Equivariant Neural Fields for Gravitational Lensing

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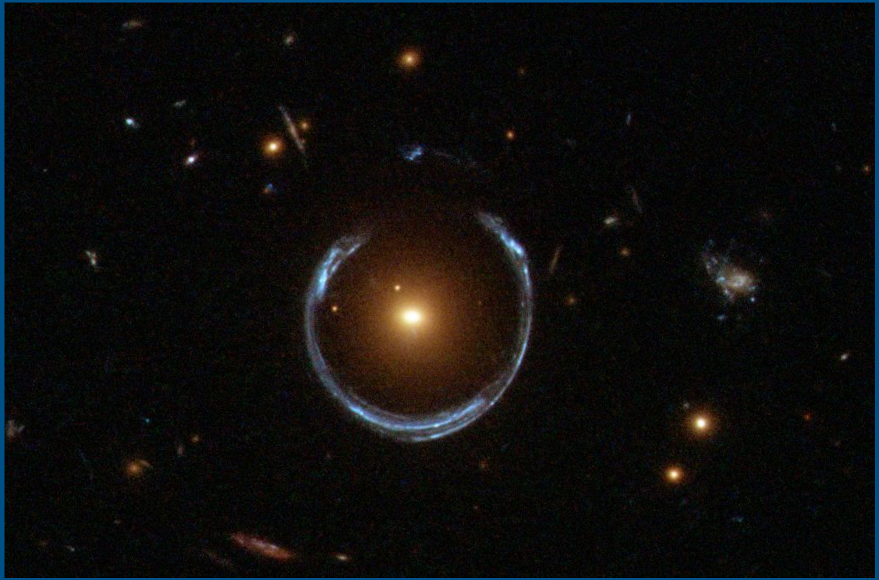
AI for Science F24



1. Gravitational Lensing
2. Equivariant Neural Fields
3. Downstream Classifiers
4. Preliminary Results
5. Next Steps & Future Work

