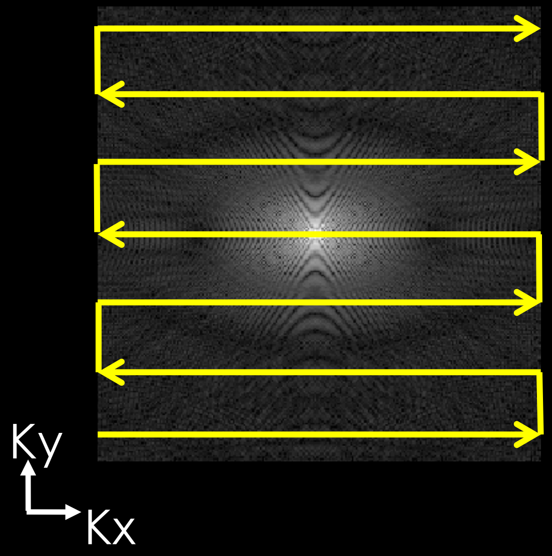
Accelerated Multi-shot EPI through Machine Learning & Joint Reconstruction

B Bilgic, I Chatnuntawech, SF Cauley,
MK Manhard, LL Wald, K Setsompop

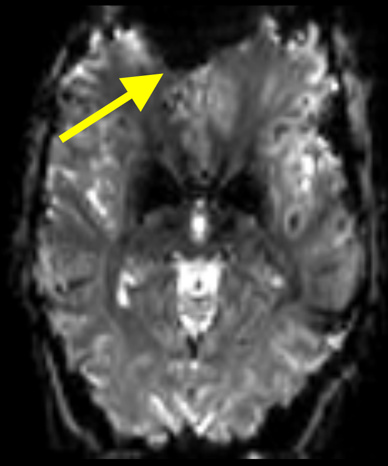
Echo Planar Imaging (EPI)

