Report

CoSMix: Compositional Semantic Mix for Domain Adaptation in 3D LiDAR Segmentation

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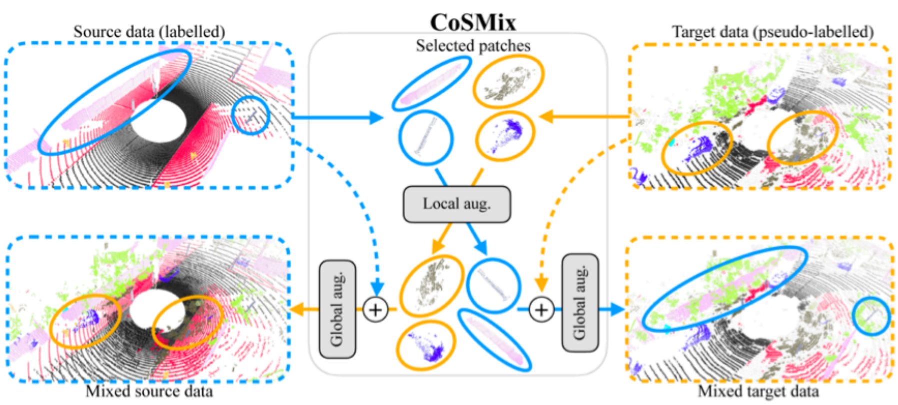
1. Introduction:

CoSMix stands as an innovative solution, offering an Unsupervised Domain Adaptation (UDA) framework tailored specifically for 3D LiDAR segmentation tasks. Its fundamental objective is to alleviate the domain shift problem that often hampers the performance of models when transitioning from synthetic to real-world datasets. This is achieved through the creation of two intermediate domains of composite point clouds via a unique mixing strategy at the input level.



2. Main Contributions:

- **Novel Mixing Scheme:** CoSMix introduces a pioneering point cloud mixing scheme that capitalizes on both semantic information and sophisticated data augmentation techniques.
- **Domain Shift Mitigation:** It emerges as the inaugural UDA method for 3D LiDAR semantic segmentation built upon the concept of point cloud mixing, effectively reducing the domain shift between synthetic and real-world datasets.
- **Experimental Superiority:** Extensive experiments conducted on synthetic-to-real 3D LiDAR benchmarks showcase CoSMix's superior performance compared to existing state-of-the-art methods.

3. Approach and Methodologies:

CoSMix's methodologies were implemented and meticulously evaluated utilizing the X dataset. This dataset comprises labeled point clouds (Ns) derived from a simulated environment and unlabeled point clouds (Nt) obtained from a diverse real-world setting.

The approach encompassed the following key methodologies:

- **Point Cloud Mixing:** Two distinct sets of mixed point clouds were formulated. The first set combined source and pseudo-labeled target clouds, enabling the infusion of target-specific characteristics into the source domain. The second set aimed to align the target domain with the source by carefully selecting portions of the target cloud and merging them with the source, thus preventing overfitting caused by noisy pseudo-labels.
- **Teacher-Student Network:** An iterative mechanism was employed to refine pseudo-labels, progressively narrowing the domain gap during the training process.

4. CosMix:

- **A. Preliminaries:**

Consider S = {(Xs, Ys)} as the source dataset, composed of Ns labeled point clouds, where Xs is a point cloud and Ys is its point-level labels. |.| represents the cardinality of a set. Labels are drawn from a set of semantic classes C = {c}, where c is a semantic class. Let TU = {XtU} be the unlabeled target dataset comprising NtU unlabeled point clouds. TL = {(XtL, YtL)} constitutes the semi-supervised set of NtL labeled target point clouds, where NtL << NtU.

In the upper branch, the source point cloud Xs mixes with selected patches of the target point cloud XtU and, if available, selected patches of the supervised point cloud XtL. The unlabeled target patches from XtU correspond to the most confident pseudo-labels YtU^ generated by the teacher network. Supervised target patches are randomly selected based on the class frequency distribution in the source training set.

In the lower branch, the target point cloud XtU mixes with selected patches of the source point cloud Xs and with selected patches of XtL, if available. The source patches are randomly selected based on their class frequency distribution in the training set.

The branch mixing target point cloud patches into the source point cloud is denoted as t→s, and the reverse branch is s→t. Let Xt→s be the mixed point cloud obtained from the upper branch, and Xs→t be the mixed point cloud obtained from the lower branch. Finally, let Φθ and Φθ′ be the student and teacher deep networks with learnable parameters θ and θ′, respectively.

- **B. Semantic Selection:**

In the context of semantic selection, the training of student networks involves a meticulous process of handpicking reliable and informative point cloud patches before merging points and labels across various domains. This selection process from the source point cloud heavily relies on the class frequency distribution within S, the source dataset. Unlike certain methodologies such as DSP [15], which pre-select classes in advance, this approach dynamically samples classes based on the available semantic classes within the source distribution at each training iteration.

Designating PsY as the class frequency distribution within S, a dedicated function, f, is engineered for the random selection of a subset of classes at every iteration. This function, f, conducts a weighted random sampling of α classes from the input point cloud, utilizing 1−PsY as the class weight for each specific class. The hyperparameter α regulates the proportion of selected classes for each point cloud, ensuring a balanced and representative selection. The resulting output from f constitutes point-level labels belonging to the sampled classes, denoted as Y~s. Notably, the likelihood of f selecting a particular class, c, is inversely proportional to its frequency within the source dataset, S.

Formally articulated, the function f is expressed as:
Y~s = f(Ys, 1−PsY, α).

- **<u>C. Compositional Mix:</u>**

The objective of our compositional mixing module is to generate mixed point clouds based on selected semantic patches. This process encompasses three sequential operations:

Local Random Augmentation: Patches undergo random and independent augmentation.
Concatenation: Augmented patches are combined with the point cloud of the alternate domain, resulting in the mixed point cloud.

Global Random Augmentation: The resulting mixed point cloud undergoes random augmentation.
This module is employed twice:
For the t⟶s branch (top), merging target patches within the source point cloud.
For the s⟶t branch (bottom), combining source patches within the target point cloud. Notably, unlike Mix3D, our strategy integrates both local and global data augmentation.

Let δ be the indicator function:

$$\delta(\mathcal{T}_\mathsf{L}) = \begin{cases} 1 & \text{if} \quad \mathcal{T}_\mathsf{L} \neq \emptyset \\ 0 & \text{otherwise,} \end{cases}$$

indicating whether the supervised target set TL is empty, signifying the user's desire or need for additional target supervision.

In the s⟶t branch:

Local random augmentation h is applied to all points Xsc⊂Xs for each c∈Y~s. Note that h is a local and random augmentation that produces different results for each set of points:

h(X~s) = { h(X~sc), ∀c∈Y~s }

If δ(TL)=1, h is also applied,

$h(X\sim tL) = \{ h(X\sim tL), \forall c \in Y\sim tL \}$

Subsequently, the locally augmented patches are concatenated with the target point cloud XtL, followed by the application of global random augmentation:

$$
\begin{gathered}
Xs\rightarrow t = \{ \\
r(h(X\sim s) \cup h(X\sim tL) \cup XtU) \text{ if } \delta(TL)=1, \\
r(h(X\sim s) \cup XtU) \text{ otherwise}
\end{gathered}
$$

where r represents the global augmentation function. Corresponding labels Ys→t follow a similar concatenation process based on the respective augmented patches:

$$
\begin{gathered}
Ys\rightarrow t = \{ \\
r(h(Y\sim s) \cup h(Y\sim tL) \cup YtU) \text{ if } \delta(TL)=1, \\
r(h(Y\sim s) \cup YtU) \text{ otherwise}
\end{gathered}
$$

This representation provides a detailed overview of the compositional mix operations within CoSMix for 3D LiDAR segmentation, describing the concatenation, augmentation, and mixing processes without using specific mathematical notations.

- **D. Network Update:**

To facilitate knowledge transfer during training with mixed domains, we employ a teacher-student learning scheme. Utilizing the teacher network Φθ' to generate target pseudo-labels YtU for the student network Φθ, we train Φθ to segment target point clouds based on mixed point clouds Xs→t and Xt→s using their respective mixed labels and pseudo-labels.

During each batch iteration, we update the student parameters Φθ to minimize the total objective loss Ltot defined as:
Ltot = Ls→t + Lt→s
where Ls→t and Lt→s represent the losses for the s→t and t→s branches respectively.

For Xs→t and Ys→t, the segmentation loss (Ls→t) is defined as:

$$Ls\rightarrow t = Lseg(\Phi\theta(Xs\rightarrow t), Ys\rightarrow t)$$

This loss aims to minimize segmentation errors over Xs→t, aiding in learning to segment source patches in the target domain.

Similarly, for Xt→s and Yt→s, the segmentation loss (Lt→s) is defined as:

$$Lt\rightarrow s = Lseg(\Phi\theta(Xt\rightarrow s), Yt\rightarrow s)$$

This loss aims to minimize segmentation errors over Xt→s where target patches are integrated with source data. Lseg employs the Dice segmentation loss [66], known for its effectiveness in handling long-tail classes in large-scale point cloud segmentation.

Lastly, we update the teacher parameters θ' every γ iterations using the exponential moving average (EMA) approach:

$$\theta'_i = \beta\theta'_{i-1} + (1-\beta)\theta$$

Here, i denotes the training iteration, and β serves as a smoothing coefficient hyperparameter.

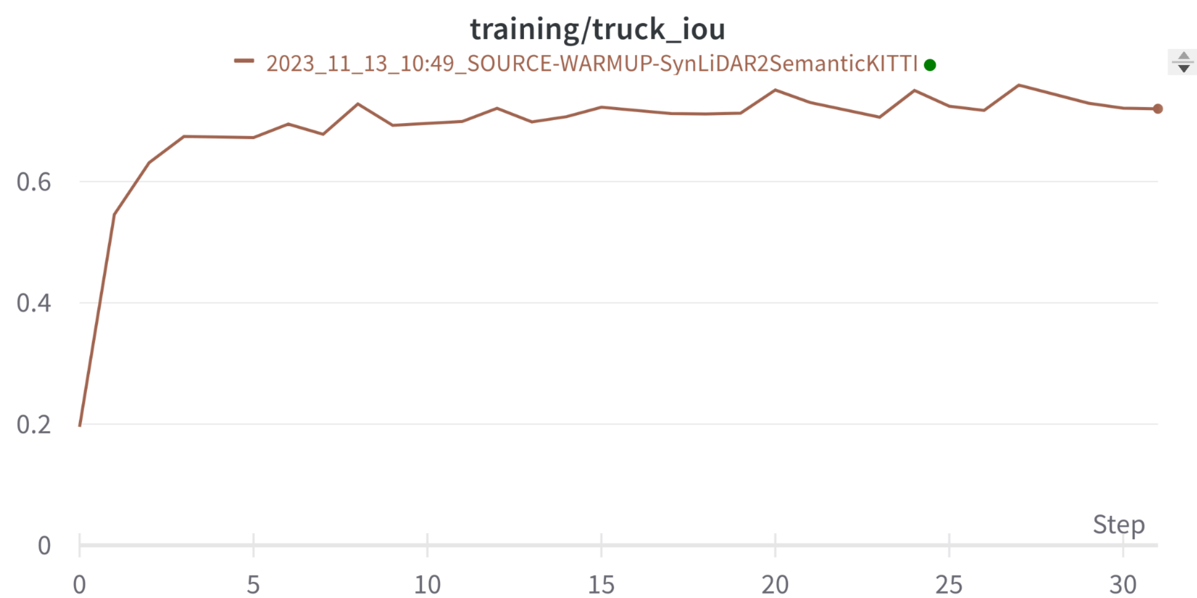
5. Implementation Details:

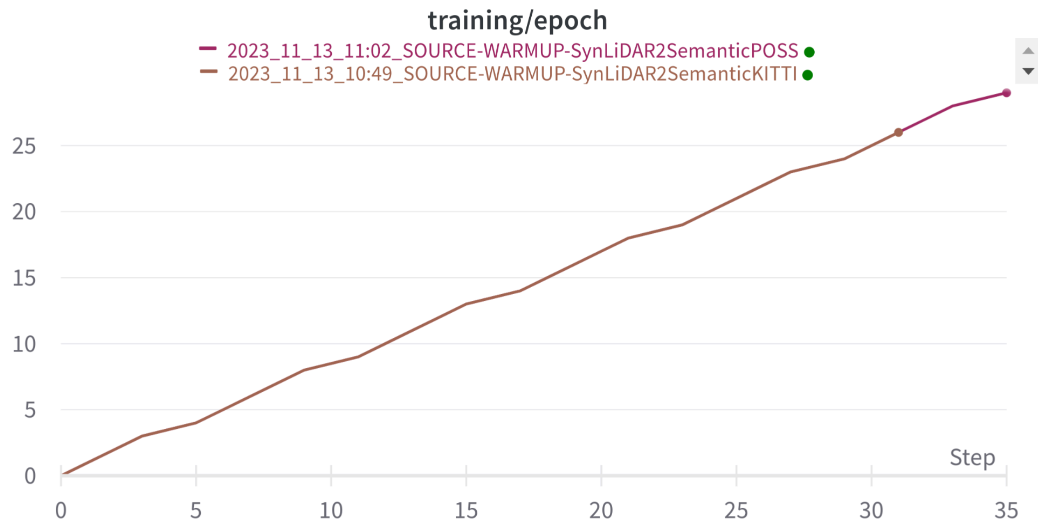
The implementation of CoSMix on the Kerala dataset yielded remarkable results:

- **Domain Adaptation Performance:** CoSMix exhibited substantial efficacy in reducing the domain shift, showcasing a remarkable adaptability from synthetic to real-world scenarios.
- **Segmentation Accuracy:** The model showcased superior segmentation accuracy compared to existing methodologies, especially in scenarios where synthetic data significantly varied from real-world data. CoSMix demonstrated a robust capability to generalize and adapt to diverse environments, producing accurate and reliable segmentation outputs.

