Data Analytics and Machine Learning Group
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Stream-based Active Learning by Exploiting Temporal Properties in Perception with Temporal Predicted Loss

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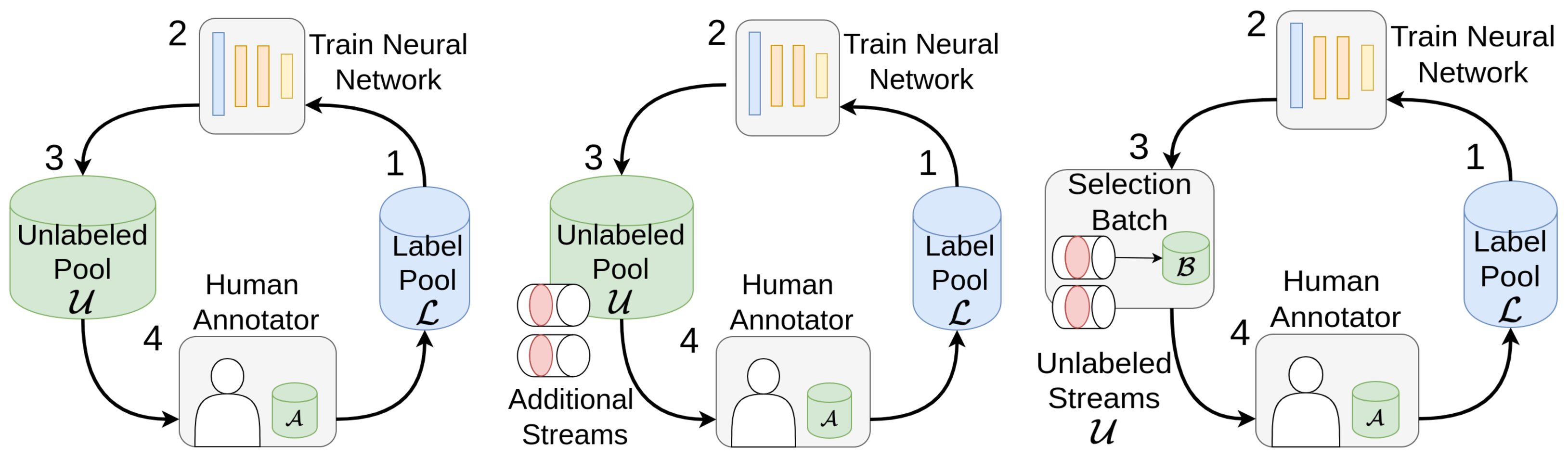
- We propose **Temporal Predicted Loss (TPL)** a novel **active learning** technique which **exploits temporal coherence** to **increase the diversity** of **uncertainty-based** selections.
- Our **TPL** demonstrated a gain of **2.5 percent points less** required data while being significantly **faster than pool-based** methods.

Motivation

- Active Learning is a technique to decide which samples should be labeled.
- Selecting the most valuable data for labeling is important for most perception techniques, especially for real-world tasks.



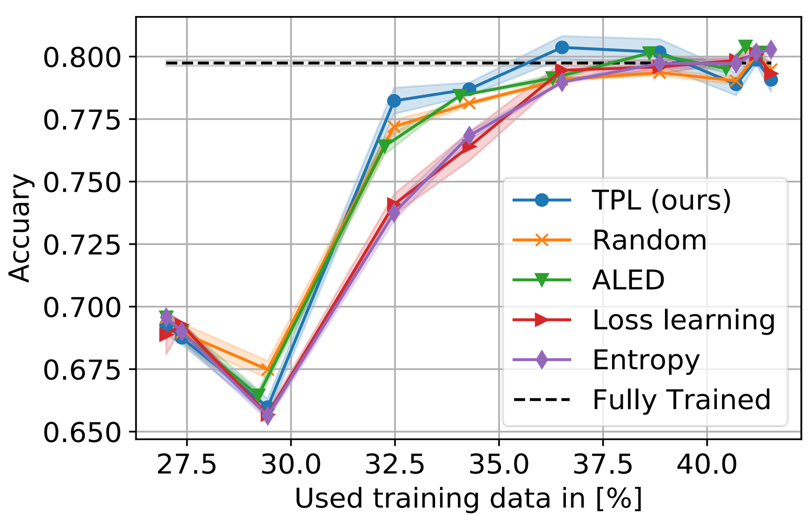
Pool scenario. Pool-based scenario. Stream-batch scenario.