- EPI is very efficient: collects entire k-space plane per excitation

k-space

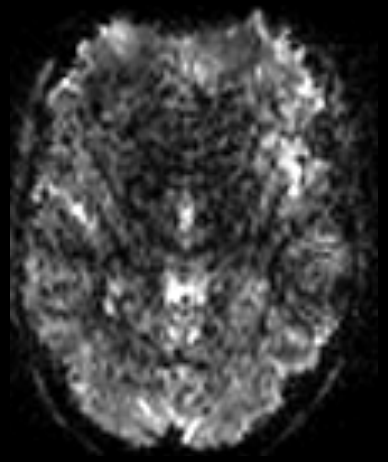


R=1



distortion

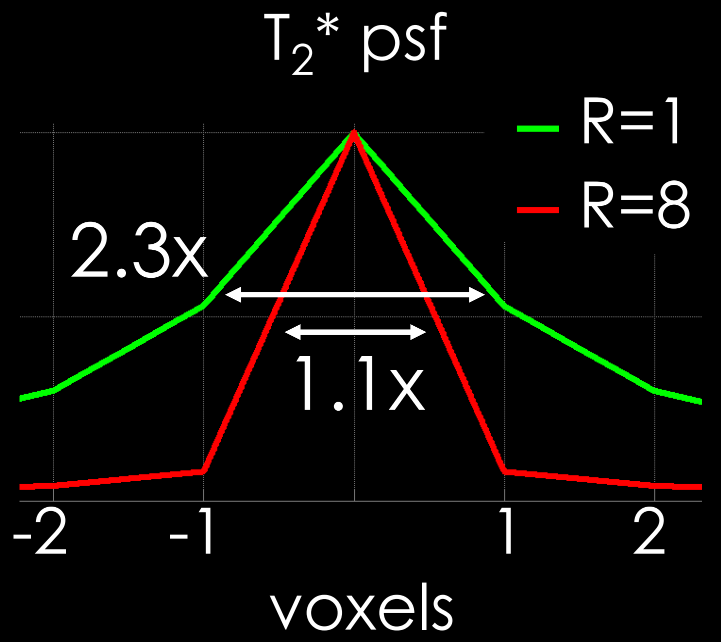
R=8

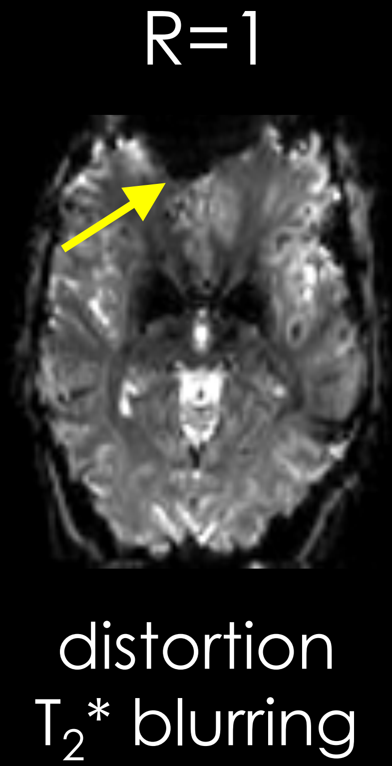


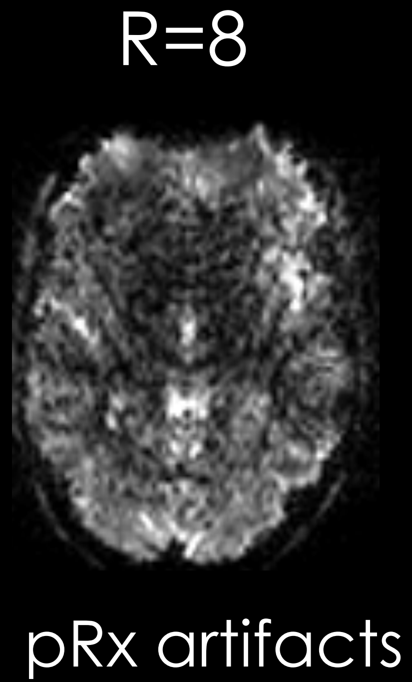
pRx artifacts

Echo Planar Imaging (EPI)

- EPI is very efficient: collects entire k-space plane per excitation
- Distortion & blurring preclude high-res EPI

