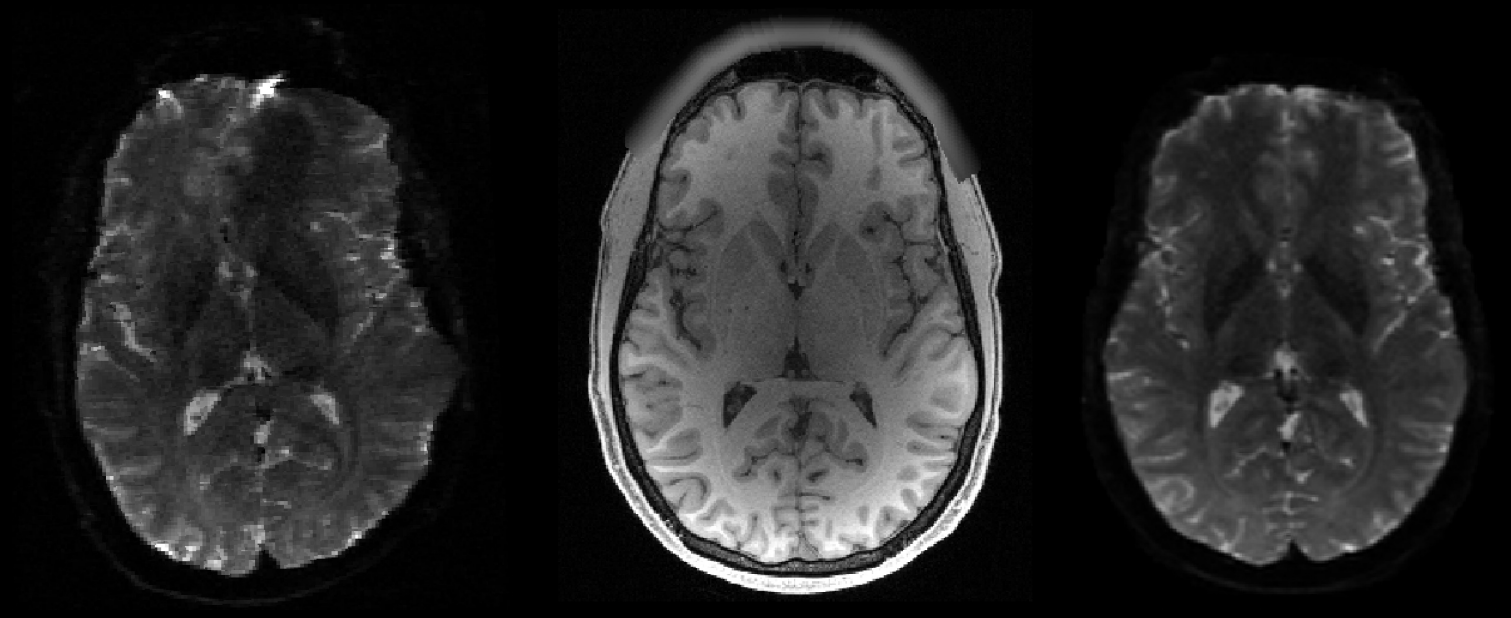


Distortion Correction of DW-MRI without Reverse Phase-encoding Scans or Field-maps

VANDERBILT UNIVERSITY
MEDICAL CENTER

MASI

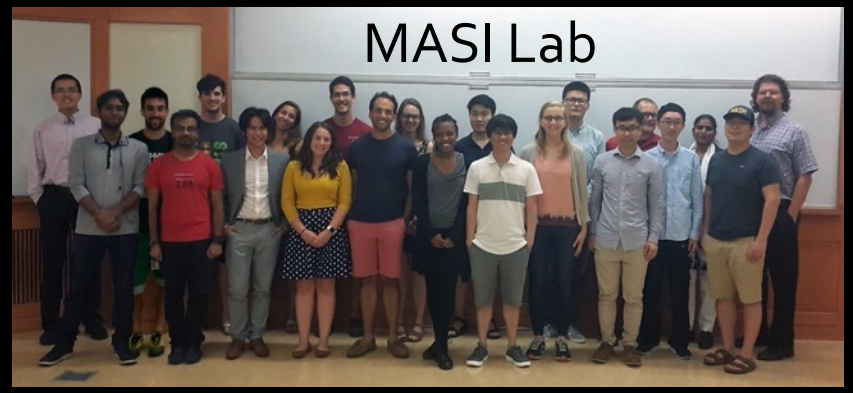
VUIIS

MICROSTRUCTURE & CONNECTIVITY
MC
LAB

Kurt Schilling
MIML 2022
Session: Preclinical & Task-based fMRI
11 May, 2022

Thank you

Vanderbilt University
Institute of Imaging Science



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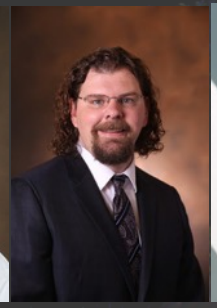
NIH: R01-EB017230
NIH: T32-EB001628
NCRR: UL1-RR024975-01
NCATS: 2UL1-TR000445-06

