Equivariant Neural Networks for Inverse Problems

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23 September 2022

Joint work with:

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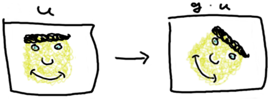
Ferdia Sherry

Outline

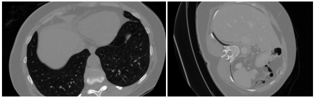
1) Inverse Problems
and Machine Learning

$$x^+ = \Psi_\theta(x - \tau \nabla D(x))$$

2) Equivariance



3) Numerical Results
for CT and MRI



Celledoni, Ehrhardt, Etmann, Owren, Schönlieb, and Sherry, "Equivariant neural networks for inverse problems," Inverse Problems 37(8), 2021.

Chen, Davies, Ehrhardt, Schönlieb, Sherry, and Tachella, "Imaging with Equivariant Deep Learning Imaging," to appear in IEEE Signal Processing Magazine, 2022.

Inverse Problems and Machine Learning

Inverse problems

$$Au = b$$

u : desired solution

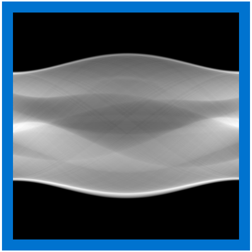
b : observed data

A : mathematical model

Goal: recover u given b

- CT: Radon / X-ray transform $Au(L) = \int_L u(x)dx$

$\longrightarrow$



Inverse problems

$$Au = b$$

u : desired solution

b : observed data

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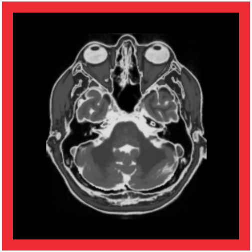
Goal: recover u given b

- MRI: Fourier transform $Au(k) = \int u(x) \exp(-ikx) dx$



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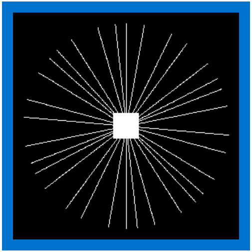


Variational regularization

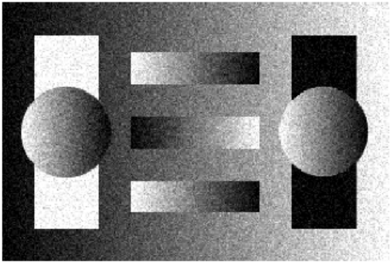
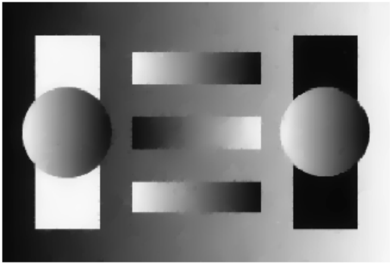
Approximate a solution u^* of $Au = b$ via

$$\hat{u} \in \arg\min_u \left\{ \mathcal{D}(u) + \lambda \mathcal{R}(u) \right\}$$

$\mathcal{D}$ measures **fidelity** between Au and b, related to noise statistics

$\mathcal{R}$ **regularizer** penalizes unwanted features and ensures stability;
e.g. TV Rudin, Osher, Fatimi '92 $\mathcal{R}(u) = \|\nabla u\|_1$,
TGV Bredies, Kunisch, Pock '10 $\mathcal{R}(u) = \inf_v \|\nabla u - v\|_1 + \beta \|\nabla v\|_1$

$\lambda \geq 0$ **regularization parameter** balances fidelity and regularization

Algorithmic Solution $\hat{u} \in \arg\min_u \{\mathcal{D}(u) + \lambda\mathcal{R}(u)\}$

Proximal Gradient Descent (PGD) Beck and Teboulle '09

$$u^{k+1} = \mathrm{prox}_{\tau^k \lambda \mathcal{R}}(u^k - \tau^k \nabla \mathcal{D}(u^k))$$

Solution $\Phi(b) := \lim_{k\to\infty} u^k$.
Choose τ^k, λ: $\Phi(b) = \hat{u} \to u^*$ if $\lambda \to 0$

