KI DATA TOOLING
The Data Kit for Automotive AI

Exploring the Unknown: Active Learning via Neural Network Uncertainty Modeling

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Acquisition, Curation and Refinement of Real Data

Need for Active Learning

The inherent process of data labelling for Autonomous Driving applications has high potential redundancies. Active Learning is a promising concept to optimize the redundancies by parsing through an unlabeled data pool and selecting the most-informative data to be labelled. Therefore, achieving higher model performance with a pre-defined labelling budget. Further, it helps to adapt to a shift in domain, tackle bias during training, handle edge-cases, and minimize Human-in-the-Loop interaction.

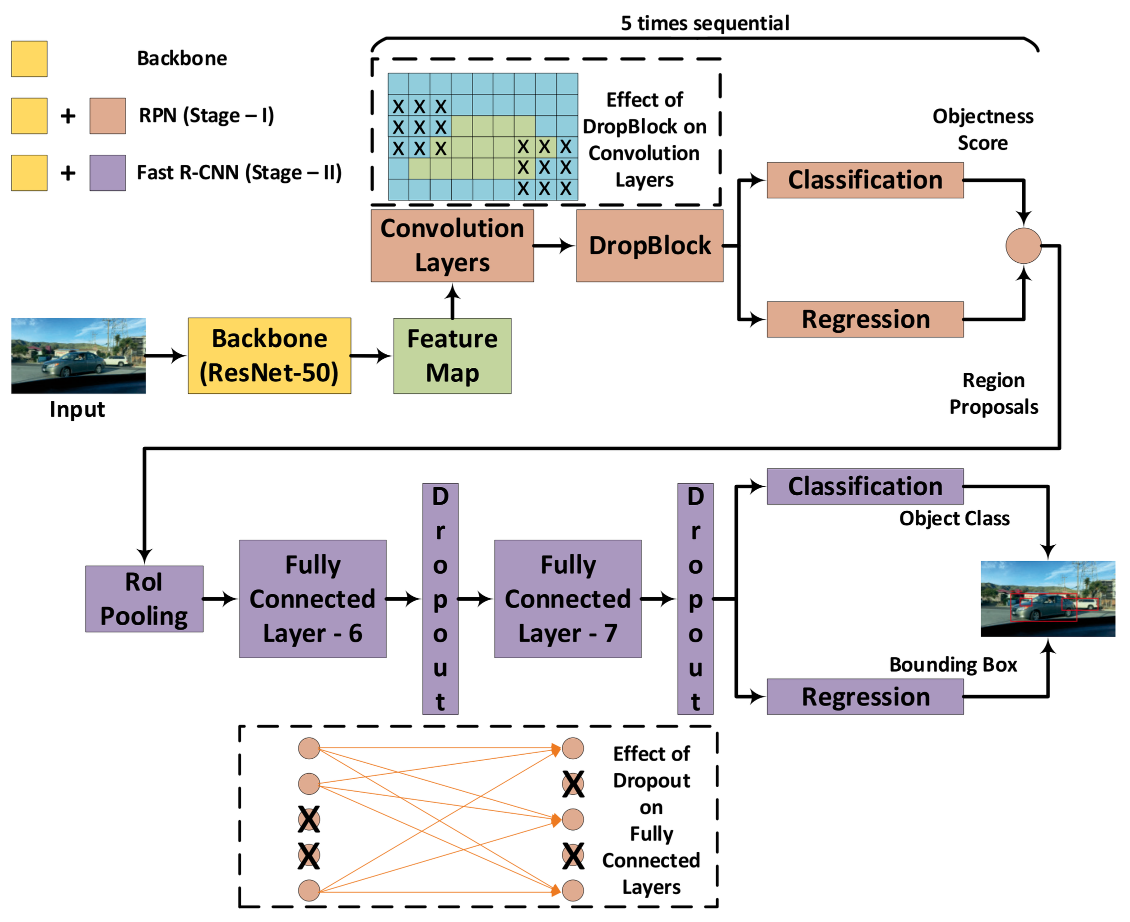

Figure 1: Architecture of Faster-RCNN with DropBlock implementation in Region Proposal Network (RPN) and Dropout implementation in Fully-Connected (FC) Layers

