Unsupervised Learning-based Registration

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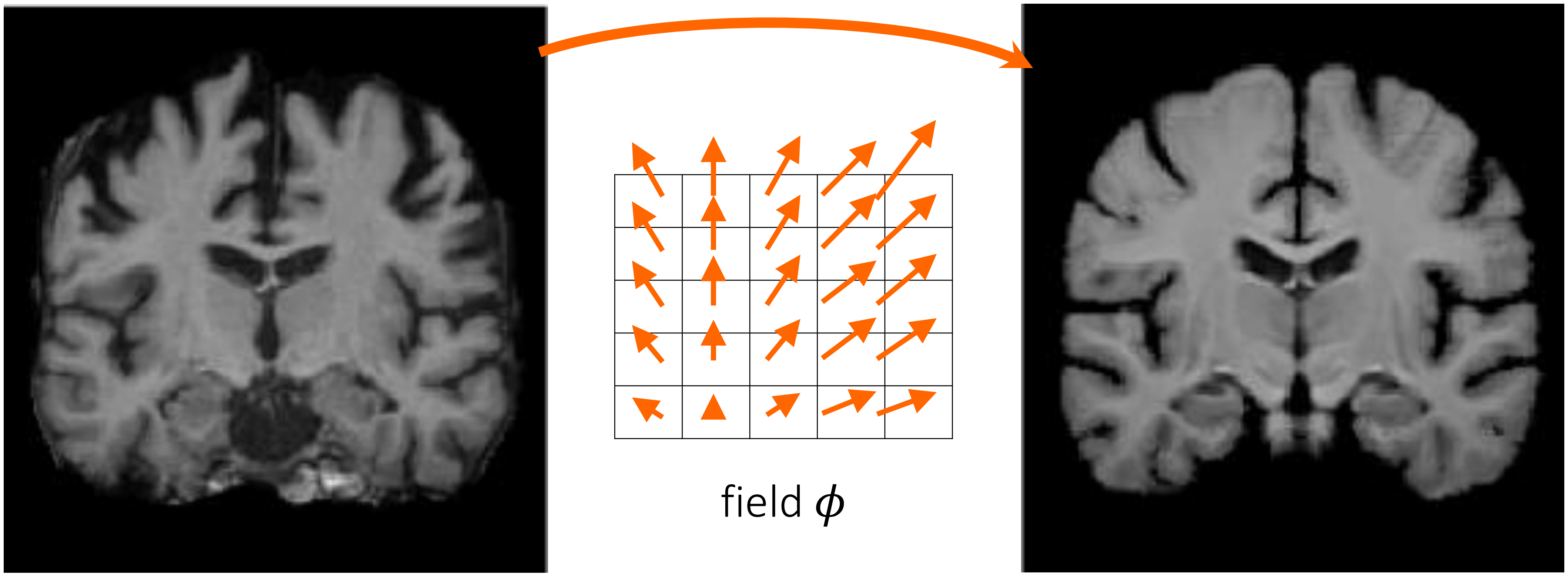
Hands-on Session:
https://www.kaggle.com/adalca/learn2reg
https://github.com/learn2reg/tutorials2019/
Code and slides based on **voxelmorph.mit.edu**

Registration

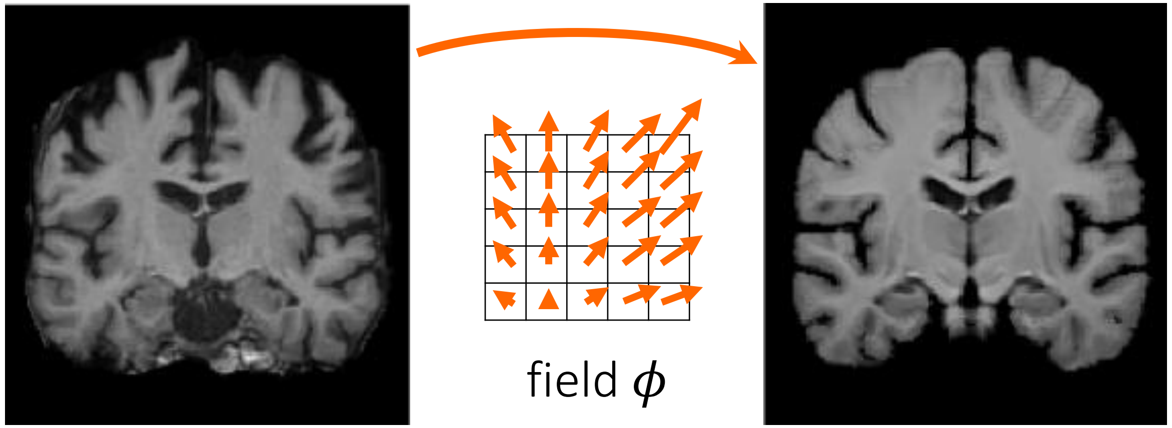


moving scan $\boldsymbol{m}$

fixed scan $\boldsymbol{f}$

Pairwise optimization

scan $\boldsymbol{m}$

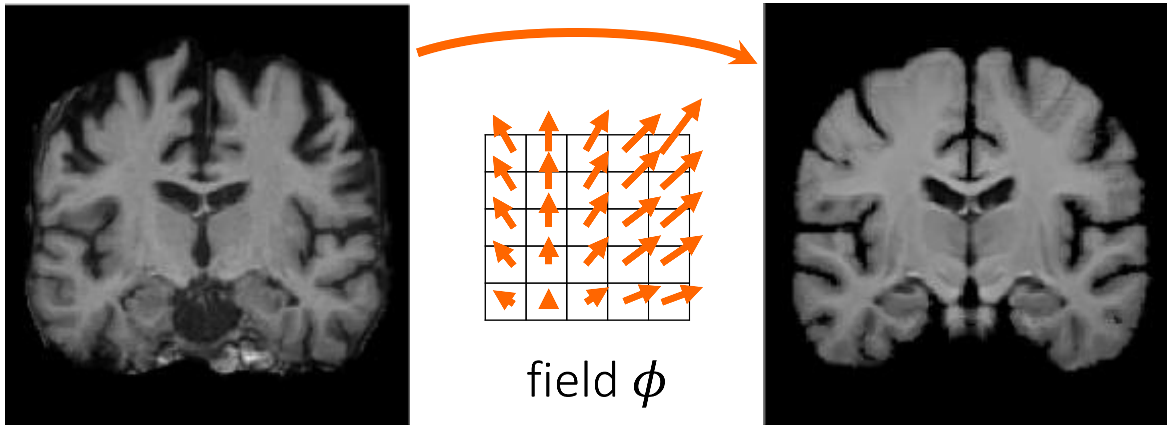


scan $\boldsymbol{f}$

$$\underset{\text{optimal deformation field}}{\hat{\phi}_{m,f}} = \mathrm{argmin}_{\phi}\ \underbrace{\|\overset{\text{warped scan } m}{m \circ \phi} - f\,\|}_{\text{images match}} + \lambda\, \underbrace{\mathrm{Reg}(\phi)}_{\text{smooth field}}$$

Pairwise optimization

scan $\boldsymbol{m}$



field ϕ

scan $\boldsymbol{f}$

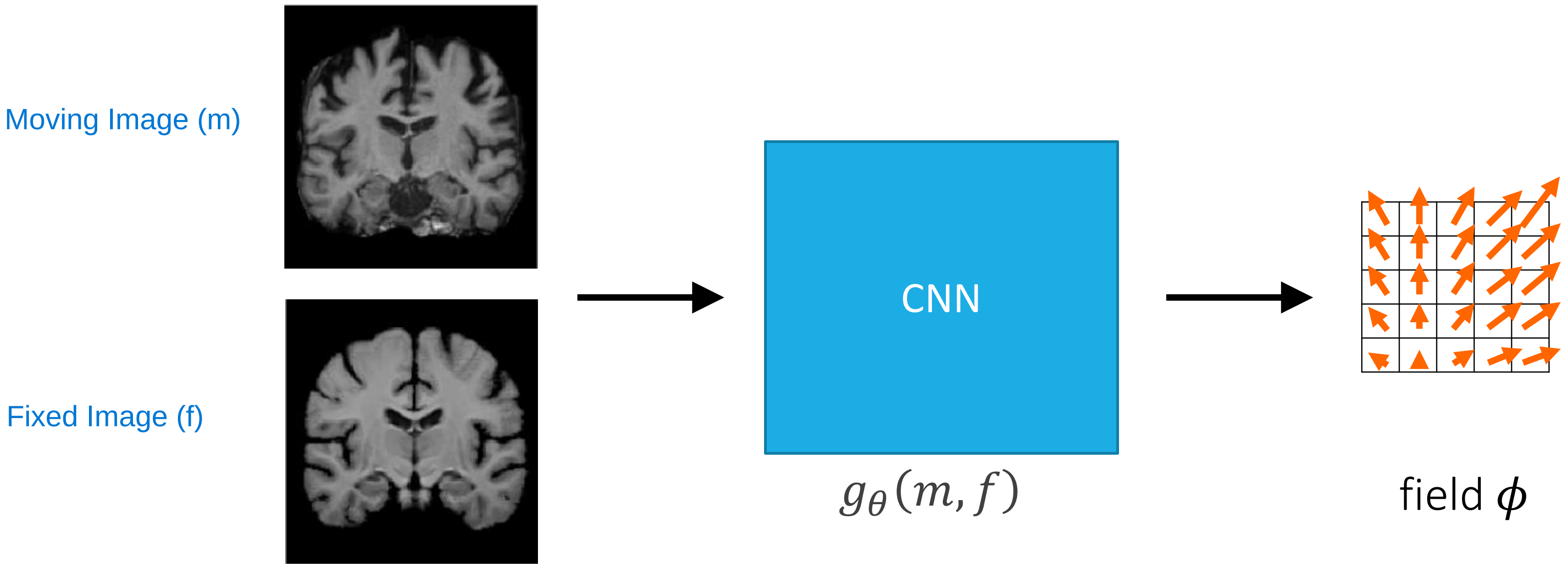
warped scan $\boldsymbol{m}$

$$\hat{\phi}_{m,f} = \text{argmin}_{\phi} \underbrace{\|m \circ \phi - f\|}_{\text{images match}} + \lambda \underbrace{\text{Reg}(\phi)}_{\text{smooth field}}$$