Adam Anderson

Bennett Landman



John Gore

Seth Smith

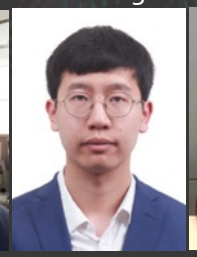
Justin Blaber

Yuankai Huo

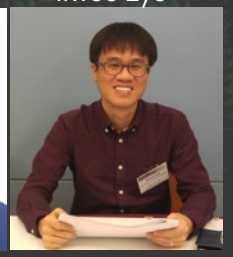
Leon Cai

Colin Hansen

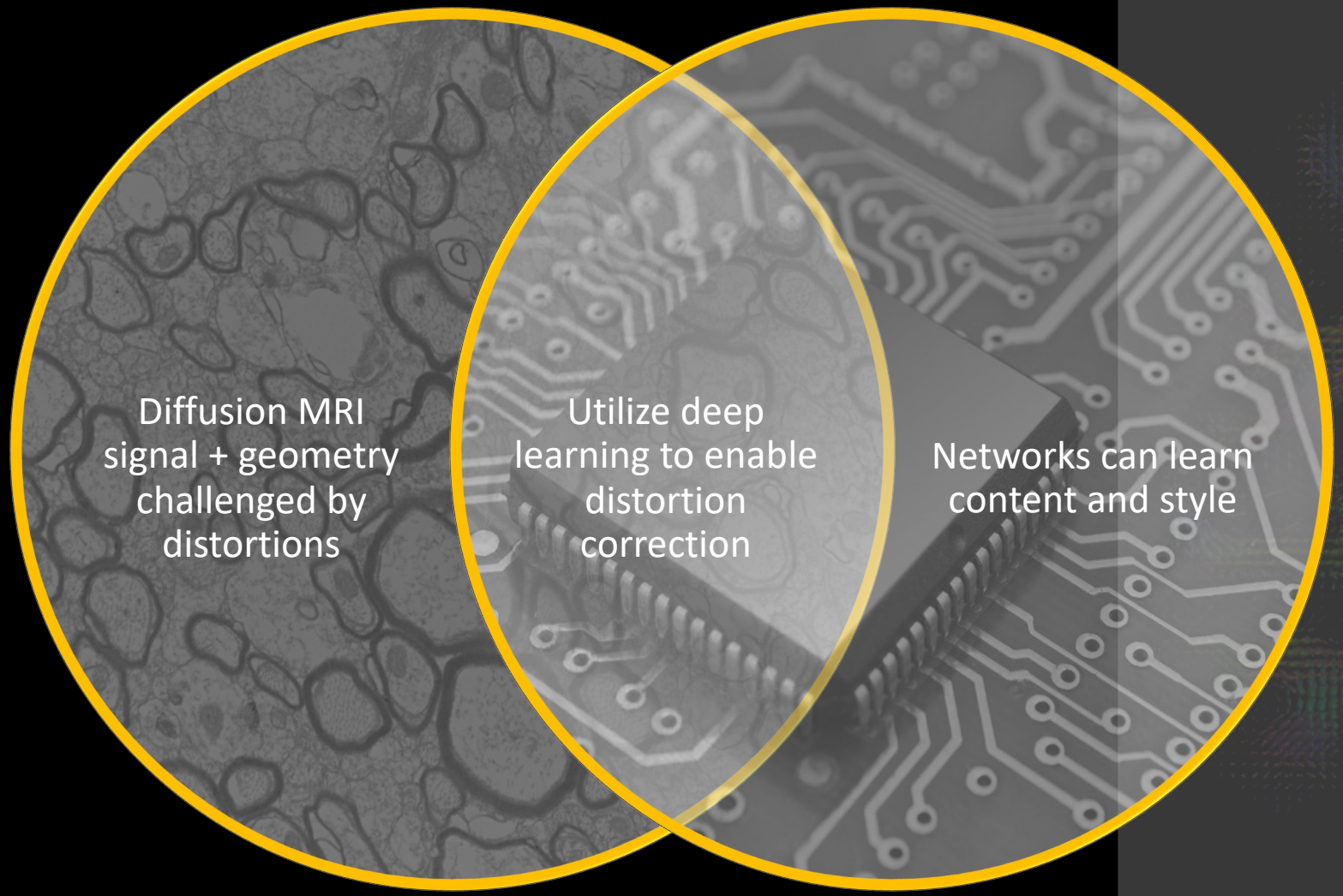
Qi Yang