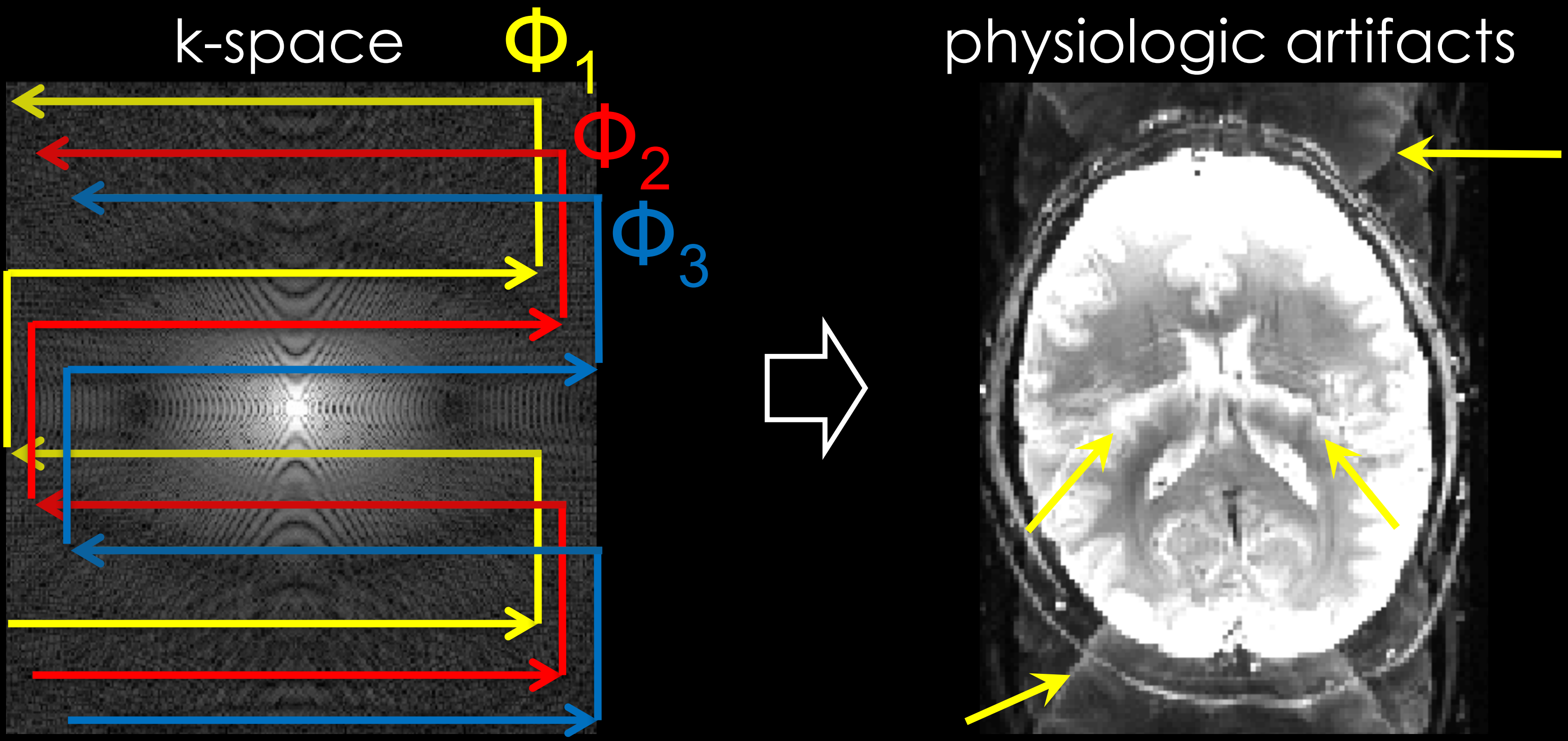






Multi-shot EPI (msEPI)

- msEPI could mitigate distortion & blurring
- Combining shots is prohibitively hard



Multi-shot EPI (msEPI)

- Shot-to-shot variations can be mitigated using navigators [1]

  reduced efficiency, remaining artifacts

- Navigator-free approaches use pRx to recon an image for each shot and estimate phase variations [2]

- pRx breaks down at R>4, limiting distortion & blurring reduction

- Navigated & nav-free methods only been applied to diffusion

[1] DA Porter, MRM'09
[2] NK Chen, NeuroImage'13

Our contribution

- We enable GRE msEPI for the first time

    where physiologic phase has higher spatial variations

- Navigator- & artifact-free multi-contrast msEPI

    spin-and-gradient-echo (SAGE) [1]

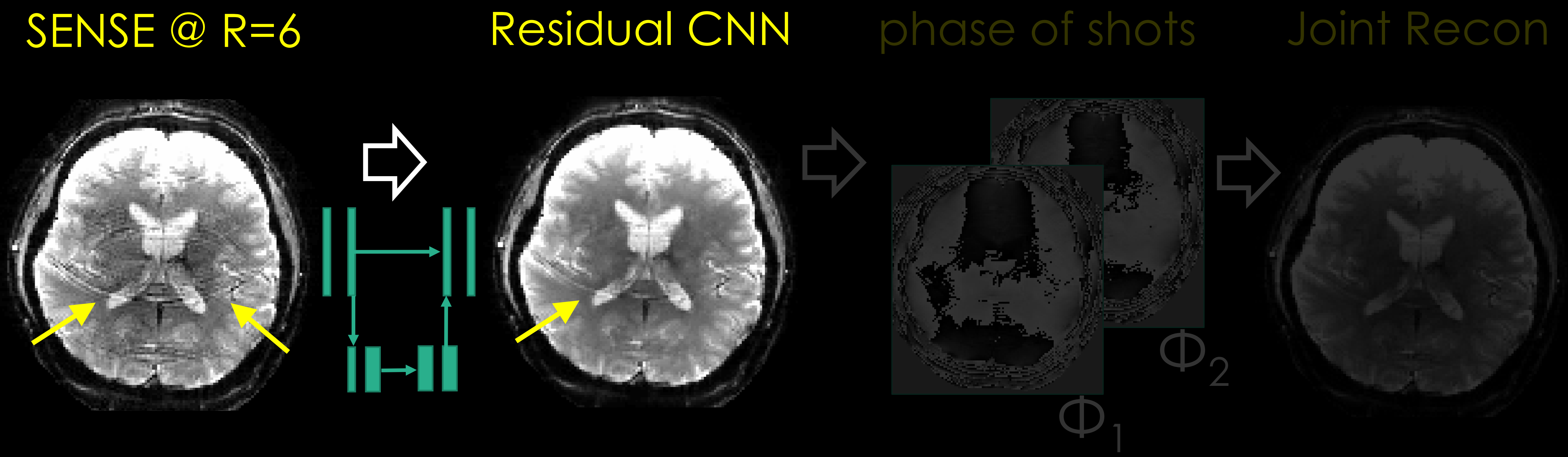
    T_2, T_2* maps & images

[1] H Schmiedeskamp, MRM'12

NEATR: Network Estimated Artifacts for Tempered Recon

- NEATR: synergistic Machine + Physics recon
- ML: interim image with minimal artifacts
- Jumpstart Physics / forward-model based recon:
  - accurately estimate & eliminate artifacts
  - validate & improve ML to avoid “black-box”