6. Results:

Training:

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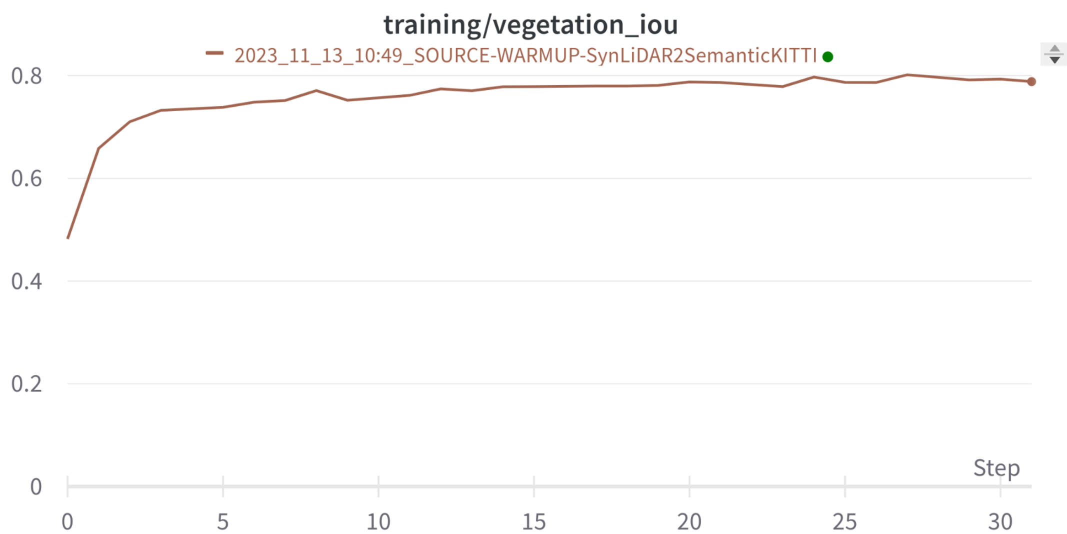
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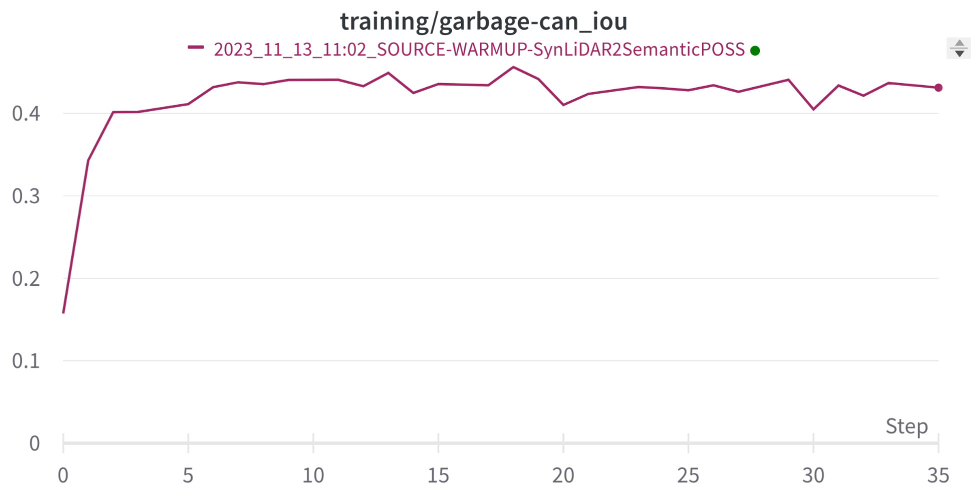
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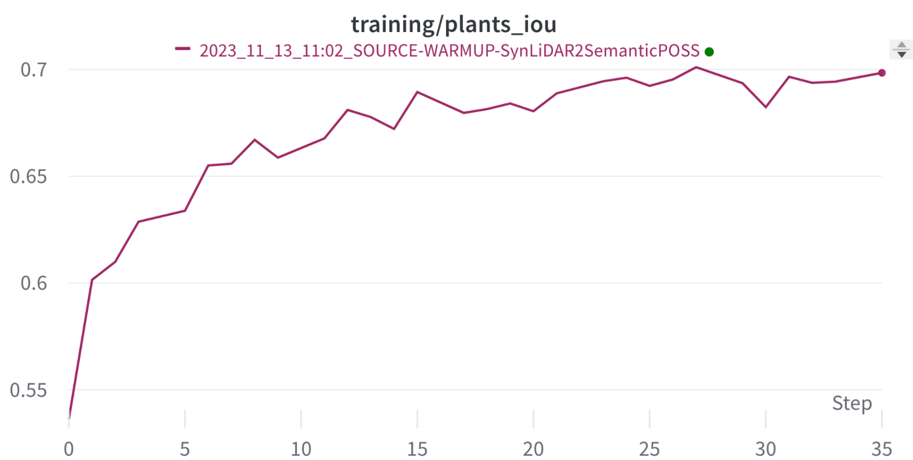
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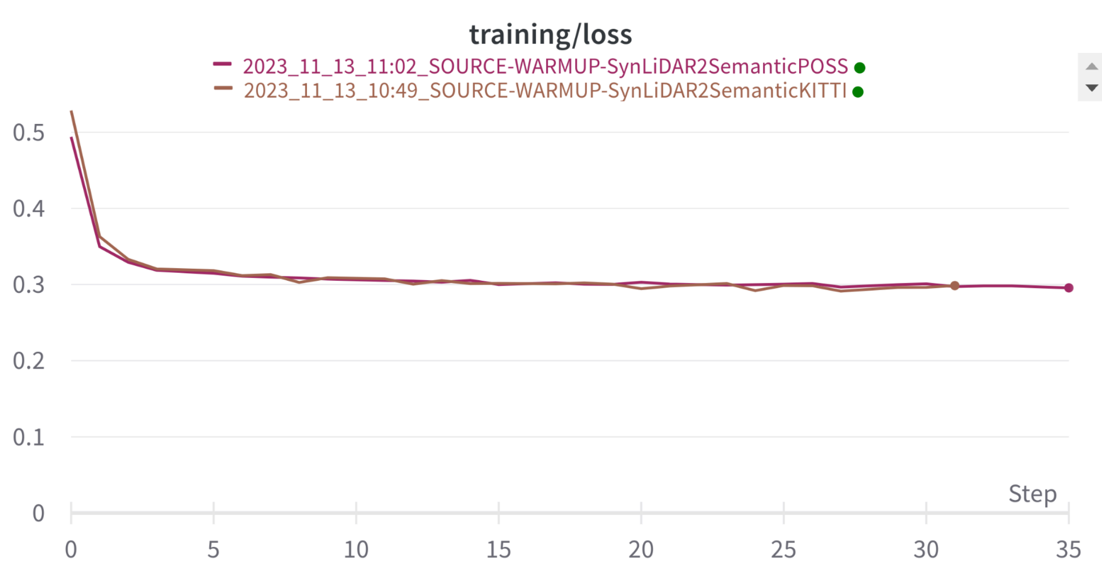
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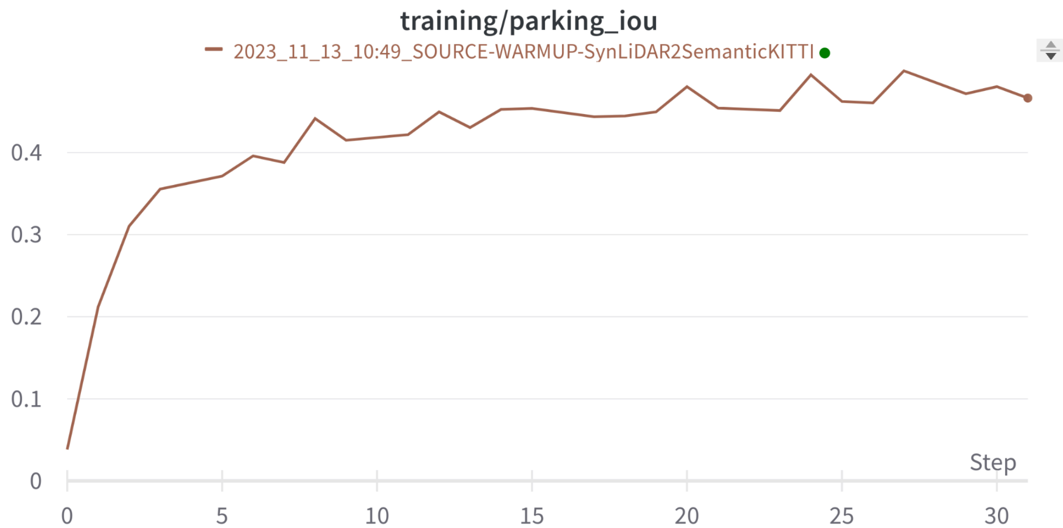
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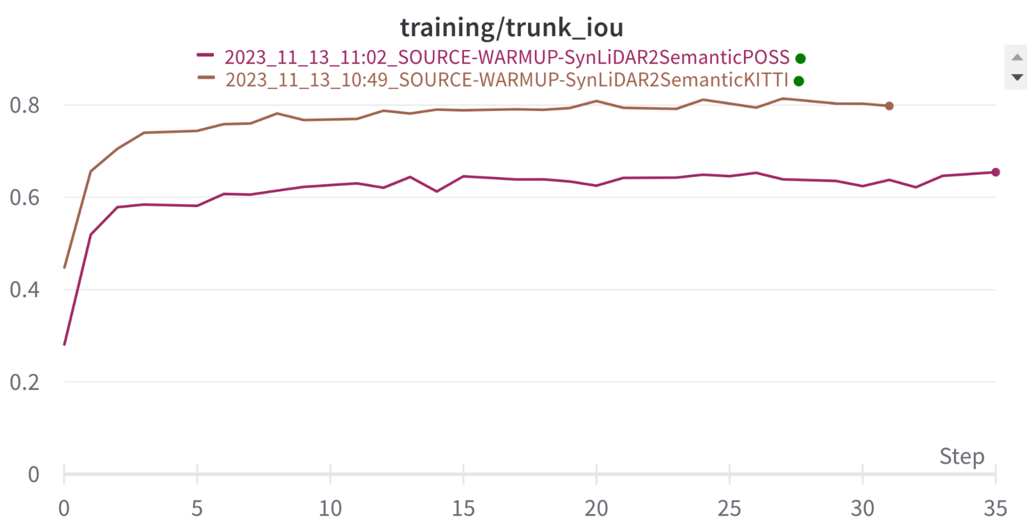
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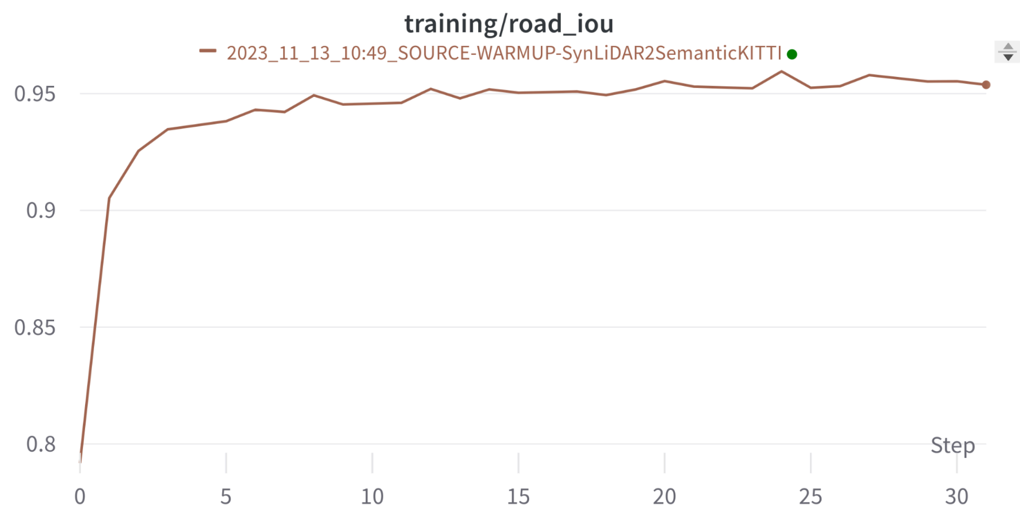
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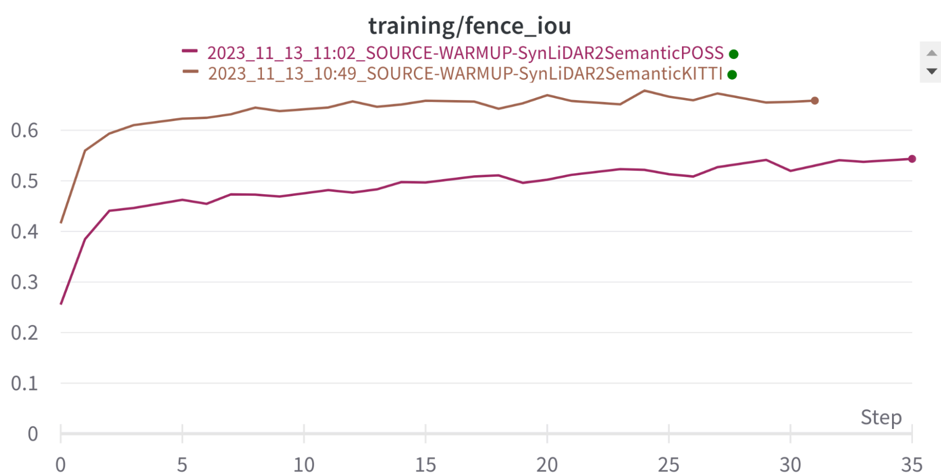
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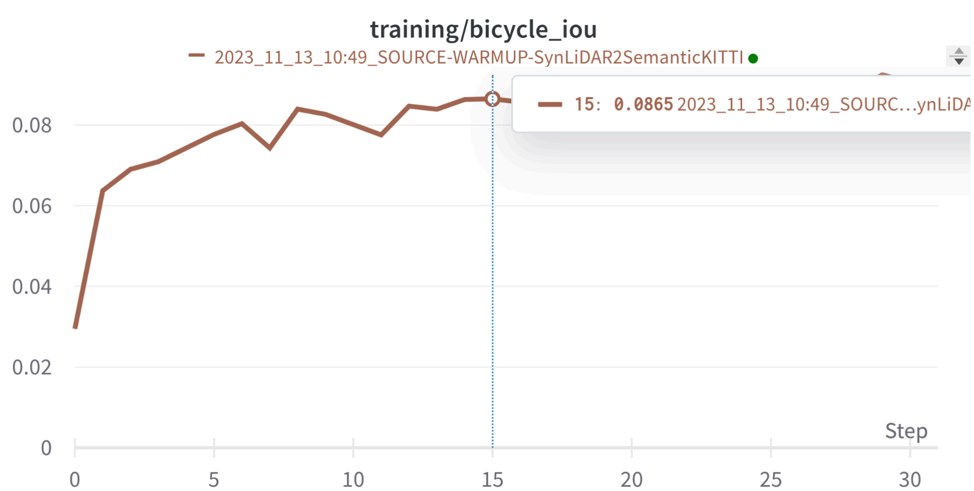
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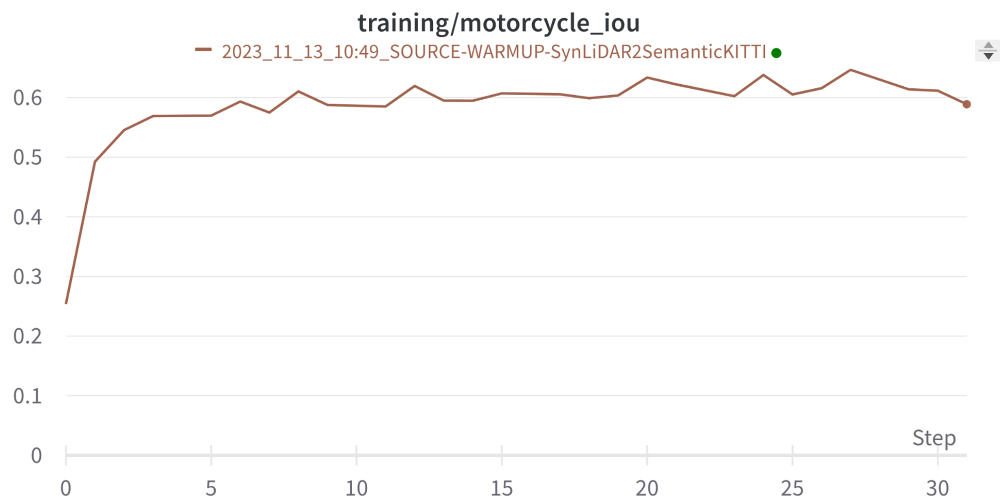
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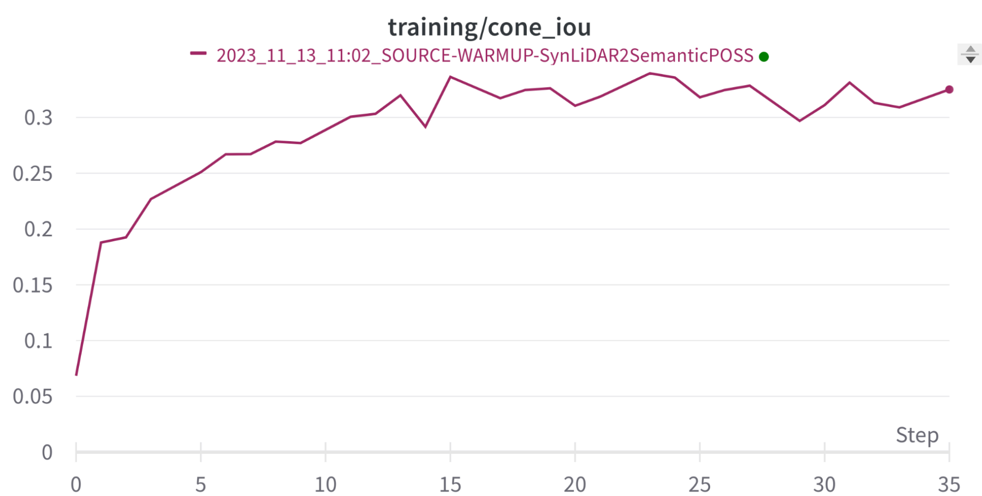
