## Deep learning on the celestial sphere

Jason McEwen

www.jasonmcewen.org

Mullard Space Science Laboratory (MSSL), UCL Kagenova Limited

In collaboration with:

Oliver Cobb · Chris Wallis · Augustine Mavor-Parker · Augustin Marignier · Matthew Price · Mayeul d'Avezac

17 December 2020

#### **Research interests**



Physics and deep learning

#### Physics and deep learning

#### Physics

Understanding the world by modelling from first principles for generative models and inference.

#### Deep Learning

Understanding the world by **learning informative representations** for generative models and inference.

#### Physics and deep learning

#### Physics

Understanding the world by modelling from first principles for generative models and inference.

Hard!

#### Deep Learning

Understanding the world by **learning informative representations** for generative models and inference.

Hard!

#### Physics $\longleftrightarrow$ Deep Learning

#### Physics $\longleftrightarrow$ Deep Learning

#### As we will see, this key factor driving the deep learning revolution.

Symmetry in deep learning



"Symmetry: key to nature's secrets."

- Steven Weinberg

#### Noether's theorem

For every continuous symmetry of the universe, there exists a conserved quantity.

Symmetries at the heart of physics:

- + Translational symmetry  $\Leftrightarrow$  conservation of momentum
- + Rotational symmetry  $\Leftrightarrow$  conservation of angular momentum
- + Time translational symmetry  $\Leftrightarrow$  conservation of energy

(Energy not conserved in general relativity since time translation broken.)



Emmy Noether

# Symmetry is the foundation underlying the fundamental laws of physics.



Encoding symmetry in deep learning models captures fundamental properties about the underlying nature of our world.

Key factor driving the deep learning revolution, with the advent of CNNs.

- CNNs resulted in a step-change in performance.
- Convolutional structure of CNNs capture translational symmetry (i.e. translational equivariance).

Geometric deep learning on the celestial sphere















#### Generalised spherical CNNs

Efficient generalised spherical CNNs developed by McEwen and colleagues (Cobb et al. 2020; arXiv:2010.11661).

Consider the s-th layer of a generalised spherical CNN to take the form of a triple

 $\mathcal{A}^{(s)} = (\mathcal{L}_1, \mathcal{N}, \mathcal{L}_2),$ 

such that

$$\mathcal{A}^{(s)}(f^{(s-1)}) = \mathcal{L}_2(\mathcal{N}(\mathcal{L}_1(f^{(s-1)}))),$$

where

- $\mathcal{L}_1, \mathcal{L}_2 : \mathcal{F}_L \to \mathcal{F}_L$  are linear operators (e.g. convolutions on  $\mathbb{S}^2$ , SO(3); generalised convolutions)
- $\mathcal{N} : \mathcal{F}_L \to \mathcal{F}_L$  is a non-linear activation operator (e.g. ReLUs, harmonic tensor product activations).





## Group theoretic approach to construction since group theory is the mathematical study of symmetry.



## Since we're concerned with rotational symmetry, leverage the machinery from the study of angular momentum in quantum mechanics.

Illustration

#### Atomization energy prediction: problem

Predict atomization energy of molecule give the atom charges and positions.



## Atomization energy prediction: architecture



#### Test root mean squared (RMS) error for QM7 regression problem

	RMS	Params
Montavon et al. 2012	5.96	-
Cohen et al. 2018	8.47	1.4M
Kondor et al. 2018	7.97	>1.1M
Ours (MST)	3.16	337k
Ours (RMST)	3.46	335k