ROBUST VISUAL REPRESENTATION ACROSS MODALITIES IN SEMANTIC SCENE UNDERSTANDING

24 March 2025

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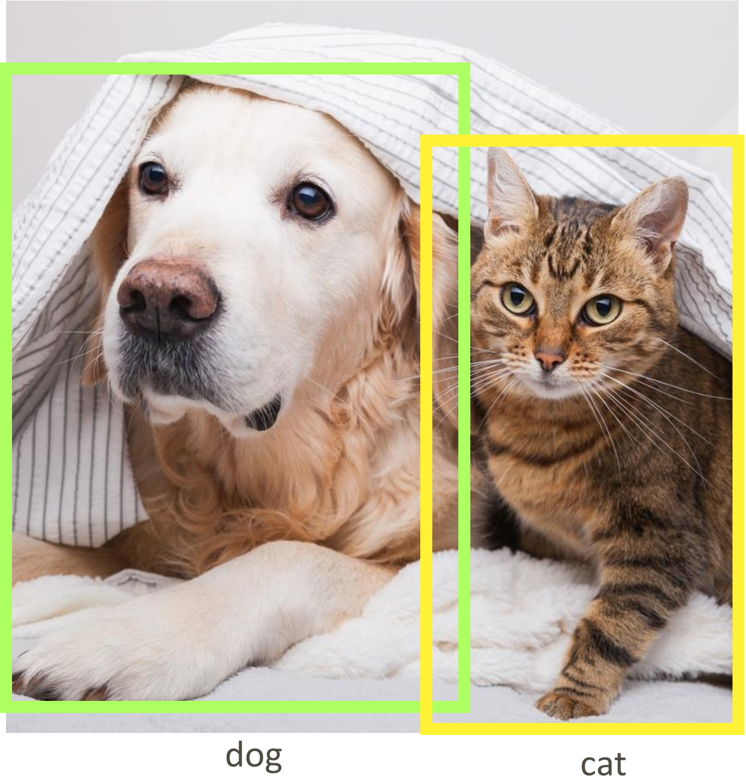
CLASSIFICATION

animals

SEMANTIC SCENE UNDERSTANDING

- Understanding **spatial and semantic relationships** between objects in a scene.
- Includes various tasks: **classification**, **object detection**, and **segmentation**.

OBJECT DETECTION



SEMANTIC SCENE UNDERSTANDING

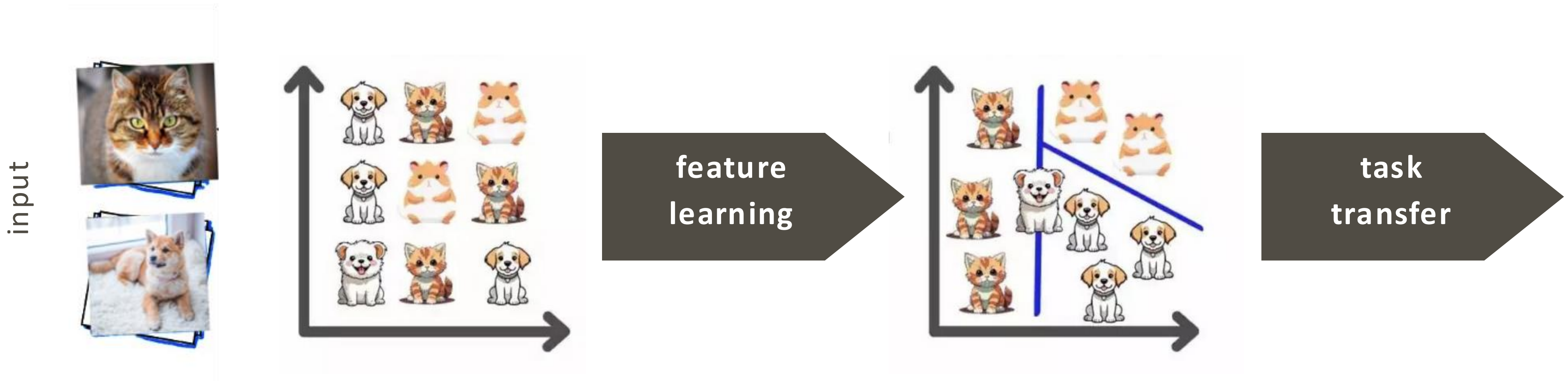
- Understanding **spatial and semantic relationships** between objects in a scene.
- Includes various tasks: **classification**, **object detection**, and **segmentation**.

SEMANTIC SEGMENTATION

SEMANTIC SCENE UNDERSTANDING

- Understanding **spatial and semantic relationships** between objects in a scene.
- Includes various tasks: **classification**, **object detection**, and **segmentation**.

ROBUST VISUAL REPRESENTATION

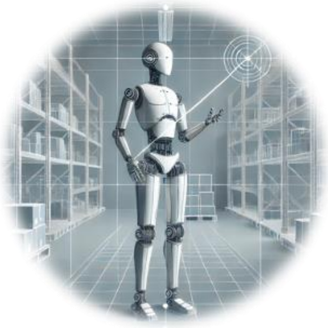


DEFAULT features

SEMANTIC features

PROBLEMS

01 **Adapt** to new tasks and integrate data from multiple sensors.



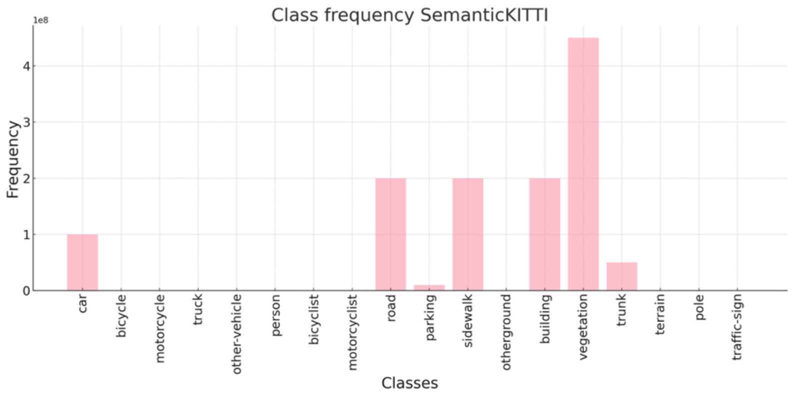
02 **Handle** imbalance datasets, limited training data and corrupted inputs.

03 **Understand** the environment accurately.

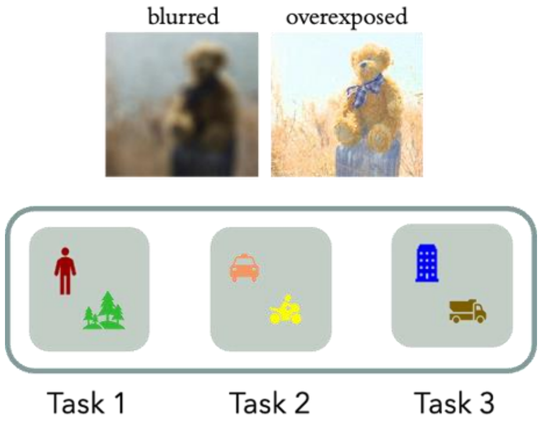
KEY CHALLENGES

01 **Adapt** to new tasks and integrate data from multiple sensors.

02 **Handle** imbalance datasets, limited training data and corrupted inputs.



DATA IMBALANCE AND SCARCITY



DATA AND LABEL DISTRIBUTION SHIFTS

INNOVATIONS TO TACKLE CHALLENGES

INNOVATIONS TO TACKLE CHALLENGES

DATA IMBALANCE AND SCARCITY

1. Class Imbalance in 3D Data

Hierarchical Learning for improved class balance.

Semantic-guided transmission.

4. Few-Shot and 3D Reconstruction

Heritage Point Cloud Instance Collection.

Improved Scan-to-BIM via Few-Shot learning.

INNOVATIONS TO TACKLE CHALLENGES

DATA AND LABEL DISTRIBUTION SHIFTS

1. Class Imbalance in 3D Data

2. Continual and Multimodal Learning

Enhanced Continual Learning on LiDAR data.

Multimodality for resilient architectures to losses.

3. Robustness to Corrupted Data

Detect corrupted images using FFT and a deep network, adapt BN layers of scene understanding models.