Modelling Epistemic Uncertainty

Epistemic Uncertainty refers to the inherent lack of knowledge or information resulting in inaccuracies in the detections. We develop the strategies using the following acquisition methods to capture the epistemic uncertainty of Faster R-CNN [1]:

- Objectness Scores of Region Proposals consider object/background detections
  1) *Map-level Entropy (1D-E and 2D-E)*
  2) *Map-level Mutual Information (MMI)*
  3) *Spatial Mutual Information (SMI)*
- Class Probabilities of Bounding Boxes
  1) *Prediction-level Entropy (E)*
  2) *Prediction-level Mutual Information (MI)*
  3) *Prediction-level Clustering (CL)*

To reach approximate Bayesian Inference, MC Dropout is implemented in Faster R-CNN [1] architecture for *T* forward passes.

Active Learning Pipeline

We conduct a study to find the best active learning approach to train Faster-RCNN [1] with minimum training data using BDD100K [2]. The aim is to achieve peak performance on a pre-defined test data as compared to a random selection.

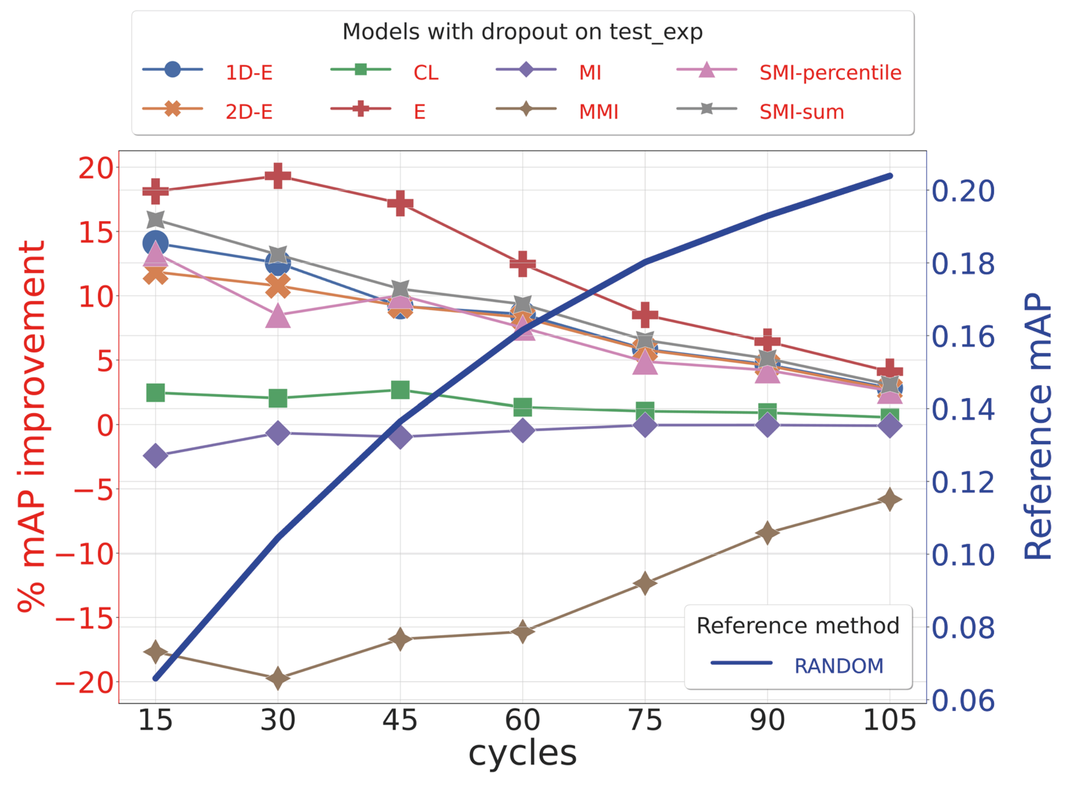

Figure 3: Performance improvement of Faster-RCNN on BDD100K dataset for different methods as compared to a random selection