Proximal operator: $\mathrm{prox}_f(z) := \arg\min_u \left\{\frac{1}{2}\|u - z\|^2 + f(u)\right\}$ Moreau '62

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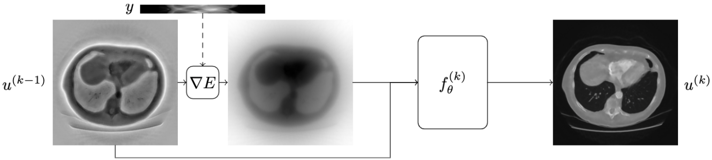
Learned PGD Gregor and Le Cun '10, Adler and Öktem '17, ...

$$u^{k+1} = \widehat{\mathrm{prox}_i}(u^k, \nabla \mathcal{D}(u^k))$$

Solution $\Phi(b) := u^K$, "small" $K \in \mathbb{N}$.
Learn $\widehat{\mathrm{prox}_i}$: $\Phi(b) \approx u^*$



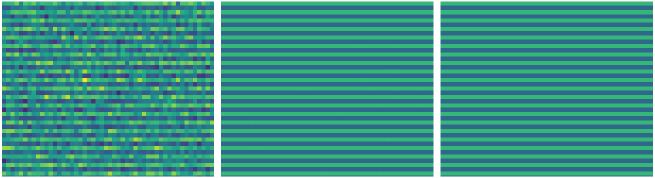
Equivariance and Inverse Problems

What happens when data is rotated?

Example: R_θ rotation by θ, Φ denoising network

$$\Phi(R_\theta b) \stackrel{?}{=} R_\theta \Phi(b)$$

Training data



noisy CNN proposed

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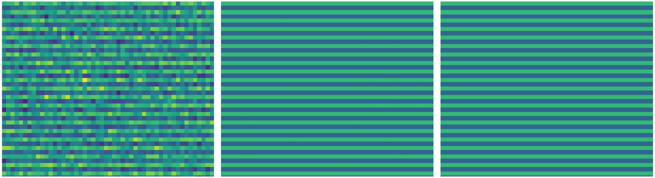

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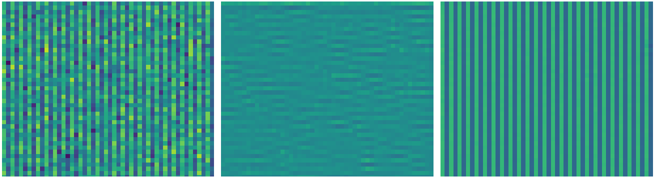
Test data



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- **equivariance by learning**: e.g. data augmentation $(b_i, u_i)_i$ becomes $(R_\theta b_i, R_\theta u_i)_{i,\theta}$
  - ✓ **simple to implement** for image-based tasks (e.g. denoising, image segmentation etc)
  - ✗ potentially **computationally costly**: larger training data
  - ✗ **no guarantees** this will translate to test data
  - ✗ **not always easy/possible** (for inverse problems only viable in simulations or if data is not paired)

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  There are alternatives: Chen et al. '21
- **equivariance by design** (this talk!)
  - ✓ **mathematical guarantees**
  - ✗ **not trivial** to do

  Equivariant neural networks have been studied a lot for segmentation, classification, denoising etc

  Bekkers et al. '18, Weiler and Cesa '19, Cohen and Welling '16, Dieleman et al. '16, Sosnovik et al. '19, Worall and Welling '19, ...