4. Few-Shot and 3D Reconstruction

INNOVATIONS TO TACKLE CHALLENGES

1. Class Imbalance in 3D Data

2. Continual and Multimodal Learning

3. Robustness to Corrupted Data

4. Few-Shot and 3D Reconstruction

5. Conclusions

Limitations and Future Work.

Bibliography and Acknowledgments.

INNOVATIONS TO TACKLE CHALLENGES

1. Class Imbalance in 3D Data
2. Continual and Multimodal Learning
3. Robustness to Corrupted Data
4. Few-Shot and 3D Reconstruction
5. Conclusions

1. Class Imbalance in 3D Data

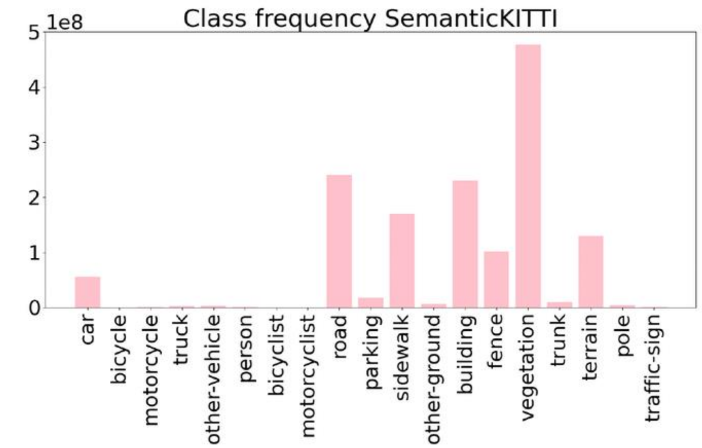
- **LEAK:** Hierarchical learning for better class balance in semantic segmentation [1].
- Improved performance on minority classes and efficient **semantic-guided transmission** [2].

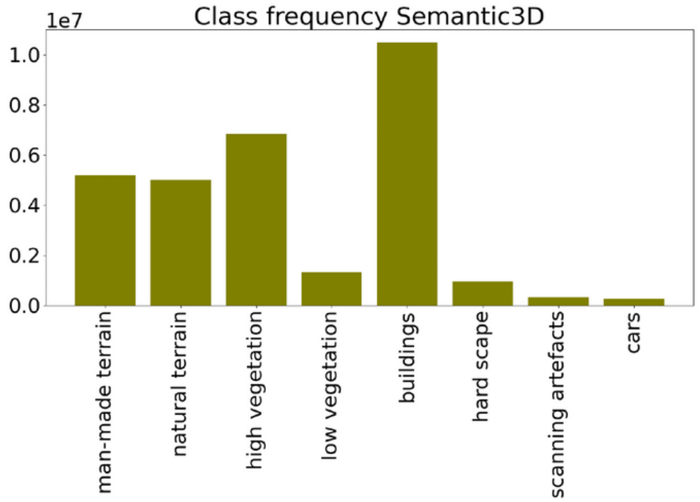
[1] **Camuffo E.**, Michieli U., Milani S. "Learning from Mistakes: Self-Regularizing Hierarchical Semantic Representations in Point Cloud Segmentation", IEEE Transactions on Multimedia, 2023.
[2] Mari D., **Camuffo E.**, Milani S. "CACTUS: Content-Aware Compression and Transmission Using Semantics for Automotive LiDAR data", Sensors, 2023.

CLASS IMBALANCE IN 3D DATA

- Point Cloud datasets are usually **not properly balanced**, and classes with less points are often misclassified by semantic understanding models.

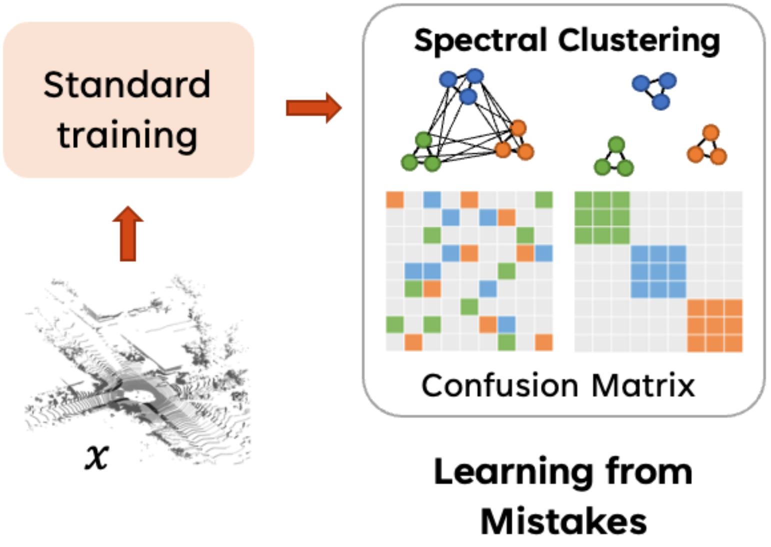
- Most of the errors occur within classes that are **sematically similar**.



