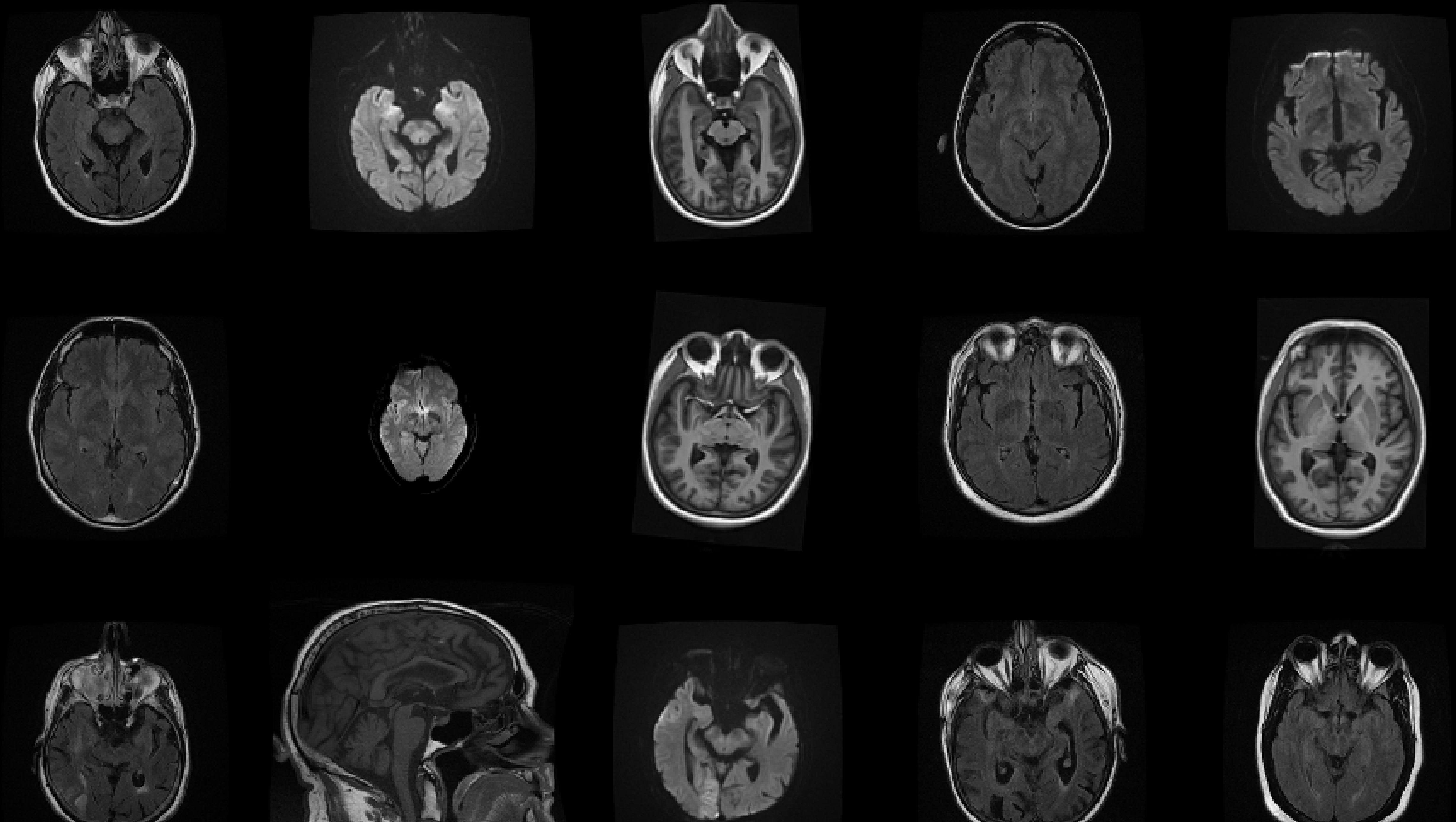
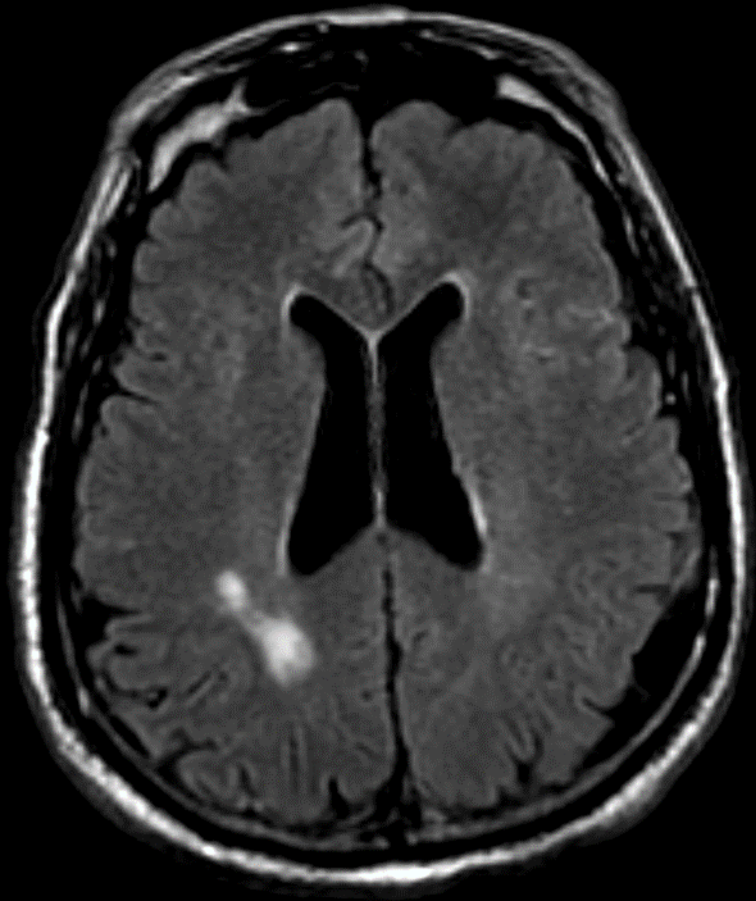
voxelmorph.mit.edu

+ in future FreeSurfer release

Unsupervised Learning of Image Correspondences in Medical Imaging Analysis

Adrian V. Dalca
HMS, MIT



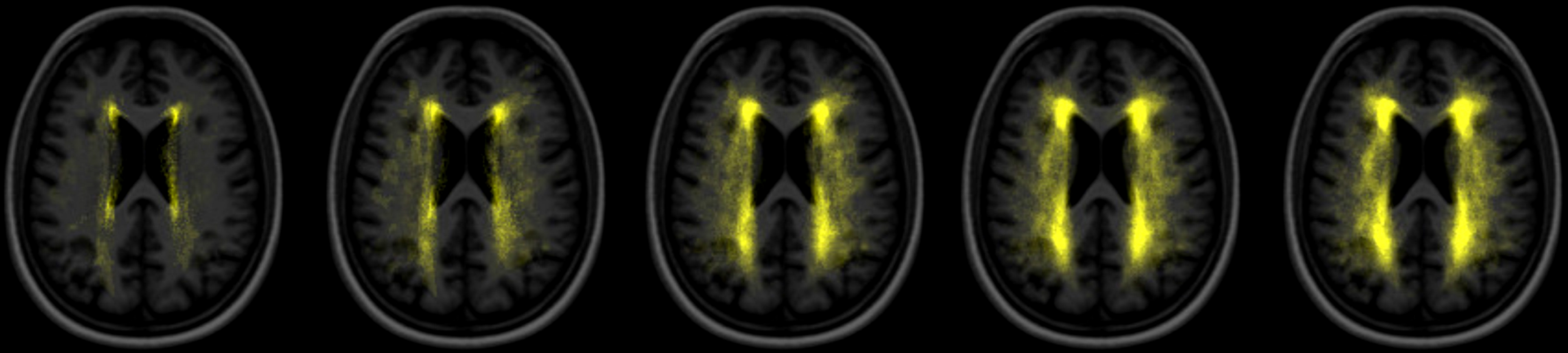


Small vessel disease

Stroke

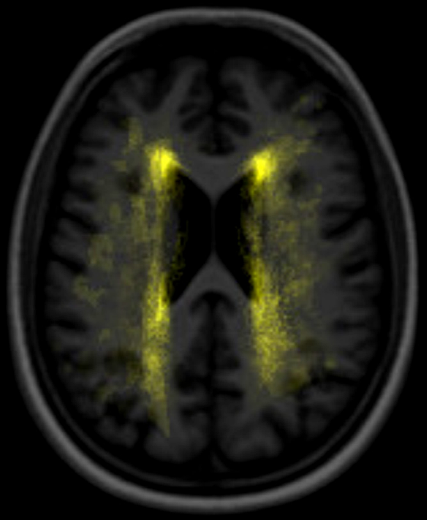
Dalca et al, MICCAI, 2014
Sridharan*, Dalca* et al, MBIA 2013

Progression with age

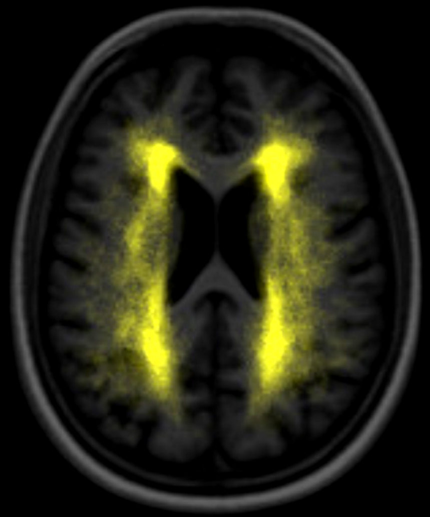


31 years average | 42.5 years average | 54 years average | 65.5 years average | 77 years average

Sridharan*, **Dalca*** et al, MBIA 2013



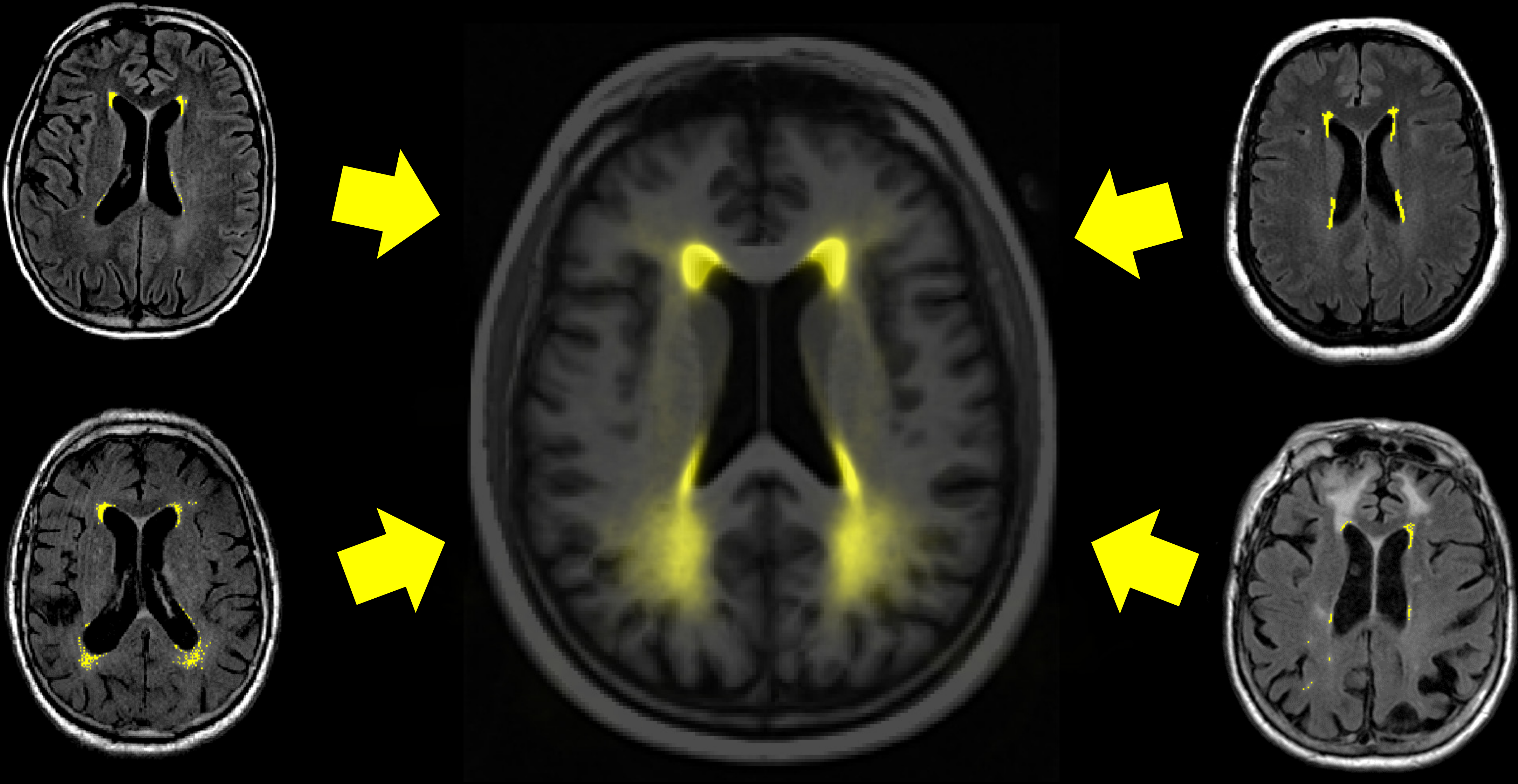
Scan at age 50

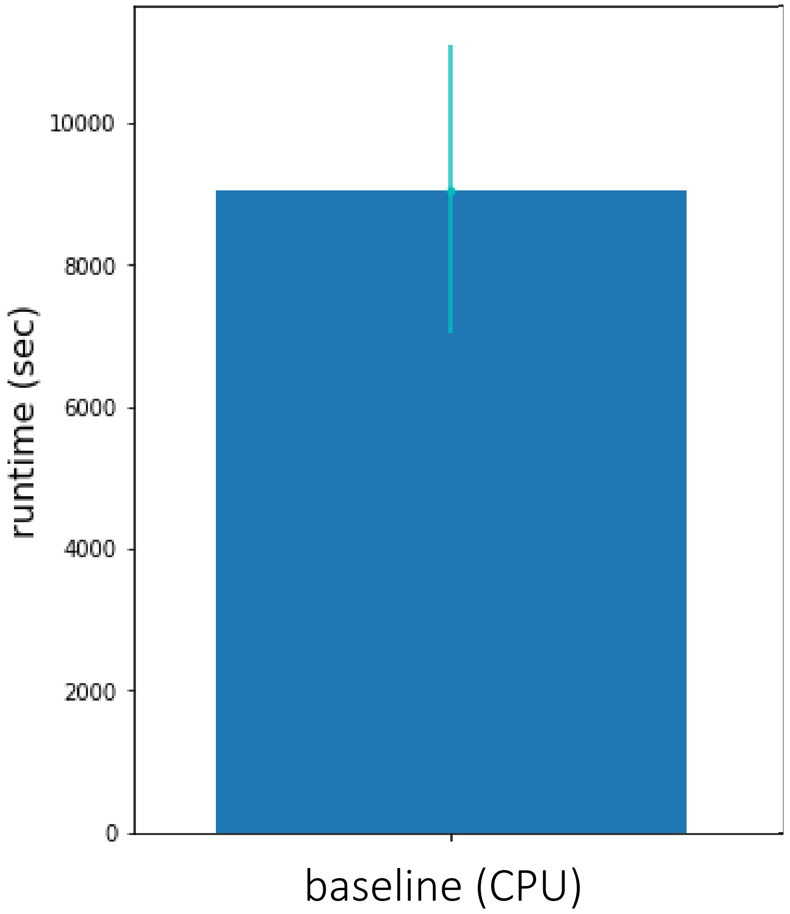


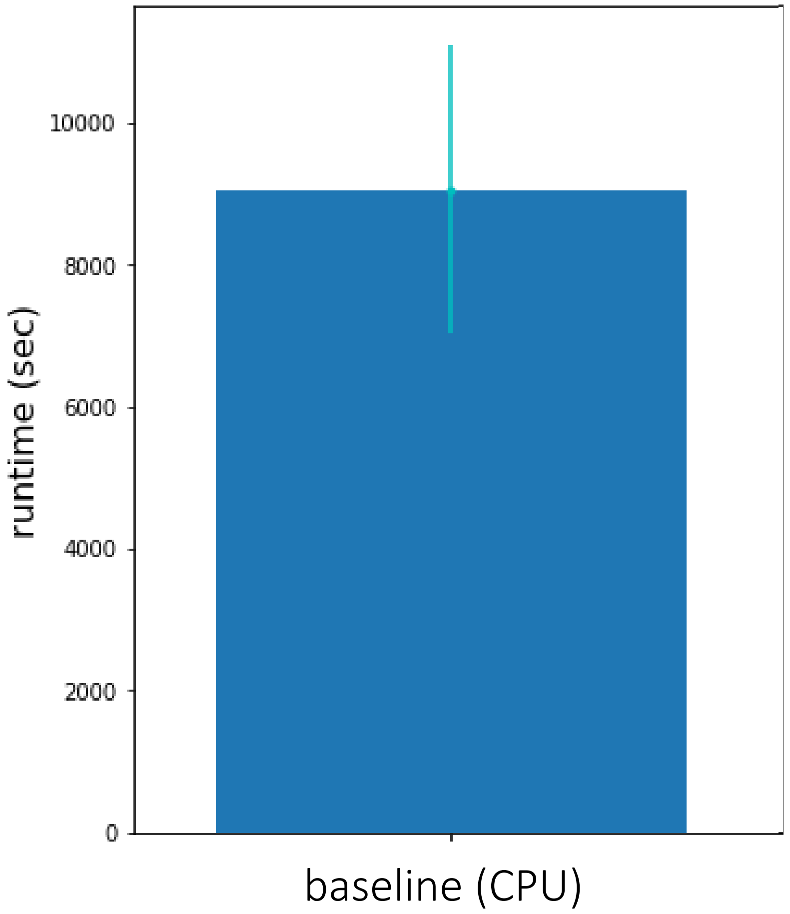
Scan at age 60

Dalca et al, MICCAI, 2015

Batmanghelich, Dalca et al, IPMI 2013, TMI 2016

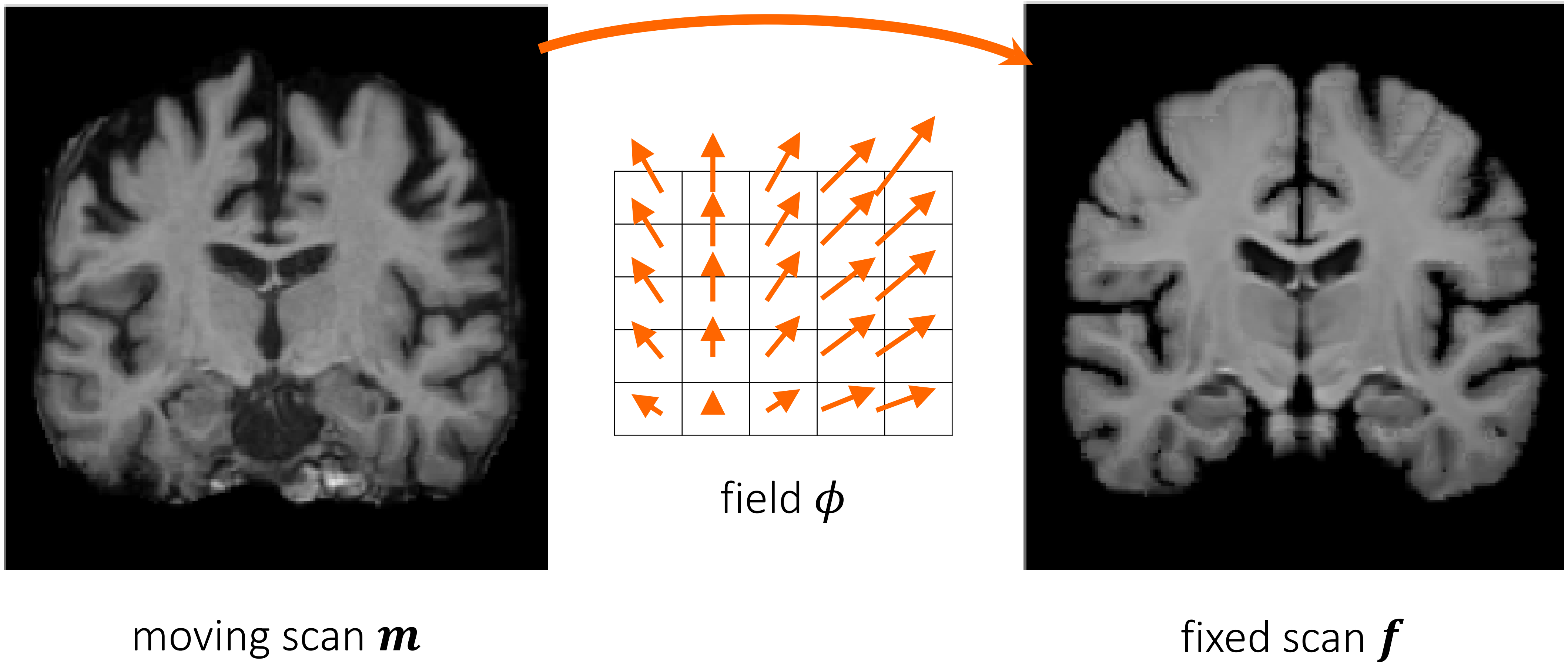



10000
8000
6000
4000
2000
0
runtime (sec)
baseline (CPU)



runtime (sec)
10000
8000
6000
4000
2000
0
baseline (CPU)

