ROBUST VISUAL REPRESENTATION ACROSS MODALITIES IN SEMANTIC SCENE UNDERSTANDING

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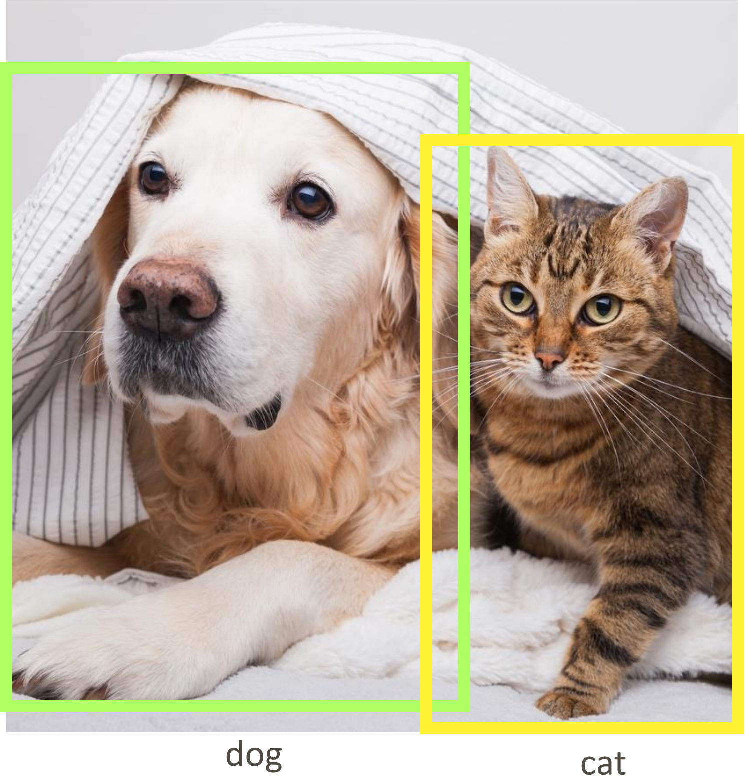
CLASSIFICATION

animals

SEMANTIC SCENE UNDERSTANDING

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

OBJECT DETECTION



SEMANTIC SCENE UNDERSTANDING

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

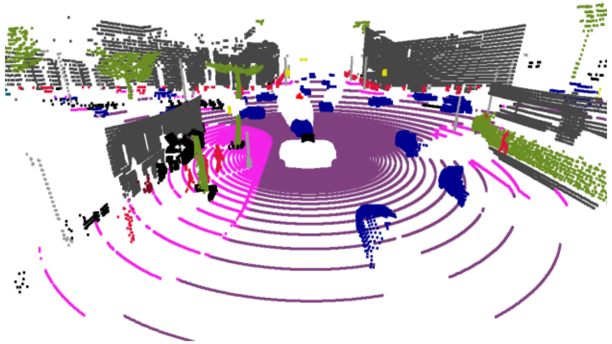
SEMANTIC SEGMENTATION

SEMANTIC SCENE UNDERSTANDING

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

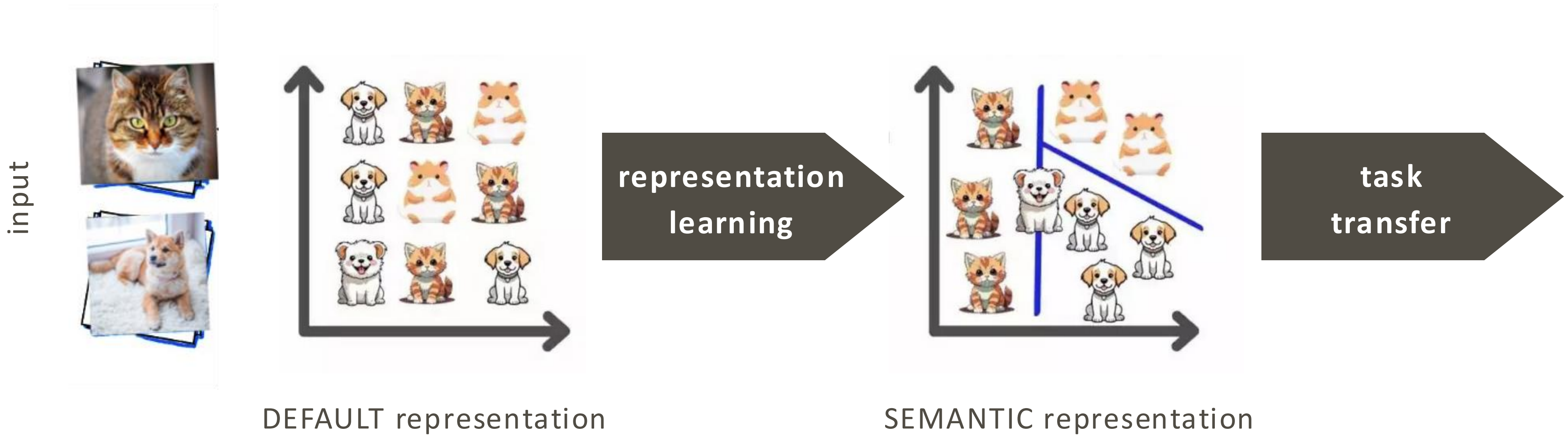
ACROSS MODALITIES

IMAGES

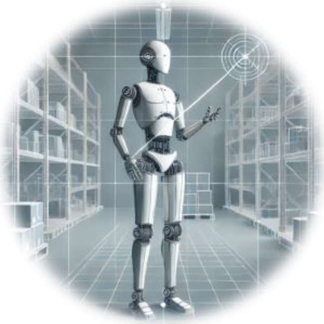


POINT CLOUDS

ROBUST VISUAL REPRESENTATION



PROBLEMS



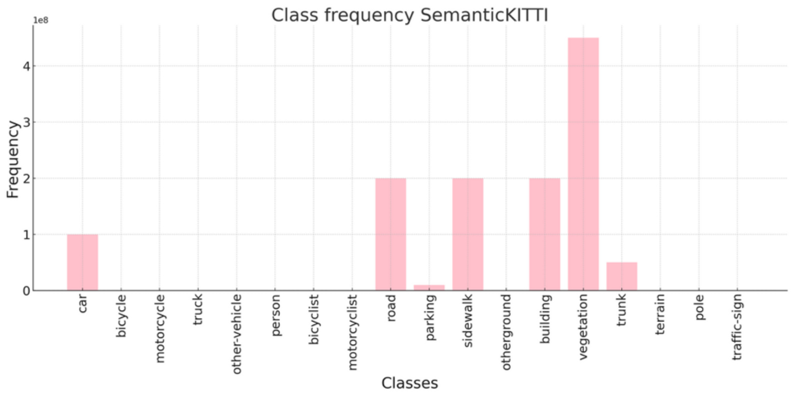
01 **Handle** imbalance datasets, limited training data and corrupted inputs.