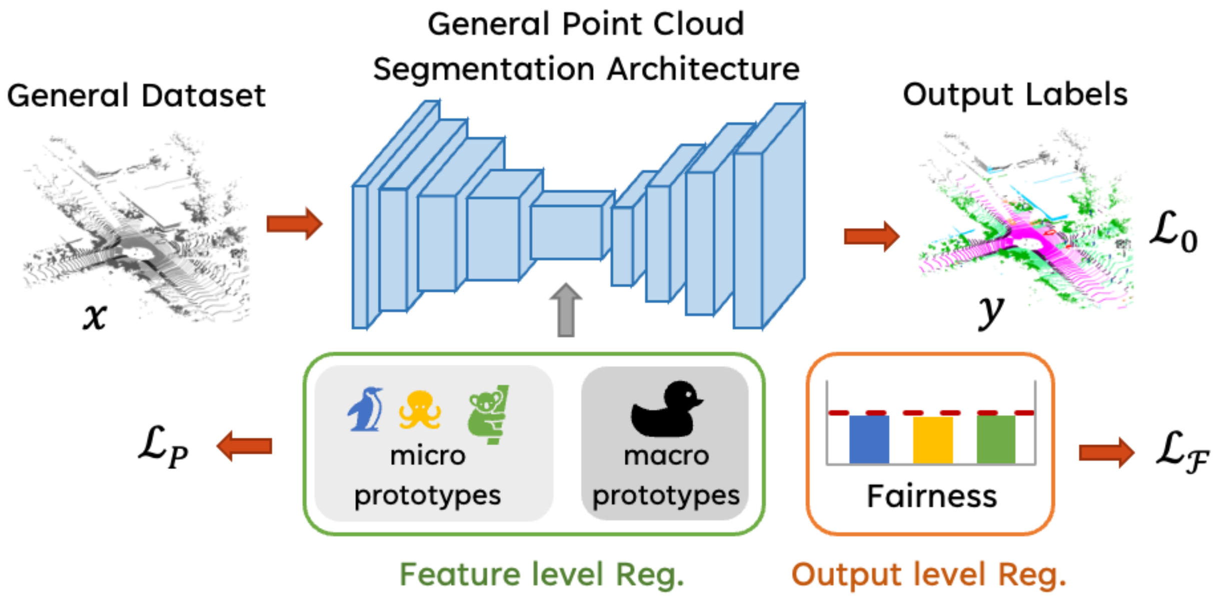


LEAK ARCHITECTURE

BUILD CLASS HIERARCHIES



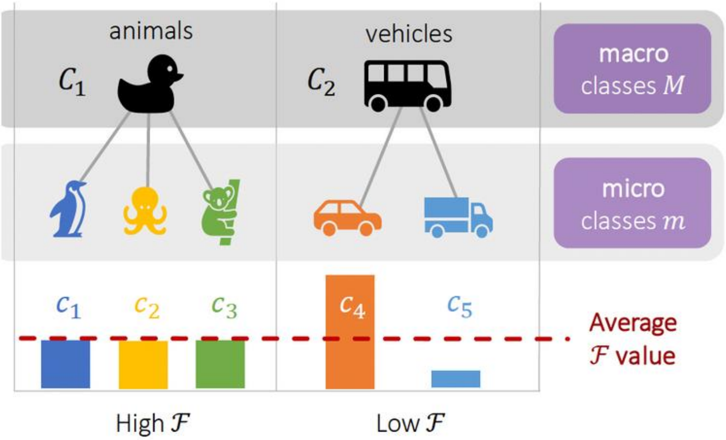
HIERARCHICAL SELF-REGULARIZATION



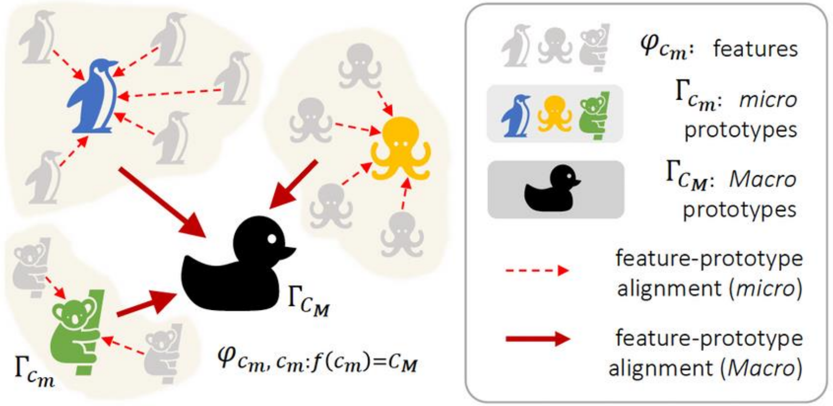
[1] **Camuffo E.**, Michieli U., Milani S. "Learning from Mistakes: Self-Regularizing Hierarchical Semantic Representations in Point Cloud Segmentation", IEEE Transactions on Multimedia, 2023.

LEAK COMPONENTS

FAIRNESS



PROTOTYPES

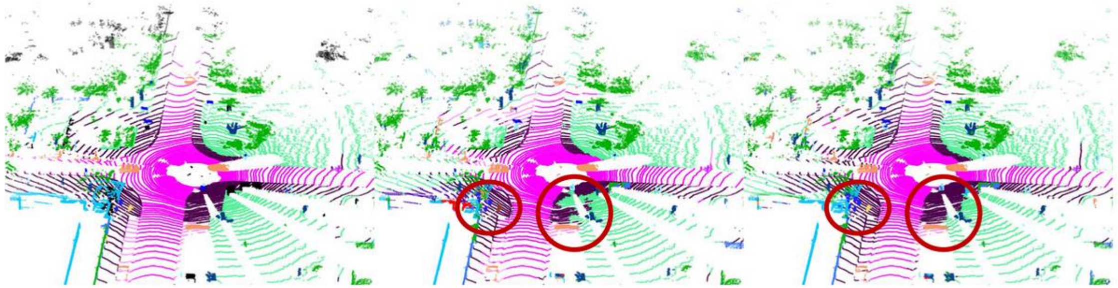


- **Macro-aware Fairness** score on the micro classes promotes homogeneous scores in macro clusters.
- Class-conditional latent **features-to-prototype alignment** at 2 levels (micro and macro) improves class-wise feature discrimination.

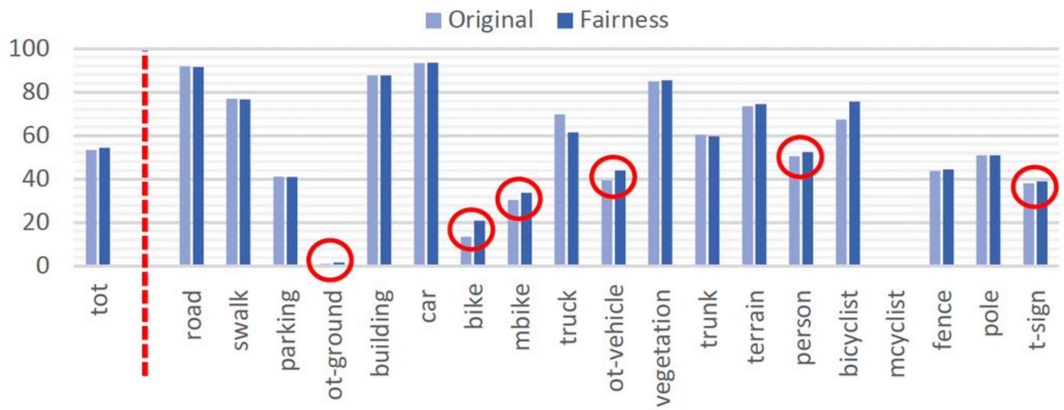
$$\mathcal{L}_{LEAK} = \mathcal{L}_0 + \lambda_{P_m} \cdot \mathcal{L}_{P_m} + \lambda_{P_M} \cdot \mathcal{L}_{P_M} + \lambda_{\mathcal{F}} \cdot \mathcal{L}_{\mathcal{F}}$$

[1] Camuffo E., Michieli U., Milani S. “Learning from Mistakes: Self-Regularizing Hierarchical Semantic Representations in Point Cloud Segmentation”, IEEE Transactions on Multimedia, 2023.

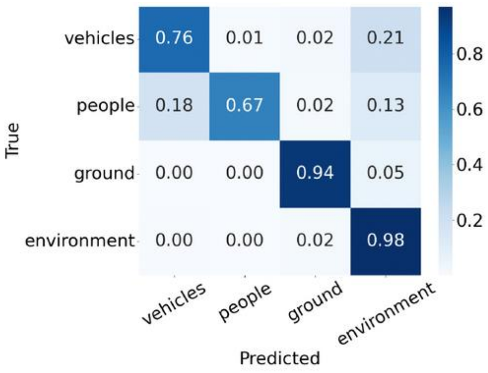
LEAK RESULTS



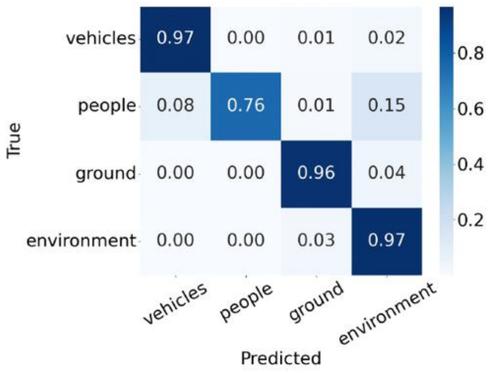
GROUND TRUTH ORIGINAL LEAK



PRE LEAK

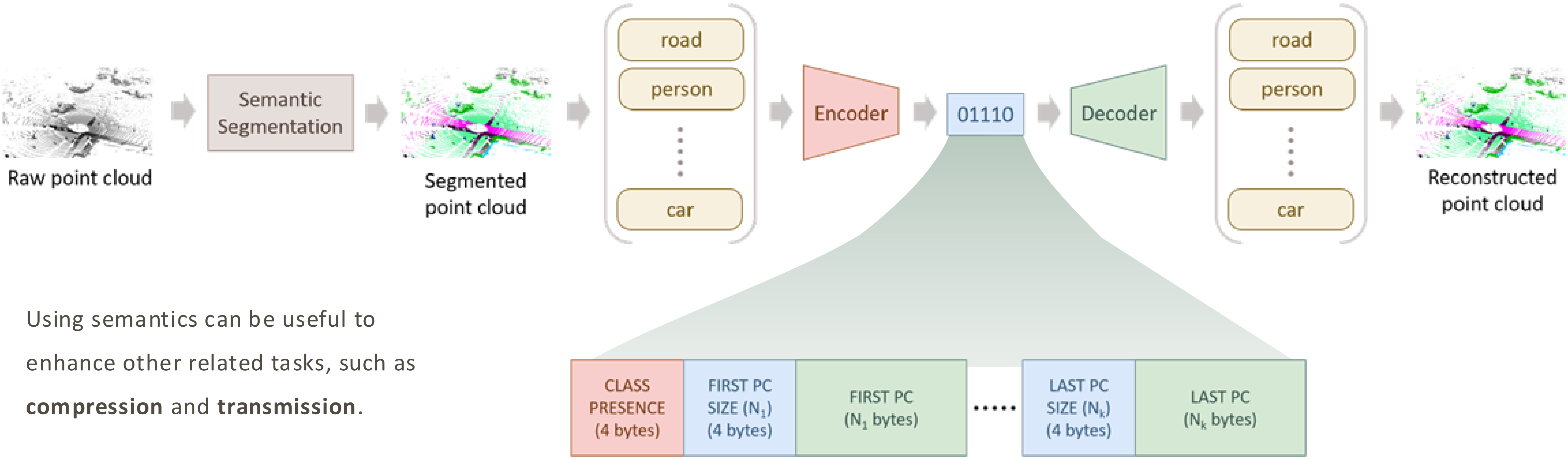


POST LEAK



[1] **Camuffo E.**, Michieli U., Milani S. "Learning from Mistakes: Self-Regularizing Hierarchical Semantic Representations in Point Cloud Segmentation", IEEE Transactions on Multimedia, 2023.