Equivariance and inverse problems

- inverse problem $Au = b$, solution operator: $\Phi : Y \to X$
- **Hope** $\Phi \circ A$ is equivariant, e.g. $R_\theta \circ \Phi \circ A = \Phi \circ A \circ R_\theta$

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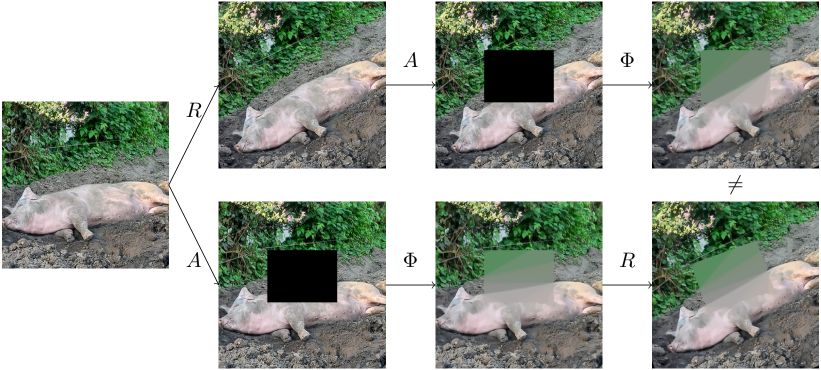
- Even if J is invariant, $\Phi \circ A$ is **not generally equivariant**
- Example: variational TV inpainting



Invariant functional implies equivariant proximal operator

Theorem Celledoni et al. '21
Let $X = L^2(\Omega)$ and J be **invariant** with respect to rotations: $J(R_\theta u) = J(u)$.
Then prox_J is **equivariant**, i.e for all $u \in X$

$$\mathrm{prox}_J(R_\theta u) = R_\theta \, \mathrm{prox}_J(u).$$

- For **example** the total variation (and higher order variants) is invariant to rigid motion

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Since we are interested in Learned Gradient Descent, equivariance of the network is a natural condition.

Equivariance revisited

What is equivariance?

Definition (Group G)

- **associativity:** $\forall g_1, g_2, g_3 \in G : (g_1 \cdot g_2) \cdot g_3 = g_1 \cdot (g_2 \cdot g_3)$,
- **identity:** $\exists e \in G \; \forall g \in G : e \cdot g = g$
- **invertibility:** $\forall g \in G \; \exists g^{-1} \in G : g^{-1} \cdot g = e$

Definition (G acts on set X)

- **group action:** $G \times X \to X, \quad (g, x) \mapsto g \cdot x$
- **identity:** $e \cdot x = x$
- **compatibility:** $g_1 \cdot (g_2 \cdot x) = (g_1 \cdot g_2) \cdot x$

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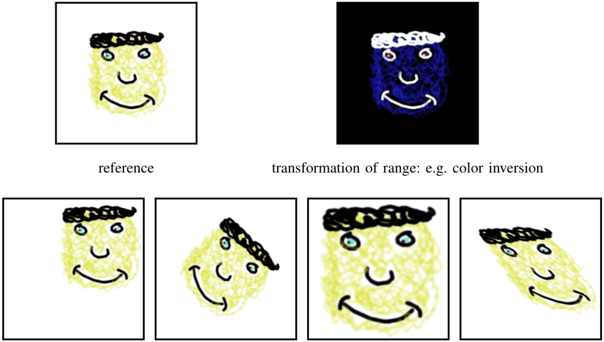
Definition (Equivariance) $\Phi : X \to Y$ is **equivariant** if for all $g \in G, x \in X$

$$g \cdot \Phi(x) = \Phi(g \cdot x)$$

Group acts on functions/images, e.g. $X = L^2(\mathbb{R}^n, \mathbb{R}^m)$

- **domain:** $({\color{red}g} \cdot {\color{blue}u})(x) = {\color{blue}u}({\color{red}g}^{-1} \cdot x)$



reference

transformation of range: e.g. color inversion

transformation of domain: e.g. translation, rotation, scaling, shearing

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- **domain:** $(g \cdot u)(x) = u(g^{-1} \cdot x)$
- **range:** $(g \cdot u)(x) = g \cdot u(x)$
- **both domain and range:** $(g \cdot u)(x) = g \cdot u(g^{-1} \cdot x)$