Registration

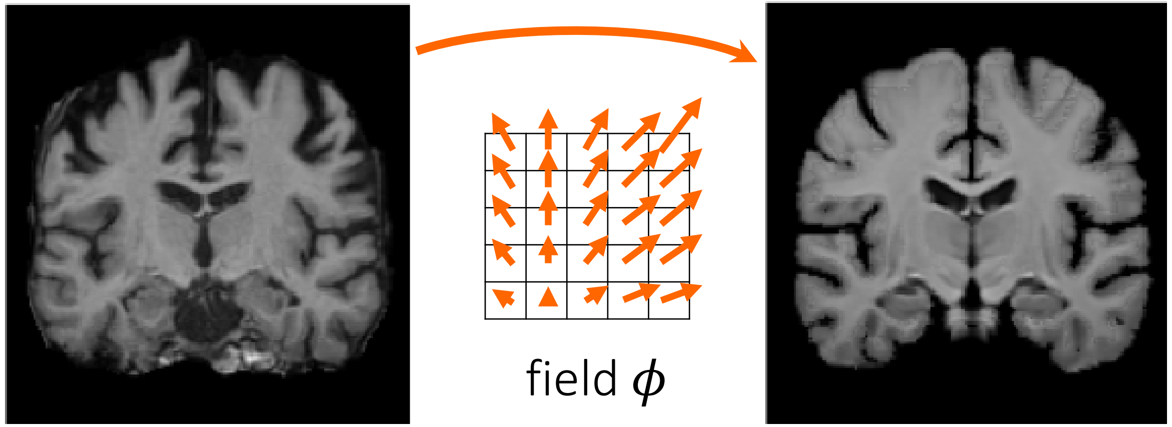


Registration is fundamental in MIA

- Register scans to a template for analysis
- Register subject scans to each other for direct comparison
- Clinical data alignment
  e.g. before and after surgery
- Segmentation
  propagate anatomical labels
- Related to alignment in other fields
  computer vision, 1D signals, computational biology

Pairwise optimization

scan $\boldsymbol{m}$



scan $\boldsymbol{f}$

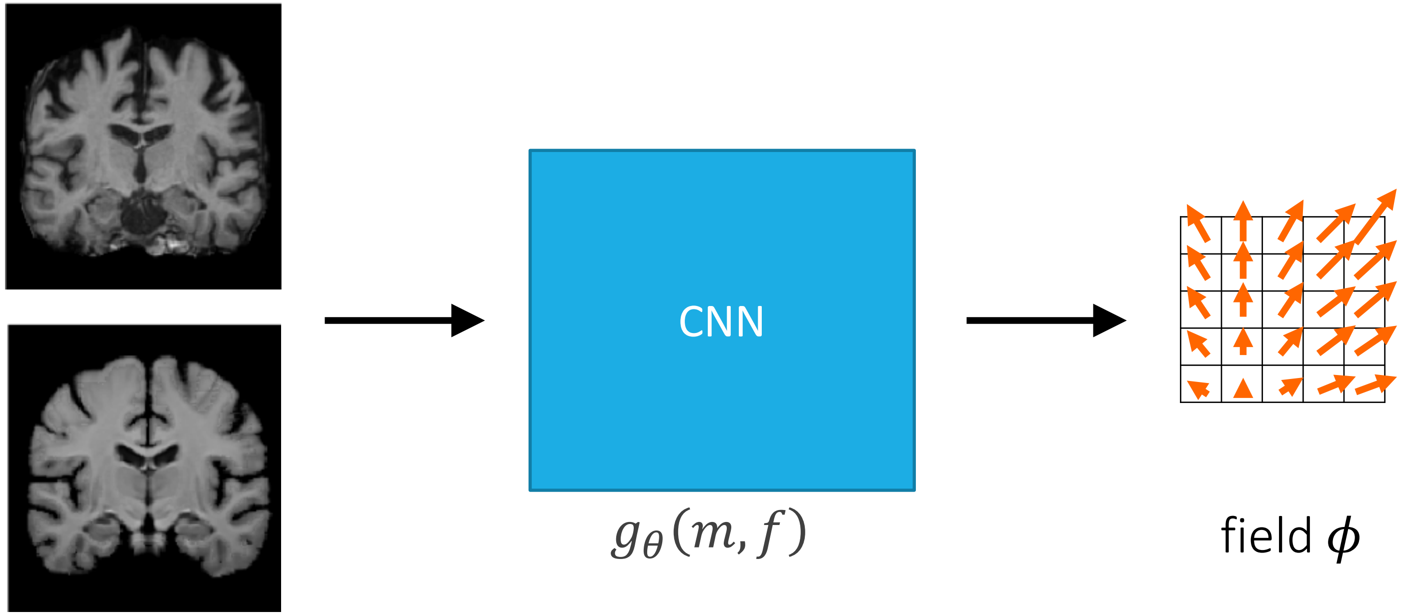
warped scan m

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

optimal deformation field

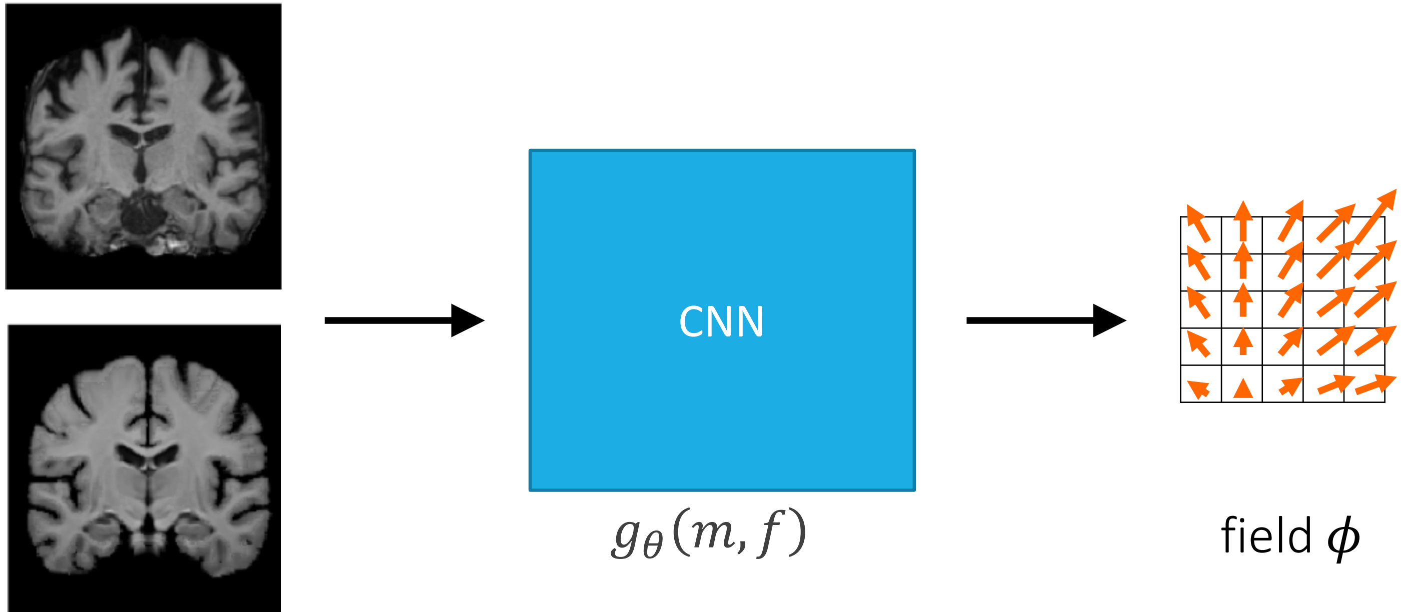
- significant development
- slow for two images

Learning-based methods



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

Learning-based methods

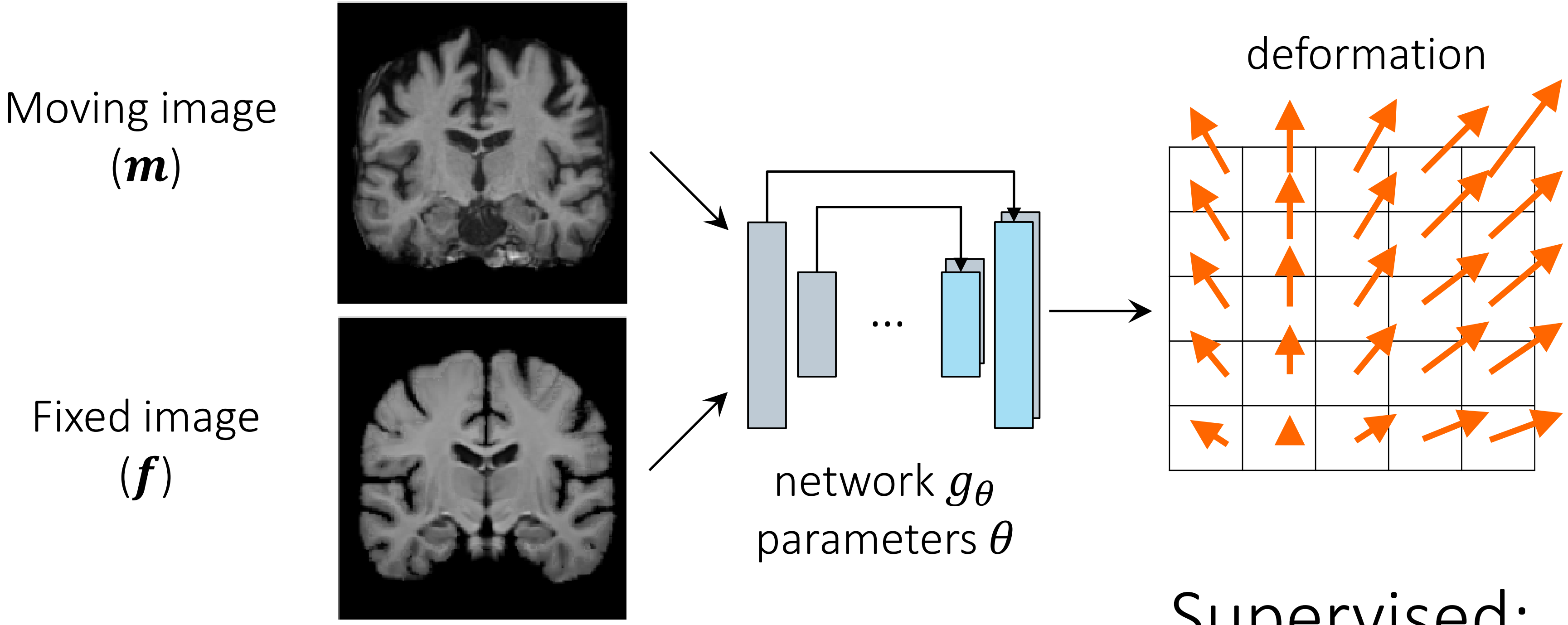


- Supervised (have example triplets $\{m, f, \phi\}$)
- Unsupervised (only have images $\{m, f\}$) **(voxelmorph)**

- limited use of classical modelling
- **fast** for new image pair

Outline

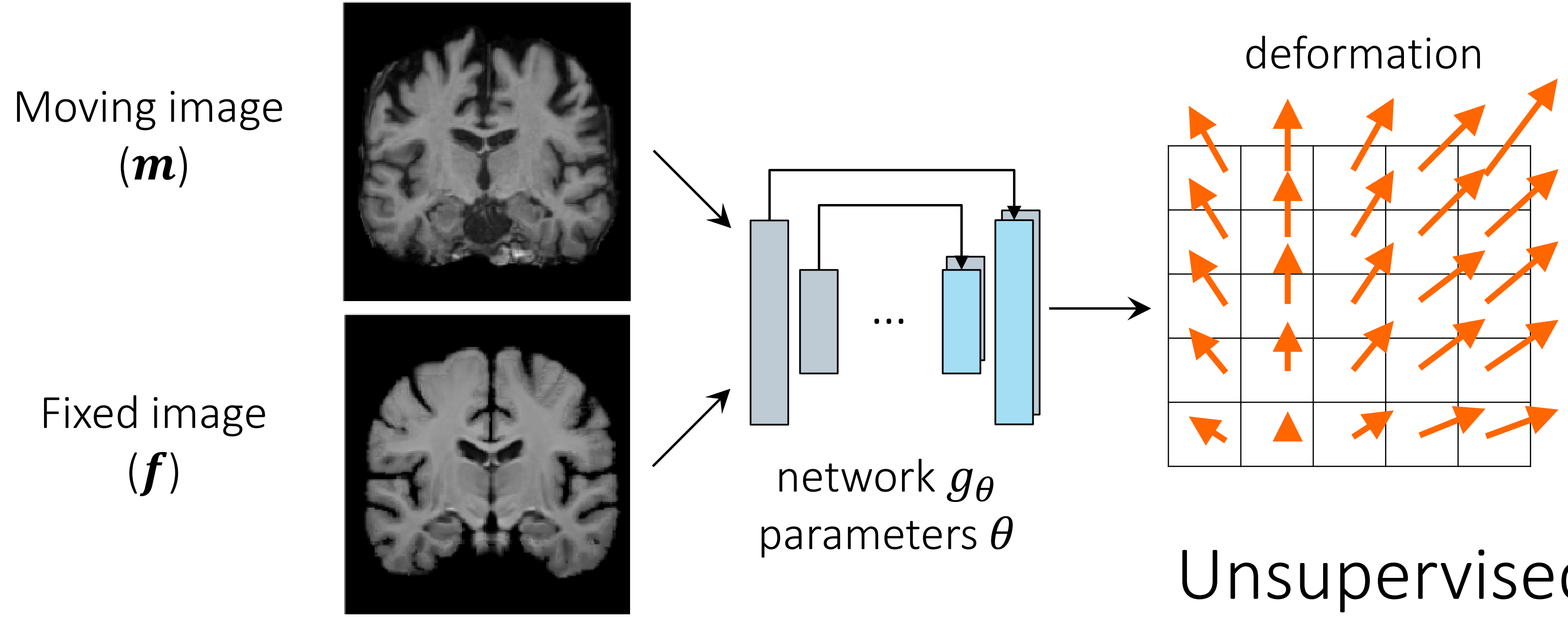
Framework



Supervised:

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

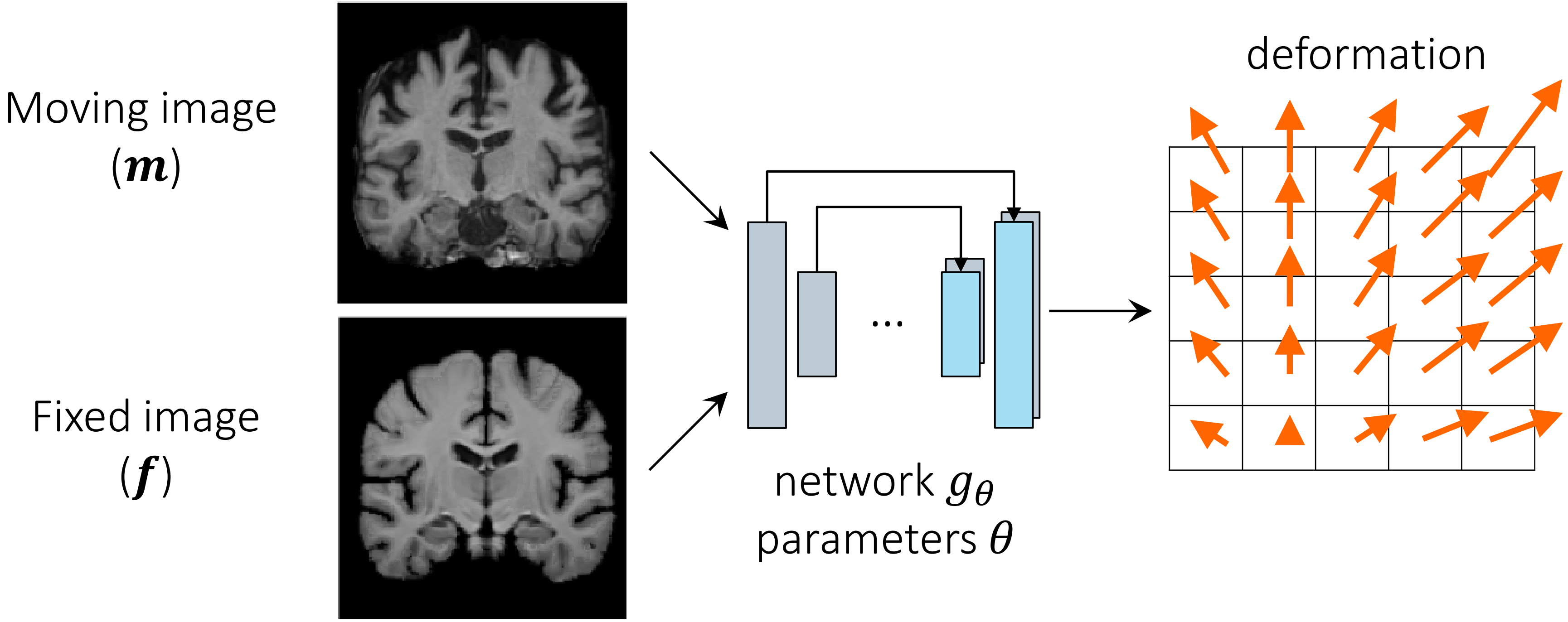
VoxelMorph



Unsupervised:

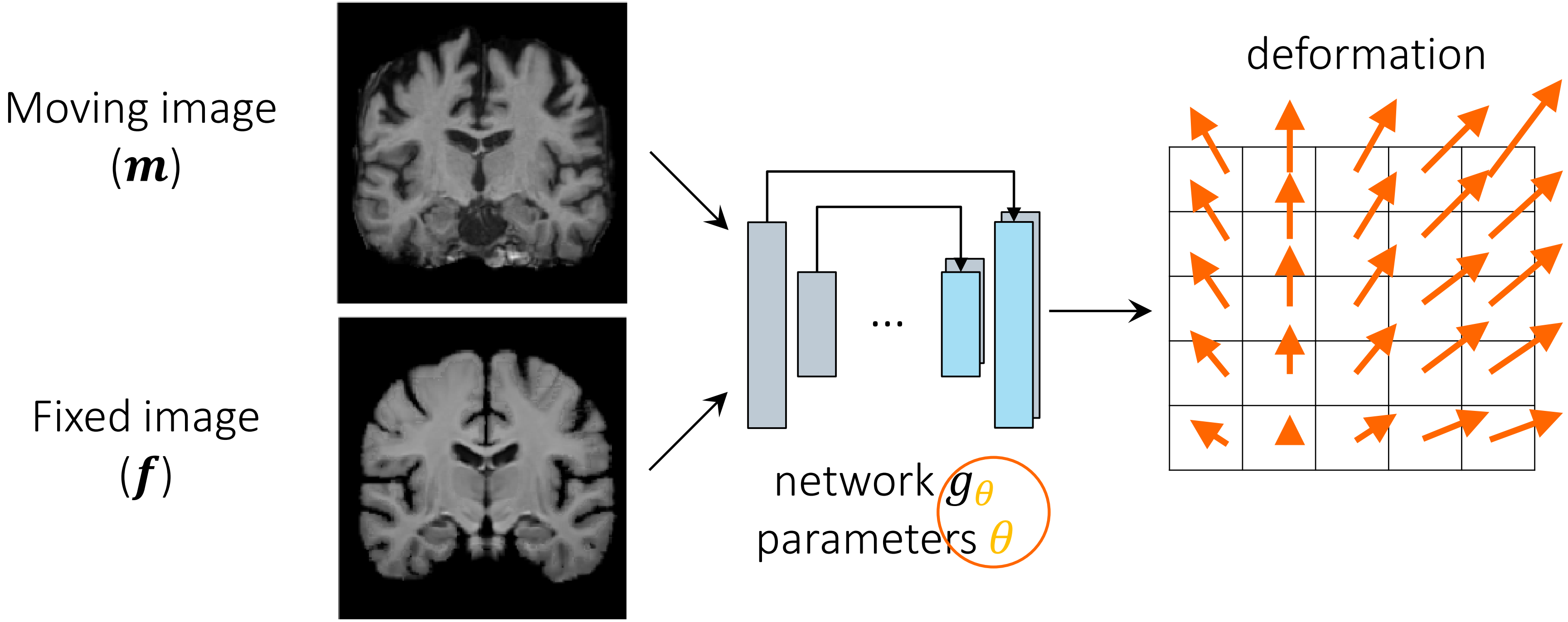
$$\mathcal{L} = \underbrace{||m \circ \phi - f||}_{\text{images match}} + \lambda\, \underbrace{\mathrm{Reg}(\phi)}_{\text{smooth field}}$$

VoxelMorph Loss



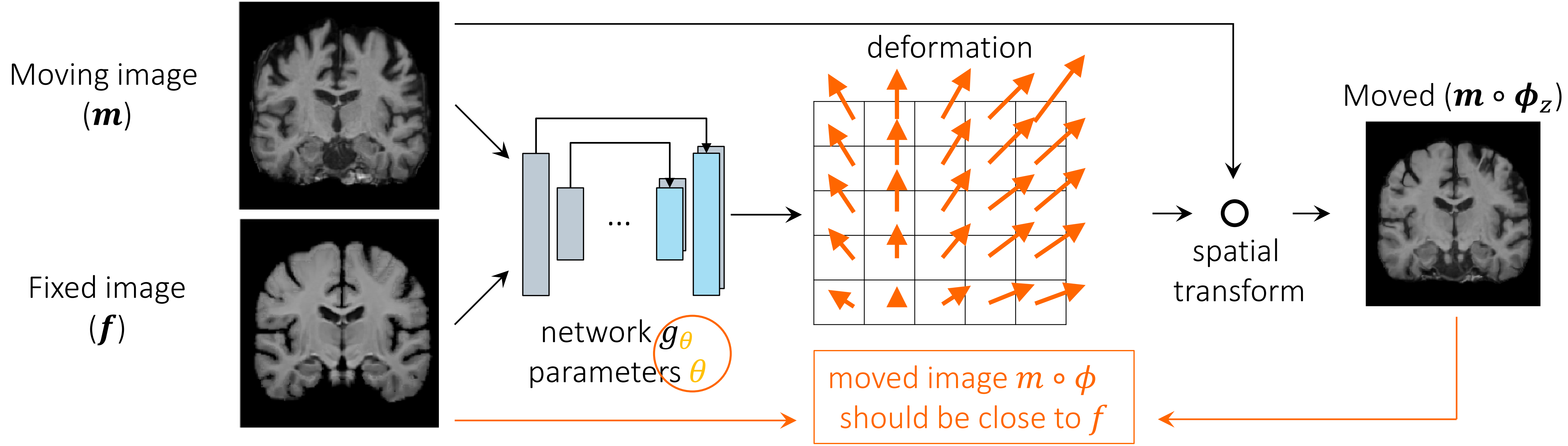
$$\mathcal{L} = \sum_{i,j} \| m_i \circ \phi_{ij} - f_{ij} \| + \lambda \, \mathrm{Reg}(\phi_{ij})$$

VoxelMorph Loss



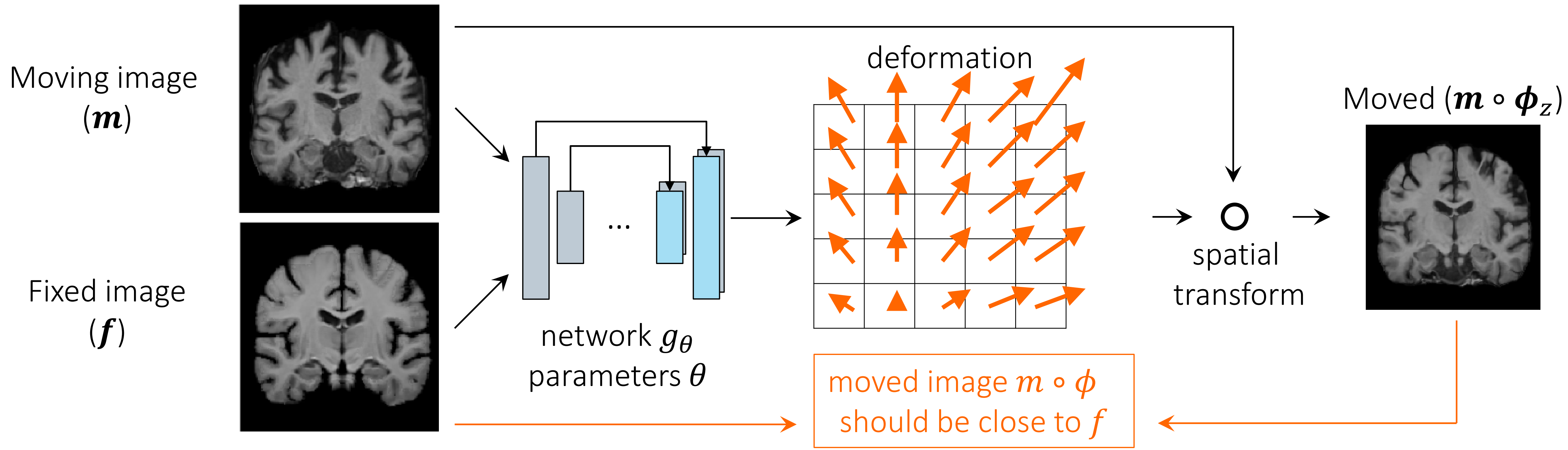
$$\mathcal{L}(\theta; \mathrm{data}) = \sum_{i,j} \| m_i \circ \underbrace{g_\theta(m_i.\, f_i)}_{\phi_{ij}} - f_{ij} \| + \lambda\, \mathrm{Reg}(\underbrace{g_\theta(m_i.\, f_i)}_{\phi_{ij}})$$

VoxelMorph Loss



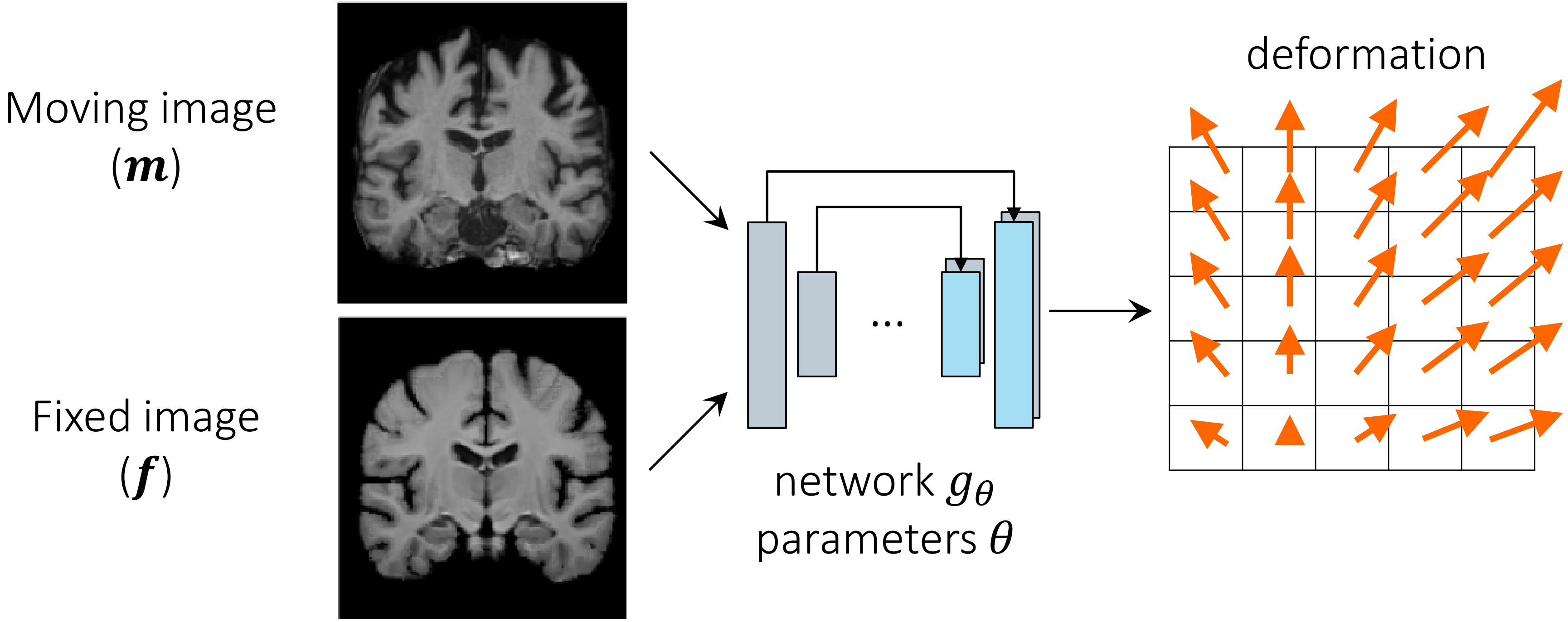
$$\mathcal{L}(\theta; \text{data}) = \sum_{i,j} \| m_i \circ \underbrace{g_\theta(m_i, f_i)}_{\phi_{ij}} - f_{ij} \| + \lambda \, \text{Reg}(\underbrace{g_\theta(m_i, f_i)}_{\phi_{ij}})$$

Training

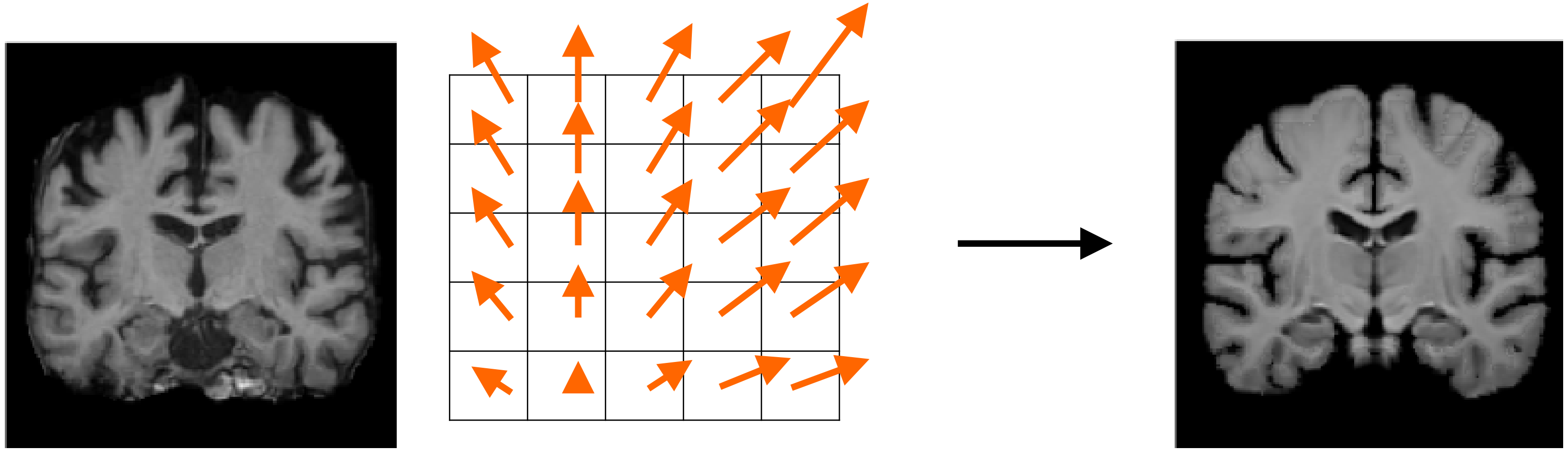


- SGD based techniques
- Each image pair contributes **slightly** to θ
  Classical optimization: slightly update ϕ for an image pair

Registration



Probabilistic model



$$m \circ \phi_z + \epsilon = f$$

$z \sim \mathcal{N}(z; 0, \Lambda^{-1})$

stationary velocity field

smoothness via Laplacian

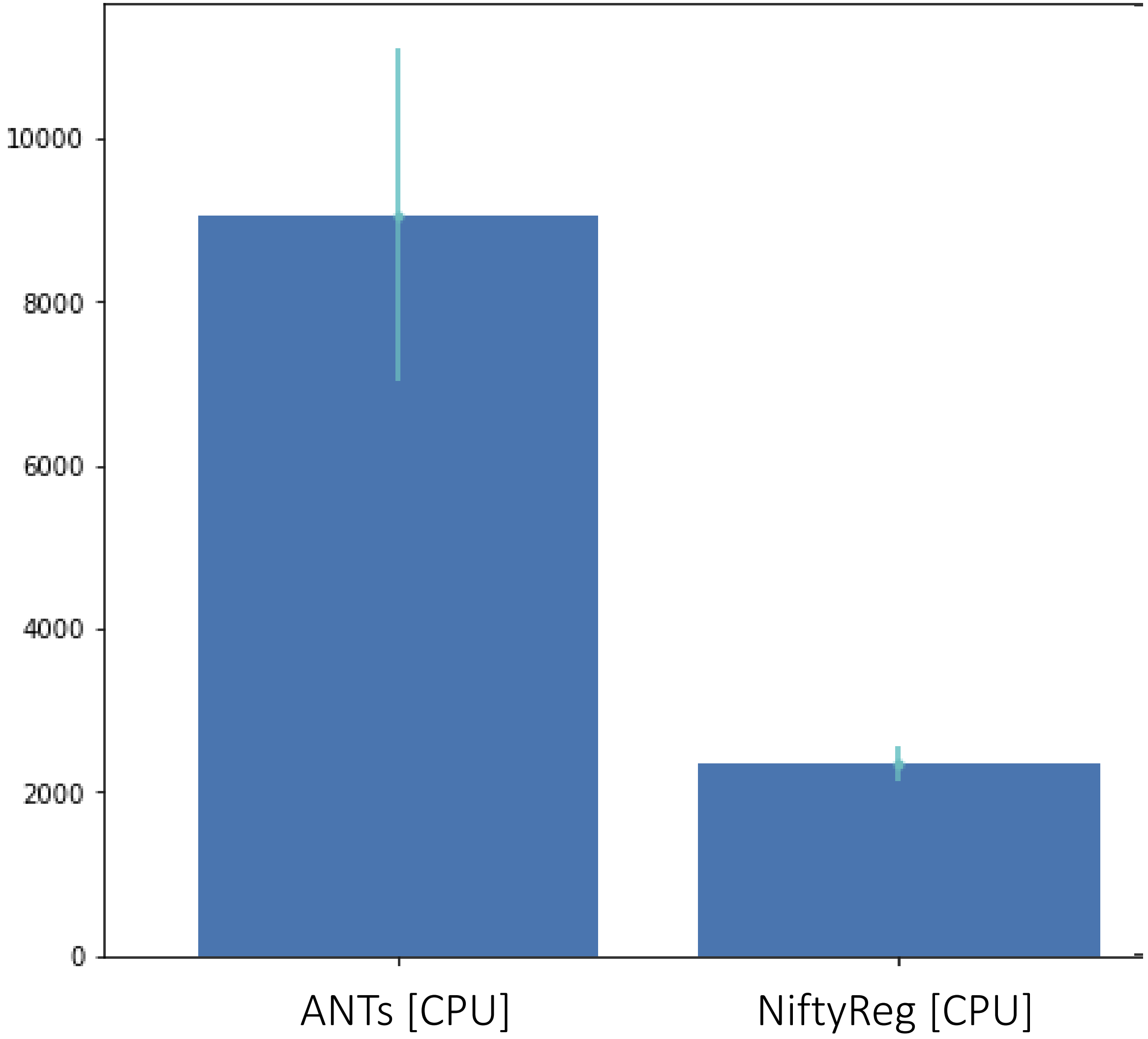
Goal: $p(z|m, f)$ posterior probability of registration

