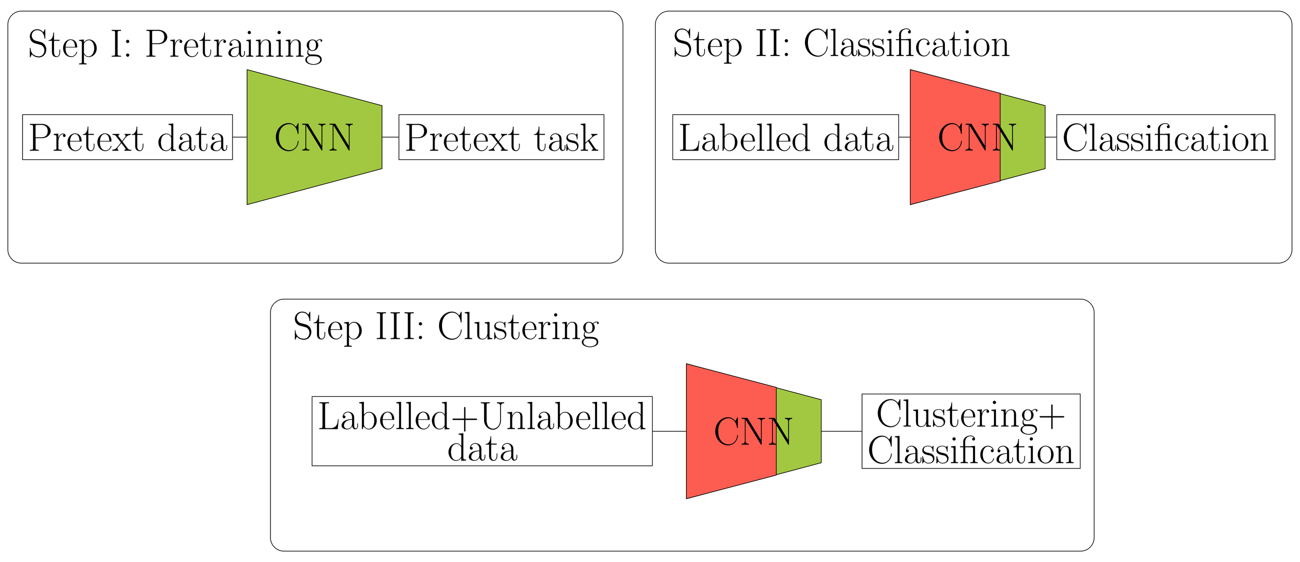
Traffic Scenario Clustering by Iterative Optimisation of Self-Supervised Networks Using a Random Forest Activation Pattern Similarity

Overview

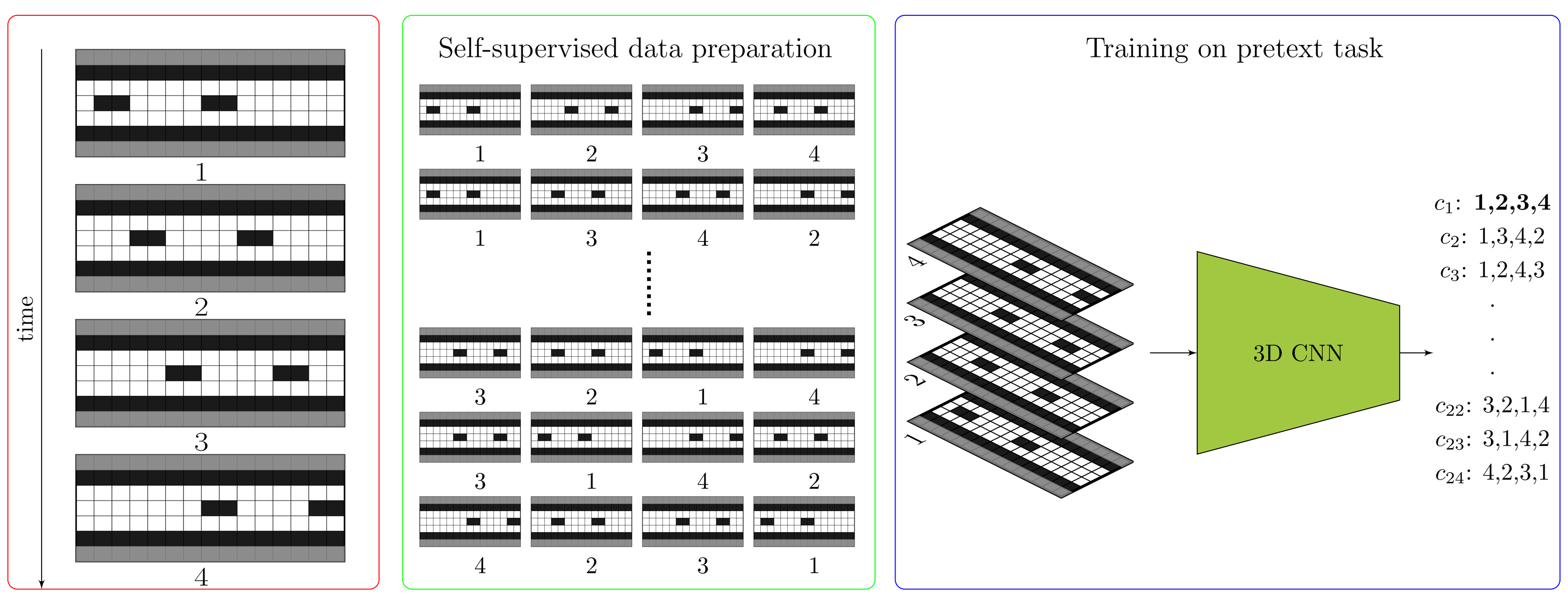
- Clustering of traffic scenarios given an unlabelled dataset $\mathcal{D}_u$
- Traffic scenarios represented as a sequence of occupancy grids
- Learn representations and introduce similarity measure for clustering
- A self-supervised learning framework for generalisation of feature representation to unseen/unknown classes
- Using a labelled dataset $\mathcal{D}_l$ for guiding the clusering of $\mathcal{D}_u$
- Three-step clustering using self-supervised pre-training
- A novel similarity measure called Random Forest Activation Pattern (RFAP) similarity is introduced [1]

