KI DELTA LEARNING
Scalable AI for Automated Driving

Meta-Learning for Continuous Class-Incremental Learning

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WP 2.1

Use-Case in Delta Learning

Learning continually, even a lifelong, seems to be an ultimate goal and is a particular challenging problem in machine learning. Sequentially incorporating new classes or data from a different domain results in a major degradation in performance, known as catastrophic forgetting. Continuous Learning aims to mitigate this effect. ZF is extending ANML [1], a meta-learning Continuous Learning algorithm, to real world data.

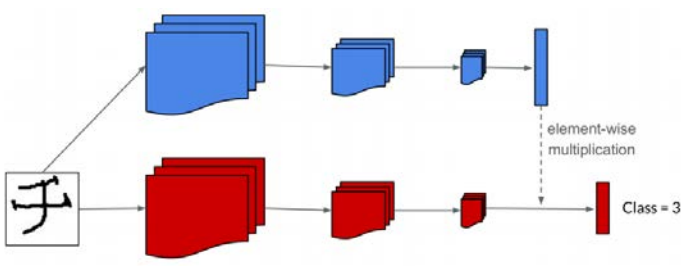

Figure 1: Principle of the ANML method. Two networks are used, one acts as a prediction network, the other acts as a gating mechanism to avoid catastrophic forgetting.

Technical Problem

The ANML method showed promising results in its publication while using the Omniglot-dataset. Omniglot is similar to the well-known MNIST dataset, with a total of 1623 characters, black font on white background. But using real-world data, even images with a much simpler environment than the automotive context, like the Core50 [2] dataset, the performance drops significantly.
Transferring this idea to object detection yields further challenges due to the specific architectures of modern object detection algorithms.

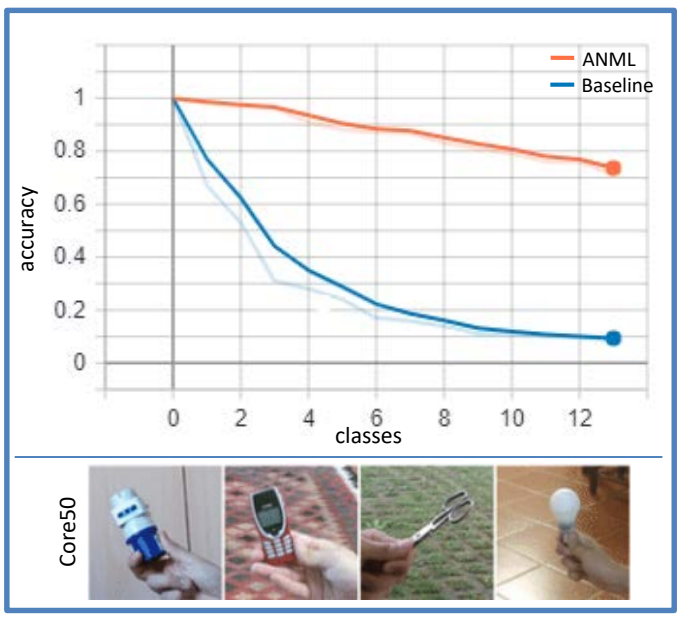

Figure 2: Results of the ANML Algorithm with the Core50 dataset. The Baseline ist no special rule for incremental learning and therefore its performance drop very fast. Below are a few examples from the Core50 dataset

Technical Solution

In order to understand the ANML algorithm properly, we recreated the results of the publication before adapting it to real world data. The authors mentioned that the algorithm is very sensitive to different learning parameters but most of all compared to the learning rate (learning rate sensitivity ~ 1e-4). We empirically found the suitable learning parameters.
In terms of object detection, an alternative approach [3] based on contrastive clustering promises to alleviate forgetting previous knowledge in combination with basic rehearsal techniques. Latent representations of classes are clustered via contrastive learning and a prototype of each class evolves with new samples.

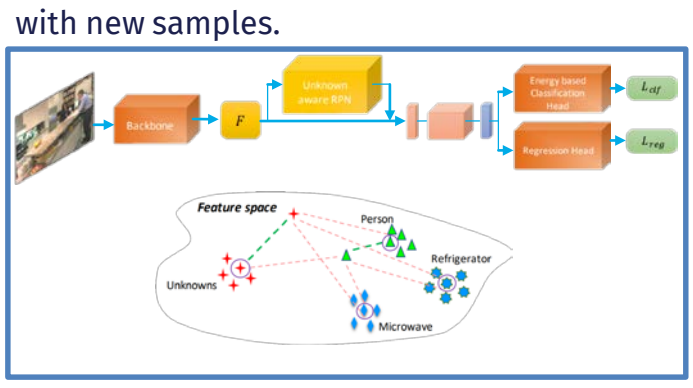

Figure 3: Architecture overview of Open World Object Detector (ORE) with abstract visualization of contrastive clustering in the feature space [3].

Evaluation

To determine the aforementioned training parameters, we used a laborious parameter search. With a decreasing learning rate for every new class, we achieved decent results for the ANML method with Core50 data. A clear trend can be seen which counteracts the catastrophic forgetting of incremental class learning (Fig. 2).
Based on the described architecture for object detection, novel extensions shall be investigated in a domain-incremental as well as class-incremental setting. Further, the recently published dataset SODA10M will be investigated for this purposes.

Time

References:

[1] "Learning to Continually Learn", Shawn Beaulieu et al., 2020, 24th European Converence on Artificial Intelligence (ECAI 2020)
[2] "CORe50: a New Dataset and Benchmark for Continuous Object Recognition". Vincenzo Lomonaco, Davide Maltoni: CoRR abs/1705.03550 (2017)
[3]: "Towards Open World Object Detection", K J Joseph et al., 2021, Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR 2021)

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Partners

External partners

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