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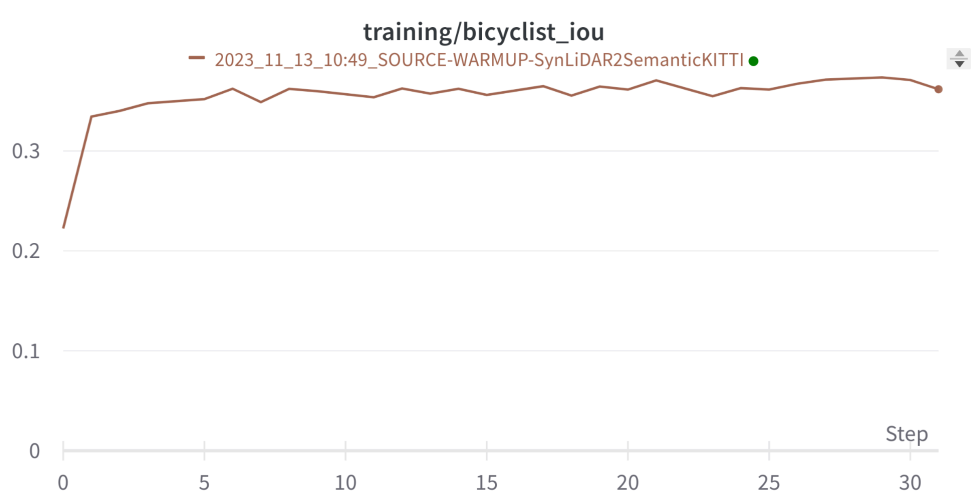
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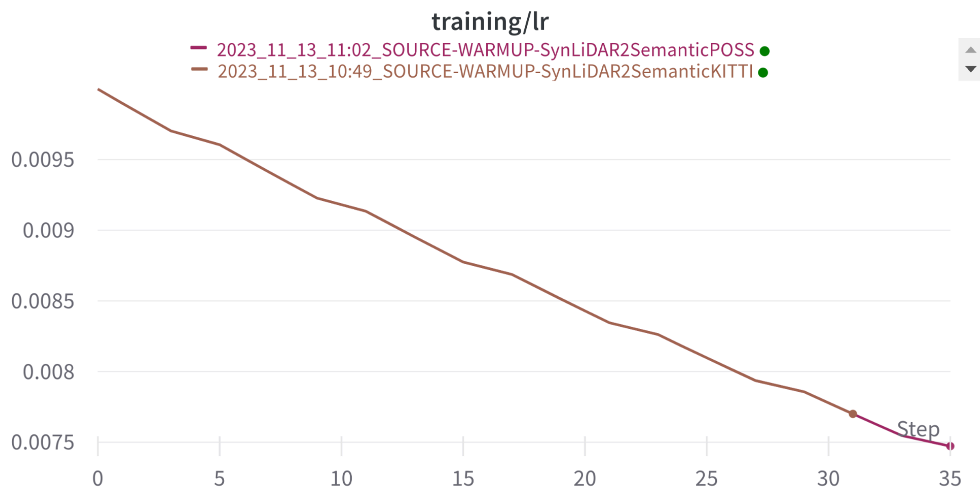
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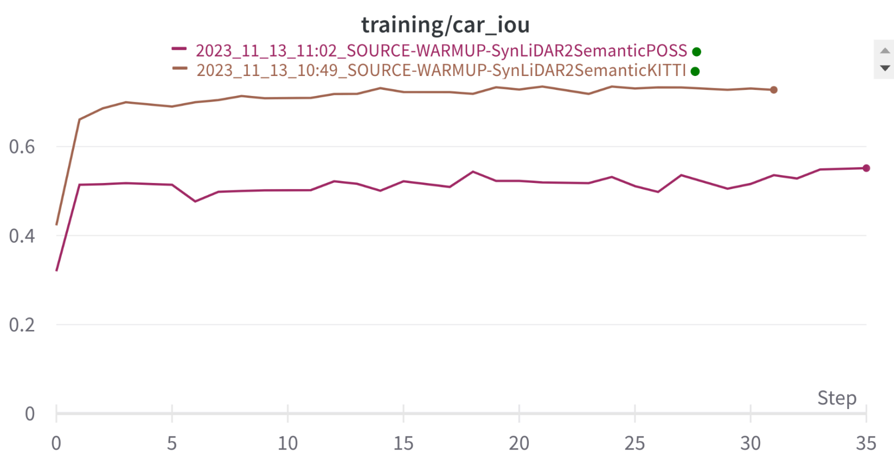
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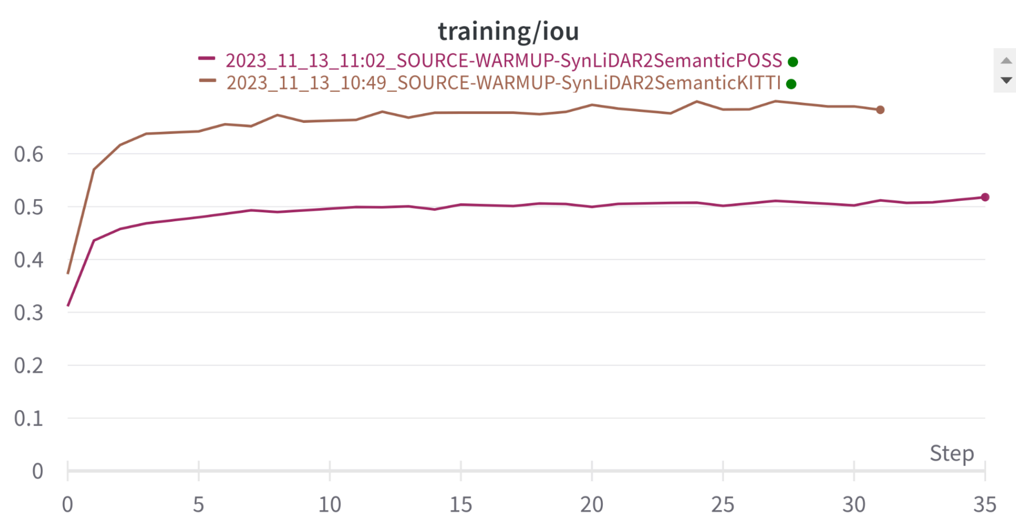
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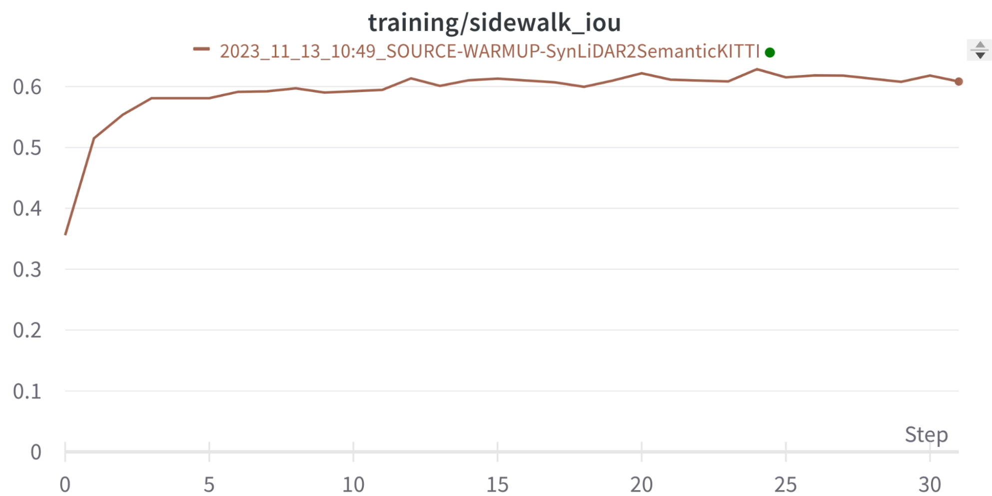
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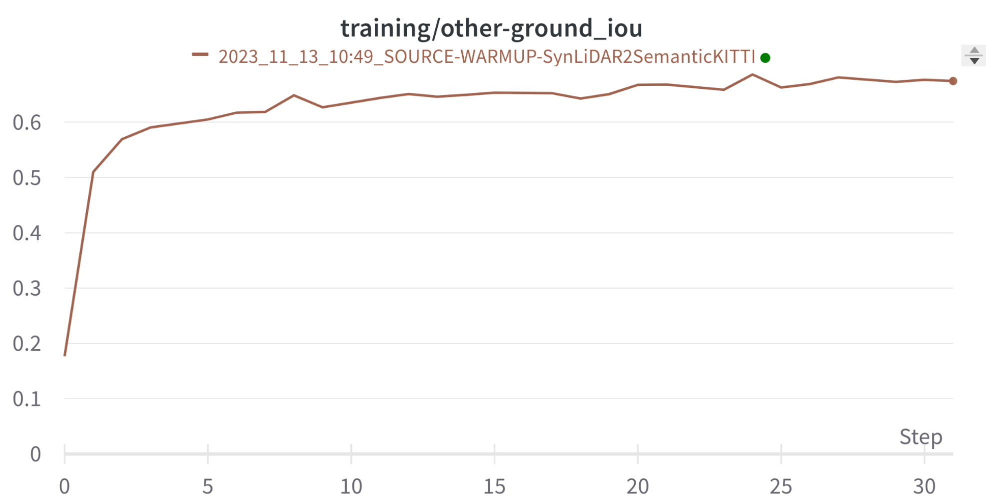
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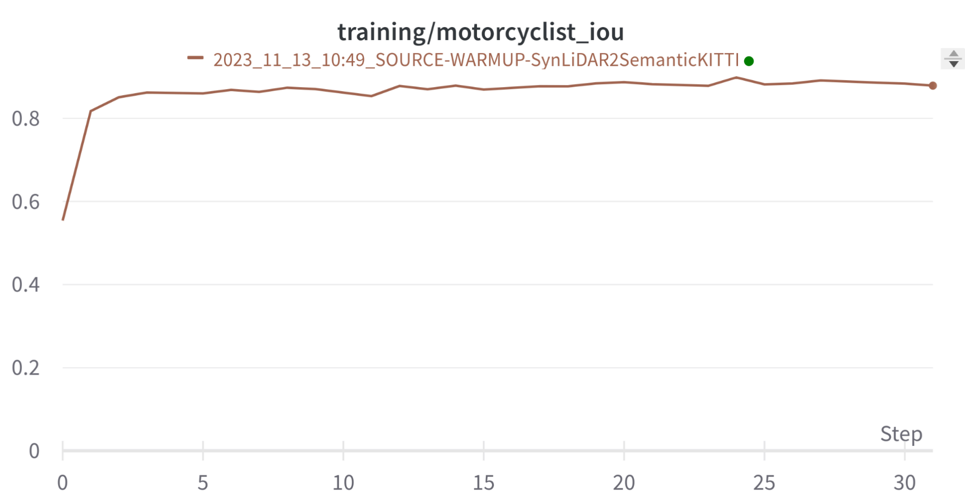
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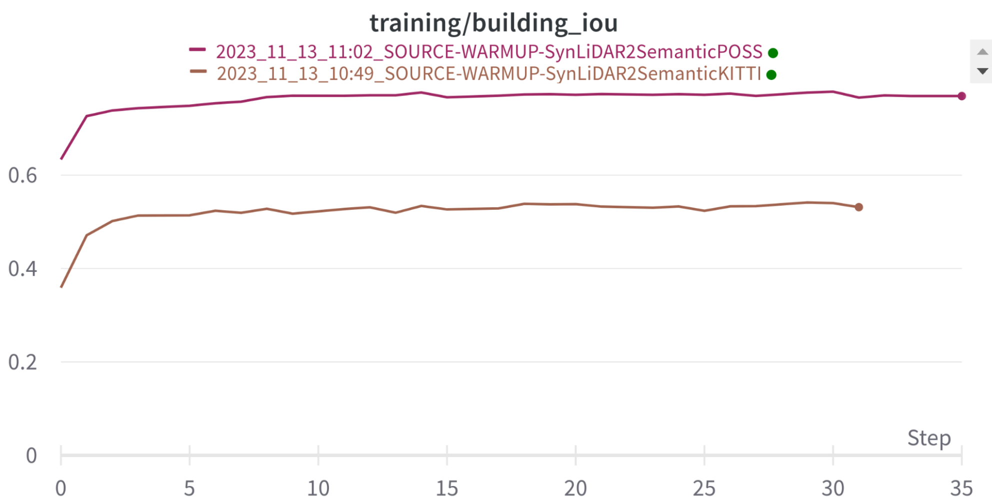
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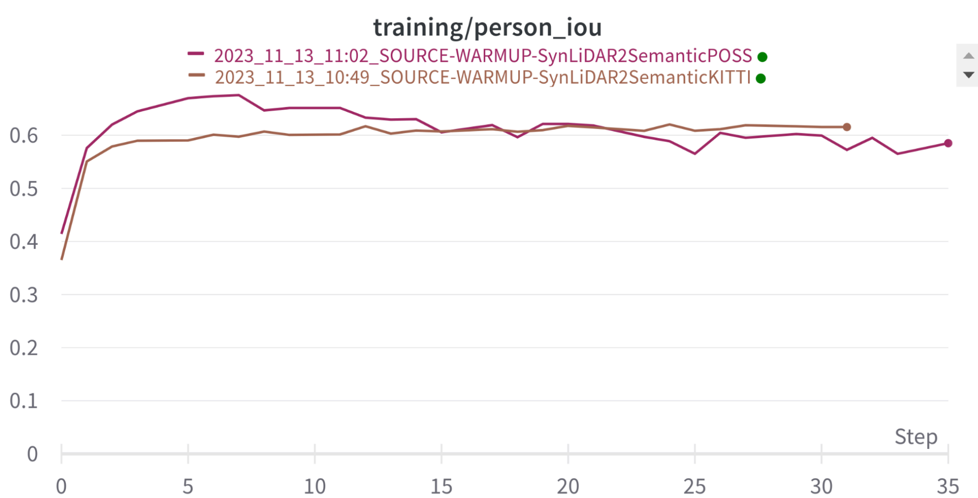
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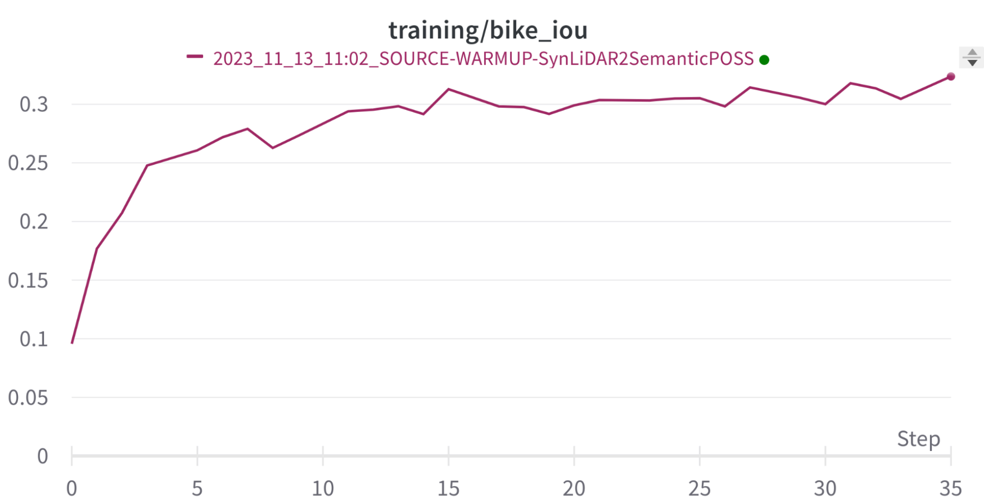
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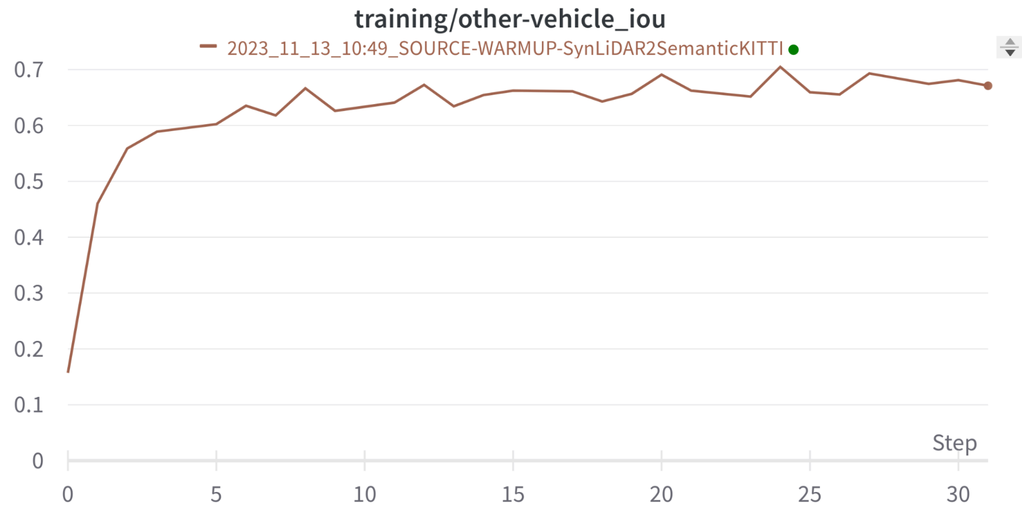

