Master Degree in ICT for Internet and Multimedia

September 6, 2021

Academic Year 2020-2021

DIPARTIMENTO DI INGEGNERIA DELL'INFORMAZIONE

Curriculum and Contrastive Learning in LiDAR Semantic Segmentation

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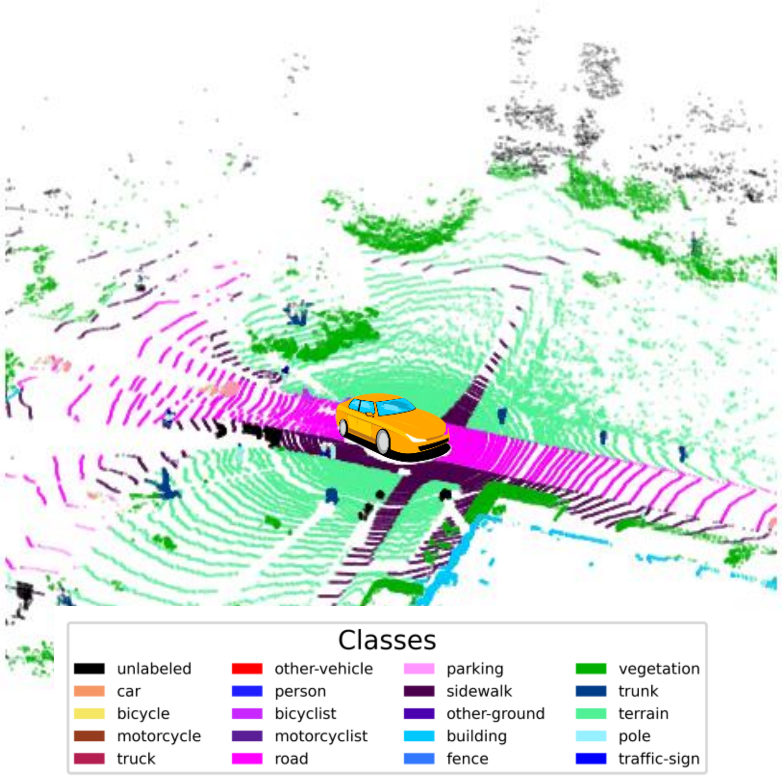
Co-supervisor: *Umberto Michieli*

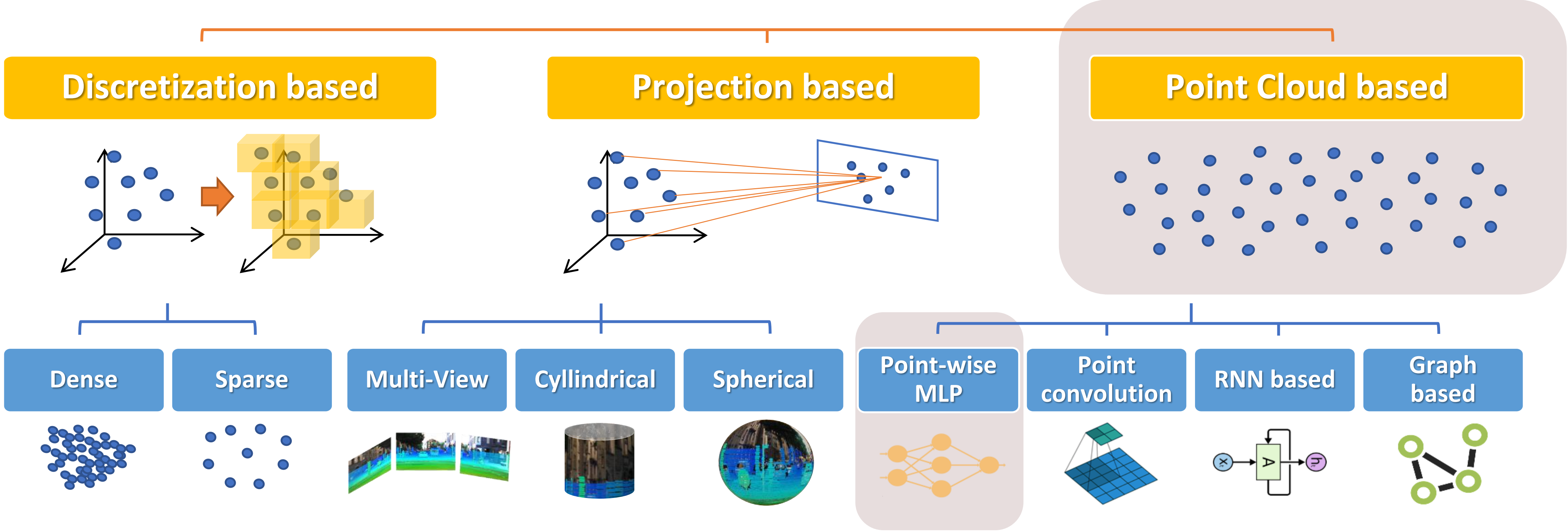
LiDAR Semantic Segmentation

- **Classification** of **3D points** for scene understanding.
- Many **applications**, e.g., autonomous driving, robotics, remote sensing.
  - > SemanticKITTI dataset [1]
- **Deep Learning** methods.
  - > RandLA-Net [2]

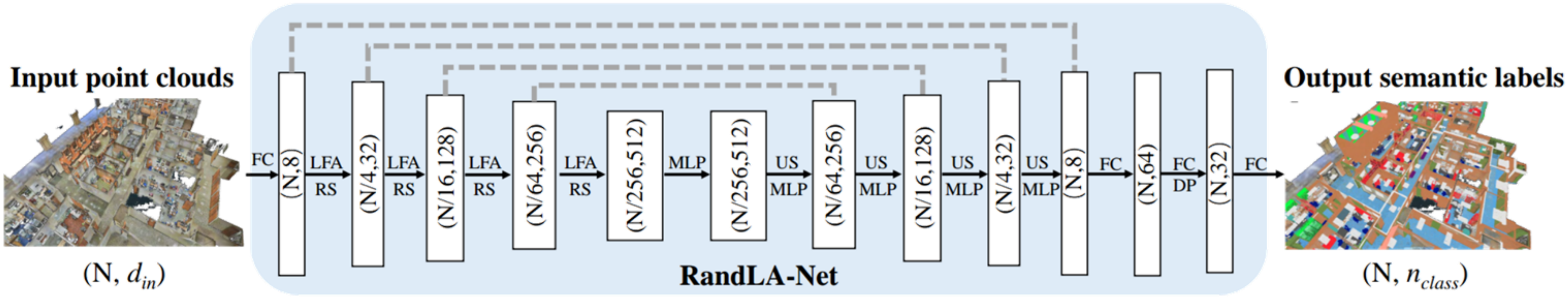


[1] J. Behley, M. Garbade, A. Milioto, J. Quenzel, S. Behnke, C. Stachniss, and J. Gall. "SemanticKITTI: A dataset for semantic scene understanding of LiDAR sequences". In International Conference on Computer Vision (ICCV), 2019.