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

03 **Understand** the environment accurately.

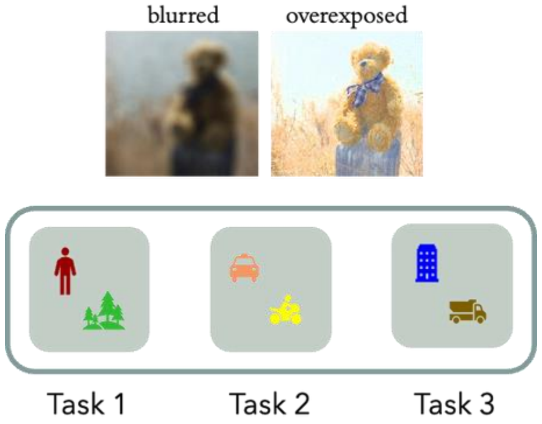
KEY CHALLENGES

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



DATA IMBALANCE AND SCARCITY

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



DATA AND LABEL DISTRIBUTION SHIFTS

CONTRIBUTION OVERVIEW

CONTRIBUTION OVERVIEW

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.

CONTRIBUTION OVERVIEW

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

CONTRIBUTION OVERVIEW

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.

Conclusion and Final Remarks.

CONTRIBUTION OVERVIEW

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

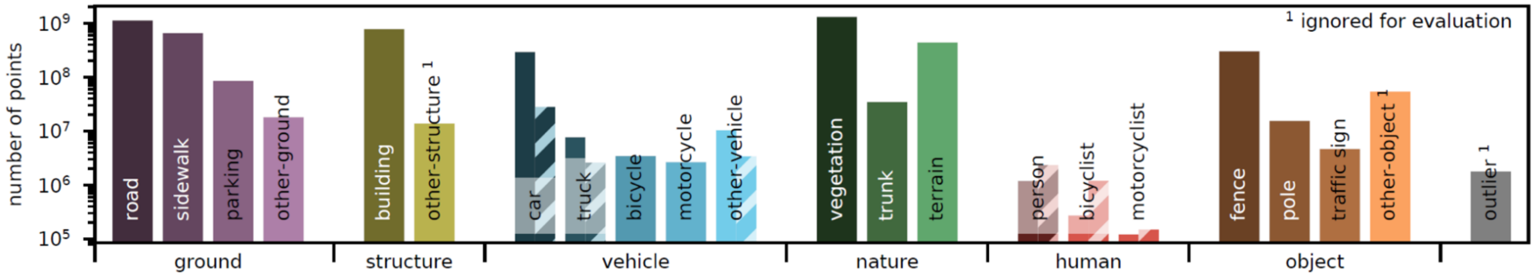
1. Class Imbalance in 3D Data

- **Hierarchical self-regularization** for better class balance in 3D 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.

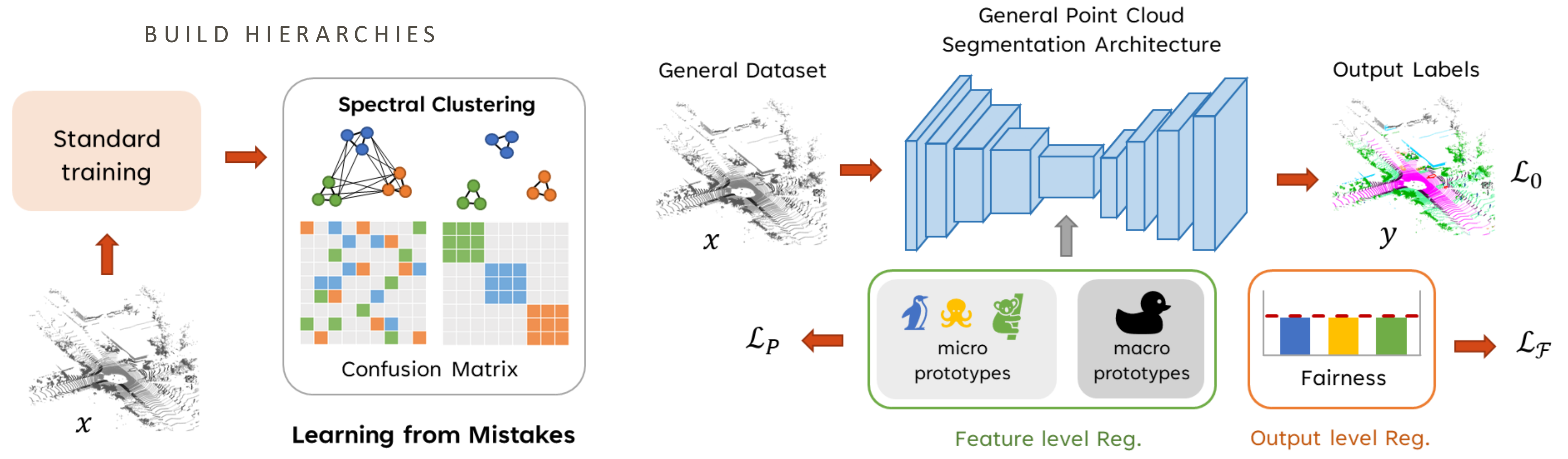
CLASS IMBALANCE IN 3D DATA

- 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 **semantically similar**.



