EE6485 Computer Vision: Homework4

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December 7, 2022

1 Q1

Figure 1 shows the accuracy with the example code, i.e. split the training and validation set with the ratio of 9:1.

Camera	Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95
170							
	all	1200	1761	0.518	0.527	0.499	0.305
	car	1200	1504	0.863	0.623	0.734	0.39
	bus	1200	210	0.64	0.533	0.629	0.426
	truck	1200	47	0.051	0.426	0.135	0.097
495							
	all	1200	2227	0.676	0.587	0.64	0.385
	car	1200	1950	0.738	0.55	0.664	0.363
	bus	1200	55	0.875	0.635	0.808	0.561
	truck	1200	222	0.414	0.577	0.447	0.23
410							
	all	1200	2331	0.505	0.633	0.541	0.336
	car	1200	2005	0.871	0.558	0.72	0.413
	bus	1200	15	0.184	0.6	0.269	0.23
	truck	1200	311	0.46	0.743	0.633	0.365
511							
	all	1200	2294	0.569	0.48	0.523	0.335
	car	1200	2077	0.924	0.351	0.665	0.35
	bus	1200	86	0.6	0.663	0.624	0.454
	truck	1200	131	0.182	0.427	0.279	0.2
398							
	all	1200	2353	0.731	0.66	0.714	0.472
	car	1200	2056	0.764	0.677	0.729	0.426
	bus	1200	104	0.879	0.558	0.745	0.514
	truck	1200	193	0.551	0.746	0.669	0.476
173							
	all	1200	1991	0.715	0.766	0.776	0.51
	car	1200	1680	0.917	0.706	0.855	0.509
	bus	1200	171	0.803	0.857	0.867	0.631
	truck	1200	140	0.425	0.736	0.607	0.391
ALL							
	all	1200	12957	0.639	0.596	0.621	0.39
	car	1200	11272	0.824	0.565	0.703	0.395
	bus	1200	641	0.731	0.565	0.649	0.46
	truck	1200	1044	0.362	0.659	0.51	0.315

Figure 1: Accuracy with the example code.

In Figure 1, we can see that the mAP@.5 of camera 173 and 398 attain **0.776** and **0.714** respectively, which are obviously higher than the other cameras. The reason is that we only use camera 173 and 398 in this question, so they should perform better than the other ones.

1.1 Random shuffle

In the original setting, we will have whole images from camera 398, which contains 160 images. Besides, we'll only 20 images from camera 173. Therefore, I develop a method that chooses the training images fairly. That is, we can perform **random shuffle** before choosing the training images. After I perform shuffling, the images from camera 173 contain a larger proportion than they used to be.

Figure 2, for example, shows the result of testing result of training on 148 images from camera 398 and the other 32 images from camera 173.

Camera	Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95
170							
	all	1200	1761	0.532	0.508	0.474	0.282
	car	1200	1504	0.883	0.647	0.778	0.416
	bus	1200	210	0.637	0.452	0.56	0.39
	truck	1200	47	0.074	0.426	0.083	0.042
495							
	all	1200	2227	0.627	0.692	0.629	0.34
	car	1200	1950	0.687	0.712	0.653	0.345
	bus	1200	55	0.853	0.738	0.808	0.484
	truck	1200	222	0.34	0.626	0.426	0.19
410							
	all	1200	2331	0.62	0.573	0.561	0.297
	car	1200	2005	0.868	0.585	0.74	0.41
	bus	1200	15	0.263	0.533	0.285	0.181
	truck	1200	311	0.73	0.6	0.658	0.3
511							
	all	1200	2294	0.57	0.471	0.502	0.314
	car	1200	2077	0.89	0.452	0.704	0.378
	bus	1200	86	0.568	0.535	0.515	0.378
	truck	1200	131	0.253	0.427	0.287	0.185
398							
	all	1200	2353	0.668	0.667	0.683	0.442
	car	1200	2056	0.714	0.752	0.735	0.415
	bus	1200	104	0.766	0.471	0.636	0.443
	truck	1200	193	0.524	0.777	0.677	0.467
173							
	all	1200	1991	0.855	0.731	0.829	0.508
	car	1200	1680	0.929	0.716	0.882	0.525
	bus	1200	171	0.845	0.83	0.865	0.579
	truck	1200	140	0.791	0.649	0.74	0.419
ALL							
	all	1200	12957	0.677	0.585	0.62	0.364
	car	1200	11272	0.812	0.621	0.721	0.397
	bus	1200	641	0.749	0.521	0.62	0.416
	truck	1200	1044	0.471	0.612	0.518	0.278