Atlas-based registration

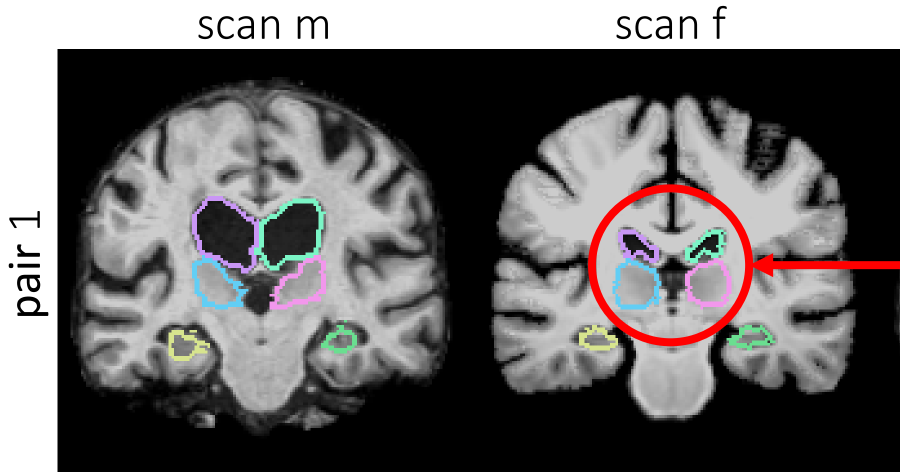
Data: 7000 training volumes, 250 validate, 250 test

Baseline: ANTs optimization method

Runtime for a new 3D image pair

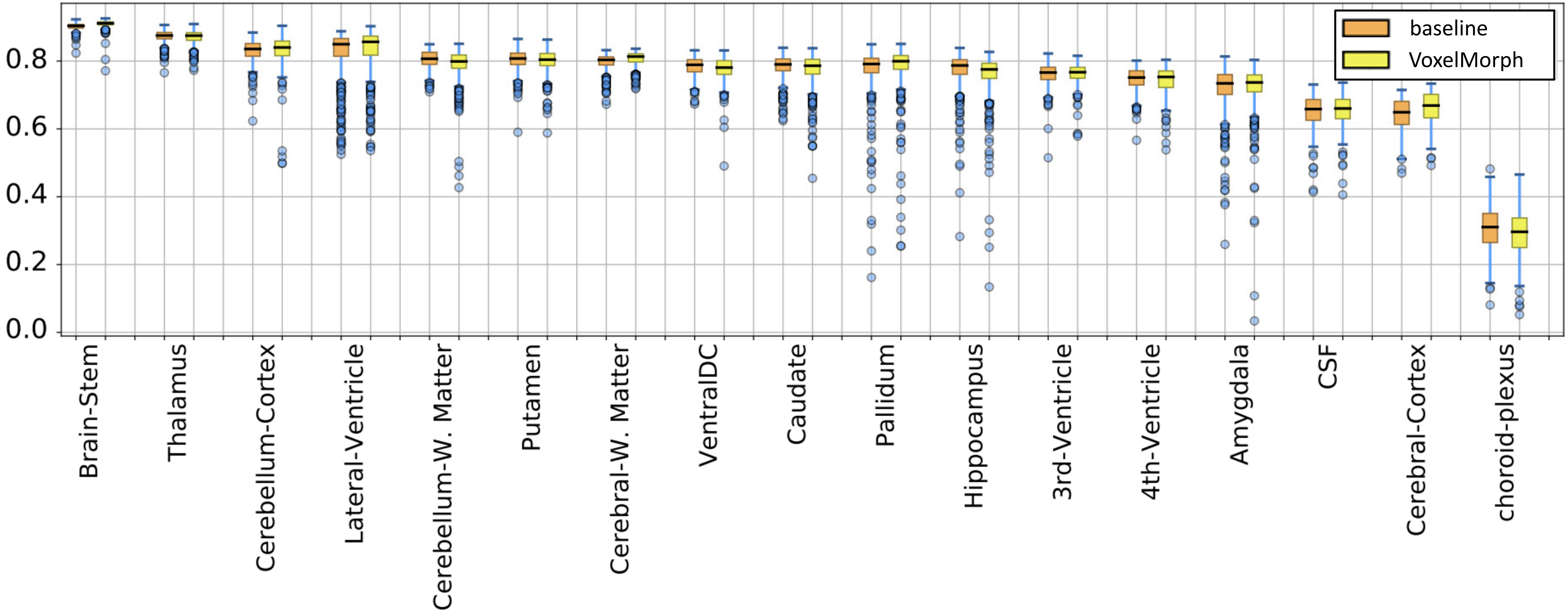


Anatomical volume overlap



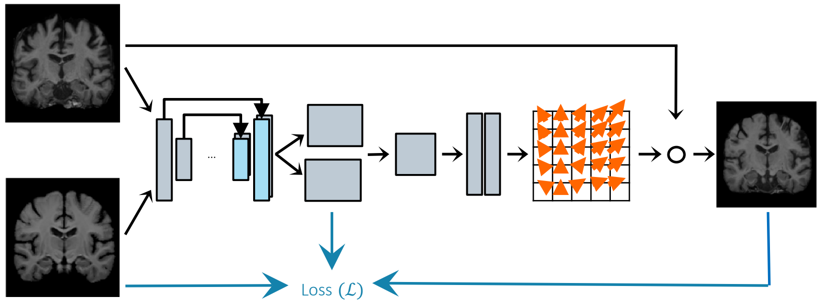
*algorithms only see images, no segmentation maps

Accuracy via volume overlap (Dice)

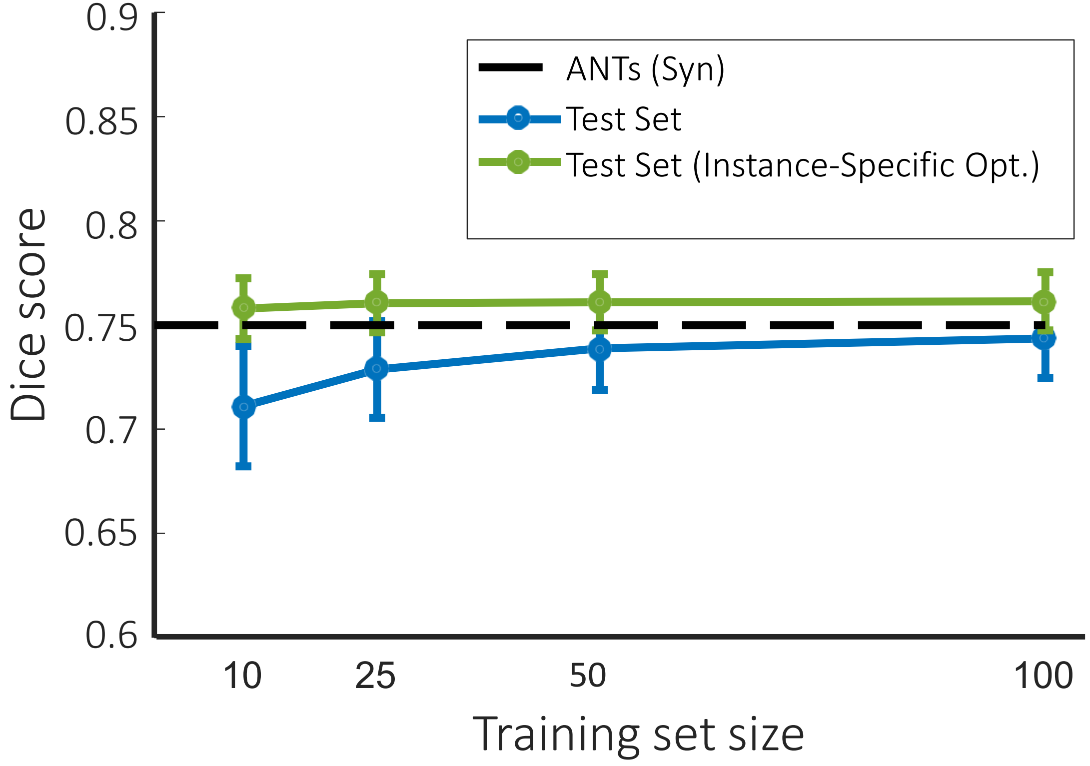


Outline

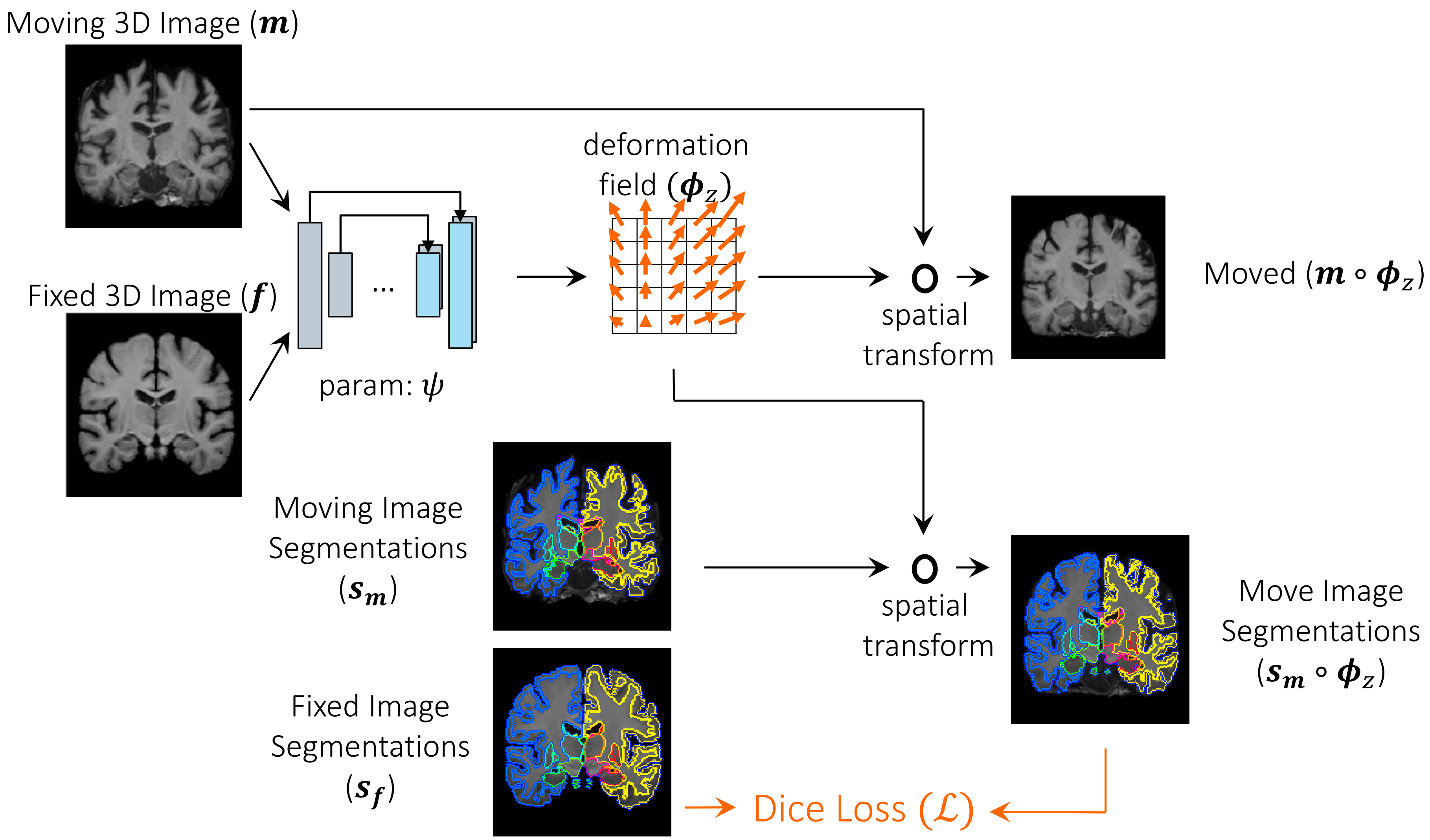
- Model
  - Variational Inference with neural networks
  - Optimization interpretation
  - Results (runtime and accuracy)



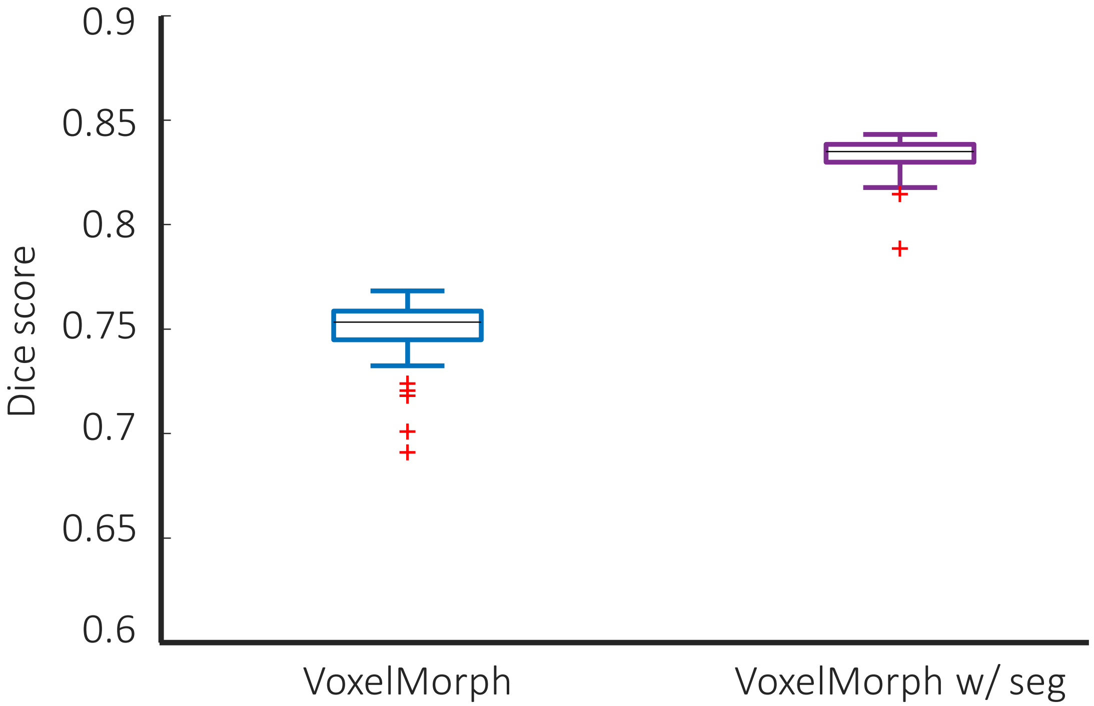
Amortized analysis: training with limited data