LiDAR SS methods taxonomy



Deep Learning architecture

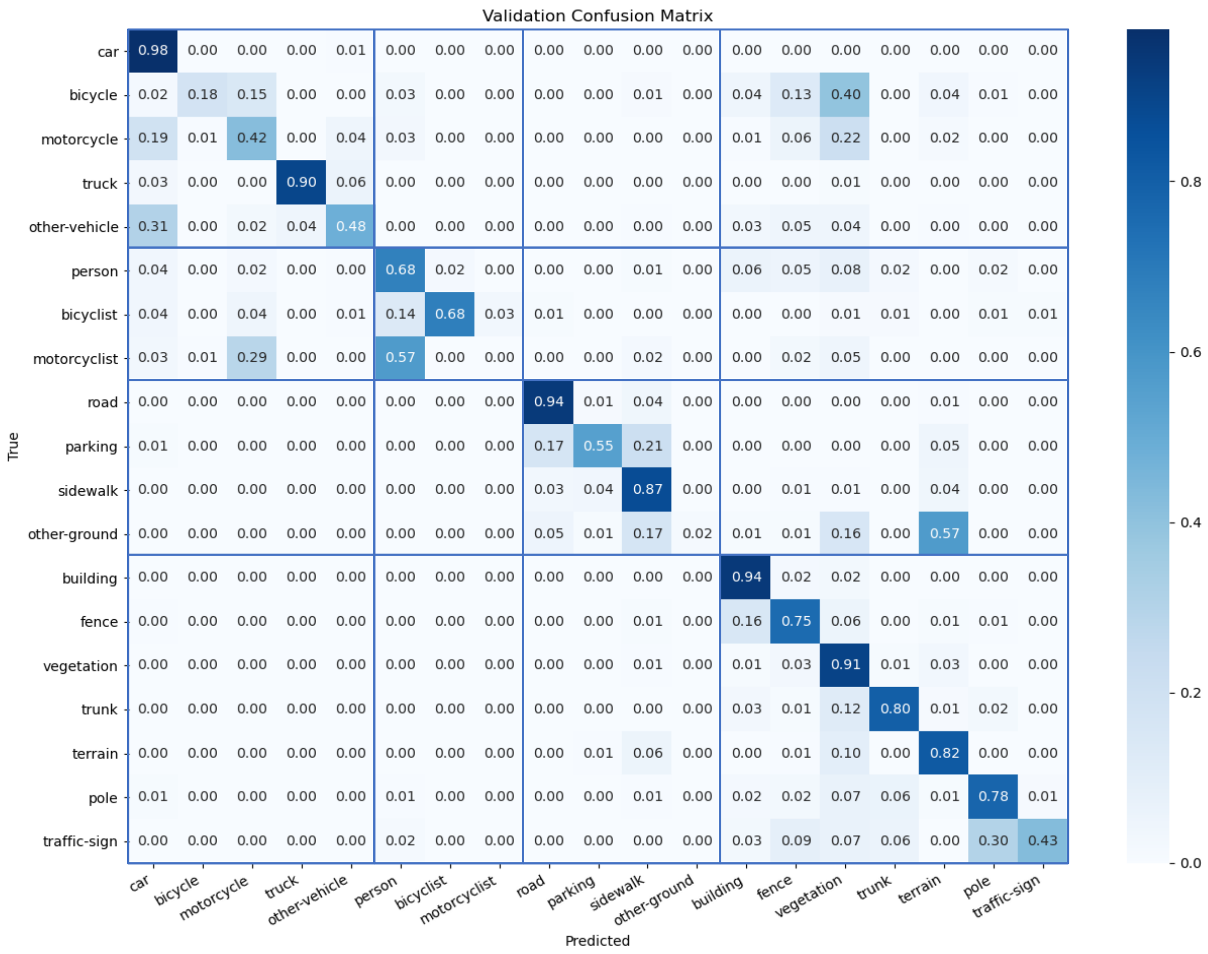


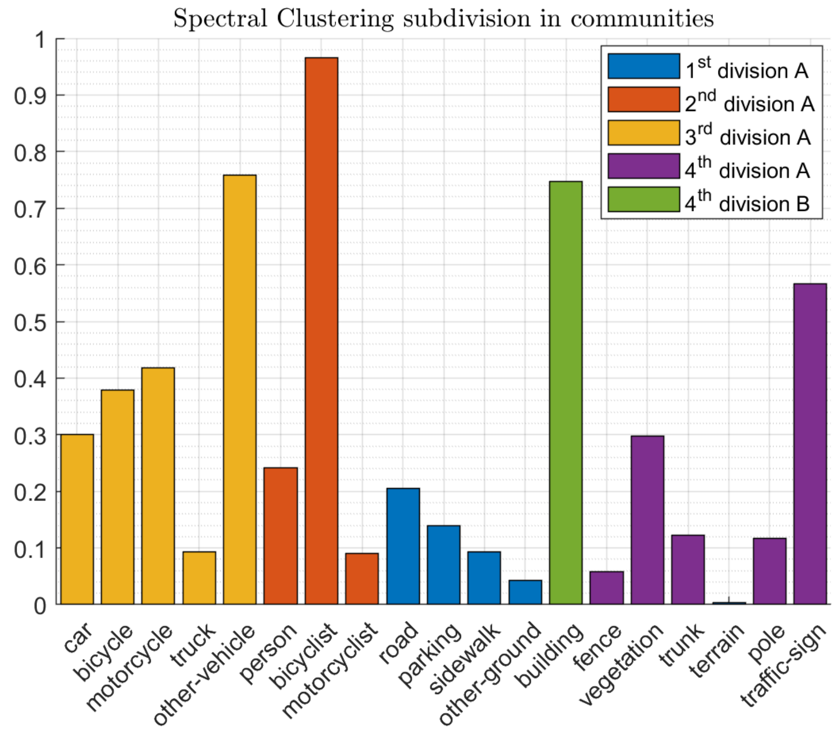
Standard training → Output ↔ Dataset → Learning methods

