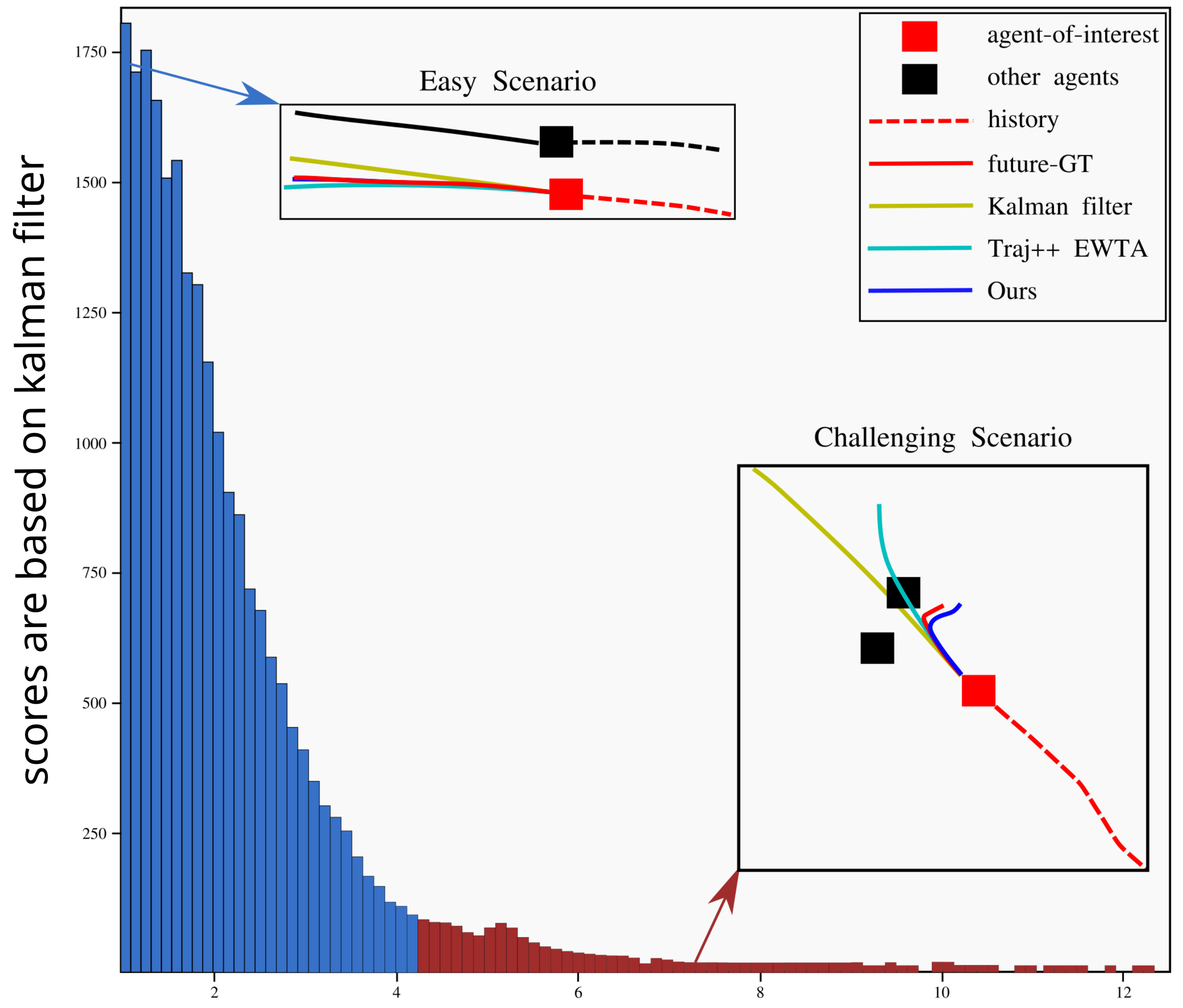
On Exposing the Challenging Long Tail in Future Prediction of Traffic Actors