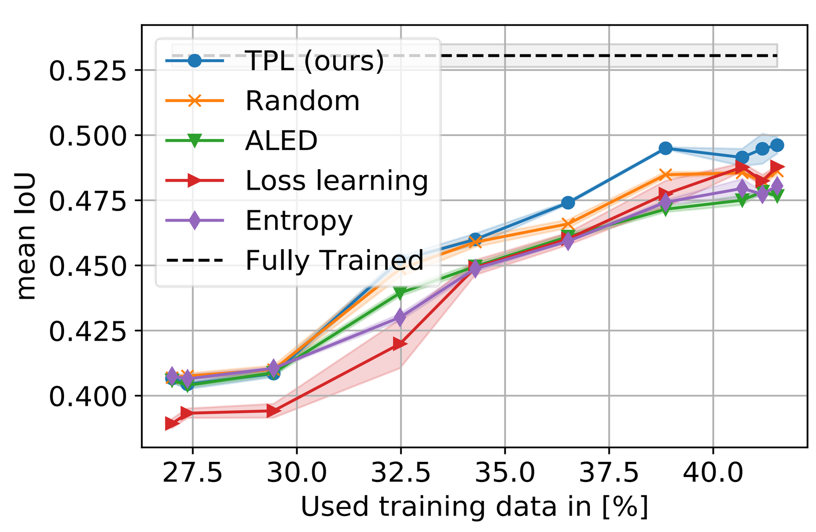
- Current approaches are focused on pool-based scenarios, which is challenging for mobile applications.
- Most datasets used for benchmarking were designed for a different purpose and do not contain temporal data streams.

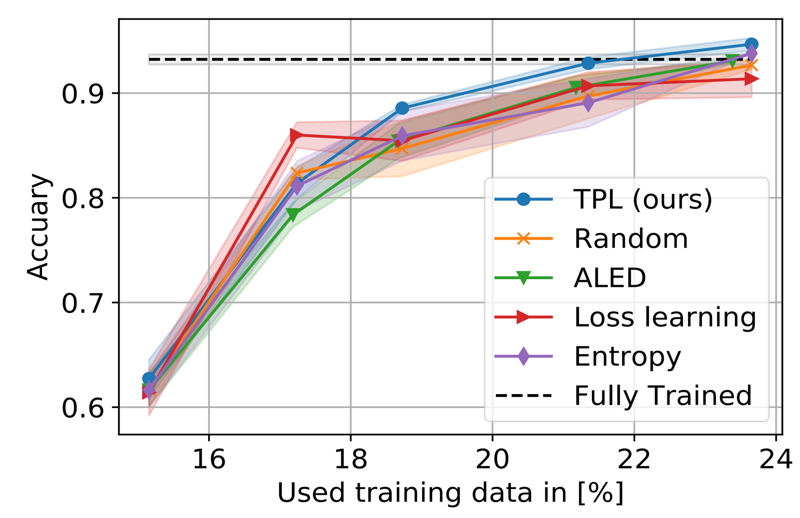
- Stream-based active learning does not require all data to be on a data center.
- Active learning should be evaluated on (sensor) data stream directly.

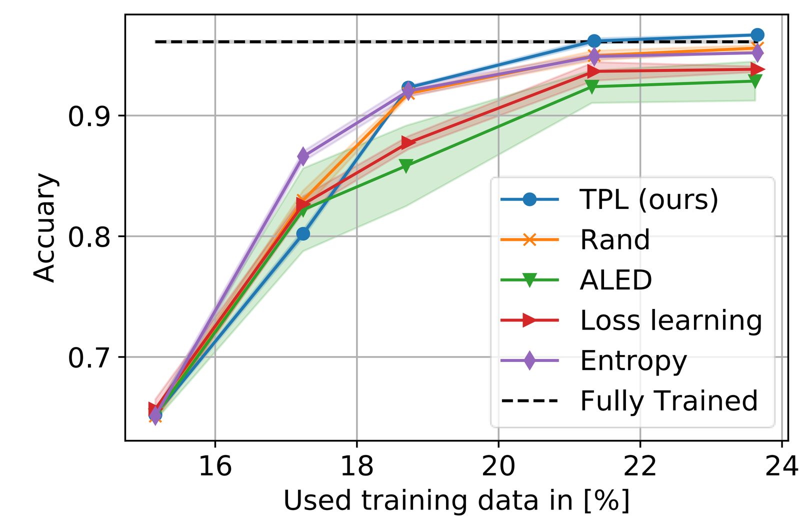
Evaluation in a stream-based setting

- We evaluate TPL against other state-of-the-art methods on the introduced AD2Ds and GTAVs as well as A2D2 datasets, which comprise of several temporal coherent recordings.



