Semantic Interpretation and Validation of Graph Attention-based Explanations for GNN Models

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Abstract-In this work, we propose a methodology for investigating the use of semantic attention to enhance the explainability of Graph Neural Network (GNN)-based models. Graph Deep Learning (GDL) has emerged as a promising field for tasks like scene interpretation, leveraging flexible graph structures to concisely describe complex features and relationships. As traditional explainability methods used in eXplainable AI (XAI) cannot be directly applied to such structures, graph-specific approaches are introduced. Attention has been previously employed to estimate the importance of input features in GDL, however, the fidelity of this method in generating accurate and consistent explanations has been questioned. To evaluate the validity of using attention weights as feature importance indicators, we introduce semantically-informed perturbations and correlate predicted attention weights with the accuracy of the model. Our work extends existing attentionbased graph explainability methods by analysing the divergence in the attention distributions in relation to semantically sorted feature sets and the behaviour of a GNN model, efficiently estimating feature importance. We apply our methodology on a lidar pointcloud estimation model successfully identifying key semantic classes that contribute to enhanced performance, effectively generating reliable post-hoc semantic explanations.

Index Terms—Attention, eXplanable AI, graph neural networks, pose estimation

I. INTRODUCTION

Trustworthy Graph Learning (TwGL) identifies reliability, explainability, accountability, and other trust-oriented features as key requirements for trustworthy Graph Deep Learning (GDL) [1], [2]. Undeniably, trust is a critical design factor for the successful development and deployment of autonomous vehicles. Trust and explainability are inherently linked. Explaining the decisions of autonomous vehicles enables users and regulatory bodies to use and work on transparent and accountable systems. Further, having a clear understanding of the capabilities and limitations of an autonomous system increases trust in the underlying technology and fosters its adoption.

In real-world deployment, autonomous vehicles are required to navigate safely in unknown and dynamic environments. To ensure safe operation, the system must effectively assess the complexity of traffic scenes and make logical decisions based on its anticipated performance. A critical prior requirement for reliable decision-making is for those vehicles to know their precise location relative to their observed surroundings. This relates to the task of *pose estimation*, which calculates the position of the ego-vehicle w.r.t. the perceived environmental features.

Our proposed research focuses on analysing and explaining the complexity of the environment using learned attention weights to identify the contribution of each semantic element, i.e. static and dynamic agents and morphological structures, to the performance of a baseline lidar pointcloud-based pose estimation model. Similar to [3], we take inspiration from perturbation-based Graph eXplainable AI (GXAI) methods to investigate the validity of using attention weights as feature-importance indicators. In our work, we extract semantic sets and rank them based on their attention scores. We conclude on their importance in the pose estimation task by verifying the correlation between attention weights and model accuracy. We semantically perturb the input and, as proposed in [4], [5], [6], we measure the distribution divergence to calculate the contribution of each set's attention weights to the overall attention distribution.

Our key contributions are as follows:

- A methodology for assigning importance scores to semantic sets based on their contribution to the performance of a Graph Neural Network (GNN) model;
- A semantic interpretation of learned attention weights in correlation with the predictions of a graph-based model;
- A semantically-informed perturbation process for evaluating the explanations for GXAI.

The model used as our baseline is a graph-attention-based pose estimation model, SEM-GAT [7], trained on the KITTI Odometry Dataset [8]. Our method examines the interpretability of the model w.r.t. its output predictions, eventually assessing its efficacy in real-world applications.

II. RELATED WORK

Recent studies have investigated the topic of explainability in GNNs proposing different approaches to explain their predictions. Following the taxonomy for instance-level explanations introduced in [9], these methods can be categorised into gradient/feature-, decomposition-, surrogate-, and perturbation-based.