Analyses

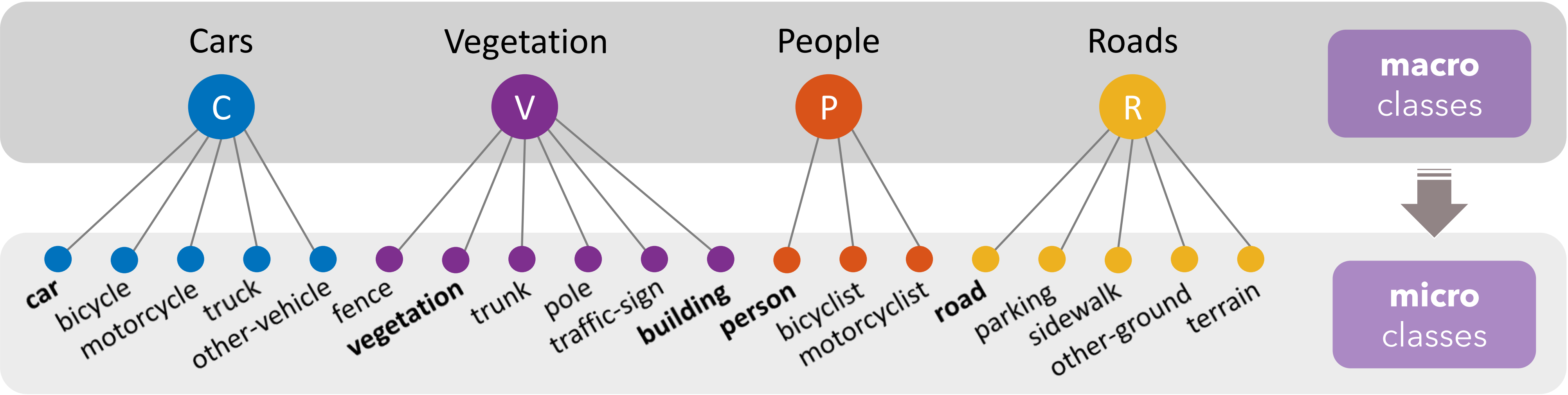
[2] Q. Hu, B. Yang, L. Xie, S. Rosa, Y. Guo, Z. Wang, N. Trigoni, and A. Markham. "RandLA-Net: efficient semantic segmentation of large-scale point clouds," in Proc. of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 2020, pp. 11 108–11 117.

Output and dataset analyses





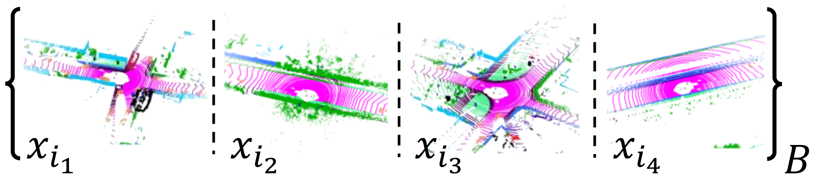
Hierarchical Grouping



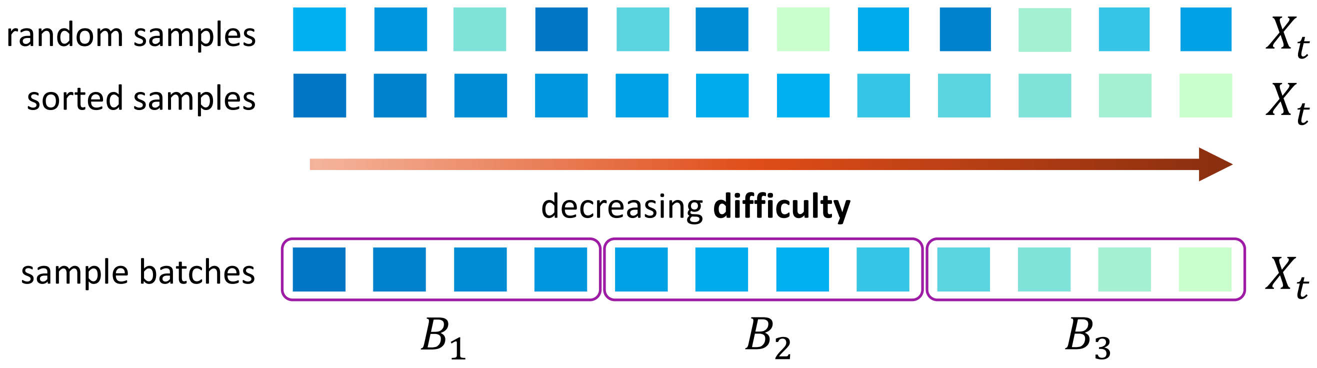
Hierarchical loss function: $\mathcal{L}_{hierarchy} = \mathcal{L}_{micro} + \gamma \cdot \mathcal{L}_{macro}$