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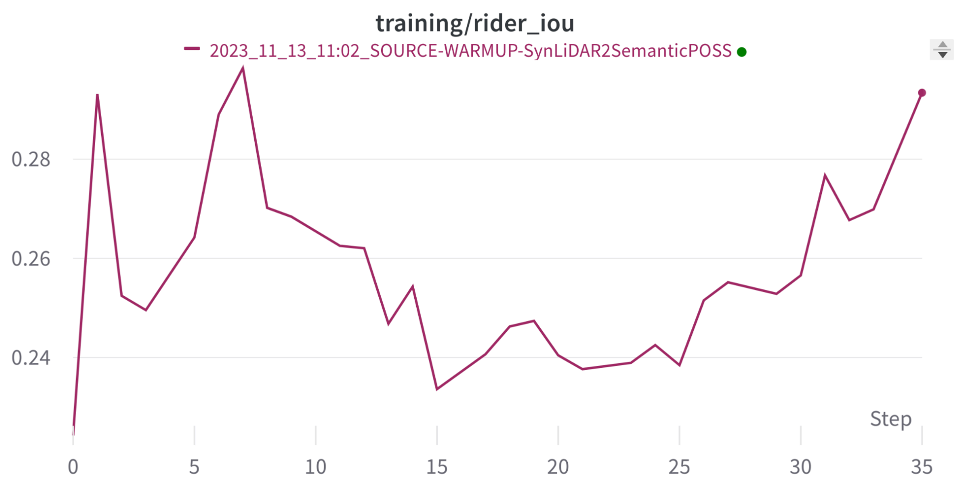

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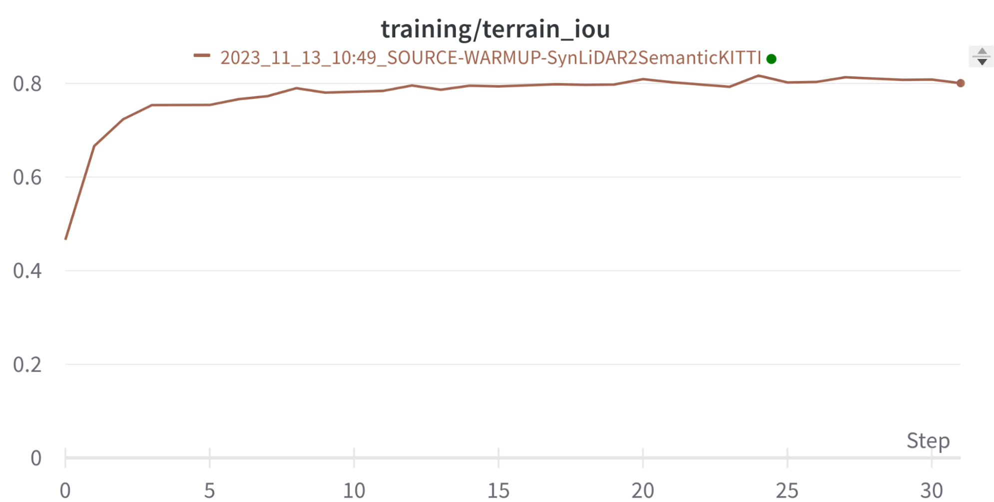

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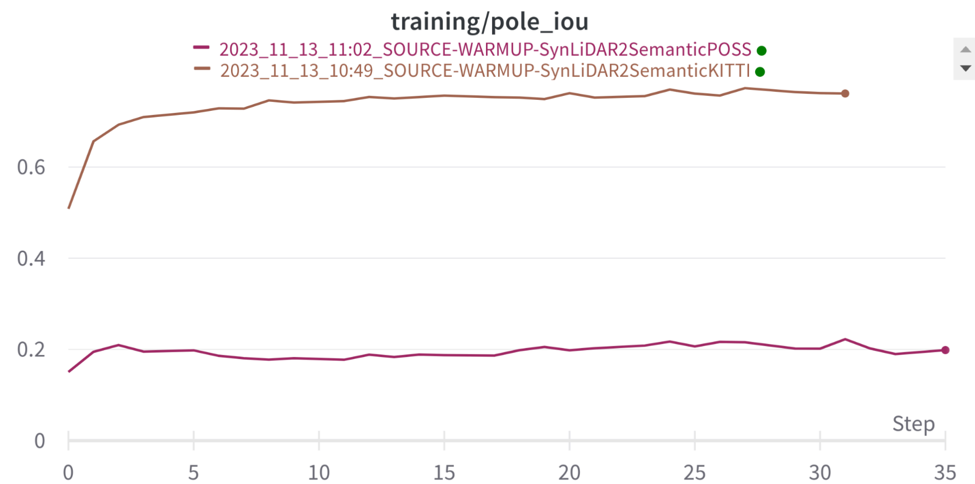