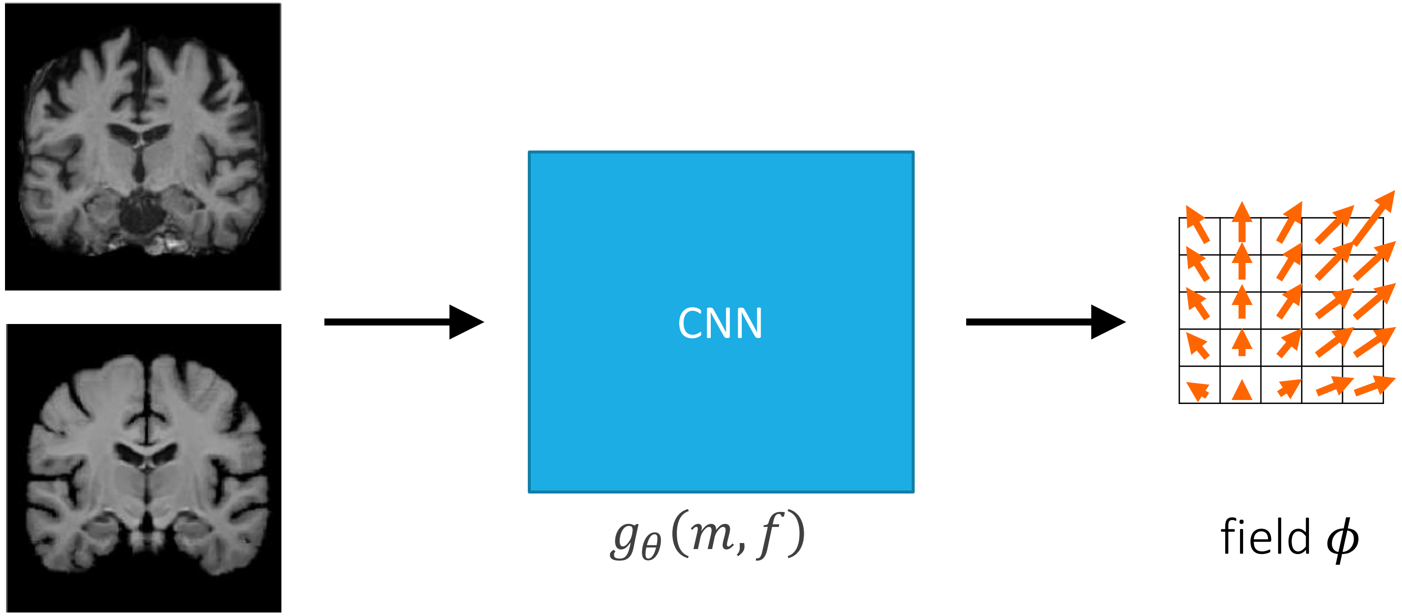
optimal deformation field

- significant development
- slow for two images

Learning-based methods

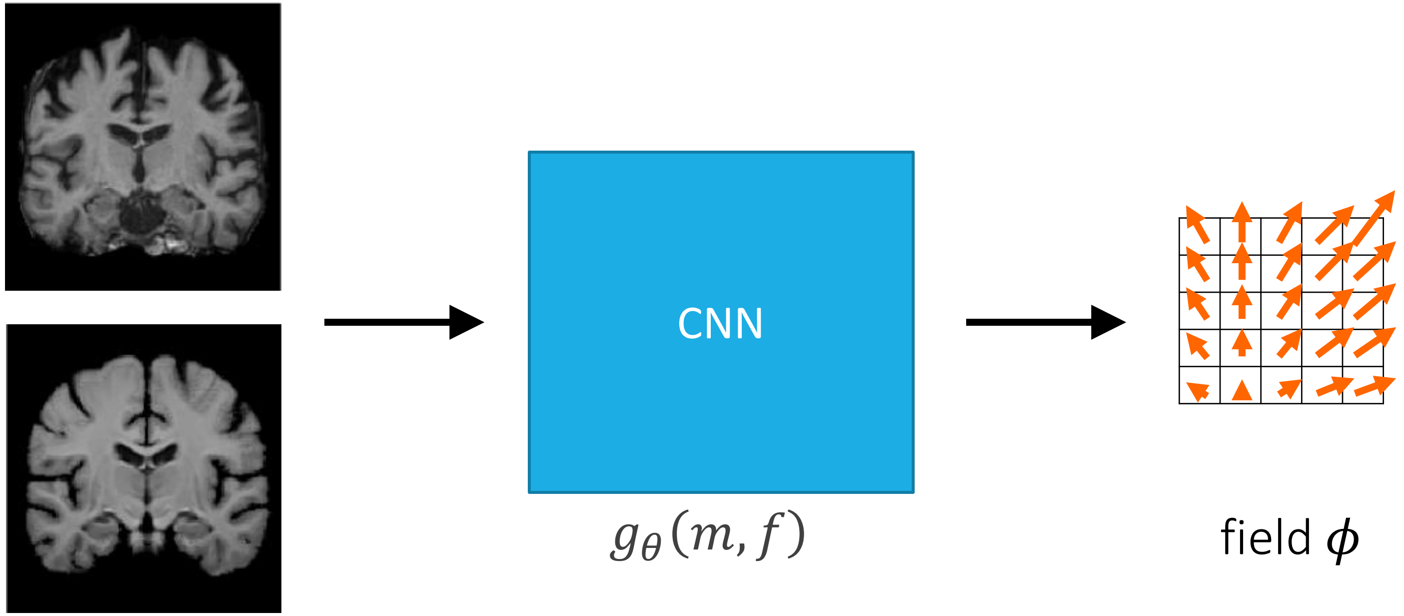


Learning-based methods



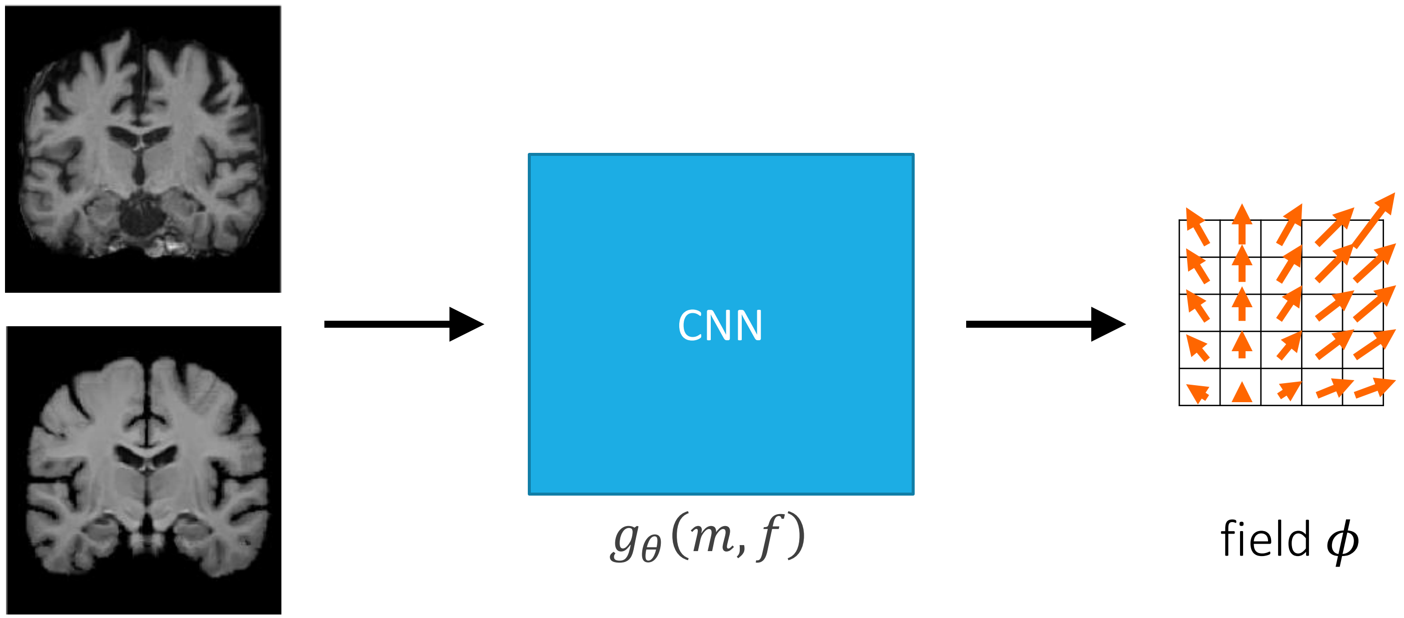
- Supervised (have example triplets $\{m, f, \phi\}$)