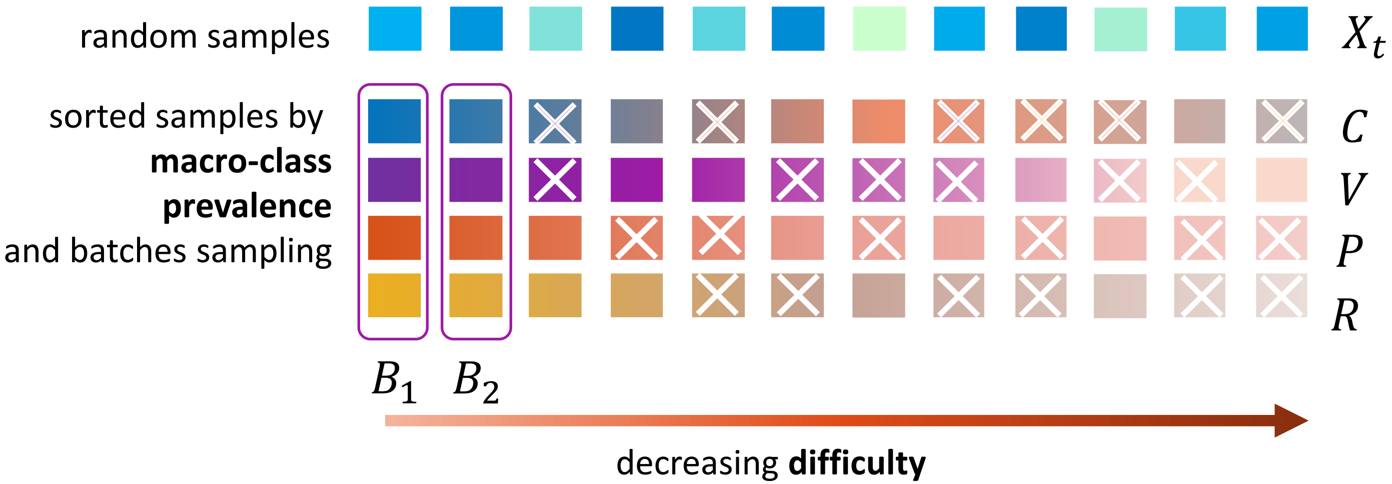
[3] Umberto Michieli, Edoardo Borsato, Luca Rossi, and Pietro Zanuttigh. Gmnet: Graph matching network for large scale part semantic segmentation in the wild. In European Conference on Computer Vision, pages 397–414. Springer, 2020.

Batch Organization



example of batch

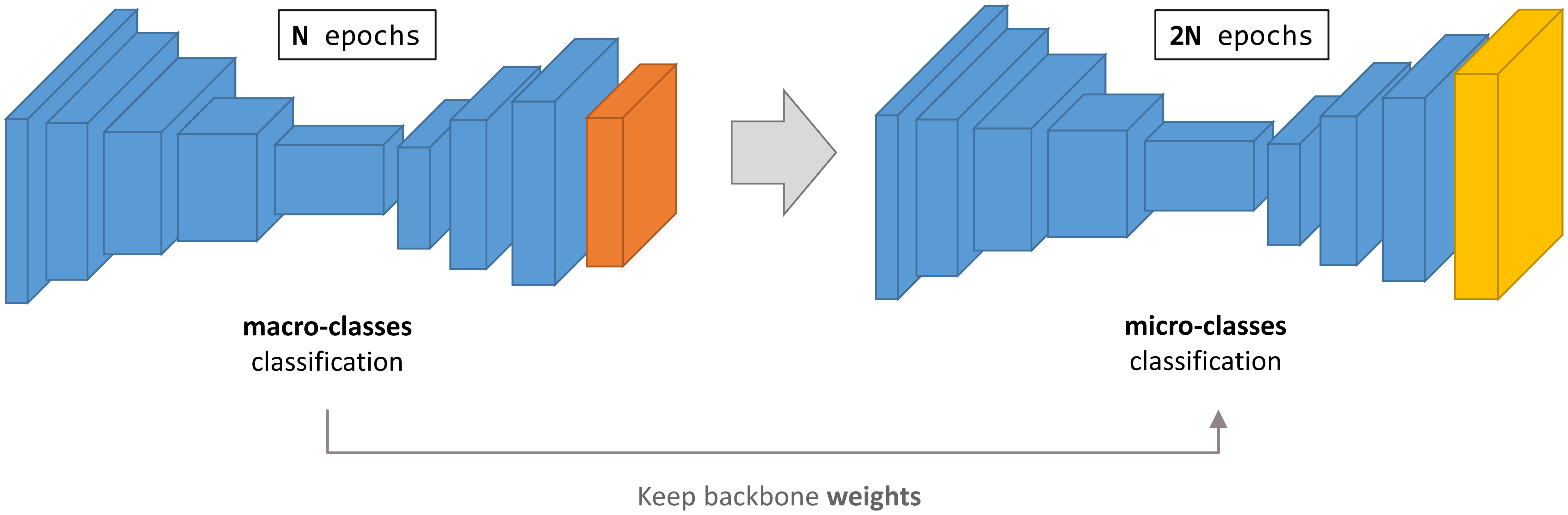




Ordering criteria:

