Supplementary

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1 More experiments for Model Selection

We add the following experiment for model selection:

- We do experiments on different combinations of models. Table 1 and Table 2 is the result with 9 models and 6 models respectively. The counting result is demonstrated in Figure 1 and Figure 2, respectively.
- While generating the center of each model, we assign a higher weight to the category of cars and pedestrians, which is shown in Table 3. The counting result is demonstrated in Figure 3

Observations:

- Table 2 and Figure 2 present the results of using six models for model selection. Compared to the results with nine models, we removed the dominating models from the nine-model set (i.e., p4, p4-o0.1, p4-o0.2). According to Table 2, which shows the frame distribution across models, removing the p4 series models results in p9 becoming the dominant model without adjustment. However, with adjustment, the dominant model shifts to p9-o0.1, while p2-o0.1 remains the second most dominant model. From the results shown in Figure 2, it is evident that applying adjustments dramatically improves accuracy. Even when compared to the best-performing model, p4-o0.2, the model selection with adjustment achieves comparable results, despite using weaker-performing models.
- We also evaluated the impact of adjusting weights for different object categories in model selection. Comparing Table 1, which applies equal weights across all object categories, with Table 3, where the weights for the "car" and "pedestrian" categories are doubled, we observe notable changes. In terms of frame distribution among models, the dominating model remains p4-o0.2. However, the second dominating model shifts from p4 to p9-o0.2. As shown in Figure 3, the adjustment significantly improves performance for the "car" and "pedestrian" categories compared to the results in Figure 1, while maintaining stable performance for other object categories.

no adjustment		ϵ = 0.1		ϵ = 0.15		ϵ = 0.2	
Model	dist	rate	dist	rate	dist	rate	dist
p2	1116	0.835	339	0.667	168	0.486	90
p2-o0.1	21	0.780	279	0.572	274	0.371	343
p2-o0.2	48	0.811	43	0.624	35	0.433	32
p4	9	0.543	556	0.379	743	0.087	752
p4-o0.1	14	0.650	9	0.379	7	0.178	8
p4-o0.2	4739	0.617	4736	0.337	4734	0.145	4735
p9	20	0.642	0	0.426	3	0.219	3
p9-o0.1	34	0.693	48	0.369	53	0.170	54
p9-o0.2	16	0.684	7	0.439	35	0.231	0

Table 1: Data distribution of model selection with adjustment with 9 models ("dist" is short for distribution)

no adjustment		ϵ = 0.1		ϵ = 0.15		ϵ = 0.2	
Model	dist	rate	dist	rate	dist	rate	dist
p2	0	0.718	0	0.475	0	0.266	0
p2-o0.1	1171	0.631	641	0.355	561	0.159	713
p2-o0.2	60	0.633	54	0.358	53	0.161	56
p9	6	0.616	0	0.336	0	0.144	1
p9-o0.1	4752	0.405	5323	0.131	5404	0.026	5237
p9-o0.2	30	0.497	1	0.207	1	0.061	12

Table 2: Data distribution of model selection with adjustment with 6 models

no adjustment		ϵ = 0.1		ϵ = 0.15		ϵ = 0.2	
Model	dist	rate	dist	rate	dist	rate	dist
p2	19	0.833	14	0.663	12	0.481	9
p2-o0.1	1133	0.809	656	0.621	461	0.429	414
p2-o0.2	20	0.837	18	0.670	17	0.490	17
p4	23	0.660	22	0.393	24	0.190	59
p4-o0.1	22	0.634	17	0.358	13	0.161	14
p4-o0.2	4728	0.578	4734	0.292	4735	0.112	4734
p9	26	0.628	19	0.352	18	0.156	19
p9-o0.1	13	0.593	502	0.309	702	0.124	717
p9-o0.2	33	0.691	35	0.435	35	0.228	34

Table 3: Data distribution of model selection with adjustment with car and pedestrian preferred

2 Query Result on KITTI dataset

On the KITTI dataset, the performance improvement is not as pronounced as it is on the nuScenes dataset. According to Table 4, while the performance for the "car" and "cyclist" categories does not show significant improvement, the improvement for the "pedestrian" category is notable.

However, the results on the KITTI dataset are consistent with those on the nuScenes dataset for our proposed solution. This difference in performance can be attributed to the varying scene scales

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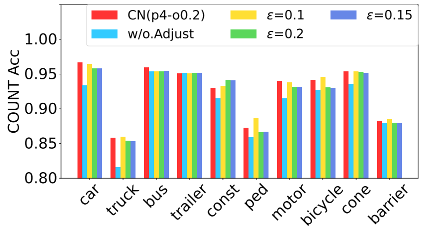

Figure 1: Result of model selection with 9 models

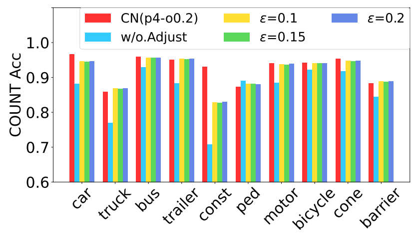

Figure 2: Result of model selection with 6 models

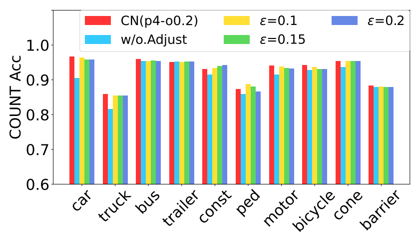

Figure 3: Result of model selection with more weight on car and pedestrian

	ACC (10% error rate)				Recall (10% error rate)			
	CP	CN	CN(p4)	CN(p4o)	CP	CN	CN(p4)	CN(p4o)
car	0.936	0.938	0.931	0.9425	**0.777**	0.75	0.771	0.772
ped	0.870	0.930	0.923	0.9595	0.519	0.647	0.624	**0.715**
cyclist	0.947	0.950	0.953	0.96	0.934	0.922	0.927	**0.936**

Table 4: Accuracy and Recall for Object Counting on KITTI

between KITTI and nuScenes. Specifically, the partitioning in KITTI introduces more negative impacts on performance, though the overlap mitigates these effects to some extent. The query result on KITTI is demonstrated in Table 7 and Table 5.