Learning-based methods



- Supervised (have example triplets $\{m, f, \phi\}$)
  - ϕ from classical methods as 'ground truth'
  - External data (segmentations, landmarks, etc)

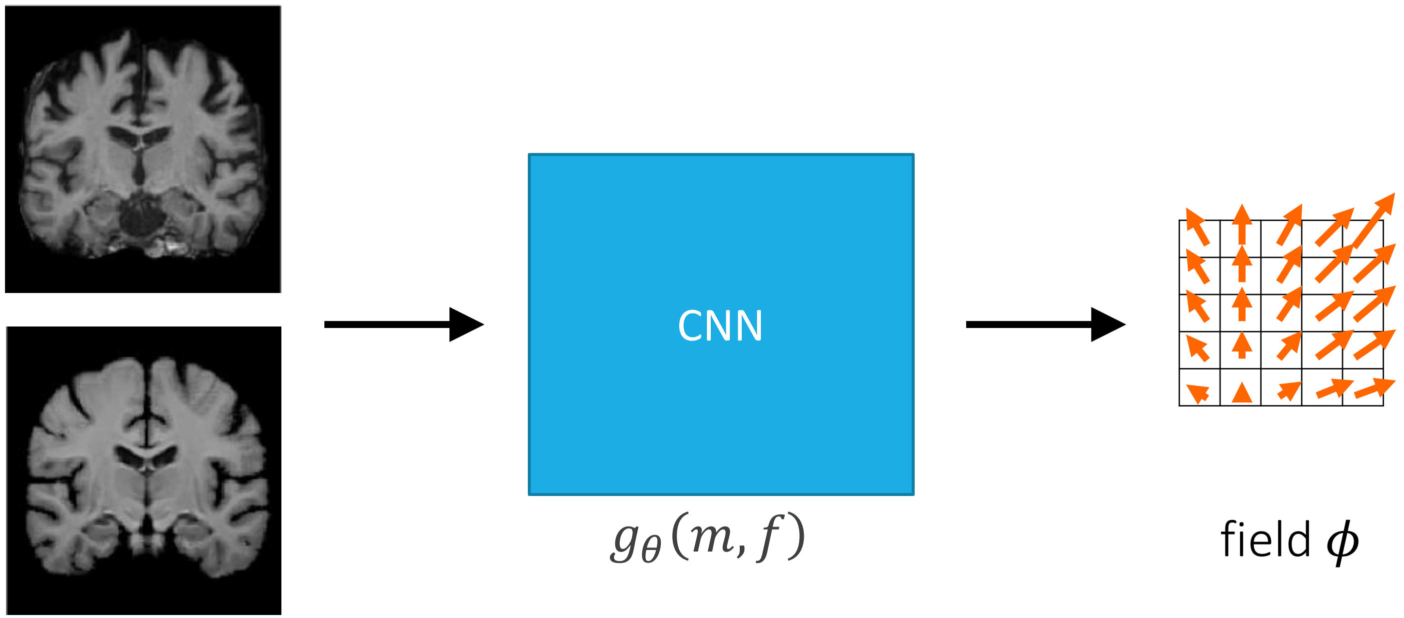
Learning-based methods



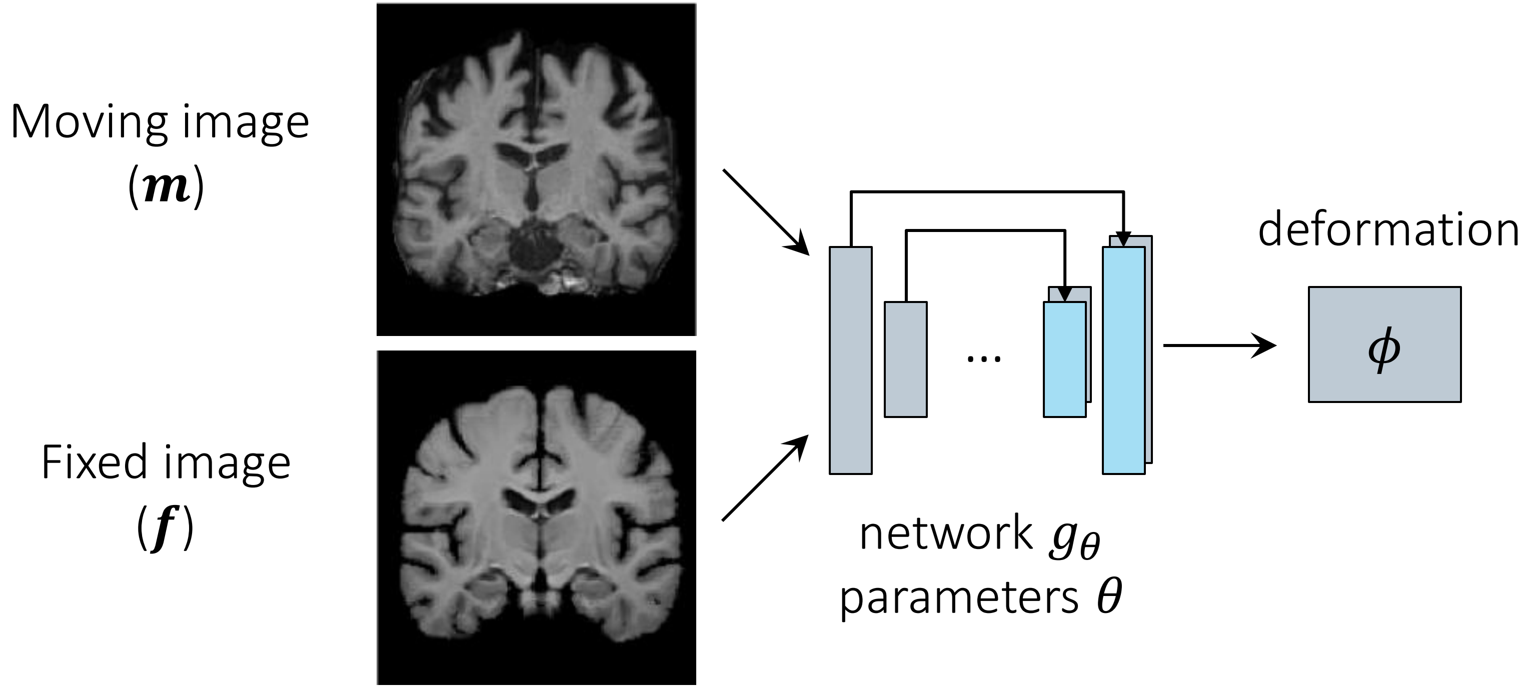
- Supervised (have example triplets $\{m, f, \phi\}$)
- Unsupervised (only have images $\{m, f\}$)