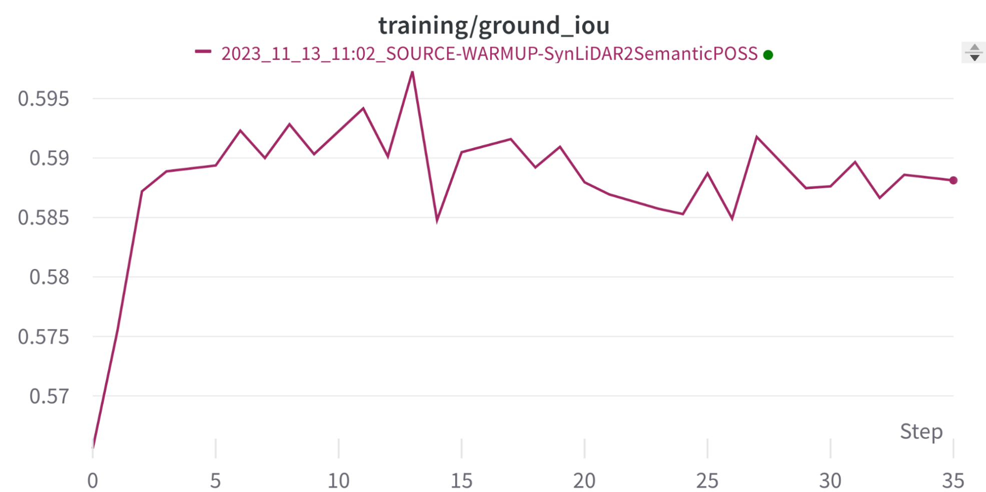

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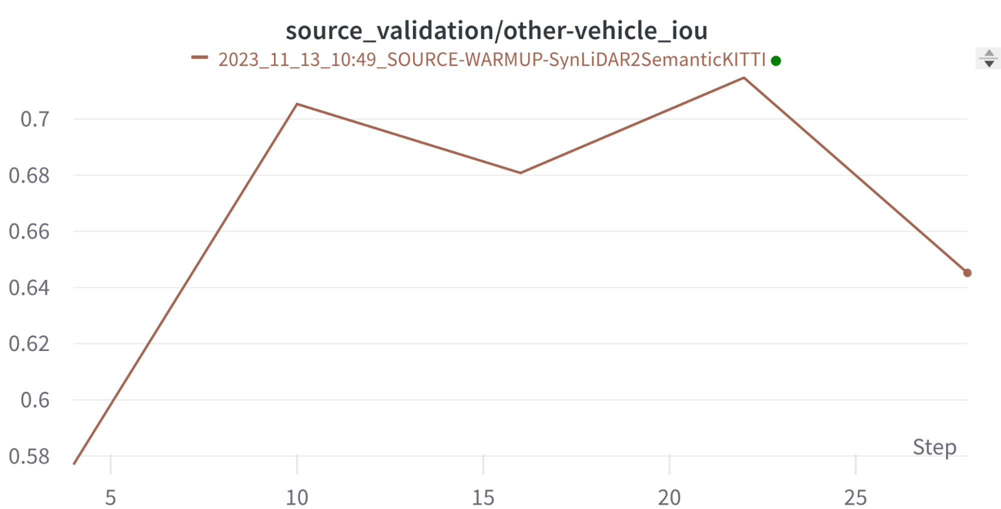

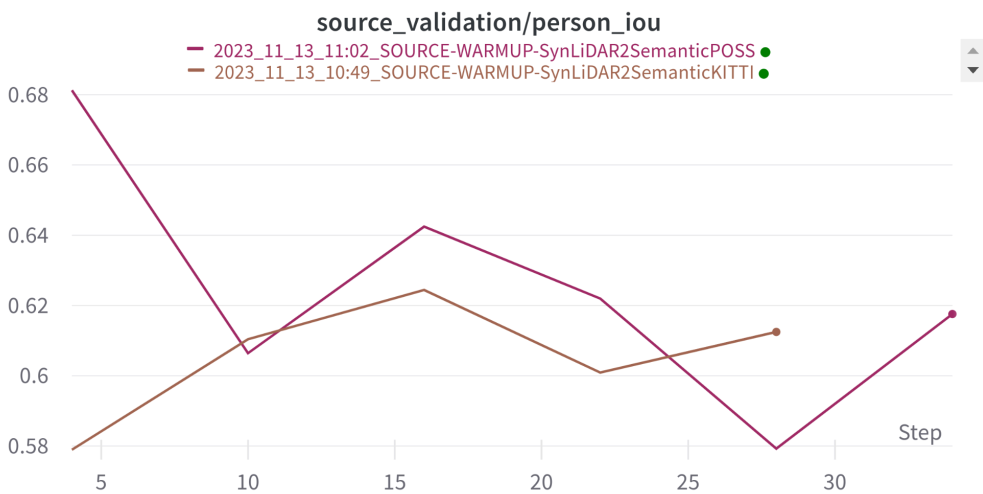

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25
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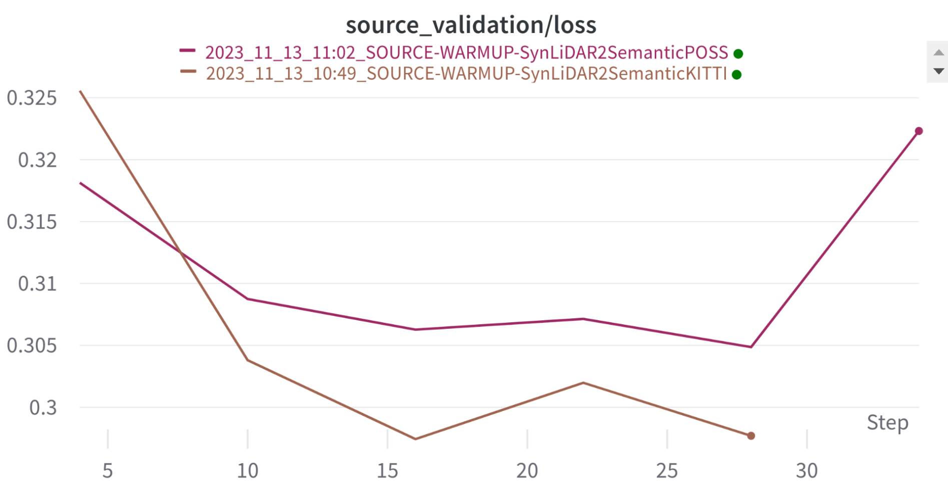
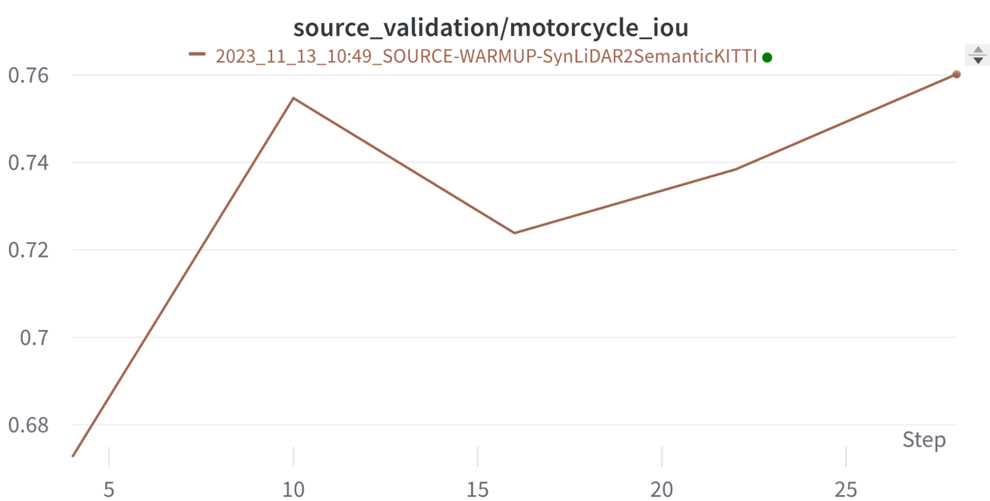
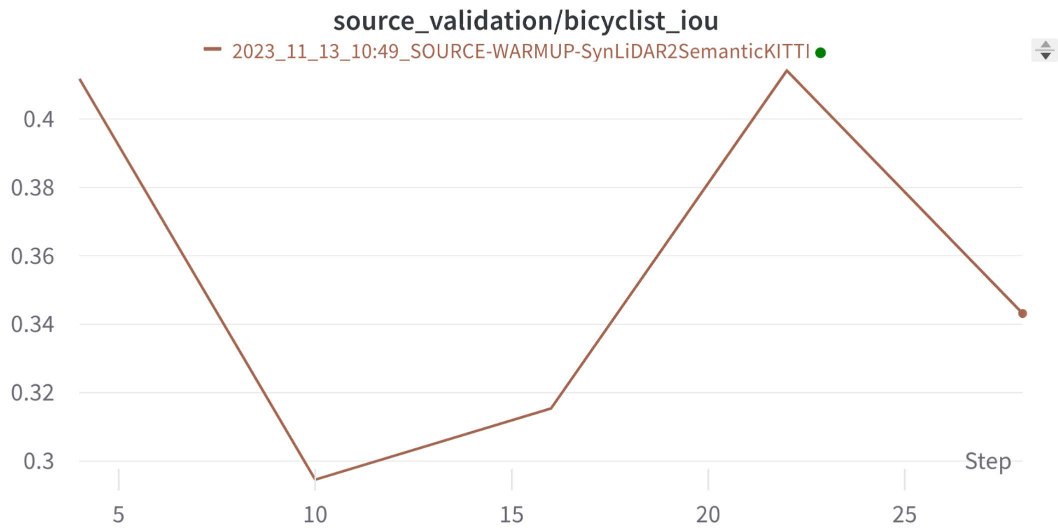
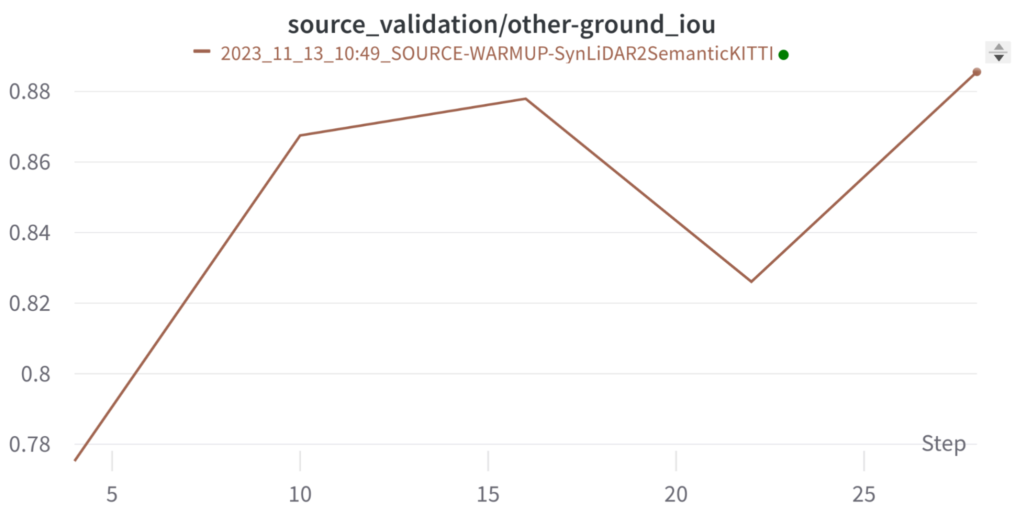


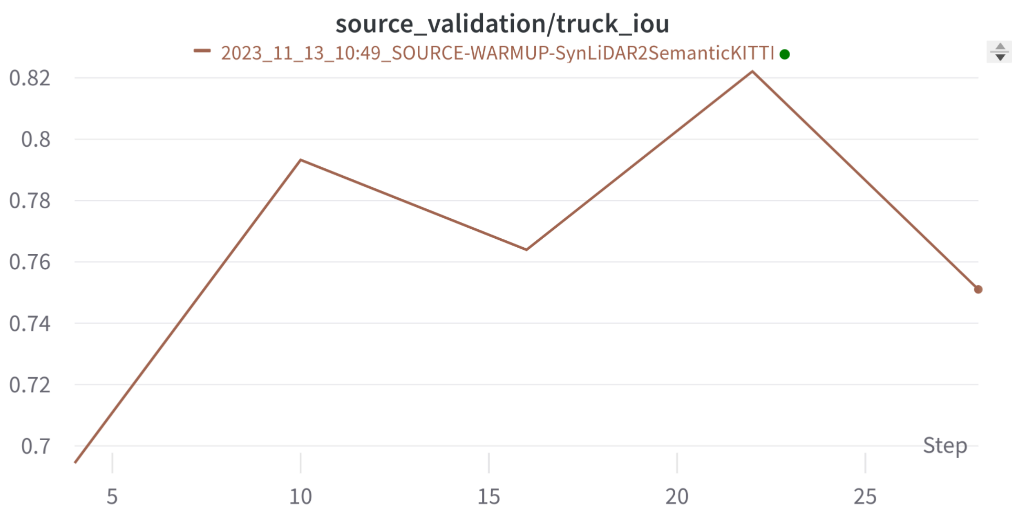
source_validation/loss
2023_11_13_11:02_SOURCE-WARMUP-SynLiDAR2SemanticPOSS
2023_11_13_10:49_SOURCE-WARMUP-SynLiDAR2SemanticKITTI
0.325
0.32
0.315
0.31
0.305
0.3
Step
5
10
15
20
25
30