Three-Step Process Overview

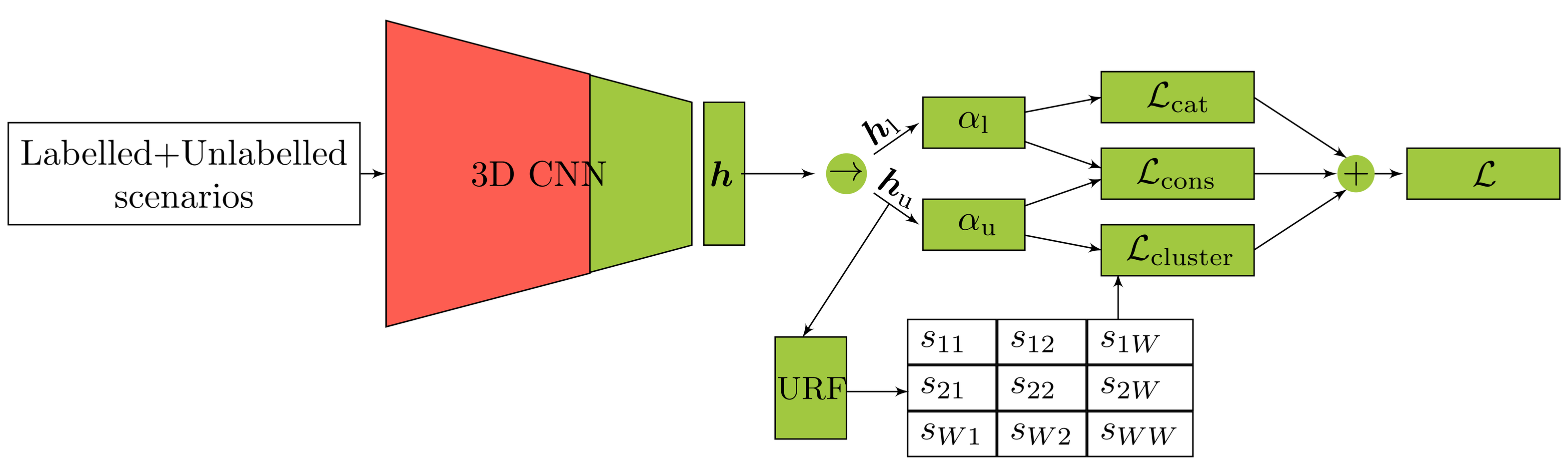
- Step I: self-supervised pre-training
- Step II: fine tuning with labelled classes
- Step III: iterative optimisation with RFAP similarity



Method



Self-supervised pre-training with the pretext task as prediction of the temporal order of a shuffled occupancy grids from a scenario