Osama Makansi Özgün Cicek Yassine Marrakchi Thomas Brox

University of Freiburg, Germany

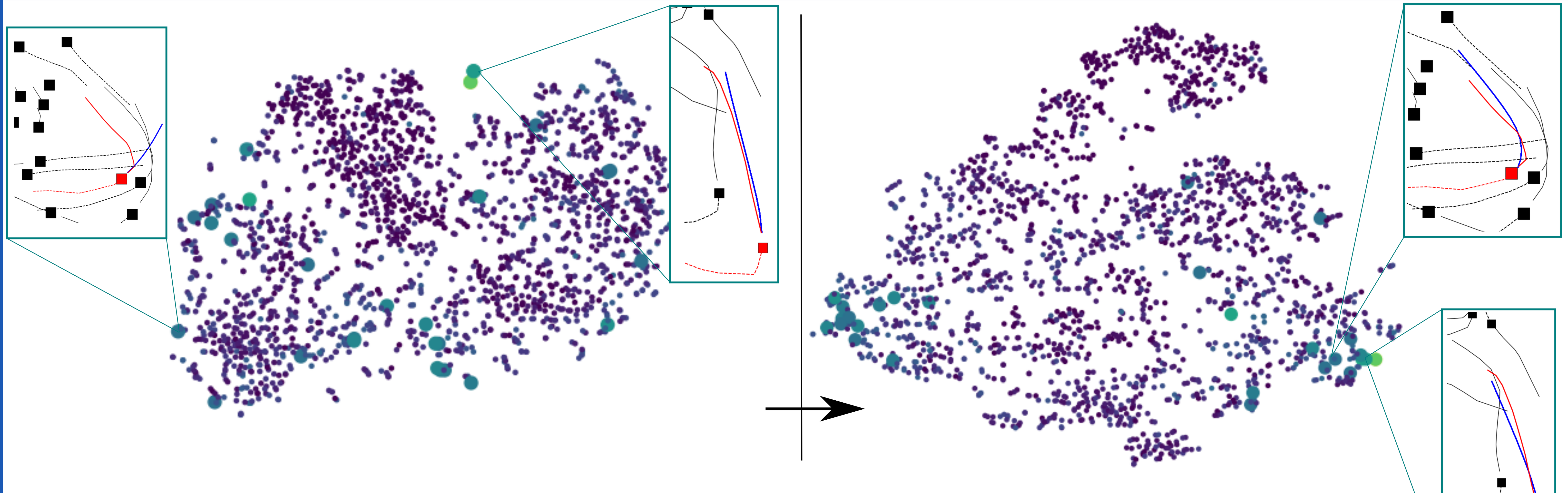
makansio,cicek,marrakch,brox@cs.uni-freiburg.de

Motivation



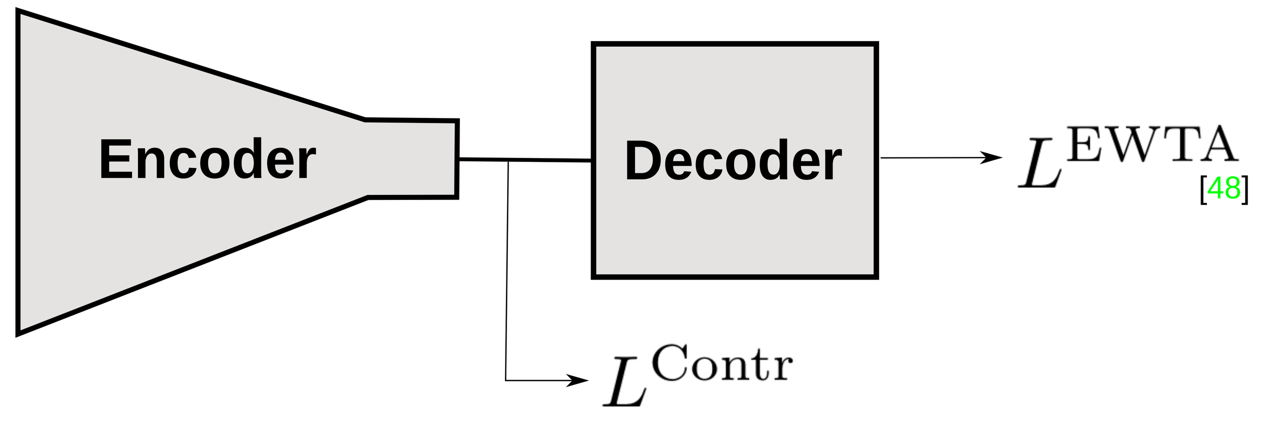
- Easy scenarios dominate existing datasets.
- Challenging scenarios are less frequent, harder and the most relevant ones for decision making.