Gradient/feature-based methods [10], [11] calculate the gradients of the output with respect to the extracted features in the input via backpropagation and use them to estimate

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Fig. 1: Overview of our proposed methodology. After retrieving the attention weights for each semantic class from vanilla SEM-GAT, we use a node mask to perturb the model's input by masking the highest-ranking semantic class set to measure the divergence in the distribution of the attention weights. We correlate this measurement with the pose estimation error from masked SEM-GAT to estimate importance scores for each semantic set. We repeat this process by masking the last layer of the model using an *edge mask*.

attribution scores. Decomposition-based methods [11], [12], [13] estimate the importance scores by expanding the network inference blocks into a sum of effects and identifying structures that contribute to the prediction. Surrogate-based methods [14], [15], [16] use simpler, interpretable models to approximate explanations on the original ones. Perturbationbased methods [17], [18], [19], [20], [21], [22] measure importance scores by iteratively masking the input and calculating the changes in the output predictions, generating post-hoc explanations. Perturbation-based methods are the most relevant to our approach. Whereas these methods rely on random masks to perturb the input, we argue for more effective and concise perturbations by conditioning the masks on the input. Specifically, our proposed methodology generates semantics-driven masks to perturb the input of a GNN model and generate explanations for its output predictions.

Attention has been employed to interpret how input features influence the predictions of deep learning models [23], [24], [25]. However, these holistic explanations have previously been regarded as insufficient and inaccurate [5], [26]. Later studies [4], [6] challenged this stark position by reclaiming attention's role as an explainability method, albeit with limitations in terms of accuracy and applicability. Combining attention weights with the models' properties has been shown to produce more reliable and consistent explanations [26]. Building upon this rationale, [3] suggests that a verification step can prove the relation between attention weights and feature importance by correlating the effects of different attention weight distributions to the accuracy of the models. This can be a prerequisite step before employing attention to explain the model's performance.

Following these studies, we evaluate the validity of using graph attention to generate explanations by correlating the accuracy of a baseline model with the distribution divergence of attention weights after iterative perturbations. Our results demonstrate that attention can be useful to identify important semantics in the environment that contribute towards reliable model performance.

III. PRELIMINARIES

In this section, we formulate the problem addressed and describe the graphs and the GNN model used as the baseline.

A. Problem Definition and Notations

Let $P_t : {\mathbf{p}_i \mid \mathbf{p}_i \in \mathbb{R}^3}$ be a pointcloud at discrete timestamp t in a total of N consecutive scans. P_t can be subdivided into a set of semantic classes \mathbb{S} that may include *terrain*, *buildings*, *trees*, *vehicles*, and *pedestrians*, among others. For each point \mathbf{p}_i , we assign a semantic label $s_i \in \mathbb{S}$. In our proposed work, we aim to identify the most significant semantic classes for accurate relative pose estimation between two consecutive pointclouds, P_t and P_{t+1} . Here, we denote the relative pose as $[\mathbf{R}_{t,t+1} | \boldsymbol{\tau}_{t,t+1}]$, where $\mathbf{R}_{t,t+1} \in \mathbb{SO}(3)$ is the rotation and $\boldsymbol{\tau}_{t,t+1} \in \mathbb{R}^3$ is the translation.

B. SEM-GAT

We employ SEM-GAT [7] for generating attention-based explanations. SEM-GAT is a semantic graph-based pose estimation GNN model, depicted in Fig. 2. It estimates the relative transformation between two pointclouds by identifying potential matching correspondences between those pointclouds for registration. SEM-GAT explicitly employs attention to weigh each candidate matching pair, making it a suitable baseline to test our evaluation methodology.

SEM-GAT's input is a static graph structure G_t comprising the two pointclouds P_t and P_{t+1} . We define the input graphs as $G_t = \langle V_t, E_t \rangle$, where V_t and E_t are the sets of nodes and edges, respectively. Each point $\mathbf{p}_i \in P_t$ and $\mathbf{p}_j \in P_{t+1}$ is a node in V_t and the edges correspond to the semantic relationships between the points according to their associated semantic label $s_i \in S$ and their geometric characterisation as *corner* or *surface* points. For the sake of the notation, from now on, we will drop the subscript t for the instant in time.