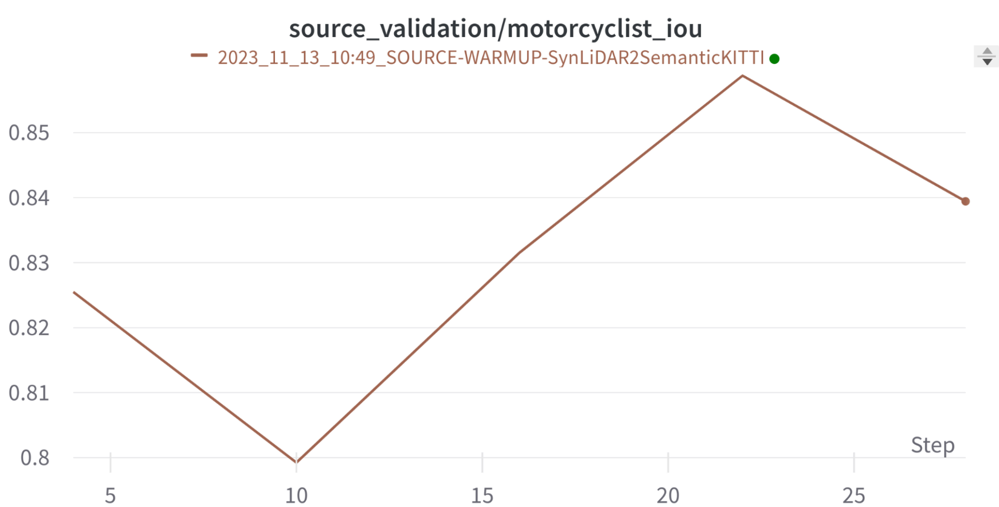


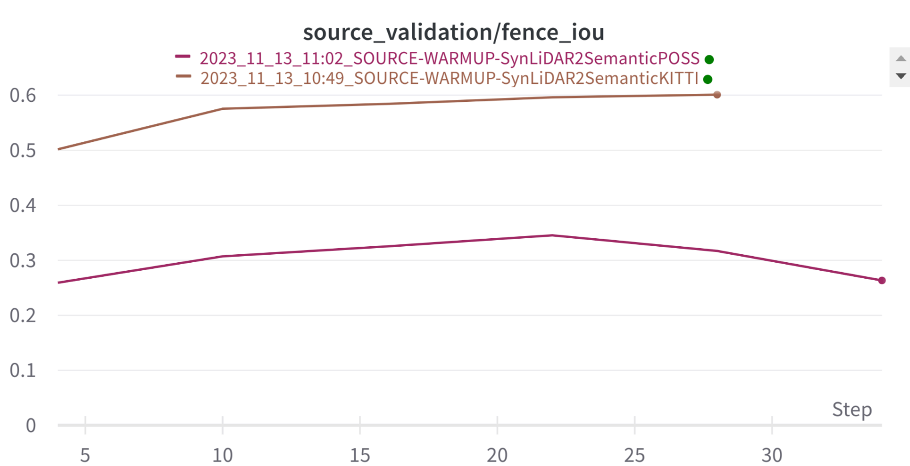
source_validation/motorcycle_iou
2023_11_13_10:49_SOURCE-WARMUP-SynLiDAR2SemanticKITTI
0.76
0.74
0.72
0.7
0.68
Step
5
10
15
20
25

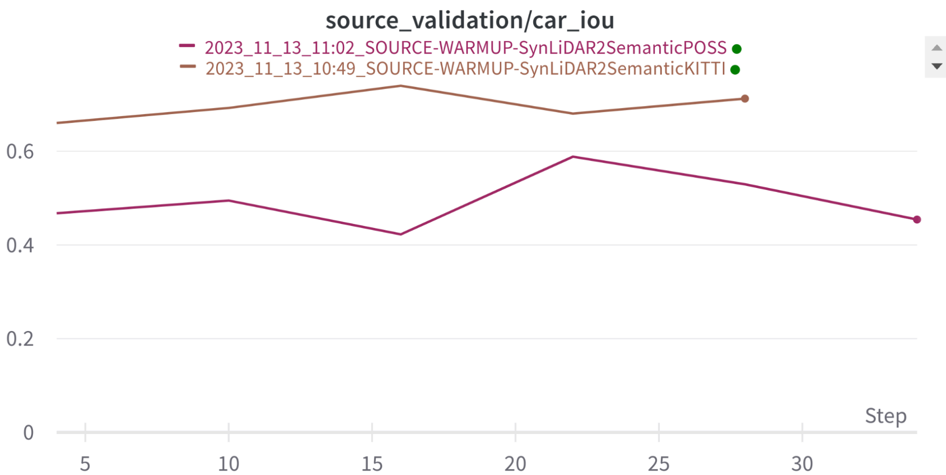

source_validation/bicyclist_iou
2023_11_13_10:49_SOURCE-WARMUP-SynLiDAR2SemanticKITTI
0.4
0.38
0.36
0.34
0.32
0.3
Step
5
10
15
20
25

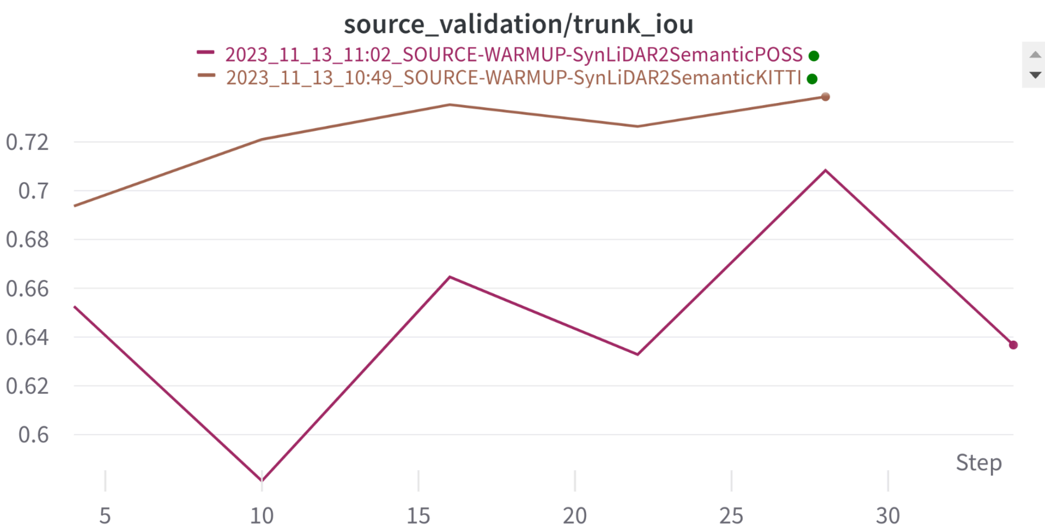

source_validation/other-ground_iou
2023_11_13_10:49_SOURCE-WARMUP-SynLiDAR2SemanticKITTI
0.88
0.86
0.84
0.82
0.8
0.78
Step
5
10
15
20
25

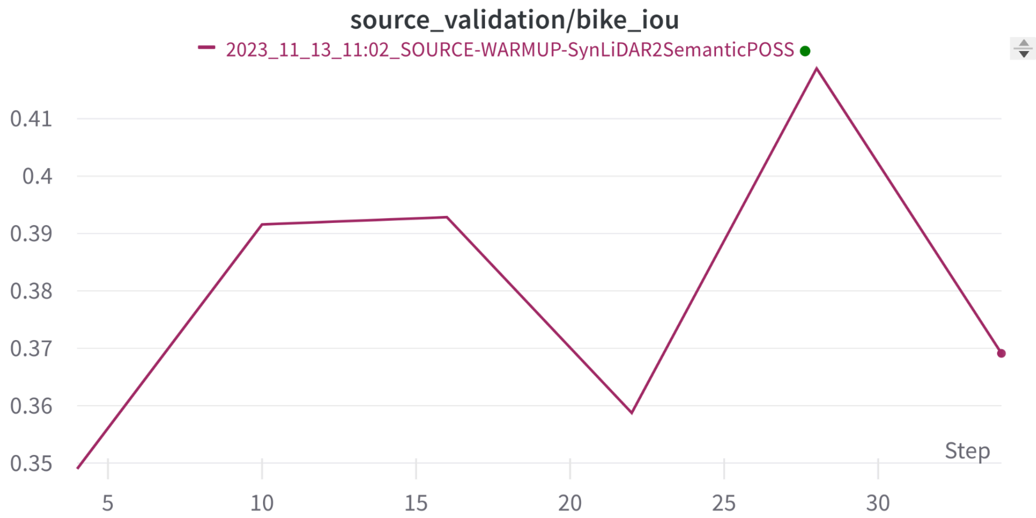

source_validation/truck_iou
2023_11_13_10:49_SOURCE-WARMUP-SynLiDAR2SemanticKITTI
0.82
0.8
0.78
0.76
0.74
0.72
0.7
Step
5
10
15
20
25

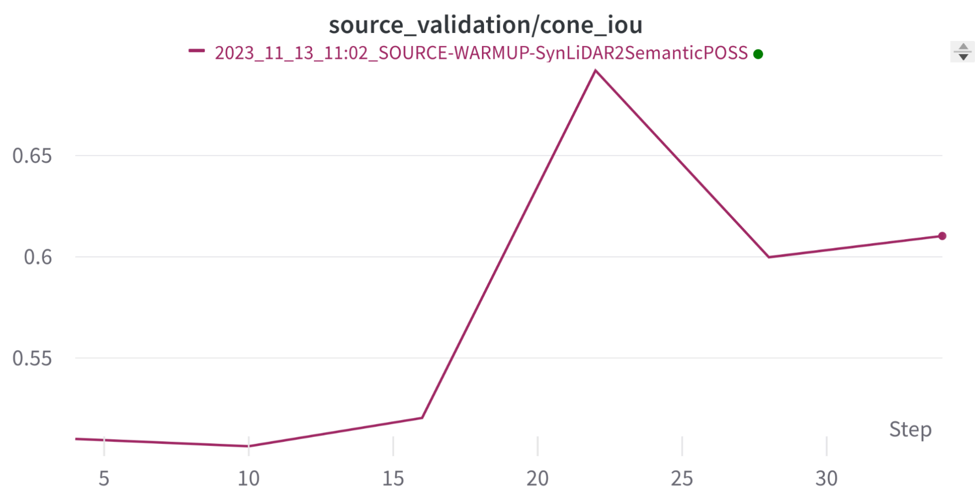

source_validation/motorcyclist_iou
2023_11_13_10:49_SOURCE-WARMUP-SynLiDAR2SemanticKITTI
0.85
0.84
0.83
0.82
0.81
0.8
Step
5
10
15
20
25

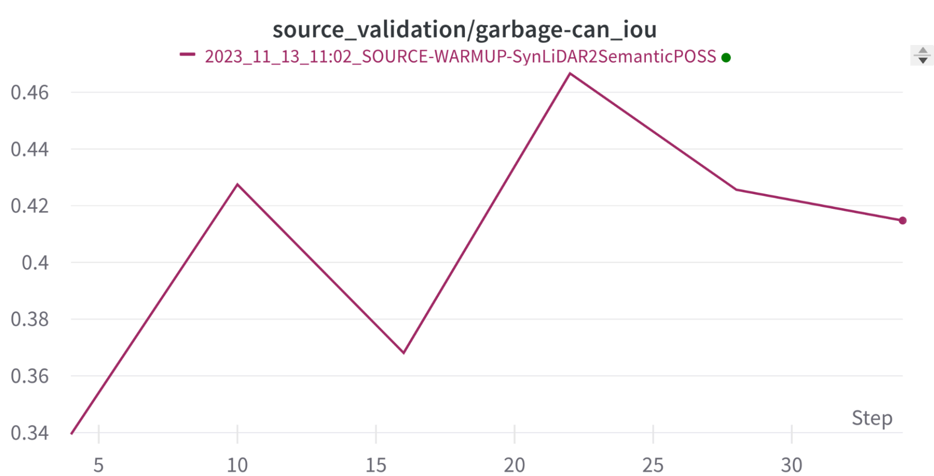

source_validation/fence_iou
2023_11_13_11:02_SOURCE-WARMUP-SynLiDAR2SemanticPOSS
2023_11_13_10:49_SOURCE-WARMUP-SynLiDAR2SemanticKITTI
0.6
0.5
0.4
0.3
0.2
0.1
0
Step
5
10
15
20
25
30

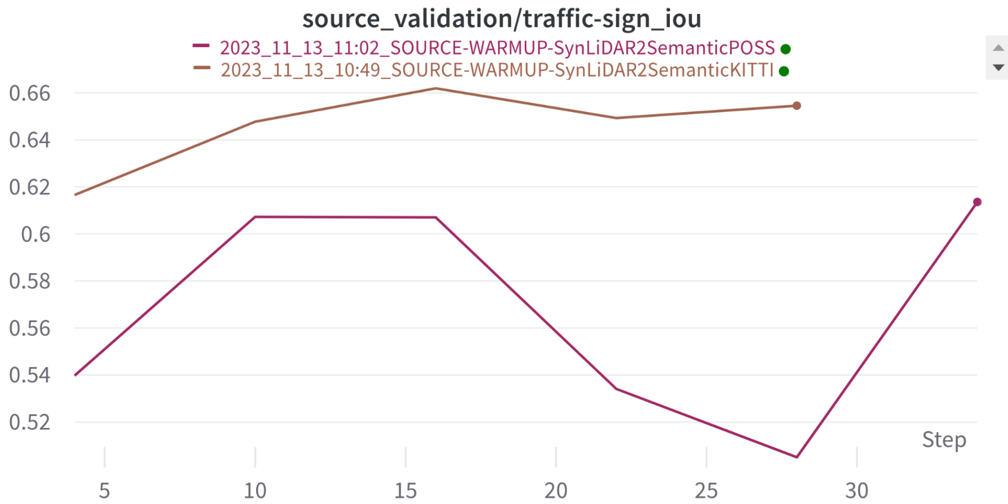

source_validation/car_iou
2023_11_13_11:02_SOURCE-WARMUP-SynLiDAR2SemanticPOSS
2023_11_13_10:49_SOURCE-WARMUP-SynLiDAR2SemanticKITTI
0.6
0.4
0.2
0
Step
5
10
15
20
25
30