Figure 2: Accuracy for random shuffle.

2 Q2

For better use of space, only `mAP@.5` of `all` index for each camera, which is defined as the performance metric for this task, will be listed and compared in the remaining report. The complete statistics will be provided in appendix.

2.1 Baseline

I randomly shuffle the whole images that I can use in Q2 and choose the first 200 images as selected images. The result is shown in Table 1 and Figure 7.

Camera	170	495	410	511	398	173	All
mAP@.5	0.632	0.629	0.718	0.707	0.664	0.764	0.709

Table 1: Accuracy of baseline in Q2.

2.2 Proposed methods

2.2.1 Method 1

I separate the images from different cameras in advance and perform random shuffle on each camera respectively. Then, I randomly select 33 (or 34) images from each camera. This approach forces the training set to contain almost same number of images from different cameras. I call this method **modified random shuffle**, and the result is shown in Table 2 and Figure 8.

Camera	170	495	410	511	398	173	All
mAP@.5	0.626	0.714	0.754	0.747	0.753	0.833	0.747

Table 2: Accuracy of modified random shuffle method in Q2.

2.2.2 Method 2

I sort the whole 1200 images that is available for Q2 by the number of objects and choose the top 200 images with most objects as selected images. According to Table 1 and 2, we know that the performance will be better if the number of images from each camera is close. So, I'll also compare this method w/ or w/o average the number of images from each camera. The results are shown in Table 3 and Figure 9, 10.

Camera	Averaging	Accuracy
170		0.587
	V	0.663
495		0.697
	V	0.662
410		0.612
	V	0.712
511		0.759
	V	0.739
398		0.723
	V	0.713
173		0.794
	V	0.828
All		0.69
	V	0.722

Table 3: `mAP@.5` of method 2 in Q2.

2.2.3 Method 3

In method 3, I choose the images with most number of class, which is different from method 2 where I choose the images with most number of objects without considering their classes. I will also test for the influence of averaging the images from each camera. The results are shown in Table 4 and Figure 11, 12.

Camera	Averaging	Accuracy
170		0.632
	V	0.654
495		0.825
	V	0.78
410		0.75
	V	0.675
511		0.602
	V	0.693
398		0.753
	V	0.759
173		0.874
	V	0.864
All		0.741
	V	0.751

Table 4: `mAP@.5` of method 3 in Q2.

2.3 Comparision

In Table 5, we see that random sample (baseline) performs poor in each camera. In Method 1$\star$, we consider the balance from each camera. The performance of all cameras improves from 0.709 to 0.747, which indicated that balancing the number of images from each camera is helpful.

Then, we choose the images with most number of objects in camera as selected images in Method 2 and 2$\star$. The accuracy drops to 0.69 w/o balancing and attains 0.722 with balancing. No matter 0.69 or 0.722, both accuracy is lower than 0.747 in Method 1*. The reason is that choosing more number of objects may lead to more bias. Figure 3, for example, contains up to 35 objects, but most of the objects are cars. This may lead to more bias in model training, so the performance of method 2 and 2$\star$ don't perform better than modified random sample method.

Instead of considering the number of objects, we consider the number of classes of objects in Method 3 and 3$\star$. We can see that the performance of method 3 with averaging attains 0.751, which outperforms any other method in this question. This implies that the number of class helps more than the number of objects, and averaging the number among every camera takes an important role in solving the problem of domain gap.