Iterative optimisation process with RFAP similarity embeded in $\mathcal{L}_{\text{cluster}}$ [2], labelled classes optimised with $\mathcal{L}_{\text{cat}}$, training stability maintained by $\mathcal{L}_{\text{cons}}$

$$\mathcal{L}_{\text{cluster}} = \frac{1}{W^2}\sum_{i=1}^{W}\sum_{j=1}^{W} S_{ij}\log(\alpha_{\text{u}}(\boldsymbol{h}_i^{\text{u}})^\top \alpha_{\text{u}}(\boldsymbol{h}_j^{\text{u}})) + (1-S_{ij})\log(1-(\alpha_{\text{u}}(\boldsymbol{h}_i^{\text{u}})^\top \alpha_{\text{u}}(\boldsymbol{h}_j^{\text{u}})))$$

References

[1] L. Balasubramanian, J. Wurst, M. Botsch, and K. Deng, "Traffic scenario clustering by iterative optimisation of self-supervised networks using a random forest activation pattern similarity," *IEEE IV*, 2021.

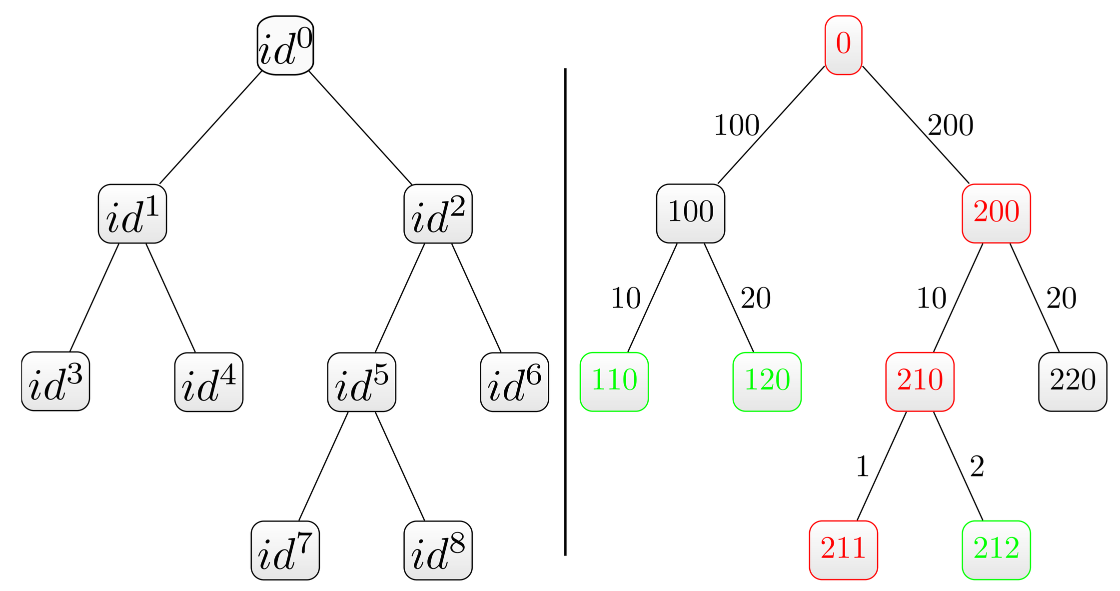
[2] K. Han, S.-A. Rebuffi, S. Ehrhardt, A. Vedaldi, and A. Zisserman, "Automatically discovering and learning new visual categories with ranking statistics," *ICLR*, 2020.

[3] R. Krajewski, J. Bock, L. Kloeker, and L. Eckstein, "The highd dataset: A drone dataset of naturalistic vehicle trajectories on german highways for validation of highly automated driving systems," in *2018 ITSC*, pp. 2118–2125, IEEE, 2018.

[4] N. Harmening, M. Bilos, and S. Günnemann, "Deep representation learning and clustering of traffic scenarios," *Workshop on Autonomous Driving, ICML*, vol. abs/2007.07740, 2020.

[5] L. McInnes, J. Healy, and J. Melville, "Umap: Uniform manifold approximation and projection for dimension reduction," *arXiv preprint arXiv:1802.03426*, 2018.