SEMANTIC KITTI CLASS FREQUENCIES

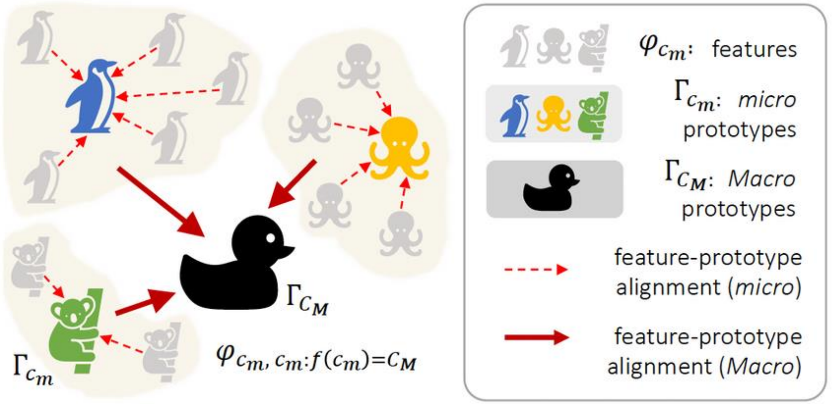
GENERAL PIPELINE



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

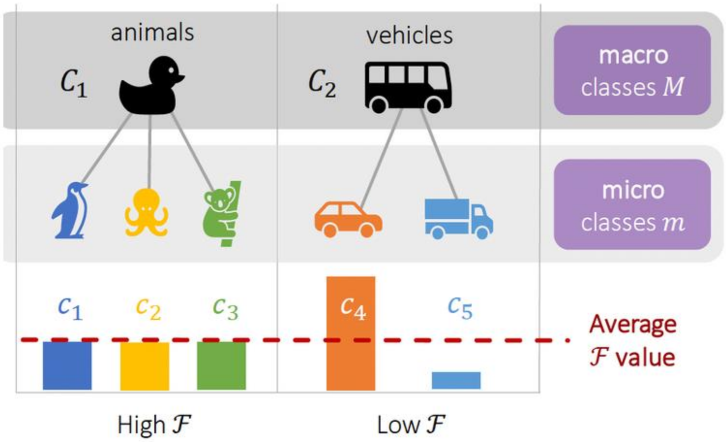
SELF-REGULARIZATION COMPONENTS

PROTOTYPES



Latent **features-to-prototype alignment** at 2 levels (micro and macro) improves class-wise feature discrimination.

FAIRNESS



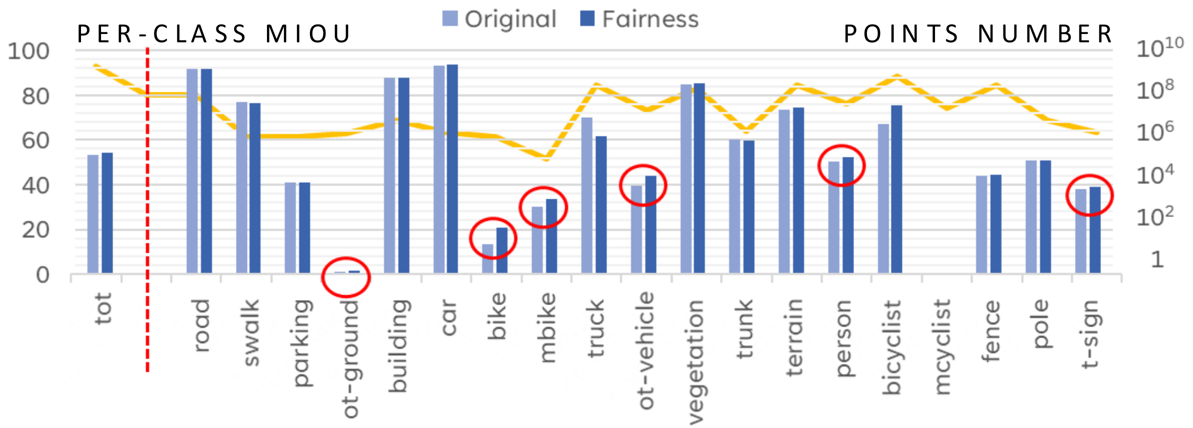
Macro-aware Fairness score on the micro classes promotes homogeneous scores in macro clusters.

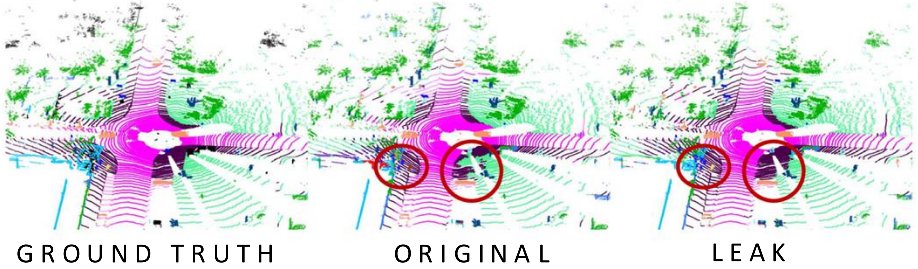
$$\mathcal{L}_{LEAK} = \mathcal{L}_0 + \lambda_{P_m} \cdot \mathcal{L}_{P_m} + \lambda_{P_M} \cdot \mathcal{L}_{P_M} + \lambda_{\mathcal{F}} \cdot \mathcal{L}_{\mathcal{F}}$$

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

RESULTS

- Per-class mIoU trend follows point frenquency distribution (yellow).
- **Balanced results** increasing especially mIoU of underrepresented classes.

