Symmetries are perhaps the most fundamental principle on which all the most fundamental theories of physics, such as general relativity and quantum field theory are based. In this project we have asked ourselves if the principles and mathematics behind symmetries could, or perhaps should play a fundamental role in deep learning. The most powerful tool from the machine learning toolbox is currently the convolutional neural networks (CNN), which is equivariant under the translation group. We have developed new CNNs that are also equivariant under a much larger group of symmetries such as translations, rotations and reflections: $E(3)$. We have shown that these models outperform traditional architectures on e.g. medical image data. Next, in almost perfect analogy of the relation between special and general relativity, we developed gauge equivariant CNNs for deep learning on arbitrary manifolds, and applied it to detecting storms on the earth. It is remarkable that gauge fields developed for the standard model of physics, now also appear in deep learning.

Our brain is approximately 100,000 times more energy efficient than the best computer chips today. We predict that energy efficiency will increasingly become a key factor in chip design because 1) the economic benefit of more AI should not be outweighed by the extra cost of running it, and 2) small edge devices such as hearing aids and phones cannot become too hot. In this project we have developed new neural network architectures where, like in the brain, neurons communicate through spikes. Until now, these types of spiking neural networks could not be trained on the same (spiking) hardware. By using the theory of “sigma-delta modulation” and adapting it so that errors do not accumulate when traveling through the layers, we have managed to build the first fully trainable spiking neural network. To make the design more biologically plausible we also replaced the biologically implausible backpropagation with equilibrium propagation and showed that spiking networks can still be successfully trained.

Publications and other output:
- T.S. Cohen, M. Weiler, B. Kicanaoglu, M. Welling, Gauge Equivariant Convolutional Networks and the Icosahedral CNN, 2019
- T.S. Cohen, M. Geiger, M. Weiler, Intertwiners between Induced Representations (with applications to the theory of equivariant neural networks), ArXiv preprint 1803.10743, 2018
- M. Winkels, T.S. Cohen, Pulmonary Nodule Detection in CT Scans with Equivariant CNNs, Medical Image Analysis, 2018
- M. Winkels, T.S. Cohen, 3D G-CNNs for Pulmonary Nodule Detection. International Conference on Medical Imaging with Deep Learning (MIDL), 2018
- M. Winkels, T.S. Cohen, 3D Group-Equivariant Neural Networks for Octahedral and Square Prism
Symmetry Groups, FAIM/ICML Workshop on Towards learning with limited labels: Equivariance, Invariance, and Beyond, 2018
- J. Linmans, J. Winkens, B.S. Veeling, T.S. Cohen, M. Welling, Sample Efficient Semantic Segmentation using Rotation Equivariant Convolutional Networks, FAIM/ICML Workshop on Towards learning with limited labels: Equivariance, Invariance, and Beyond, 2018
- T.S. Cohen, M. Geiger, J. Koehler, M. Welling, Spherical CNNs. ICLR 2018 (Best paper award)

We have applied for one patent on this work: Nr. P100250PC00, Device and method for generating a group equivariant convolutional neural network. Inventors: Taco Cohen and Max Welling.

- Sigma-delta position derivative networks P. O’connor, M. Welling US Patent App. 15/705,161