Segmentation Maps available at training

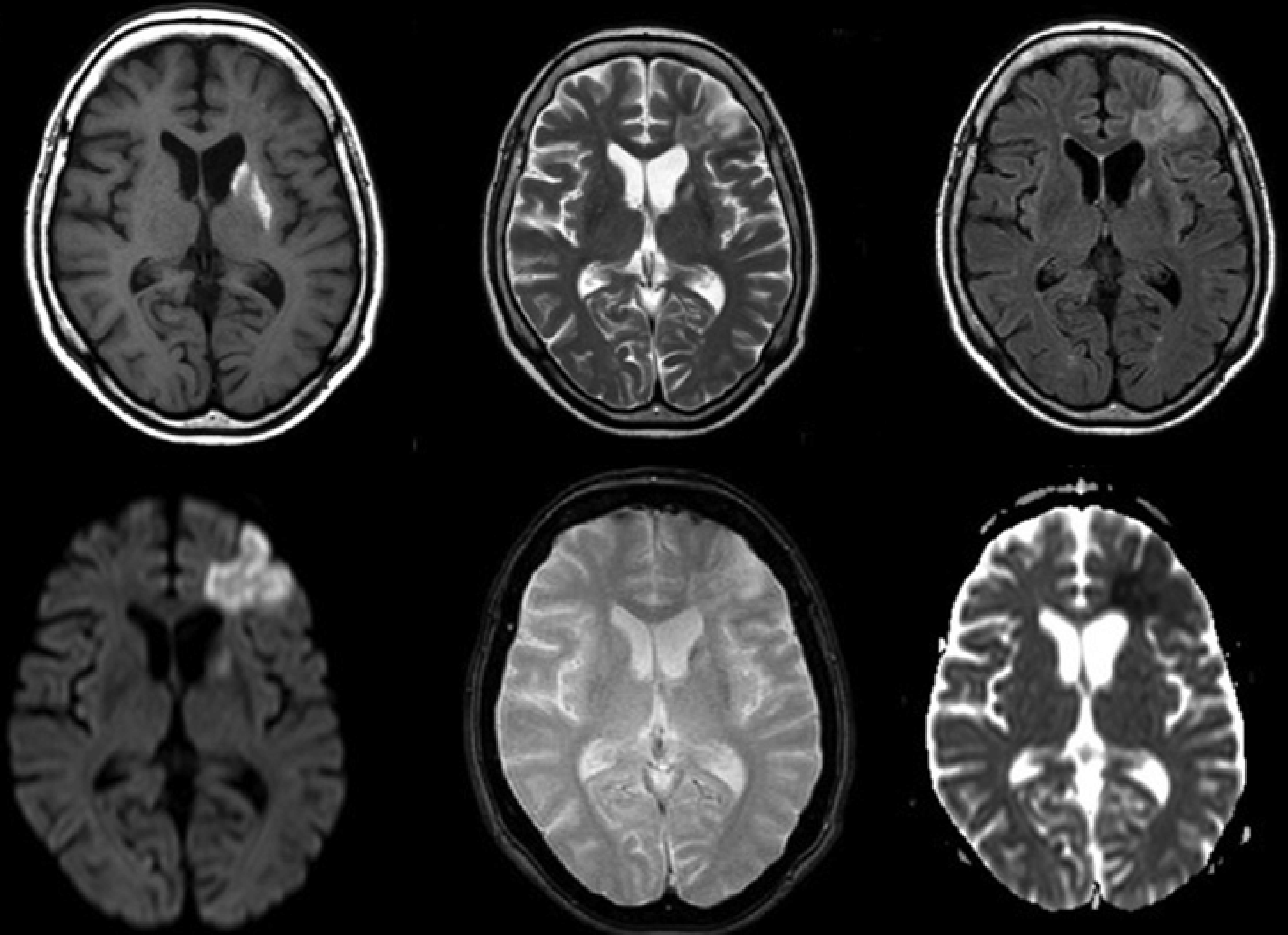


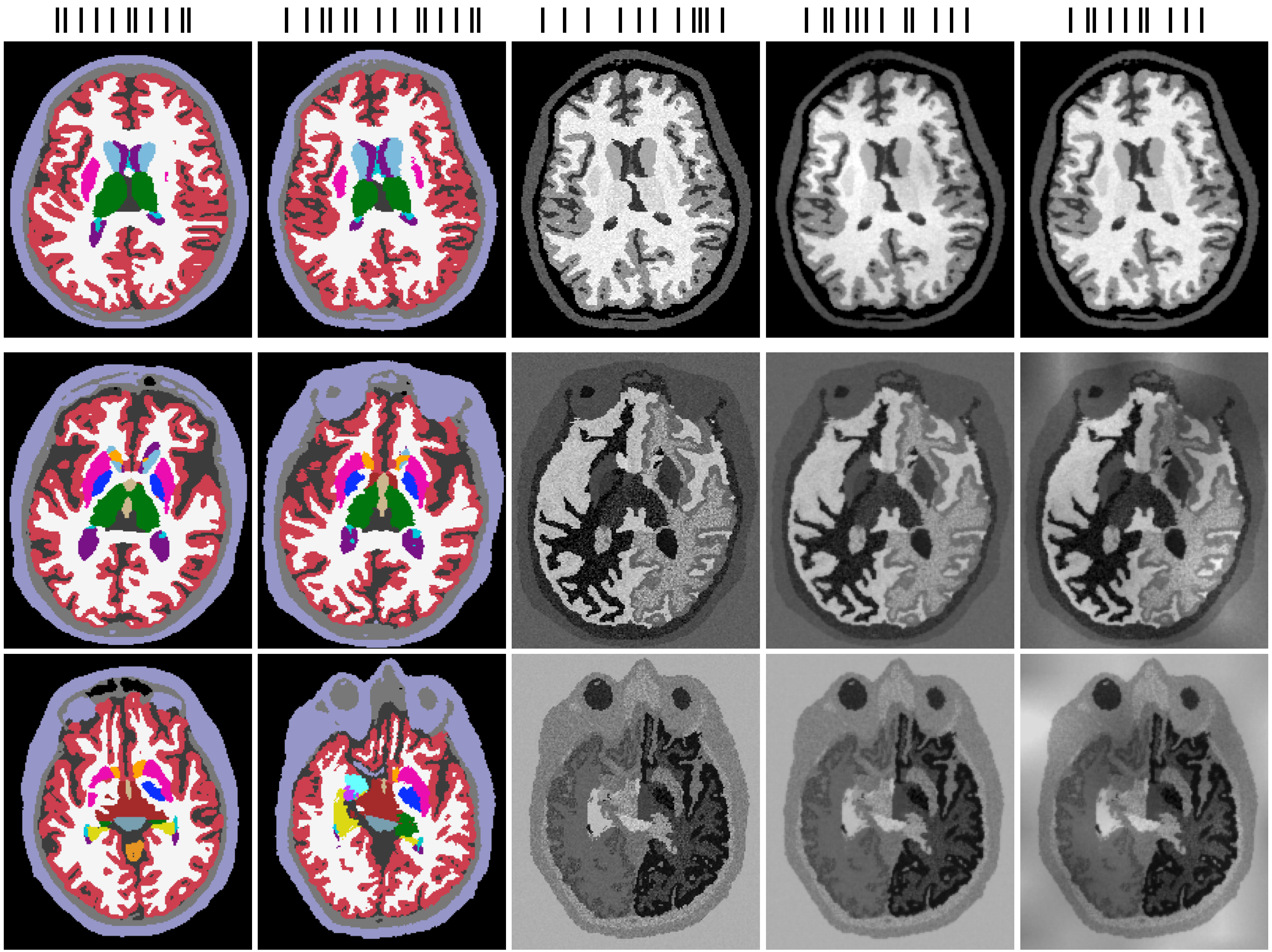
Test time performance



SynthMorph
(do we need real data?)

Hoffmann et al in submission



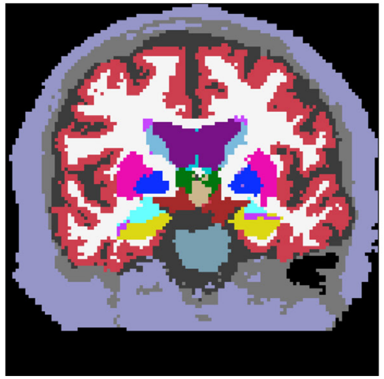


Billot MIDL 2020
Billot MICCAI 2020

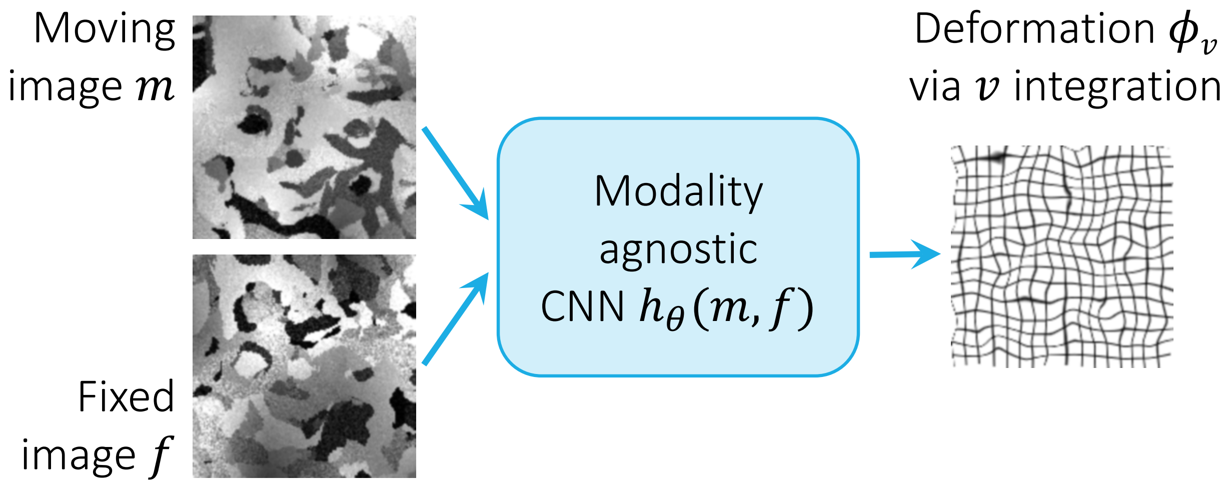
https://github.com/BBillot/lab2im

Do we need anatomical images to train?

Brains

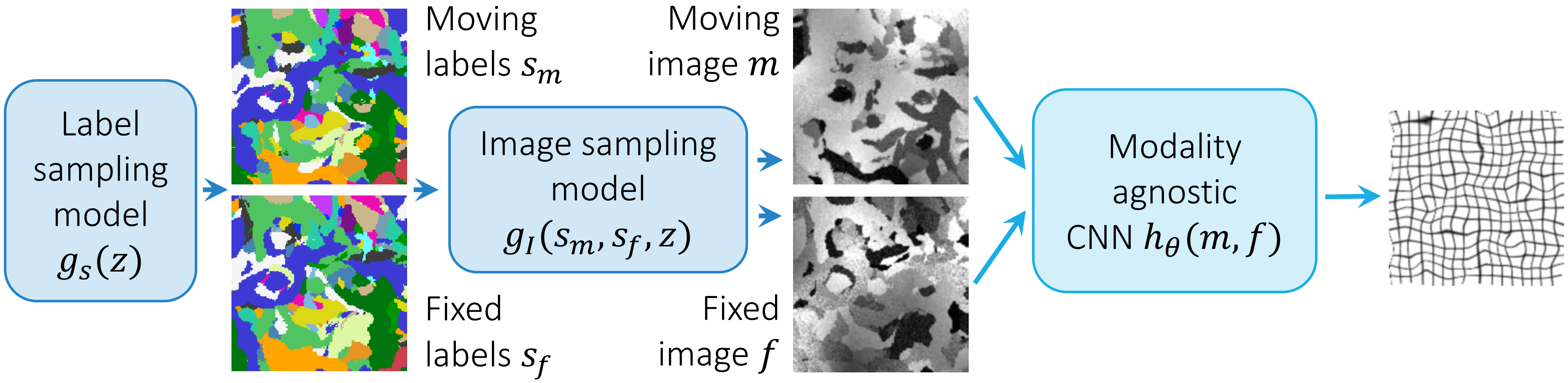


Do we <u>need</u> anatomical images to train?



Hoffman et al, in revision

Do we need anatomical images to train?



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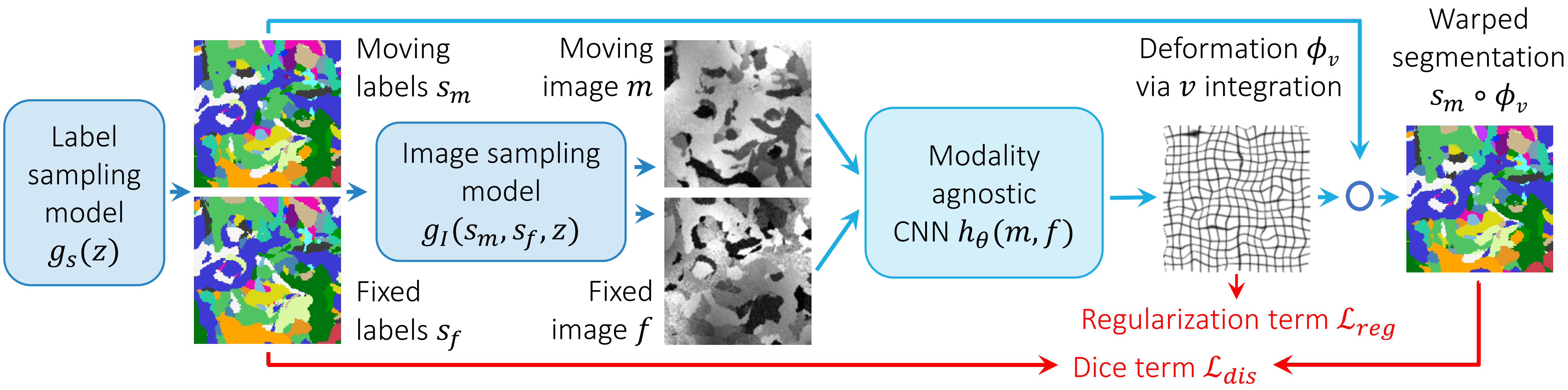
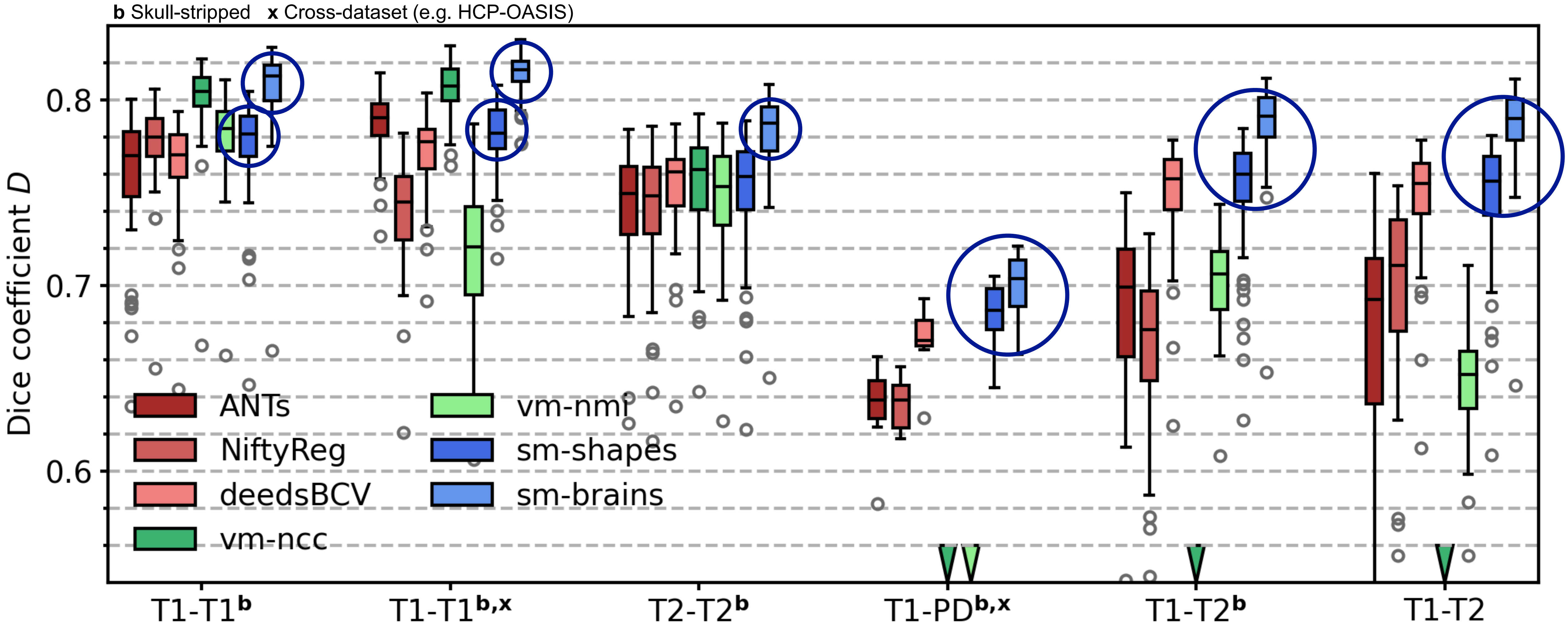
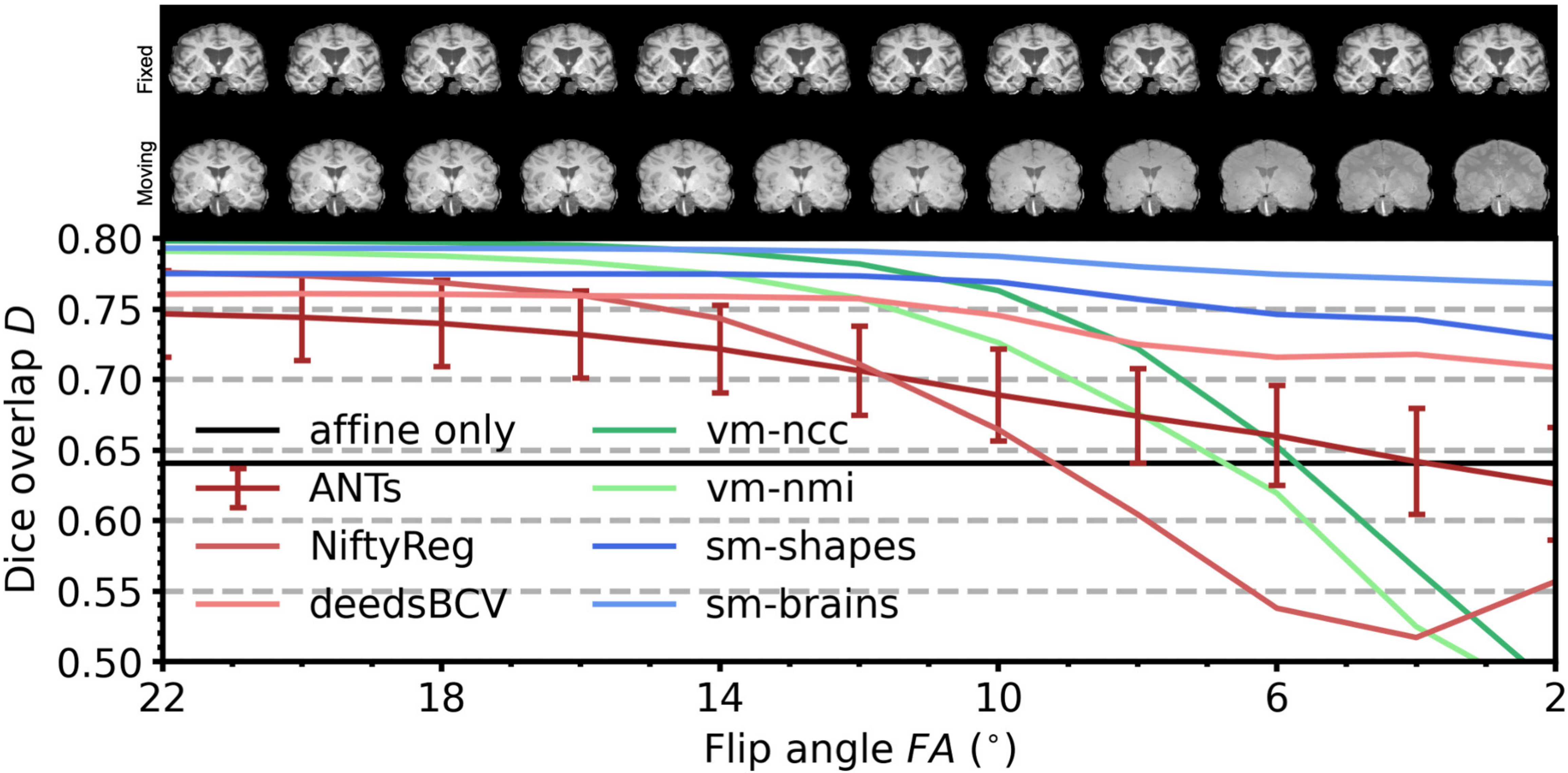
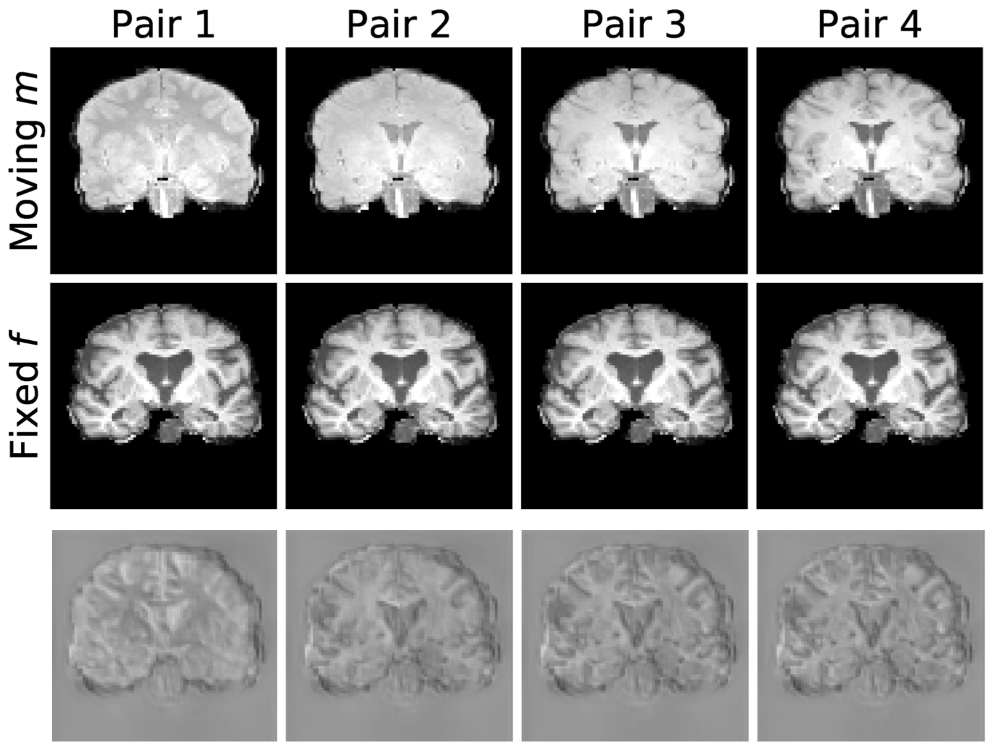