Notably, $C \subset E$ is the set of registration-candidate pairs – where $c_{ij} \in C$ links $\mathbf{p}_i \in P_t$ and $\mathbf{p}_j \in P_{t+1}$ – which SEM-GAT uses to estimate the relative-pose transformations $[\hat{\mathbf{R}}_{t,t+1}|\hat{\boldsymbol{\tau}}_{t,t+1}]$. The model generates feature embedding representations, encoding structural and semantic information



Fig. 2: SEM-GAT, the attention-based GNN used as baseline for generating and validating semantic explanations.

through convolutions and multi-head graph attention [27]. It then assigns attention weights $\alpha_{ij} \in \mathbb{R}$ as confidence scores to edges connecting potential registration candidate pairs c_{ij} . The scores $A : {\alpha_{ij}}$ are used as weights in a Singular Value Decomposition (SVD) module to align the pointclouds and recover their relative transformation.

IV. ATTENTION-BASED SEMANTIC EXPLANATIONS

Fig. 1 depicts the overview of our pipeline. We estimate the importance of the semantic elements in the environment using the attention weights A predicted in the last layer of SEM-GAT. To validate the suitability of using attention to explain the performance of SEM-GAT semantically, we iteratively perturb the input, correlating the attention-weightsdistribution divergence with the changes in the model's accuracy.

We first investigate the semantic interpretation of the attention weights A by ranking the semantic classes at inference according to their predicted total weights, normalised on the number of points. Based on this ranking, we extract semantic feature sets to iteratively mask the model while measuring the output variations. We propose two different methodologies, visualised in Fig. 3:

- 1) Masking the nodes of the input graph according to the average overall attention score of the semantic sets calculated in post-processing. This effectively alters the elements *and* context of the input.
- Zeroing the edge attention weights of our estimated most important semantic sets at the last layer of SEM-GAT, directly masking the edges with the highest confidence weights for SVD.

Following the outcome of the perturbations, we evaluate the adequacy of using attention weights as importance indicators. The validation process can be split into two parts: 1) measuring the attention distribution divergence and 2) correlating the attention scores with the model's performance before and after masking.

A. Attention Distribution Divergence

Given a graph G, we follow the works [4], [5], [6] and calculate the variation in the predicted attention scores caused by the perturbation with the Jensen-Shannon Divergence



(c) Edge masking at the last layer of SEM-GAT.

Fig. 3: Overview of the perturbation process as $Input \rightarrow Model \rightarrow$ Output: (a) visualises the process of extracting the semantic importance weights from vanilla SEM-GAT. These weights then inform the two independent steps of (b) node-and (c) edge-attention-weights masking.

(JSD) distance. Defining α^b and α^a as the distributions of weights before and after the perturbation, with *b* corresponding to vanilla SEM-GAT:

$$JSD(\alpha^b, \alpha^a) = \sqrt{\frac{D_{KL}(\alpha^b \parallel \bar{\alpha}) + D_{KL}(\alpha^a \parallel \bar{\alpha})}{2}} \quad (1)$$

 $0 \leq JSD(\cdot, \cdot) \leq 1$. D_{KL} corresponds to the Kullback-Leibler divergence and $\bar{\alpha}$ is the distribution of attention weights averaged edgewise between before and after perturbation. We consider the total JSD of a sequence of pointclouds as the average of the JSDs on the sequence.

B. Attention-Performance Correlation

As we mask the graph, we measure the variations in SEM-GAT's pose estimation accuracy to assess the correlation between attention and model performance. The authors in [3] propose using the discrepancy in the model's accuracy before and after masking; similarly, we calculate the Average Absolute Discrepancy (AAD) of an accuracy score \hat{y} from before and after masking as:

$$AAD(\hat{\mathbf{y}}^b, \hat{\mathbf{y}}^a) = |\hat{\mathbf{y}}^b - \hat{\mathbf{y}}^a|$$
(2)

This metric is a good indicator of the fluctuations in the output predictions in each perturbation step.