- **fast** for new image pair

Learning-based methods

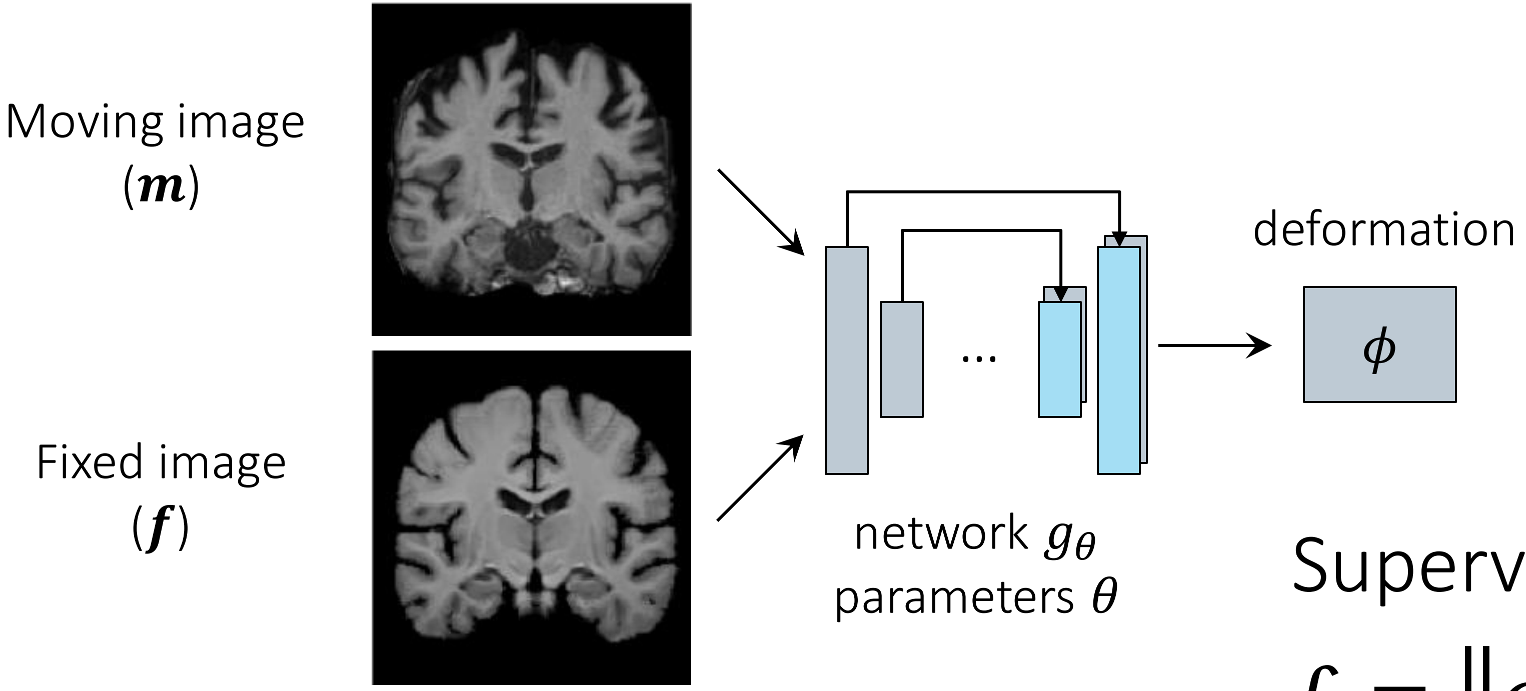


Network architecture?



Network: full volume (e.g. 256x256x256x2) to full volume (256x256x256x3)
FCNN, UNet, etc.

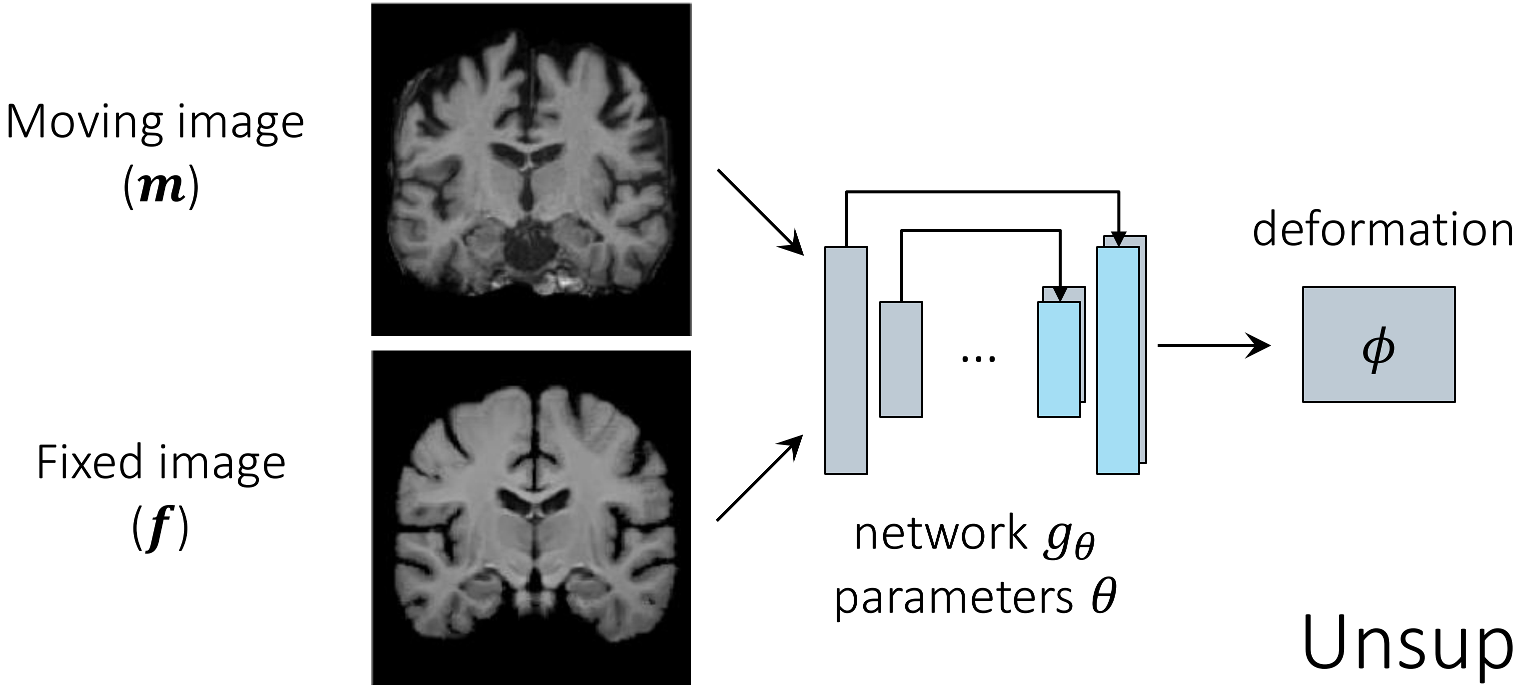
Framework Loss



Supervised:

$$\mathcal{L} = \left\|\phi - \phi_{gt}\right\|^2$$

Framework Loss



Unsupervised: There is no ground truth for you. So, you evaluate your result in comparison with fixed image.

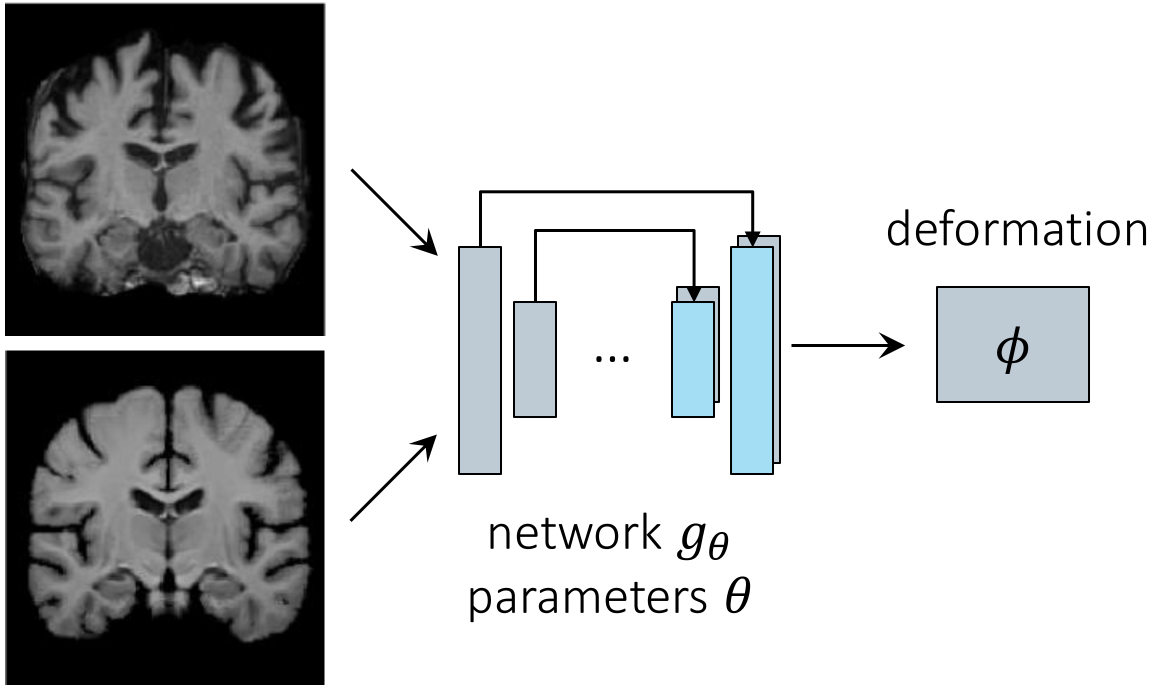
Unsupervised:

$$\mathcal{L} = ||m \circ \phi - f|| + \lambda \, \mathrm{Reg}(\phi)$$

Framework Loss

Moving image
($\boldsymbol{m}$)

Fixed image
($\boldsymbol{f}$)