Hoffman et al, in revision



b Skull-stripped x Cross-dataset (e.g. HCP-OASIS)
Dice coefficient D
0.8
0.7
0.6
ANTs
NiftyReg
deedsBCV
vm-ncc
vm-nmi
sm-shapes
sm-brains
T1-T1b
T1-T1b,x
T2-T2b
T1-PDb,x
T1-T2b
T1-T2


Fixed
Moving
Dice overlap D
0.80
0.75
0.70
0.65
0.60
0.55
0.50
22
18
14
10
6
2
Flip angle FA (°)
affine only
ANTs
NiftyReg
deedsBCV
vm-ncc
vm-nmi
sm-shapes
sm-brains



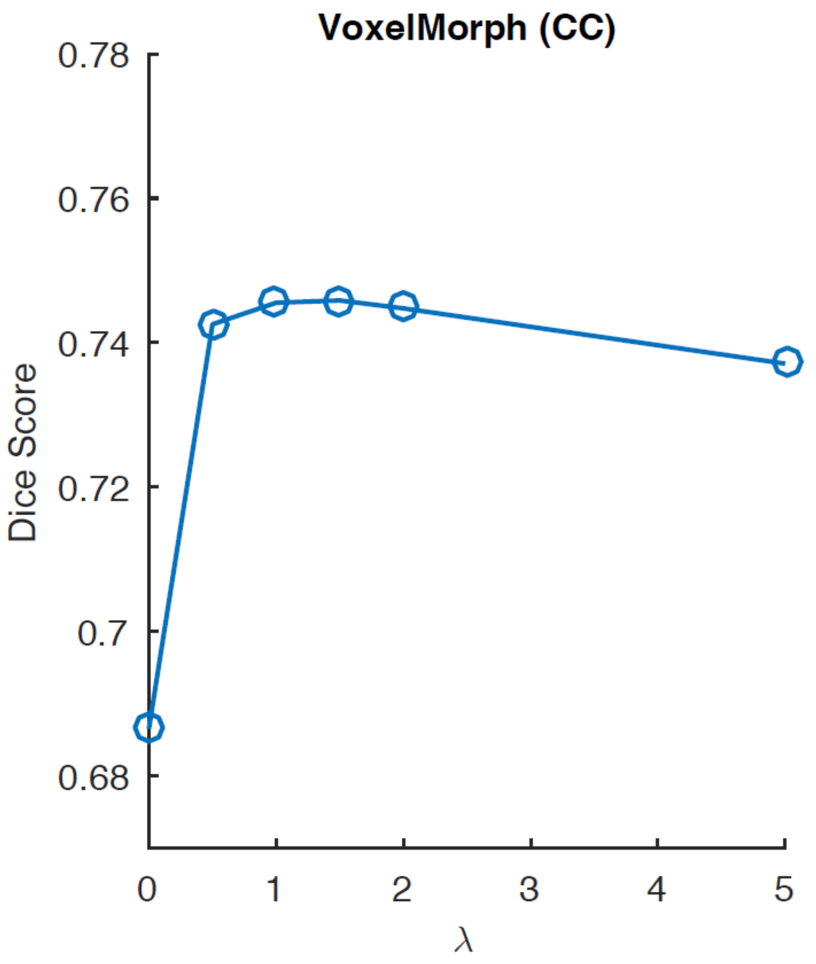
Pair 1 Pair 2 Pair 3 Pair 4

VoxelMorph - NMI

HyperMorph: Amortized parameter learning

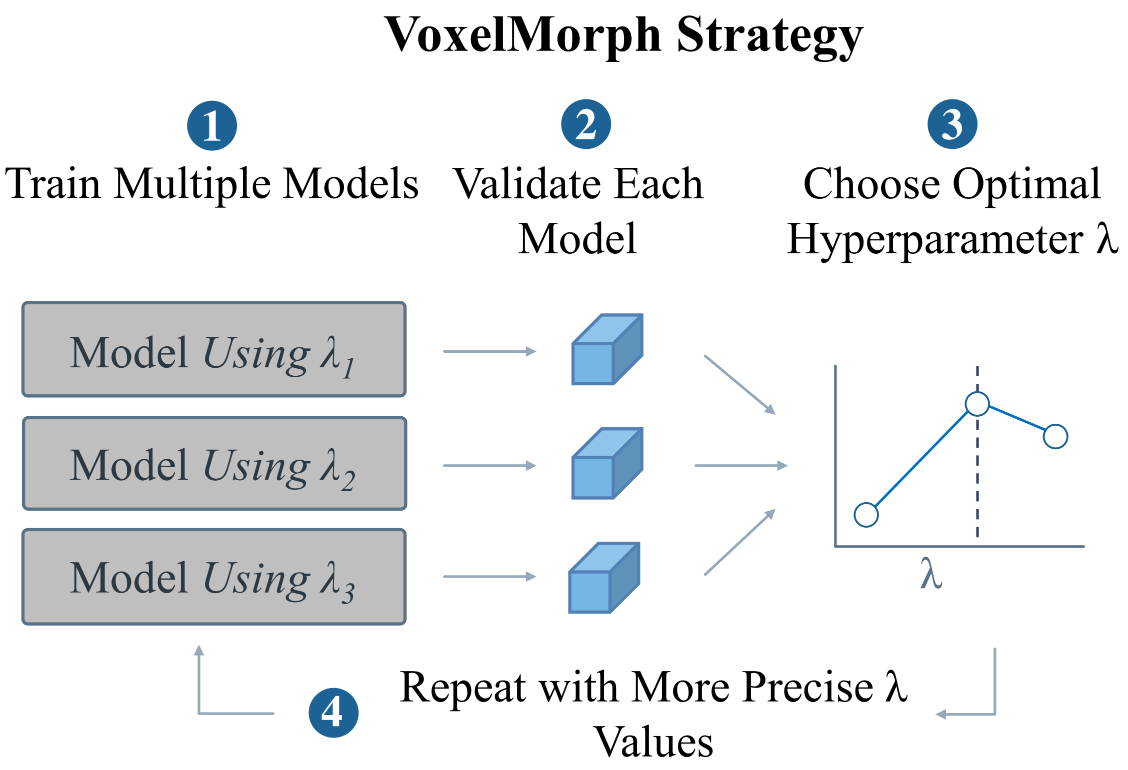
Hoopes, Hoffmann, Fischl, Guttag, Dalca, IPMI 2021

Regularization Analysis (hyperparameters)



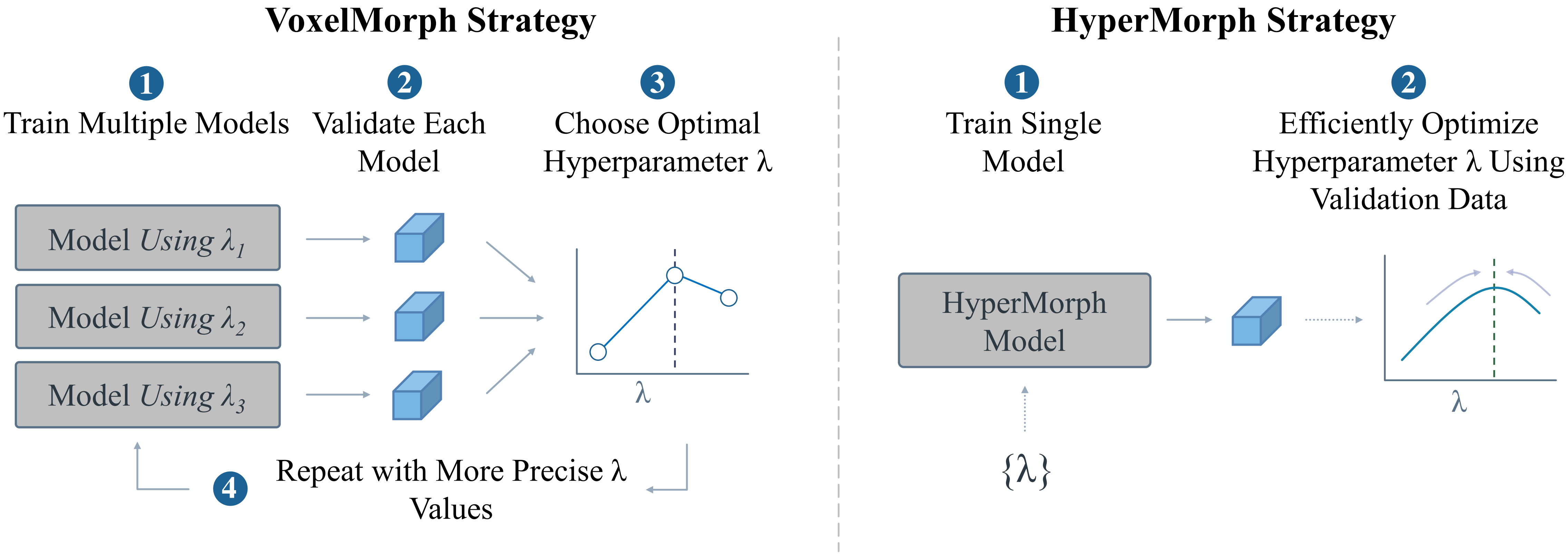
$$\mathcal{L} = \underbrace{\|m \circ \phi - f\|}_{\text{images match}} + \lambda \underbrace{\mathrm{Reg}(\phi)}_{\text{smooth field}}$$

HyperMorph



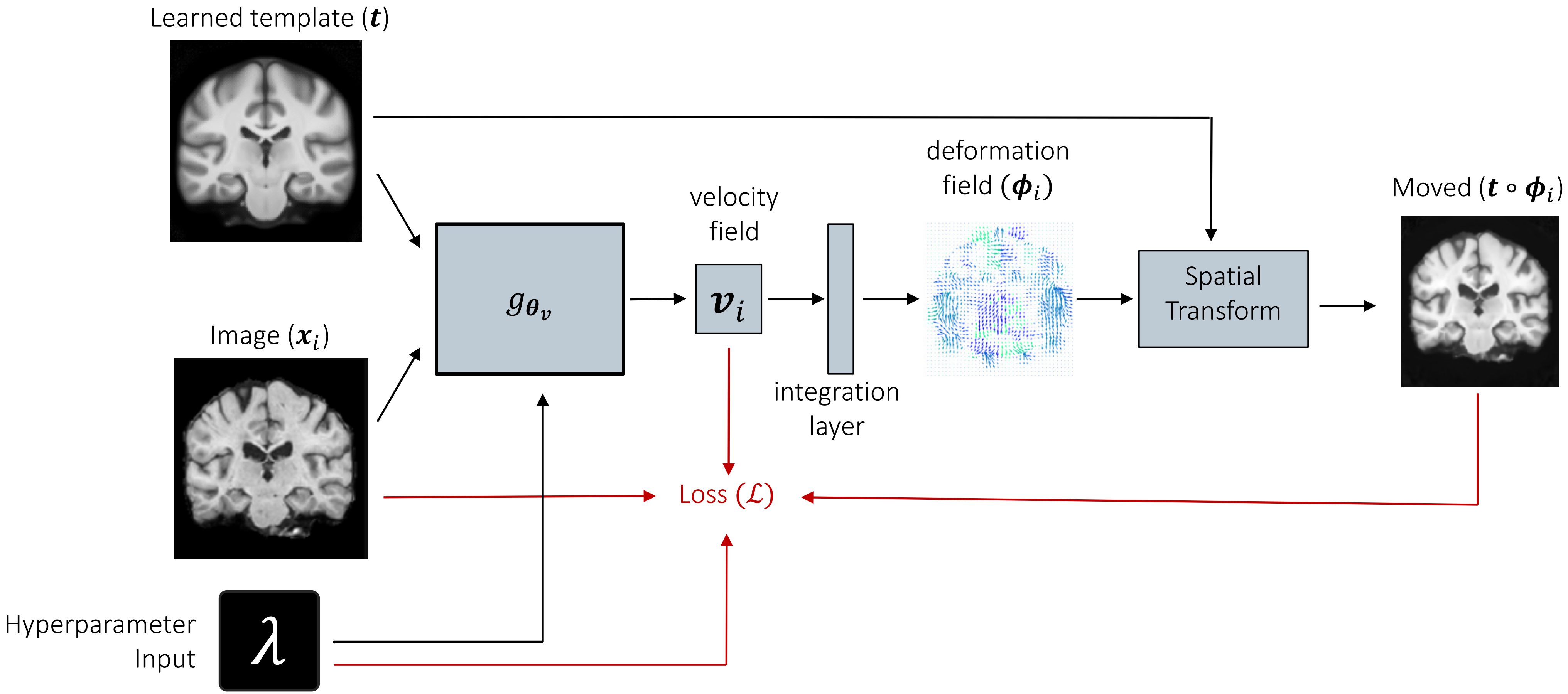
Hoopes et al, IPMI 2021

HyperMorph

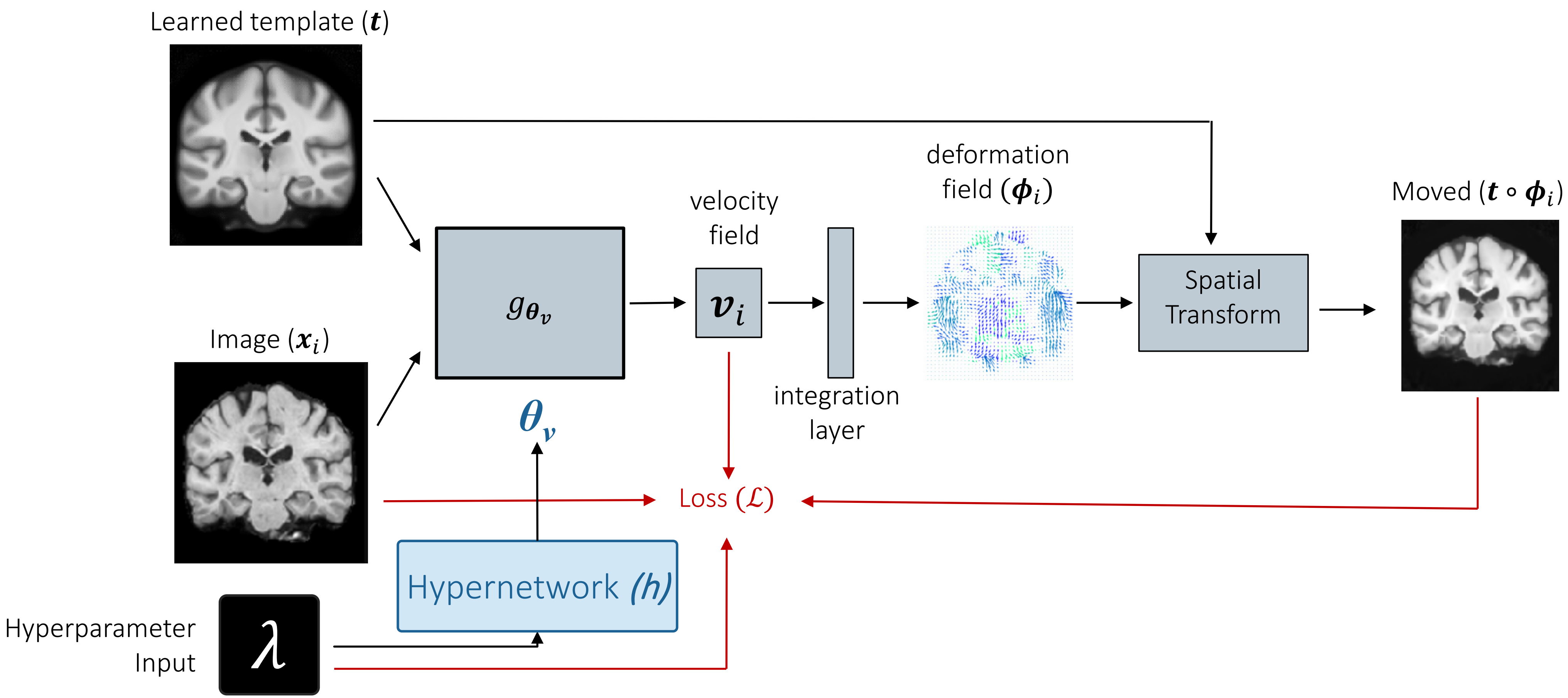


Hoopes et al, IPMI 2021

HyperMorph

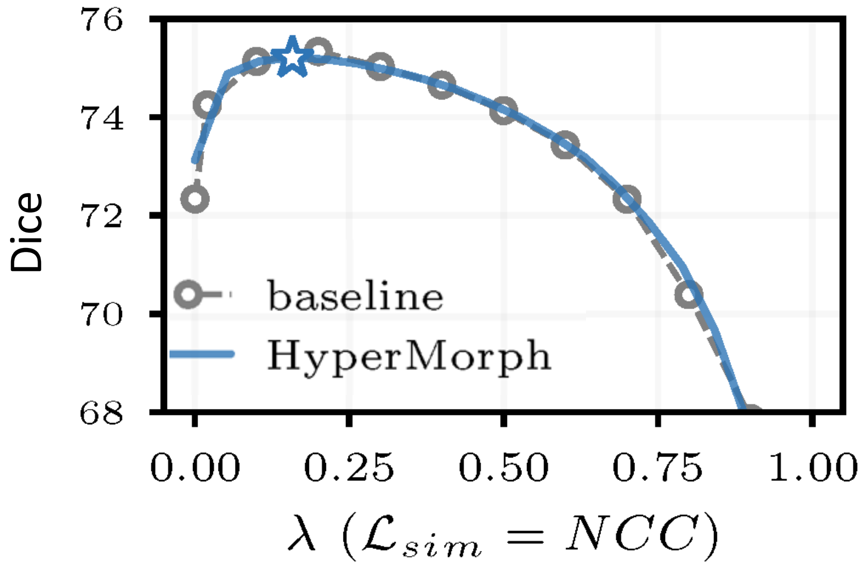

Learned template ($\boldsymbol{t}$)
Image ($\boldsymbol{x}_i$)
Hyperparameter Input
λ
$g_{\boldsymbol{\theta}_v}$
velocity field
$\boldsymbol{v}_i$
integration layer
deformation field ($\boldsymbol{\phi}_i$)
Spatial Transform
Moved ($\boldsymbol{t} \circ \boldsymbol{\phi}_i$)
Loss ($\mathcal{L}$)