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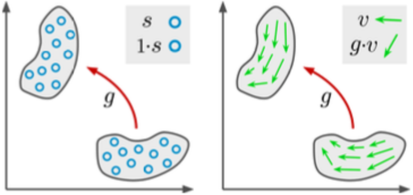
Acting on domain and range: $(g \cdot u)(x) = g \cdot u(g^{-1} \cdot x)$

- $\overline{G} = \mathbb{R}^n \rtimes H, \quad H$ subgroup of the general linear group $\mathrm{GL}(n)$
- $g \cdot x = Rx + t, g = (t, R) \in \overline{G}, t \in \mathbb{R}^n, R \in H$
- $\pi : H \to GL(m)$ representation of H
- $(g \cdot u)(x) = \pi(R)u(R^{-1}(x - t))$

Examples

- **Translations:** $H = \{e\}$
- **Roto-Translations:** $H = \mathrm{SO}(n)$
- **Finite Roto-Translations** $H = Z_M$ (finite subgroup of $\mathrm{SO}(n)$)
- Example: u vector-field, move and transform vectors



Weiler and Cesa '19

More details: implies equivariant proximal operator

Theorem Celledoni et al. '21

- G acts **isometrically** on X ($\|g \cdot u\| = \|u\|$)
- $J : X \to \mathbb{R} \cup \{+\infty\}$ is **invariant** ($J(g \cdot u) = J(u)$)
- J has **well-defined single-valued proximal operator**

Then prox_J is **equivariant**, i.e for all $u \in X$ and $g \in G$

$$\mathrm{prox}_J(g \cdot u) = g \cdot \mathrm{prox}_J(u).$$

- Proof does **generalize** to variatial regularization with L^2-datafit **if A is equivariant**

Equivariance and Neural Networks

How to get "equivariant" networks?

Proposition Let G be any group.

- The **composition** $\Phi \circ \Psi$ is equivariant if Φ and Ψ are equivariant.
- The **sum** $\Phi + \Psi$ is equivariant if Φ and Ψ are equivariant.
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Proposition (bias) Let $\Phi : X \to X, (\Phi u)(x) = u(x) + b(x)$. For any group G, Φ is equivariant if b is invariant, i.e. $g \cdot b = b$.

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Outlook (nonlinearity) There are $\overline{G}$-equivariant nonlinearities.

Construct $\overline{G}$-equivariant neural networks the usual way:

- layers $\Phi = \Phi_n \circ \cdots \circ \Phi_1$
- $\Phi(u) = \sigma(Au + b)$
- ResNet $\Phi(u) = u + \sigma(Au + b)$

Equivariant linear functions ($\pi_X \equiv id$)

In a nutshell: Linear $\overline{G}$-equivariant operators are convolutions with a kernel satisfying an additional constraint.

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Theorem paraphrasing e.g. Weiler and Cesa '19

Let X, Y be function spaces, e.g. $X = L^2(\mathbb{R}^n, \mathbb{R}^m)$, $Y = L^2(\mathbb{R}^n, \mathbb{R}^M)$. The linear operator $\Phi : X \to Y$,

$$\Phi f(x) = \int K(x, y) f(y) dy$$

with $K : \mathbb{R}^n \to \mathbb{R}^{M \times m}$ is $\overline{G}$-**equivariant** iff there is a k such that

$$\Phi f(x) = \int k(x - y) f(y) dy$$

and k is H-invariant, i.e. for all $R \in H$, $x \in \mathbb{R}^n$: $k(Rx) = k(x)$.

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Let $\psi : \mathbb{R} \to \mathbb{R}$ be any non-linear function.

- **Pointwise and componentwise nonlinearity** $\Psi_P : X \to X$,

$$[\Psi_P(u)](x) = \vec{\psi}(u(x)), \quad \vec{\psi}(x)_i = \psi(x_i)$$

- **Norm nonlinearity** $\Psi_N : X \to X$,

$$[\Psi_N(u)](x) = u(x) \cdot \psi(\|u(x)\|)$$

Lemma Both nonlinearities are $\overline{G}$-equivariant.

