
| fire hydrant | 75.3 | 59.1 | 74.4 | 59.3 | 74.9 | 59.5 |
| stop sign | 83.2 | 63.6 | 84.4 | 63.8 | 85.6 | 66.4 |
| parking meter | 62.2 | 37.5 | 64.9 | 38.5 | 64.5 | 37.6 |
| bench | 38.1 | 19.6 | 39.3 | 20.1 | 40.6 | 21.4 |
| bird | 60.2 | 29.4 | 61.9 | 33.0 | 63.3 | 34.2 |
| cat | 64.2 | 58.1 | 68.0 | 61.9 | 67.9 | 62.4 |
| dog | 62.6 | 52.9 | 66.1 | 56.2 | 66.9 | 57.3 |
| horse | 67.2 | 53.5 | 70.8 | 57.0 | 71.3 | 57.0 |
| sheep | 64.4 | 43.6 | 64.8 | 45.4 | 66.7 | 46.3 |
| cow | 70.7 | 45.4 | 71.9 | 47.4 | 73.3 | 48.9 |
| elephant | 75.1 | 64.1 | 77.3 | 66.4 | 76.1 | 65.5 |
| bear | 70.5 | 66.9 | 74.5 | 69.8 | 72.7 | 70.0 |
| zebra | 71.0 | 59.3 | 71.5 | 60.4 | 71.3 | 61.0 |
| giraffe | 75.3 | 67.4 | 75.9 | 69.0 | 75.9 | 69.3 |
| backpack | 19.6 | 12.8 | 19.5 | 14.7 | 18.5 | 15.1 |
| umbrella | 46.2 | 28.9 | 50.7 | 32.3 | 50.4 | 32.8 |
| handbag | 14.7 | 9.7 | 13.7 | 10.9 | 16.1 | 12.0 |
| tie | 50.8 | 26.3 | 53.2 | 27.9 | 51.5 | 28.4 |
| suitcase | 40.4 | 26.7 | 44.4 | 30.3 | 46.9 | 32.5 |
| frisbee | 53.4 | 43.8 | 55.3 | 48.6 | 58.6 | 48.3 |
| skis | 1.5 | 18.1 | 3.0 | 20.0 | 2.3 | 20.7 |
| snowboard | 45.7 | 29.3 | 47.0 | 33.3 | 43.9 | 32.1 |
| sports ball | 41.8 | 35.6 | 48.7 | 37.6 | 42.3 | 38.6 |
| kite | 39.4 | 37.5 | 33.9 | 38.9 | 35.9 | 40.0 |
| baseball bat | 8.3 | 23.4 | 6.7 | 25.1 | 9.9 | 27.5 |
| baseball glove | 35.6 | 27.4 | 33.7 | 31.2 | 41.9 | 31.8 |
| skateboard | 42.2 | 40.0 | 48.6 | 44.7 | 49.2 | 44.4 |
| surfboard | 48.5 | 31.1 | 51.7 | 32.8 | 52.4 | 33.9 |
| tennis racket | 53.1 | 42.6 | 55.1 | 44.1 | 55.4 | 45.1 |
| bottle | 61.2 | 28.6 | 61.8 | 30.5 | 61.6 | 30.8 |


| Initialization $\rightarrow$ | ImageNet |  | 300M |  | ImageNet+300M |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | AP@. 5 | AP | AP@. 5 | AP | AP@.5 | AP |
| wine glass | 53.8 | 30.2 | 56.3 | 33.3 | 58.7 | 34.7 |
| cup | 64.7 | 32.5 | 67.5 | 35.6 | 68.4 | 35.9 |
| fork | 45.7 | 23.2 | 45.1 | 26.5 | 50.1 | 27.8 |
| knife | 29.9 | 12.8 | 37.1 | 15.7 | 37.2 | 16.4 |
| spoon | 13.0 | 10.0 | 11.4 | 11.7 | 11.6 | 13.3 |
| bowl | 49.4 | 32.1 | 53.6 | 35.4 | 52.2 | 35.4 |
| banana | 38.1 | 18.7 | 39.8 | 20.4 | 40.0 | 21.1 |
| apple | 49.4 | 19.1 | 50.1 | 20.8 | 51.5 | 21.7 |
| sandwich | 44.0 | 29.6 | 45.2 | 31.3 | 47.8 | 34.1 |
| orange | 48.7 | 25.0 | 50.7 | 26.2 | 49.0 | 26.1 |
| broccoli | 30.6 | 22.9 | 32.5 | 24.8 | 31.9 | 24.6 |
| carrot | 25.9 | 14.0 | 28.6 | 16.1 | 21.5 | 16.4 |
| hot dog | 43.7 | 21.8 | 46.5 | 24.8 | 48.2 | 25.8 |
| pizza | 67.9 | 51.1 | 69.0 | 52.3 | 68.7 | 52.8 |
| donut | 60.2 | 40.1 | 64.8 | 43.9 | 66.8 | 46.4 |
| cake | 42.7 | 25.5 | 46.4 | 28.1 | 46.5 | 29.1 |
| chair | 33.0 | 21.1 | 36.7 | 24.0 | 35.9 | 24.4 |
| couch | 41.3 | 36.2 | 44.5 | 38.9 | 44.9 | 39.4 |
| potted plant | 25.6 | 20.1 | 27.3 | 21.9 | 30.0 | 23.4 |
| bed | 44.5 | 40.6 | 45.6 | 41.7 | 47.2 | 43.4 |
| dining table | 33.9 | 25.3 | 36.3 | 27.5 | 36.8 | 27.6 |
| toilet | 61.1 | 54.8 | 61.8 | 56.1 | 63.3 | 57.4 |
| tv | 61.8 | 50.0 | 63.0 | 51.9 | 63.7 | 52.7 |
| laptop | 65.8 | 54.5 | 68.3 | 56.6 | 68.9 | 57.5 |
| mouse | 72.1 | 44.4 | 72.0 | 47.6 | 75.6 | 47.3 |
| remote | 56.4 | 22.1 | 55.8 | 24.4 | 59.1 | 26.0 |
| keyboard | 57.1 | 45.4 | 57.5 | 45.9 | 61.4 | 48.3 |
| cell phone | 54.0 | 23.4 | 58.5 | 26.1 | 57.5 | 26.7 |
| microwave | 53.9 | 50.3 | 53.7 | 50.5 | 58.7 | 53.1 |
| oven | 40.9 | 31.7 | 41.9 | 33.5 | 43.2 | 34.6 |
| toaster | 32.6 | 14.7 | 39.9 | 20.5 | 32.9 | 20.1 |
| sink | 43.2 | 31.0 | 44.8 | 34.4 | 44.0 | 33.9 |
| refrigerator | 48.6 | 42.3 | 51.7 | 44.6 | 52.4 | 46.1 |
| book | 15.2 | 7.4 | 18.7 | 8.8 | 21.3 | 9.8 |
| clock | 56.7 | 43.7 | 56.7 | 45.3 | 55.8 | 45.1 |
| vase | 57.1 | 32.3 | 61.5 | 35.9 | 61.4 | 36.5 |
| scissors | 31.1 | 20.8 | 38.9 | 25.2 | 34.8 | 25.9 |
| teddy bear | 50.4 | 35.4 | 54.7 | 40.2 | 54.7 | 40.4 |
| hair drier | 2.3 | 1.0 | 4.8 | 1.8 | 4.0 | 1.9 |
| toothbrush | 48.5 | 34.3 | 50.7 | 36.7 | 51.2 | 37.4 |