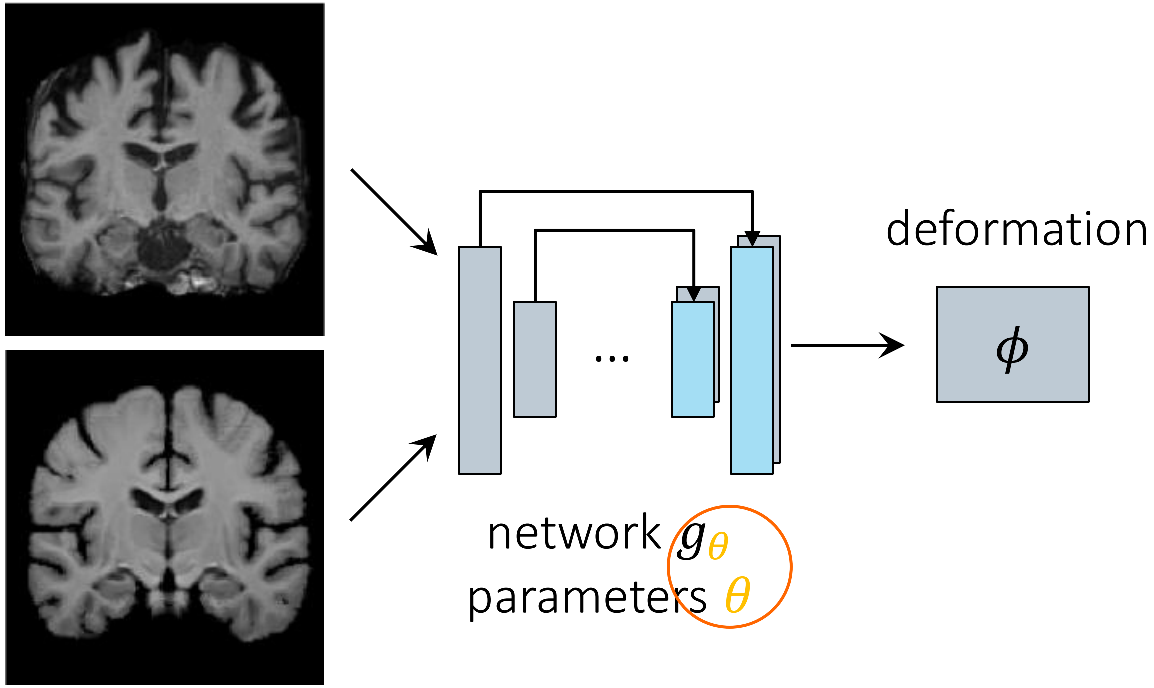


$$\mathcal{L} = \sum_{i,j} \|m_i \circ \phi_{ij} - f_{ij}\| + \lambda \, \mathrm{Reg}(\phi_{ij})$$

Framework Loss

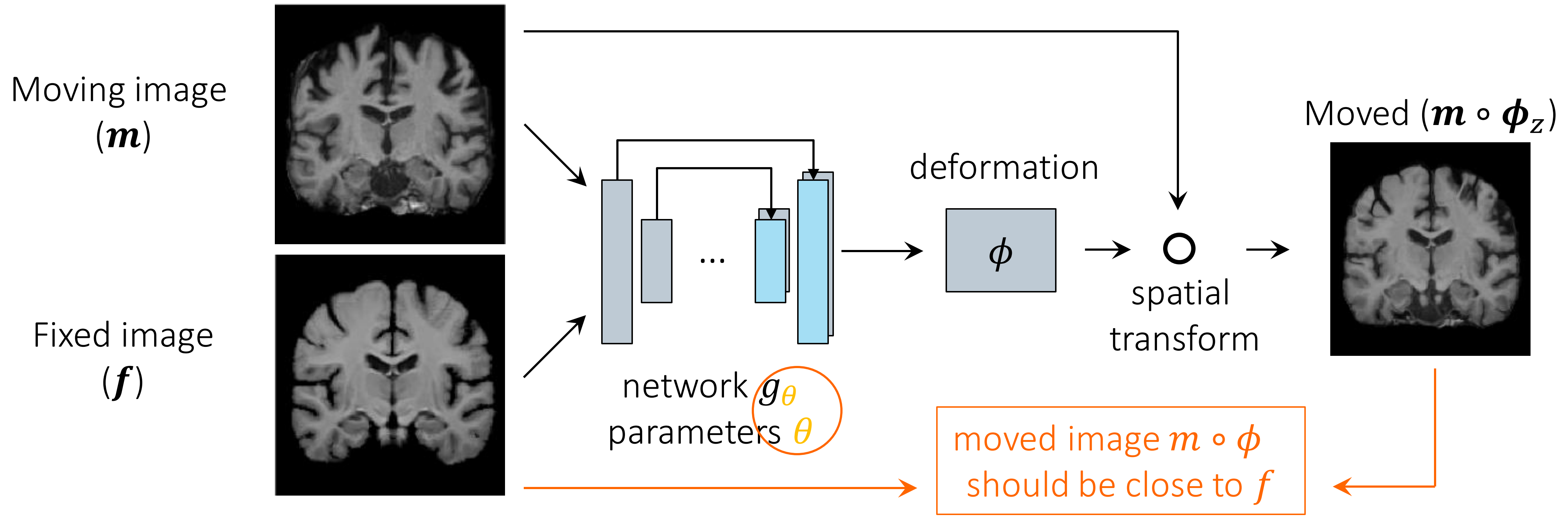
Moving image
$(\boldsymbol{m})$

Fixed image
$(\boldsymbol{f})$



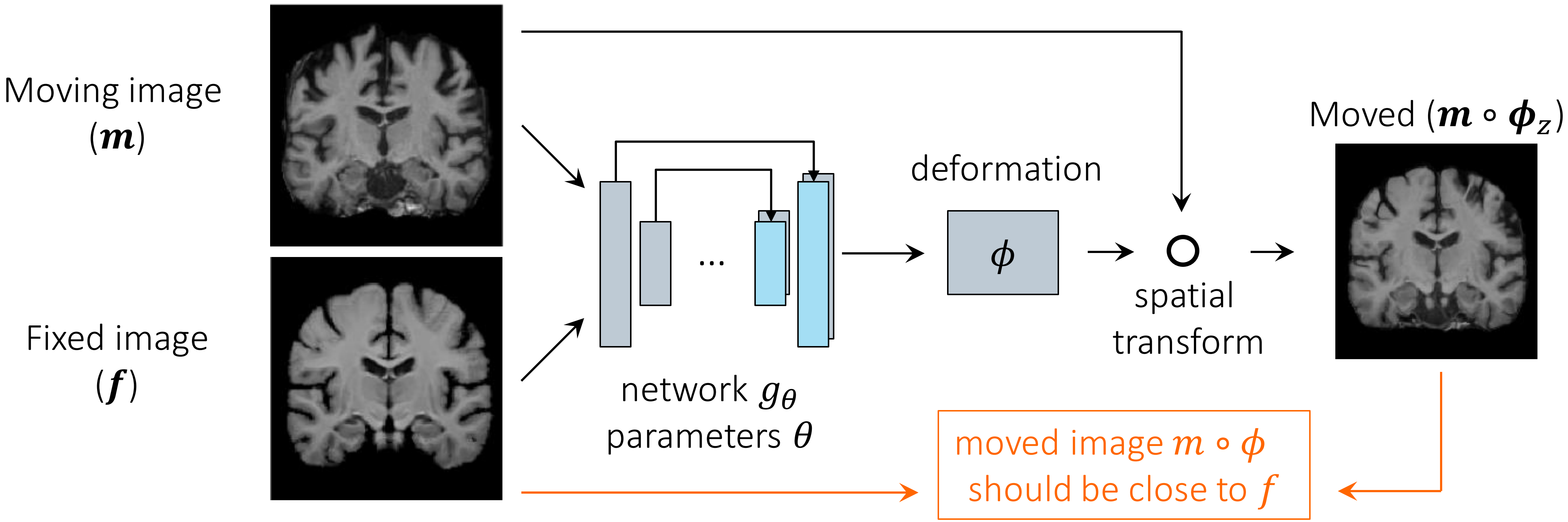
$$\mathcal{L}(\theta; \mathrm{data}) = \sum_{i,j} \|m_i \circ \underbrace{g_\theta(m_{i.}\, f_i)}_{\phi_{ij}} - f_{ij}\| + \lambda\, \mathrm{Reg}(\underbrace{g_\theta(m_{i.}\, f_i)}_{\phi_{ij}})$$

Framework Loss



$$\mathcal{L}(\theta; \text{data}) = \sum_{i,j} \| m_i \circ \underbrace{g_\theta(m_{i.} f_i)}_{\phi_{ij}} - f_{ij} \| + \lambda \, \text{Reg}(\underbrace{g_\theta(m_{i.} f_i)}_{\phi_{ij}})$$