SEMANTIC GUIDED TRANSMISSION



Using semantics can be useful to enhance other related tasks, such as **compression** and **transmission**.

[2] Mari D., **Camuffo E.**, Milani S. "CACTUS: Content-Aware Compression and Transmission Using Semantics for Automotive LiDAR data", Sensors, 2023.

INNOVATIONS TO TACKLE CHALLENGES

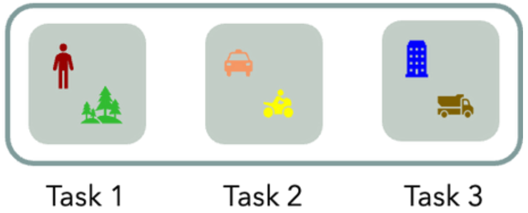
1. Class Imbalance in 3D Data
2. Continual and Multimodal Learning
3. Robustness to Corrupted Data
4. Few-Shot and 3D Reconstruction
5. Conclusions

2. Continual and Multimodal Learning

- Enhanced **Continual Learning** on LiDAR data via knowledge distillation and self-inpainting [3].
- Robust **Multimodal** (LiDAR + RGB) architecture, resilient to sensory loss and malfunctioning [4].

[3] **Camuffo E.**, Milani S., "Continual Learning for LiDAR Semantic Segmentation: Class-Incremental and Coarse-to-Fine strategies on Sparse Data", CVPRW, 2023.
[4] Barbato F., **Camuffo E.**, Milani S., Zanuttigh P., "Multi-Modal Continual Learning for Semantic Segmentation", ICIP, 2024.

CONTINUAL AND MULTIMODAL LEARNING



CONTINUAL LEARNING

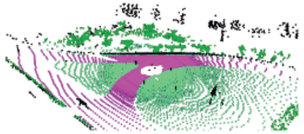
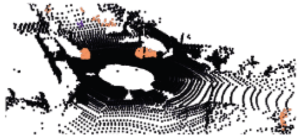
Learning **continuously and adaptively**, enabling the autonomous incremental development of ever more complex skills and knowledge.

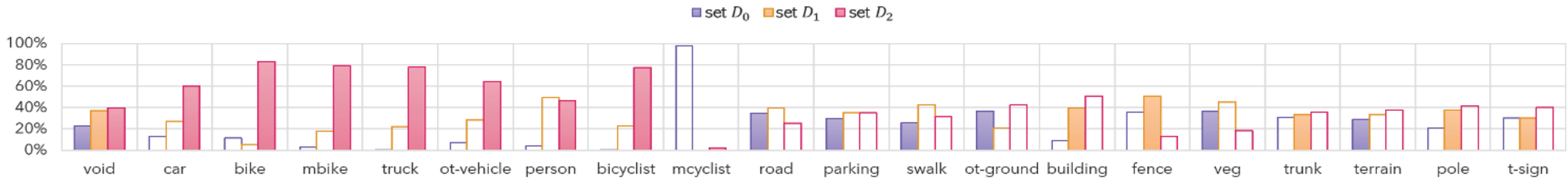
MULTIMODAL LEARNING

Inclusion of **heterogeneous data** to learn more information about the scene 2D and 3D information together.

[3] **Camuffo E.**, Milani S., “Continual Learning for LiDAR Semantic Segmentation: Class-Incremental and Coarse-to-Fine strategies on Sparse Data”, CVPRW, 2023.
[4] Barbato F., **Camuffo E.**, Milani S., Zanuttigh P., “Multi-Modal Continual Learning for Semantic Segmentation”, ICIP, 2024.

DISCOVERY OF NOVEL SEMANTIC CATEGORIES

	Training Subset T_0	Training Subset T_1	Training Subset T_2	Validation Set
		SemanticKITTI train		SemanticKITTI val
Sequences	$D_0 = \{01, 02, 03\}$	$D_1 = \{04, 05, 09, 10\}$	$D_2 = \{00, 06, 07\}$	$D = \{08\}$
Labeled classes	$C_0 = \{$*road*, *parking*, *sidewalk*, *other-ground*, *vegetation*, *terrain*$\}$	$C_1 = \{$*building*, *fence*, *trunk*, *pole*, *traffic-sign*$\}$	$C_2 = \{$*bicycle*, *motorcycle*, *truck*, *other-vehicle*, *person*, *bicyclist*, *motorcyclist*, *car*$\}$	$C = \{C_0 \cup C_1 \cup C_2\}$
				
# Clouds	6563	4623	4541	4071
# Points	355280	375140	121494	19130
% Labeled pt.	81.73%	19.21%	8.82%	95.53%



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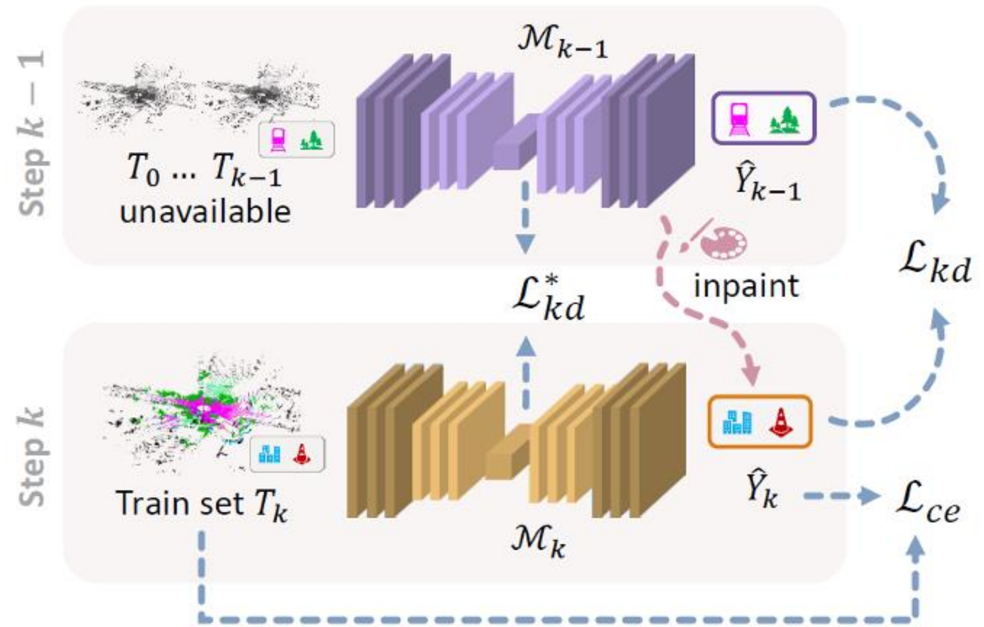
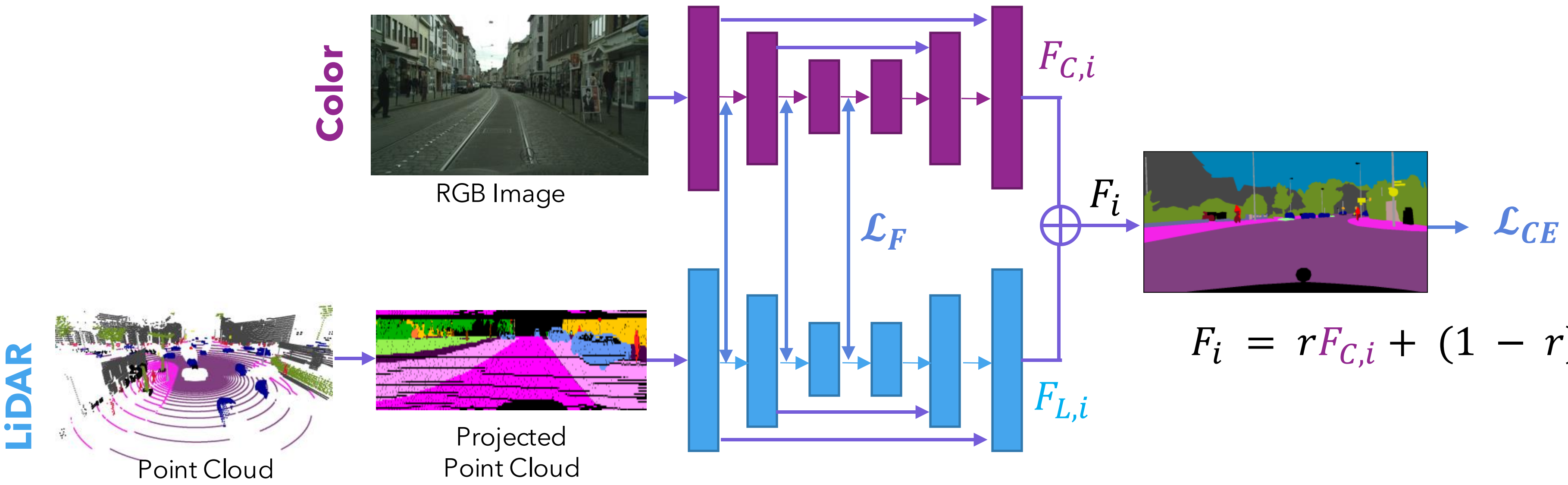