Camera	Baseline	Method 1$\star$	Method 2	Method 2$\star$	Method 3	Method 3$\star$
170	0.632	0.626	0.587	**0.663**	0.632	0.654
495	0.629	0.714	0.697	0.662	**0.825**	0.78
410	0.718	**0.754**	0.612	0.712	0.75	0.675
511	0.707	0.747	**0.759**	0.739	0.602	0.693
398	0.664	0.753	0.723	0.713	0.753	**0.759**
173	0.764	0.833	0.794	0.828	**0.874**	0.864
All	0.709	0.747	0.69	0.722	0.741	**0.751**

Table 5: `mAP@.5` of each method in Q2. The method ends with $\star$ token means it averages the number of images from each camera. Notice that method 1 is just the modified version of baseline, so it's ended with $\star$ token.

Figure 3: The image that may lead to more bias.

3 Q3

3.1 Pseudo label

I use the best weight in the last experiment in Q2 to generate pseudo labels for the unlabeled images in Q3. The original image is shown in Figure 4 and the pseudo label generated by the model under `confidence` equaling to 0.7 is shown in Figure 5.

Figure 4: Original image without label.

Figure 5: Pseudo label with `confidence` = 0.7.

In Figure 5, we can see that some objects in the image is not labeled by the model, which means the `confidence` may be too high. Therefore, I lower the `confidence` threshold to 0.5 and train the model with new pseudo labels again. The new label result is shown in Figure 6. Some objects that are not labeled in 5 is now labeled with lower confidence threshold in 6.

Figure 6: Pseudo label with `confidence` = 0.5.

3.2 Positive weight

Since the number of objects may diverse a lot in the dataset. The loss of some classes are easy to update while some are not. Positive weight is here to solve this problem. So, I'll compare the accuracy w/ and w/o positive weights.

3.3 Focal loss

Add focal loss into training process to increase the accuracy, improving the classes that perform not well and decreasing the influence of capturing background in bounding box. The formula is listed below. α is the key term that can achieve this goal.

$$FL(p_t) = -\alpha(1 - p_t)^r \log(p_t)$$

3.4 Comparison

The overall result is shown in Table 6. No matter which method we use, the accuracy only achieves about 0.4   0.5, which is far worse than that in Q2. From my opinion, the main reason is **the quality of psuedo label**. The weight I use to generate pseudo label is the model trained with Method 3 in Q2, which attains the overall accuracy of 0.751 in Table 5. Although it seems to minimize the domain gap in Q2, 0.751 is still not a decent weight. Therefore, if I use this weight to generate 1000 pseudo labels, their quality may not be so good, which leads to the low accuracy in this question.

Although the accuracy is not so high, we can still find some insights from Table 6. Firstly, observing the best performance for each camera, none of them happens at $\mathrm{PL}_{0.7}$ or $\mathrm{PL}_{0.5}$. In other words, if we just train the model with the generated pseudo label, no matter how the confidence threshold is set, it will perform worse than those tasks training with 200 images in Q2. Since the label in Q2 is ground truth, it may help the model a lot. Hence, adding 200 labeled imaged in Q2 is a necessary step to improve the performance.

Besides, if we compare the columns w/ and w/o PW, we can find that their performance is similar, which means positive weight does not help so much in this question. Moreover, the overall accuracy is lower than the method w/o positive weights. The reason is that positive weight can be tuned, rather than just set it to ± 1.

Finally, if we introduce FL into our method, the accuracy obviously increases. The reason is that the pseudo labels generated by the weight in Q2 contains some false positive (FP) and false negative (FN) cases. With focal loss, we can minimize the FP and FN cases in pseudo label. As a result, the performance of camera 495, 410, 398 and the overall accuracy achieves the highest value in this method.