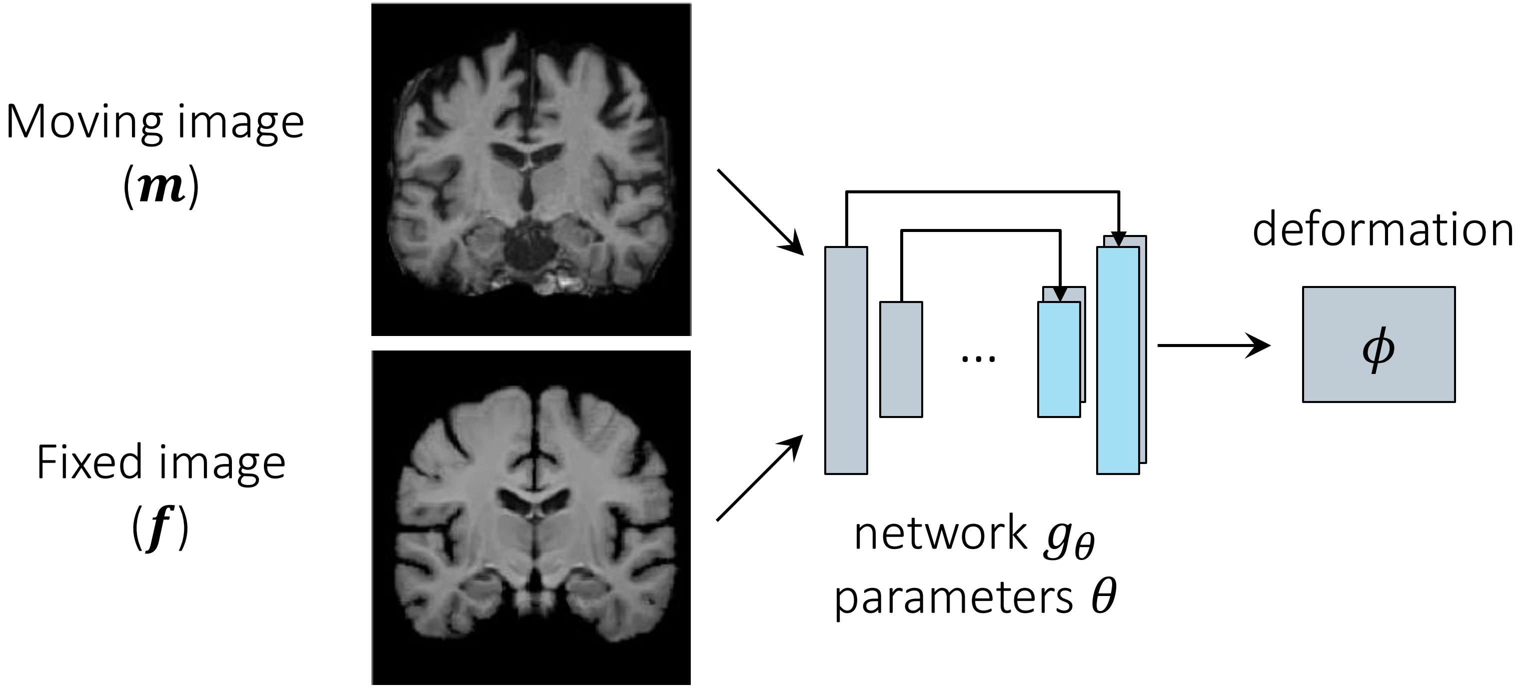
Training



- SGD based techniques
- Each image pair contributes **slightly** to θ

  Classical optimization: slightly update ϕ for an image pair

Registration



Amortized Inference

Classical Methods

Pair-specific optimization

$$\hat{\phi}_{m,f} = argmin_{\phi}\mathcal{L}(\phi; m, f)$$

Learning-based

One-time unsupervised network training

$$\hat{\theta} = argmin_{\theta}\sum_{m,f}\mathcal{L}(g_{\theta}(m, f); m, f)$$

Pair-specific function evaluation $\hat{\phi}_{m,f} = g_{\hat{\theta}}(m, f)$

Experiments

Using VoxelMorph implementation