HyperMorph



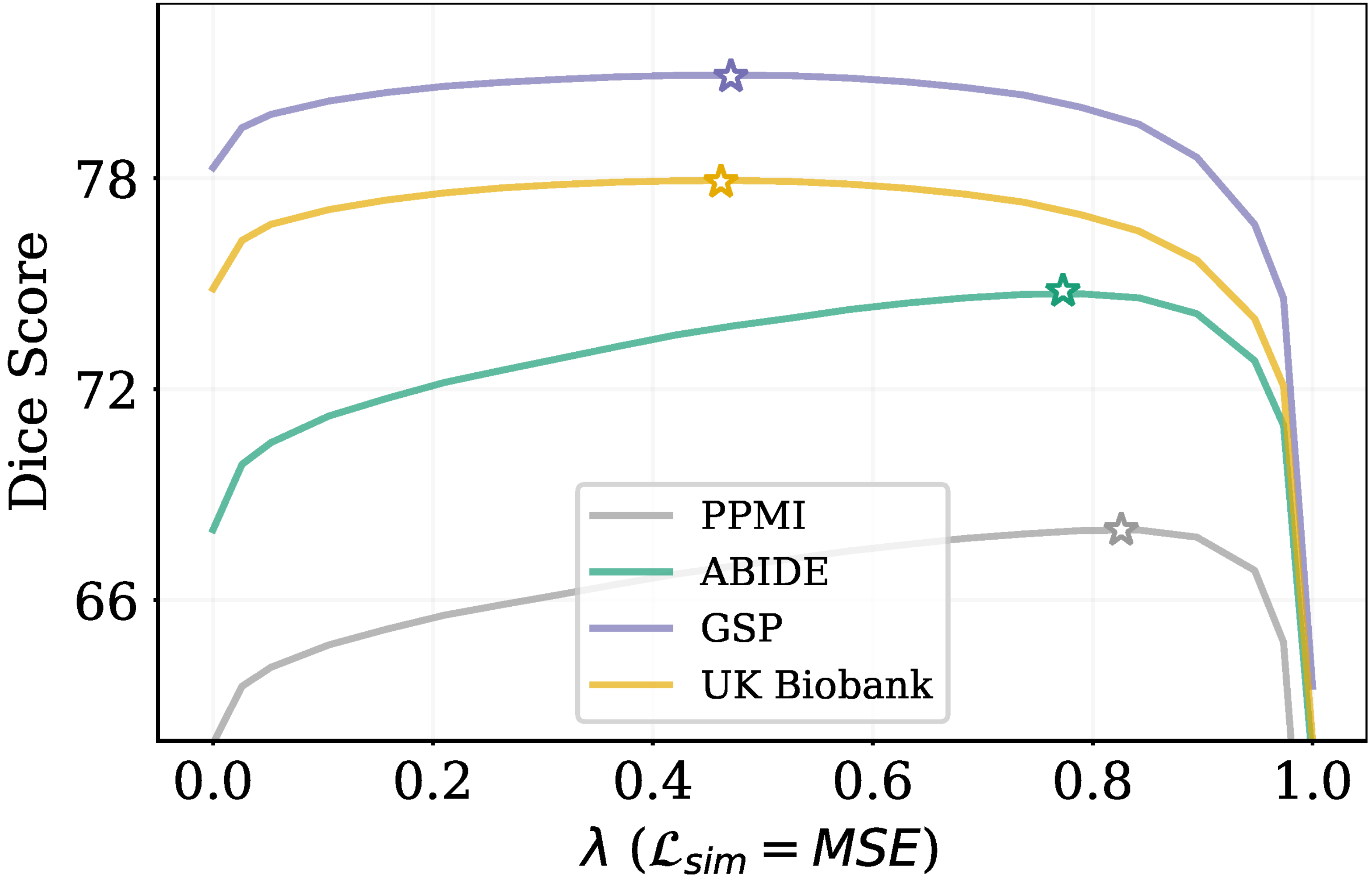
Learned template ($\boldsymbol{t}$)
Image ($\boldsymbol{x}_i$)
$g_{\boldsymbol{\theta}_v}$
$\boldsymbol{\theta}_v$
velocity field
$\boldsymbol{v}_i$
integration layer
deformation field ($\boldsymbol{\phi}_i$)
Spatial Transform
Moved ($\boldsymbol{t} \circ \boldsymbol{\phi}_i$)
Loss ($\mathcal{L}$)
Hypernetwork *(h)*
Hyperparameter Input
λ

Baseline Comparison

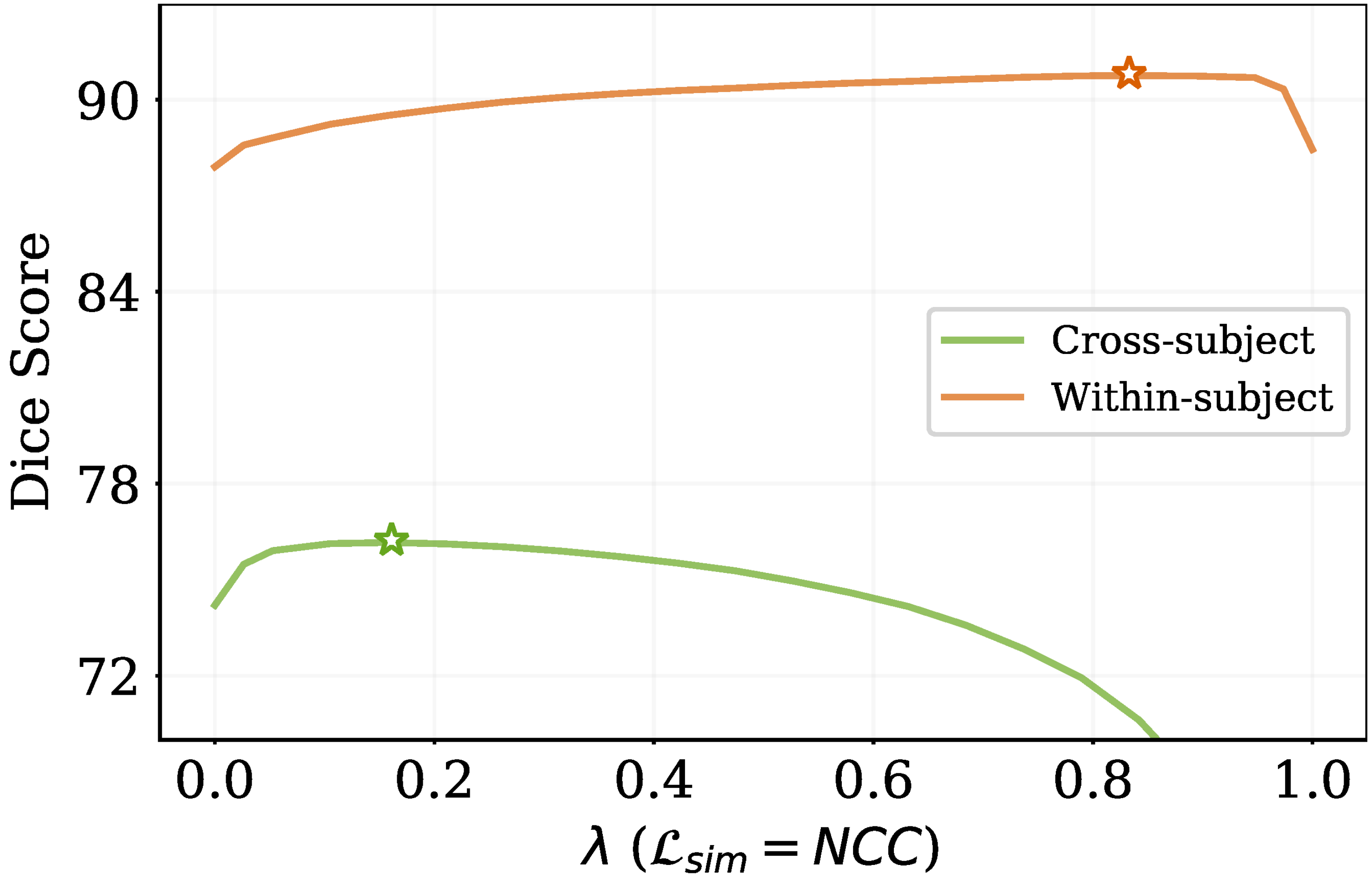


Runtime (GPU-hours)
VoxelMorph (~10 models): 765
HyperMorph: **147**

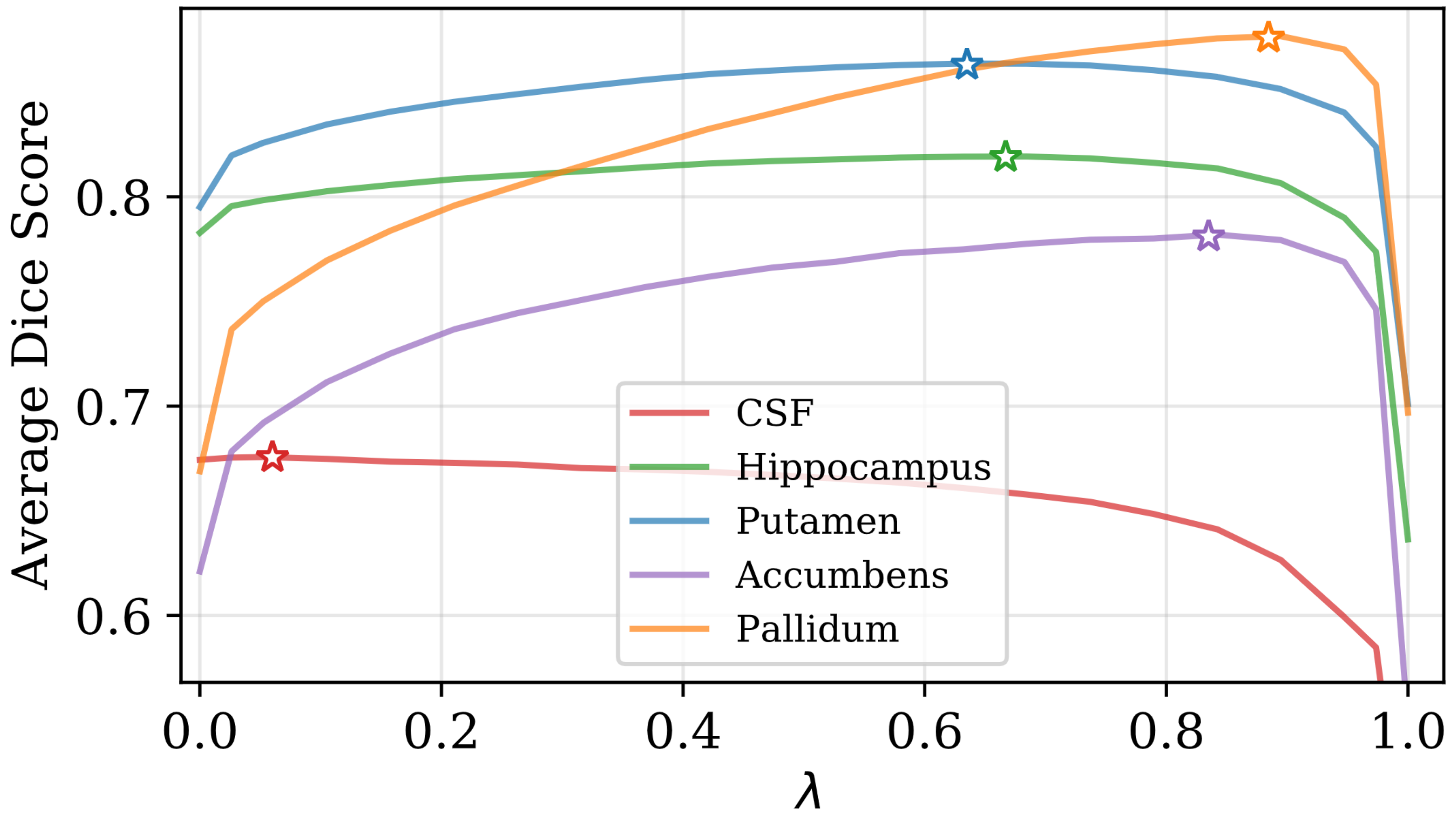
Optimal Hyperparameters vary by dataset



Optimal Hyperparameters vary by task

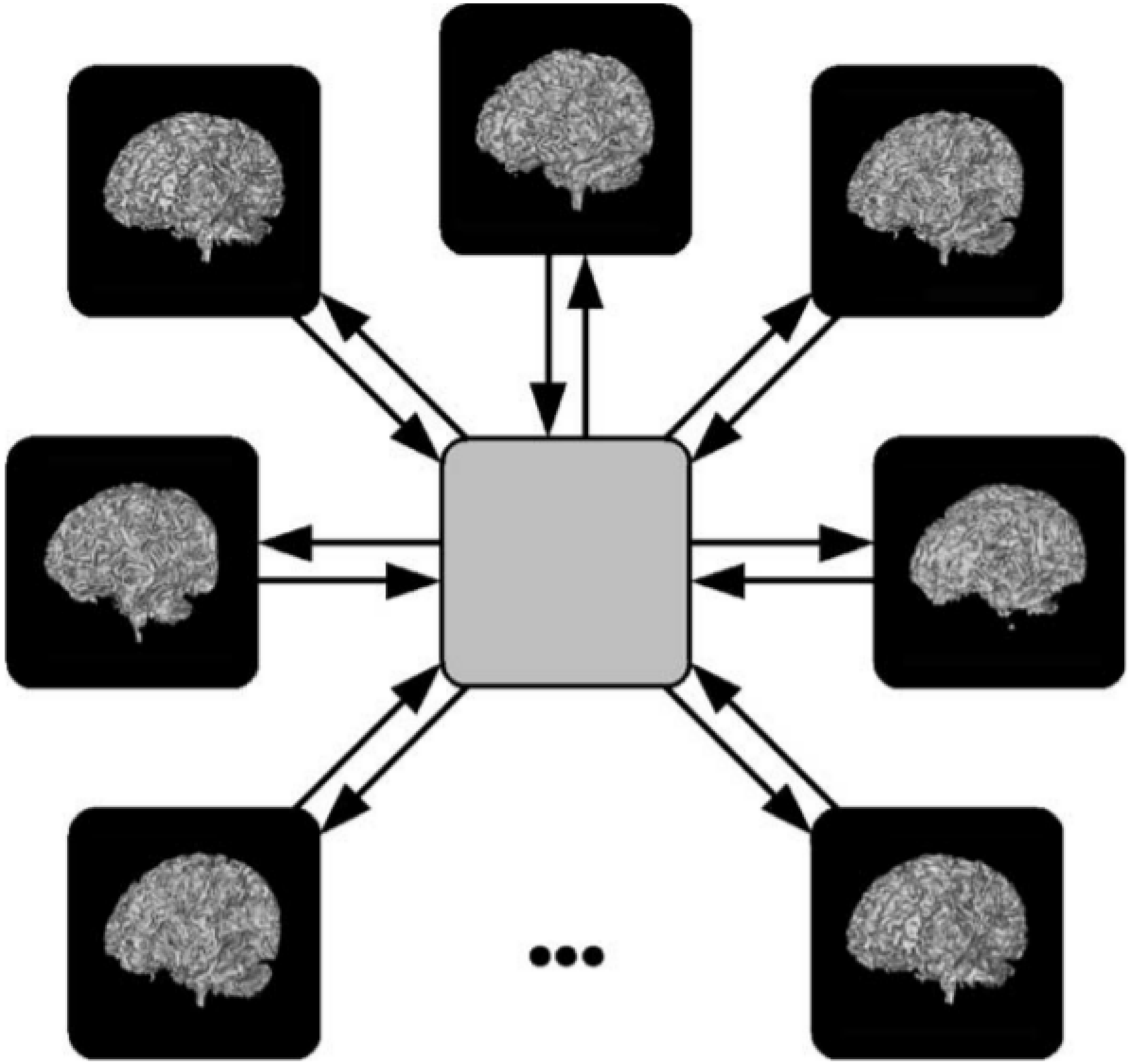


… even by anatomical region!