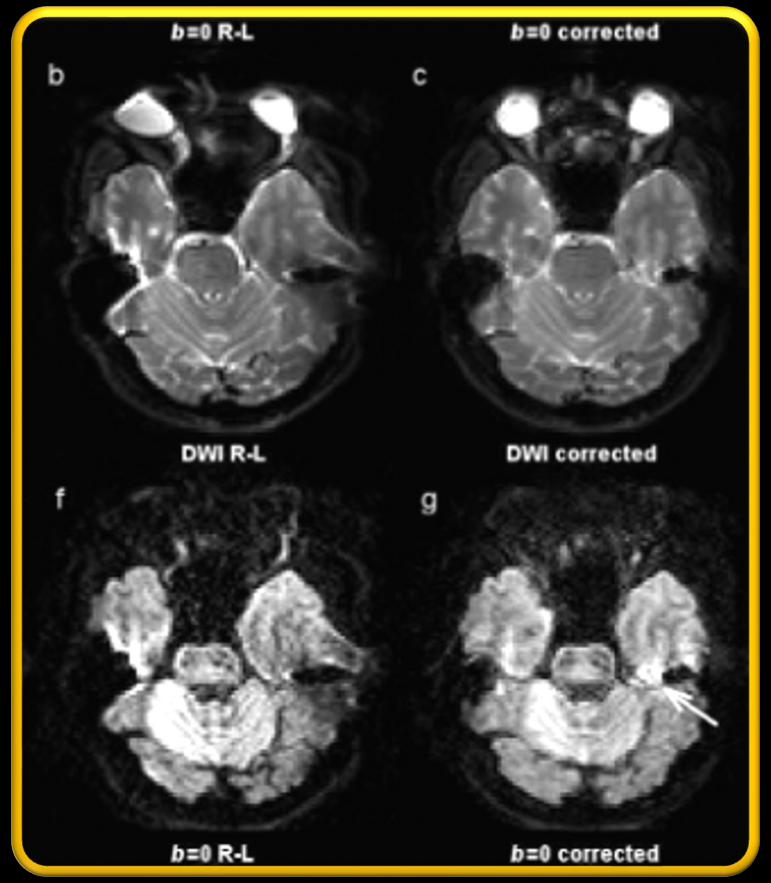
Ilwoo Lyu



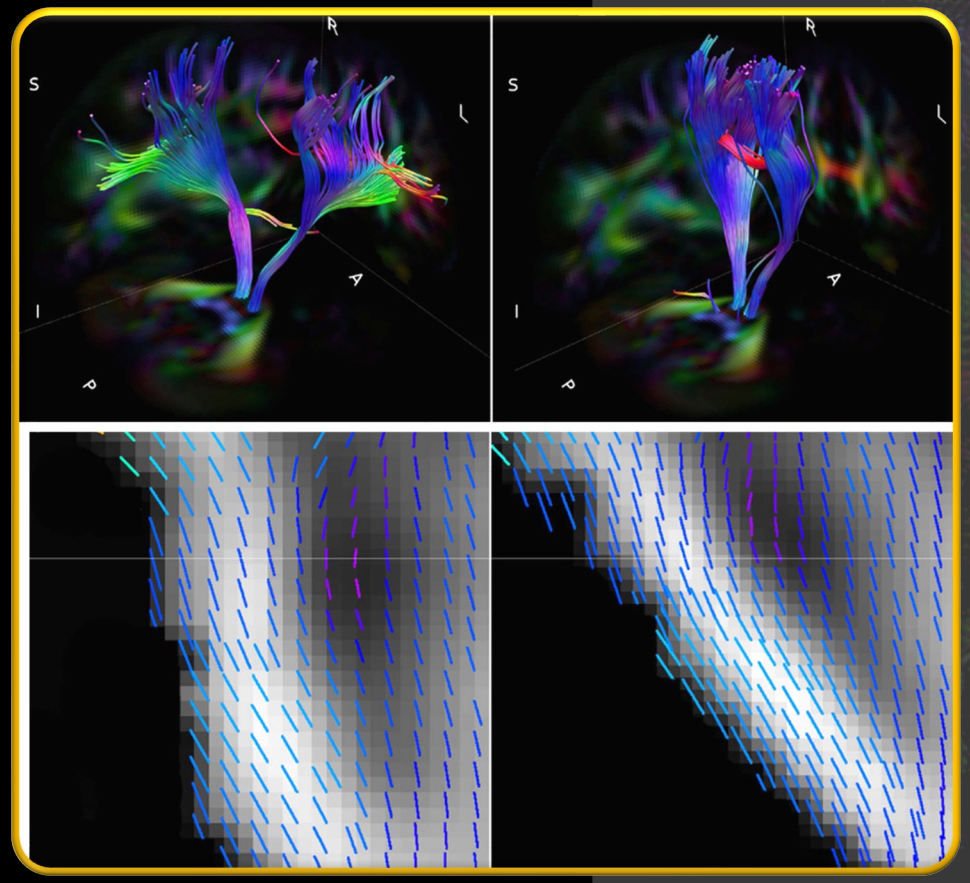
Microstructure Imaging Meets Machine Learning



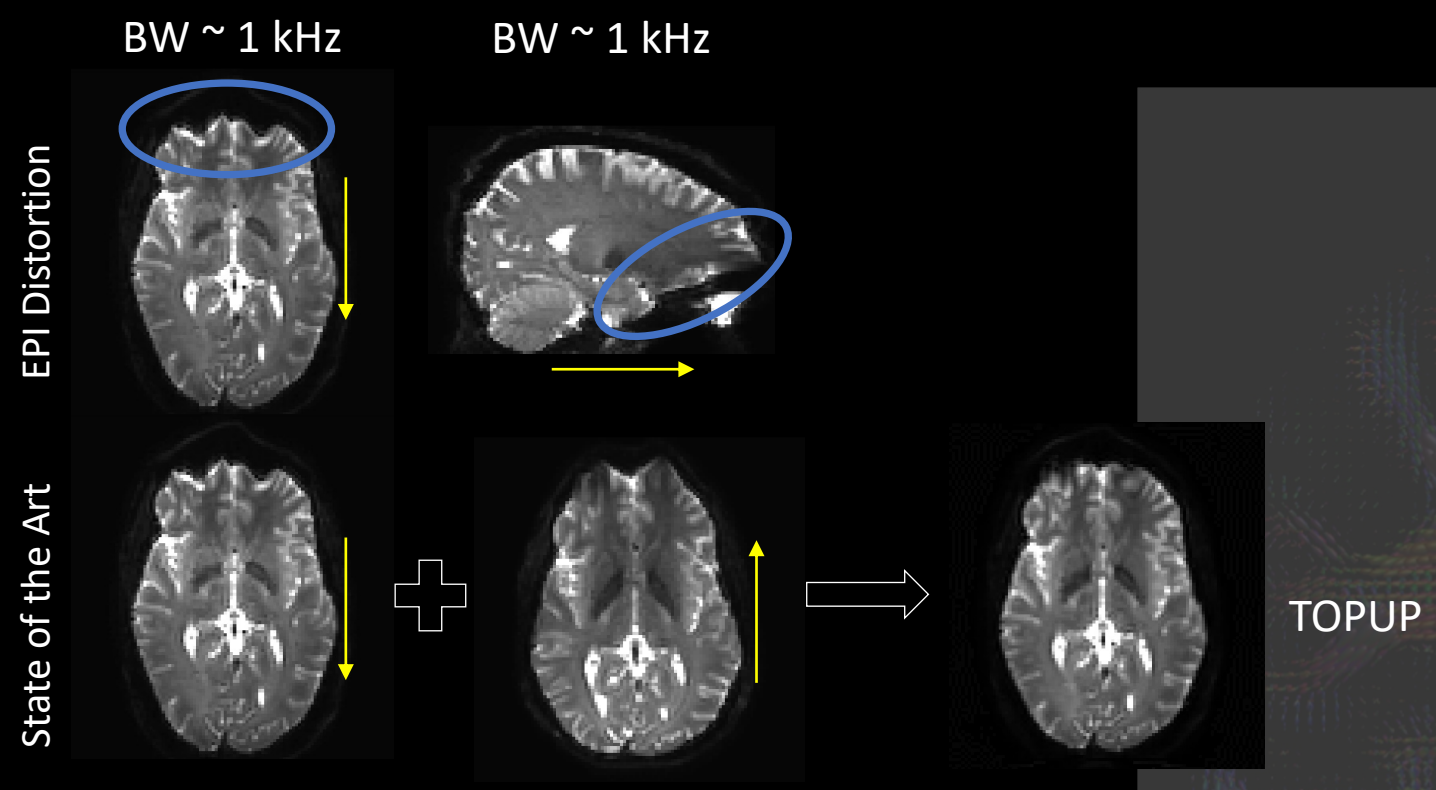
Susceptibility distortions affect microstructure, fiber trajectories, and connectivity