Data: 7000 training volumes, 250 validate, 250 test

Baseline: ANTs, Niftireg

Train time

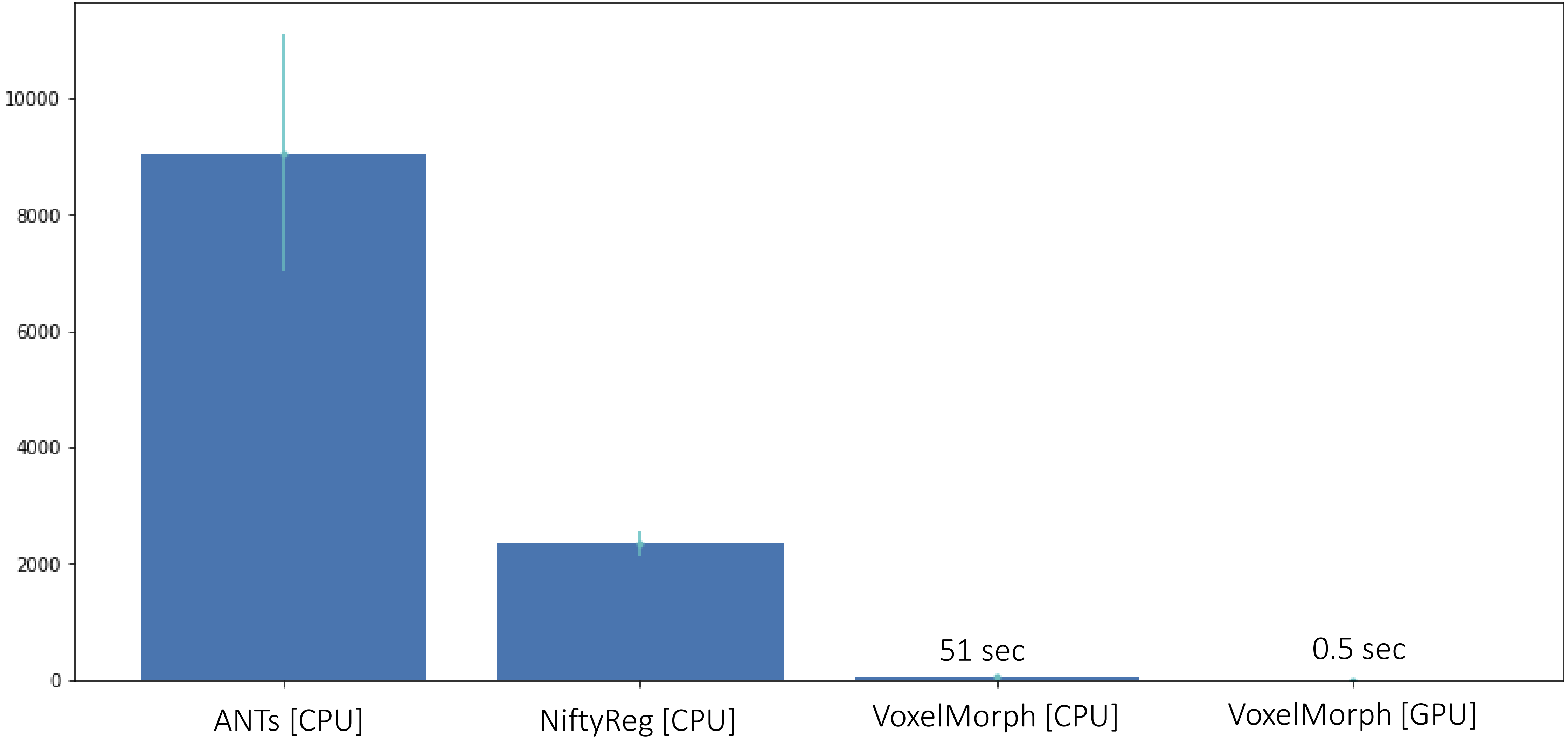
3D volumes

- Hours to 1-2 days on single GPU

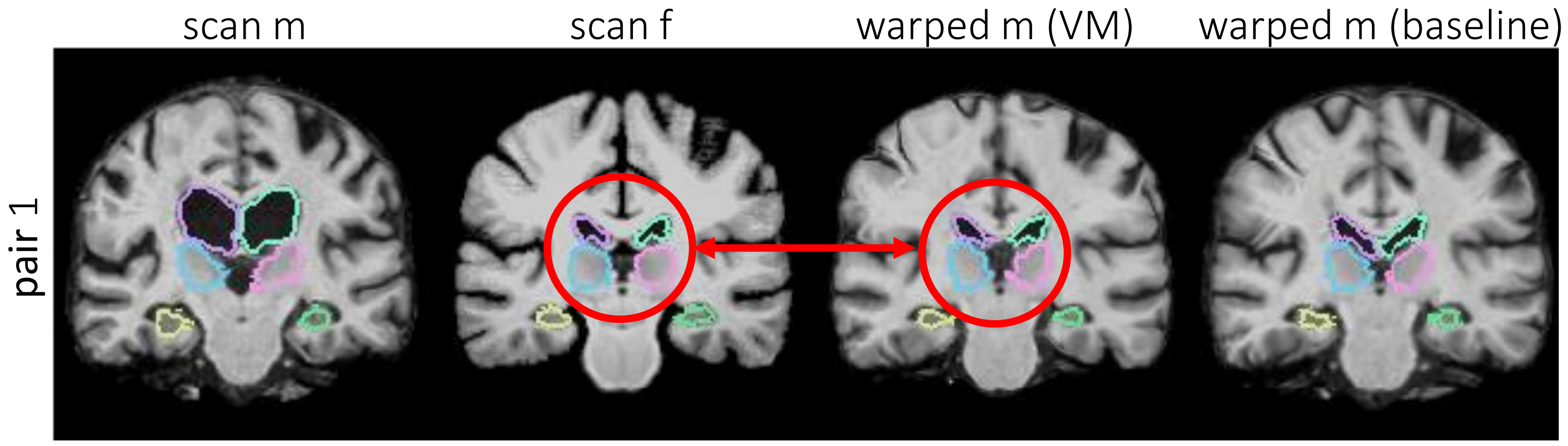
2D images/slices

- Minutes to hours

Runtime for a new 3D image pair

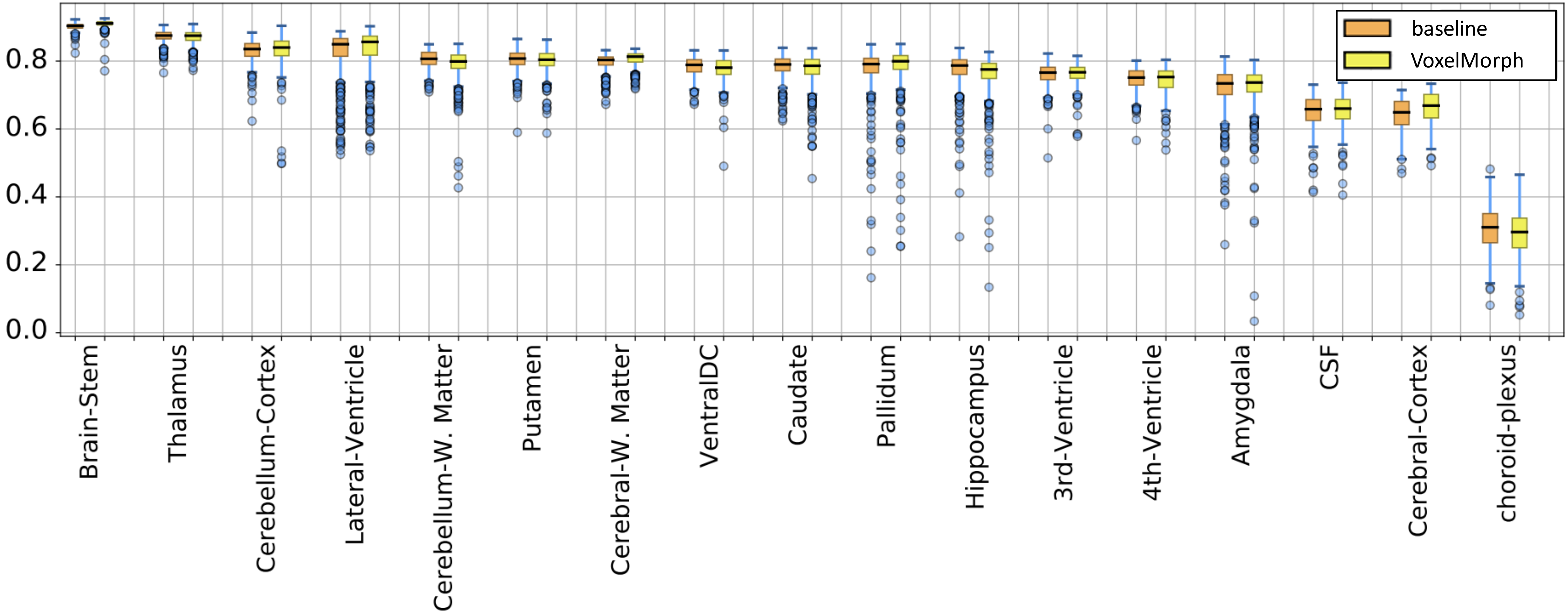


Anatomical volume overlap



*algorithms only see images, no segmentation maps

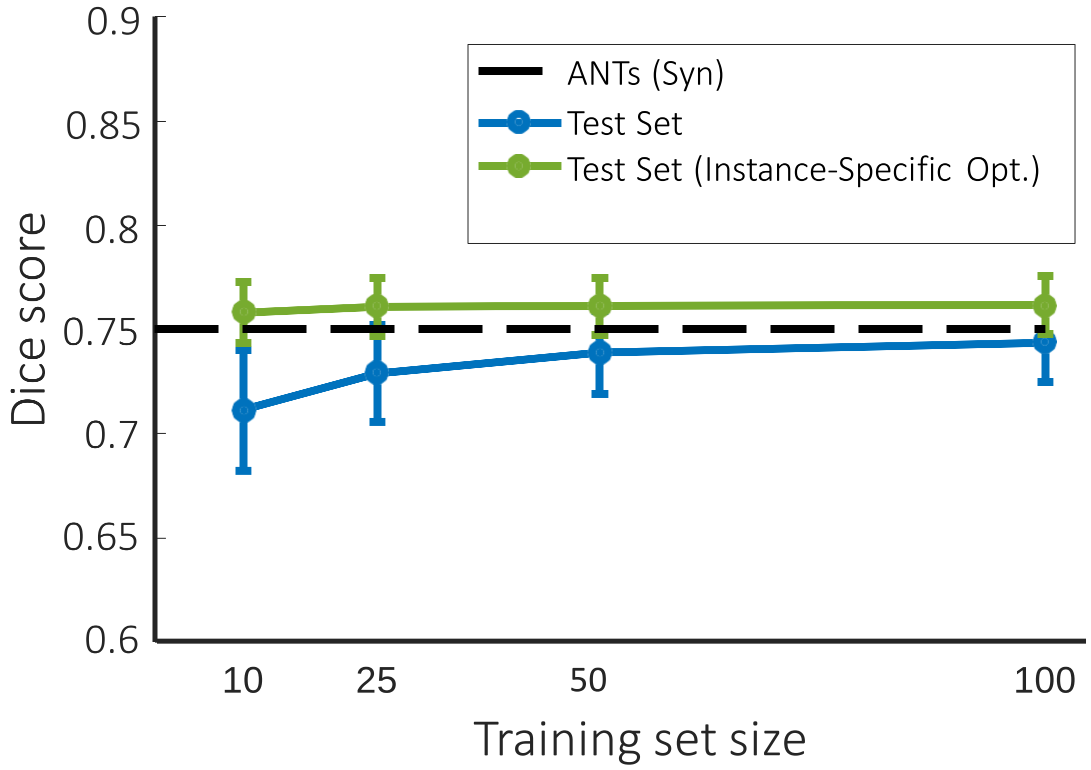
Accuracy via volume overlap (Dice)



Properties and Limitations

Analysis from
TMI: https://arxiv.org/abs/1809.05231
MedIA: https://arxiv.org/abs/1903.03545