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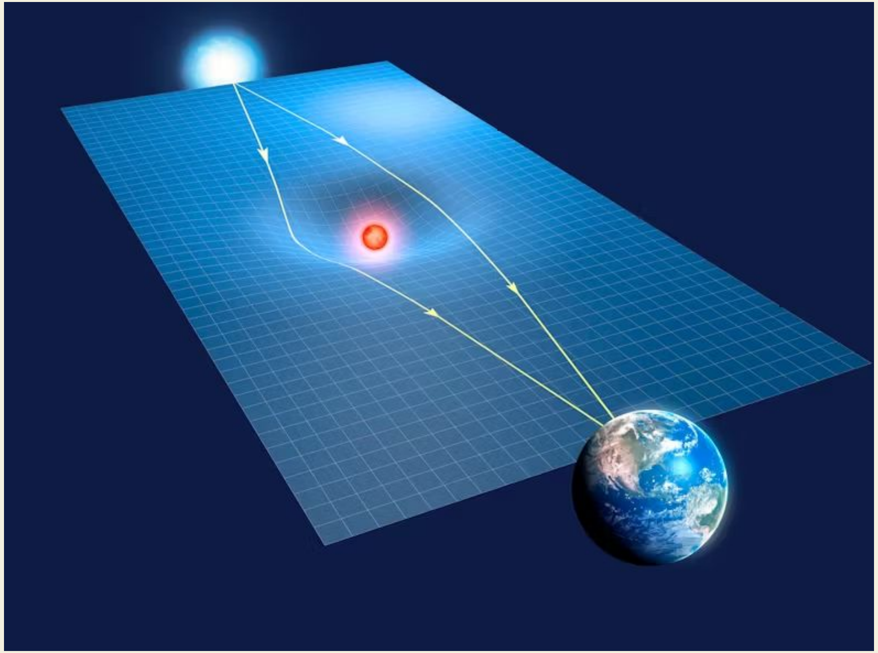
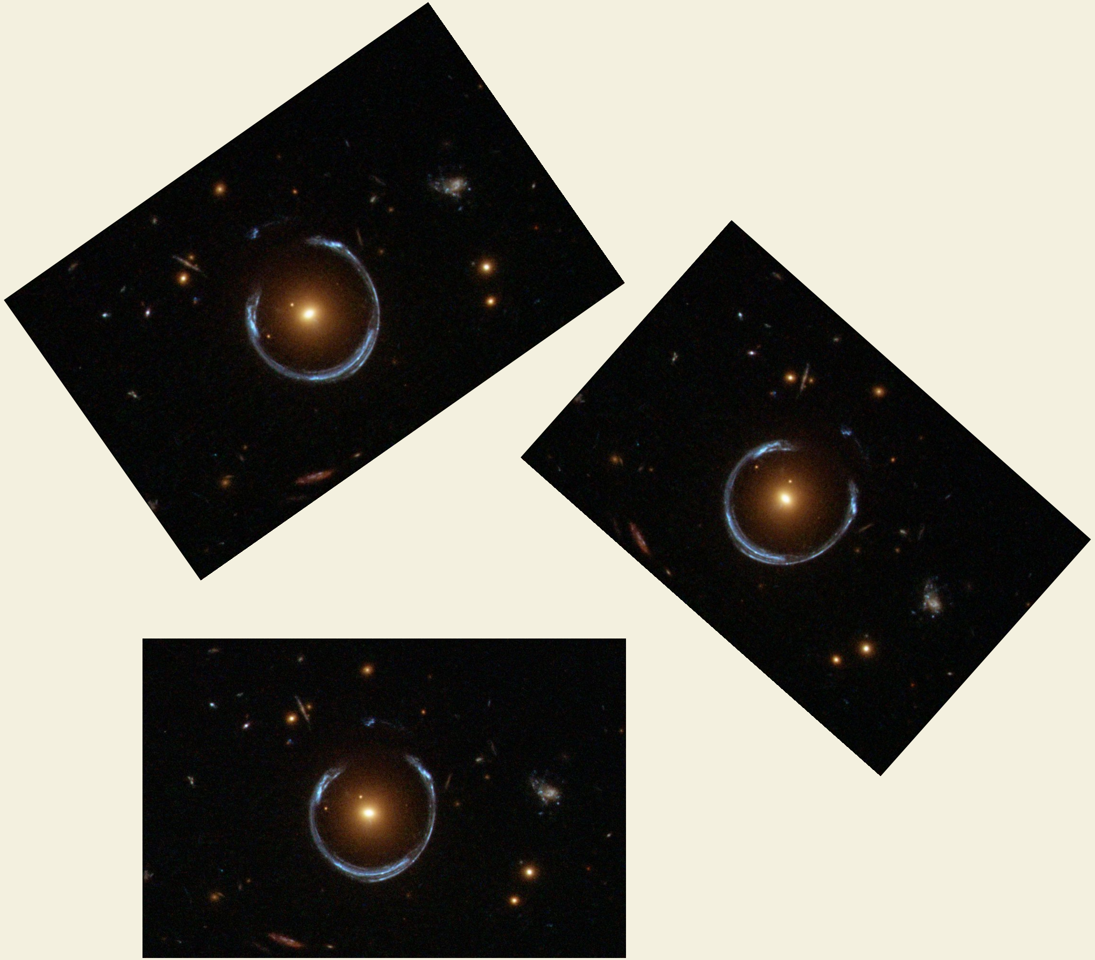
Gravitational Lensing

- Gravity bends emitted light into our view, revealing **invisible** objects or **making copies** of objects
- Massive object is called the **lens,** and we consider 3 types
- Impact: measuring **cosmological parameters** and detecting **dark matter**