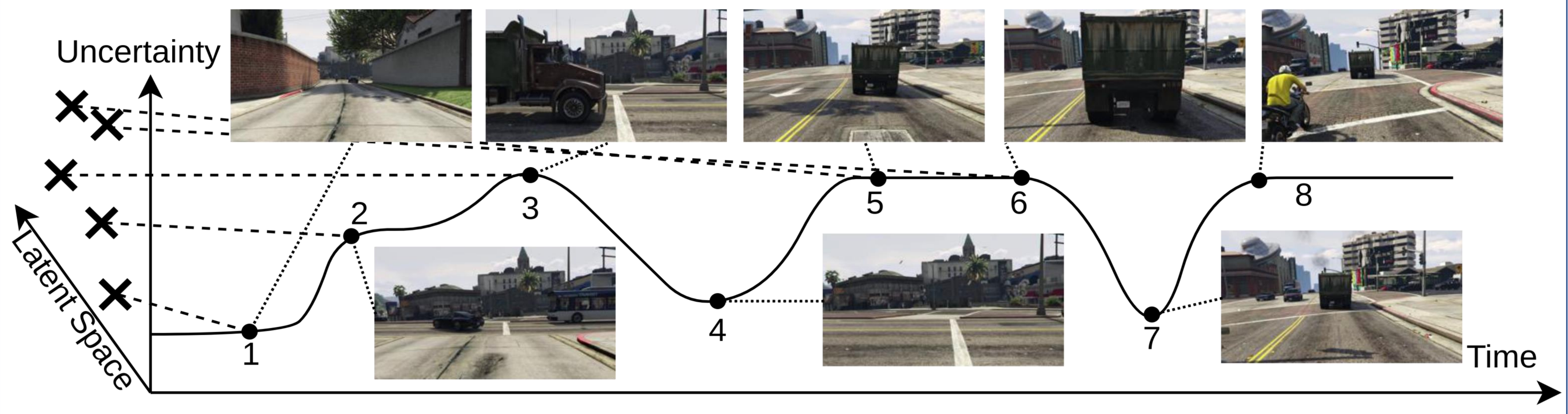




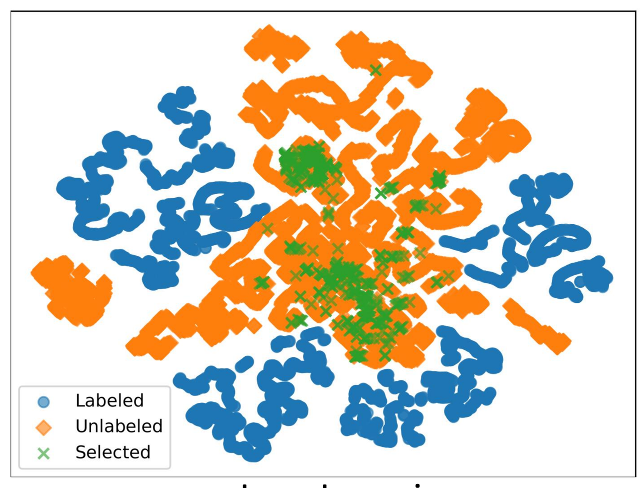


- TPL achieves the highest accuracy and intersects the fully trained networks line as first method.