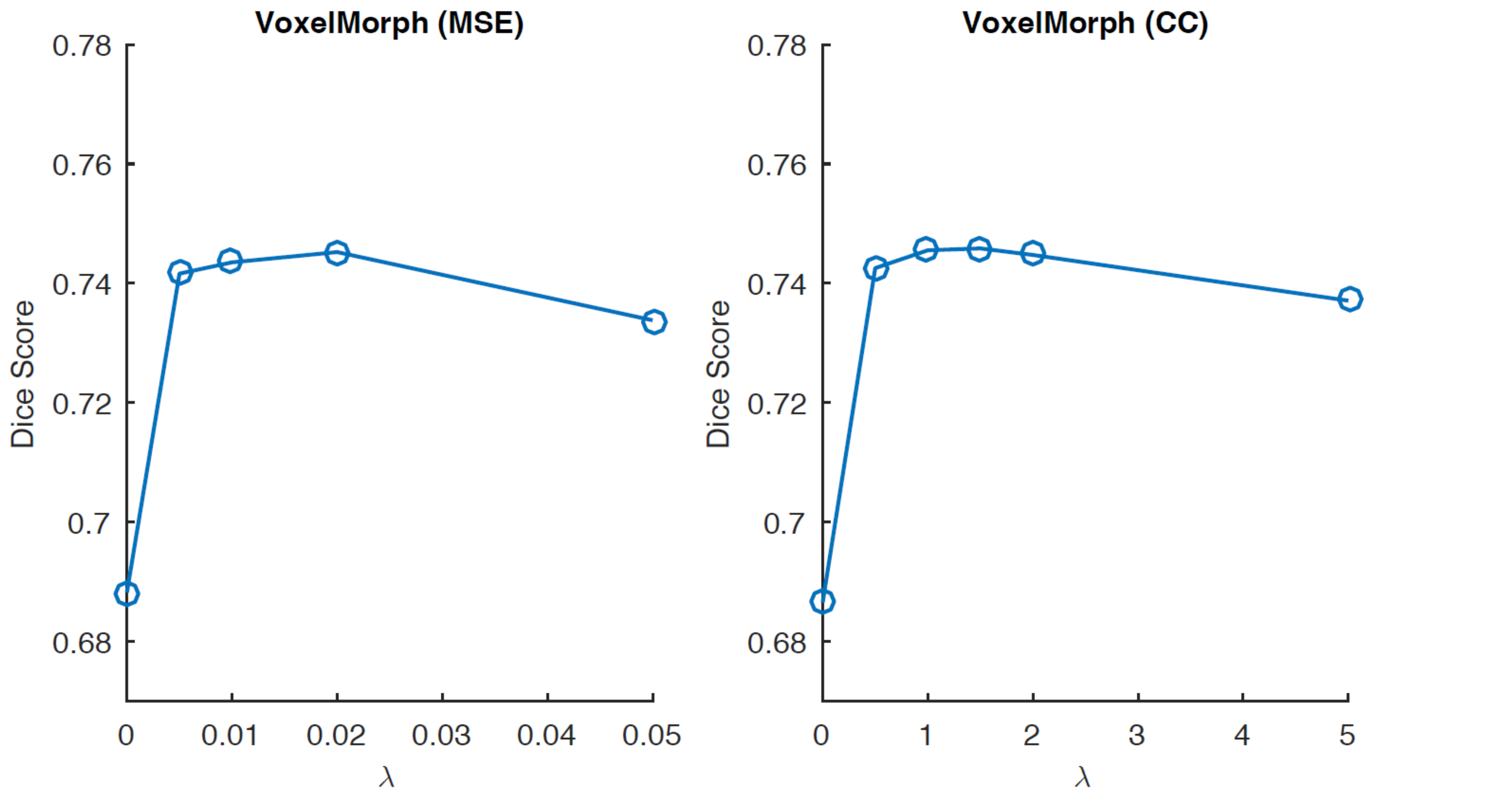
Training with limited data



Registering out of training sample

- Unexpected behavior
- Might work (!)
- Might fail completely
- >> hands-on session!

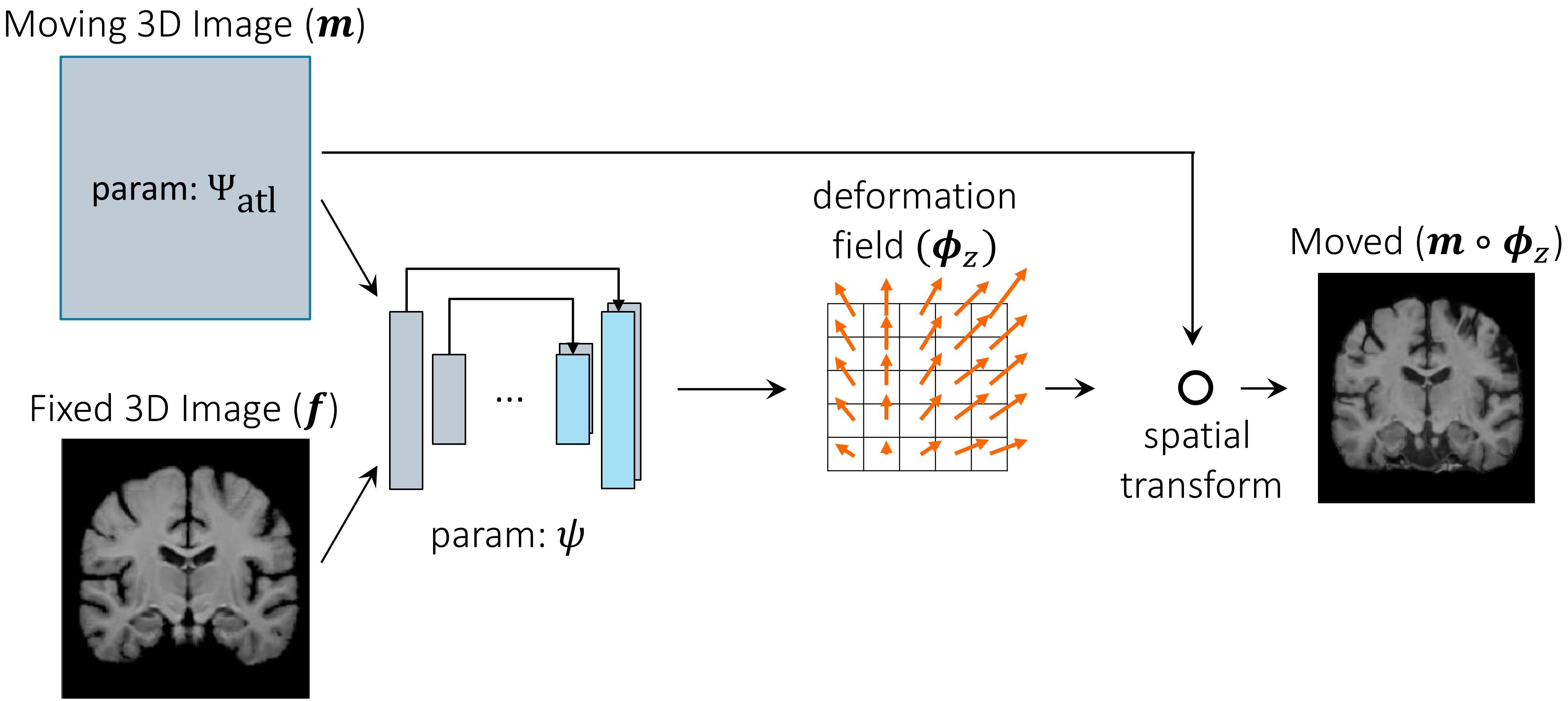
Regularization Analysis



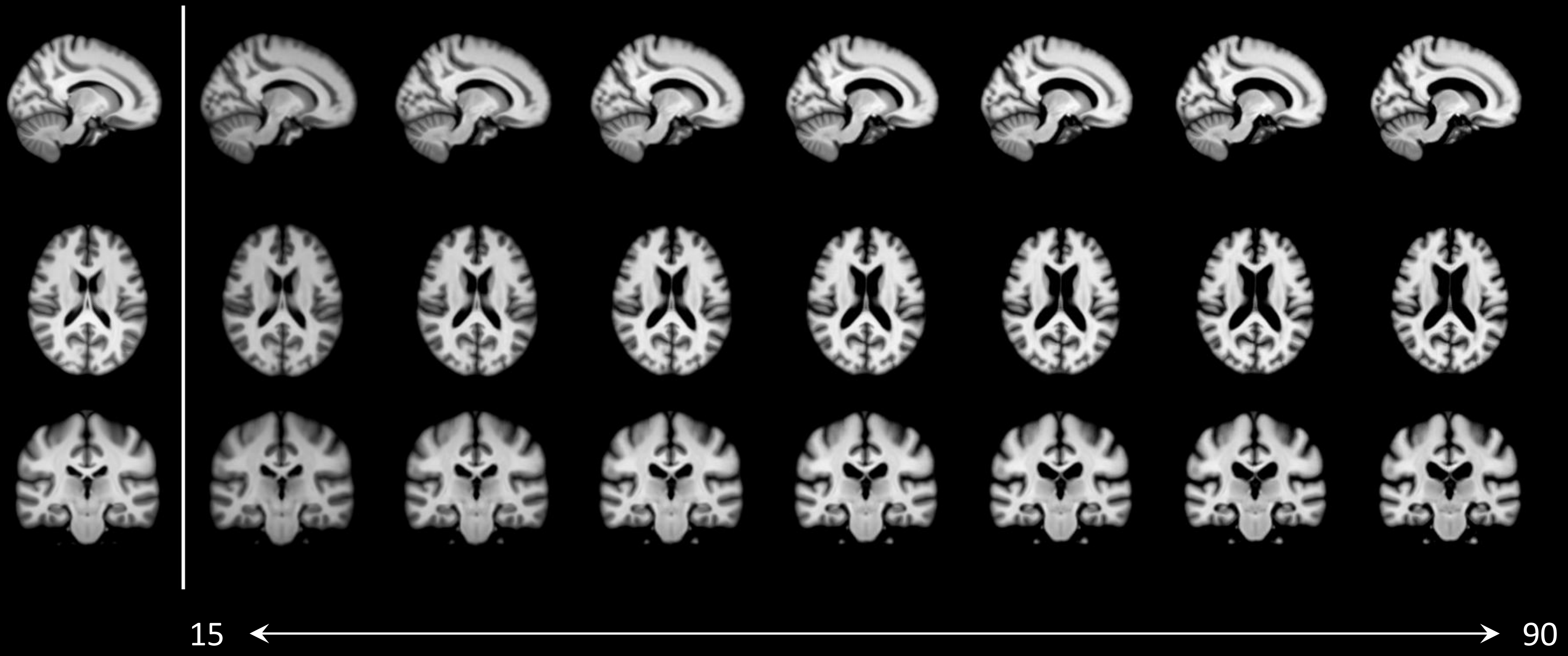
Promises

- Fast
  - Easy to iterate research!
  - Easy to build more powerful models!
- Supervise with external data (next talk)
- Automatic atlas-building
- Easy to incorporate other constraints
  - e.g. Diffeomorphisms
- Getting out of local minima

Template Construction



NeurIPS2019: https://arxiv.org/abs/1908.02738


15
90

Jupyter notebook: hands-on session

- **Core concepts with MNIST**
  We will first learn to deal with data, building a model, training, registration and generalization
- **More realistic complexity: Brain MRI (2D slices)**
  We will then show how these models work for 2d slices of brain scans, presenting a more complex scenario
- **Realistic 3D Brain MRI**
  We will illustrate full 3D registration

Code heavily based on voxelmorph.mit.edu

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