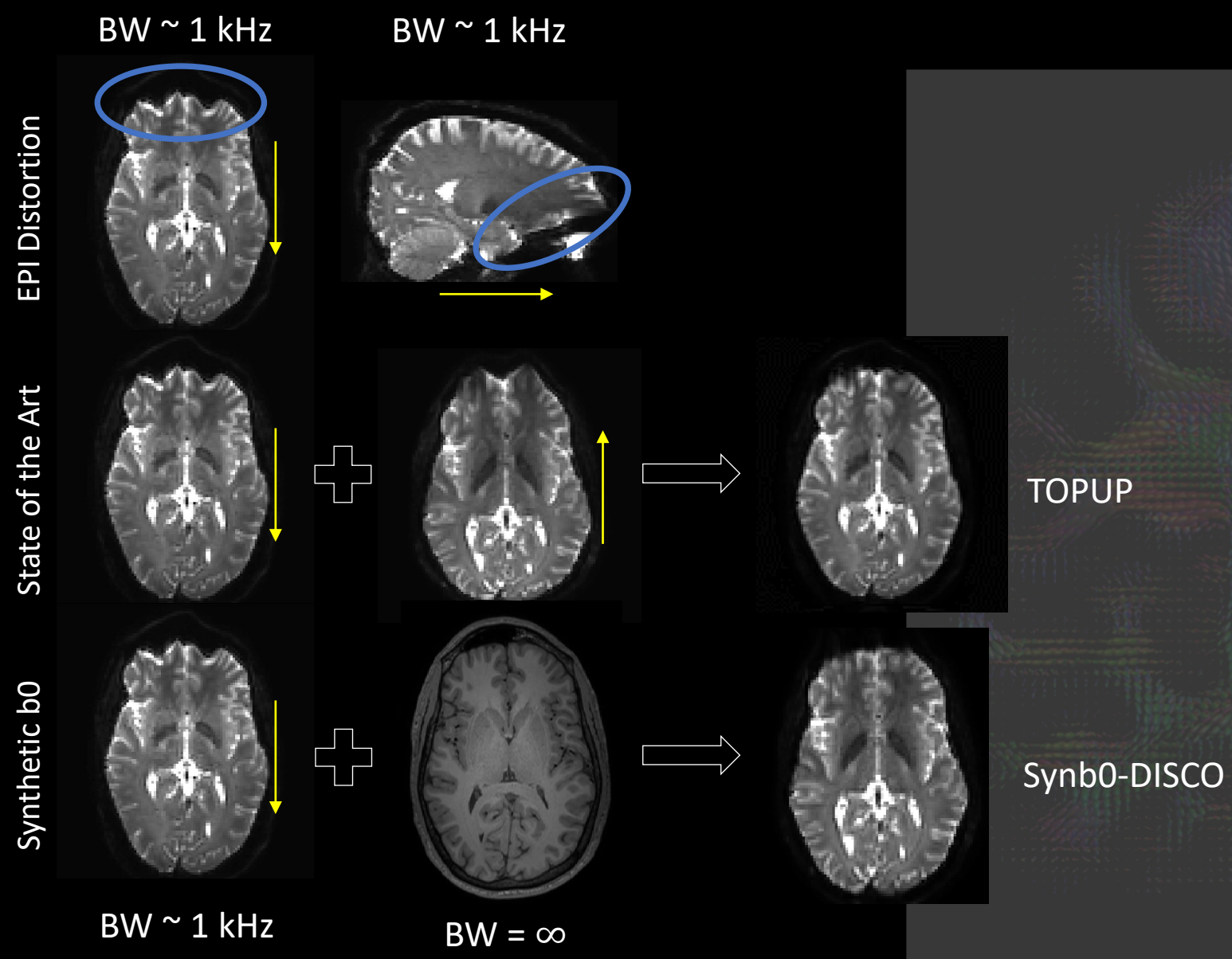
Embleton et al., HBM, 2020



Irfanoglu et al., NI, 2013



Use deep learning to enable susceptibility distortion correction with historical and/or limited diffusion datasets that do not include specific sequences for distortion correction


BW ~ 1 kHz
BW ~ 1 kHz
EPI Distortion
State of the Art
Synthetic b0
TOPUP
Synb0-DISCO
BW ~ 1 kHz
BW = ∞