NEATR allows R=6 msEPI from 2-shots



refine magnitude
using CNN

fix CNN magnitude
solve for shot phase

use shot phases for extra
encoding & all data

Deep Residual CNN[1,2]

- Optimization for residual is easier than clean image

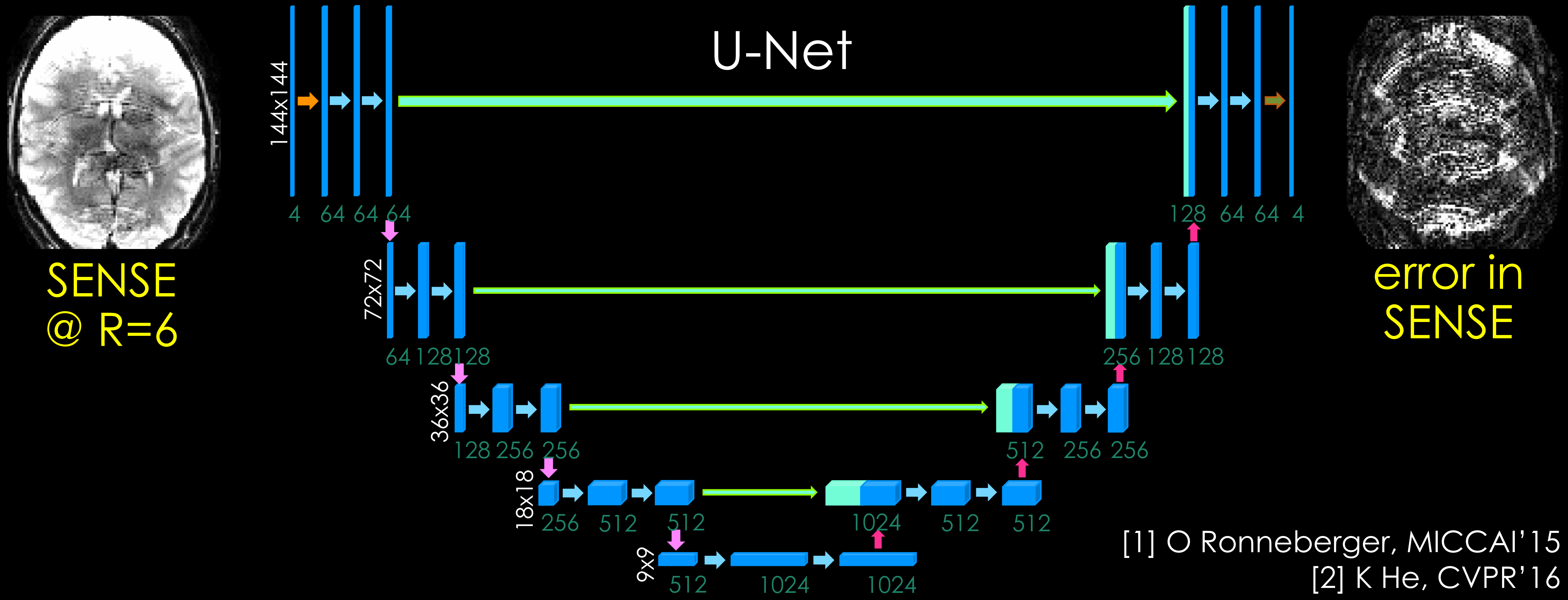
SENSE
@ R=6

error in
SENSE

[1] O Ronneberger, MICCAI'15
[2] K He, CVPR'16

Deep Residual CNN[1,2]