- **Feature Level Distillation ($\mathcal{L}^*_{\mathbf{kd}}$):** L_p (L_1 or L_2) norm between the features of current and previous models.
- **Output Level Distillation ($\mathcal{L}_{\mathbf{kd}}$):** additional Cross-Entropy, where labels for past classes are obtained from previous model predictions.
- **Background Self-Inpainting:** labels for old classes C_{k-1} are predicted by previous model M_{k-1} and inpainted onto background labels of current training set T_k.

[3] **Camuffo E.**, Milani S., "Continual Learning for LiDAR Semantic Segmentation: Class-Incremental and Coarse-to-Fine strategies on Sparse Data", CVPRW, 2023.

MULTIMOLDAL DATA INTEGRATION



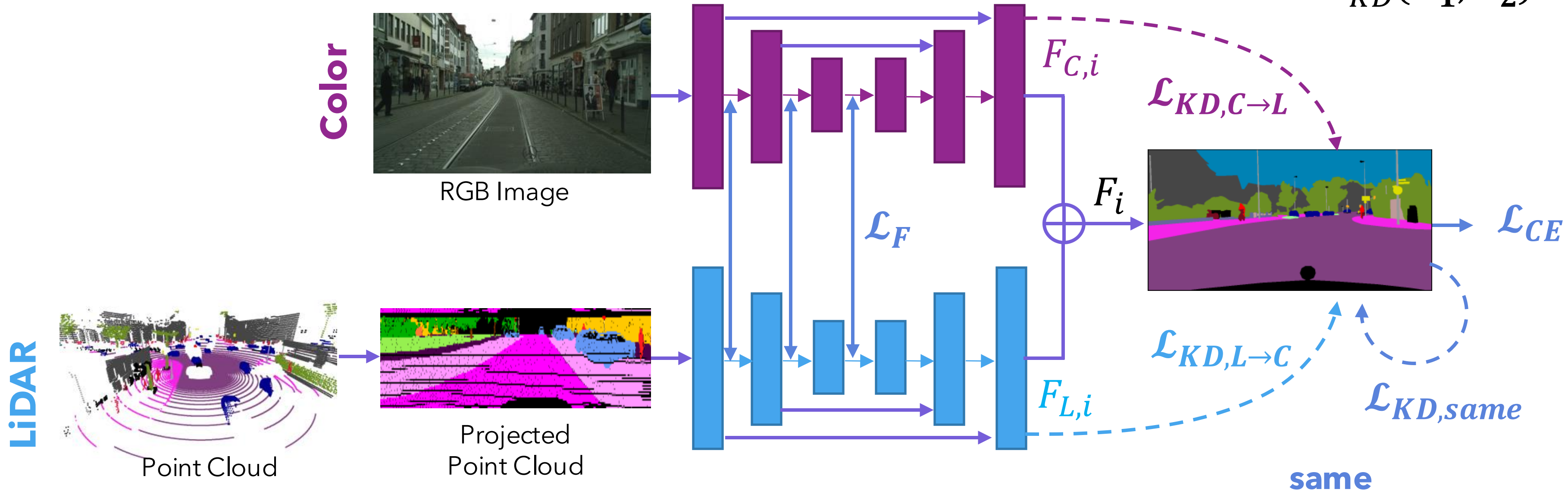
$$F_i = rF_{C,i} + (1 - r)F_{L,i} \quad \text{for} \quad r \in [0,1]$$

$$\mathcal{L}_F = \sum_{i=0,1,2,3} \left\|F_{C,i} - F_{L,i}\right\|_2 + (1 - \theta(F_{C,i}, F_{L,i}))$$

[4] Barbato F., **Camuffo E.**, Milani S., Zanuttigh P., “Multi-Modal Continual Learning for Semantic Segmentation”, ICIP, 2024.

MULTIMOLDAL DATA INTEGRATION

$$\mathcal{L}_{KD}(\boldsymbol{Y_1}, \boldsymbol{Y_2}) = -\sum \boldsymbol{Y_1} \log \boldsymbol{Y_2}$$



same C→L

$$\mathcal{L}_{KD,cross} = \boxed{\mathcal{L}_{KD}(\hat{\mathbf{Y}}_{C,k-1}, \hat{\mathbf{Y}}_{C,k})} + \boxed{\mathcal{L}_{KD}(\hat{\mathbf{Y}}_{L,k-1}, \hat{\mathbf{Y}}_{C,k})}$$
$$\boxed{\mathcal{L}_{KD}(\hat{\mathbf{Y}}_{L,k-1}, \hat{\mathbf{Y}}_{L,k})} + \boxed{\mathcal{L}_{KD}(\hat{\mathbf{Y}}_{C,k-1}, \hat{\mathbf{Y}}_{L,k})}$$

L→C

[4] Barbato F., **Camuffo E.**, Milani S., Zanuttigh P., "Multi-Modal Continual Learning for Semantic Segmentation", ICIP, 2024.

INNOVATIONS TO TACKLE CHALLENGES

1. Class Imbalance in 3D Data
2. Continual and Multimodal Learning
3. Robustness to Corrupted Data
4. Few-Shot and 3D Reconstruction
5. Conclusions

3. Robustness to Corrupted Data

- FROST and PAN frameworks to detect corruptions using FFT and deep models and mitigate corruptions via adaptation of BN layers [5,6,7].

[5] **Camuffo E.**, Michieli U., Moon J., Kim D., Ozay M., "FFT-based Selection and Optimization of Statistics for Robust Recognition of Severely Corrupted Images", ICASSP, 2024.
[6] **Camuffo E.**, Michieli U., Milani S., Moon J., Ozay M., "Enhanced Model Robustness to Input Corruptions by Per-corruption Adaptation of Normalization Statistics", IROS, 2024.
[7] Michieli U., Ozay M., Moon J., Kim D., **Camuffo E.**, "Performing a Computer Vision Task", US Patent App. 18/933,406, 2025.