Methods - synthesis

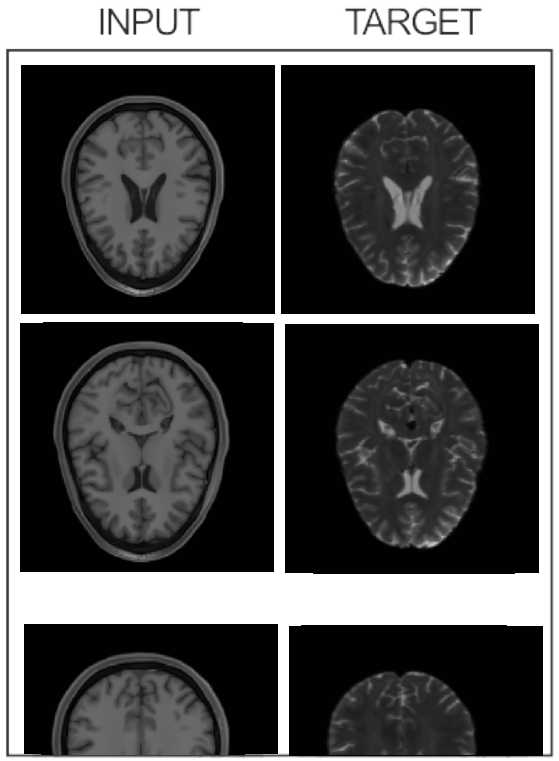


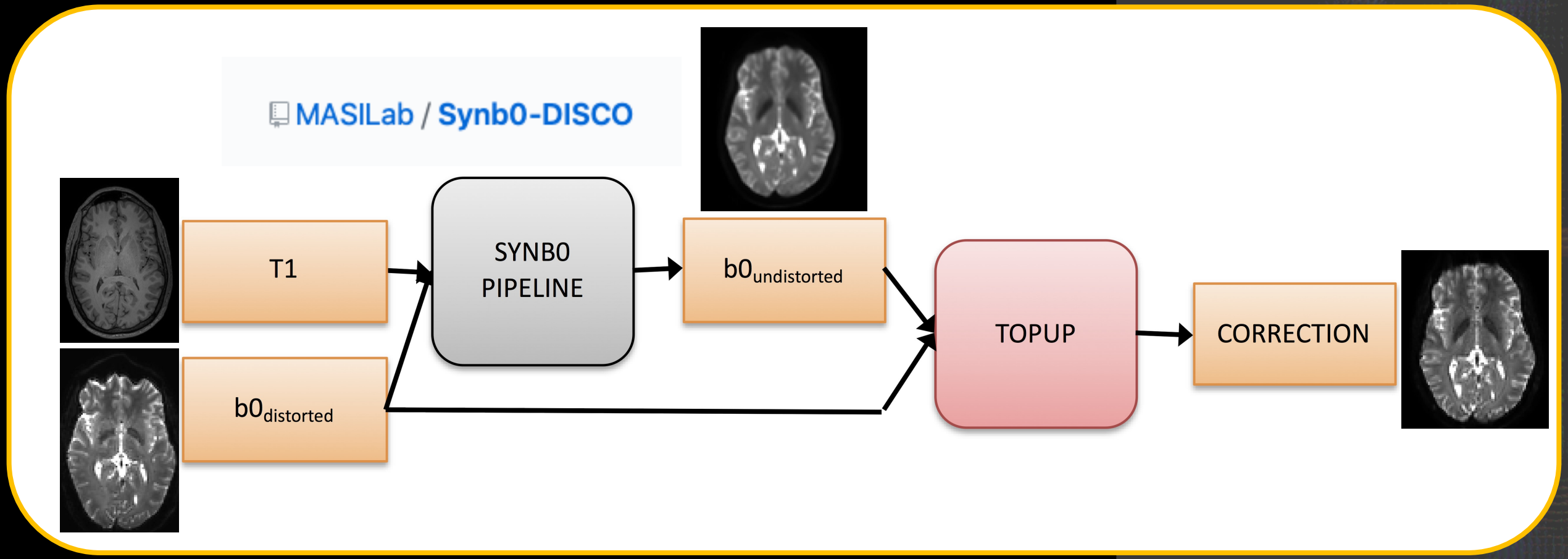
Image-to-Image Translation with Conditional Adversarial Nets

Phillip Isola Jun-Yan Zhu Tinghui Zhou Alexei A. Efros

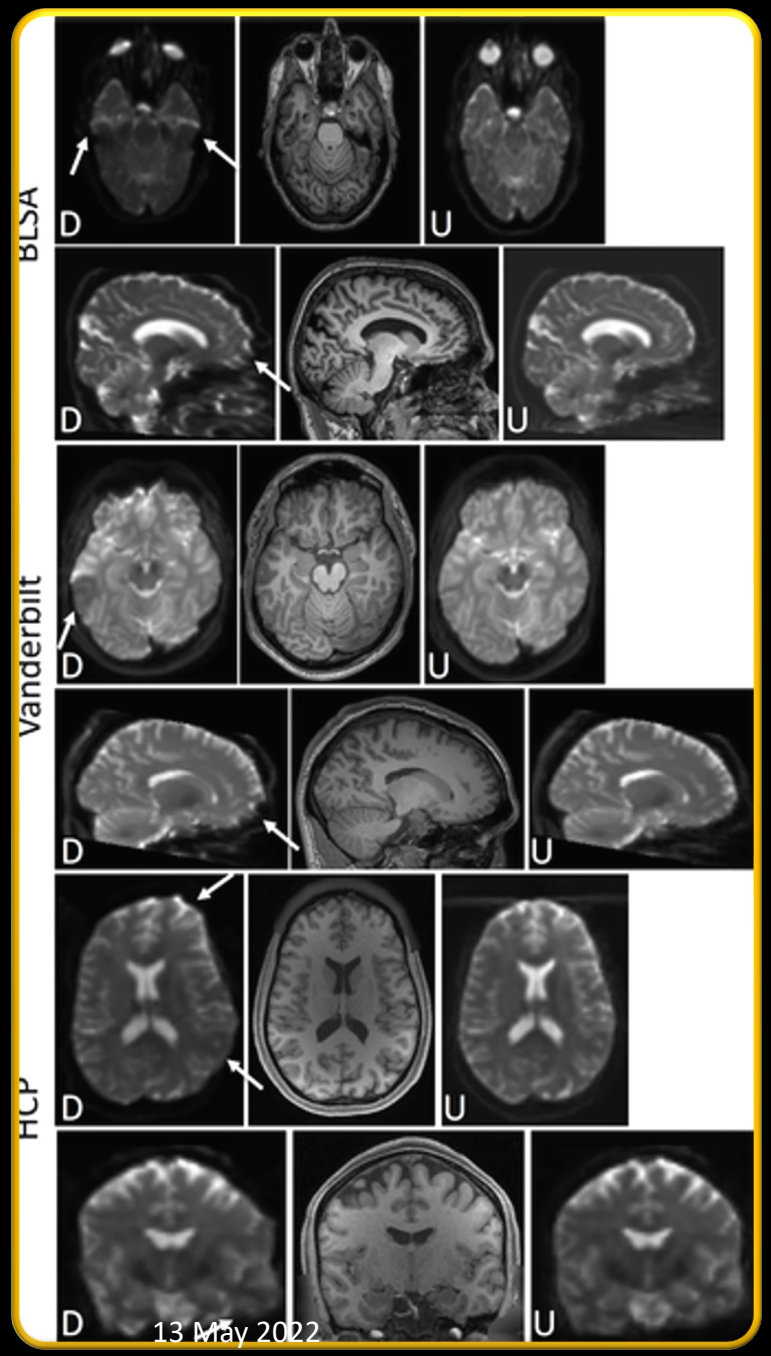
University of California, Berkeley
In CVPR 2017