Camera	$PL_{0.7}$	$PL_{0.5}$	$PL_{0.5}$ + Q_2	$PL_{0.5}$ + Q_2 + PW	$PL_{0.5}$ + Q_2 + PW + FL
170	0.349	0.427	**0.366**	0.365	0.363
495	0.386	0.422	0.41	0.382	**0.493**
410	0.477	0.513	0.461	0.512	**0.564**
511	0.266	0.335	0.33	**0.357**	0.355
398	0.378	0.392	0.509	0.419	**0.529**
173	0.468	0.419	**0.502**	0.422	0.47
All	0.389	0.423	0.443	0.409	**0.461**

Table 6: `mAP@.5` of Q3. Q_2 means uses the 200 selected images in Q2 together with 1000 images in Q3. PL_{th} stands for the pseudo label generated with confidence threshold equaling to th. PW means the model training with positive weight. FL stands for the model training with focal loss. For each camera, the best performance in Q3 is marked with **bold** font.

4 Appendix

Camera	Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95
170							
	all	1200	1761	0.591	0.679	0.632	0.394
	car	1200	1504	0.9	0.819	0.897	0.522
	bus	1200	210	0.745	0.794	0.792	0.497
	truck	1200	47	0.127	0.424	0.208	0.163
495							
	all	1200	2227	0.73	0.608	0.629	0.408
	car	1200	1950	0.769	0.769	0.76	0.428
	bus	1200	55	0.926	0.454	0.619	0.461
	truck	1200	222	0.495	0.599	0.509	0.334
410							
	all	1200	2331	0.65	0.727	0.718	0.495
	car	1200	2005	0.881	0.65	0.812	0.499
	bus	1200	15	0.454	0.665	0.539	0.46
	truck	1200	311	0.614	0.865	0.801	0.526
511							
	all	1200	2294	0.771	0.637	0.707	0.454
	car	1200	2077	0.917	0.708	0.857	0.476
	bus	1200	86	0.948	0.86	0.918	0.649
	truck	1200	131	0.446	0.344	0.346	0.237
398							
	all	1200	2353	0.726	0.629	0.664	0.446
	car	1200	2056	0.775	0.694	0.77	0.459
	bus	1200	104	0.927	0.385	0.598	0.437
	truck	1200	193	0.475	0.808	0.623	0.442
173							
	all	1200	1991	0.686	0.733	0.764	0.51
	car	1200	1680	0.901	0.821	0.919	0.585
	bus	1200	171	0.767	0.602	0.772	0.545
	truck	1200	140	0.39	0.776	0.6	0.399
ALL							
	all	1200	12957	0.706	0.68	0.709	0.456
	car	1200	11272	0.836	0.734	0.814	0.481
	bus	1200	641	0.822	0.592	0.732	0.496
	truck	1200	1044	0.458	0.713	0.582	0.391

Figure 7: Accuracy of baseline in Q2.

Camera	Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95
170							
	all	1200	1761	0.645	0.606	0.626	0.393
	car	1200	1504	0.907	0.79	0.882	0.521
	bus	1200	210	0.707	0.771	0.775	0.511
	truck	1200	47	0.32	0.255	0.221	0.146
495							
	all	1200	2227	0.65	0.748	0.714	0.449
	car	1200	1950	0.677	0.889	0.771	0.451
	bus	1200	55	0.738	0.873	0.857	0.593
	truck	1200	222	0.536	0.484	0.514	0.303
410							
	all	1200	2331	0.739	0.676	0.754	0.503
	car	1200	2005	0.89	0.664	0.802	0.472
	bus	1200	15	0.442	0.733	0.63	0.497
	truck	1200	311	0.883	0.63	0.832	0.541
511							
	all	1200	2294	0.864	0.656	0.747	0.493
	car	1200	2077	0.933	0.76	0.893	0.505
	bus	1200	86	0.926	0.872	0.924	0.675
	truck	1200	131	0.734	0.336	0.425	0.298
398							
	all	1200	2353	0.835	0.631	0.753	0.499
	car	1200	2056	0.784	0.644	0.768	0.457
	bus	1200	104	0.93	0.538	0.722	0.547
	truck	1200	193	0.792	0.709	0.768	0.495
173							
	all	1200	1991	0.825	0.726	0.833	0.549
	car	1200	1680	0.91	0.842	0.924	0.594
	bus	1200	171	0.839	0.702	0.814	0.558
	truck	1200	140	0.727	0.636	0.762	0.496
ALL							
	all	1200	12957	0.733	0.717	0.747	0.477
	car	1200	11272	0.812	0.802	0.819	0.485
	bus	1200	641	0.752	0.739	0.766	0.529
	truck	1200	1044	0.635	0.611	0.655	0.419

Figure 8: Accuracy of modified random shuffle method in Q2.

