Geodesic Information Flows:
Information propagation and its application to segmentation, fusion and data synthesis

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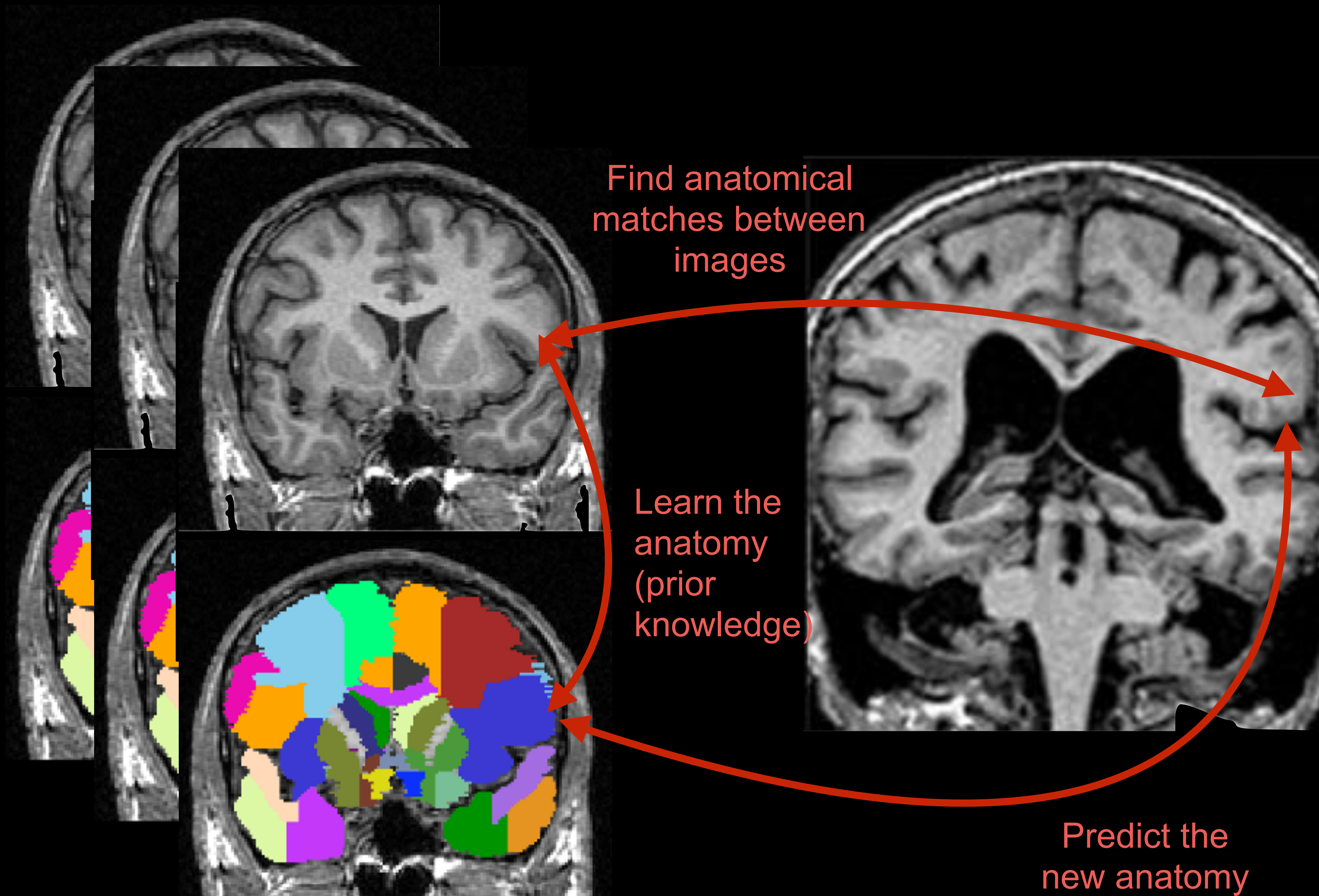
Information Propagation



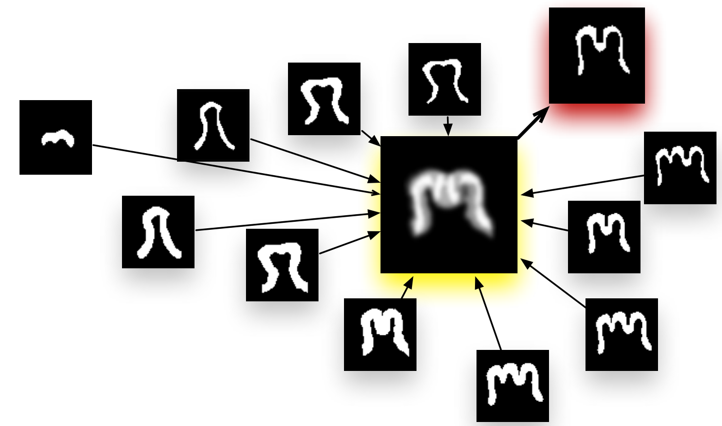
Information Propagation

If I know this subject is normal, then…

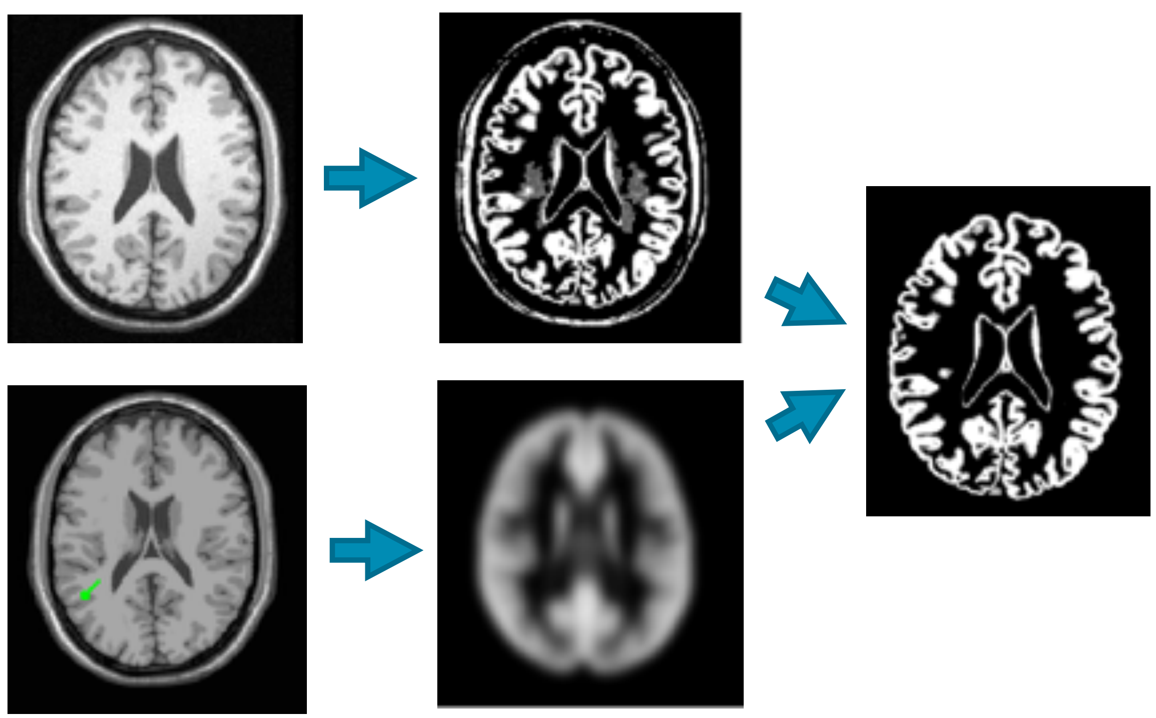
This are looks the same in this image…

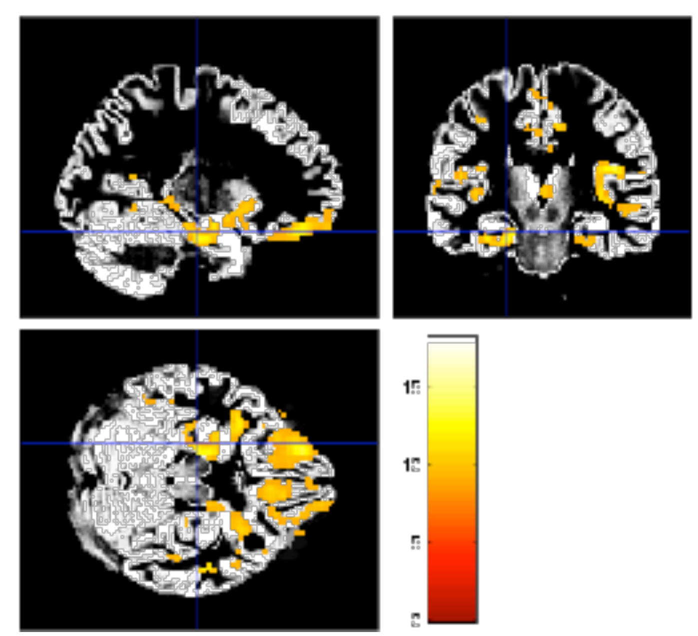
Propagation via a Group Mean

Affine/Non-Linear → Resampling → Groupwise



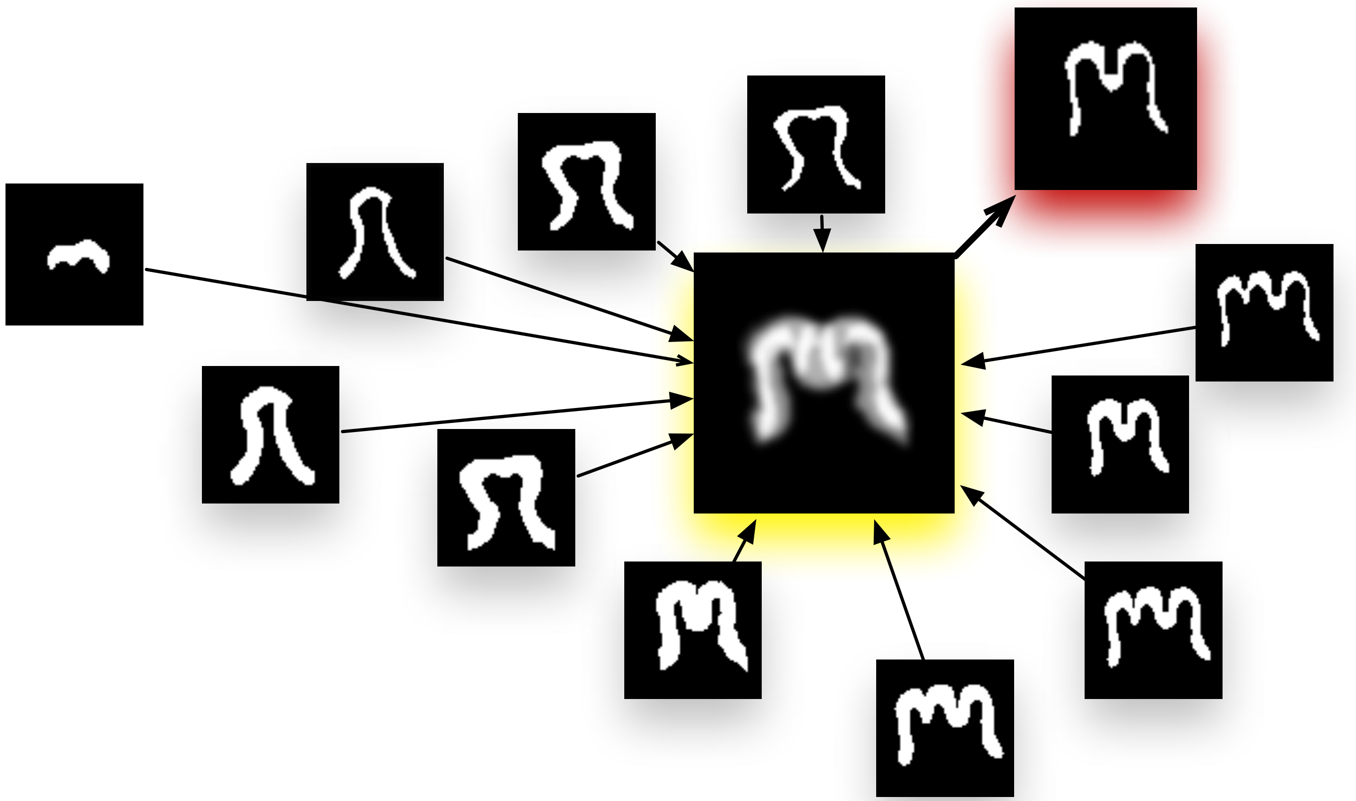
- Tissue segmentation
  - Anatomical Priors
- Morphometry
  - VBM/TMB