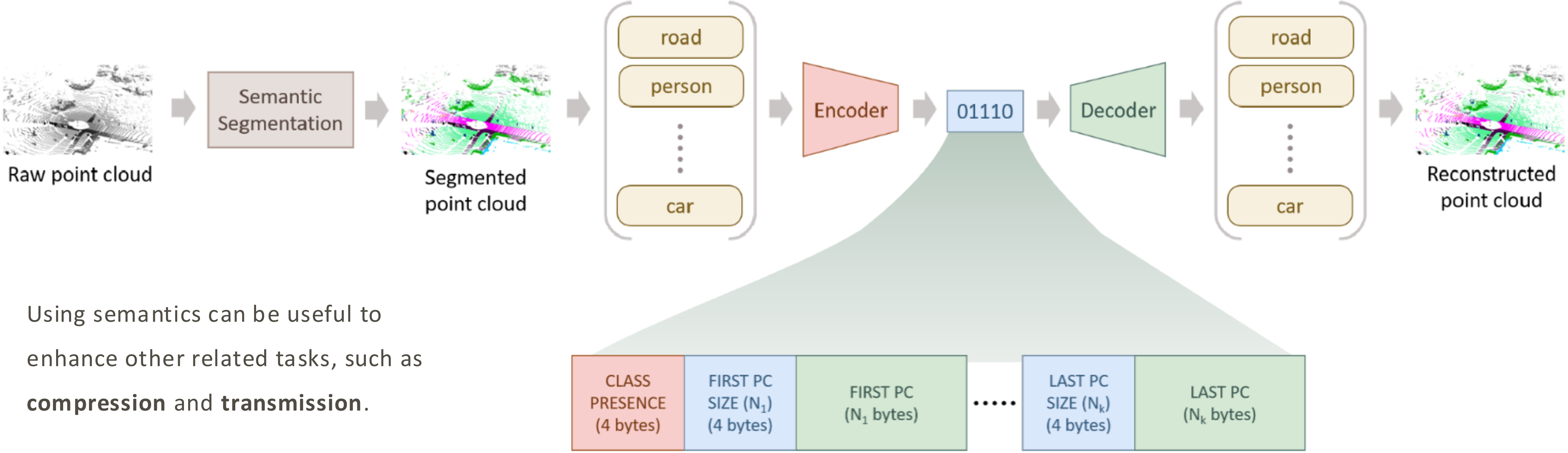




Qualitative improvements on **underrepresented classes** and across semantically dissimilar clusters.

[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.

CONTRIBUTION OVERVIEW

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.

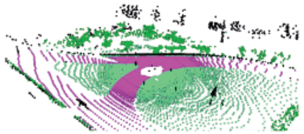
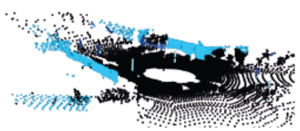
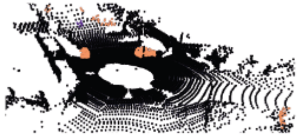
MULTIMODAL LEARNING

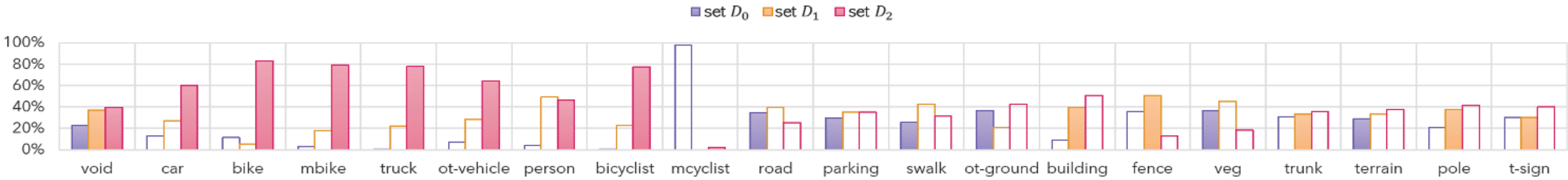
Inclusion of **heterogeneous data** to learn more information about the scene.

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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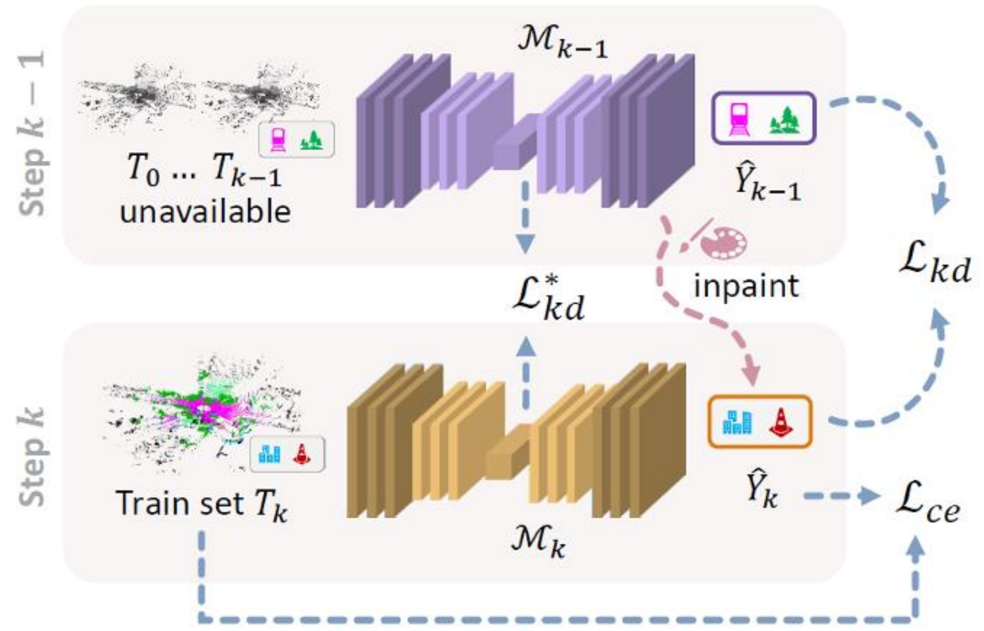
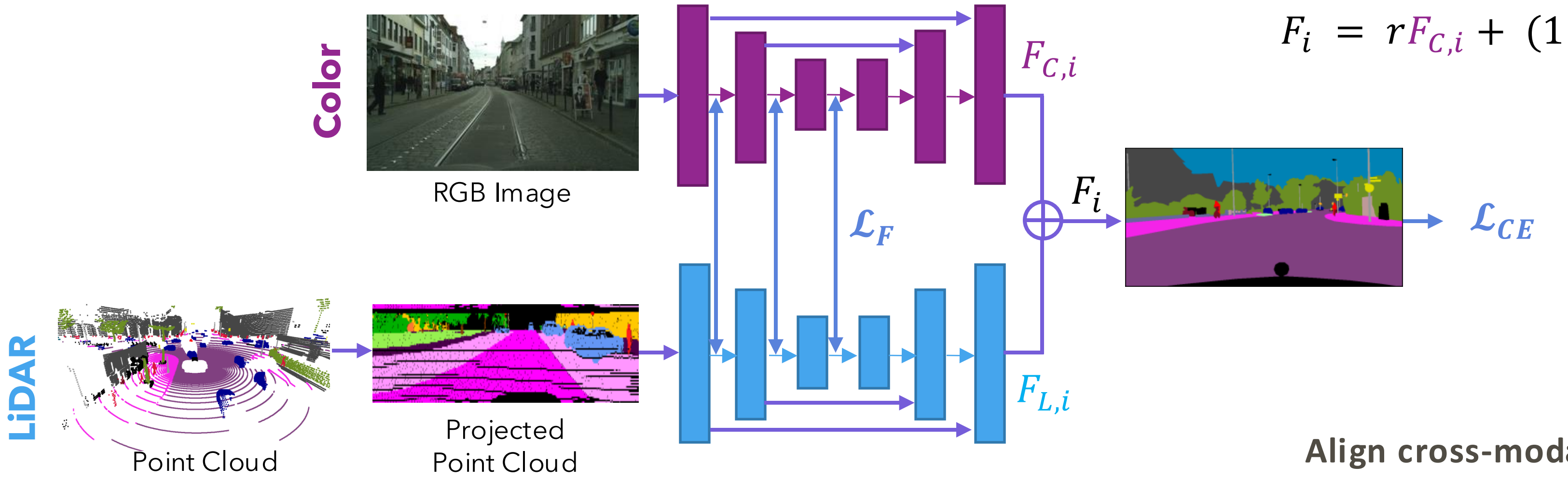
DISCOVERY OF NOVEL SEMANTIC CATEGORIES