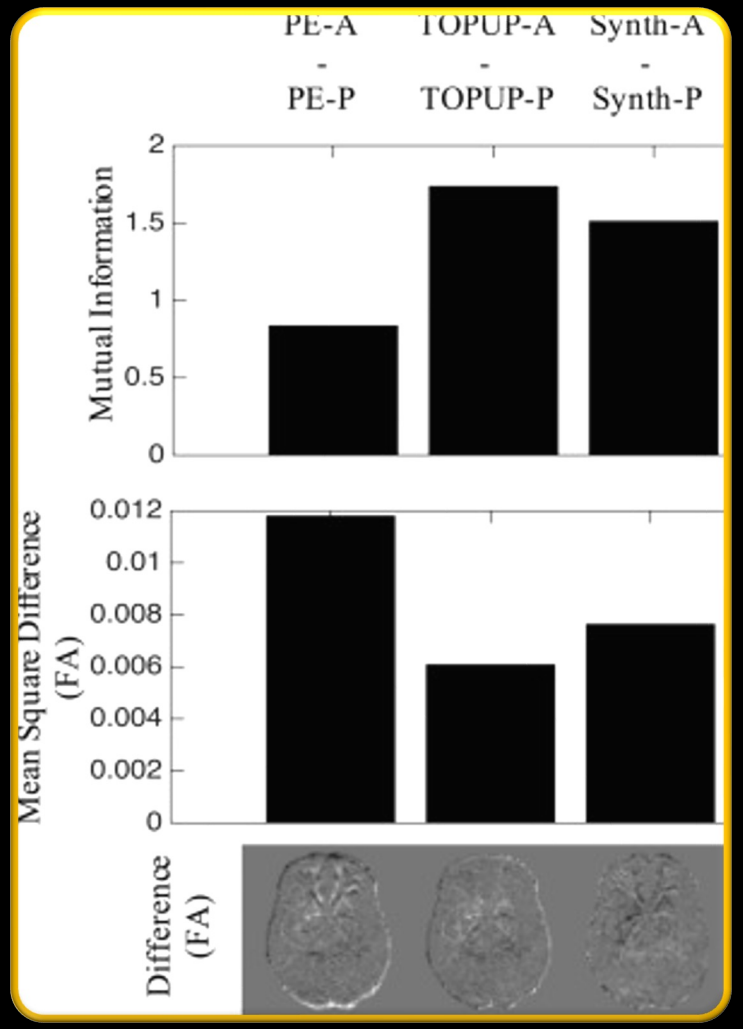
	Vanderbilt	HCP	BLSA
Subjects	38	488	424
Sessions	80	488	529
Phase Encoding	A-P	L-R	A-P
Correction	Topup	Topup	Multishot EPI
Resolution (mm)	1.7–2.5 iso	1.25mm iso	0.83x0.83x2.2
TE/TR	101/5891	89.5/5520	75/6801
Training splits (subjects)			
Learning (Training + Validation)	35	433	381
Testing (with-held)	3	55	43