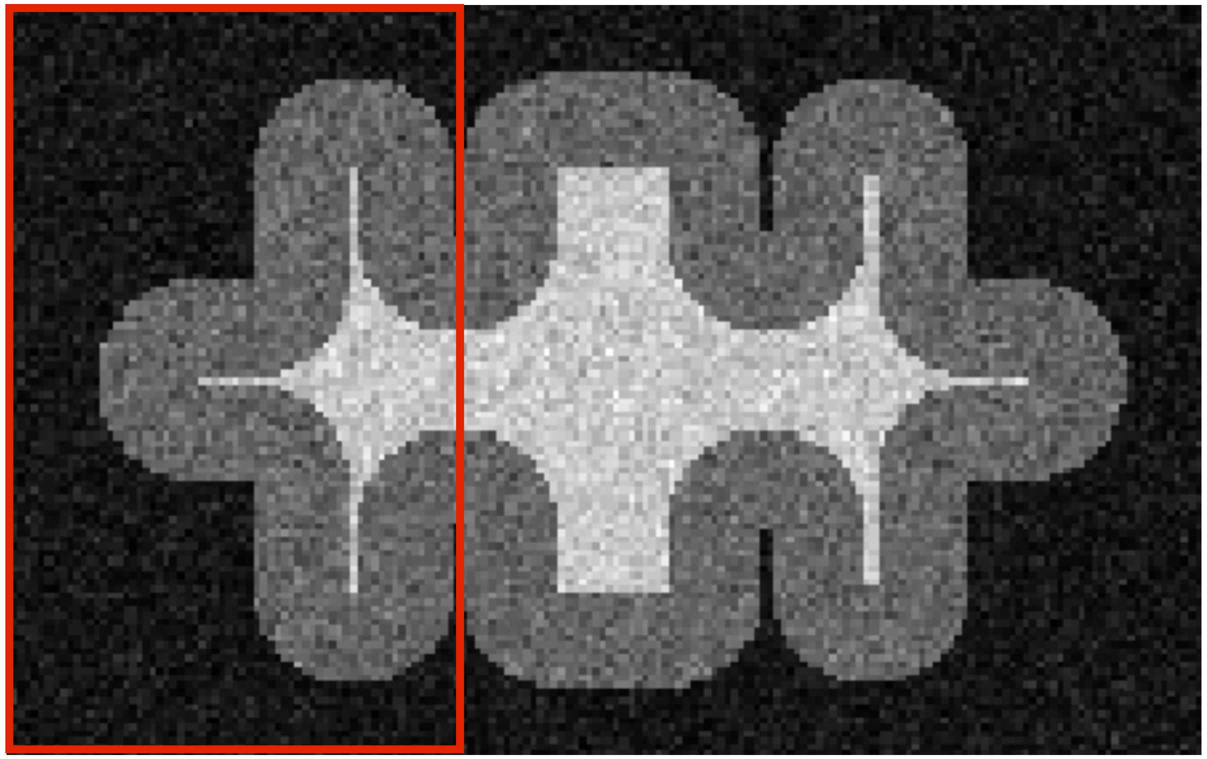
Propagation via a Group Mean

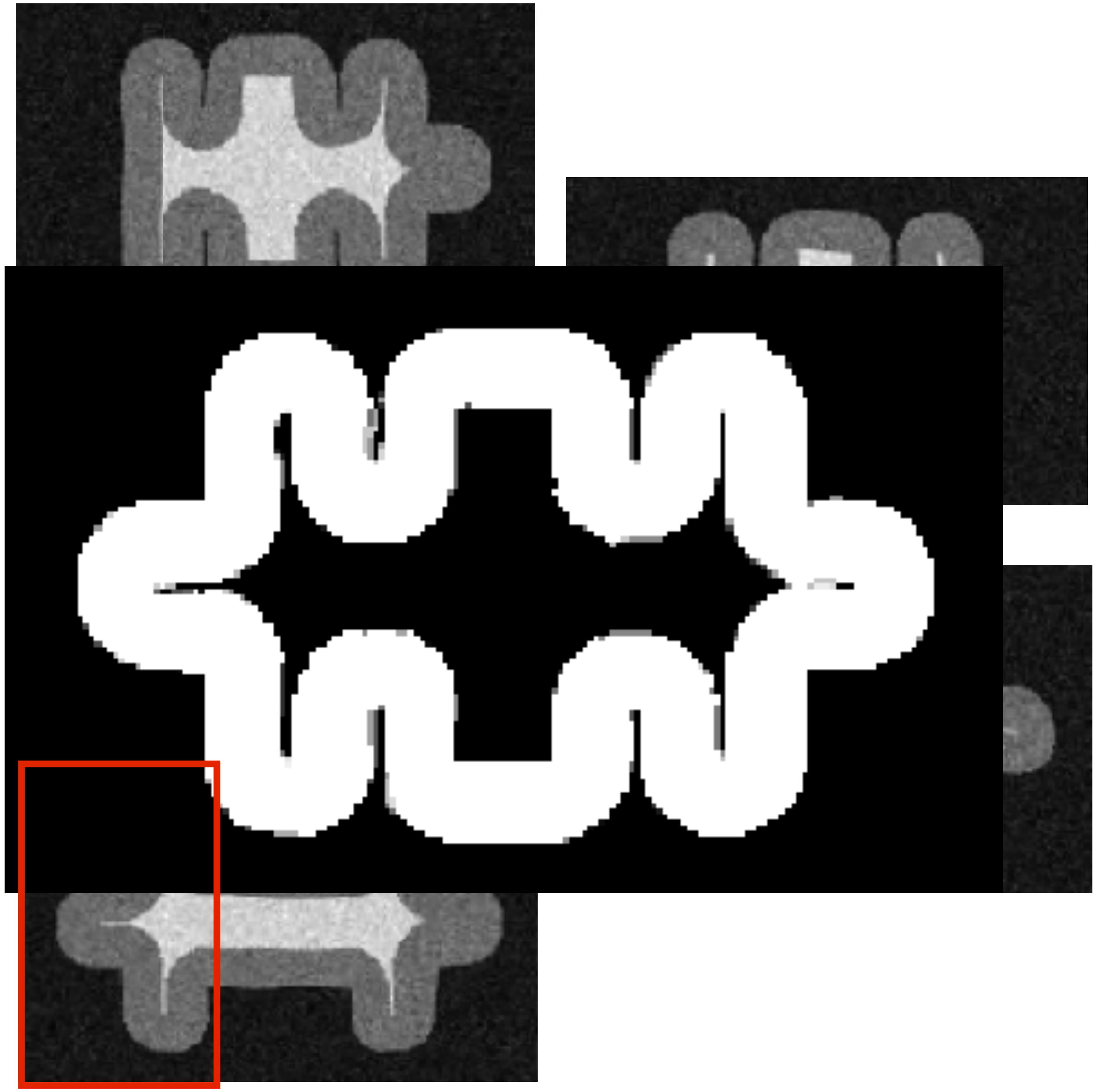
- Advantages:
  - Efficient
  - Unified space
    - Comparison
    - Resampling
    - Learning
  - Compresses information



- Disadvantages
  - Compresses information
  - Can be biased towards certain morphologies
  - Not ideal for inter-subject matching
    - Frequency, appearance, diffeomorphic path

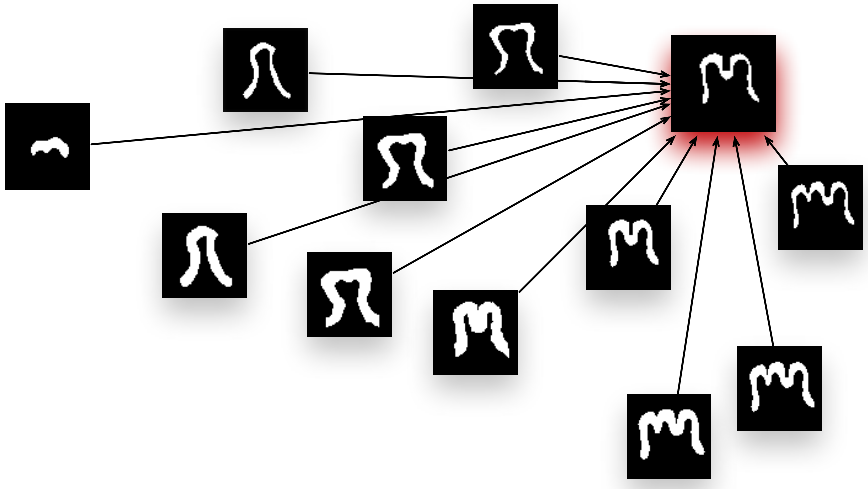
- Label Fusion
  - How to propagate/fuse
  - Morphology differences



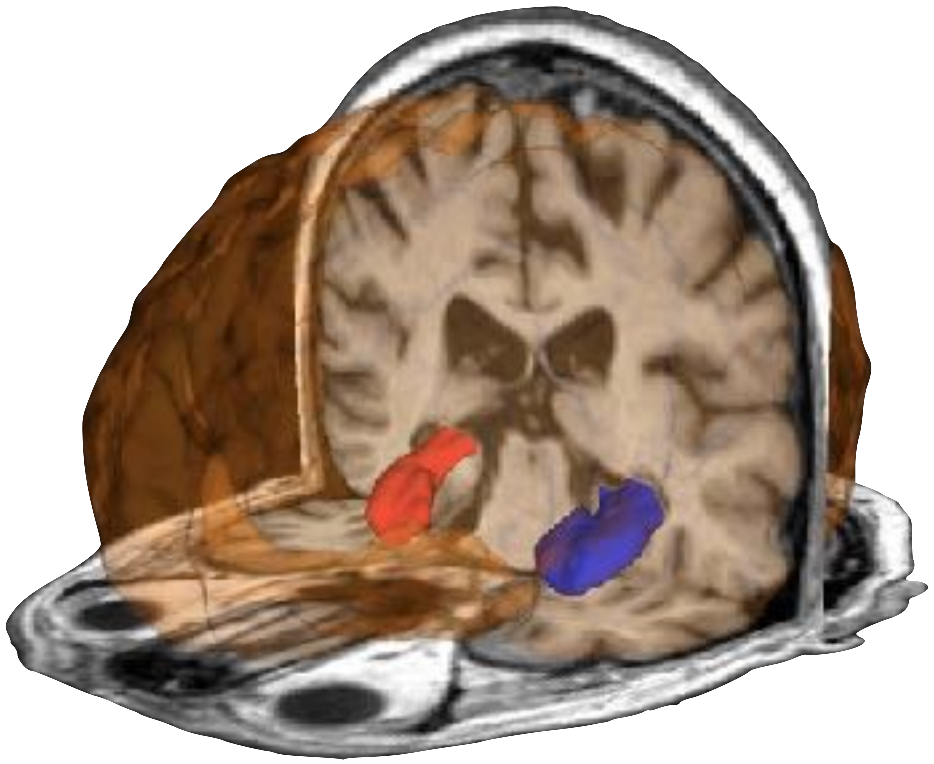


Propagation via Pairwise

- Advantages:
  - Flexible
  - Very accurate
  - Less biased
  - Uncompressed information



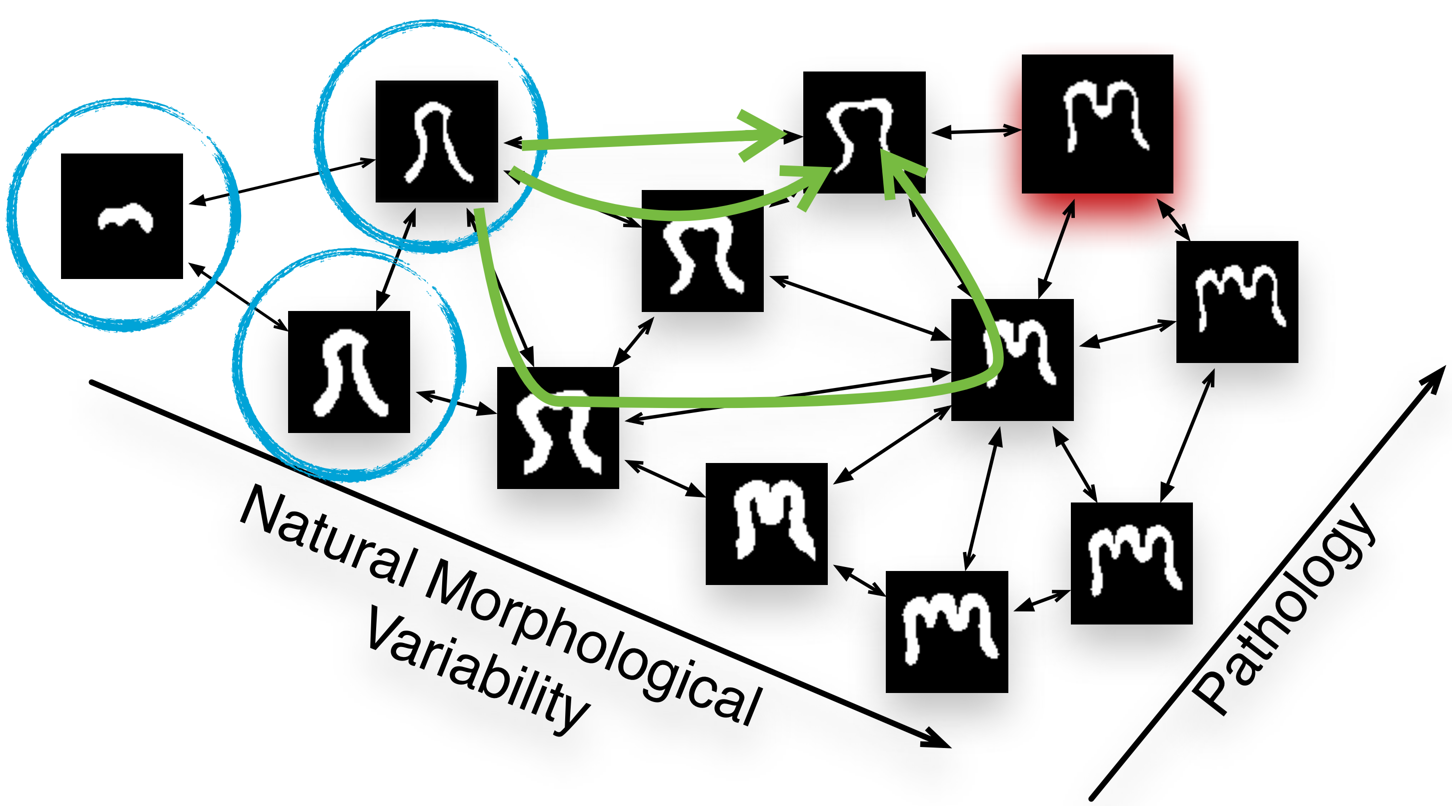
- Disadvantages
  - Less efficient
  - Maybe too flexible
  - Can be biased
  - Not ideal for inter-subject matching
    - Appearance?
    - Diffeomorphic?



Geodesic Information Flows

"Information only propagates between images if they are morphologically similar to each other"

- Does not resample the images to a standard space
- Its pairwise, symmetric and unbiased by construction
- Geodesic information propagation



Application to Label Fusion

- Let $\mathcal{L}_i(\vec{v})$, be the label at image *i* and location *v*

- Using a weighted voting strategy we have

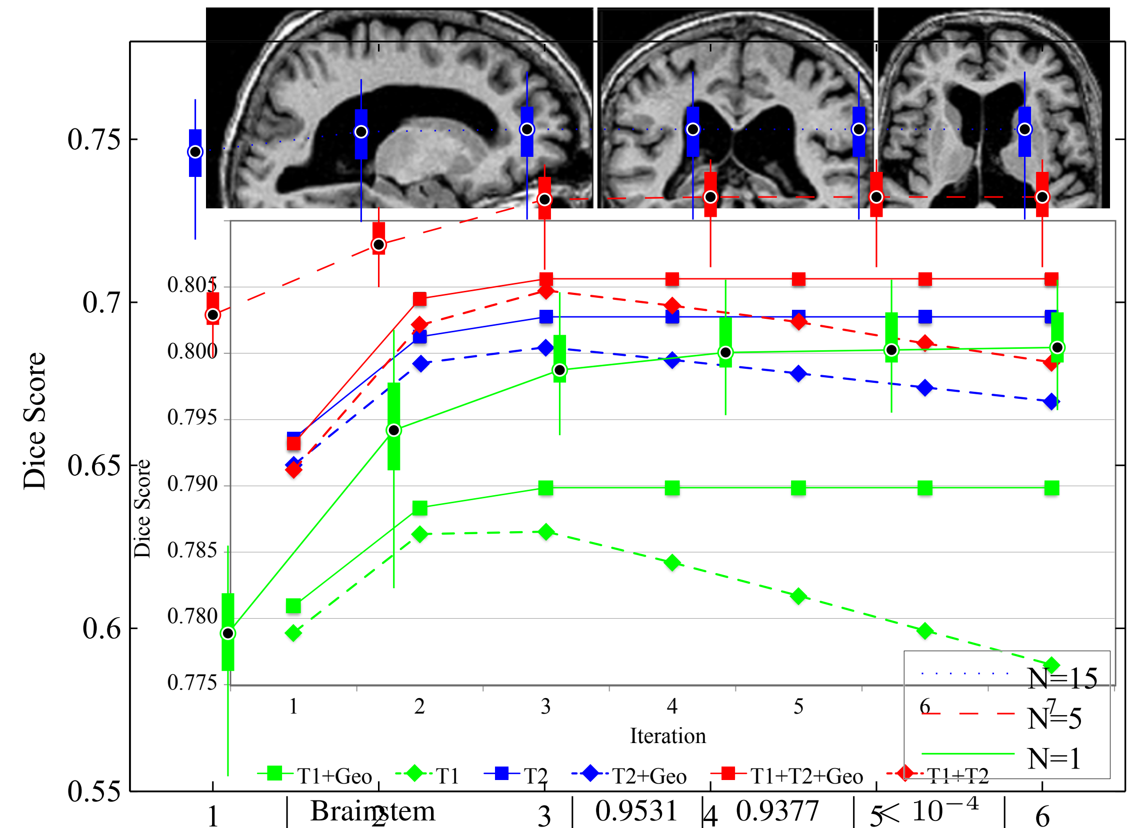
$$\mathcal{L}_i(\vec{v}) = \frac{\sum W_{ij}(\vec{v})\mathcal{L}_{i;}(T_{ij}(\vec{v}))}{\sum W_{ij}(\vec{v})},$$

- As higher proximity to the source of information will result in higher weights, the information will propagate faster using G, analogously to a fast marching wave front propagation.