- **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.

MULTIMODAL DATA INTEGRATION



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

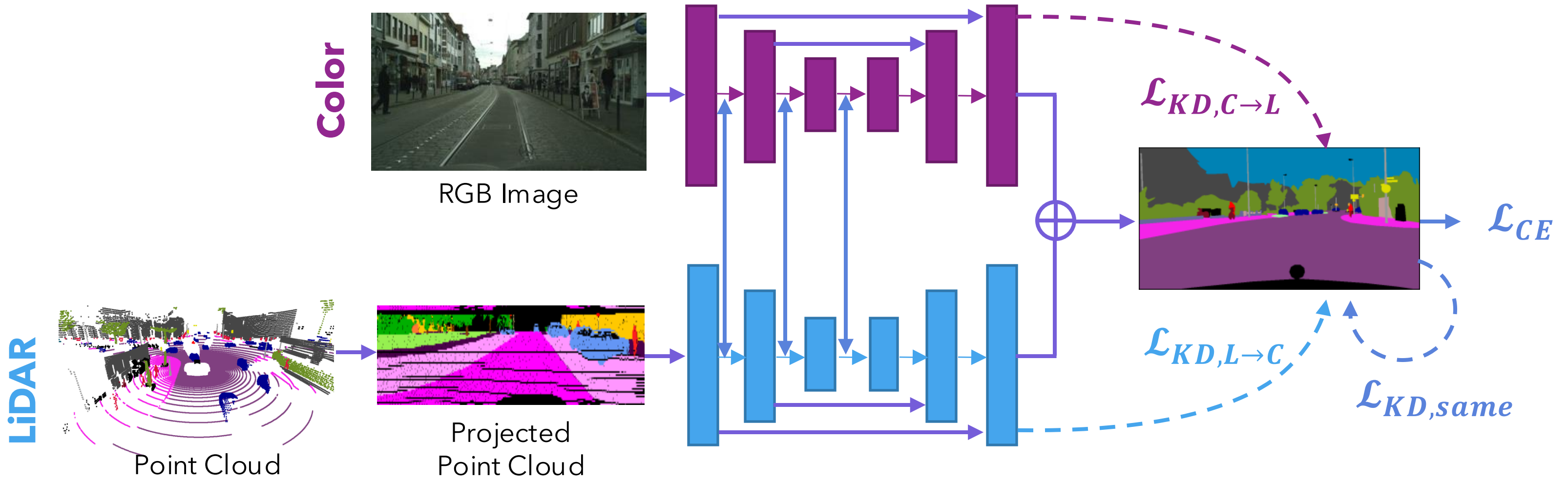
OUTPUT FEATURE

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

Align cross-modal features to create a **symmetric architecture** that allows understanding even if one modality is missing.

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

MULTIMODAL DATA INTEGRATION



Allows to consider continual learning: Knowledge distillation performed **within the same branch** or **across branches**.

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

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

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

CONTRIBUTION OVERVIEW

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 normalization layers of understanding models [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

BLURRED OVEREXPOSED

FOG SNOW

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

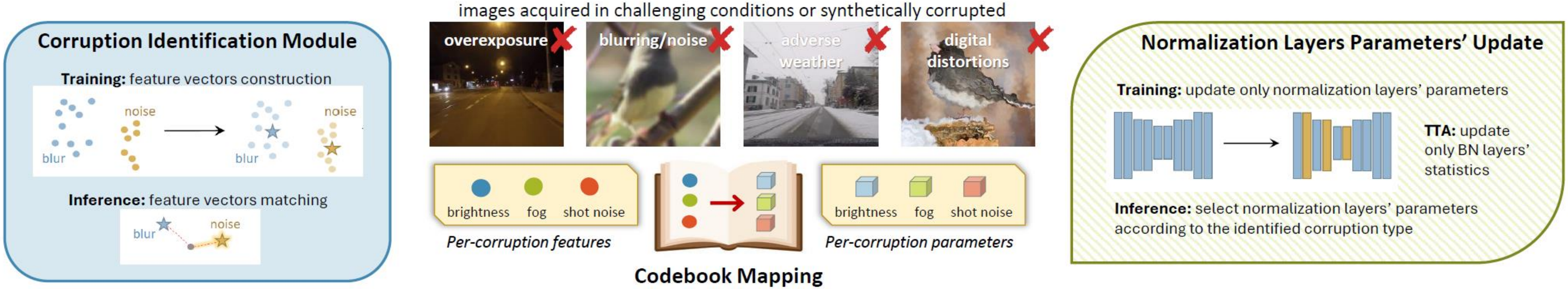
$$\tilde{x} = \underbrace{x}_{\text{clean image}} + \underbrace{\psi(x)}_{\text{corruption}}$$