ROBUSTNESS TO CORRUPTED DATA

- Scene understanding models suffer corrupted images
- **Real** vs **Synthetic** Corruptions (approximations)

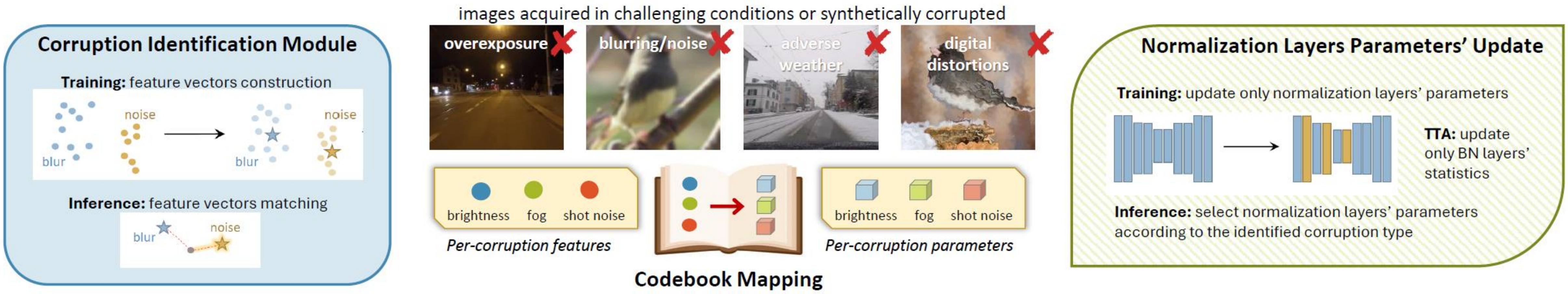
$$\tilde{x} = \underbrace{x}_{\text{clean image}} + \underbrace{\psi(x)}_{\text{corruption}}$$

Corrupted Image

- $\psi(\cdot)$: corruption operator – introduces **noise**, shift

[5] **Camuffo E.**, Michieli U., Moon J., Kim D., Ozay M., "FFT-based Selection and Optimization of Statistics for Robust Recognition of Severely Corrupted Images", ICASSP, 2024.
[6] **Camuffo E.**, Michieli U., Milani S., Moon J., Ozay M., "Enhanced Model Robustness to Input Corruptions by Per-corruption Adaptation of Normalization Statistics", IROS, 2024.
[7] Michieli U., Ozay M., Moon J., Kim D., **Camuffo E.**, "Performing a Computer Vision Task", US Patent App. 18/933,406, 2025.

HANDLE CORRUPTED IMAGES

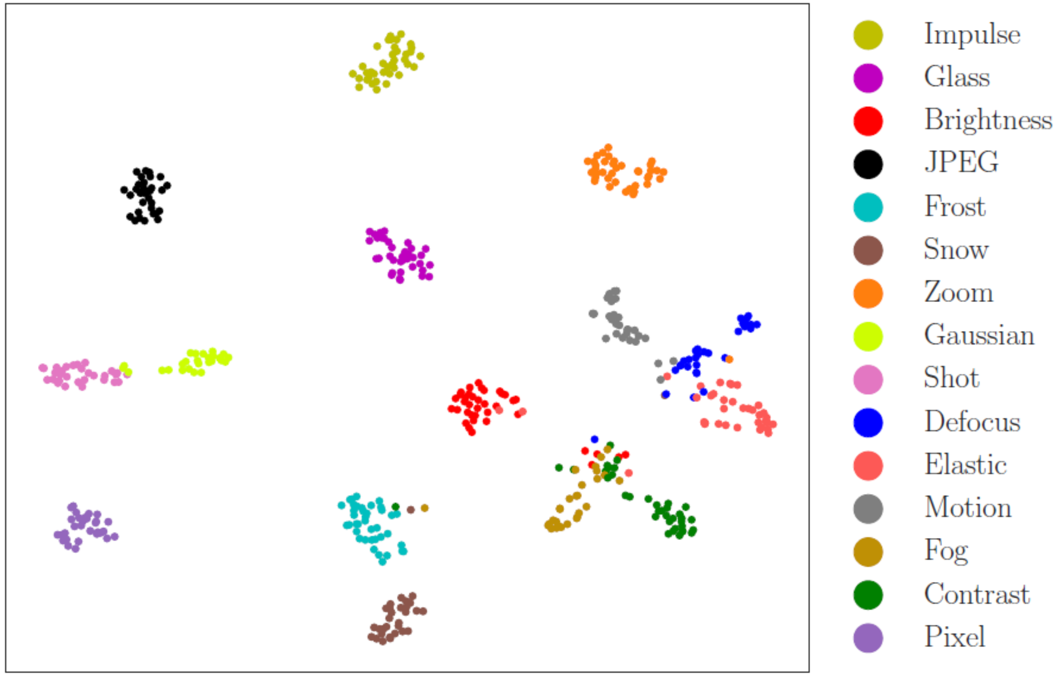


1. **FROST:** FFT features
2. **PAN:** CIM network

1. **FROST:** trained BN layers
2. **PAN:** adapted BN layers

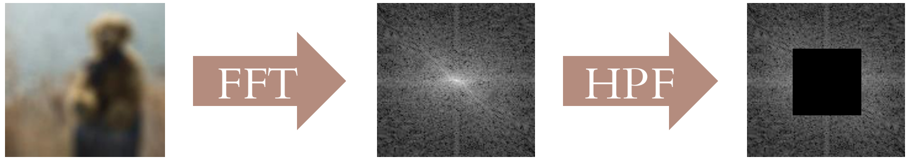
[5] **Camuffo E.**, Michieli U., Moon J., Kim D., Ozay M., "FFT-based Selection and Optimization of Statistics for Robust Recognition of Severely Corrupted Images", ICASSP, 2024.
[6] **Camuffo E.**, Michieli U., Milani S., Moon J., Ozay M., "Enhanced Model Robustness to Input Corruptions by Per-corruption Adaptation of Normalization Statistics", IROS, 2024.
[7] Michieli U., Ozay M., Moon J., Kim D., **Camuffo E.**, "Performing a Computer Vision Task", US Patent App. 18/933,406, 2025.

CORRUPTION IDENTIFICATION

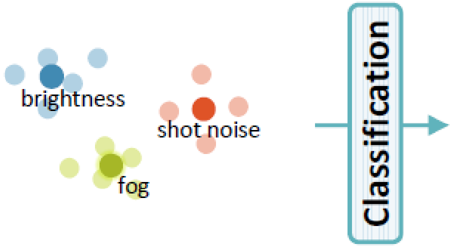


TSNE OF CORRUPTIONS FEATURES (PAN)

FROST: Uses High-Frequency FFT amplitudes.



PAN: Uses a Deep Convolutional Network.



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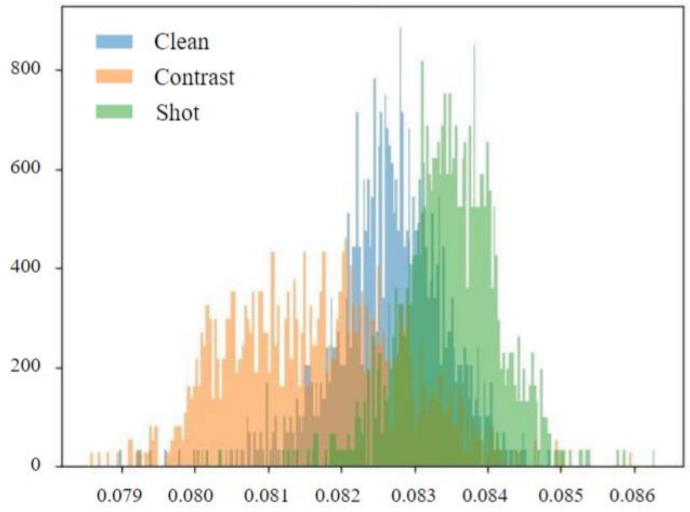
[7] Michieli U., Ozay M., Moon J., Kim D., **Camuffo E.**, "Performing a Computer Vision Task", US Patent App. 18/933,406, 2025.

NORMALIZATION LAYERS' ADAPTATION

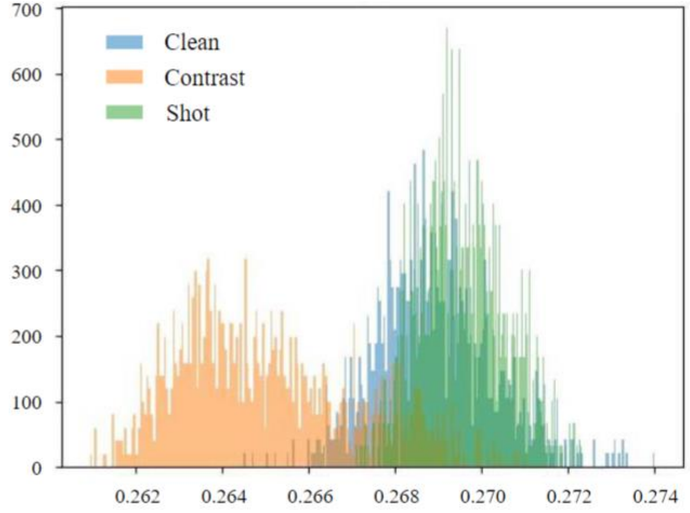
FROST: Train normalization layers' params for each corruption type separately and use them at inference time.