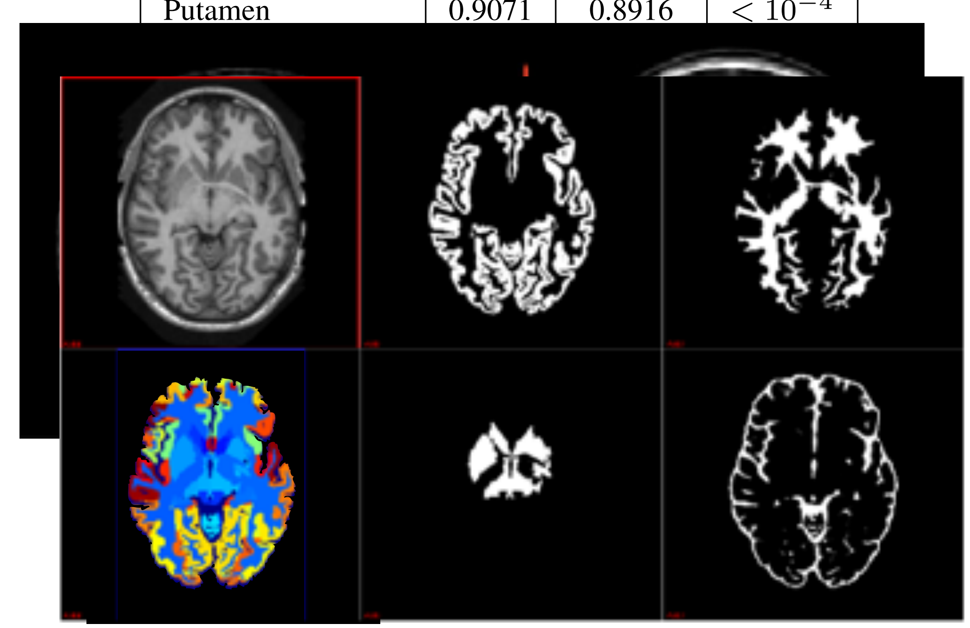
Information Propagation for Labels

Some experiments

- Hammers
  - 30 subjects, young controls
  - Parcellation into 82 labels
  - Leave-one-out cross validation
  - Comparison to MAPER
- ALBERT
  - 20 T1- and T2-weighted MRI images
  - 5 term subjects and 15 preterm subjects
  - 50 key structures
  - Advantages of using multimodal data
- Oasis/Neuromorphometrics
  - 35 Subjects
  - 143 regions
  - Ability to extrapolate results



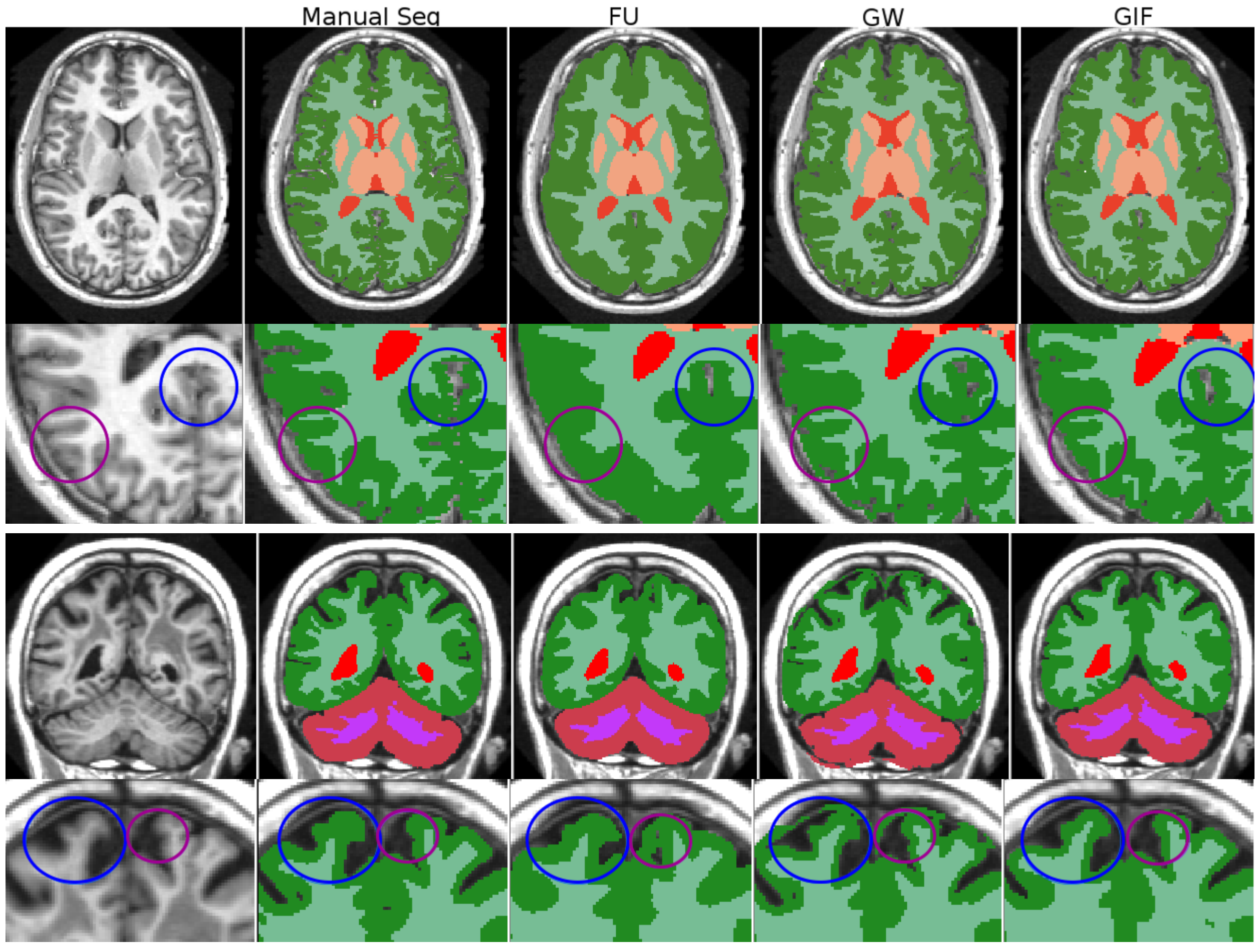
Brainstem	0.9531	0.9377	$< 10^{-4}$
Structure	Left Side		
	GIF	MAPER	p-value
Hippocampus	0.8442	0.8335	0.0046
Amygdala	0.8263	0.7922	$< 10^{-4}$
Cerebellum	0.9712	0.9664	0.0020
Caudate nucl.	0.8985	0.8923	0.0370
Nucleus acc.	0.7582	0.6834	$< 10^{-4}$
Putamen	0.9071	0.8916	$< 10^{-4}$



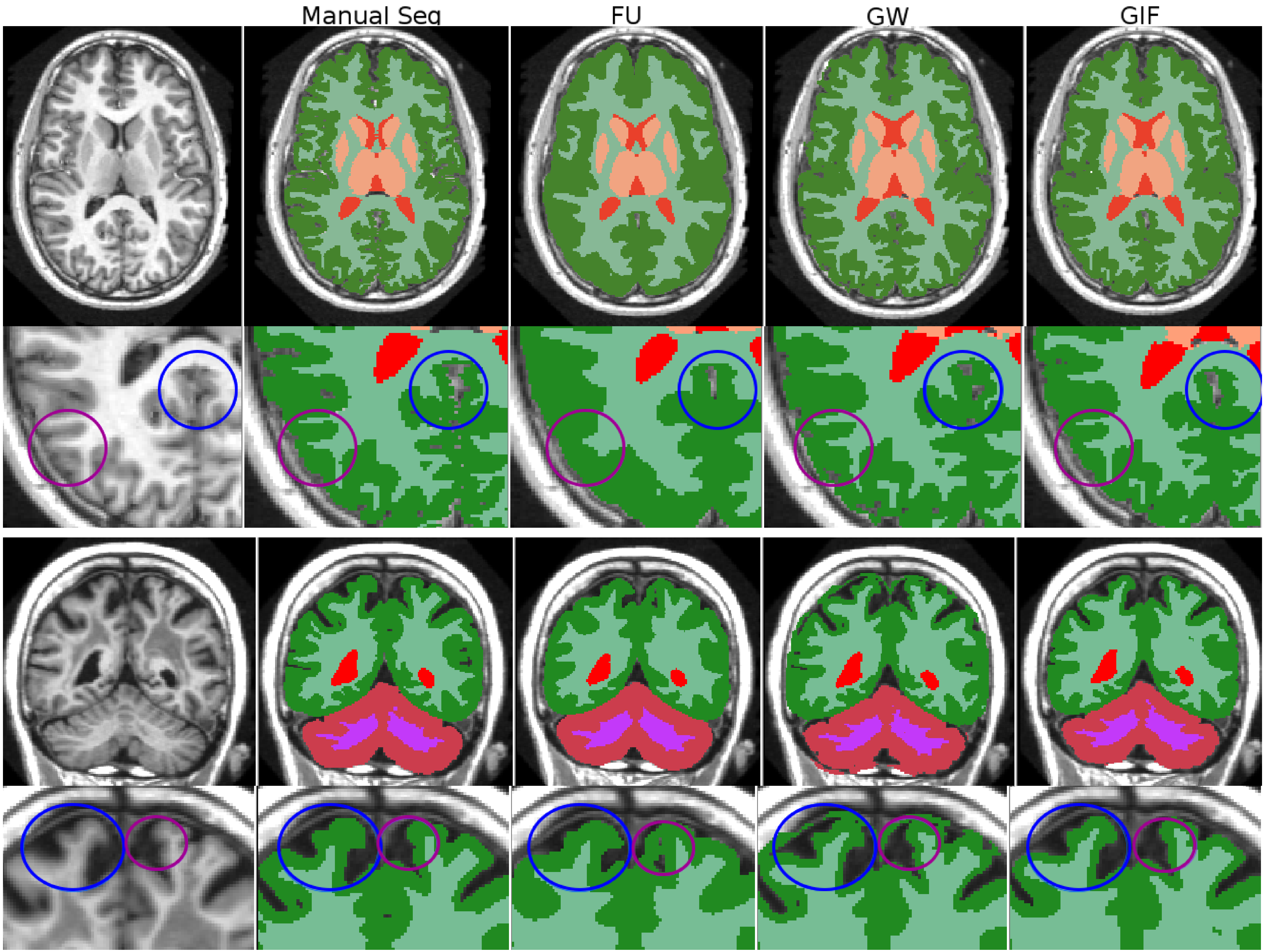
Oasis Experiment

Full Data	Cortical GM			Cortical WM			Cerebellar GM			Cerebellar WM			Deep GM		
	FU	GW	GIF	FU	GW	GIF	FU	GW	GIF	FU	GW	GIF	FU	GW	GIF
Average	0.863	0.912	**0.925**	0.879	0.930	**0.940**	0.924	0.927	**0.933**	0.880	0.905	**0.921**	**0.894**	0.825	0.849
Std	0.018	0.025	0.018	0.011	0.015	0.013	0.019	0.029	0.016	0.007	0.008	0.008	0.009	0.019	0.014
p-value	$<10^{-4}$	$<10^{-4}$	-	$<10^{-4}$	$<10^{-4}$	-	$<10^{-3}$	$<10^{-4}$	-	$<10^{-4}$	$<10^{-4}$	-	$<10^{-4}$	$<10^{-4}$	-

Limited Data	Cortical GM			Cortical WM			Cerebellar GM			Cerebellar WM			Deep GM		
	FU	GW	GIF	FU	GW	GIF	FU	GW	GIF	FU	GW	GIF	FU	GW	GIF
Average	0.833	0.805	**0.915**	0.848	0.832	**0.936**	0.916	0.881	**0.912**	0.877	0.866	**0.933**	**0.873**	0.789	0.844
Std	0.017	0.043	0.023	0.010	0.039	0.015	0.011	0.018	0.014	0.018	0.033	0.022	0.040	0.083	0.027
p-value	$<10^{-4}$	$<10^{-4}$	-	$<10^{-4}$	$<10^{-4}$	-	$<10^{-4}$	$<10^{-4}$	-	$<10^{-4}$	$<10^{-4}$	-	$<10^{-4}$	$<10^{-4}$	-

