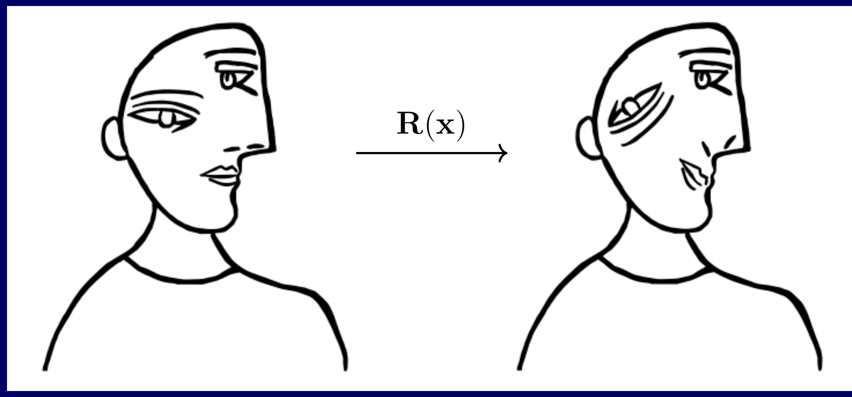
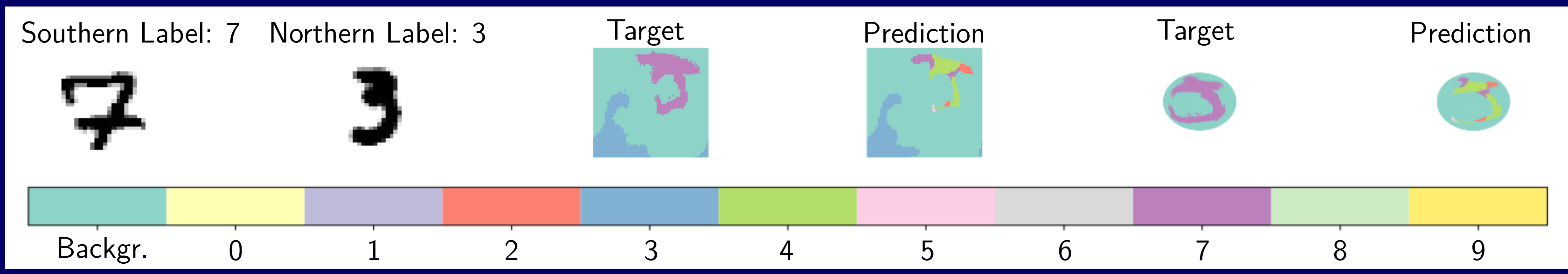
Local rotations don't matter with appropriate **layers**.





Gauge equivariant convolutional neural networks

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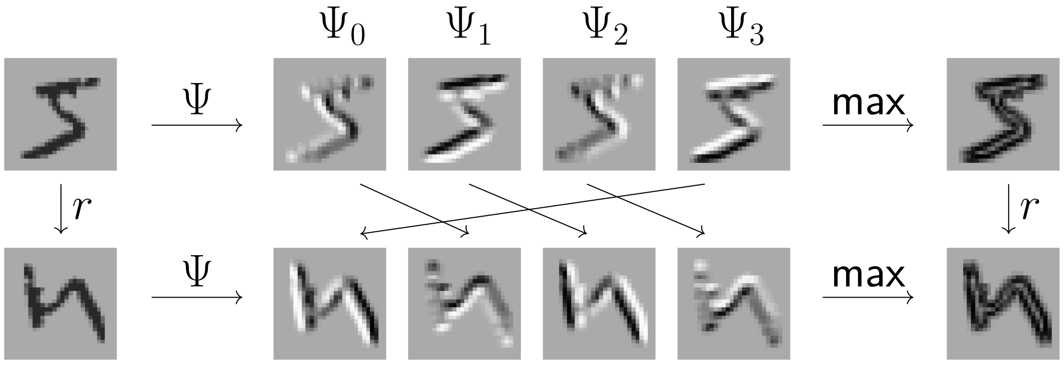
Intro

How does one deal with rotations? Options are:

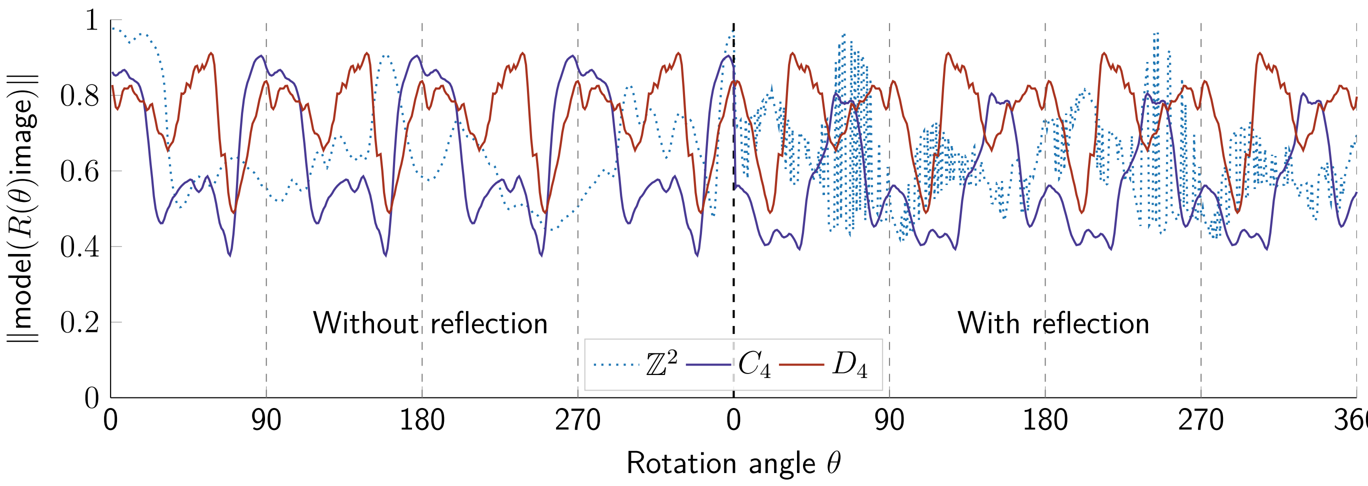
- You don't, you know all your data will have your prefered orientation. (Dangerous: real life throws curveballs at your models)
- Augement training data so that everything is represented. (Every orientation becomes a **lot** of data to deal with)
- Make sure that all your data has the right orientation. (A lot of work, either manually or making an algorithm to unrotate data)
- Modify your architecture and layers to deal with the rotation automatically. (The easy way.)

(Bullet image source: "rotation" by Adrien Coquet from the Noun Project)

One way: transform kernels [Cohen and Welling 2016]



Magnitude of classification invariance for four fold rotation symmetry applied to single MNIST digit



Some mathematics

A map Φ is equivariant with respect to a transformation T of the data if it doesn't matter if one transforms the data before or after one applies the map Φ:

$$\Phi \circ T = T \circ \Phi. \tag{1}$$

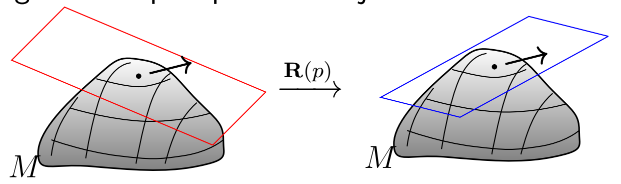
An example is that normal convolutions are equivariant to translation. One can extend this to a larger equivariance if we allow convolution kernels and data to be functions on a group:

$$[\Psi \star f](g) = \int_G \Psi(g^{-1}g')f(g')\,dg'. \tag{2}$$

This is equivariant if the kernel transforms in a special way under the group action:

$$\Psi(hgh') = \rho_2(h)\Psi(g)\rho_1(h'). \tag{3}$$

[Cohen and Welling 2016] discretise this to allow for easy computation, see figure on the left. Generalise this to local transformations by taking a viewpoint of local coordinates changes, see figure on top of poster and just below:



Equivariant convolutions in this general context was introduced by [Cheng et al. 2019] without much mathematical details. These details are expanded on in our upcoming article and in [Carlsson 2020].

Current work

We're currently examining the limits of the more general framework, how it compares to different classical approaches, in both classification and semantic segmentation tasks.

References

Carlsson, Oscar (2020). "Gauge Equivariant Convolutional Neural Networks". In.

Cheng, Miranda C. N. et al. (June 6, 2019). *Covariance in Physics and Convolutional Neural Networks*. arXiv: `1906.02481 [hep-th, stat]`.

Cohen, Taco S. and Max Welling (June 3, 2016). *Group Equivariant Convolutional Networks*. arXiv: `1602.07576 [cs, stat]`.

← Download [Carlsson 2020]

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