PAN: Adjust normalization layers for each corruption type at inference time.

AVERAGE



VARIANCE



They respond differently depending on the corruption type.

[5] **Camuffo E.**, Michieli U., Moon J., Kim D., Ozay M., "FFT-based Selection and Optimization of Statistics for Robust Recognition of Severely Corrupted Images", ICASSP, 2024.
[6] **Camuffo E.**, Michieli U., Milani S., Moon J., Ozay M., "Enhanced Model Robustness to Input Corruptions by Per-corruption Adaptation of Normalization Statistics", IROS, 2024.
[7] Michieli U., Ozay M., Moon J., Kim D., **Camuffo E.**, "Performing a Computer Vision Task", US Patent App. 18/933,406, 2025.

RESULTS

PAN RESULTS

Model	Backbone	Dataset	Task	Real	Src	PAN	Gain (%)	Metric	Model (MB)	BN (MB)
ResNet18 [110]	-	ImageNet-C [113]	OR		31.7	39.0	23.0	CA ↑	44.6	0.04
ResNet50 [110]	-	ImageNet-C [113]	OR		46.1	47.7	3.5	CA ↑	97.7	0.20
ResNet101 [110]	-	ImageNet-C [113]	OR		53.0	55.5	4.7	CA ↑	170.3	0.40
MobileNetV3 [121]	-	ImageNet-C [113]	OR		32.9	34.4	4.6	CA ↑	9.7	0.05
ResNeXt50 [337]	-	ImageNet-C [113]	OR		49.6	51.3	3.4	CA ↑	95.7	0.26
Wide-ResNet50 [346]	-	ImageNet-C [113]	OR		49.0	50.2	2.4	CA ↑	263.0	0.26
ResNet50 [110]	-	VizWiz [13]	OR	✓	39.1	43.8	12.0	CA ↑	97.7	0.20
ResNet50 [110]	-	OpenLORIS [270]	OR	✓	42.5	43.8	3.1	CA ↑	97.7	0.20
YOLOv8n [142]	CSPNet [315]	VOC-C [197]	OD		34.6	36.3	4.9	mAP^{50-95} ↑	12.1	0.04
YOLOv8n [142]	CSPNet [315]	ExDARK [176]	OD	✓	39.4	40.3	2.3	mAP^{50-95} ↑	12.1	0.04
DeepLabV2 [328]	MobileNetV2 [266]	Cityscapes-C [197]	SS		34.5	41.5	20.3	mIoU ↑	42.2	0.11
DeepLabV2 [328]	MobileNetV2 [266]	ACDC [262]	SS	✓	37.8	40.1	6.1	mIoU ↑	42.2	0.11

- Applicable on both **synthetic** and **real** corruptions.
- Applicable to different models, datasets and tasks.

[5] **Camuffo E.**, Michieli U., Moon J., Kim D., Ozay M., “FFT-based Selection and Optimization of Statistics for Robust Recognition of Severely Corrupted Images”, ICASSP, 2024.
[6] **Camuffo E.**, Michieli U., Milani S., Moon J., Ozay M., “Enhanced Model Robustness to Input Corruptions by Per-corruption Adaptation of Normalization Statistics”, IROS, 2024.
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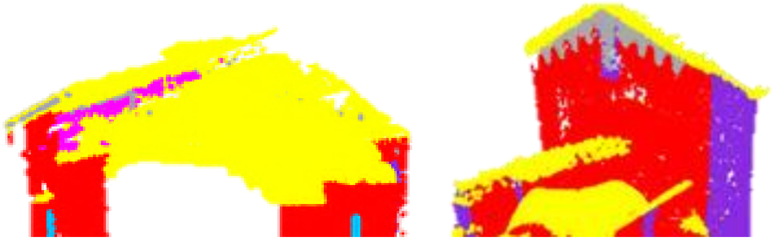
2. Continual and Multimodal Learning
3. Robustness to Corrupted Data
4. **Few-Shot and 3D Reconstruction**
5. **Conclusions**

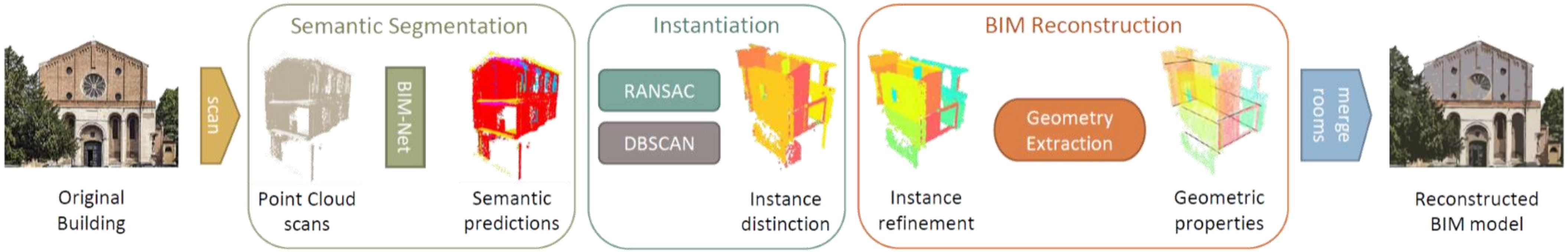


4. Few-Shot and 3D Reconstruction

- **HePIC** Dataset: heritage point cloud instance collection of large-scale buildings.
- **Few-shot** learning for Scan-to-BIM instances reconstruction [8].

[8] Campagnolo D., **Camuffo E.**, Michieli U., Borin P., Milani S., Giordano A., "Fully-Automated Scan-to-BIM via Point Cloud Instance Segmentation", ICIP, 2023.

SCAN-TO-BIM RECONSTRUCTION



FULLY AUTOMATED SCAN-TO-BIM PIPELINE

- **Heritage Point cloud Instance Collection** (HePIC).
- Novel **ad hoc deep network** (BIM-Net++)
- Novel **model pre-training and class re-weighting.**

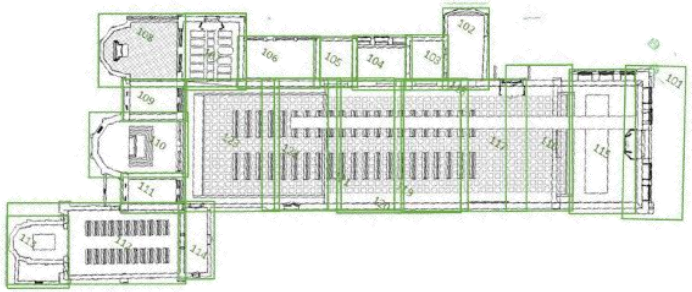
[8] Campagnolo D., **Camuffo E.**, Michieli U., Borin P., Milani S., Giordano A., “Fully-Automated Scan-to-BIM via Point Cloud Instance Segmentation”, ICIP, 2023.

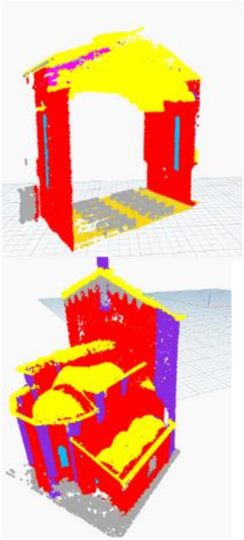
HEPIC DATASET

Acquired via terrestrial laser scanning and labeled using BIM models manually generated.

91 rooms, each composed of 100k points with both semantic and instance labels.