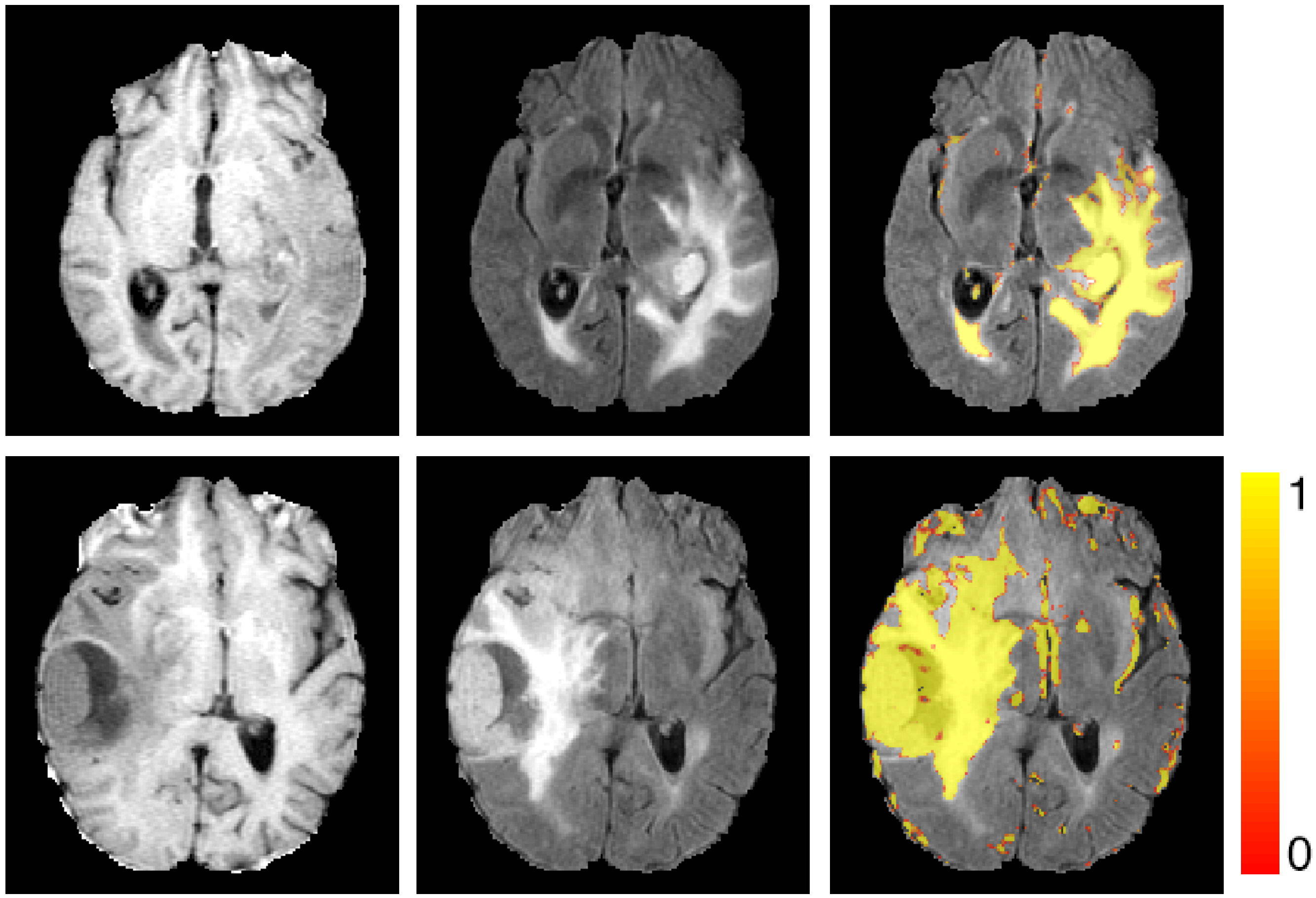


Oasis Experiment

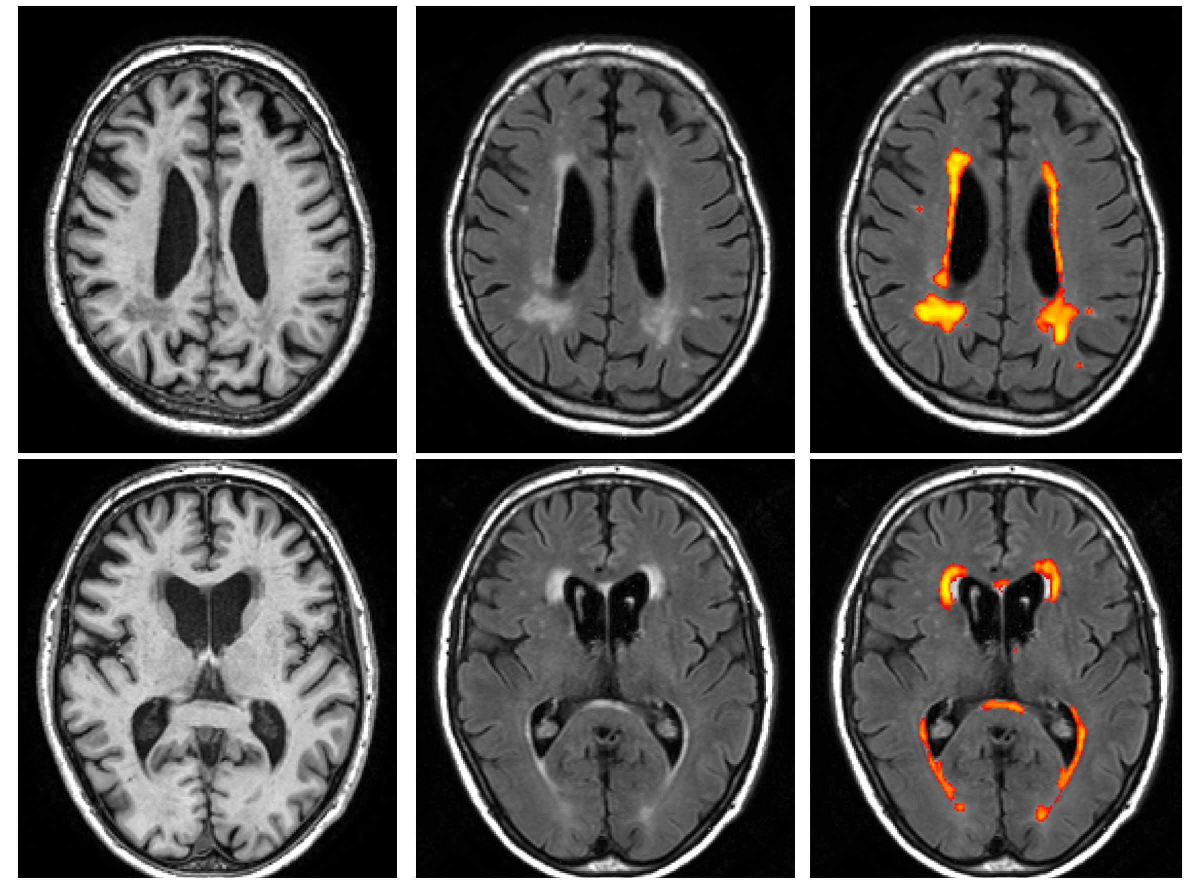


Information Propagation for out-of-model predictions

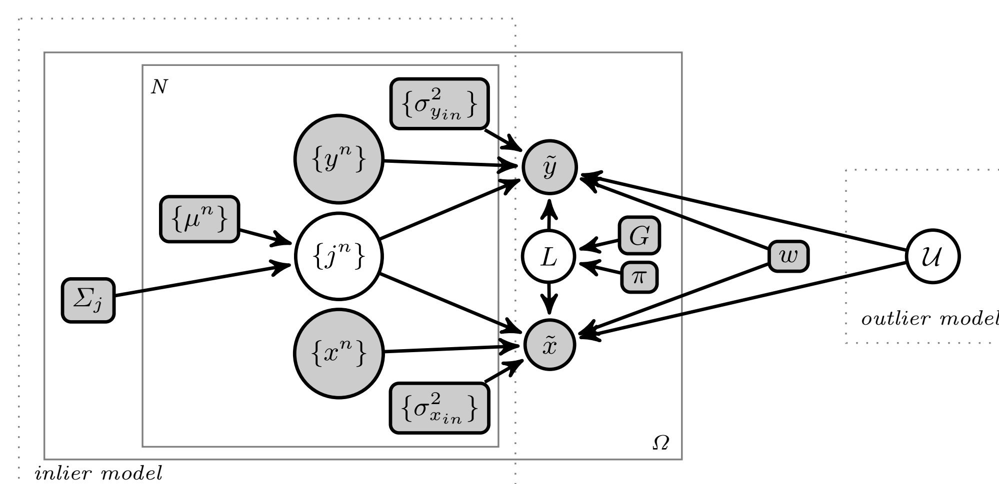
Complex Pathologies



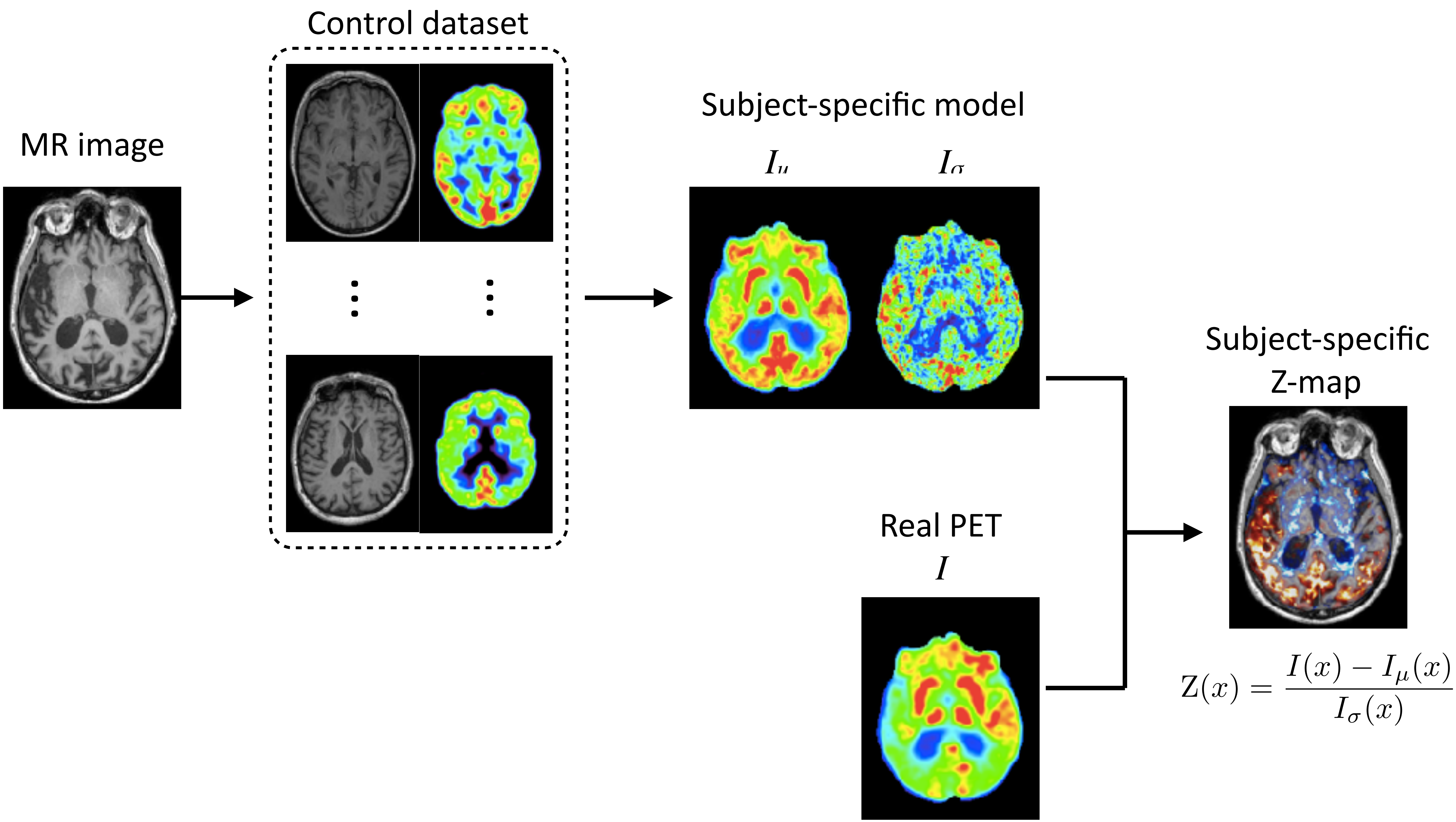
Subtle Pathologies



Possible triage system for acute pathology?



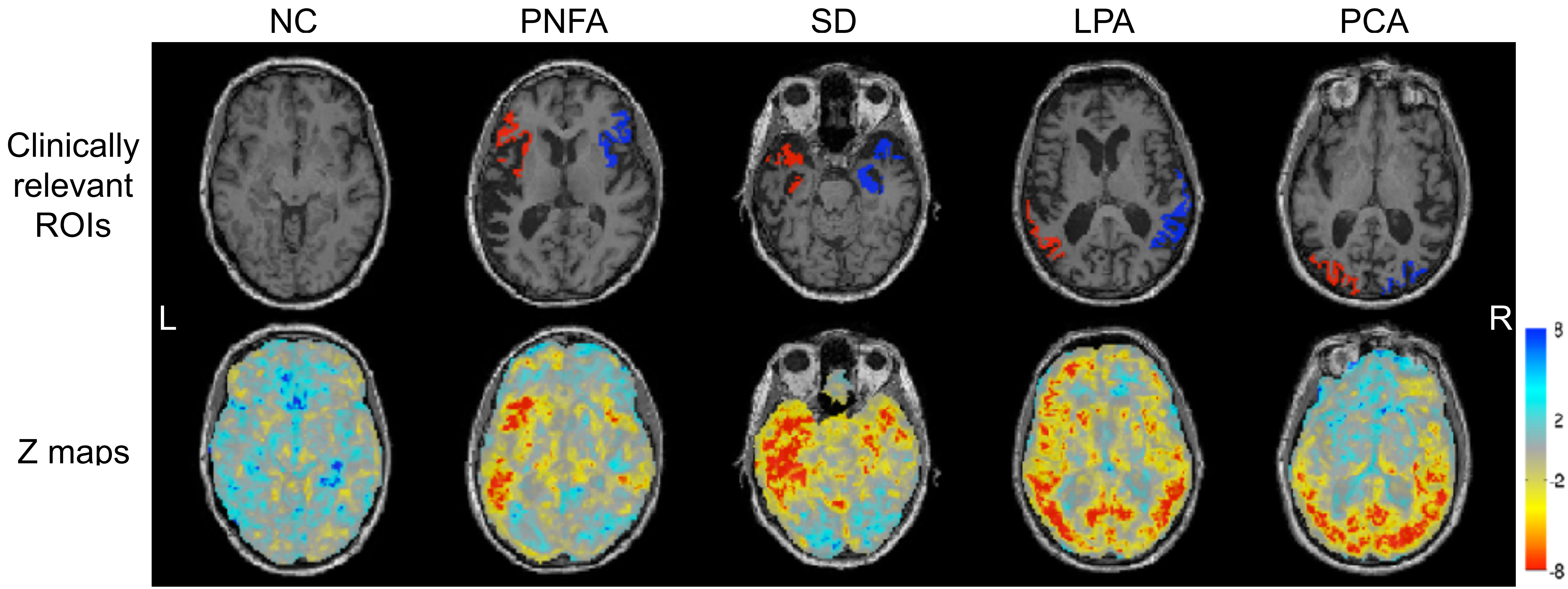
Synthesis for abnormality detection in PET



$$Z(x) = \frac{I(x) - I_\mu(x)}{I_\sigma(x)}$$

Voxel-wise subject-specific analysis

- Subject-specific Z-maps



T1 images overlaid with the selected ROIs (top) and the patient-specific Z-scores (bottom) for a representative subject of each condition.