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 DATA

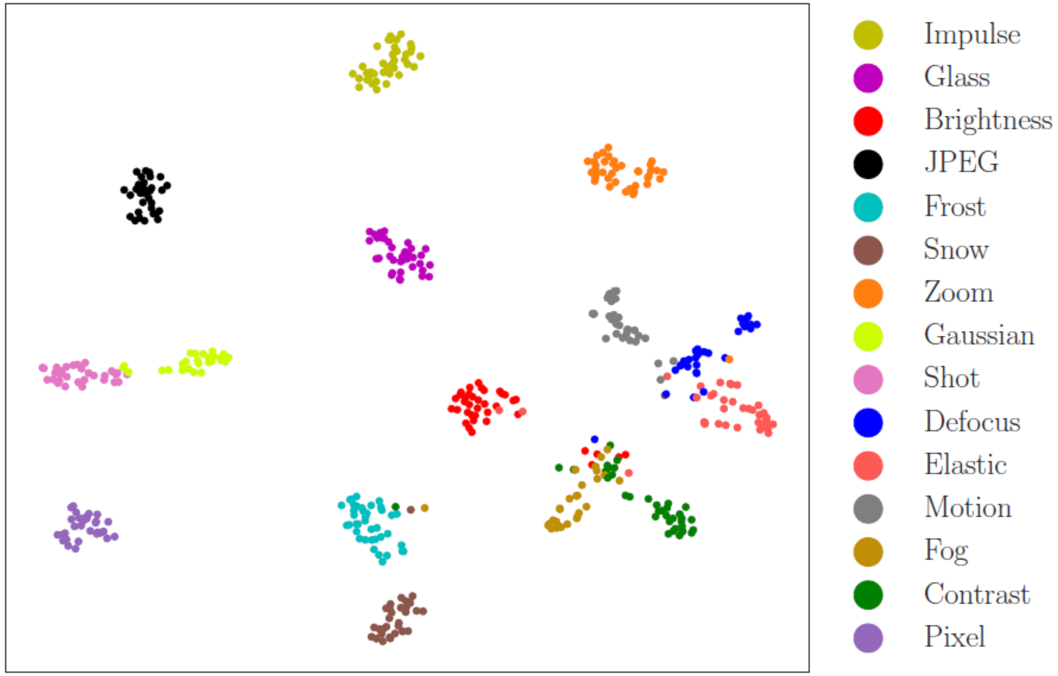


1. **FROST:** FFT features
2. **PAN:** Deep neural network

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

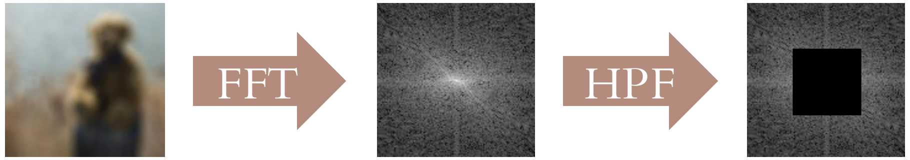
[5] **Camuffo E.**, Michieli U., Moon J., Kim D., Ozay M., "FFT-based Selection and Optimization of Statistics for Robust Recognition of Severely Corrupted Images", ICASSP, 2024.
[6] **Camuffo E.**, Michieli U., Milani S., Moon J., Ozay M., "Enhanced Model Robustness to Input Corruptions by Per-corruption 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

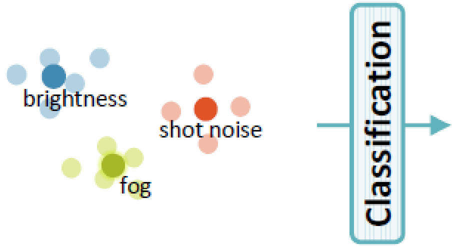


TSNE OF CORRUPTIONS FEATURES (PAN)

FROST: Uses High-Frequency FFT amplitudes.



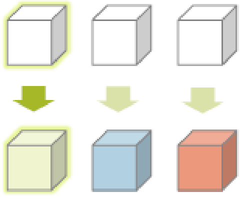
PAN: Uses a Deep Convolutional Network.



[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.

NORMALIZATION LAYERS' ADAPTATION

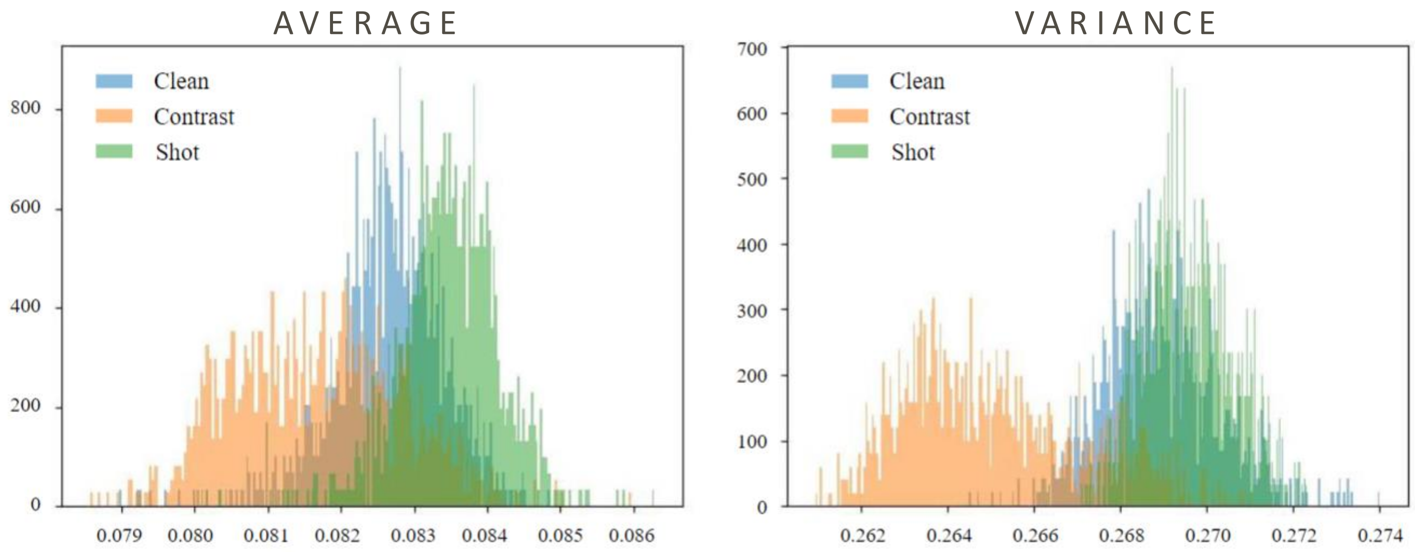
FROST: Train normalization layers for each corruption type separately and use them at inference time.