Class	# items Church	# items Castle	# items Tot	total # points Church	total # points Castle	total # points Tot
unassigned	23	66	89	216132	296201	512333
beams	147	1809	1956	6393	415069	421462
columns	18	238	256	18951	74588	93539
doors	27	265	292	13962	133257	147219
floors	83	314	397	146516	745314	891830
roofs	218	535	753	564371	632383	1196754
stairs	16	104	120	2394	77089	79483
walls	417	1141	1558	1229115	4229447	5458562
windows	189	81	270	62056	46512	108568
Tot	1250	4441	**5691**	2299983	6609767	**8909750**



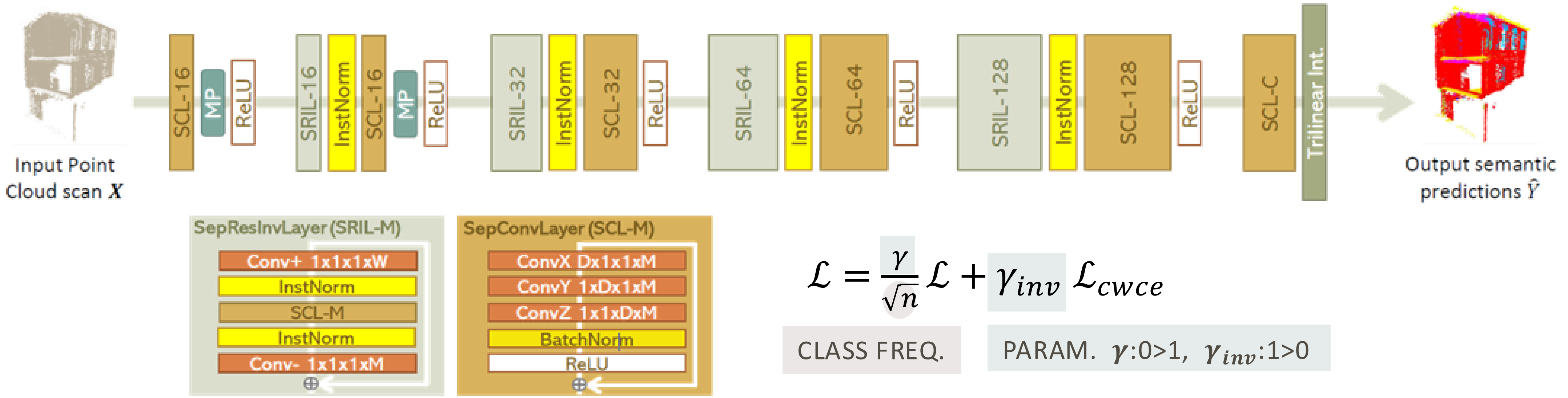


FLOORMAP AND SAMPLES
FROM EREMITANI CHURCH

[8] Campagnolo D., **Camuffo E.**, Michieli U., Borin P., Milani S., Giordano A., "Fully-Automated Scan-to-BIM via Point Cloud Instance Segmentation", ICIP, 2023.

FEW-SHOT AND REWEIGHTING SCHEMES

Ad hoc lightweight Network (BIM-Net) using **few-shot learning** (BIM-Net++) and loss weighting schemes.



$$\mathcal{L} = \frac{\gamma}{\sqrt{n}}\mathcal{L} + \gamma_{inv}\,\mathcal{L}_{cwce}$$

CLASS FREQ.

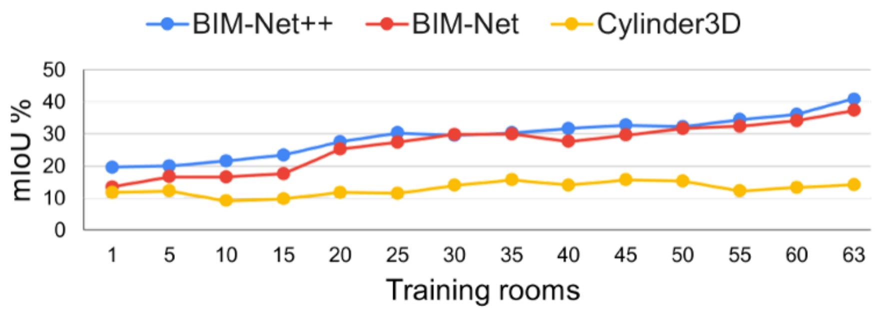
PARAM. $\boldsymbol{\gamma}$:0>1, $\boldsymbol{\gamma_{inv}}$:1>0

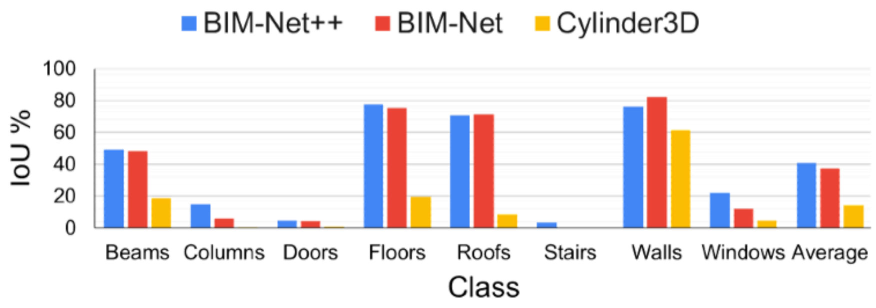
[8] Campagnolo D., **Camuffo E.**, Michieli U., Borin P., Milani S., Giordano A., “Fully-Automated Scan-to-BIM via Point Cloud Instance Segmentation”, ICIP, 2023.

SCAN-TO-BIM RESULTS

	5k steps			25k steps		
model	**PA%**	**PP%**	**IoU%**	**PA%**	**PP%**	**IoU%**
SegCloud [8]	17.6	24.7	13.2	17.6	24.7	13.2
Cylinder3D [7]	21.0	23.2	14.2	21.0	23.2	14.2
RandLA-Net [9]	35.4	49.3	27.8	35.6	56.2	28.8
PVCNN [11]	40.7	45.3	32.9	43.3	48.1	34.9
BIM-Net	44.0	**54.4**	37.3	47.1	**58.9**	40.6
BIM-Net++	**56.2**	49.4	**40.9**	**59.1**	53.0	**43.7**

COMPARISON WITH OTHER
STATE-OF-THE-ART ARCHITECTURES





[8] Campagnolo D., <u>**Camuffo E.**</u>, Michieli U., Borin P., Milani S., Giordano A., "Fully-Automated Scan-to-BIM via Point Cloud Instance Segmentation", ICIP, 2023.

INNOVATIONS TO TACKLE CHALLENGES

1. Class Imbalance in 3D Data
2. Continual and Multimodal Learning
3. Robustness to Corrupted Data
4. Few-Shot and 3D Reconstruction
5. **Conclusions**

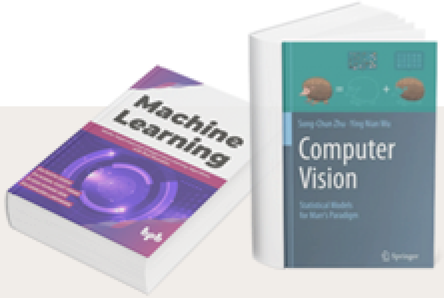
5. Conclusions

[8] Campagnolo D., **Camuffo E.**, Michieli U., Borin P., Milani S., Giordano A., “Fully-Automated Scan-to-BIM via Point Cloud Instance Segmentation”, ICIP, 2023.

LIMITATIONS AND FUTURE WORK: SEMANTICS FOR NOVEL REPRESENTATIONS

CONCLUSION

BIBLIOGRAPHY



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[2] Mari D., Camuffo E., Milani S. “CACTUS: Content-Aware Compression and Transmission Using Semantics for Automotive LiDAR data”, Sensors, 2023.

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[4] Barbato F., Camuffo E., Milani S., Zanuttigh P., “Multi-Modal Continual Learning for Semantic Segmentation”, ICIP, 2024.

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[6] Camuffo E., Michieli U., Milani S., Moon J., Ozay M., “Enhanced Model Robustness to Input Corruptions by Per-corruption Adaptation of Normalization Statistics”, IROS, 2024.

[7] Michieli U., Ozay M., Moon J., Kim D., Camuffo E., “Performing a Computer Vision Task”, US Patent App. 18/933,406, 2025.

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[9] Camuffo E., Battisti F., Pham F., Milani S. “3D Model Optimization for Immersive and Interactive Applications”, EUVIP, 2022.

[10] Camuffo E., Mari D., Milani S., “Recent advancements in learning algorithms for point clouds: An updated overview”, Sensors, 2022.

THANK YOU

"It is kind of fun to do the impossible"

Walt Disney