NC: normal control - PNFA: progressive nonfluent aphasia - SD: semantic dementia
LPA: logopenic progressive aphasia - PCA: posterior cortical atrophy

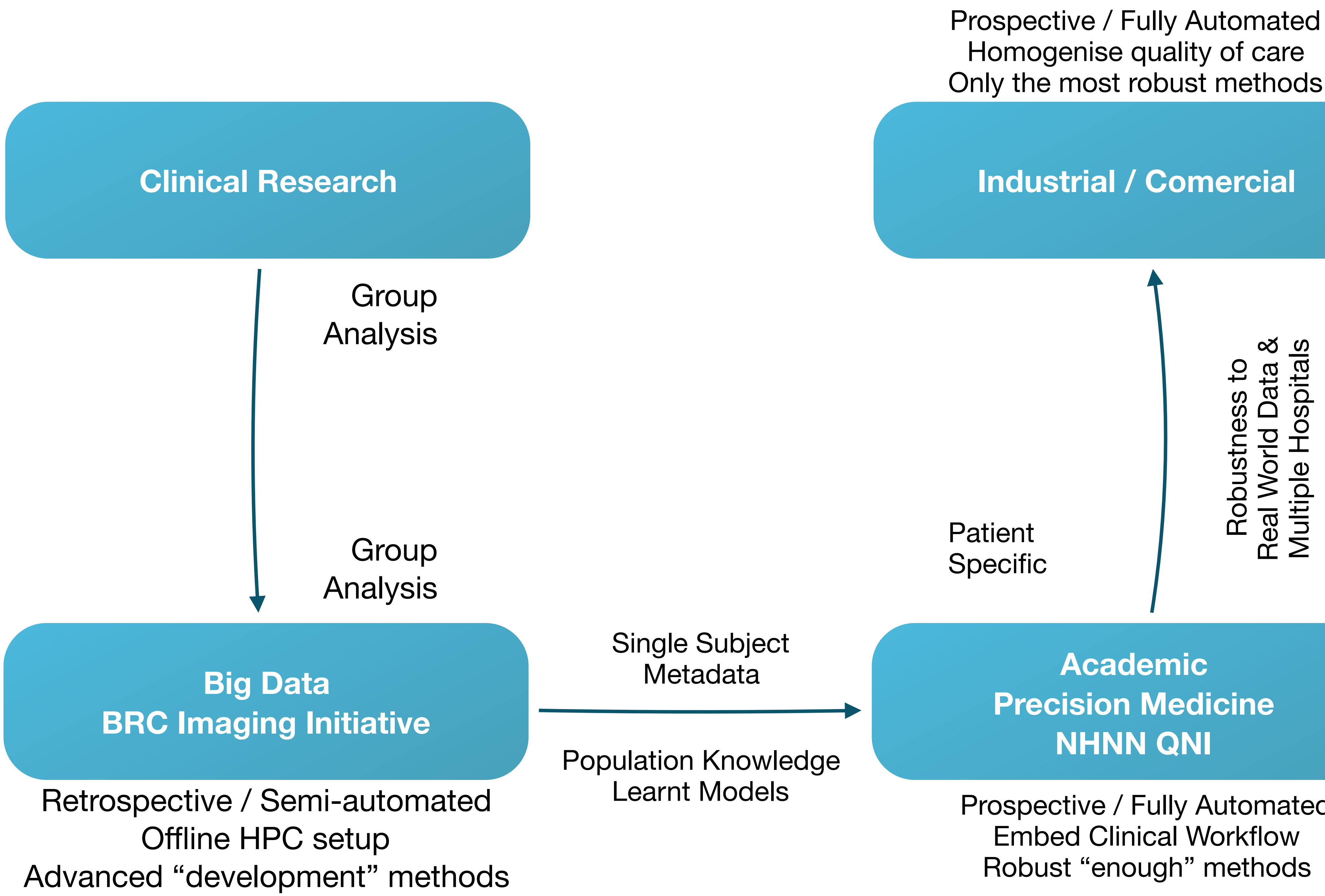
Advantages/Disadvantages

- Disadvantages:
  - Computational complexity - 1h30min @ 8 cores (pairwise registration)
    - Can be greatly speed up - scales linearly with the # of cores

- Advantages (Methods):
  - Flexible - multiple applications, e.g. Image synthesis, sVBM
  - Geodesic - Implicitly handles limited training data
  - Accuracy - Geodesic propagation provide highest accuracy
  - Unbiased - Symmetry by construction

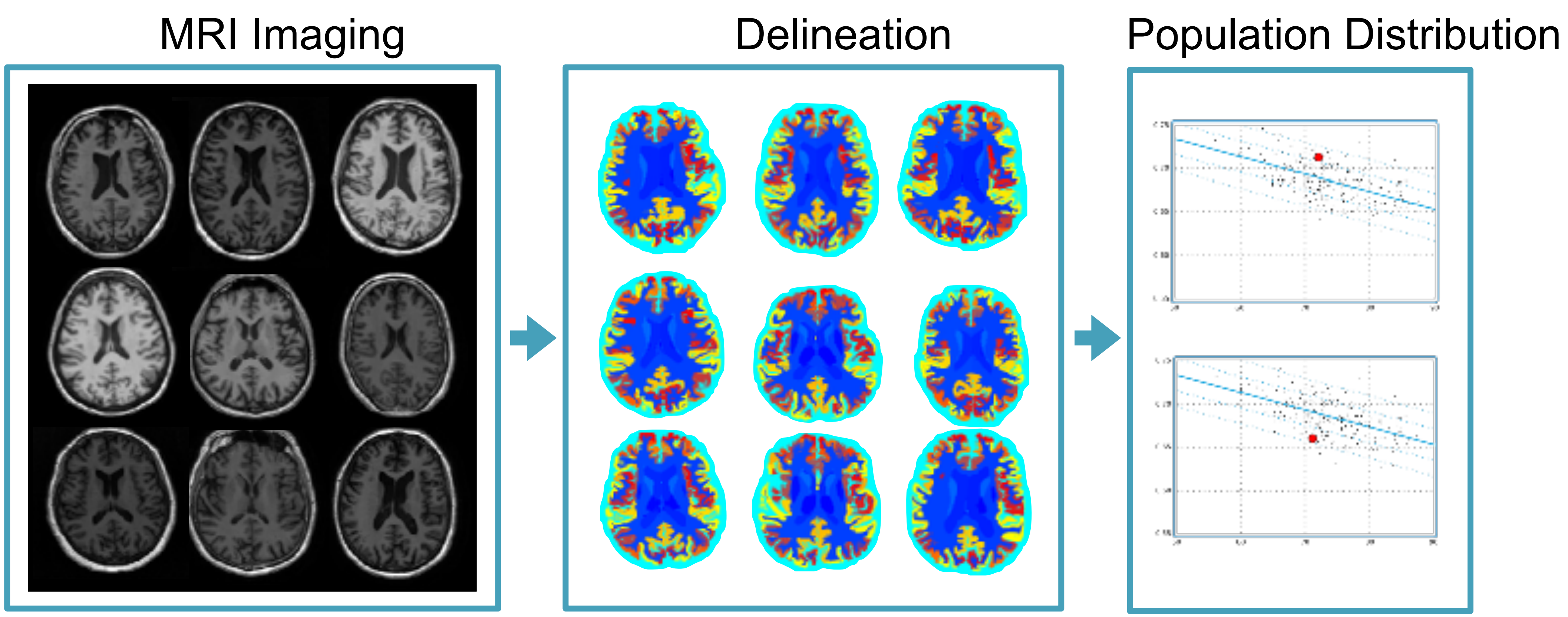
- Advantages (Software):
  - Fully automated while still allowing QC
  - Windows/Linux/OSX support
  - Will be part of NiftySeg

UCL TIG Translational Pathway



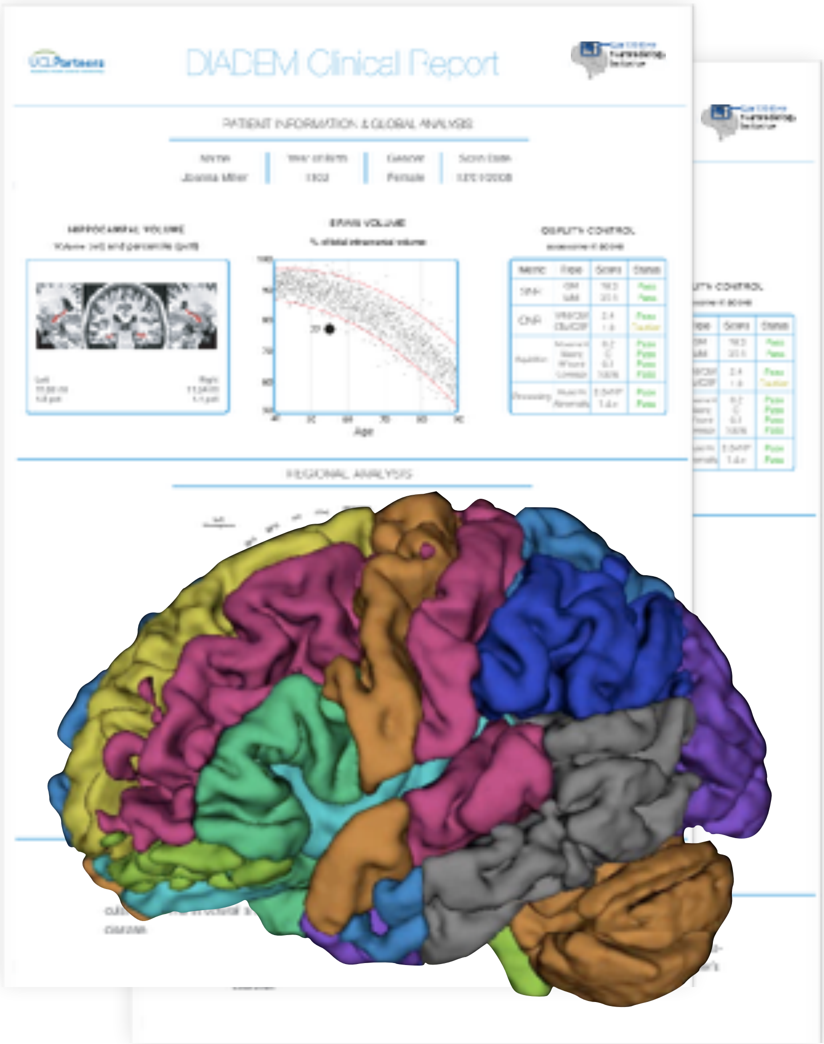
Population Analysis

- Select:
  - Large Radiologically normal population
    - 40000 Radiologically Normals or 6207 Asserted Normals
  - Research grade database (ADNI?)
    - ~500 controls
- Regional GLM with Age, Sex, TIV and Scanner as covariates



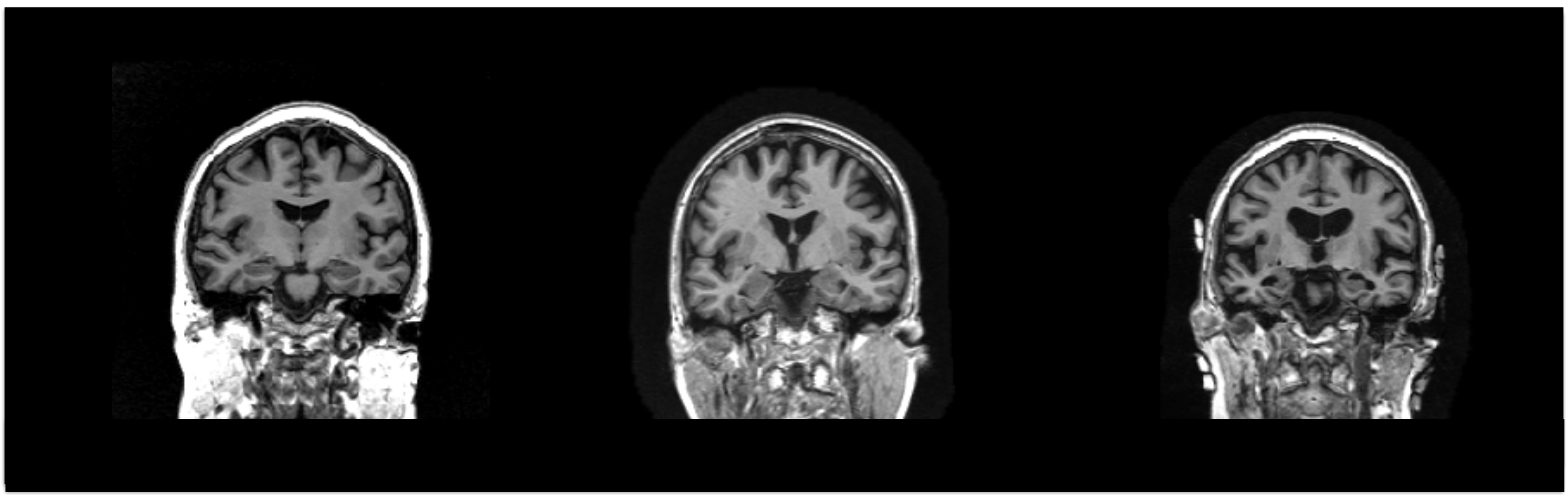
Quantitative Neuroradiology Initiative

- Patient-specific phenotyping tools for clinical data
- The Data
  - Can be low resolution (slice thick. 3/5/7mm)
  - Artefacts
  - Inconsistent scanning parameters
  - Inconsistent availability of modalities
- Homogenising data acquisition across sites
  - Quality Control/Assurance, data identification
- Extracted metadata is integrated into a clinical report
- Collaboration with ION & NHNN



Translation to Clinical Usage

- Automatic generation of QNI report using clinical data



Healthy | Early Alzheimer's Disease | Alzheimer's Disease

Translation to Clinical Usage

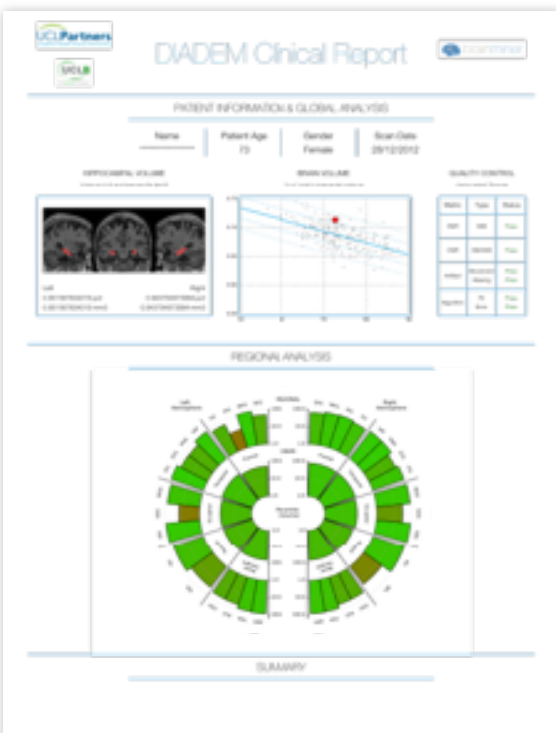
- Automatic generation of QNI report using clinical data