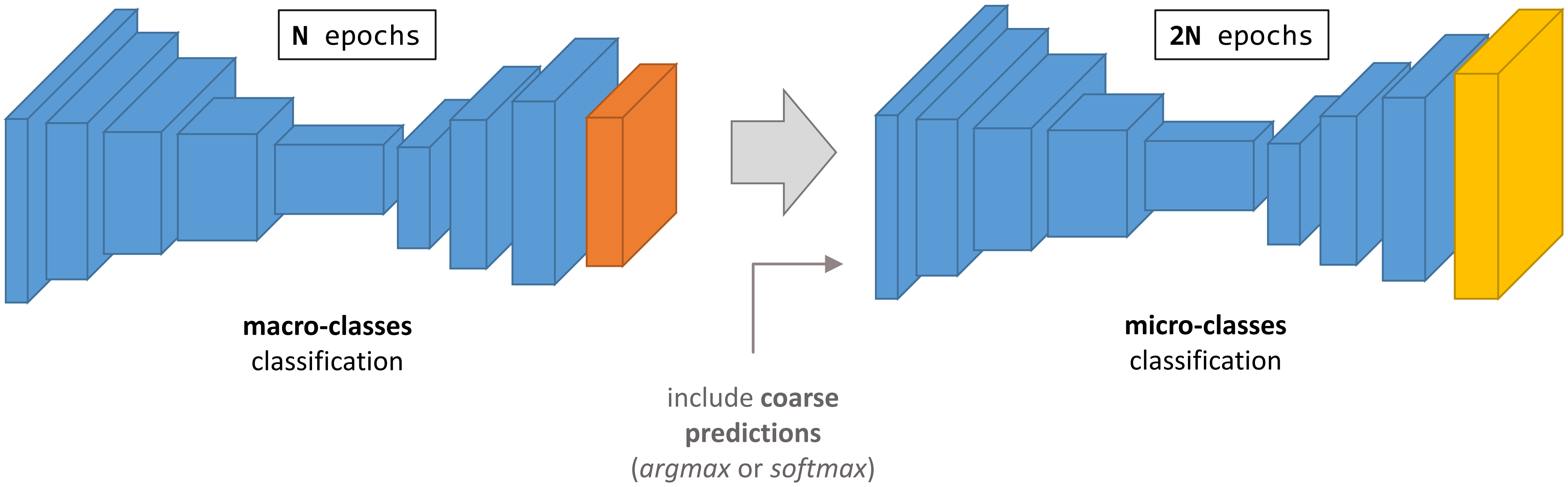
- mIoU
- number of points

Coarse-to-Fine training



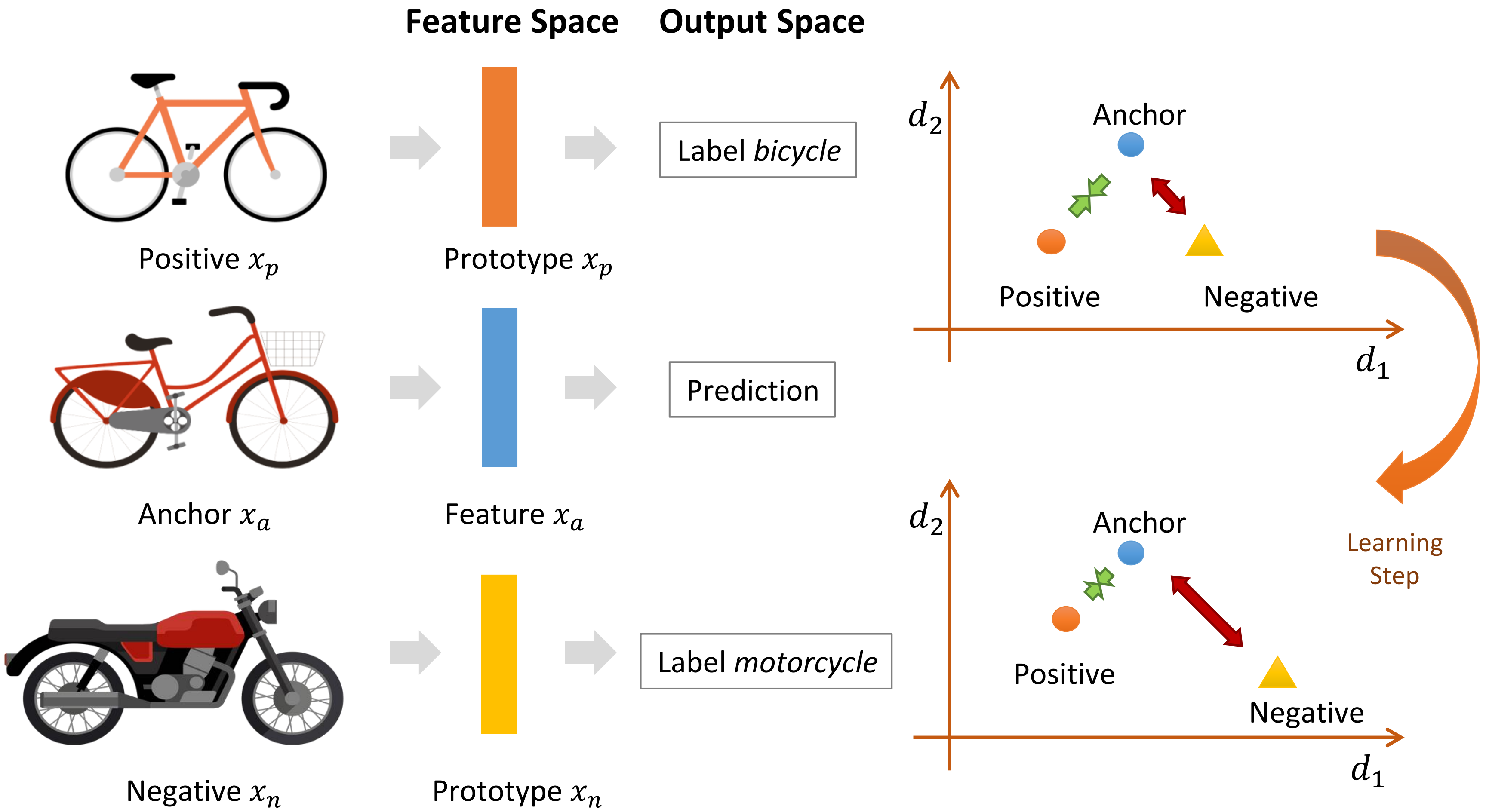
[4] Otilia Stretcu, Emmanouil Antonios Platanios, Tom Mitchell, and Barnabás Póczos. Coarse-to-fine curriculum learning. arXiv preprint arXiv:2106.04072, 2021.