Camera	Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95
170							
	all	1200	1761	0.656	0.527	0.587	0.362
	car	1200	1504	0.823	0.851	0.875	0.502
	bus	1200	210	0.838	0.476	0.674	0.442
	truck	1200	47	0.308	0.255	0.212	0.14
495							
	all	1200	2227	0.676	0.686	0.697	0.409
	car	1200	1950	0.663	0.849	0.741	0.421
	bus	1200	55	0.872	0.618	0.836	0.542
	truck	1200	222	0.494	0.59	0.513	0.263
410							
	all	1200	2331	0.567	0.709	0.612	0.367
	car	1200	2005	0.772	0.751	0.781	0.458
	bus	1200	15	0.268	0.732	0.393	0.298
	truck	1200	311	0.662	0.643	0.663	0.346
511							
	all	1200	2294	0.755	0.727	0.759	0.478
	car	1200	2077	0.751	0.896	0.889	0.504
	bus	1200	86	0.834	0.849	0.885	0.631
	truck	1200	131	0.678	0.435	0.503	0.299
398							
	all	1200	2353	0.729	0.648	0.723	0.488
	car	1200	2056	0.719	0.742	0.746	0.45
	bus	1200	104	0.913	0.404	0.683	0.493
	truck	1200	193	0.554	0.798	0.74	0.521
173							
	all	1200	1991	0.761	0.739	0.794	0.53
	car	1200	1680	0.765	0.93	0.912	0.57
	bus	1200	171	0.878	0.63	0.784	0.585
	truck	1200	140	0.64	0.657	0.685	0.436
ALL							
	all	1200	12957	0.66	0.701	0.69	0.43
	car	1200	11272	0.708	0.863	0.809	0.474
	bus	1200	641	0.79	0.577	0.666	0.467
	truck	1200	1044	0.481	0.662	0.593	0.348

Figure 9: Accuracy of choosing most object w/o averaging in Q2.

Camera	Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95
170							
	all	1200	1761	0.601	0.68	0.663	0.431
	car	1200	1504	0.756	0.85	0.882	0.523
	bus	1200	210	0.699	0.872	0.827	0.588
	truck	1200	47	0.347	0.319	0.278	0.182
495							
	all	1200	2227	0.628	0.652	0.662	0.432
	car	1200	1950	0.613	0.848	0.724	0.438
	bus	1200	55	0.921	0.636	0.84	0.588
	truck	1200	222	0.35	0.473	0.421	0.27
410							
	all	1200	2331	0.665	0.709	0.712	0.479
	car	1200	2005	0.85	0.692	0.777	0.476
	bus	1200	15	0.396	0.8	0.613	0.499
	truck	1200	311	0.749	0.633	0.747	0.463
511							
	all	1200	2294	0.779	0.623	0.739	0.49
	car	1200	2077	0.866	0.797	0.887	0.532
	bus	1200	86	0.939	0.721	0.892	0.649
	truck	1200	131	0.533	0.351	0.438	0.288
398							
	all	1200	2353	0.736	0.596	0.713	0.475
	car	1200	2056	0.741	0.681	0.713	0.439
	bus	1200	104	0.926	0.361	0.755	0.525
	truck	1200	193	0.541	0.746	0.67	0.463
173							
	all	1200	1991	0.759	0.794	0.828	0.569
	car	1200	1680	0.859	0.836	0.923	0.609
	bus	1200	171	0.854	0.825	0.874	0.638
	truck	1200	140	0.565	0.721	0.688	0.461
ALL							
	all	1200	12957	0.696	0.685	0.722	0.477
	car	1200	11272	0.776	0.776	0.803	0.494
	bus	1200	641	0.79	0.672	0.79	0.567
	truck	1200	1044	0.523	0.605	0.573	0.369

Figure 10: Accuracy of choosing most object w/ averaging in Q2.