RFAP Similarity

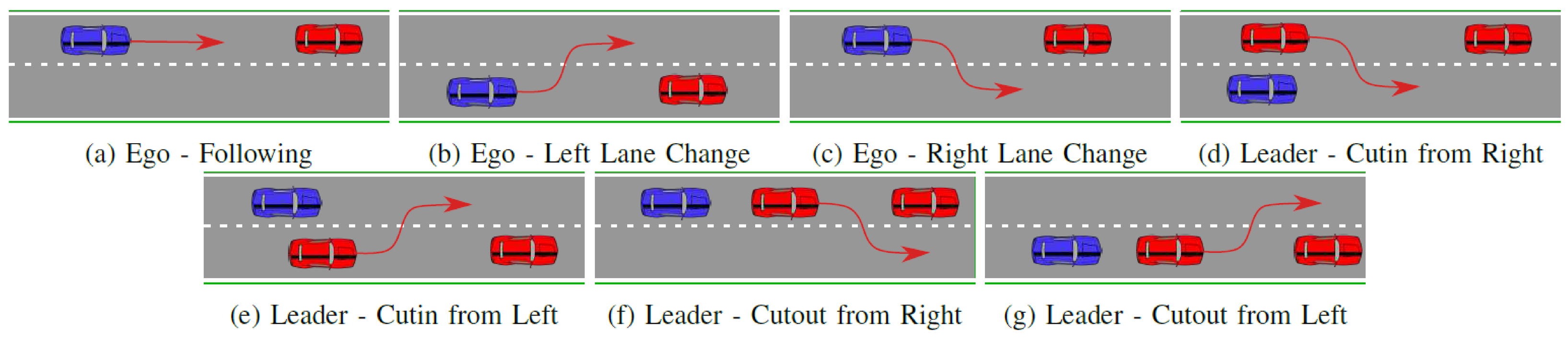


- A novel indexing scheme capturing the path information with an id
- Each sample produces a vector $\boldsymbol{r}_i = [id_1^i, id_2^i, \ldots, id_B^i]^T$
- Hamming distance between two vectors $\boldsymbol{r}_i$ and $\boldsymbol{r}_j$ used to calculate $\boldsymbol{S}$

$$S_{ij} = 1 - \frac{1}{B}\sum_{b=1}^{B}\frac{|\{o \in \{1,\ldots,|\boldsymbol{r}_i^b|\}\,|\,\boldsymbol{r}_i^b[o] \neq \boldsymbol{r}_j^b[o])\}|}{|\boldsymbol{r}_j^b|}.$$

Results

- Comparison with other clustering methods using 7 common scenarios from highD [3] dataset



(a) Ego - Following (b) Ego - Left Lane Change (c) Ego - Right Lane Change (d) Leader - Cutin from Right
(e) Leader - Cutin from Left (f) Leader - Cutout from Right (g) Leader - Cutout from Left

- 4 classes as labelled and 3 classes as unlabelled

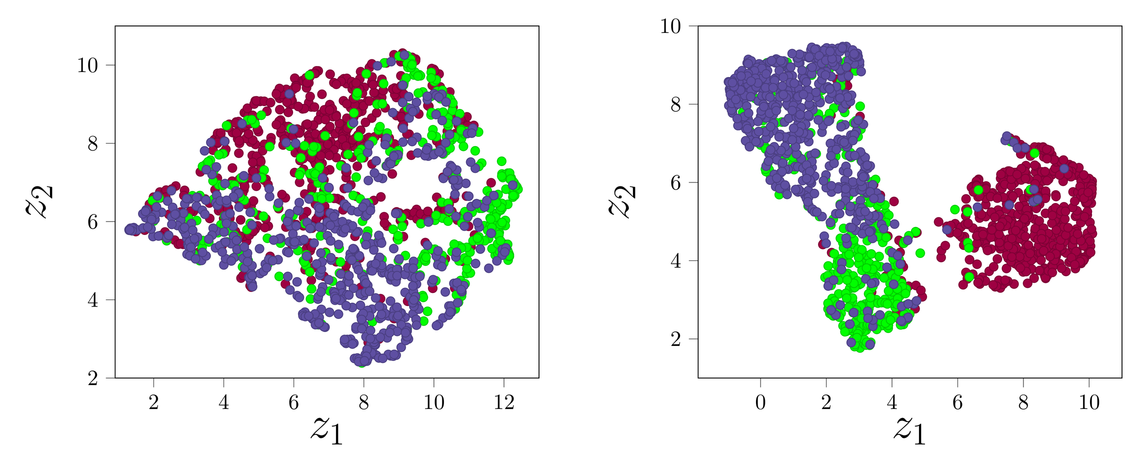
Method	ACC (↑)
K-means	0.391
STAE+HC [4]	0.52
Autonovel [2]	0.794
Proposed method (RFAPs)	**0.810**

Ablations

- Comparison with other similarity measures

Similarity	cosine	l_2	KNN	rank	RFAPs
ACC (↑)	0.707	0.703	0.793	0.794	**0.810**

- UMAP [5] projection before (left) & after (right) iterative optimisation



Conclusion

- RFAP similartiy is introduced to adapt the feature generation process of the CNN and is also compared with other similarity measures
- Pretext task for training CNNs on large unlabalLed traffic scenario datasets is presented
- Experiments on real-world highway dataset show the advantages of the three-step method with RFAP similarity over the baselines

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