3 KITTI result with model selection

The model selection result on KITTI is demonstrated in Table 6 and Figure 4.

4 Case studies

We demonstrate the performance of the actual query on different scenarios and selectivity as shown in Figure 6. We do the experiment query result on accuracy, precision, and recall. Basically,

	CP	CN	CN(p4)	CN(p4o)
(car, pedestrian)	0.812	0.856	0.854	0.902
(car, cyclist)	0.885	0.887	0.880	0.903
(pedestrian, cyclist)	0.833	0.886	0.868	0.926
(car, pedestrian, cyclist)	0.776	0.821	0.811	0.869

Table 5: Result of JOIN query on KITTI

no adjustment		ϵ = 0.05		ϵ = 0.1		ϵ = 0.15	
Model	dist	rate	dist	rate	dist	rate	dist
p2	937	0.956	0	0.838	0	0.672	0
p2-o0.2	597	0.555	94	0.095	1052	0.005	1648
p4	512	0.775	0	0.362	0	0.101	61
p4-o0.2	165	0.307	3675	0.008	2717	0.00002	2060
p9	1525	0.965	0	0.868	0	0.728	0
p9-o0.2	33	0.890	0	0.628	0	0.351	0

Table 6: Data distribution of model selection with adjustment on KITTI

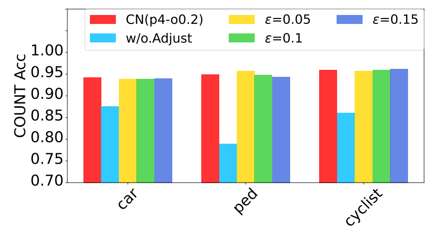

Figure 4: Result of model selection on KITTI

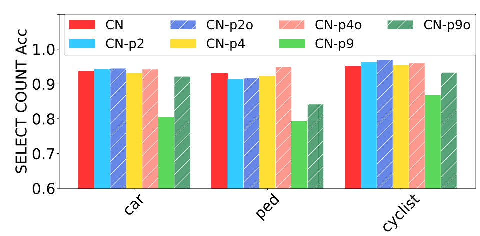

Figure 5: Result of different number of partition on KITTI

- Our proposed method can outperform baselines in accuracy. However, to look into the precision and recall, the performance varies on the query.
- Overall, the performance is better on the high selectivity case, while it will introduce more error on the low selectivity case across all methods.
- For Q1, our proposed Counternet is prone to have higher recall compared to precision, while it is contrary to the baselines. It indicates that within all the queried frames, CounterNet has a higher accuracy, however, it may miss some frames that should be selected. For the baselines, they are prone to select a large collection of frames, which covers

	SELECT-BINARY				COUNT				AGGREGATION			
	CP	CN	CN(p4)	CN(p4o)	CP	CN	CN(p4)	CN(p4o)	CP	CN	CN(p4)	CN(p4o)
car	**0.952**	0.9156	0.929	0.934	0.692	0.705	0.681	**0.731**	**0.135**	0.280	2.25	0.172
ped	0.602	0.675	0.639	**0.792**	0.776	0.778	0.781	**0.828**	0.704	**0.167**	3.07	0.447
cyclist	0.760	0.797	0.773	**0.812**	0.901	0.925	0.922	**0.931**	0.152	**0.121**	2.183	0.211

Table 7: Query result on KITTI dataset

Query Info			ACC					Recall					Precision				
Query	Predict	selectivity	VN	TF	CN	CN-p4	CN-p4o	VN	TF	CN	CN-p4	CN-p4o	VN	TF	CN	CN-p4	CN-p4o
Q1	SELECT(car>5)	67.9%	0.812	0.768	0.614	0.778	0.850	0.815	0.769	0.996	0.972	0.929	0.995	0.997	0.615	0.796	0.908
Q2	SELECT(barrier>3)	76.2%	0.639	0.748	0.859	0.866	0.764	0.954	0.953	0.905	0.893	0.934	0.641	0.752	0.943	0.967	0.807
Q3	SELECT(bus>0)	33.2%	0.488	0.507	0.553	0.445	0.557	0.504	0.628	0.898	0.762	0.759	0.940	0.949	0.591	0.515	0.632
Q5	JOIN(car>5, ped>0)	31.5%	0.635	0.604	0.520	0.624	0.702	0.638	0.605	0.967	0.857	0.841	0.962	0.966	0.529	0.697	0.809
Q6	JOIN(truck>0, barrier>5)	16.8%	0.404	0.448	0.332	0.465	0.529	0.411	0.452	0.761	0.882	0.678	0.964	0.977	0.371	0.496	0.706

Figure 6: Case study of different query scenario

more true positive frames, however, the low recall rate indicates that within all the frames selected, the accuracy is lower. A similar trend can be found in all other queries.