Conclusions

Based on the model architecture being trained on and the nature of dataset for selection, a suitable Active Learning approach improves the model performance while keeping an equal labelling budget. The extent of improvement depends on the size of the training dataset, as a larger random sample would select also more diverse data the effect becomes smaller.

References

[1] Ren, Shaoqing, et al. "Faster R-CNN: Towards real-time object detection with region proposal networks. Advances in neural information processing systems, 28, 2015.
[2] Yu, Fisher, et al. "Bdd100k: A diverse driving dataset for heterogeneous multitask learning." Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2020.

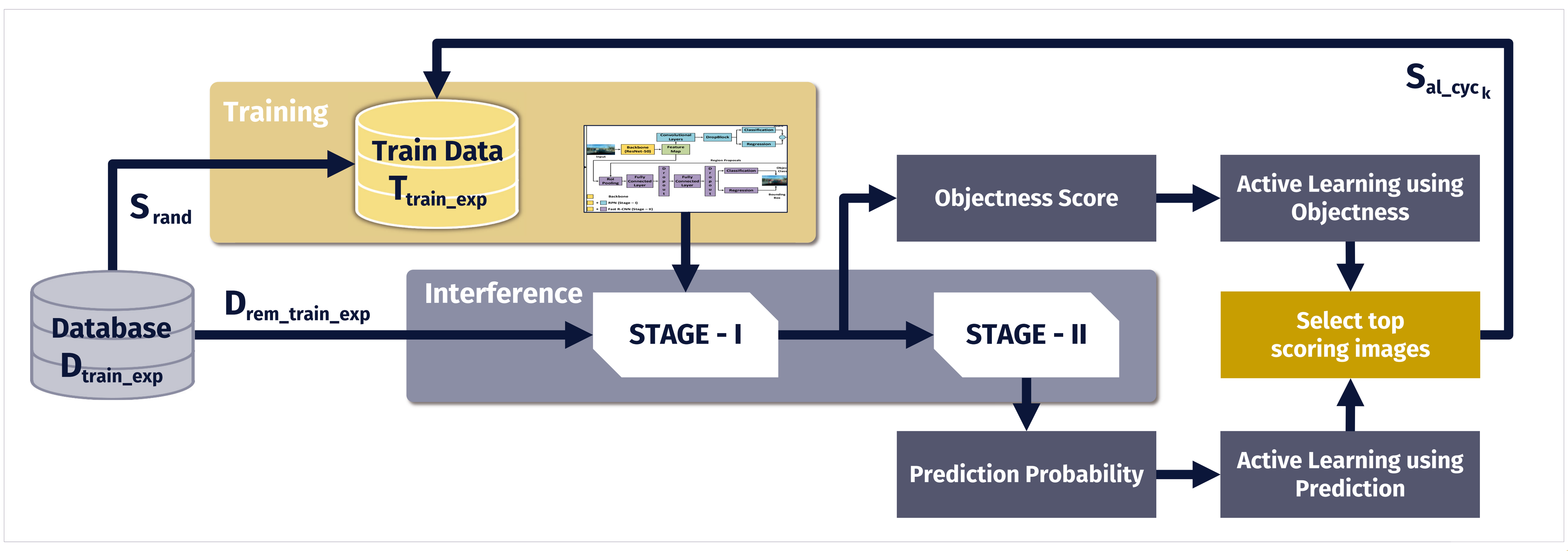

Figure 2: Active Learning Pipeline for training Faster-RCNN

Partners

External partners

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