Coarse-to-Fine training

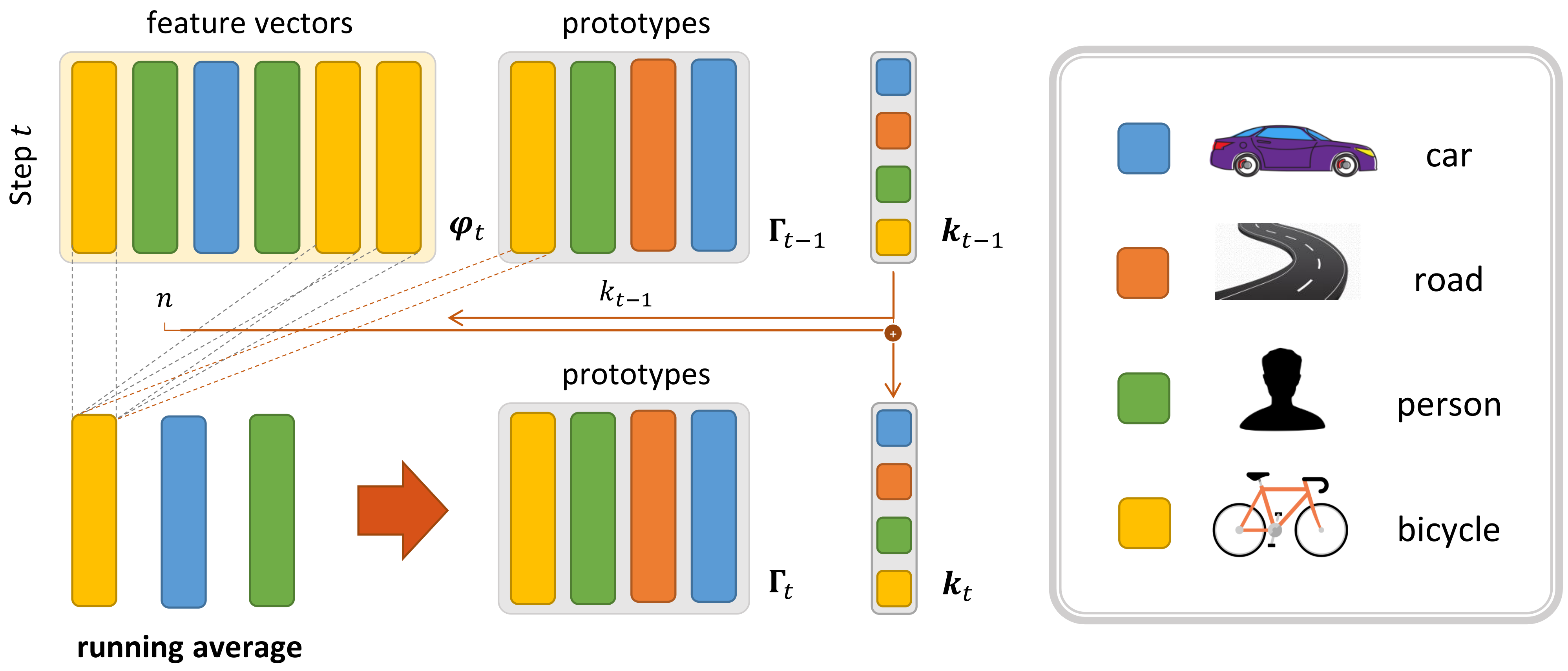


[4] Otilia Stretcu, Emmanouil Antonios Platanios, Tom Mitchell, and Barnabás Póczos. Coarse-to-fine curriculum learning. arXiv preprint arXiv:2106.04072, 2021.

Contrastive Learning



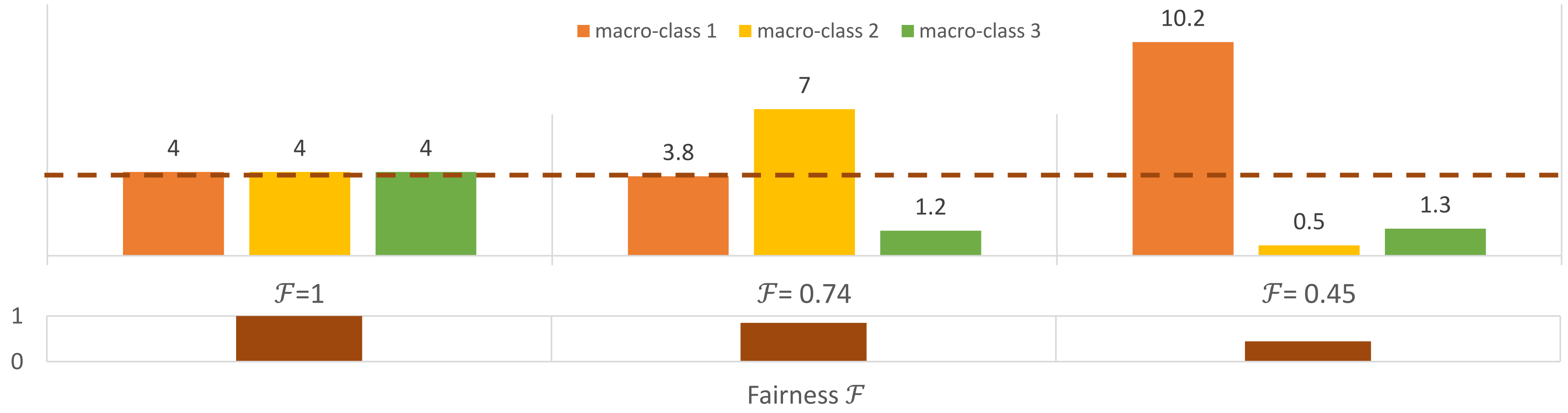
Feature Level



Jain's fairness index

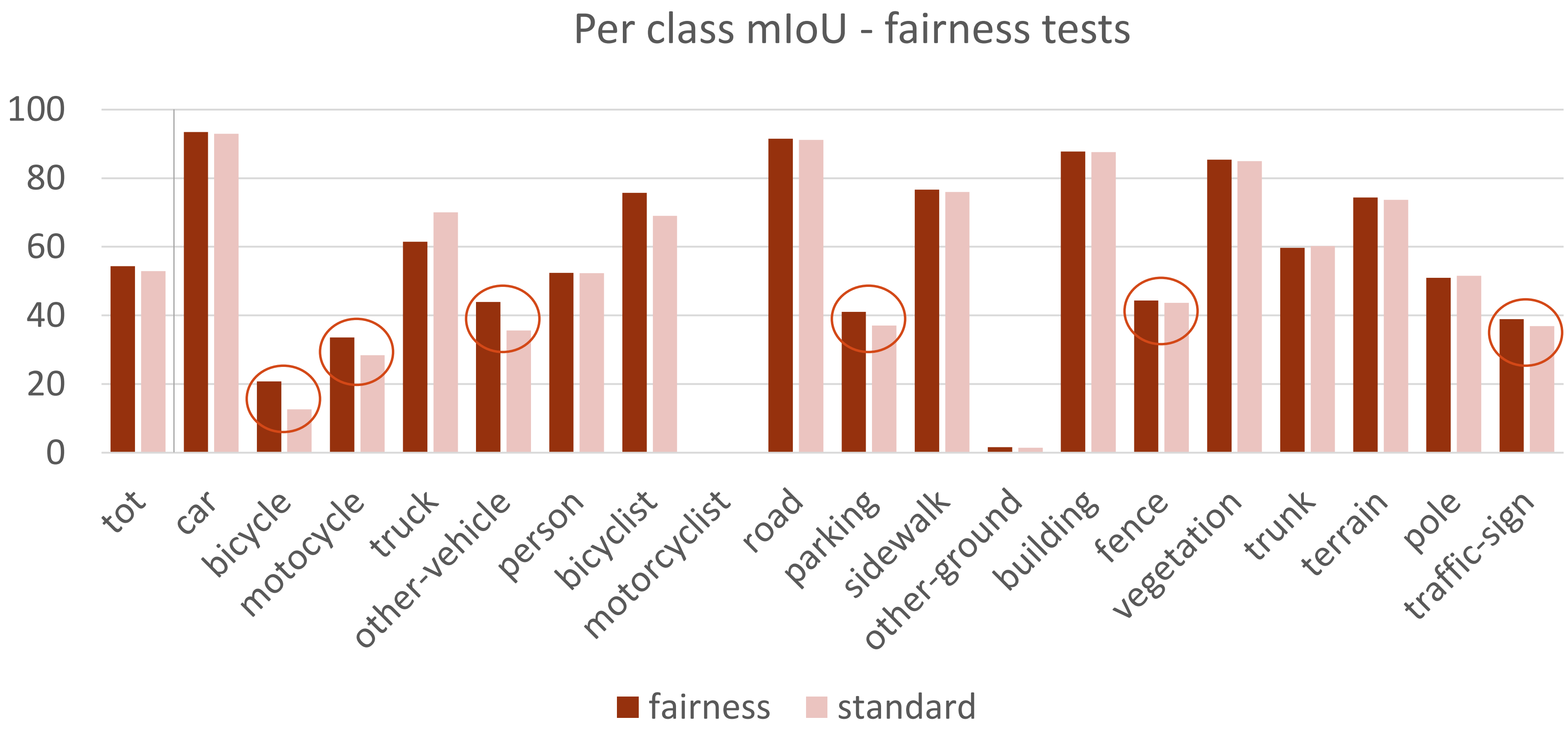
Fairness index: $\mathcal{F} = \sum_{k=1}^{M} \mathcal{F}_k, \quad \mathcal{F}_k = \frac{\left(\sum_{i=1}^{n} p_i\right)^2}{n \cdot \sum_{i=1}^{n} p_i^2}$