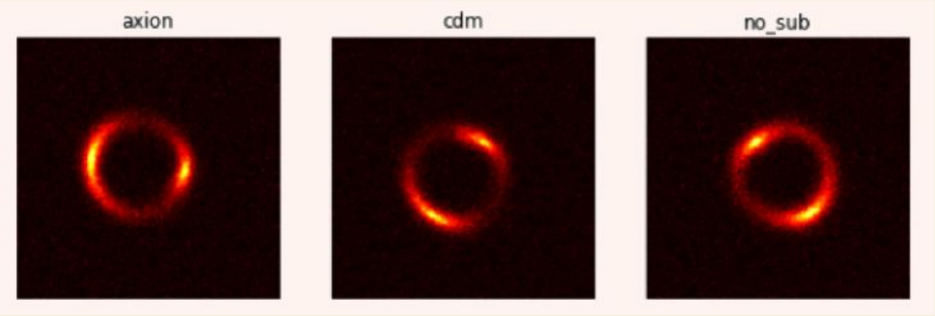
Expected Equivariance

- We expect **SE(2) equivariance** in classification between 3 kinds of gravitational lensing
- Image orientation should not matter, it is a 2D capture of an arbitrary view in a 3D space (universe)



Cheeramvelil et al.

- NIPS '23 Machine Learning in Physical Sciences Paper (link)
- Surveys equivariant architectures on this problem using simulated lensing data
  - Equiv. transformer, steerable CNN, harmonic net, and benchmark ResNet50



Still particle | Slow particle(s) | No structure

Dataset	Model name	Accuracy	AUC
Model A	ResNet50	96.86	0.99740
	C8Steerable CNN	**99.02**	**0.99967**
	Harmonic Net	90.95	0.98516
	Equivariant transformer	92.413	0.99321

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Neural Fields

- **Field**: spatial distribution of some quantity
- **Neural Field**: field defined by a NN
- **Conditional Neural Field (CNF)**: a network which can take on different values depending on the conditioning latent

$$f_\theta : \mathbb{R}^d \to \mathbb{R}^c$$

Neural Field

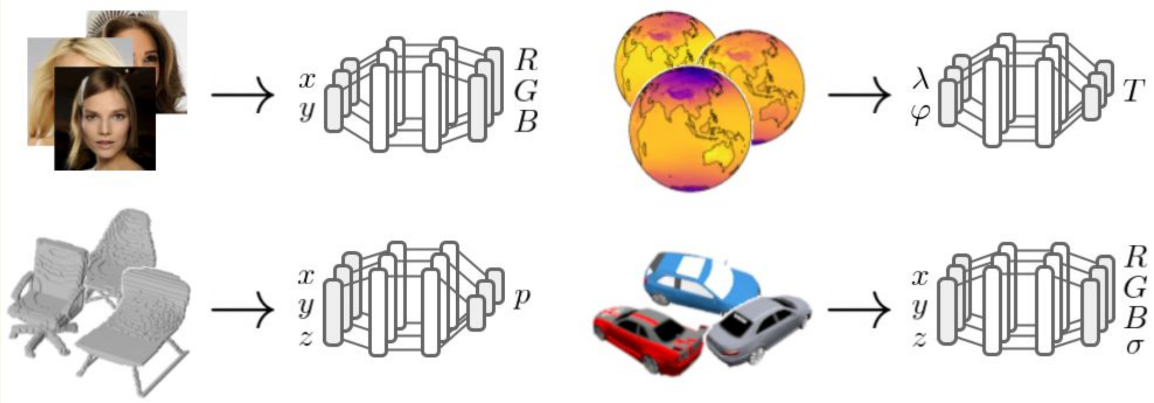
$$\mathcal{D} = \{f_i : \mathbb{R}^d \to \mathbb{R}^c\}_{i=1}^N$$
$$\forall x : f_i(x) \approx f_\theta(x; z_i)$$

Conditional Neural Field

CNF Big Picture

- **Independent of Modality** in a way AE/VAE is not

- Treat data as continuous functions learned by NN, then represent each by its conditioning latent