Camera	Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95
170							
	all	1200	1761	0.616	0.629	0.632	0.406
	car	1200	1504	0.913	0.725	0.85	0.496
	bus	1200	210	0.689	0.671	0.771	0.54
	truck	1200	47	0.247	0.489	0.275	0.183
495							
	all	1200	2227	0.731	0.883	0.825	0.551
	car	1200	1950	0.699	0.904	0.802	0.482
	bus	1200	55	0.873	0.873	0.936	0.707
	truck	1200	222	0.622	0.874	0.737	0.463
410							
	all	1200	2331	0.663	0.772	0.75	0.502
	car	1200	2005	0.855	0.679	0.793	0.458
	bus	1200	15	0.324	0.933	0.65	0.514
	truck	1200	311	0.811	0.704	0.807	0.534
511							
	all	1200	2294	0.682	0.604	0.602	0.38
	car	1200	2077	0.91	0.657	0.845	0.479
	bus	1200	86	0.729	0.581	0.613	0.421
	truck	1200	131	0.406	0.573	0.347	0.242
398							
	all	1200	2353	0.732	0.7	0.753	0.492
	car	1200	2056	0.736	0.747	0.753	0.447
	bus	1200	104	0.905	0.644	0.799	0.603
	truck	1200	193	0.554	0.71	0.707	0.426
173							
	all	1200	1991	0.863	0.78	0.874	0.593
	car	1200	1680	0.95	0.753	0.909	0.576
	bus	1200	171	0.899	0.832	0.898	0.655
	truck	1200	140	0.741	0.756	0.816	0.548
ALL							
	all	1200	12957	0.736	0.71	0.741	0.482
	car	1200	11272	0.833	0.732	0.808	0.478
	bus	1200	641	0.77	0.686	0.76	0.546
	truck	1200	1044	0.605	0.713	0.654	0.422

Figure 11: Accuracy of choosing most type w/o averaging in Q2.

Camera	Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95
170							
	all	1200	1761	0.625	0.688	0.654	0.429
	car	1200	1504	0.898	0.8	0.869	0.52
	bus	1200	210	0.633	0.881	0.792	0.546
	truck	1200	47	0.345	0.382	0.303	0.22
495							
	all	1200	2227	0.731	0.824	0.78	0.523
	car	1200	1950	0.735	0.845	0.759	0.448
	bus	1200	55	0.833	0.927	0.921	0.724
	truck	1200	222	0.624	0.698	0.659	0.398
410							
	all	1200	2331	0.575	0.85	0.675	0.444
	car	1200	2005	0.828	0.771	0.804	0.496
	bus	1200	15	0.203	0.999	0.439	0.322
	truck	1200	311	0.696	0.78	0.782	0.515
511							
	all	1200	2294	0.623	0.736	0.693	0.456
	car	1200	2077	0.894	0.736	0.853	0.488
	bus	1200	86	0.598	0.907	0.852	0.622
	truck	1200	131	0.378	0.565	0.372	0.258
398							
	all	1200	2353	0.712	0.775	0.759	0.494
	car	1200	2056	0.72	0.768	0.742	0.446
	bus	1200	104	0.915	0.728	0.835	0.559
	truck	1200	193	0.501	0.829	0.699	0.476
173							
	all	1200	1991	0.833	0.813	0.864	0.59
	car	1200	1680	0.943	0.811	0.924	0.601
	bus	1200	171	0.829	0.906	0.881	0.628
	truck	1200	140	0.727	0.721	0.789	0.54
ALL							
	all	1200	12957	0.711	0.762	0.751	0.492
	car	1200	11272	0.827	0.764	0.805	0.486
	bus	1200	641	0.716	0.827	0.805	0.568
	truck	1200	1044	0.59	0.696	0.643	0.423

Figure 12: Accuracy of choosing most type w/ averaging in Q2.