1 - Image Acquisition

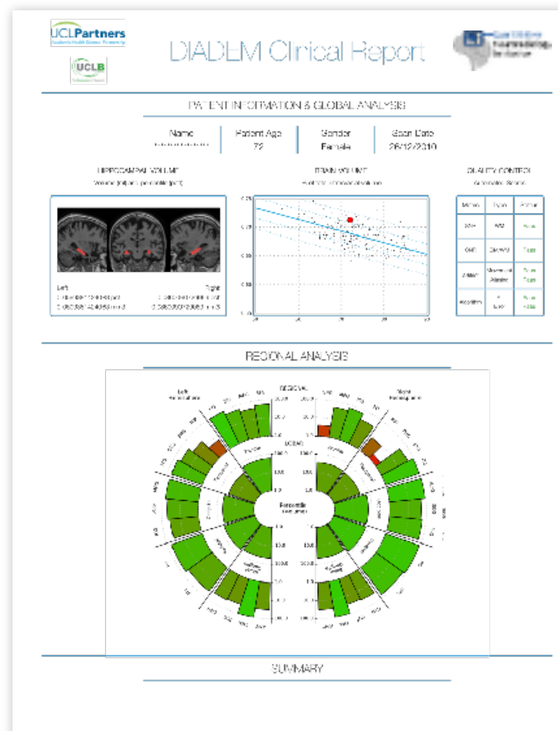
2 - Automated quality control & biomarker estimation

3 - Automated clinical report & comparison to healthy population

4 - Quantitative neuroradiology & improved patient care



Healthy



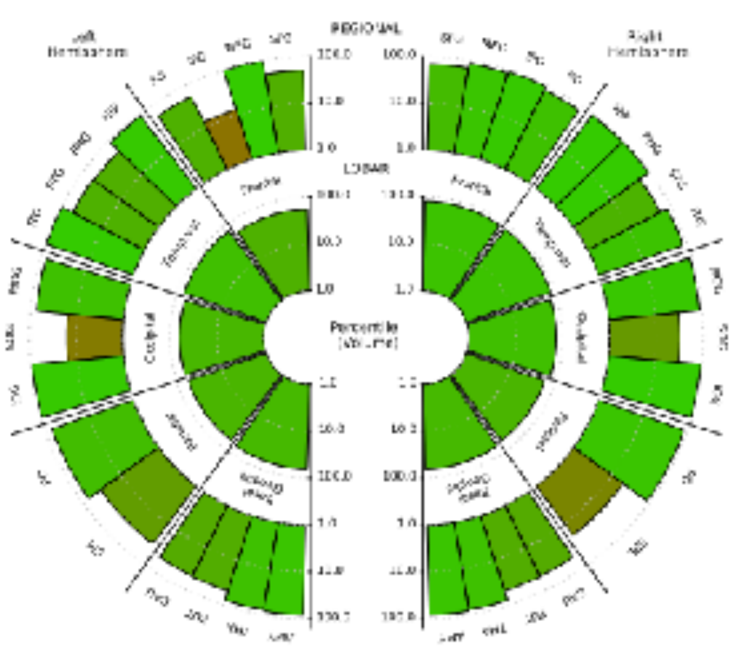
Early Alzheimer's Disease

Alzheimer's Disease

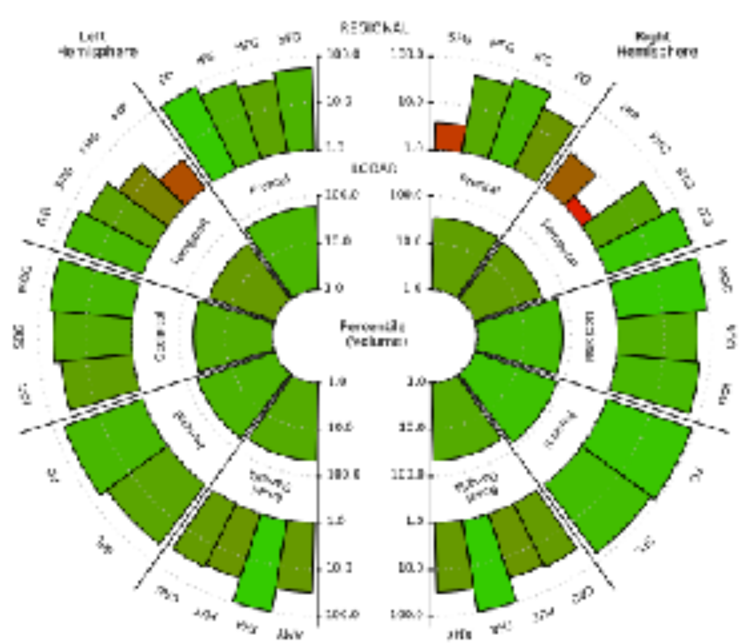
Translation to Clinical Usage

- Automatic generation of QNI report using clinical data

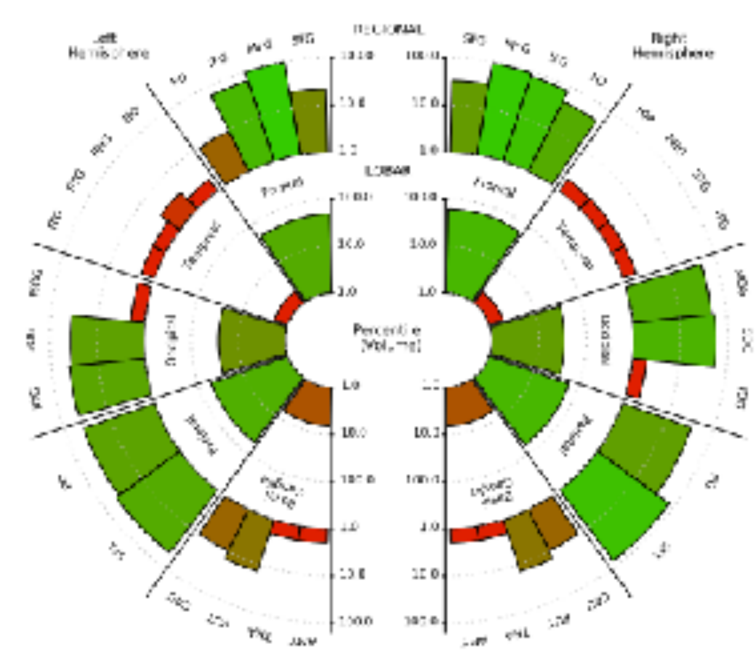
1 - Image Acquisition | 2 - Automated quality control & biomarker estimation | 3 - Automated clinical report & comparison to healthy population | 4 - Quantitative neuroradiology & improved patient care



Healthy



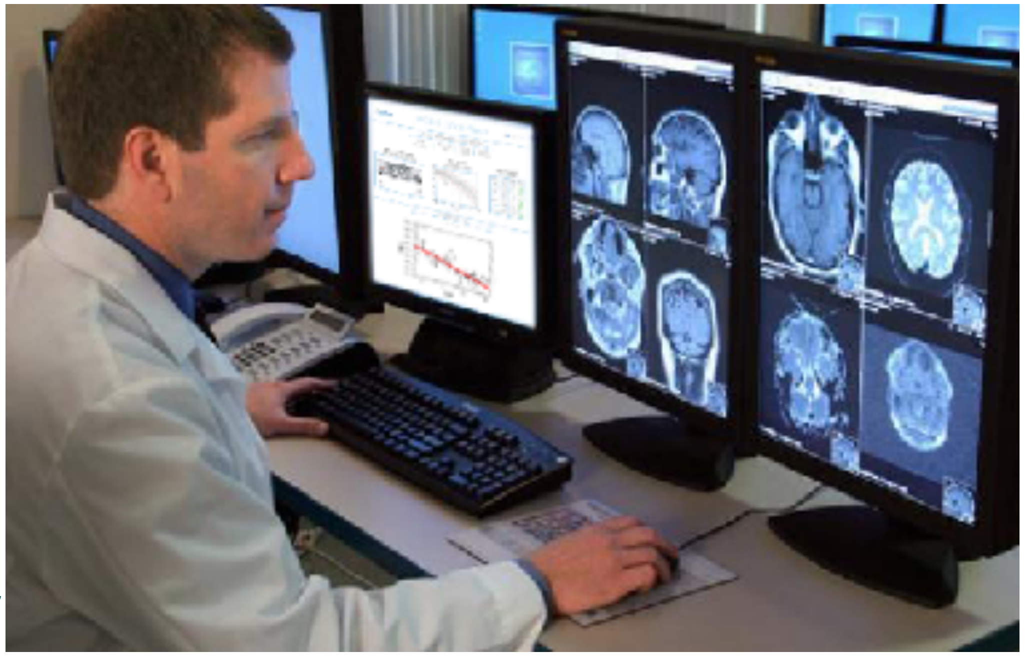
Early Alzheimer's Disease



Alzheimer's Disease

Translation to the Real World

- Validation and Safety Case
  - Stringent testing process to support the safety case
  - Need to test in relevant environment
  - Broad accuracy study
- Integration into the Neuroradiological workflow
  - – Deploy results into reporting platform
    - – Disease specific biomarkers
    - – Available at reporting time (HPC)
  - – Push to patient health care record
    - – Available to referring physician
    - – Retrievable for longitudinal analysis



NiftyNet

An open-source community-driven framework for neural networks in medical imaging

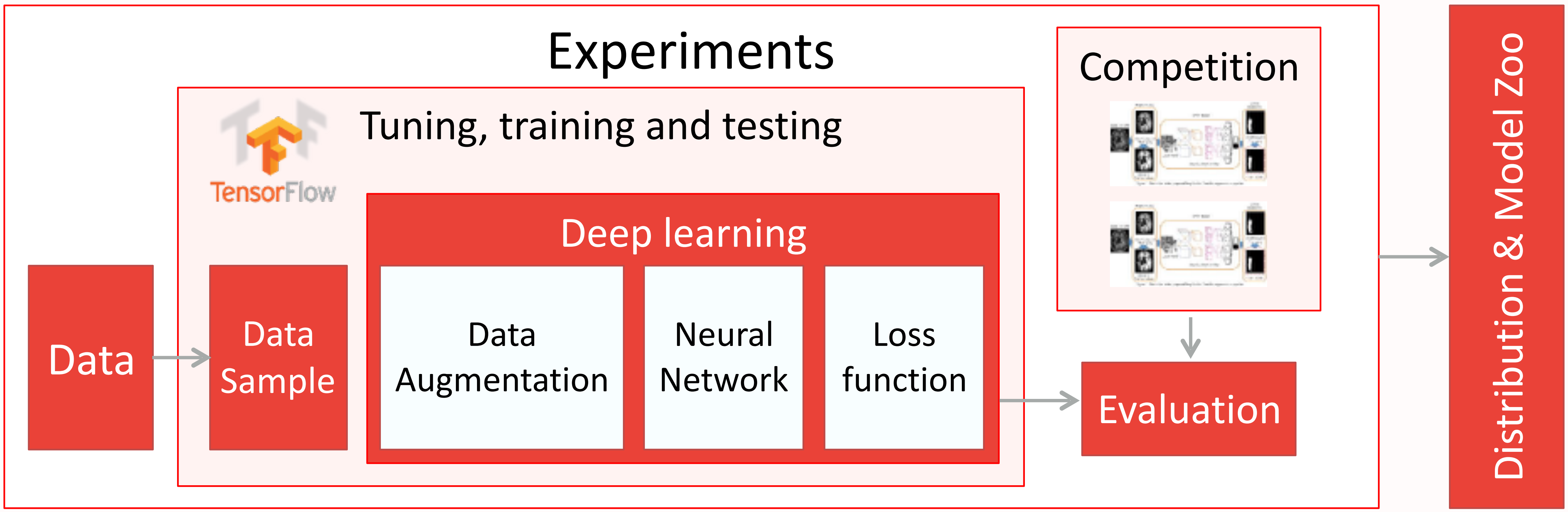
www.niftynet.io

What is NiftyNet?