Fairness loss function: $\mathcal{L}_{\mathcal{F}} = \mathcal{L}_{micro} + \gamma \cdot (1 - \mathcal{F})$

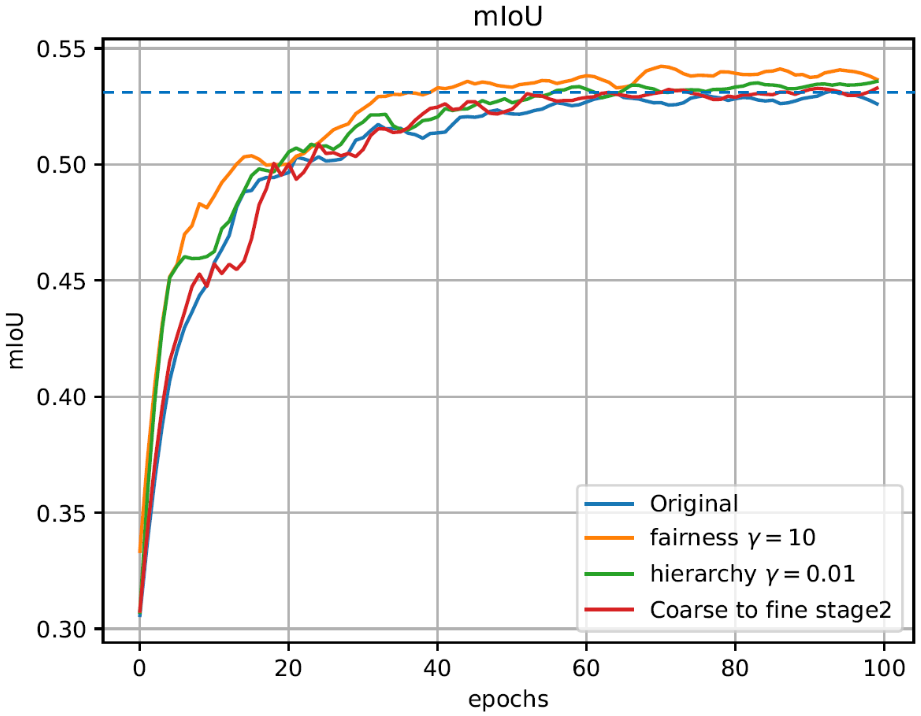


[5] Adian Fatchur Rochim, A. Muis, and R. Sari. A discrimination index based on jain's fairness index to differentiate researchers with identical h-index values. Journal of Data and Information Science, 5:5 – 18, 2020.

Quantitative Results



Additional Results



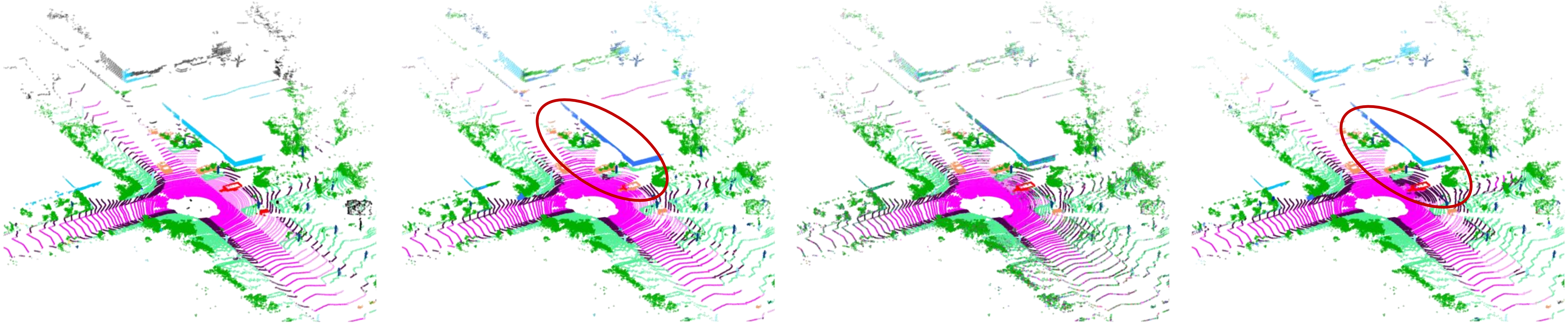
Tests with original batch size
$\boldsymbol{b = 6}$