For our case, we consider as $\hat{\mathbf{y}}$ the Relative Rotational Error (RRE) [°] and Relative Translational Error (RTE) [m] between SEM-GAT's rotation and translation estimations $[\hat{\mathbf{R}}|\hat{\boldsymbol{\tau}}]$ and ground-truth values $[\mathbf{R}|\boldsymbol{\tau}]$, respectively. The two metrics are defined as:

$$RRE = \operatorname{acos}\left(\frac{1}{2}(\operatorname{tr}(\mathbf{R}^{\top}\hat{\mathbf{R}}) - 1)\right)$$
(3)

$$RTE = \|\boldsymbol{\tau}_{gt} - \hat{\boldsymbol{\tau}}\|_2 \tag{4}$$

We consider the total AAD over an entire sequence as the average of the two metrics' AADs. The combined average absolute discrepancy AAD is then calculated as follows:

$$AAD = \frac{\sum_{t=1}^{N-1} |RRE_b - RRE_a|}{N-1} + \frac{\sum_{t=1}^{N-1} |RTE_b - RTE_a|}{N-1}$$
(5)

V. RESULTS

SEM-GAT is trained and evaluated on Sequences 00, 02, and 03 of the KITTI Odometry Dataset [8]. We test our approach on every sequence in the dataset, from 00 to 10. We use the ground-truth labels and poses from SemanticKITTI [28] to generate our semantic graphs and evaluate the performance of SEM-GAT by correlating AAD with JSD to estimate the contribution of the query semantic importance scores to the accuracy of the model.

A. Semantic Masking

We use the predicted attention weights from the last layer of SEM-GAT to rank the semantic classes in the dataset according to their average learned attention scores for each sequence. Tab. I reports each sequence's five most important semantic classes and their average attention values.

According to the ranking in Tab. I, we split and perturb the input data in the following semantic sets:

- Single-class; separately masking the top 3 highestscoring classes.
- Multi-class; masking the top 3 and top 5 highest-scoring classes, as well as 3 random classes.
- Single-feature; masking corner or surface points.

We then evaluate whether the attention weights of these sets represent key semantic structures in the environment based on their contribution to SEM-GAT's performance.

B. Attention-JSD Correlation

To estimate the contribution of each masking set to the total distribution of attention weights predicted in the last layer of SEM-GAT, we calculate the JSD distance of the distributions before and after removing the weights corresponding to each set during node masking. Higher JSD values correspond to a larger overall contribution of the query set of semantic attention weights to the total distribution of attention. As can be seen in the vertical axis in Fig. 4, the attention weight masking sets corner, 5-class, and Random 3-class produce higher overall JSD scores compared to the scores from single-class masking. Similarly, the attention weights in the corner set have the highest probability density corresponding to almost half the distribution.

C. JSD-Performance Correlation

To investigate the correlation between attention weights and model performance, we retrieve the total AAD from each sequence and correlate it with the JSD results. When masking the larger semantic sets, corner, 5-class, and



Fig. 4: Average JSD distance correlation with the average absolute discrepancy AAD, calculated after perturbing the last layer of SEM-GAT for Seq. 00 to 10 in SemanticKITTI.

Random 3-class, AAD fluctuations are also caused by the large number of points masked. Thus, we are mainly interested in the single-class masking sets in which the number of points masked is negligible compared to the entire pointcloud. Consequently, any AAD fluctuation is caused by the divergence in the attention weights' distribution and not the downsampling of the pointcloud.

As can be seen in Fig. 4, there is a strong linear correlation between JSD and AAD for all single-class sets. Our results indicate that AAD is proportional with JSD on every masking set, proving the validity of using attention weights as importance indicators and correlating them with the changes in the model's performance.

To investigate this further, for each sequence, we compare the results in Tab. II and correlate them with Fig. 4. For all sequences, except Seq. 4, the ranking of AAD scores is proportional to the ranking in JSD scores. For example, in Seq. 00 we observe the highest AAD and highest JSD when masking the first semantic class. These results indicate that the semantic sets with the highest JSD are the most important for SEM-GAT. In the single-class sets, there is no clear ordering relationship between them. This is expected because, as seen in Tab. I, their average attention scores are very similar.

