More efficient training using equivariant neural networks

Master Thesis Proposal in Image Analysis and Machine Learning at the Division for Visual Information and Interaction, Department of Information Technology.

A character from the MNIST dataset, rotated by 90, 180 and 270 degrees.

Supervisors and contact

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Background

Convolutional Neural Networks (CNN) have resulted in high accuracy in many image analysis tasks such as classification and segmentation. In 2012, a CNN architecture achieved a top-5 error of 15.3% in the ImageNet classification challenge, more than 10 percentage points lower than the previous best. Since then, newer architectures have improved the results further, and CNNs have seen increased competition from vision transformers. One of the key drivers of increasing performance is the growth of the number of trainable parameters, leading to increasing training time and demands on more capable hardware such as GPUs (Graphical Processing Units).

One of the most desired properties of CNNs is translation equivariance, meaning a shift of the input is shifted in the same way in the output layer. A more general class of CNNs is called equivariant neural networks, which seek to encode the equivariance property to other symmetries such as rotations and reflections. This is highly relevant for microscopy data where these symmetries are present. One of the most common ways of achieving this on 2D image data is group-equivariant neural networks, which can be implemented using libraries such as E2CNN.
By deploying equivariant architectures instead of CNNs, a number of benefits can be achieved. There is less need to perform data augmentation by e.g. rotations if the rotation-equivariance is already encoded by the network. This further means a reduction of the number of parameters in the network is possible, since the parameters are shared across the rotated versions of the filter kernels. This in turn leads to lower overfitting and higher accuracy on the test set. Furthermore, it is possible to decrease the training time by two effects. First, the network converges in fewer iterations during training. Secondly, the network converges using less data than a CNN.

**Aim**

We want to explore if the advantages of equivariant neural networks over regular CNNs hold for a larger set of experimental conditions. To perform this, we want to vary the hyperparameters of the optimization process, the underlying architectures, the datasets, and the symmetry groups for the equivariant operations. So far, we have looked at a dataset for oral cancer classification, and another for semantic instance segmentation of cells in various conditions. To begin with, we would like to repeat the experimental procedure on another dataset, possibly from another domain than microscopy. Investigating different symmetry groups is the second priority. The scope and priority of the work can be changed depending on the interests of the student. We encourage anyone curious about the project to get in touch with us at any time.

**Prerequisites**

- Proficiency in computer programming (Python is a must).
- Some experience in image analysis required.
- Some background in machine learning and deep learning is required. An overview of CNNs as well as the training and optimization procedure is recommended. Knowledge of equivariance is a plus but not required.
- Some experience in deep learning environments (PyTorch recommended, or Tensorflow/Keras) and GPU optimization is a plus but not required.

**References**