Analysis



- Challenging scenarios are scattered among the frequent easy ones.
- **Propose**: reshape the feature space by pushing challenging scenarios closer to each other.
- **Why**: they can share relevant features.

Framework



Optimizing jointly:

- The supervised future prediction loss (e.g., EWTA).
- The contrastive loss.

$$L_i = L_i^{\text{EWTA}} + \lambda \cdot L_i^{\text{Contr}}$$

Contrastive loss:

- Positive: samples with similar difficulty scores.
- Negative: samples with different difficulty scores.

Results

	ETH-UCY (BEV)			nuScenes (BEV)			nuScenes (EGO)			Waymo (EGO)		
	All	Top 3%	Top 1%	All	Top 3%	Top 1%	All	Top 3%	Top 1%	All	Top 3%	Top 1%
Baseline [60, 47]	**0.16/0.32**	0.47/1.07	0.42/0.87	0.19/0.32	0.48/0.88	0.59/1.02	7.10	29.98	36.16	**6.39**	24.87	27.32
+ LDAM [5]	0.17/0.33	0.47/1.04	0.42/0.83	**0.18**/0.32	0.48/0.88	0.60/1.10	8.04	25.23	31.13	7.61	23.00	25.05
+ BAGS [41]	0.17/**0.32**	0.48/1.08	0.42/0.85	**0.18**/0.31	0.48/0.88	0.61/1.11	7.28	29.54	35.74	6.67	24.45	26.66
+ contrastive	**0.16/0.32**	**0.46/1.03**	**0.38/0.71**	**0.18/0.30**	**0.44/0.73**	**0.54/0.85**	**7.04**	**25.05**	**27.49**	6.49	**22.36**	**24.09**

- Joint optimization with contrastive learning yields significant improvements on the challenging cases (top 1-3%).
- Joint optimization with contrastive learning maintains the performance on all cases (All).
- Optimizing jointly with LDAM or BAGS bias the challenging scenarios

	ETH-UCY	nuScenes-B	nuScenes-E	Waymo
	All/Top 1%	All/Top 1%	All/Top 1%	All/Top 1%
Baseline [60, 47]	0.32/0.87	0.32/1.02	7.10/36.16	**6.39**/27.32
+ resample [61]	0.53/1.22	0.37/1.33	10.20/21.62	10.48/19.69
+ reweight [29]	0.56/0.76	0.58/1.67	14.47/**16.20**	14.00/**16.44**
+ contrastive	**0.32/0.71**	**0.30/0.85**	**7.04**/27.49	6.49/24.09

- Resampling/reweighting techniques bias the challenging scenarios.
- Ours maintains the performance on average.

For source code:

Bird's eye view

Ego centric view

Acknowledgment

KI DELTA LEARNING Scalable AI for Automated Driving

CIBSS Centre for Integrative Biological Signalling Studies

References

[5] K. Cao, C. Wei, A. Gaidon, N. Arechiga, and T. Ma. Learning imbalanced datasets with label-distribution-aware margin loss. In NeurIPS , 2019.
[29] C. Huang, Y. Li, C. C. Loy, and X. Tang. Learning deep representation for imbalanced classification. In CVPR, 2016.
[41] Y. Li, T. Wang, B. Kang, S. Tang, C. Wang, J. Li, and J. Feng. Overcoming classifier imbalance for long-tail object detection with balanced group softmax. In CVPR, 2020.
[47] O. Makansi, O. Cicek, K. Buchicchio, and T. Brox. Multimodal future localization and emergence prediction for objects in egocentric view with a reachability prior. In CVPR, 2020.
[48] O. Makansi, E. Ilg, Ö. Cicek, and T. Brox. Overcoming limitations of mixture density networks: A sampling and fitting framework for multimodal future prediction. In CVPR, 2019.
[60] T. Salzmann, B. Ivanovic, P. Chakravarty, and M. Pavone. Trajectron++: Dynamically-feasible trajectory forecasting with heterogeneous data. In ECCV, 2020.
[61] L. Shen, Z. Lin, and Q. Huang. Relay back-propagation for effective learning of deep convolutional neural networks. In ECCV, 2016.