Camera	Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95
170							
	all	1200	1761	0.939	0.353	0.349	0.274
	car	1200	1504	0.986	0.388	0.389	0.298
	bus	1200	210	0.831	0.586	0.567	0.456
	truck	1200	47	1.0	0.085	0.09	0.07
495							
	all	1200	2227	0.851	0.419	0.386	0.299
	car	1200	1950	0.832	0.432	0.371	0.271
	bus	1200	55	0.914	0.582	0.575	0.465
	truck	1200	222	0.806	0.243	0.211	0.162
410							
	all	1200	2331	0.804	0.464	0.477	0.376
	car	1200	2005	0.894	0.383	0.444	0.338
	bus	1200	15	0.555	0.667	0.608	0.519
	truck	1200	311	0.964	0.341	0.379	0.272
511							
	all	1200	2294	0.752	0.291	0.266	0.212
	car	1200	2077	0.994	0.301	0.305	0.226
	bus	1200	86	1.0	0.442	0.447	0.369
	truck	1200	131	0.262	0.13	0.047	0.04
398							
	all	1200	2353	0.872	0.41	0.378	0.289
	car	1200	2056	0.845	0.399	0.357	0.271
	bus	1200	104	0.922	0.567	0.547	0.435
	truck	1200	193	0.85	0.264	0.231	0.162
173							
	all	1200	1991	0.979	0.473	0.468	0.364
	car	1200	1680	0.992	0.468	0.472	0.375
	bus	1200	171	0.945	0.608	0.584	0.442
	truck	1200	140	1.0	0.343	0.348	0.274
ALL							
	all	1200	12957	0.856	0.42	0.389	0.299
	car	1200	11272	0.911	0.41	0.385	0.293
	bus	1200	641	0.865	0.571	0.542	0.428
	truck	1200	1044	0.791	0.28	0.24	0.177

Figure 13: Accuracy of $PL_{0.7}$ in Q3.

Camera	Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95
170							
	all	1200	1761	0.913	0.442	0.427	0.33
	car	1200	1504	0.983	0.454	0.455	0.345
	bus	1200	210	0.756	0.724	0.673	0.522
	truck	1200	47	1.0	0.149	0.154	0.121
495							
	all	1200	2227	0.813	0.48	0.422	0.315
	car	1200	1950	0.824	0.556	0.476	0.335
	bus	1200	55	0.85	0.618	0.576	0.442
	truck	1200	222	0.766	0.266	0.214	0.167
410							
	all	1200	2331	0.758	0.557	0.513	0.399
	car	1200	2005	0.895	0.539	0.518	0.39
	bus	1200	15	0.439	0.733	0.598	0.515
	truck	1200	311	0.939	0.399	0.422	0.292
511							
	all	1200	2294	0.809	0.39	0.335	0.262
	car	1200	2077	0.991	0.356	0.359	0.264
	bus	1200	86	1.0	0.5	0.505	0.415
	truck	1200	131	0.436	0.313	0.14	0.109
398							
	all	1200	2353	0.857	0.424	0.392	0.306
	car	1200	2056	0.822	0.495	0.449	0.34
	bus	1200	104	0.919	0.548	0.516	0.413
	truck	1200	193	0.83	0.228	0.211	0.166
173							
	all	1200	1991	0.968	0.427	0.419	0.331
	car	1200	1680	0.988	0.528	0.53	0.415
	bus	1200	171	0.915	0.567	0.535	0.422
	truck	1200	140	1.0	0.186	0.191	0.154
ALL							
	all	1200	12957	0.833	0.467	0.423	0.322
	car	1200	11272	0.9	0.491	0.459	0.342
	bus	1200	641	0.819	0.615	0.564	0.443
	truck	1200	1044	0.778	0.296	0.247	0.18

Figure 14: Accuracy of $PL_{0.5}$ in Q3.