Numerical Results

Datasets

- **CT:** LIDC-IDRI data set, 5000+200+1000 images, 50 views

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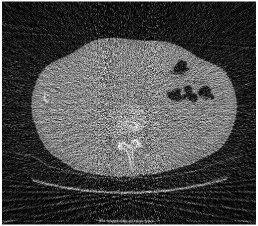
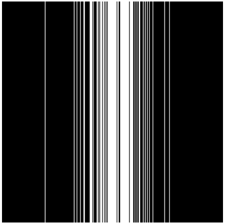
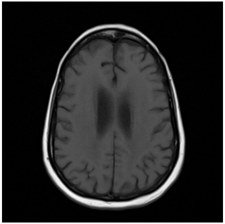


$\mathrm{FBP}(y)$

- **MR:** FastMRI data set, 5000+200+1000 images



$\mathcal{S}$



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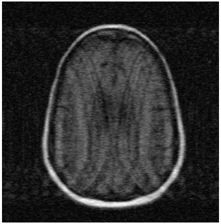


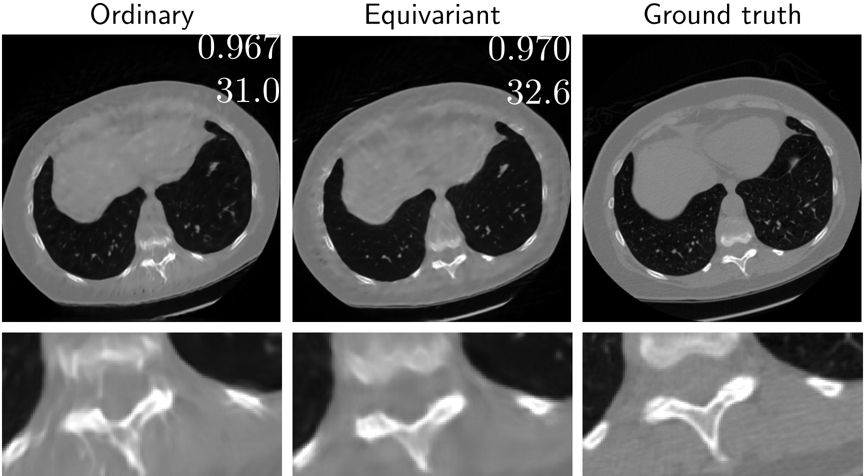
$\mathcal{F}^{-1}(\mathcal{S}^* y)$

CT Results

Equivariant = roto-translations; Ordinary = translations

Equivariant improves upon Ordinary:

- **higher** SSIM and PSNR
- **fewer** artefacts and **finer** details

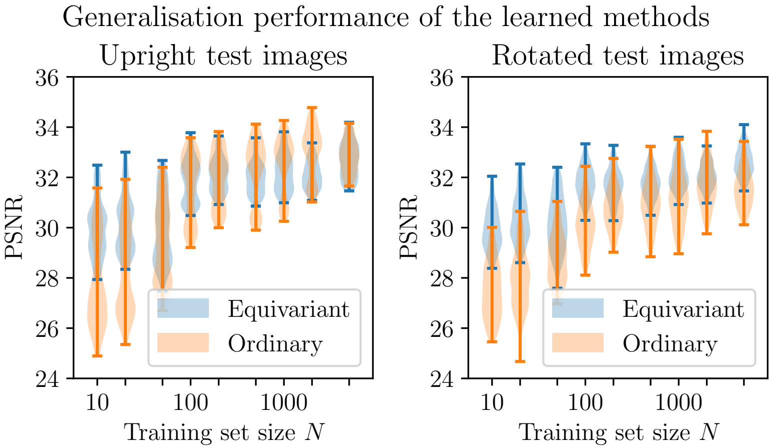


CT Results

Equivariant = roto-translations; Ordinary = translations

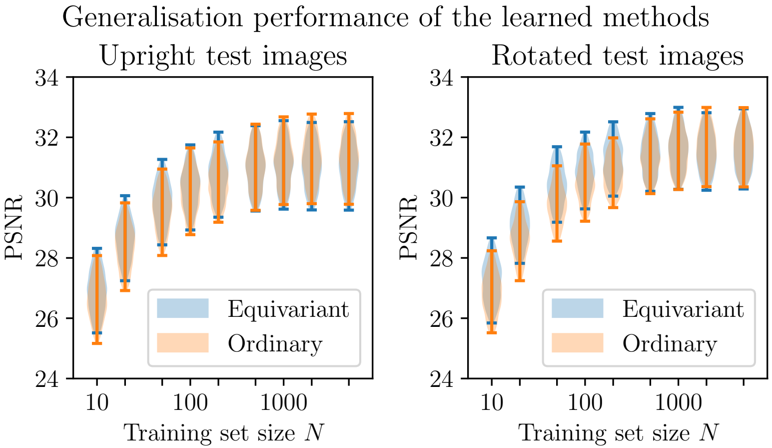
Equivariant improves upon Ordinary:

- **small** training sets
- **unseen** orientations



MR Results

- **similar** observations in MR (as in CT); smaller difference
- results for both methods **better on rotated** images



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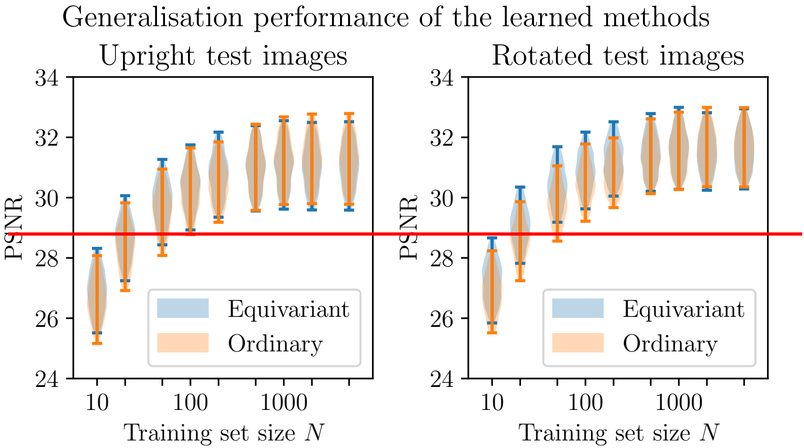
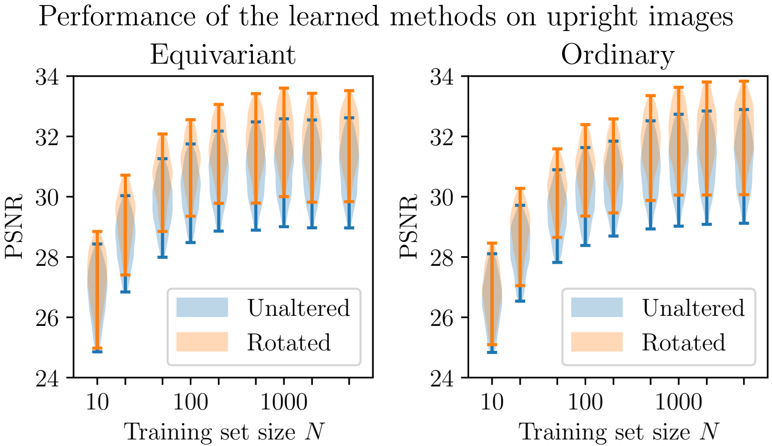


MR Results: Smoothing

- **smoothing helps:** easier to train on smoother images



Conclusions and Outlook

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- **no need for data augmentation**: mathematically guaranteed equivariant neural networks exist
- **solution operators** may **not** be equivariant, but **proximal operators** usually are **equivariant**
- computationally **efficient**: as CNNs at run time
- useful for many **applications**: **fewer data** and **robustness**

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Future work

- **other groups**, e.g. scaling of itensities; scaling of domain
- **other inverse problems**, e.g. compressed sensing or trivial kernel
- **higher dimensions** e.g. 3D or dynamic inverse problems

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