Methods - application



Validation

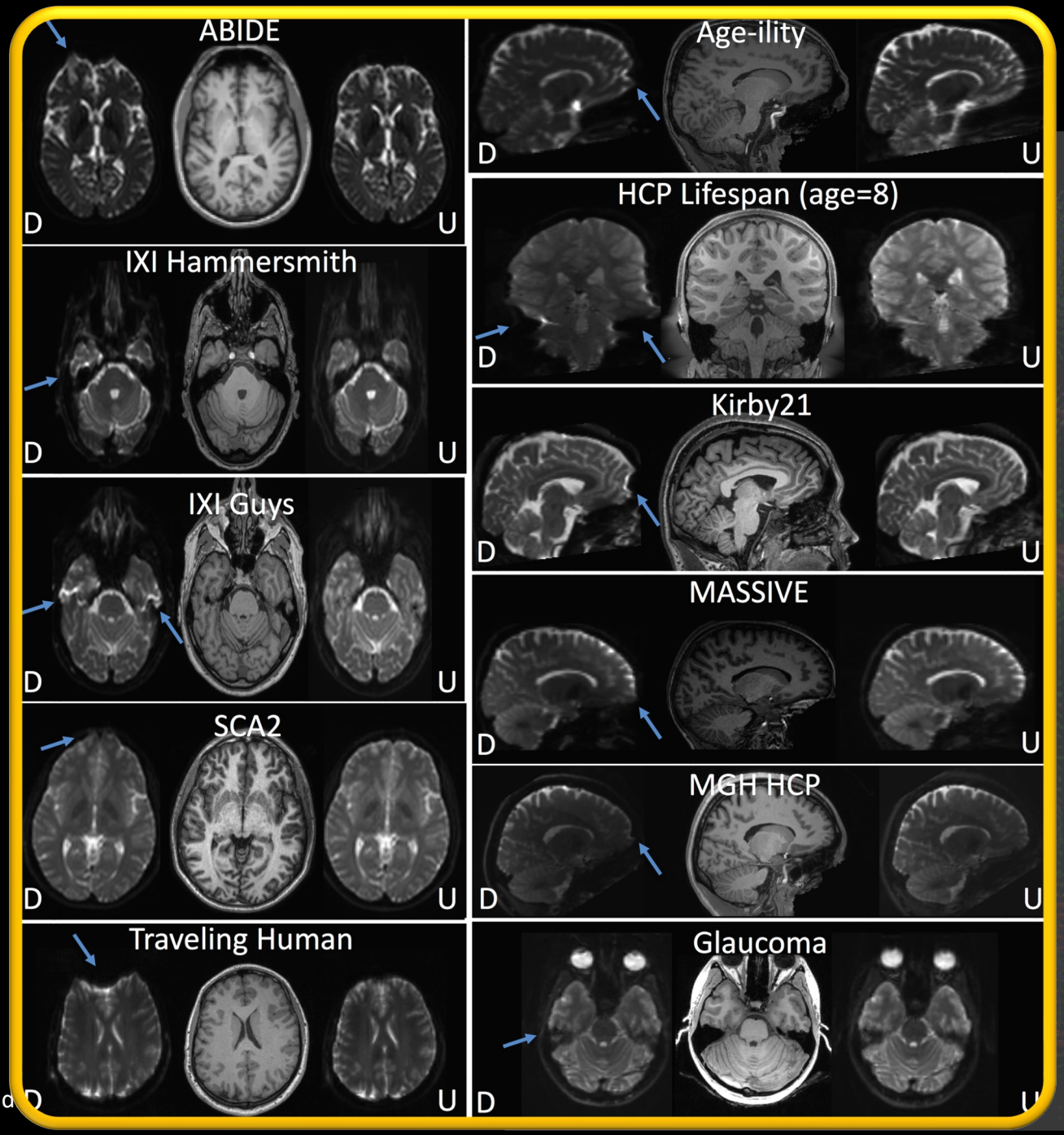




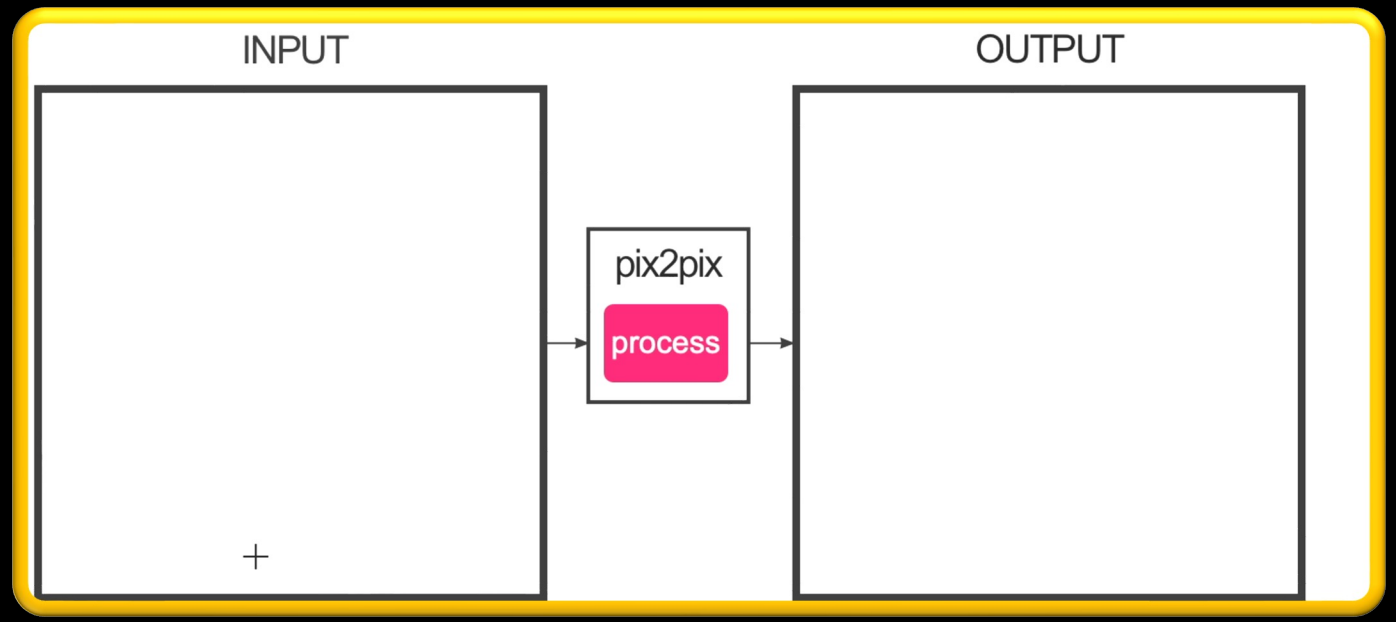
- Final images geometrically more similar to T1
- Correction using our pipeline closely matches state-of-the-art processing (reverse PE)
- Quantitative indices more reproducible

Correcting distortions

- Enabled diffusion distortion correct when otherwise not possible
  - Faithful to geometry of brain
  - No signal loss or pileup
  - Reduces variation in diffusion modeling
- Applied to legacy datasets or clinical datasets with time constraints
- Docker, Singularity, DIPY



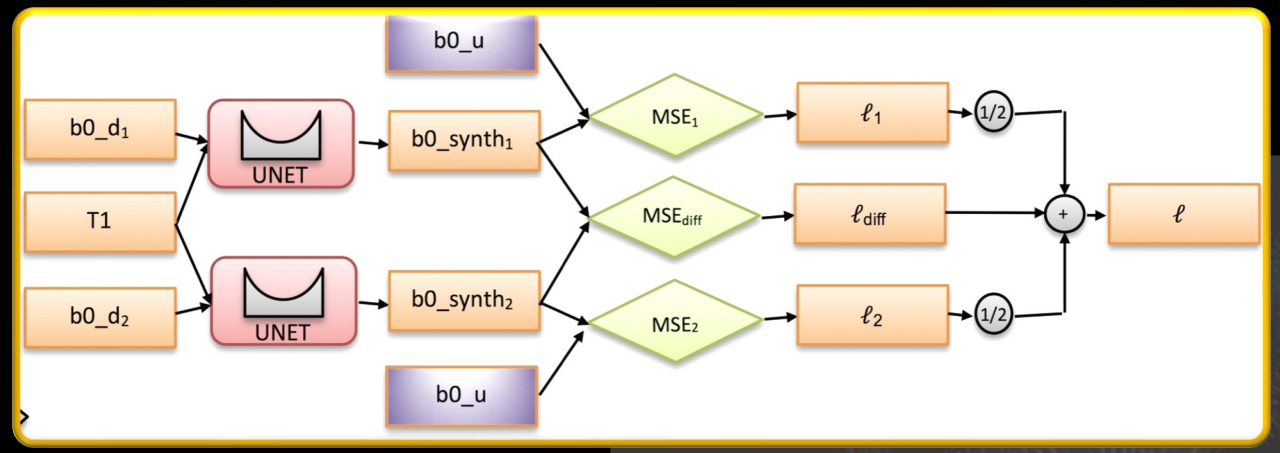
Trust deep learning in medical imaging?