	Random Classes; A	verage Attention Score	es in Descending $Order(\rightarrow)$
00	vegetation (0.38)	trunk (0.34)	terrain (0.29)
01	terrain (0.39)	car (0.29)	other-ground (0.18)
02	car (0.34)	building (0.33)	terrain (0.31)
03	car (0.3)	building (0.28)	traffic-sign (0.15)
04	trunk (0.33)	building (0.2)	traffic-sign (0.18)
05	trunk (0.31)	pole (0.29)	other-vehicle (0.1)
06	other-ground (0.27)	truck (0.16)	bicycle (0.14)
07	bicycle (0.11)	other-vehicle (0.1)	traffic-sign (0.1)
08	person (0.17)	other-vehicle (0.16)	traffic-sign (0.12)
09	car (0.34)	traffic-sign (0.12)	person (0.1)
10	trunk (0.25)	other-ground (0.04)	person (0.1)

	Highest Ranking Classes; Average Attention Scores in Descending Order (\rightarrow)							
00	pole (0.55)	sidewalk (0.53)	fence (0.44)	building (0.4)	bicycle (0.4)			
01	fence (0.51)	vegetation (0.42)	terrain (0.39)	car (0.29)	ground (0.18)			
02	sidewalk (0.56)	fence (0.48)	trunk (0.45)	vegetation (0.4)	pole (0.36)			
03	pole (0.55)	sidewalk (0.55)	fence (0.5)	vegetation (0.38)	terrain (0.38)			
04	sidewalk (0.6)	pole (0.49)	fence (0.45)	car (0.44)	vegetation (0.43)			
05	sidewalk (0.56)	terrain (0.5)	fence (0.47)	car (0.4)	building (0.4)			
06	pole (0.6)	sidewalk (0.57)	trunk (0.52)	terrain (0.45)	car (0.45)			
07	pole (0.56)	sidewalk (0.54)	fence (0.46)	building (0.4)	car (0.39)			
08	sidewalk (0.55)	pole (0.51)	terrain (0.43)	trunk (0.42)	building (0.4)			
09	sidewalk (0.55)	terrain (0.44)	trunk (0.43)	vegetation (0.39)	fence (0.38)			
10	pole (0.49)	fence (0.47)	sidewalk (0.44)	vegetation (0.38)	building (0.37)			

TABLE I: Attention-based importance ranking of semantic classes in Sequences 00 to 10 of SemanticKITTI [28]. This ranking guides the perturbations. Seq. 00, 02, and 06 to 09 were captured in urban environments, Seq. 03 to 05 and 10 in the countryside, and Seq. 01 in a highway.

D. Qualitative Discussion

Notably, the SemanticKITTI dataset [28] is particularly interesting due to its diverse domain coverage. It is then well-suited to analyse how SEM-GAT performs in different environments. On every urban or countryside sequence, the highest ranking class is either pole or sidewalk as seen in Tab. I. In Seq. 01, captured in a highway, such semantics are not observed and thus, naturally, the class fence is found to be the most important one. Moreover, we observe higher attention scores assigned to corner points than to surface points, further justifying the high ranking of classes like vegetation, sidewalk, and fence which mainly consist of corner points.

It is particularly interesting that large semantic classes like building are not assigned high-importance scores from the model. After examining the model's architecture, we conclude that SEM-GAT assigns lower overall attention scores to these semantic classes due to the dense distribution of points in each instance, making it challenging for the model to identify the most important segments within them.

VI. CONCLUSIONS

In this work, we investigated the semantic interpretation of attention scores for identifying key elements in a pointcloud and introduced a methodology to evaluate the fidelity of our findings. Our analysis provides a thorough insight into the validity of using attention as an indicator of semantic importance. Our experimental results indicate a strong correlation between attention weights and model performance, allowing us to draw conclusions on expected model behaviour in diverse environments. In our approach, we identify important semantic features in the environment for graph-attentionbased pose estimation models. This methodology can be used to explain the model's performance in correlation with the semantics present.

