Deep Radial Basis-Function Networks for Open-Set Classification

The task of classifying objects from images has been a hot research topic in the last years, and the advent of deep learning has improved performance drastically. Typically, deep networks for image classification contain several convolutional layers, followed by at least one fully-connected layer to produce the logits, which are later going through a SoftMax classifier. Oftentimes, categorical cross-entropy loss is used to classify a set of known classes, and lately these networks are also able to detect that samples come from unknown classes [Dhamija et al., 2018]. Modern approaches for open-set classification exploit the distributions of deep features extracted from these networks [Bendale and Boult, 2016, Rudd et al., 2017, Dhamija et al., 2018].

Radial Basis Function (RBF) networks [Bishop, 1995] have been developed in early times, but they have been forgotten since. In RBF networks, a fully-connected layer is replaced with a set of prototype vectors, so-called basis functions, that represent the distribution of features in feature space. The goal of this Master thesis is to try to incorporate RBF layers into deep networks for image classification. As a first step, the last fully-connected layer will be replaced with an RBF layer that provides one basis function for each class, mimicking the Mean Activation Vector (MAV) in the OpenMax approach [Bendale and Boult, 2016]. Later, an RBF layer with fewer basis functions will be placed in front of the last fully-connected layer in order to shape the feature space better. It will be tested whether this approach improves open-set classification accuracies when trained with standard SoftMax loss, and with well-known open-set classification methods [Dhamija et al., 2018].

The dataset for experimentation will first be MNIST, which can be used to understand and fix difficulties with the implementation and instantiation of the RBF layers. Later, ImageNet [Russakovsky et al., 2015] and our newly introduced open-set protocols [Bhoumik, 2021] will be employed.

Requirements:

- Participation in my Deep Learning course.
- A reasonable understanding of deep neural networks and how they learn.
- Programming experience in python and a deep learning framework, optimally, pytorch.
- Decent understanding of written English.

References

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[Dhamija et al., 2018] Dhamija, A. R., Günther, M., and Boult, T. E. (2018). Reducing network agnostophobia. In *Advances in Neural Information Processing Systems (NeurIPS*, pages 9157–9168.

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