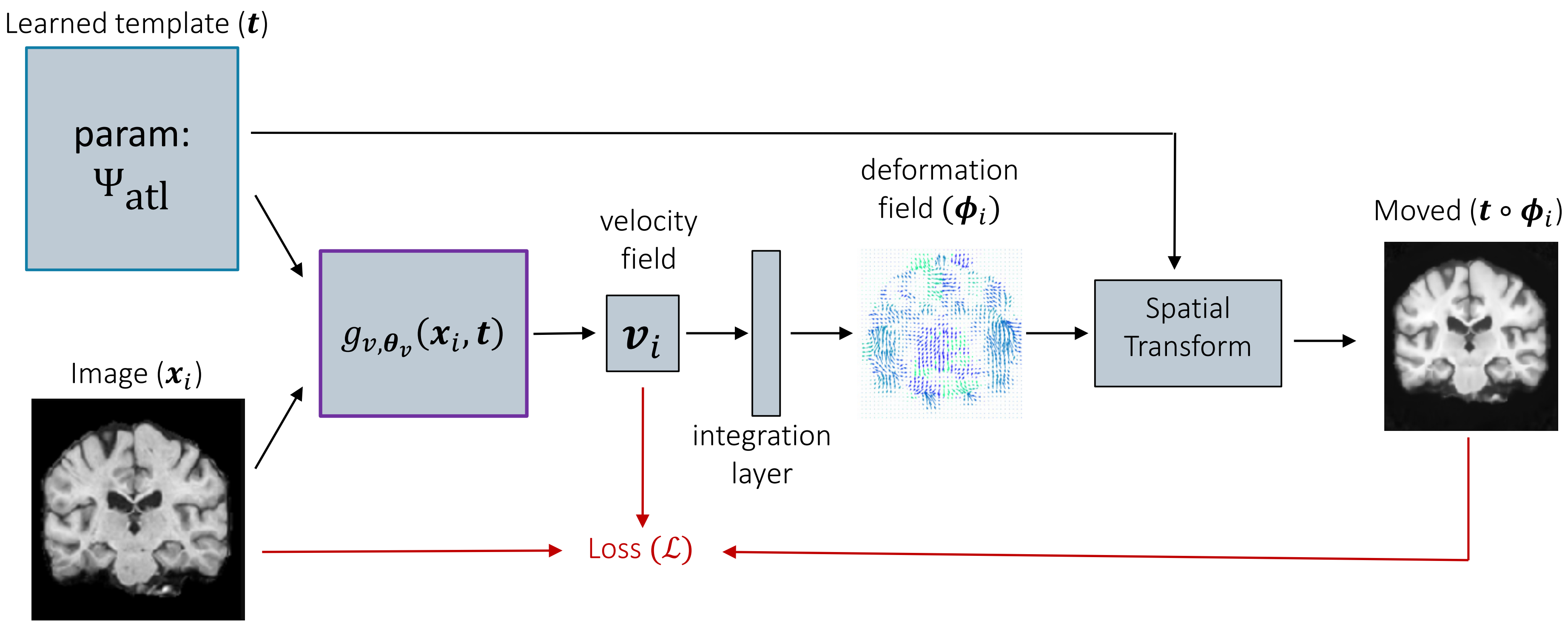
Template construction

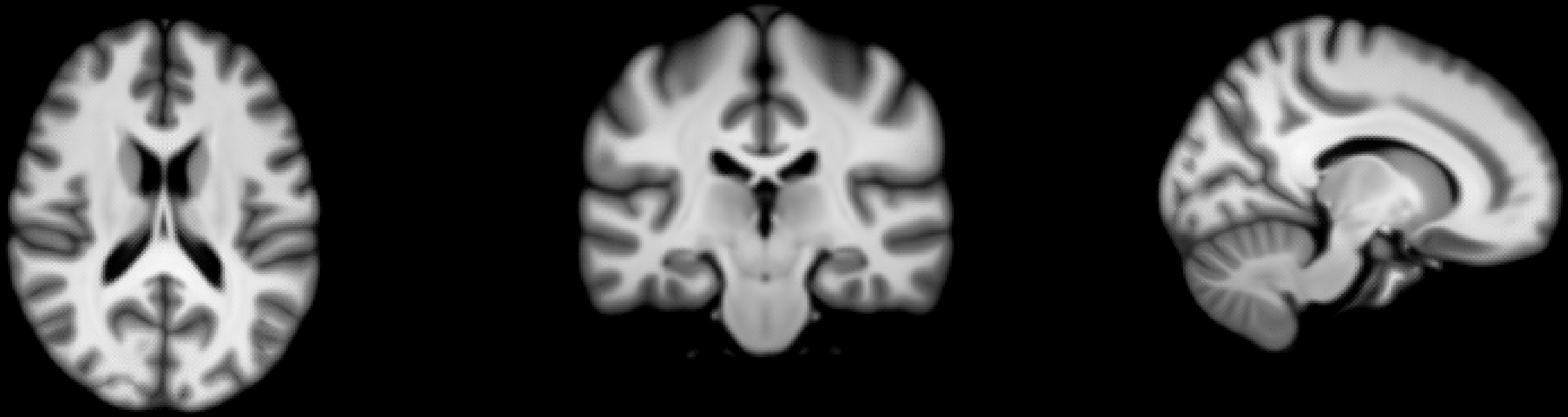
Dalca, Rakic, Guttag, Sabuncu, NeurIPS 2019



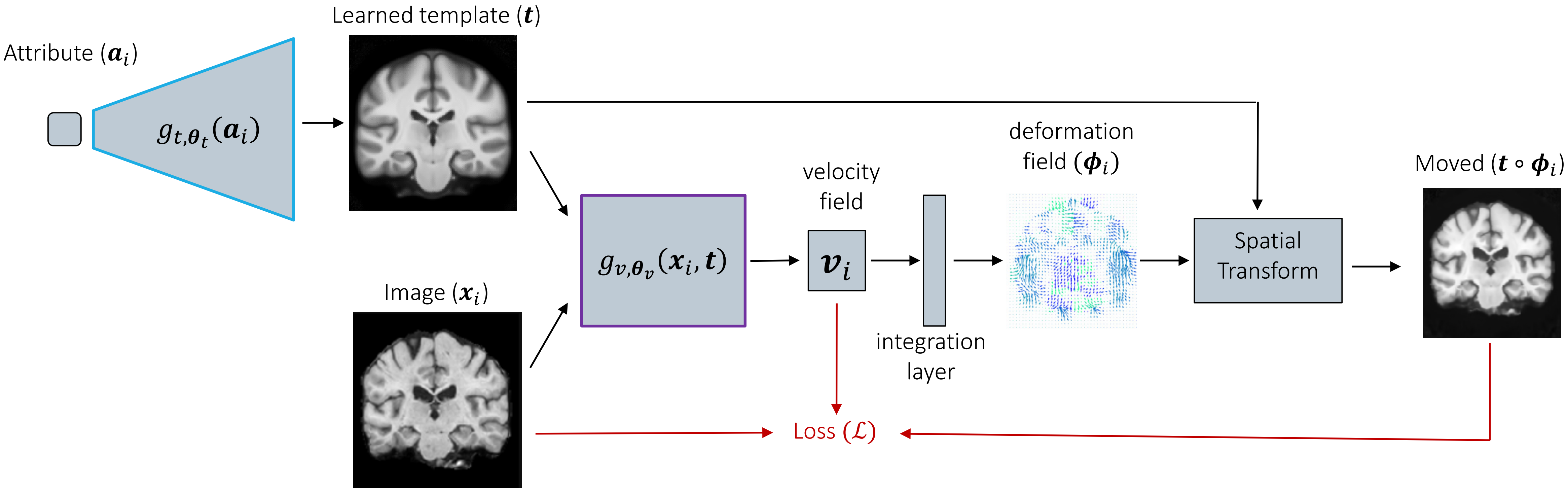
Joshi et al, 2004

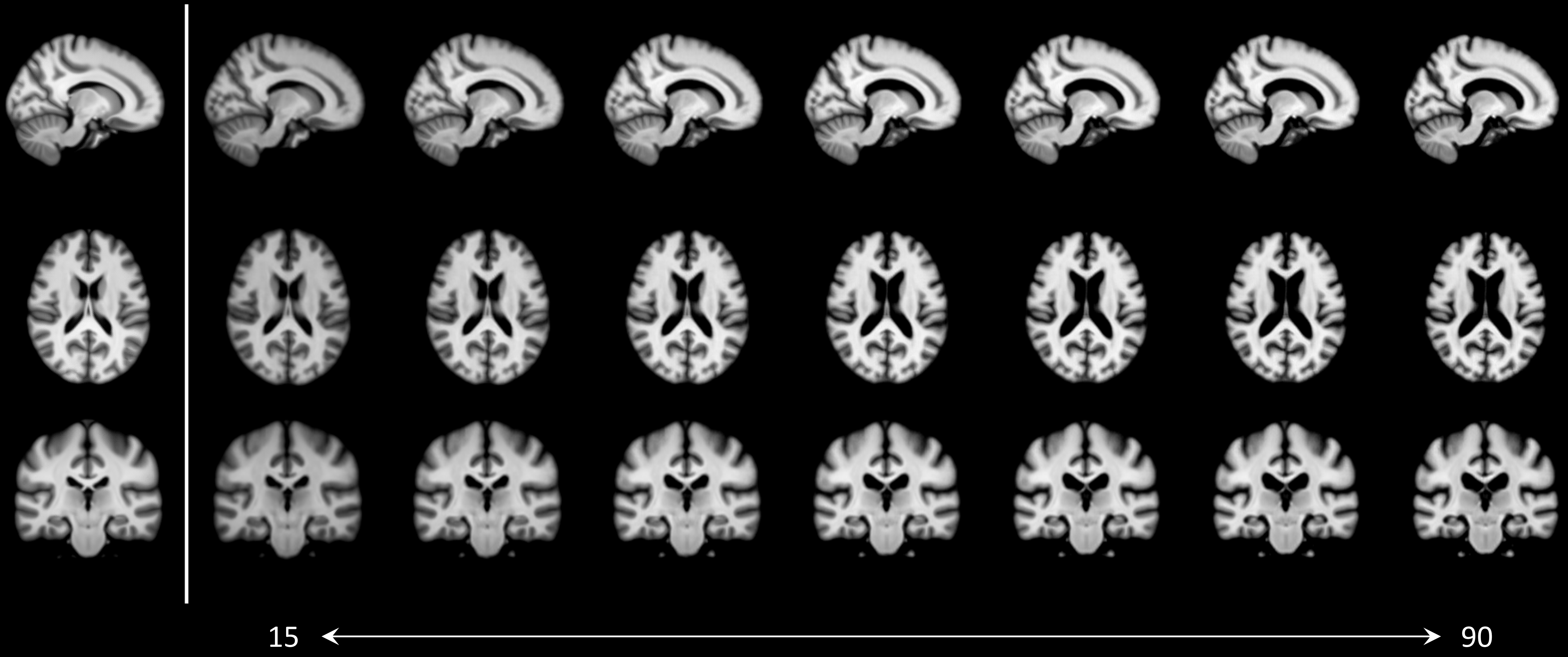
Template Construction

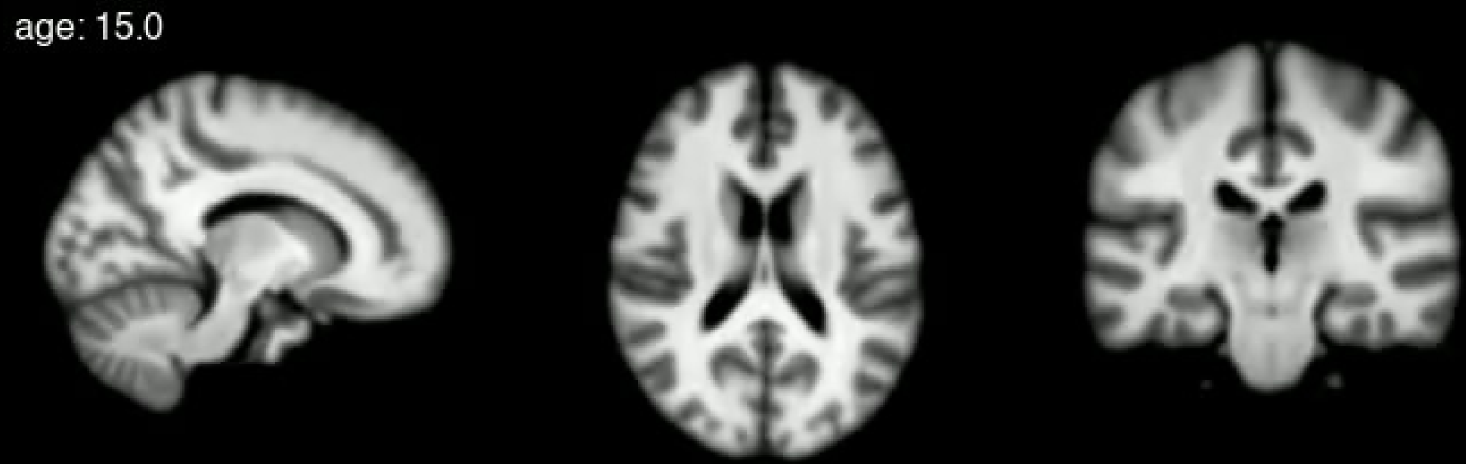


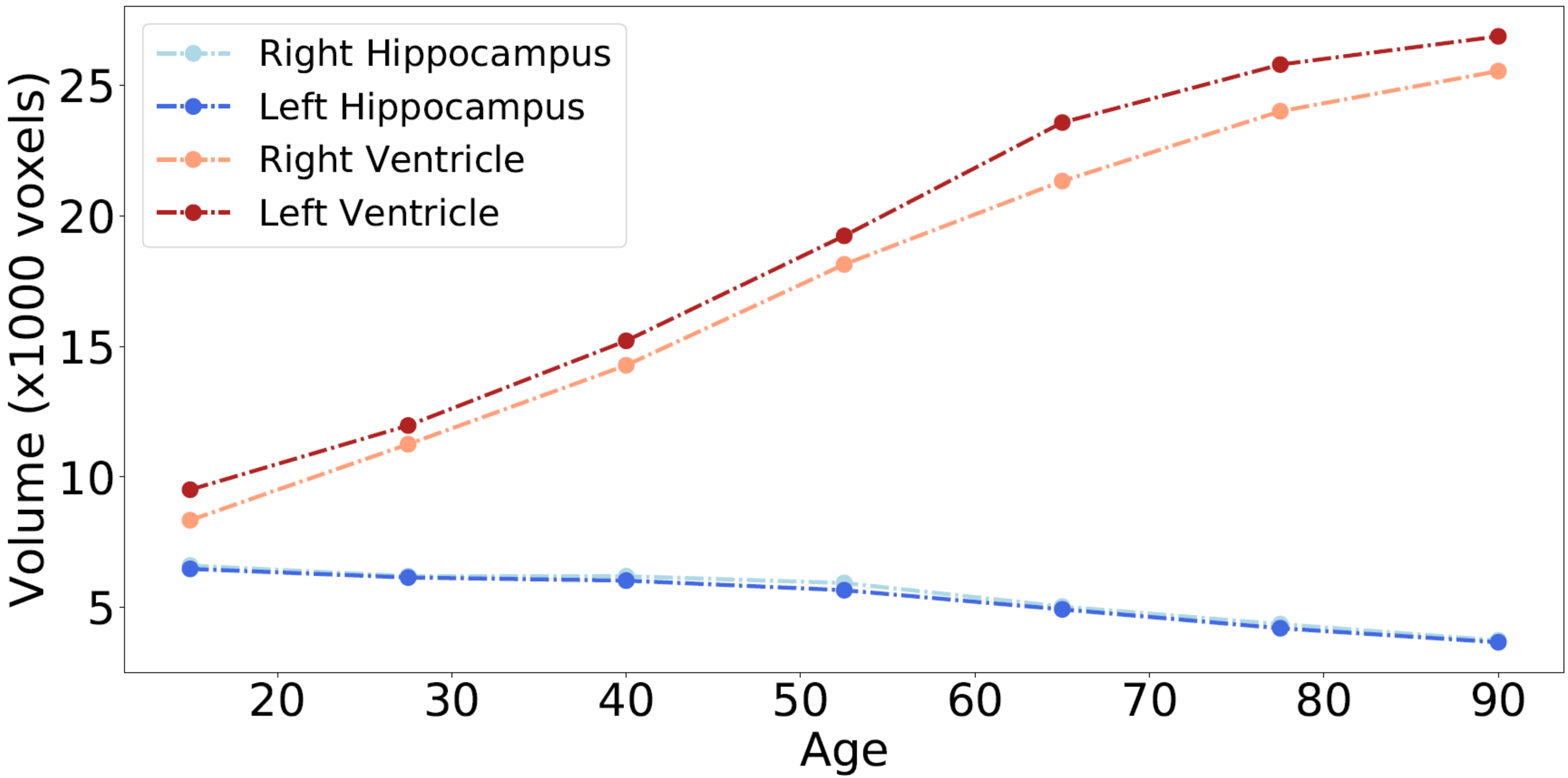


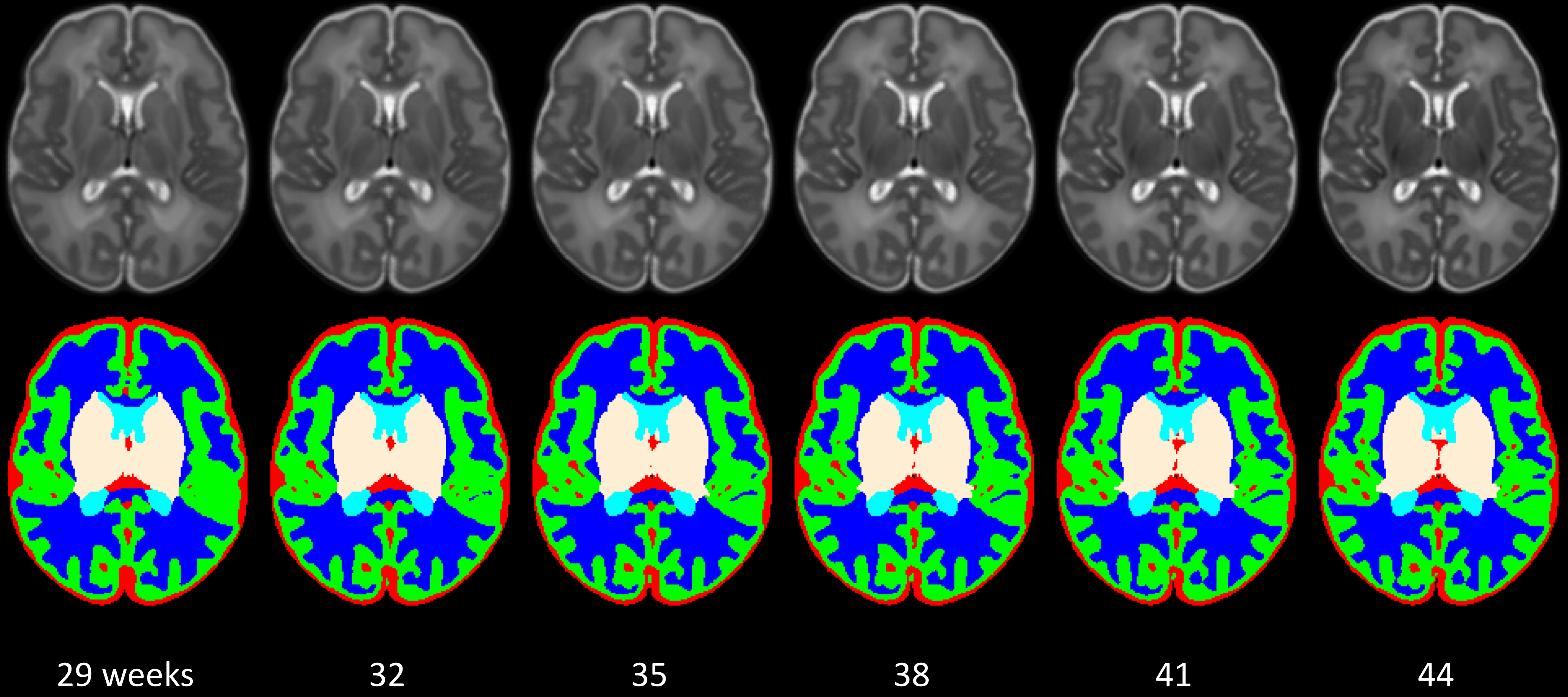
Conditional template construction




15
90


age: 15.0


Right Hippocampus
Left Hippocampus
Right Ventricle
Left Ventricle
Volume (x1000 voxels)
5
10
15
20
25
20
30
40
50
60
70
80
90
Age



dHCP atlas

Dey et al, in submission

Acknowledgements

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Bruce Fischl (HMS/MGH LCN)

John Guttag (MIT CSAIL DDIG)

Malte Hoffmann (MGH LCN)

Andrew Hoopes (MGH LCN)

Eugenio Iglesias (MIT CSAIL, MGH HMS, UCL CMIC)

Kathleen Lewis (MIT CSAIL DDIG)

Marianne Rakic (MIT CSAIL DDIG, ETH)

Mert Sabuncu (Cornell ECE, HMS/MGH LCN)

Amy Zhao (MIT CSAIL DDIG)

voxelmorph

- Probabilistic generative model for diffeomorphisms
- Variational Inference
- Unsupervised Neural Network

- Very **fast** for new image pair
- State-of-the-art **accuracy**
- **Diffeomorphic** deformations
- **Uncertainty** estimation

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- Limited training data → use VM as initialization
- Segmentation at training → better test Dice performance
- No atlas → construct atlas automatically
- Synthesis → invariant representations
- Can apply to wider domains

voxelmorph

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