Equivariant Neural Fields

- Same paradigm as CNFs, but the conditioning latent contains geometric information that the ENF is equivariant to
- Under the hood: **equivariant cross attention** in latent point cloud
- **Result:** geometric reasoning from the latent space

$$\mathcal{D} = \{f_i : \mathbb{R}^d \to \mathbb{R}^c\}_{i=1}^N$$
$$\forall x : f_i(x) \approx f_\theta(x; z_i)$$

condition equivariantly
on geometric information

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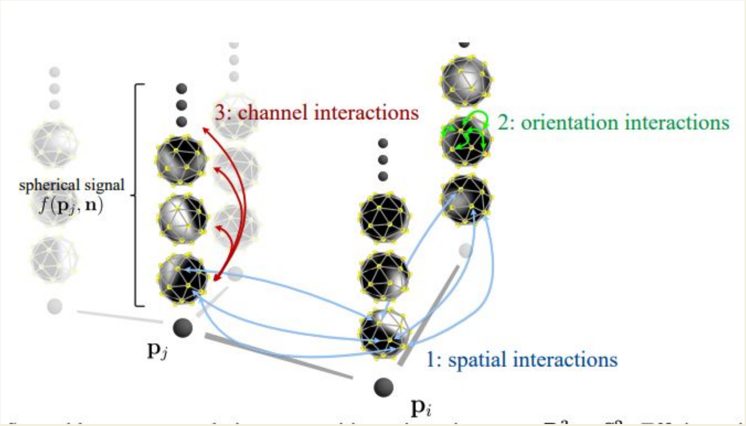
Downstream Classifiers

- How to classify once we have equivariant latents
- Three options:
  1. MLP (ignore geometry)
  2. PONITA (from same group, Clebsch-Gordan free equiv. in point clouds, optimized for ENF)
  3. Equivariant Transformer



PONITA Architecture

Preliminary Results

- Slow to train, due to three-phase learning:
  - Meta-learning Neural Fields
    - Learn field, then adjust params, and learn again (learning how to learn)
  - Learning ENF latents
  - Learning classification
- Slow training is not a major concern for many accuracy-only focused tasks

Preliminary Results cont.

- Partial results of small # epochs:
  - 1 epoch of meta-learning with batch SGD
  - 35 epochs of PONITA learning
  - loss < 0.5, acc = 0.8
  - Underfit geometric latents with partially trained classifier shows predictive power of point cloud latents
  - Higher accuracy than ordinary CNF + MLP of same training time

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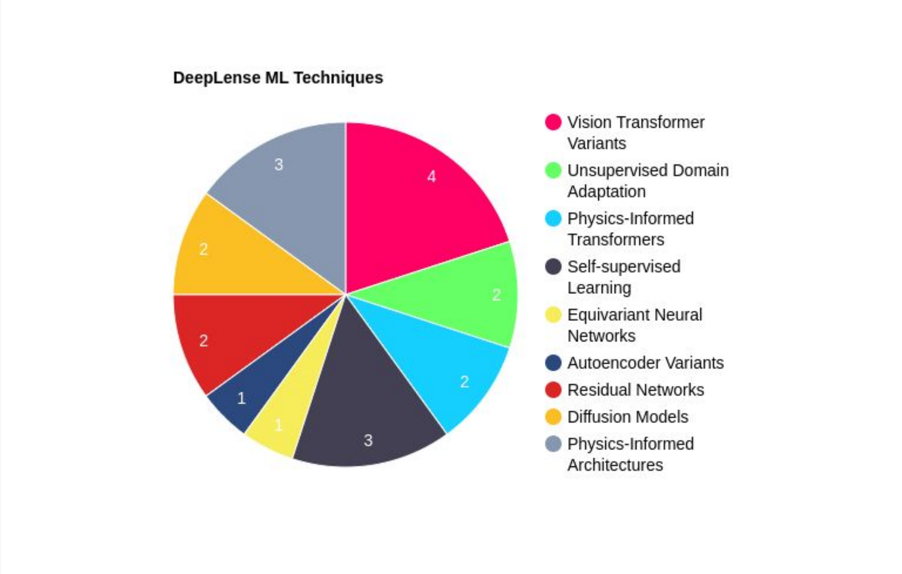
Next Steps & Future Work

- Full training run with simulated lensing dataset
- Ablations of downstream classifiers
- In contact with **DeepLense**, who published survey presented. Contribute this work to the ongoing collaboration.
- Other project branch: PI-ENF



Thank you