STANDARD

SPECIALIZED

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



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.
[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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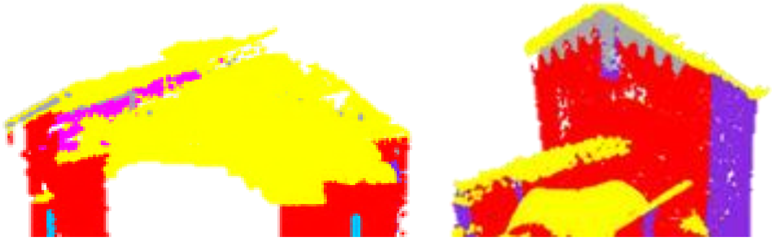
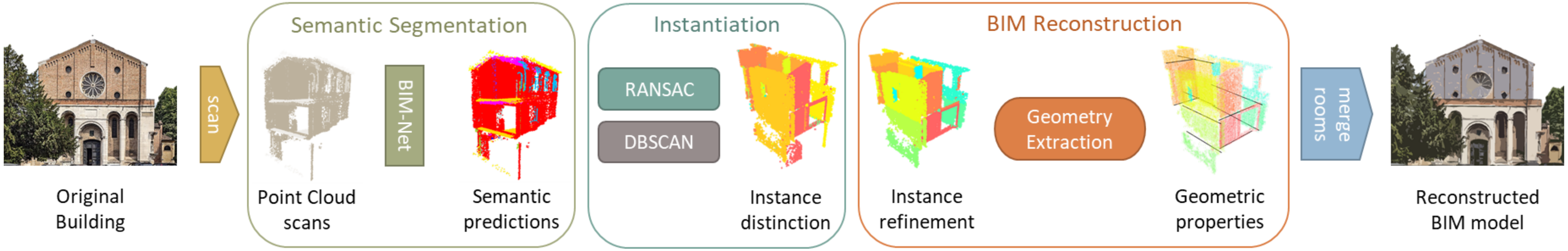


4. Few-Shot and 3D Reconstruction

- **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.**

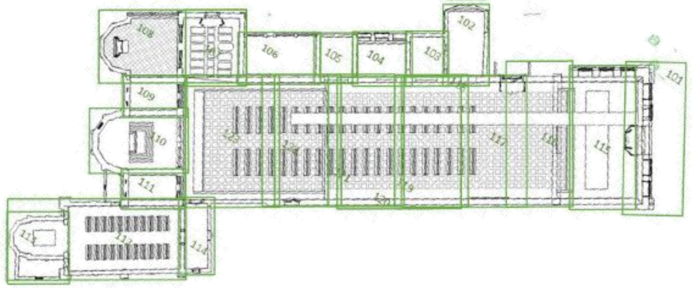
[8] Campagnolo D., **Camuffo E.**, Michieli U., Borin P., Milani S., Giordano A., “Fully-Automated Scan-to-BIM via Point Cloud Instance Segmentation”, ICIP, 2023.

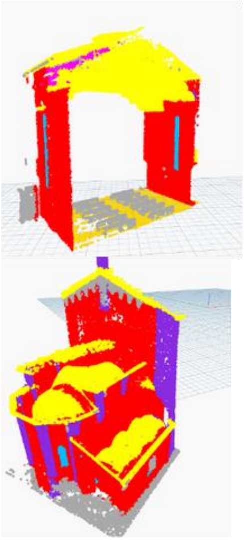
HEPIC DATASET

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			total # points		
	Church	*Castle*	Tot	*Church*	*Castle*	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**



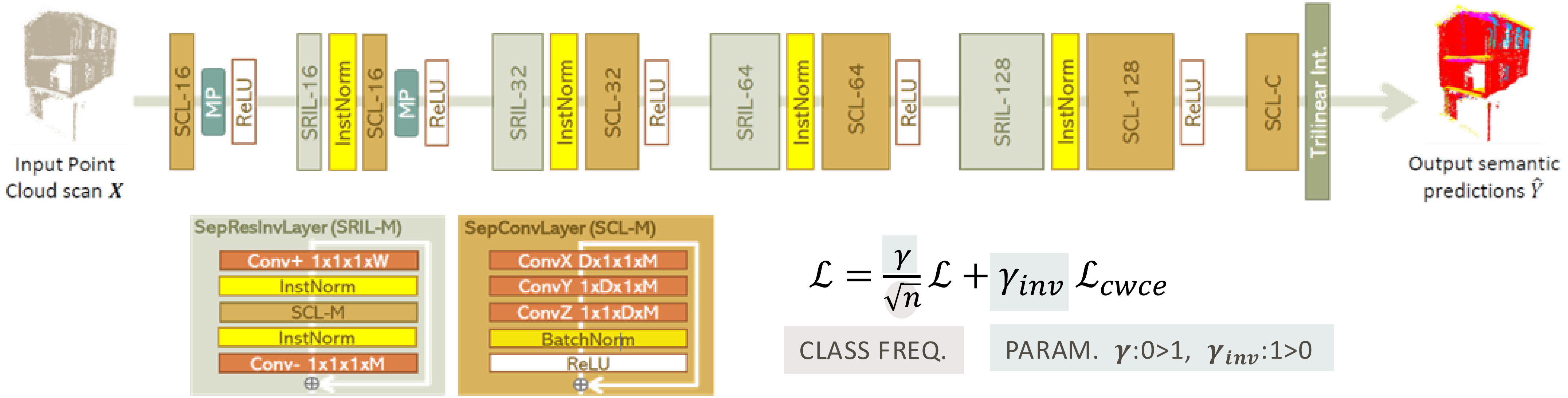


FLOORMAP AND SAMPLES FROM EREMITANI CHURCH

[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** and loss weighting schemes (BIM-Net++).



