SCALABLE ACTIVE LEARNING FOR OBJECT DETECTION

INTRODUCTION

Active learning is a powerful technique to improve data efficiency for supervised learning methods.
DNNs is used for autonomous driving system and having a large and diverse training dataset is the main key to achieve the accuracy.
The key idea behind active learning is that a machine learning algorithm can achieve greater accuracy with fewer training labels if it is allowed to choose the data from which it learns.

ALGORITHM

Our methodology uses pool-based active learning and an acquisition function based on disagreement between models. The acquisition function can be applied to unlabeled frames and is designed to identify the frames which are most informative to the model. We enable a repetitive loop that performs the following operations:

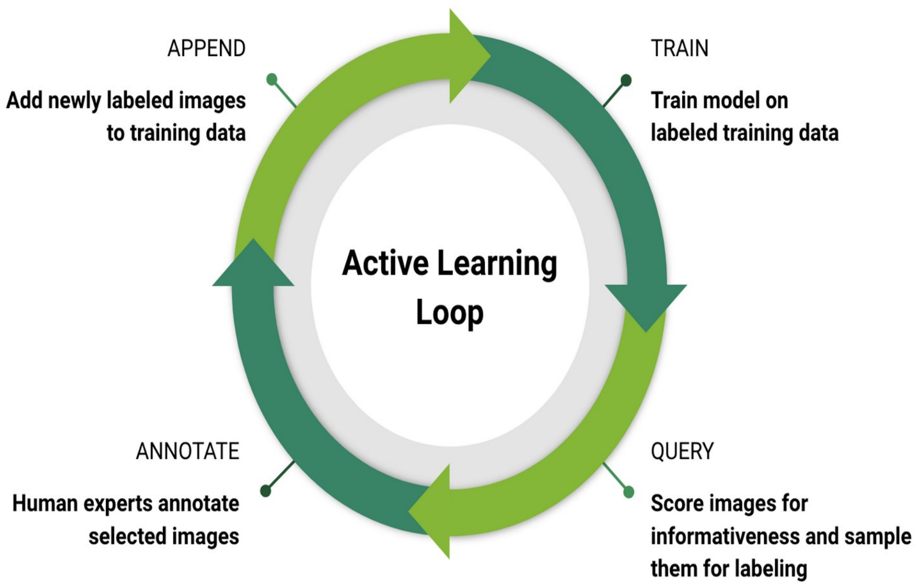
1.TRAIN: Train N models initialized with different random parameters on all currently labeled training data.

2.QUERY: Select examples from unlabeled pool using acquisition function that leverages “disagreement” between the N models. For querying we use scoring functions and sampling strategies.

3.ANNOTATE: Send selected examples to human labelers.

4.APPEND: Append newly labeled examples to training data.

5.Go back to 1.



SCORING FUNCTIONS

It is to compute a single score per image indicating its informativeness.
It can be calculated using

1. Entropy
2. Mutual Information
3. Gradient of the output layer (Grad)
4. Bounding boxes with confidence (Det-Ent)

SAMPLING STRATEGIES

Selecting the top N scoring images for labelling and using their scores. Prone to rank similar images.
For the diversity-based methods:
Extract image embeddings for all the unlabeled samples.
Then, we compute a similarity matrix D based on euclidean distance as well as cosine similarity.

ADVANTAGES

Automation: The decision about which images to label would otherwise need to be done manually, which can be labor intensive.
Performance: By involving the model in building the training dataset, it may be possible to achieve higher performance with fewer data samples.

DISADVANTAGES

A large compute and data cluster: Active learning requires to continuously train new models and run inference on unlabeled data at scale (billions of frames). This requires high-performance hardware for training and inference as well as large and efficient data storage.
A scalable workflow management platform: The ability to describe complex task dependencies with high parallelism, traceability, caching and auto-scheduling is essential to build automation.

CONCLUSIONS

Compared two methods of selecting data: automatically via active learning and manually via a selection by experts. Results show very strong performance improvements for the automatic selection, in some cases giving more than 4x the mean average precision improvement compared to the manual selection. This validates that active learning is a very promising avenue to continuously and automatically improve performance for autonomous driving. 4× the relative MAP improvement compared to a manual selection process by experts.