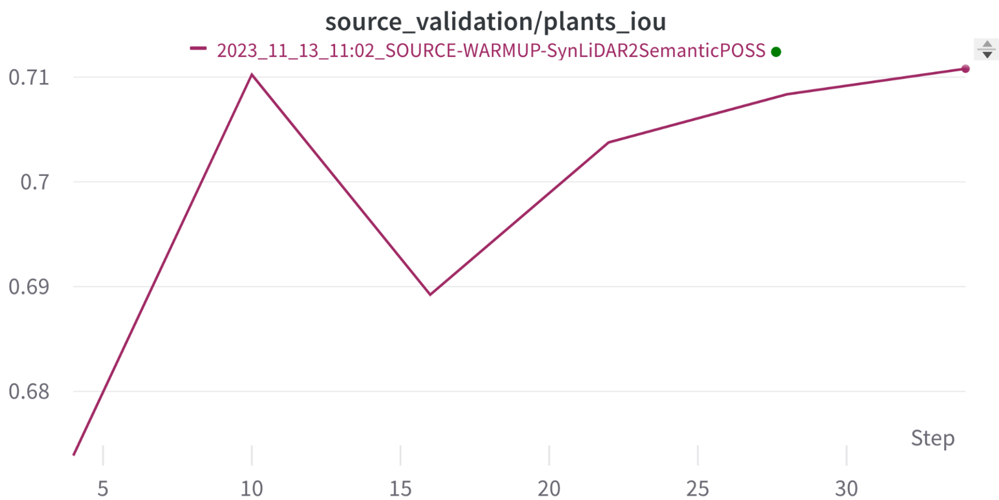

source_validation/trunk_iou
2023_11_13_11:02_SOURCE-WARMUP-SynLiDAR2SemanticPOSS
2023_11_13_10:49_SOURCE-WARMUP-SynLiDAR2SemanticKITTI
0.72
0.7
0.68
0.66
0.64
0.62
0.6
Step
5
10
15
20
25
30

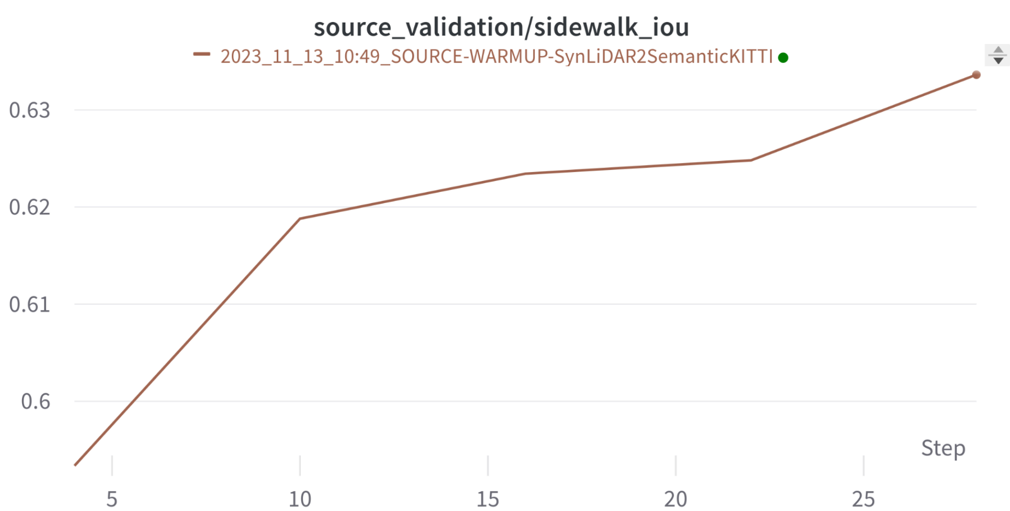

source_validation/bike_iou
2023_11_13_11:02_SOURCE-WARMUP-SynLiDAR2SemanticPOSS
0.41
0.4
0.39
0.38
0.37
0.36
0.35
Step
5
10
15
20
25
30

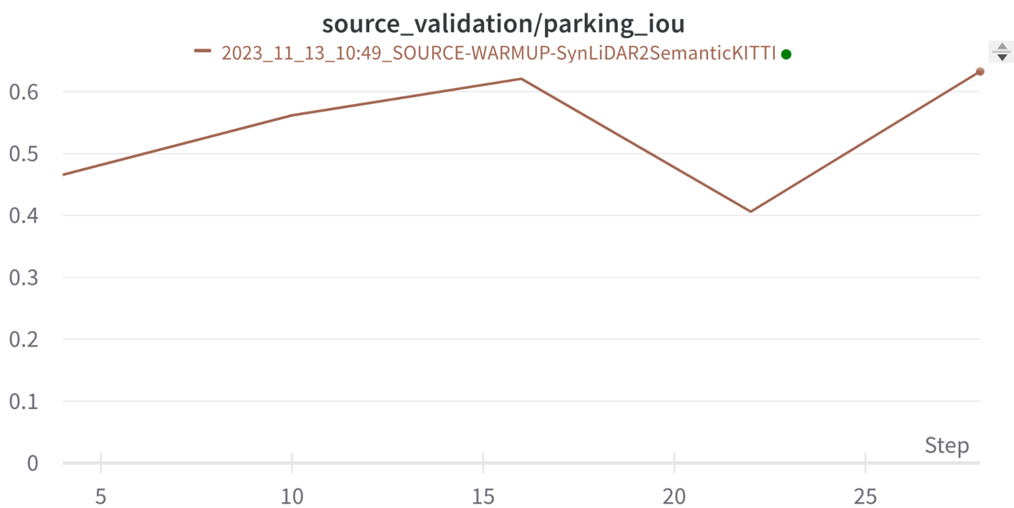

source_validation/cone_iou
2023_11_13_11:02_SOURCE-WARMUP-SynLiDAR2SemanticPOSS
0.65
0.6
0.55
Step
5
10
15
20
25
30


source_validation/garbage-can_iou
2023_11_13_11:02_SOURCE-WARMUP-SynLiDAR2SemanticPOSS
0.46
0.44
0.42
0.4
0.38
0.36
0.34
Step
5
10
15
20
25
30

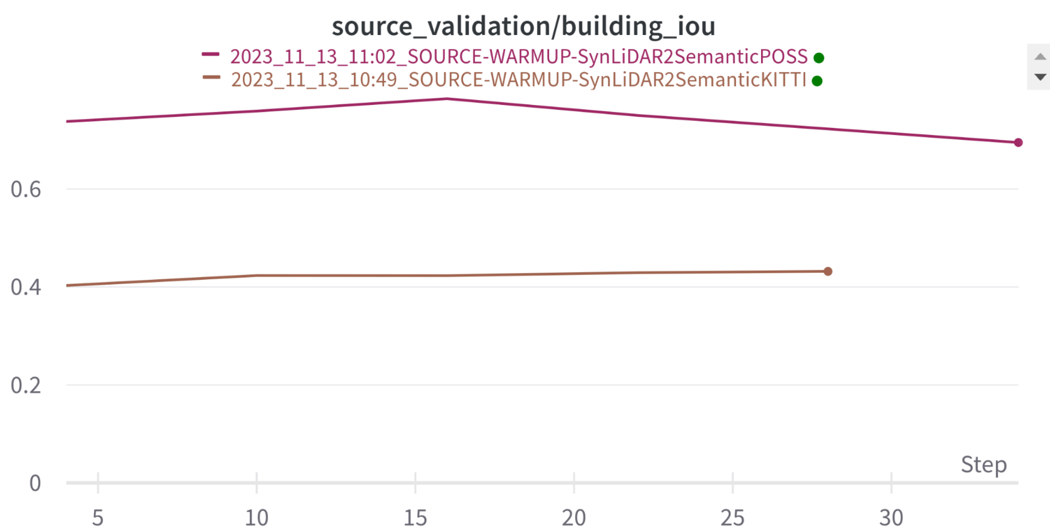

source_validation/traffic-sign_iou
2023_11_13_11:02_SOURCE-WARMUP-SynLiDAR2SemanticPOSS
2023_11_13_10:49_SOURCE-WARMUP-SynLiDAR2SemanticKITTI
0.66
0.64
0.62
0.6
0.58
0.56
0.54
0.52
Step
5
10
15
20
25
30


source_validation/plants_iou
2023_11_13_11:02_SOURCE-WARMUP-SynLiDAR2SemanticPOSS
0.71
0.7
0.69
0.68
Step
5
10
15
20
25
30

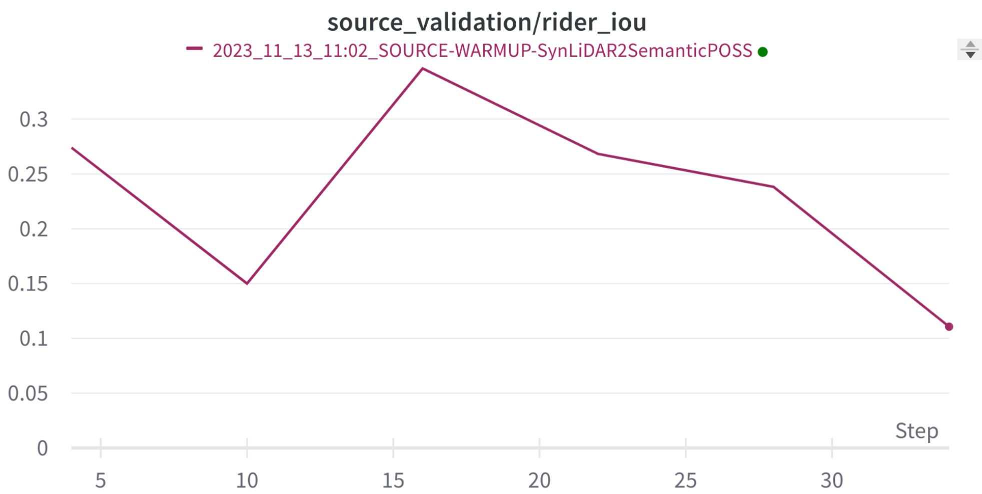

source_validation/sidewalk_iou
2023_11_13_10:49_SOURCE-WARMUP-SynLiDAR2SemanticKITTI
0.63
0.62
0.61
0.6
Step
5
10
15
20
25

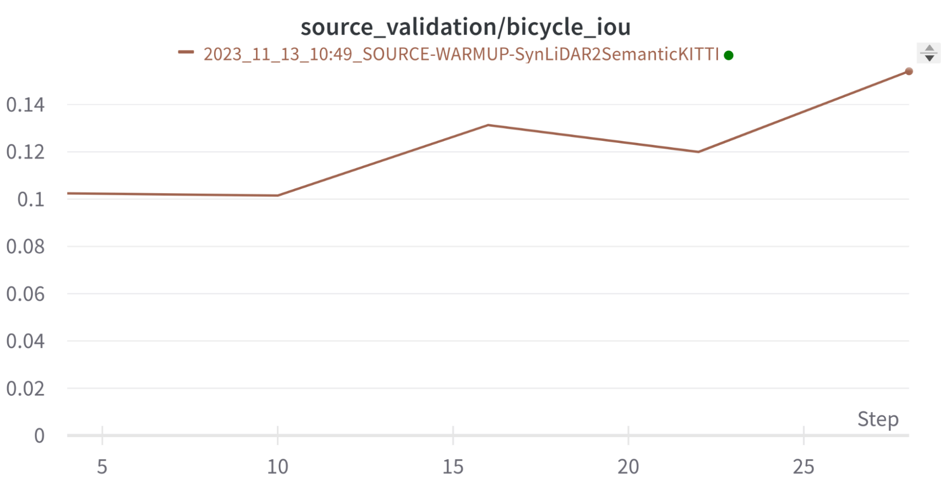


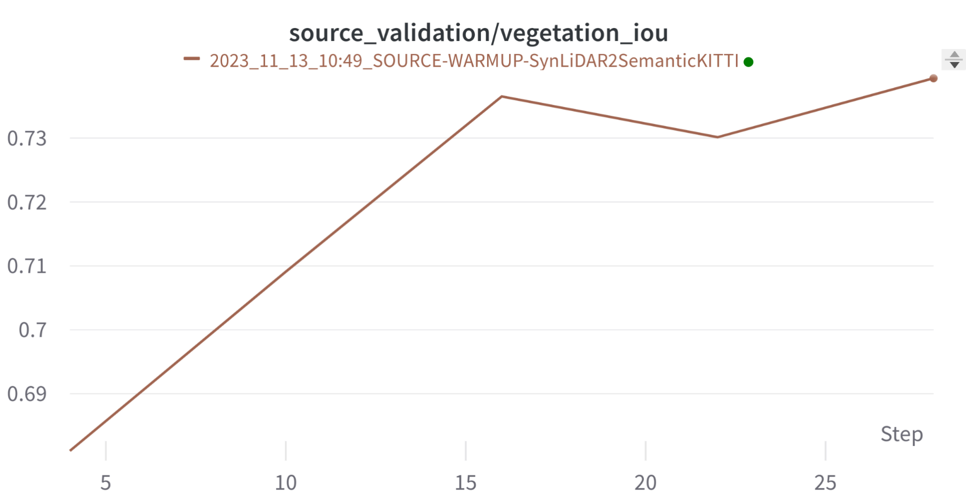
source_validation/parking_iou
2023_11_13_10:49_SOURCE-WARMUP-SynLiDAR2SemanticKITTI
0.6
0.5
0.4
0.3
0.2
0.1
0
Step
5
10
15
20
25