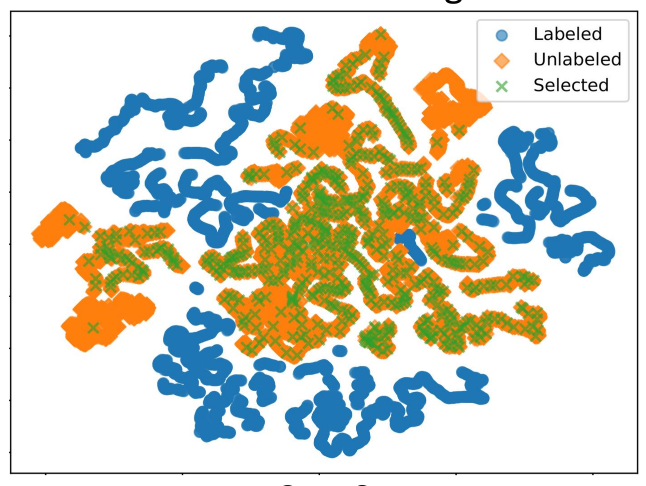
Temporal Predicted Loss



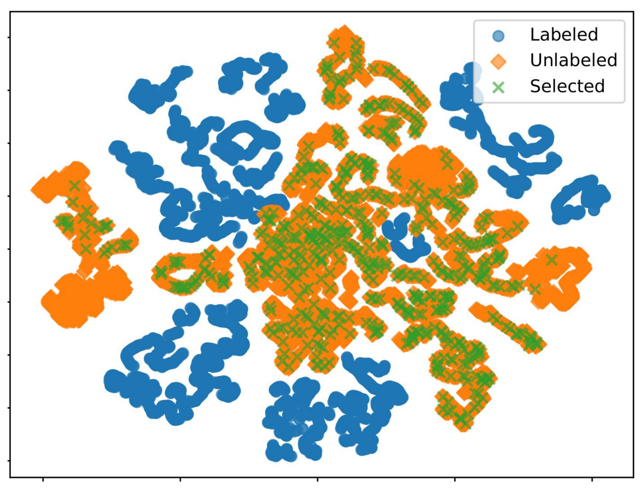
- Diversity-based and learning-based approaches are unsuitable for stream-based AL.
- We leverage the temporal information in uncertainty to improve uncertainty-based methods.
- Based on temporal structures, we exploit the change of uncertainty (by predicted loss) over time and select samples based on the highest change - **Temporal Predicted loss (TPL).**
- TPL increases the diversity of the batch selection, while avoiding expensive diversity calculations.



Loss Learning

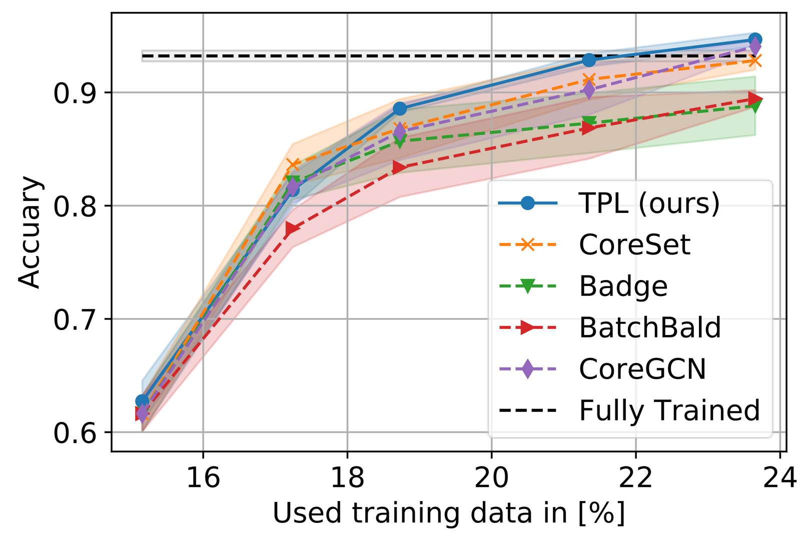


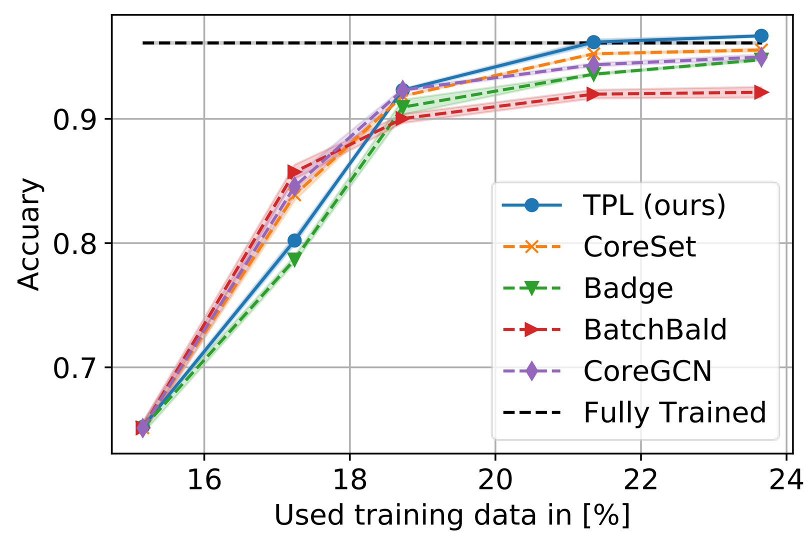
CoreSet



TPL

Evaluation in a pool-based setting





- TPL outperforms other pool-based methods with the stream-batch scenario.
- TPL achieves the second fastest selection time.

Method	Loss learn.	TPL	Entropy	ALED	BatchBald	Badge	CoreSet	CoreGCN
Time [s]	**4.5**	4.6	6.3	427.2	835.2	49.7	32.7	49.7

Conclusion

- TPL and stream-batch settings are a suitable alternative for pool-based active learning.
- Leveraging an additional advantage in data logistics enabling large scale active learning.
- TPL, outperforming other state-of-the-art methods, is applicable for mobile application by avoiding diversity estimations.