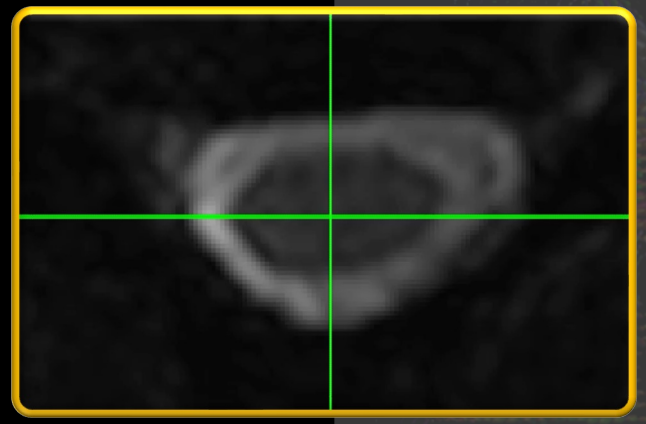


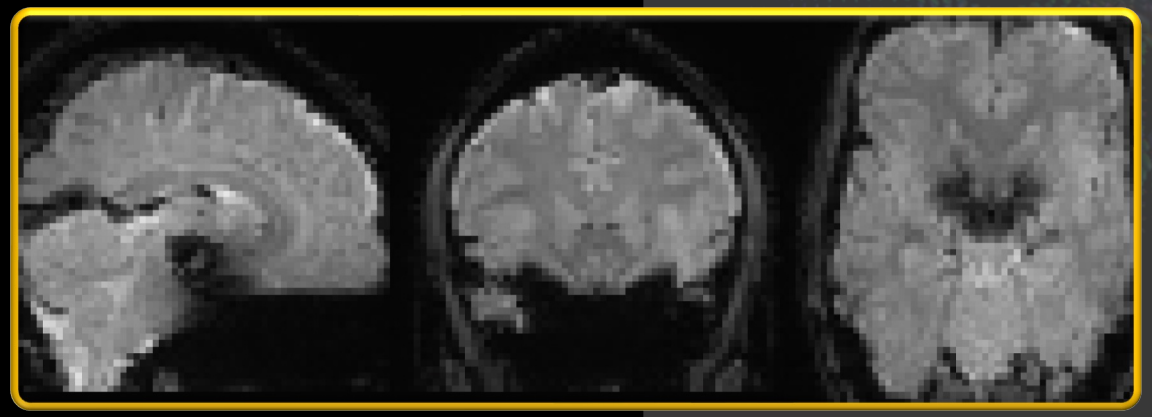
- Edges2Cats
- Geometry2b0
- Scaffold for registration
  - Anatomically faithful
- Physics informed deformation correction
  - Signal dropout/pileup
  - Motion

Future work

- Pipeline improvements
  1. Inputs both distorted data and T1: learns geometry and contrast (signal intensity)
  2. Utilize 3D information
  3. Trained on larger cohorts: generalizability
- Alternative contrasts
- Other anatomies
- Artifact detection







MASILab/Synb0-DISCO

```
singularity run –e \
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-B OUTPUTS/:/OUTPUTS \
-B license.txt:/extra/freesurfer/license.txt \
synb0_latest.sif
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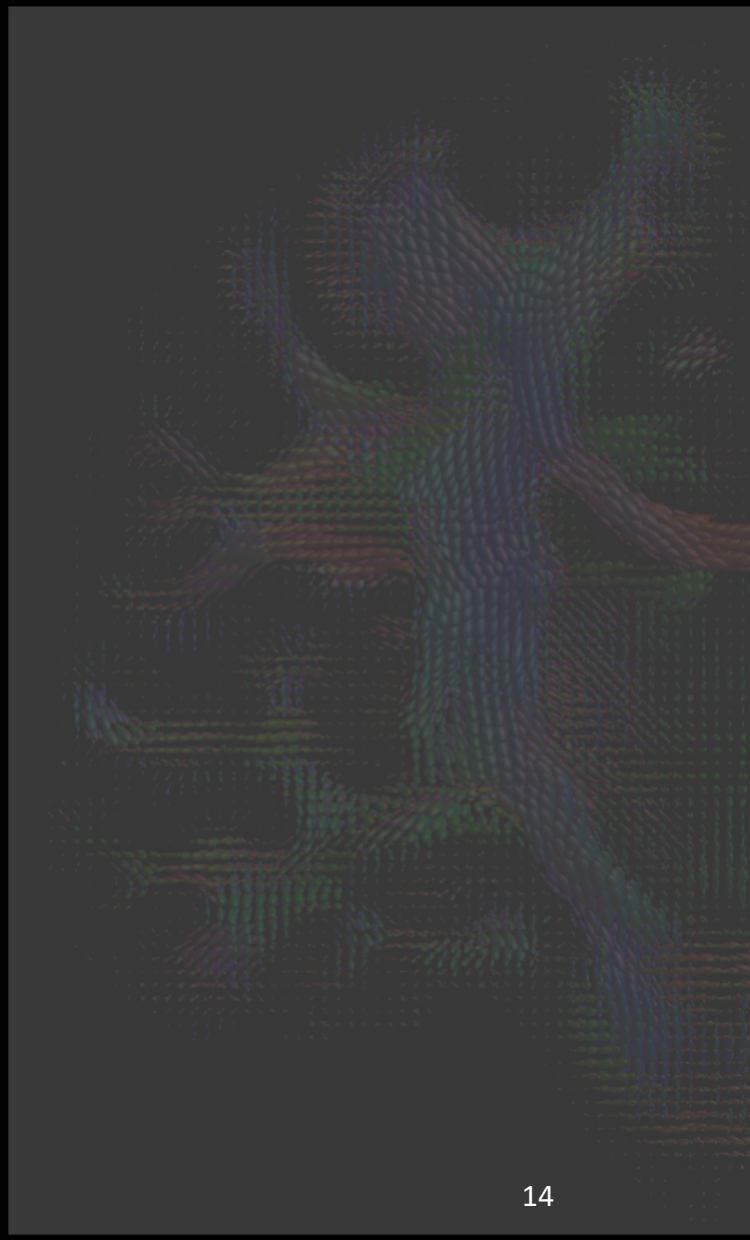

Thank you

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NIH: R01-NS113832
NIH: R01-EB017230
VUIIS Human Imaging Core

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