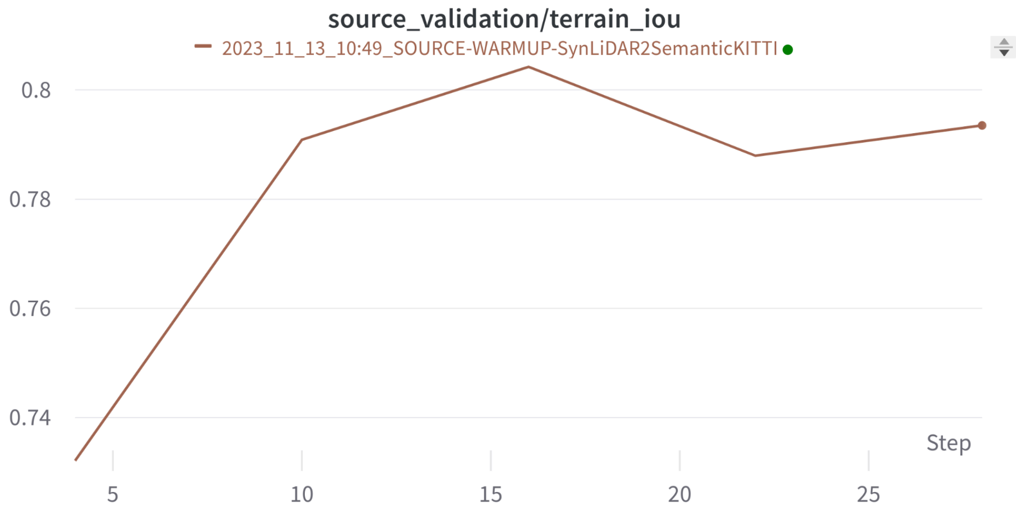


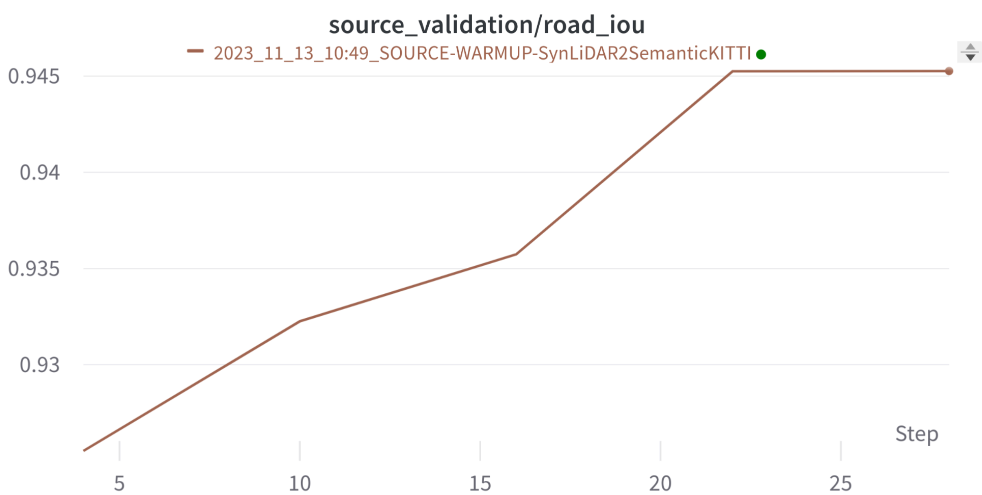
source_validation/building_iou
2023_11_13_11:02_SOURCE-WARMUP-SynLiDAR2SemanticPOSS
2023_11_13_10:49_SOURCE-WARMUP-SynLiDAR2SemanticKITTI
0.6
0.4
0.2
0
Step
5
10
15
20
25
30

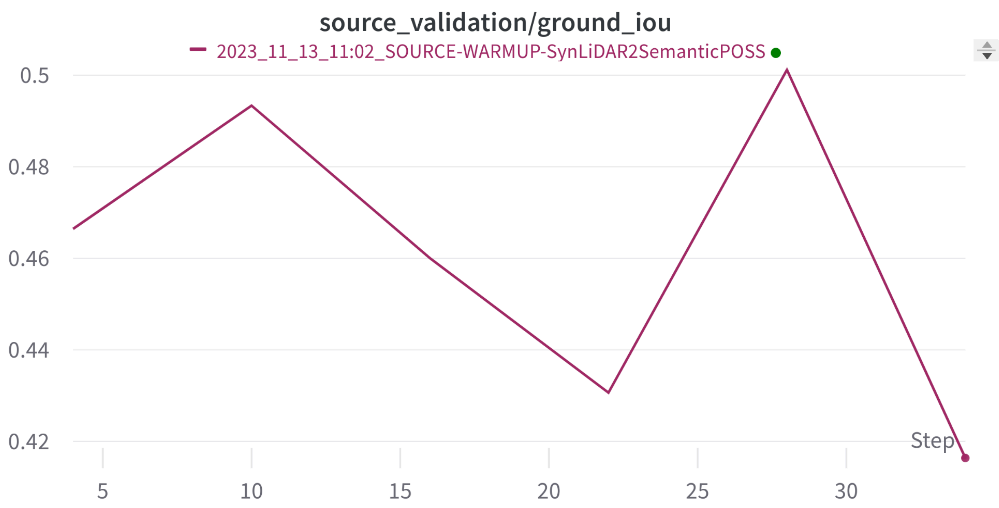

source_validation/rider_iou
2023_11_13_11:02_SOURCE-WARMUP-SynLiDAR2SemanticPOSS
0.3
0.25
0.2
0.15
0.1
0.05
0
Step
5
10
15
20
25
30

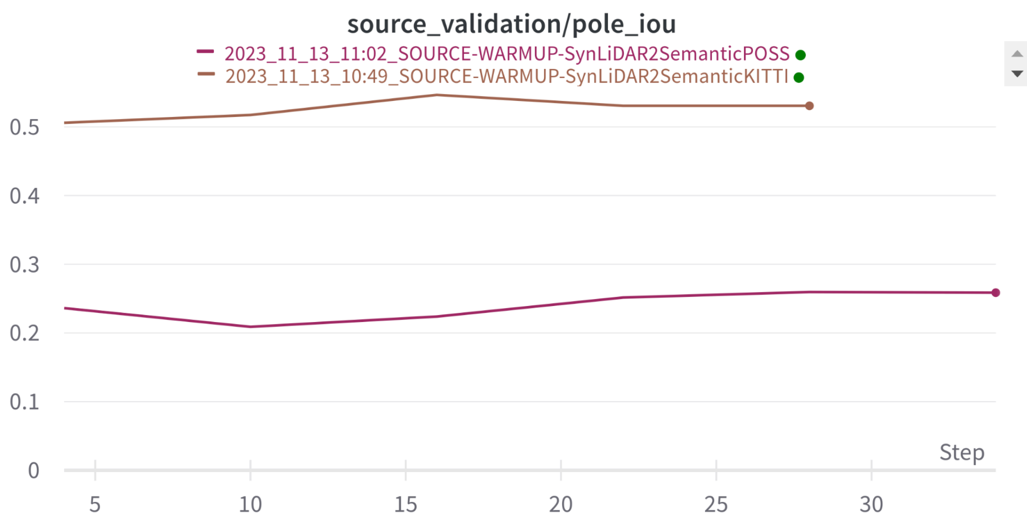

source_validation/bicycle_iou
2023_11_13_10:49_SOURCE-WARMUP-SynLiDAR2SemanticKITTI
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
Step
5
10
15
20
25


source_validation/vegetation_iou
2023_11_13_10:49_SOURCE-WARMUP-SynLiDAR2SemanticKITTI
0.73
0.72
0.71
0.7
0.69
Step
5
10
15
20
25


source_validation/terrain_iou
2023_11_13_10:49_SOURCE-WARMUP-SynLiDAR2SemanticKITTI
0.8
0.78
0.76
0.74
Step
5
10
15
20
25


source_validation/road_iou
2023_11_13_10:49_SOURCE-WARMUP-SynLiDAR2SemanticKITTI
0.945
0.94
0.935
0.93
Step
5
10
15
20
25





For synlidar2semantickitti

Evaluation:

1) epoch=14-step=74384_test.csv

iou,car,bicycle,motorcycle,truck,other-vehicle,person,bicyclist,motorcyclist,road,parking,sidewalk,other-ground,building,fence,vegetation,trunk,terrain,pole,traffic-sign

70.61327637319796,73.97735907413994,13.213684328744083,72.85524342511349,76.39424341512743,75.05121279557268,65.26919163341073,26.326153008166177,91.43499044737953,94.49686758679611,62.09408164833494,81.219543777787,87.79520903560962,90.57195231914314,66.51950747482424,83.83068550960948,77.9828759337149,76.92575881919429,57.93558612282163,67.75810473527181

2) epoch=19-step=99179_test.csv

Iou,car,bicycle,motorcycle,truck,other-vehicle,person,bicyclist,motorcyclist,road,parking,sidewalk,other-ground,building,fence,vegetation,trunk,terrain,pole,traffic-sign

69.57359581304934,68.02892985871513,12.080865793540328,74.29707995637354,82.21074115288336,78.76733087634396,62.32986944906135,38.06861690524372,93.47119653961713,94.6892784028762

1,40.62036682636694,82.09489033997464,82.60751789661927,90.6760034855973,67.230972003477,8
2.80229037919334,75.1031268689163,74.80924012303646,55.786331243522845,66.2236723465788

3) epoch=24-step=123974_test.csv

iou,car,bicycle,motorcycle,truck,other-vehicle,person,bicyclist,motorcyclist,road,parking,sidewalk,other-g
round,building,fence,vegetation,trunk,terrain,pole,traffic-sign
70.85144566287266,71.23227271563796,15.511730112037142,76.46946684625854,75.1030484771688
5,71.13675567071247,64.20383466454803,29.622199881880345,92.25337446460134,95.226521591246
03,63.285848500340414,82.93769040159806,88.55796998657638,90.79385449495389,69.48713300335
704,83.22906131877703,76.3228251630013,74.38400014091904,57.048672944089404,69.37120721687
734

4) epoch=29-step=148769_test.csv

iou,car,bicycle,motorcycle,truck,other-vehicle,person,bicyclist,motorcyclist,road,parking,sidewalk,other-g
round,building,fence,vegetation,trunk,terrain,pole,traffic-sign
69.88752631586758,71.89974670988516,16.491484143538397,80.3424758408153,81.65251853589336,
78.54453397879047,61.593461036469456,0.0016008071871676166,89.32536509620421,95.175791767
68487,65.23808552946963,83.20735681769501,86.58650554092729,91.18037075626818,68.690947462
35717,85.21404273004956,69.96859112230979,76.13431475570495,59.8060869452855,66.8097204249
4841

5) epoch=34-step=173564_test.csv

iou,car,bicycle,motorcycle,truck,other-vehicle,person,bicyclist,motorcyclist,road,parking,sidewalk,other-g
round,building,fence,vegetation,trunk,terrain,pole,traffic-sign
68.14117273467241,70.4229534878484,14.880608675620849,75.84330539715872,77.95248886600973,
76.87466378648676,61.994629417176796,0.0012048848294175412,91.6078830230071,94.8516620612
147,55.42722491545442,81.44463996799925,84.85383331742243,90.67060450604791,65.34207530756
406,84.38273959527575,75.62337240163833,77.51379225169495,54.21372535116179,60.78087474516
454

6) epoch=4-step=24794_test.csv

iou,car,bicycle,motorcycle,truck,other-vehicle,person,bicyclist,motorcyclist,road,parking,sidewalk,other-g
round,building,fence,vegetation,trunk,terrain,pole,traffic-sign
65.04381891044837,66.037577378053,10.328237181279503,67.69848351245835,69.4419543122493,63
.66719837940007,61.070678393541776,37.323757067530444,90.49660096824927,92.69179704393966,
46.56844565100579,75.23533339631075,77.52518985199703,88.42586495844674,54.12724167584329,
80.89866539756126,69.17171390026445,72.43050854605939,52.093745811977264,60.5995658723515
05

7) epoch\=9-step\=49589_test.csv

iou,car,bicycle,motorcycle,truck,other-vehicle,person,bicyclist,motorcyclist,road,parking,sidewalk,other-g
round,building,fence,vegetation,trunk,terrain,pole,traffic-sign
69.14226881084787,69.23661384080914,10.222689138587342,75.93653424033197,79.3242638110453
3,77.52555902692937,63.563479091125764,23.078427203561784,89.42487504113109,94.36519362163
783,56.18466432003262,80.48804183875514,86.75248794174782,90.0185483834586,65.158446621111
28,80.97771844831453,74.04710211643274,75.33784510271879,55.903860376974265,66.15675724140
398

Predictions:

Can be visualized using cloud compare

- **Adaptation on Kerala Dataset**

Approach 1: Comprehensive Point-by-Point Dictionary Storage

One strategy involves consolidating the entire dataset point-by-point into a single dictionary and saving it to disk for subsequent use in the data loader. However, this approach faces significant challenges. The dataset's sheer size prevents it from being accommodated entirely in memory, and iterating through the dataset point-by-point proves to be time-consuming.

Approach 2: CSV-Backed Dictionary with Associated Labels

An alternative method entails constructing a dictionary for the dataset, where each entry is a CSV file accompanied by a corresponding label list. This organized dictionary is then stored on disk for utilization within the data loader. This approach aims to overcome the memory limitations associated with Approach 1 while providing a structured and efficient means of dataset access.

By adopting Approach 2, the dataset is logically partitioned, allowing for more manageable storage and retrieval. This structured approach not only enhances the data loading process but also offers a more systematic way to handle the diverse characteristics of SemanticKITTI, SynLidar, and the Kerala dataset.

7. Conclusion:

The successful implementation of CoSMix with the dataset signifies a significant breakthrough in addressing the challenge of domain shift in 3D LiDAR segmentation. Its robust performance in adapting to real-world scenarios and delivering accurate segmentations underscores its potential as a pioneering methodology in this field.

8. Contribution :

Mayur:

Mayur is tasked with initiating the project by writing the initial code. His responsibilities include setting up the foundational codebase and establishing the groundwork for the creation of a data loader specifically tailored for the Kerala dataset.

Mohit:

Mohit is responsible for the preprocessing and loading of the Kerala dataset. This involves handling any data transformations, cleaning, and organizing necessary for the subsequent stages. Additionally, he will contribute to the creation of the data-loader, ensuring seamless integration with the preprocessed data.

Anushka:

Anushka's role focuses on the documentation and report creation. She will compile detailed documentation on the codebase, including explanations of data preprocessing steps, dataloader functionalities, and any key decisions made during the process. Anushka's contributions will facilitate a clear understanding of the project, aiding future development and troubleshooting.