Hierarchy + Fairness + Coarse-to-Fine

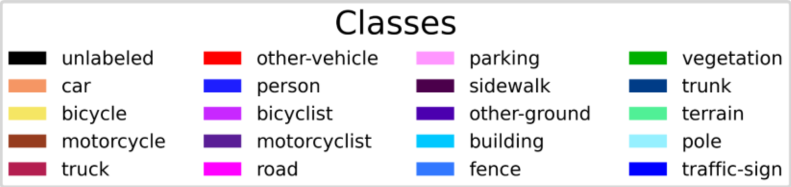
Trial name	accuracy	mIoU
Original	89.25	52.91
fairness $\gamma = 10$ + C2F	87.96	53.00
hierarchy $\gamma = 0.01$ + fairness $\gamma = 10$	89.86	53.87
hierarchy $\gamma = 0.01$ + C2F	89.60	52.95
hierarchy $\gamma = 0.05$ + fairness $\gamma = 10$	89.56	53.99
hierarchy $\gamma = 0.05$ + C2F	89.53	54.12
hierarchy $\gamma = 0.05$ + fairness $\gamma = 10$ + C2F	89.69	**54.34**

Ablation Study

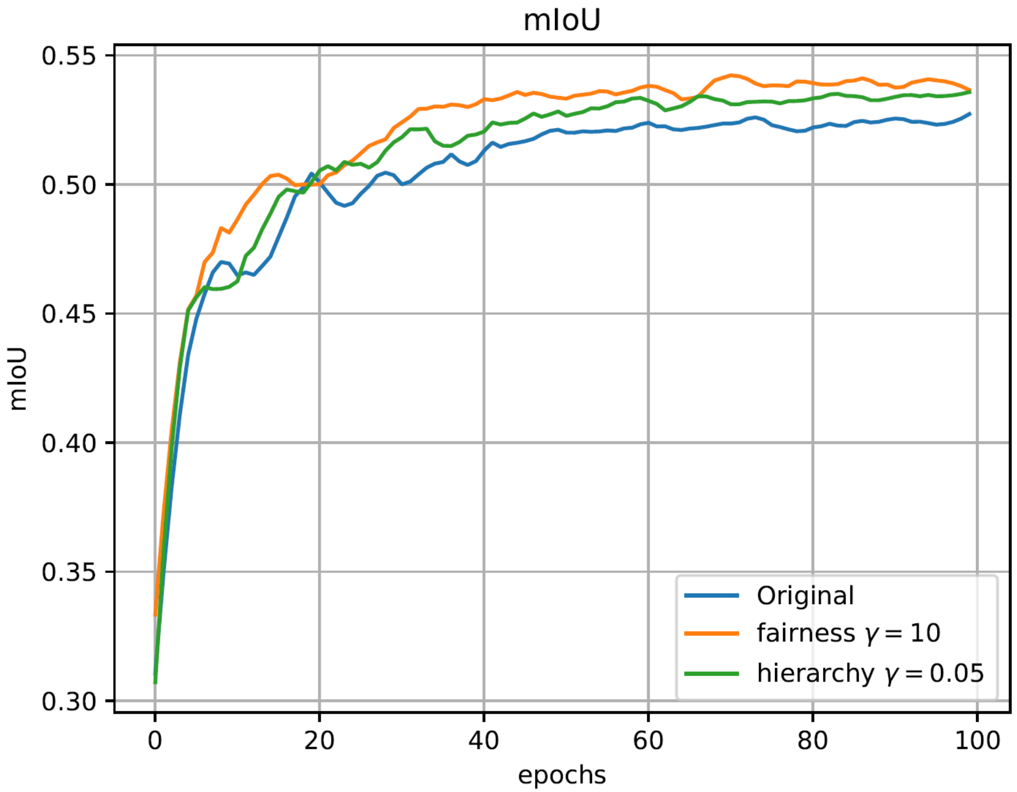
Qualitative Results



Groundtruth | Standard | Fairness $\gamma = 10$ | Hierarchical $\gamma = 0.05$

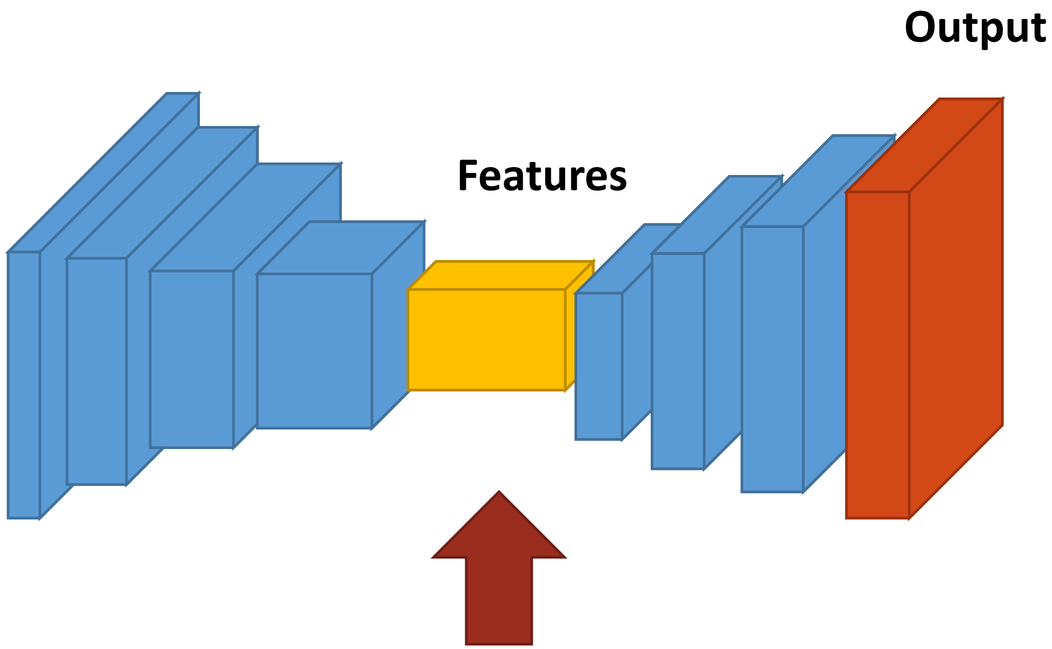


Conclusions



- **Faster** in convergence time and better in terms of **mIoU.**
- Better results in **macro-classes** classification.
- Better **balancement** of classes.

Future works



- Focus on **Feature level** regularization, rather than on **Output level**.
- For methods generalization, **change:**
  - **Dataset**
  - **Architecture**
  - **Task**

Thank you!