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	Average Absolute Discrepancy: Nodes Masking							
seq	Top 5 Classes	Top 3 Classes	Random 3 Classes	Surfaces	Corners	1st Class	2nd Class	3rd Class
00	4.932	1.019	1.463	3.807	5.214	1.99	1.998	2.017
01	—	—	0.540	8.688	9.162	0.128	0.115	0.162
02	_	—	1.011	9.316	2.043	0.61	0.589	0.585
03	_	1.888	1.251	3.629	9.378	0.339	0.311	0.401
04	_	2.424	0.181	5.538	7.228	0.945	1.034	0.991
05	7.64	2.592	0.137	2.698	6.970	0.687	0.711	0.756
06	2.308	0.903	0.159	4.196	3.734	1.865	1.867	1.844
07	24.263	0.837	0.034	5.642	6.305	2.099	2.108	2.281
08	1.929	0.374	0.156	3.329	4.162	1.169	1.183	1.166
09		2.22	1.096	5.211	1.506	1.057	1.067	1.057
10	— —	2.314	0.331	3.010	10.656	0.59	0.696	0.56
	Average Absolute Discrepancy: Edges Masking							
500			Average Absolute Di	screpancy: l	Edges Mask	ing		
seq	Top 5 Classes	Top 3 Classes	Average Absolute Di Random 3 Classes	screpancy: l Surfaces	Edges Mask Corners	ing 1st Class	2nd Class	3rd Class
seq	Top 5 Classes	Top 3 Classes	Average Absolute Di Random 3 Classes 4.653	screpancy: I Surfaces 3.969	Edges Mask Corners 4.653	ing 1st Class 1.98	2nd Class 1.967	3rd Class
seq 00 01	Top 5 Classes 4.954 —	Top 3 Classes 0.989	Average Absolute Di Random 3 Classes 4.653 8.198	screpancy: 1 Surfaces 3.969 9.481	Edges Mask Corners 4.653 8.198	ing 1st Class 1.98 0.149	2nd Class 1.967 0.113	3rd Class 1.99 0.143
seq 00 01 02	Top 5 Classes 4.954	Top 3 Classes 0.989	Average Absolute Di Random 3 Classes 4.653 8.198 1.907	screpancy: 1 Surfaces 3.969 9.481 9.826	Edges Mask Corners 4.653 8.198 1.907	ing 1st Class 1.98 0.149 0.593	2nd Class 1.967 0.113 0.591	3rd Class 1.99 0.143 0.605
seq 00 01 02 03	Top 5 Classes 4.954 — — —	Top 3 Classes 0.989 1.861	Average Absolute Di Random 3 Classes 4.653 8.198 1.907 8.047	screpancy: I Surfaces 3.969 9.481 9.826 4.211	Edges Mask Corners 4.653 8.198 1.907 8.047	ing 1st Class 1.98 0.149 0.593 0.351	2nd Class 1.967 0.113 0.591 0.364	3rd Class 1.99 0.143 0.605 0.331
seq 00 01 02 03 04	Top 5 Classes 4.954 — — — —	Top 3 Classes 0.989 1.861 2.502	Average Absolute Di Random 3 Classes 4.653 8.198 1.907 8.047 5.743	screpancy: I Surfaces 3.969 9.481 9.826 4.211 5.884	Edges Mask Corners 4.653 8.198 1.907 8.047 5.743	ing 1st Class 1.98 0.149 0.593 0.351 0.948	2nd Class 1.967 0.113 0.591 0.364 0.925	3rd Class 1.99 0.143 0.605 0.331 0.855
seq 00 01 02 03 04 05	Top 5 Classes 4.954 — — — 7.605	Top 3 Classes 0.989 1.861 2.502 2.556	Average Absolute Di Random 3 Classes 4.653 8.198 1.907 8.047 5.743 5.935	screpancy: I Surfaces 3.969 9.481 9.826 4.211 5.884 2.916	Edges Mask Corners 4.653 8.198 1.907 8.047 5.743 5.935	ing 1st Class 1.98 0.149 0.593 0.351 0.948 0.684	2nd Class 1.967 0.113 0.591 0.364 0.925 0.695	3rd Class 1,99 0.143 0,605 0.331 0.855 0,733