Camera	Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95
170							
	all	1200	1761	0.851	0.375	0.366	0.285
	car	1200	1504	0.975	0.486	0.484	0.364
	bus	1200	210	0.829	0.576	0.556	0.454
	truck	1200	47	0.75	0.064	0.058	0.038
495							
	all	1200	2227	0.809	0.462	0.41	0.323
	car	1200	1950	0.779	0.519	0.438	0.324
	bus	1200	55	0.872	0.618	0.592	0.489
	truck	1200	222	0.775	0.248	0.2	0.157
410							
	all	1200	2331	0.716	0.603	0.461	0.355
	car	1200	2005	0.884	0.572	0.527	0.394
	bus	1200	15	0.308	0.8	0.422	0.353
	truck	1200	311	0.958	0.437	0.433	0.317
511							
	all	1200	2294	0.794	0.365	0.33	0.253
	car	1200	2077	0.967	0.372	0.374	0.277
	bus	1200	86	0.956	0.5	0.503	0.402
	truck	1200	131	0.46	0.221	0.112	0.079
398							
	all	1200	2353	0.851	0.55	0.509	0.401
	car	1200	2056	0.815	0.497	0.434	0.327
	bus	1200	104	0.925	0.702	0.688	0.557
	truck	1200	193	0.813	0.45	0.405	0.318
173							
	all	1200	1991	0.958	0.514	0.502	0.391
	car	1200	1680	0.986	0.562	0.564	0.44
	bus	1200	171	0.886	0.637	0.595	0.467
	truck	1200	140	1.0	0.343	0.348	0.265
ALL							
	all	1200	12957	0.846	0.485	0.443	0.342
	car	1200	11272	0.885	0.5	0.464	0.348
	bus	1200	641	0.832	0.612	0.566	0.454
	truck	1200	1044	0.821	0.343	0.299	0.222

Figure 15: Accuracy of $PL_{0.7}$ + Q_2 in Q3.

Camera	Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95
170							
	all	1200	1761	0.792	0.384	0.365	0.267
	car	1200	1504	0.967	0.451	0.452	0.332
	bus	1200	210	0.785	0.595	0.54	0.387
	truck	1200	47	0.625	0.106	0.102	0.084
495							
	all	1200	2227	0.785	0.437	0.382	0.266
	car	1200	1950	0.794	0.496	0.434	0.312
	bus	1200	55	0.832	0.545	0.492	0.333
	truck	1200	222	0.728	0.27	0.218	0.152
410							
	all	1200	2331	0.726	0.579	0.512	0.379
	car	1200	2005	0.887	0.528	0.507	0.369
	bus	1200	15	0.385	0.8	0.608	0.484
	truck	1200	311	0.907	0.408	0.42	0.285
511							
	all	1200	2294	0.793	0.396	0.357	0.253
	car	1200	2077	0.932	0.417	0.407	0.282
	bus	1200	86	0.939	0.535	0.534	0.4
	truck	1200	131	0.508	0.237	0.131	0.077
398							
	all	1200	2353	0.743	0.469	0.419	0.307
	car	1200	2056	0.793	0.482	0.407	0.298
	bus	1200	104	0.807	0.644	0.606	0.458
	truck	1200	193	0.628	0.28	0.244	0.166
173							
	all	1200	1991	0.915	0.439	0.422	0.315
	car	1200	1680	0.977	0.53	0.533	0.403
	bus	1200	171	0.863	0.515	0.472	0.341
	truck	1200	140	0.905	0.271	0.262	0.2
ALL							
	all	1200	12957	0.799	0.459	0.409	0.293
	car	1200	11272	0.878	0.49	0.45	0.327
	bus	1200	641	0.778	0.574	0.517	0.375
	truck	1200	1044	0.742	0.311	0.261	0.176

Figure 16: Accuracy of $PL_{0.7}$ + Q_2 + PW in Q3.