Equivariance versus Augmentation for Spherical Images

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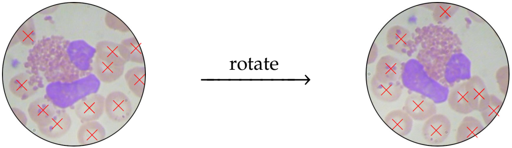
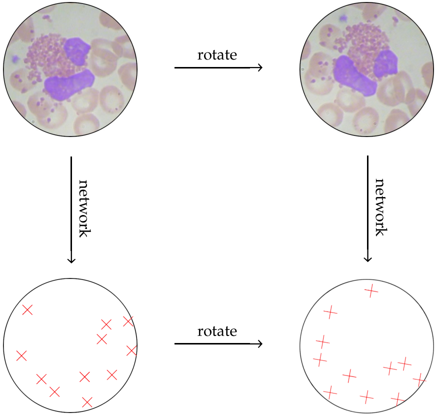
Equivariance

- Many machine learning problems have inherent symmetry, e.g.



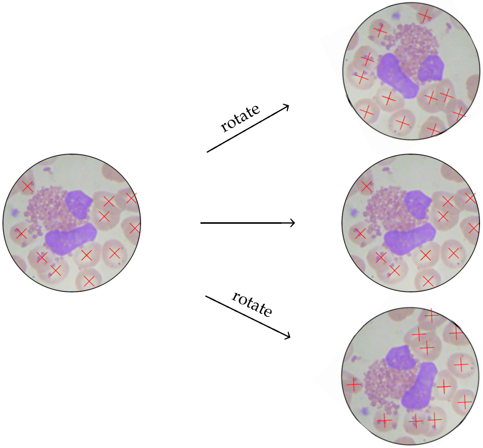
Equivariance

- Equivariant neural networks build symmetries of problem into network architecture:



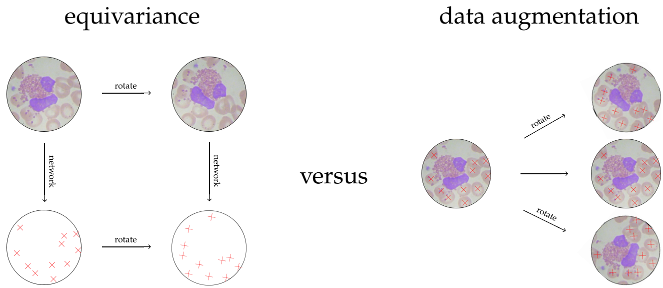
- Requires specialized architectures
- Widely used principle to construct networks, often beneficial in practice

Data augmentation



- Train on randomly transformed training samples ⇒ enlarges training dataset
- No special architectures required, easy to implement
- No guarantee for equivariance

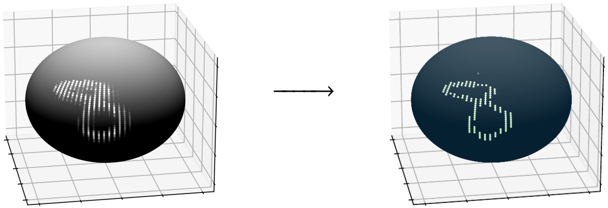
Our contribution



- Contrast equivariance and data augmentation
- Study invariant and equivariant problems
- Use “clean” academic problems and simple networks to minimize influence of dataset and optimized architectures / training procedures

Tasks and Dataset

- Dataset: MNIST digits projected onto the sphere
- Tasks: Classification and semantic segmentation



- Symmetry: 3d rotations = SO(3)
- Classification is an ***invariant*** task, semantic segmentation is ***equivariant***
- Variants with FashionMNIST and more digits on one sphere

Models

Equivariant models

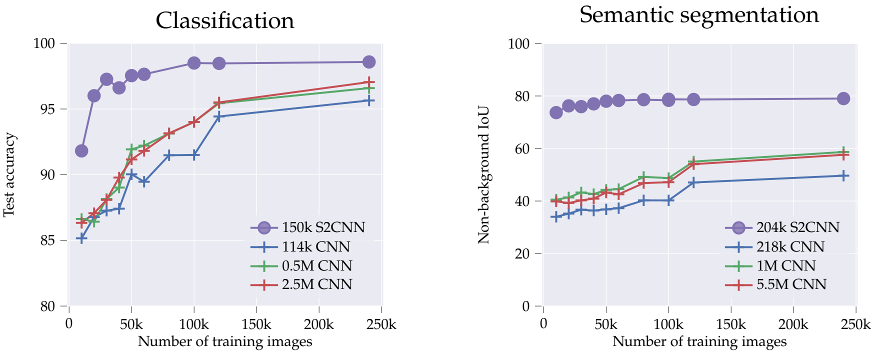
- S2CNN — equivariant convolutions with respect to SO(3) [2018 Cohen et al.]
- Perform convolutions in Fourier space of S^2 or SO(3)
- New projection layer from SO(3) back to S^2
- Trained on ***unrotated*** input samples

Non-equivariant models

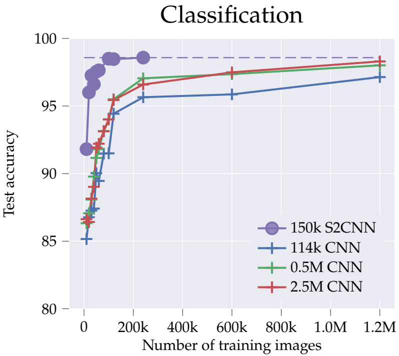
- Fully-convolutional networks with bottleneck
- Trained on ***rotated*** input samples

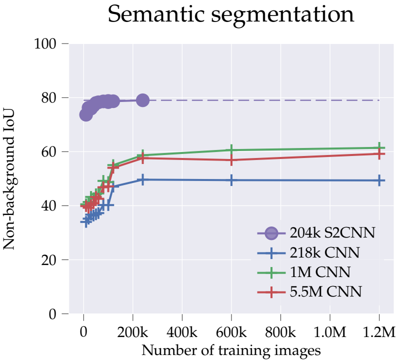
Results

Equivariance vs data augmentation



Performance saturation





Conclusions

- Equivariant architectures outperform non-equivariant networks trained with large amounts of data augmentation
- This is particularly pronounced for equivariant tasks and reduced for invariant tasks
- In the future, it would be interesting to extend our work to more general non-flat manifolds as studied in geometric deep learning