seq 00 01 02 03 04 05 06	Top 5 Classes 4.954 — — — 7.605 2.362	Top 3 Classes 0.989 1.861 2.502 2.556 0.872	Average Absolute Di Random 3 Classes 4.653 8.198 1.907 8.047 5.743 5.935 3.187	screpancy: l Surfaces 3.969 9.481 9.826 4.211 5.884 2.916 4.776	Edges Mask Corners 4.653 8.198 1.907 8.047 5.743 5.935 3.187	ing 1st Class 1.98 0.149 0.593 0.351 0.948 0.684 1.911	2nd Class 1.967 0.113 0.591 0.364 0.925 0.695 1.854	3rd Class 1,99 0.143 0,605 0.331 0.855 0.733 1.873
seq 00 01 02 03 04 05 06 07	Top 5 Classes 4.954 — — — 7.605 2.362 24.082	Top 3 Classes 0.989 1.861 2.502 2.556 0.872 0.859	Average Absolute Di Random 3 Classes 4.653 8.198 1.907 8.047 5.743 5.935 3.187 5.158	screpancy: I Surfaces 3.969 9.481 9.826 4.211 5.884 2.916 4.776 6.280	Edges Mask Corners 4.653 8.198 1.907 8.047 5.743 5.935 3.187 5.158	ing 1.98 0.149 0.593 0.351 0.948 0.684 1.911 2.170	2nd Class 1.967 0.113 0.591 0.364 0.925 0.695 1.854 2.176	3rd Class 1.99 0.143 0.605 0.331 0.855 0.733 1.873 2.302
seq 00 01 02 03 04 05 06 07 08	Top 5 Classes 4.954 	Top 3 Classes 0.989 1.861 2.502 2.556 0.872 0.859 0.384	Average Absolute Di Random 3 Classes 4.653 8.198 1.907 8.047 5.743 5.935 3.187 5.158 3.504	screpancy: I Surfaces 3.969 9.481 9.826 4.211 5.884 2.916 4.776 6.280 3.493	Edges Mask Corners 4.653 8.198 1.907 8.047 5.743 5.935 3.187 5.158 3.504	ing 1.st Class 1.98 0.149 0.593 0.351 0.948 0.684 1.911 2.170 1.15	2nd Class 1.967 0.113 0.591 0.364 0.925 0.695 1.854 2.176 1.141	3rd Class 1.99 0.143 0.605 0.331 0.855 0.733 1.873 2.302 1.166
seq 00 01 02 03 04 05 06 07 08 09	Top 5 Classes 4.954 	Top 3 Classes 0.989 1.861 2.502 2.556 0.872 0.859 0.384 2.2	Average Absolute Di Random 3 Classes 4.653 8.198 1.907 8.047 5.743 5.935 3.187 5.158 3.504 1.268	screpancy: 1 Surfaces 3.969 9.481 9.826 4.211 5.884 2.916 4.776 6.280 3.493 5.375	Edges Mask Corners 4.653 8.198 1.907 8.047 5.743 5.743 5.935 3.187 5.158 3.504 1.268	ing 1st Class 1.98 0.149 0.593 0.351 0.948 0.684 1.911 2.170 1.15 1.054	2nd Class 1.967 0.113 0.591 0.364 0.925 0.695 1.854 2.176 1.141 1.055	3rd Class 1.99 0.143 0.605 0.331 0.855 0.733 1.873 2.302 1.166 1.086

TABLE II: Total AAD $\times 10^{-2}$ across Sequences 00 to 10 in SemanticKITTI after masking the nodes from the input graphs (up) and masking the edges at the last layer of SEM-GAT (down). The colours indicate the highest discrepancy scores after perturbation. **Red** indicates highest scores overall, **blue** highest scores after semantic masking, and **purple** highest scores for each semantic class. For multi-class masking, the symbol "—" indicates an error in pose estimation due to insufficient registration points or confidence loss.

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