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

CLASS FREQ.

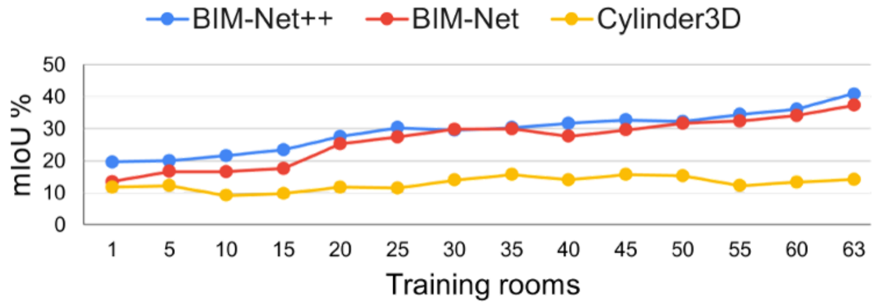
PARAM. γ:0>1, γ_{inv}:1>0

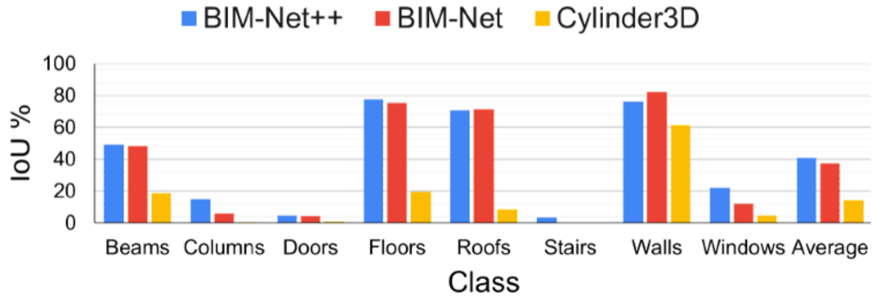
[8] Campagnolo D., **Camuffo E.**, Michieli U., Borin P., Milani S., Giordano A., “Fully-Automated Scan-to-BIM via Point Cloud Instance Segmentation”, ICIP, 2023.

RESULTS

model	5k steps PA%	5k steps PP%	5k steps IoU%	25k steps PA%	25k steps PP%	25k steps 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., **Camuffo E.**, Michieli U., Borin P., Milani S., Giordano A., “Fully-Automated Scan-to-BIM via Point Cloud Instance Segmentation”, ICIP, 2023.

CONTRIBUTION OVERVIEW

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.

CONCLUSION

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.

DATA AND LABEL DISTRIBUTION SHIFTS

2. Continual and Multimodal Learning

Enhanced Continual Learning on LiDAR data.

Multimodality for resilient architectures to losses.

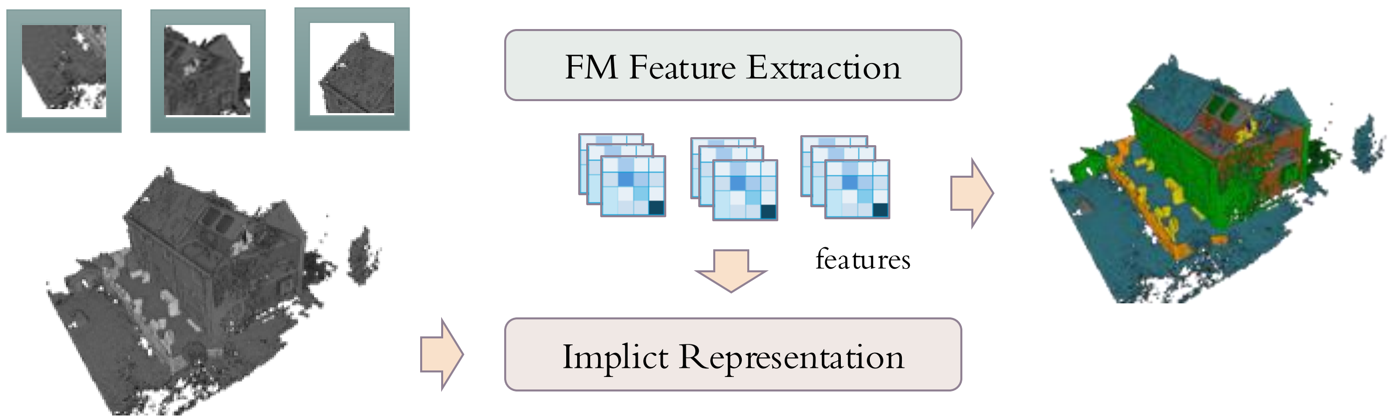
3. Robustness to Corrupted Data

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

Overall **improvement of existing scene understanding models** using these advanced learning techniques.

LIMITATIONS AND FUTURE WORK: SEMANTICS FOR NOVEL REPRESENTATIONS

- Rapid development of these technologies in the last few years: **foundation models** and **novel visual representations**.
- Future Work: Develop on top of state-of-the-art technologies to obtain better and faster scene understanding models.

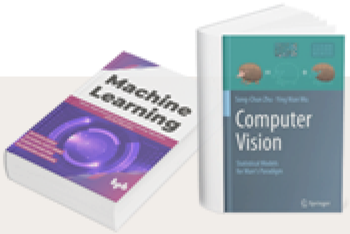


THANK YOU

"It is kind of fun to do the impossible."

Walt Disney

BIBLIOGRAPHY



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