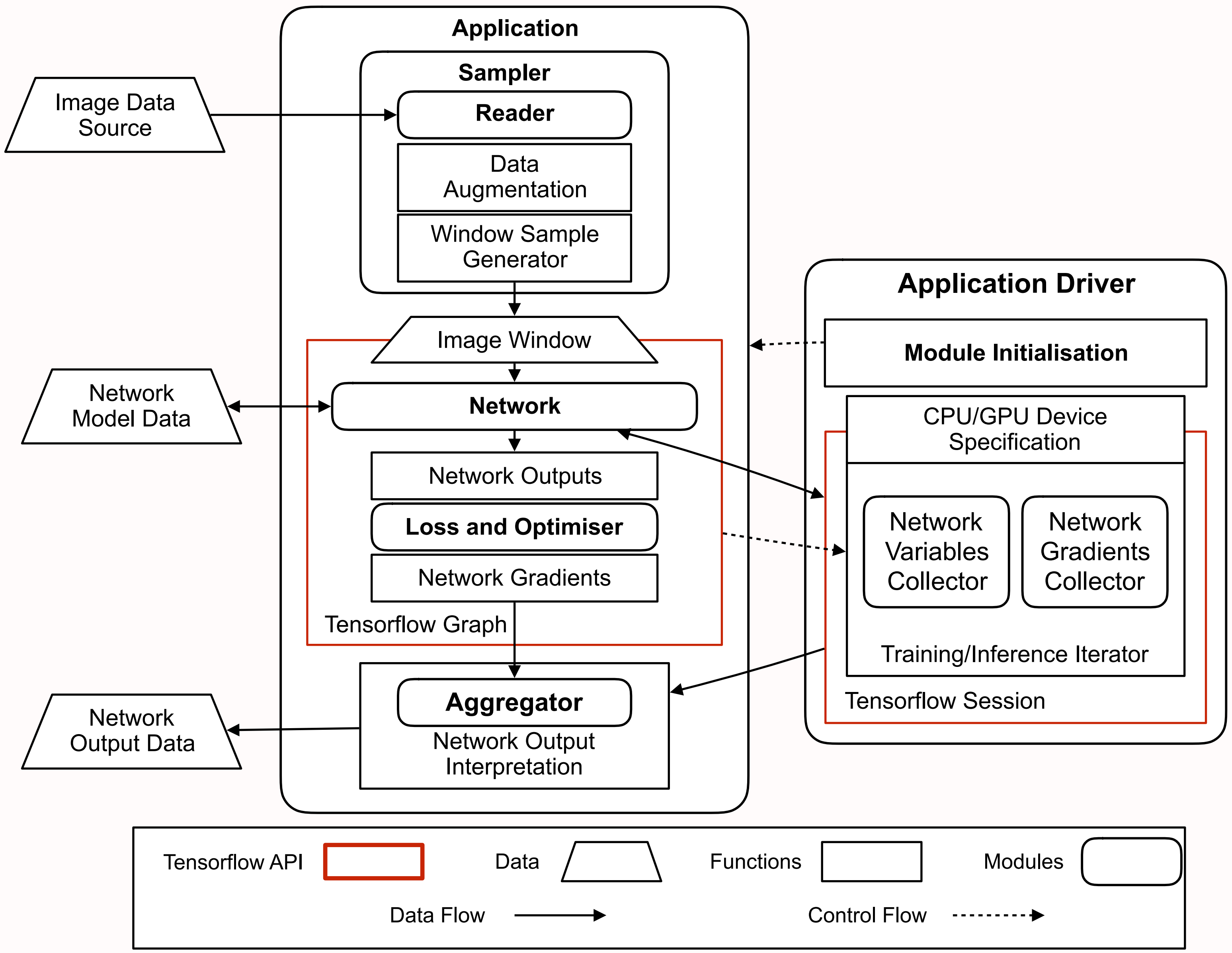
- An open-source library for convolutional networks in medical image analysis

= TensorFlow × Medical image domain knowledge

- Apache-2.0 licensed
- Easy-to-customise interfaces of network components
- Dissemination of architectures and pre-trained models
- Support for 2-D, 2.5-D, 3-D, 4-D inputs
- Multiple-GPU and tensorboard support
- Implementation of SOTA networks, loss functions, samplers, etc

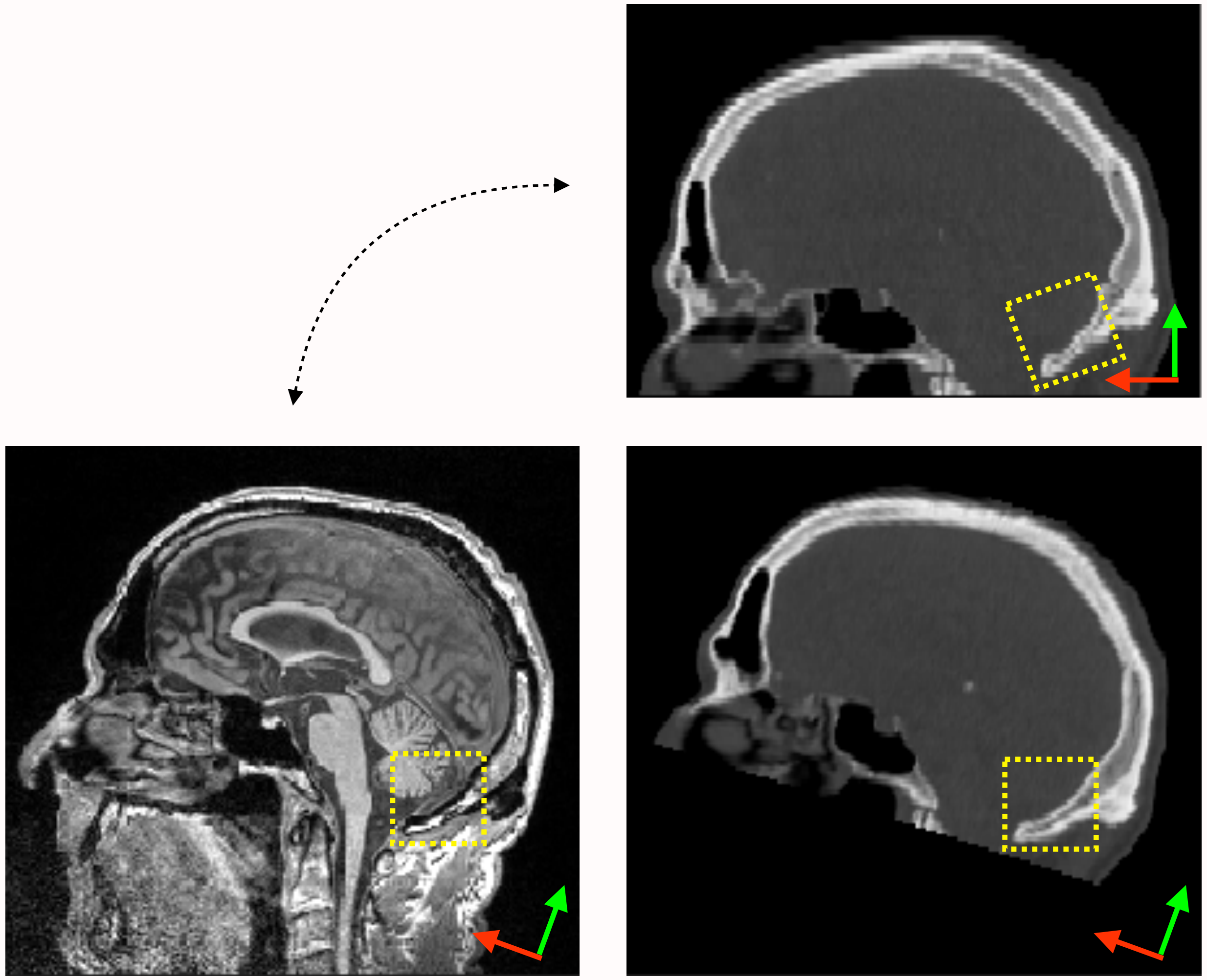

Experiments
Tuning, training and testing
TensorFlow
Deep learning
Data
Data Sample
Data Augmentation
Neural Network
Loss function
Competition
Evaluation
Distribution & Model Zoo

- MultiGPU Driver
- I/O
  - Volume loader
  - Augmentation
  - Patch sampling
  - Outputs Aggregation
- Network model
  - Params. management
  - Layer operations
  - Loss functions
- Evaluation
- Applications
- Model Zoo



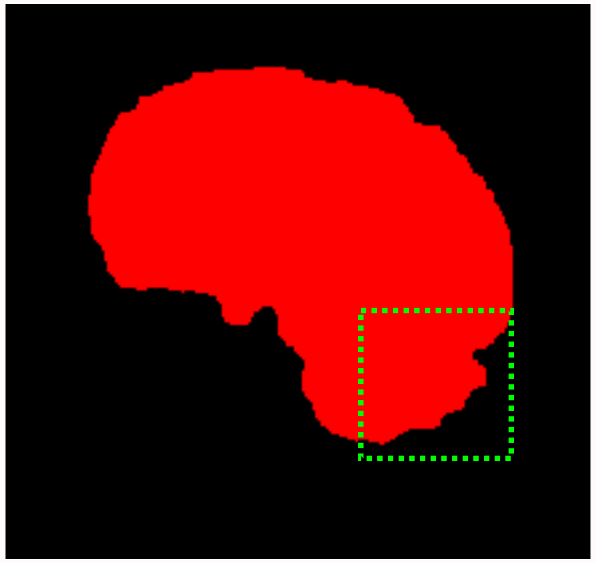
I/O: Image Loader

- Multi image-format loader
  - Uses tf.data API
- Supports multimodal inputs
  - Internally or externally
  - Resolution matching
- Handling a set of image volumes
  - Subject or filename grouping
  - Handling missing modalities
- Preprocessing
  - Handling NIfTI/MHD/DICOM file headers
    - Resampling
    - Reorientation
    - Lazy Sampling
  - Intensity normalisation



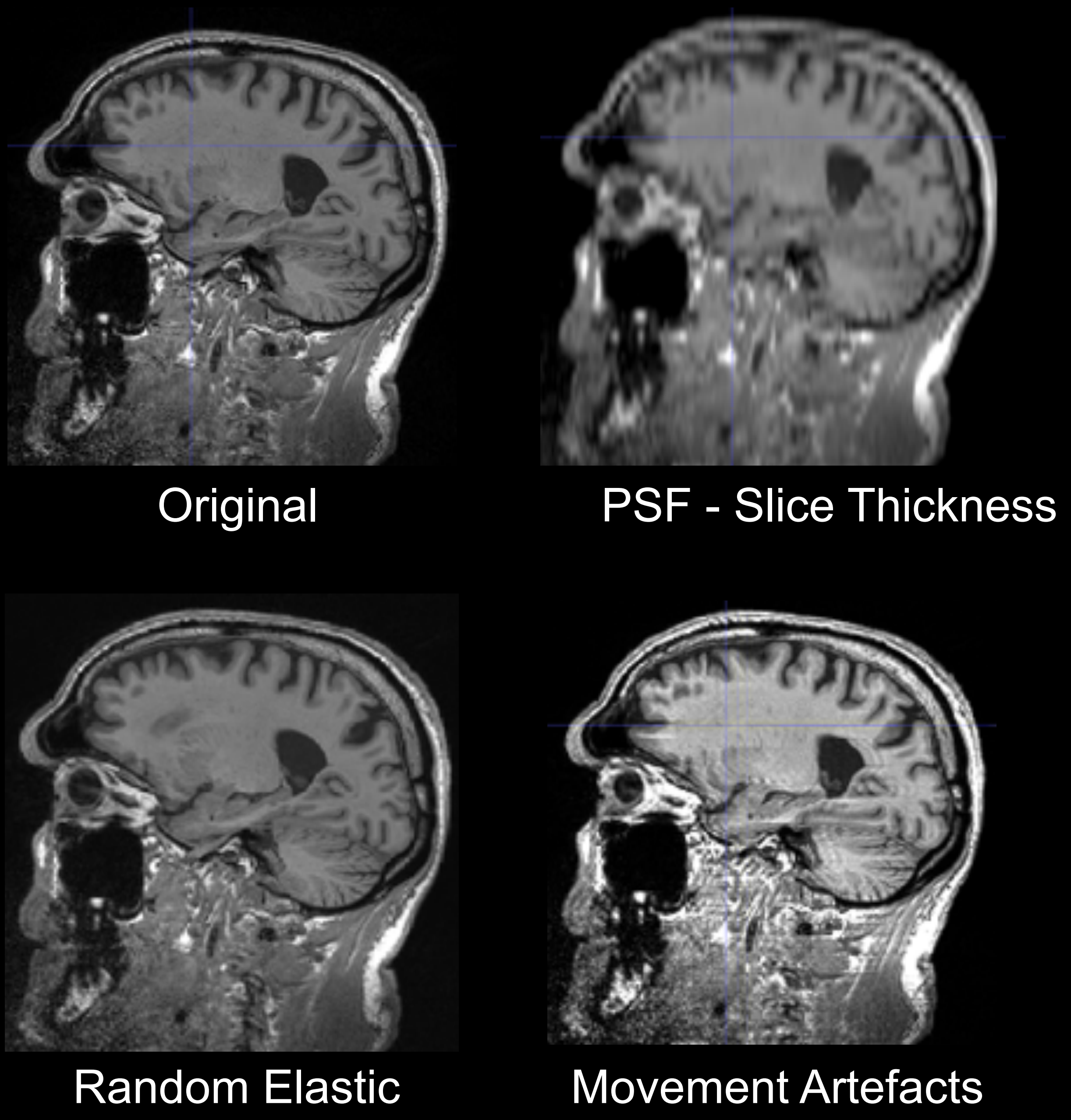
I/O: Window Sampling and Output Agregation

- Window properties
  - Size in “voxels”
  - Size in “mm”
  - Augmentation by composition
- Sampling
  - Uniform
  - Label Constrained
    - Sample only from areas with specific labels
    - Prescribe certain label sampling rates
  - Frequency Sampler
    - Sample a location given an externally defined map
    - Sample from locations with large errors
- Aggregation
  - Uniform & Overlapping (Effective Receptive Field)
  - Uncertainty Sampling



I/O: Data augmentation

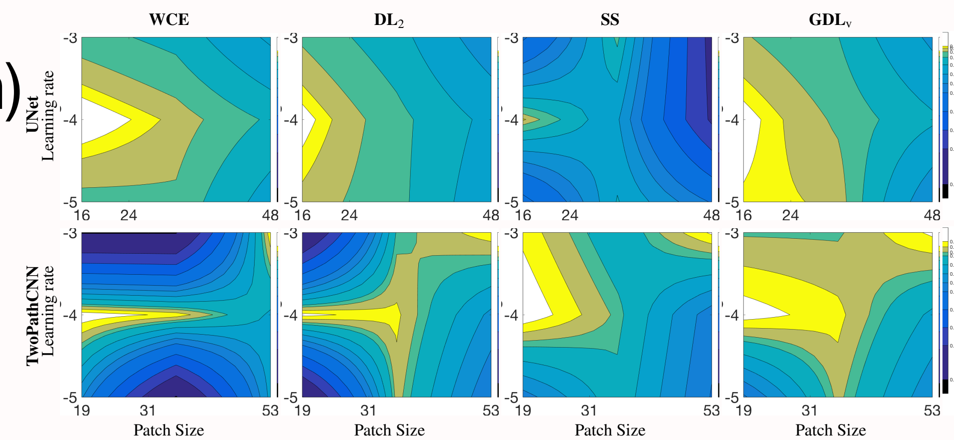
- Training with data augmentation
  - Application-dependent
- Geometrical augmentation
  - Rotation, Translation, Mirror
  - Random elastic deformation
  - Biologically-inspired elastic deformation
- Intensity augmentation
  - Histogram/Physics
  - Noise
  - Point-spread-function
  - Artefacts
  - Pathology/lesions



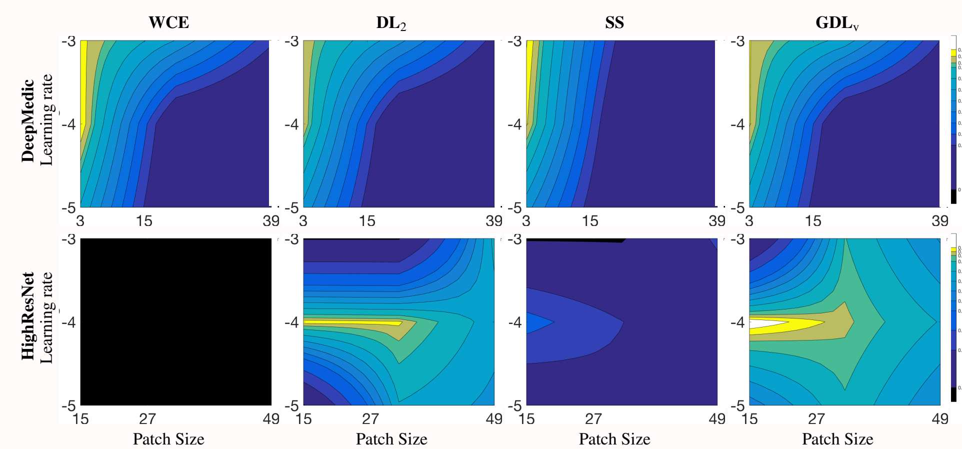
Network: Designing loss functions

- Losses:
  - Categorical
    - Cross-Entropy
    - Dice (Standard, Generalised, Wasserstein)
    - Sensitivity/Specificity
  - Continuous
    - L2/L1
    - Huber
  - Adversarial
  - Variational
    - KLD
- Metrics
  - Image-wide
  - Voxel-wise
  - Weighted & probabilistic losses

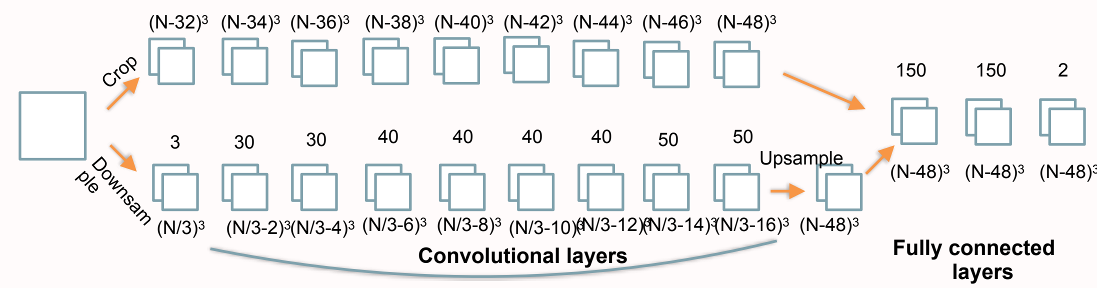
2D

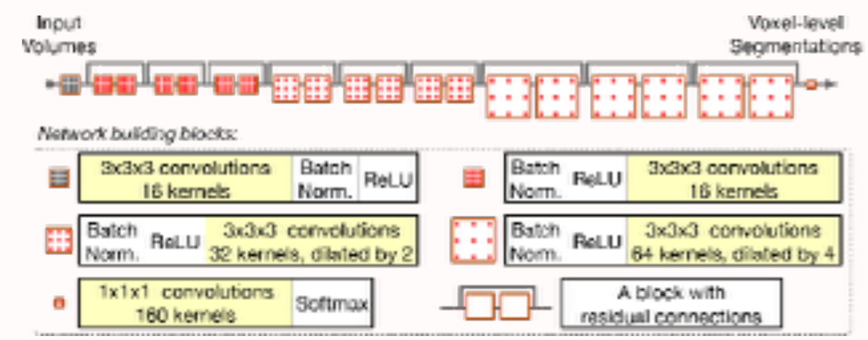


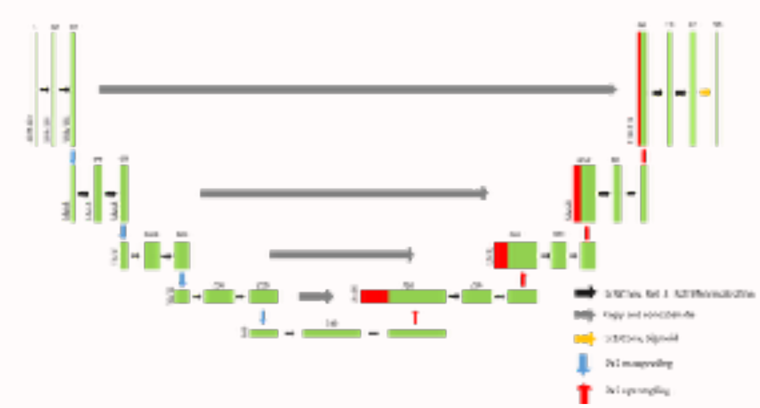
3D



- Image-to-image: 2D, 3D, 4D (multimodal)
  - UNet
  - VNet
  - Highway Network
  - DeepMedic
  - HighResNet
- Generative/AutoEncoders
  - AE, dAE, VAE
  - GAN
- Image-to-label
- Multi-task

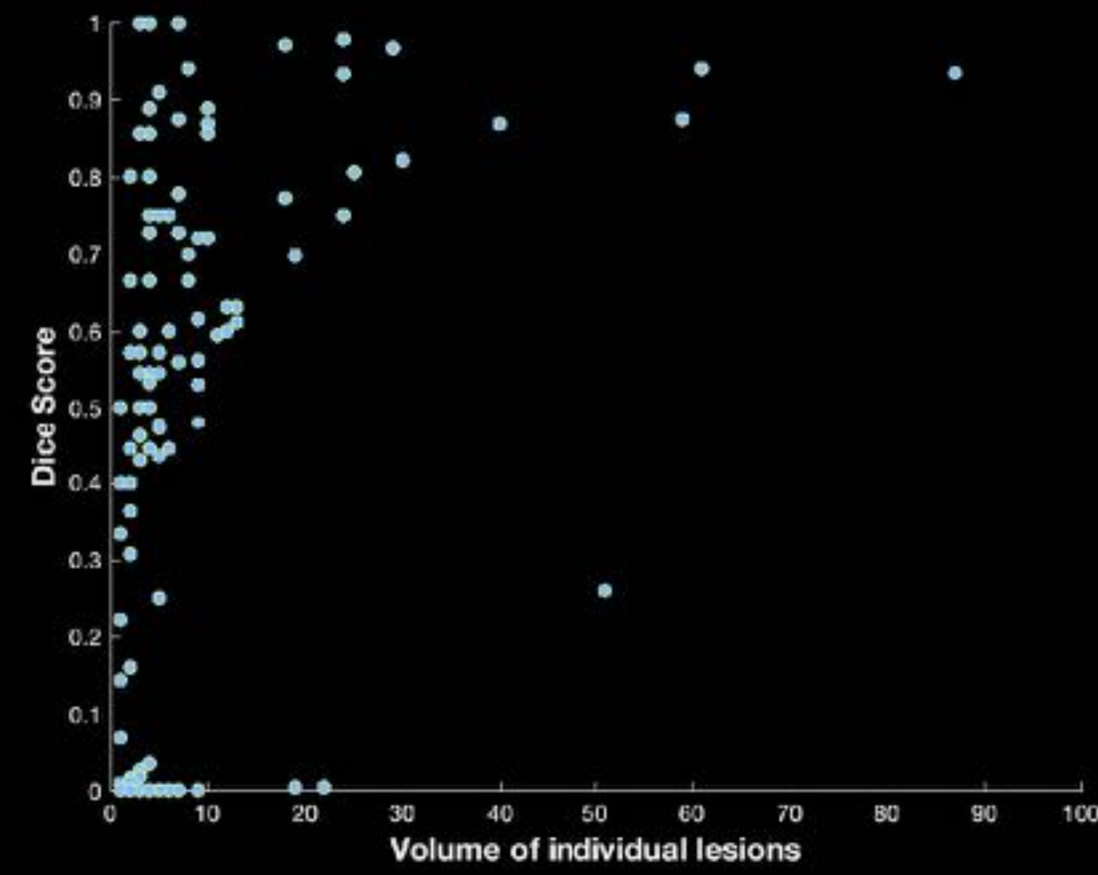


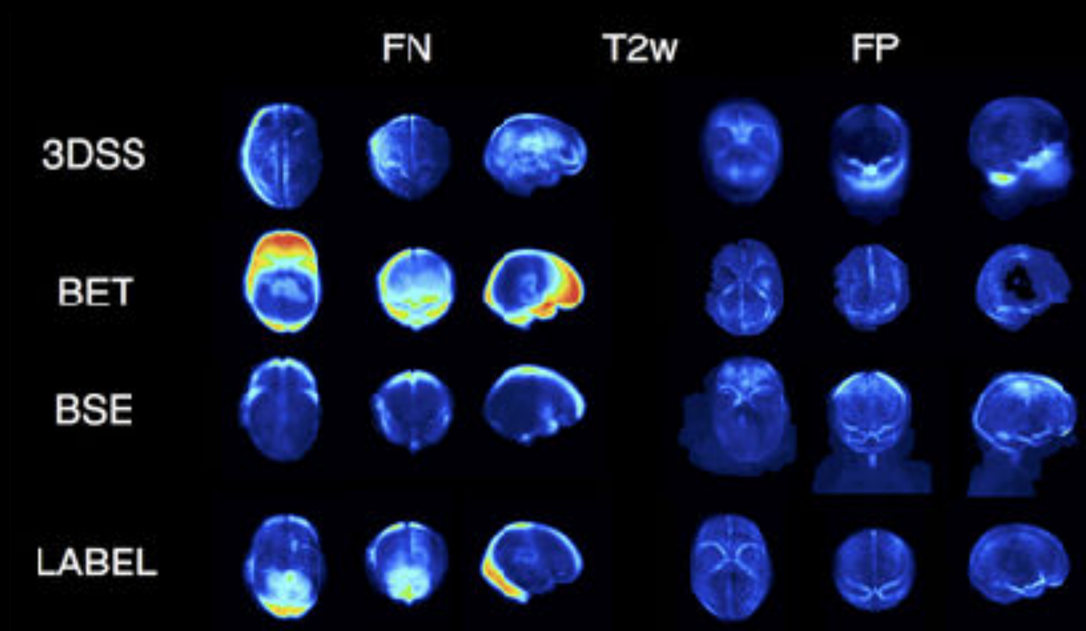




Evaluation: Standardised and Validated

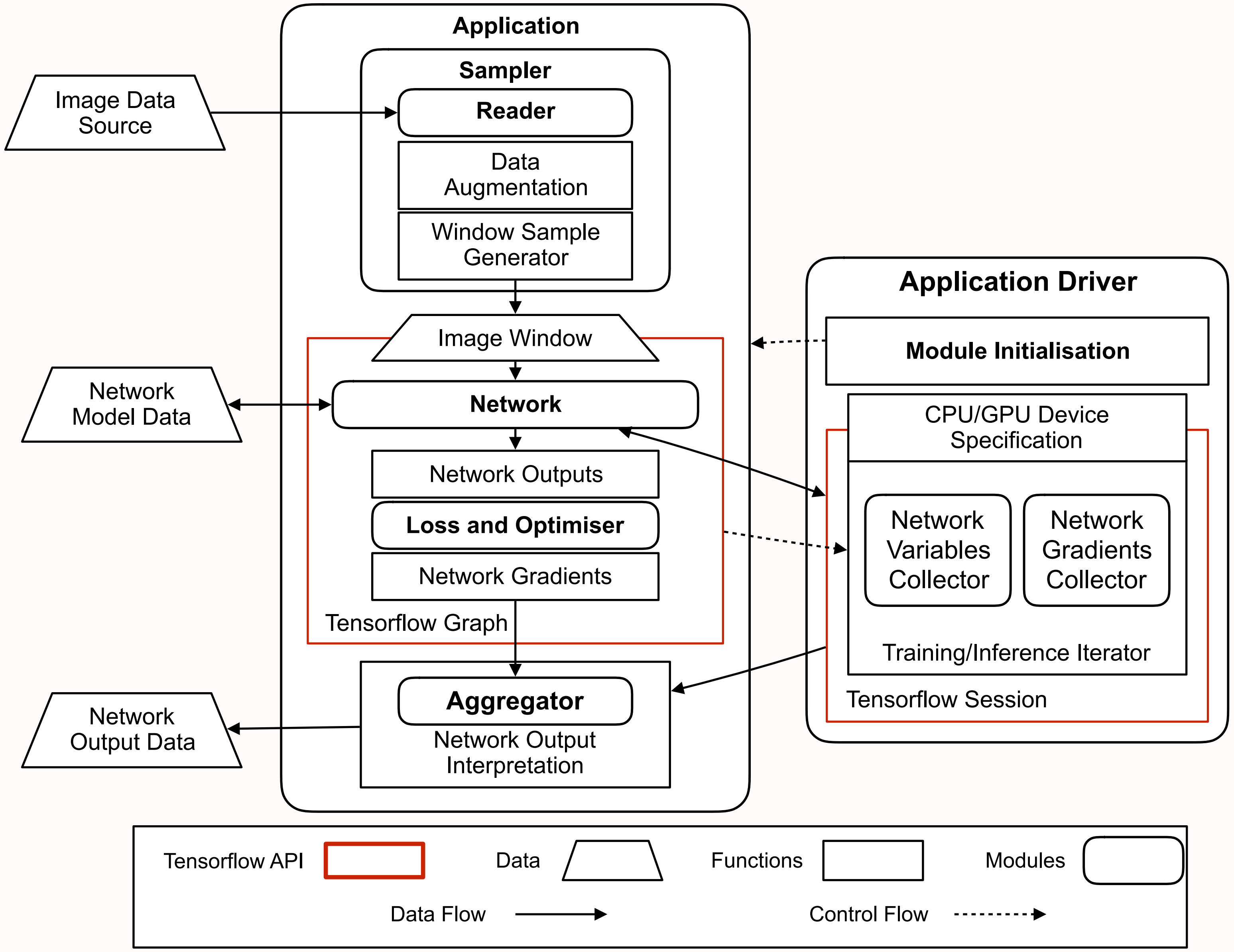
- Tensorboard Integration
- Image-level
  - Categorical
    - Overlap: Dice/Jaccard
    - Distance: Hausdorf/MSD
    - Statistical: Sensitivity/Specificity/Recovery
  - Continuous
    - Direct: Mean Absolute Error/L_2
    - Perceptual: PSNR/SSIM
- Object Level (Categorical)
  - Volume: Size
  - Overlap, Distance and Statistical metrics
  - F1 stats
- Pixel-level
  - Generation of error maps
- Hyperparameter Optimisation
  - Grid, Random and Divide-and-Conquer Search





Application: Definition

- Define task-specific elements
  - loss functions
  - window sampling schemes
  - augmentation models
  - networks
  - aggregators
- Connect data stream
- Define behaviour during
  - Training
  - Inference
  - Evaluation



Long-term goal

- A popular repository of successful deep learning models
  - Model zoo (under construction)
  - Integration into popular pipeline infrastructures, e.g NiPype
  - Offer a baseline general-purpose implementation for “simple” segmentation, regression classification tasks

- Training general medical image convnet models on large medical image repositories
  - Medical ImageNet

- NiftyNet as a consortium of research groups
  - WEISS, CMIC, HIG
  - Other groups are planning to join

- Website: www.niftynet.io
- Slack: niftynet.slack.com
- Mailing List: nifty-net@live.ucl.ac.uk

- Paper
  - Gibson and Li et al., (2017); NiftyNet: a deep-learning platform for medical imaging;
  - arXiv: 1709.03485


NiftyNet: a deep-learning platform for medical imaging

Abstract

Questions?