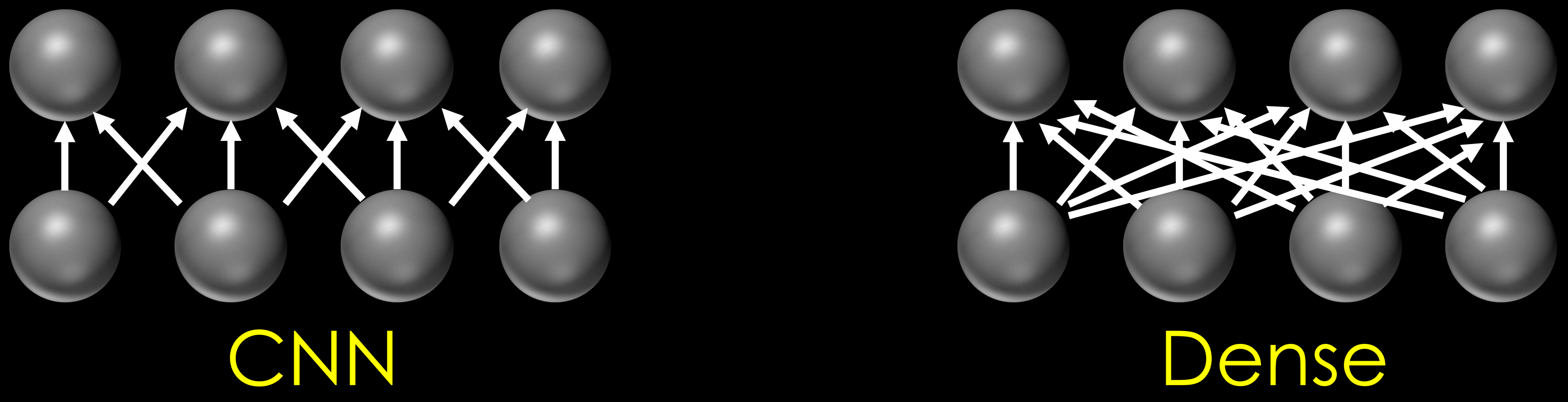
- Optimization for residual is easier than clean image



[1] O Ronneberger, MICCAI'15
[2] K He, CVPR'16

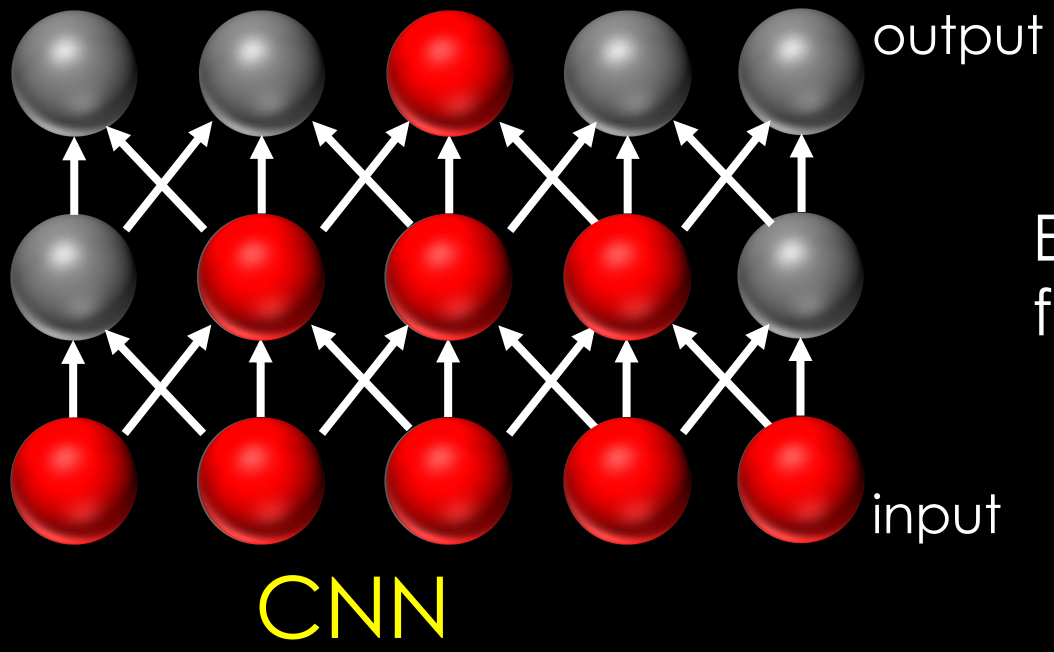
Deep Residual CNN

- Why Convolutional
- Sparse interactions: much fewer unknowns
- Each arrow: one unknown



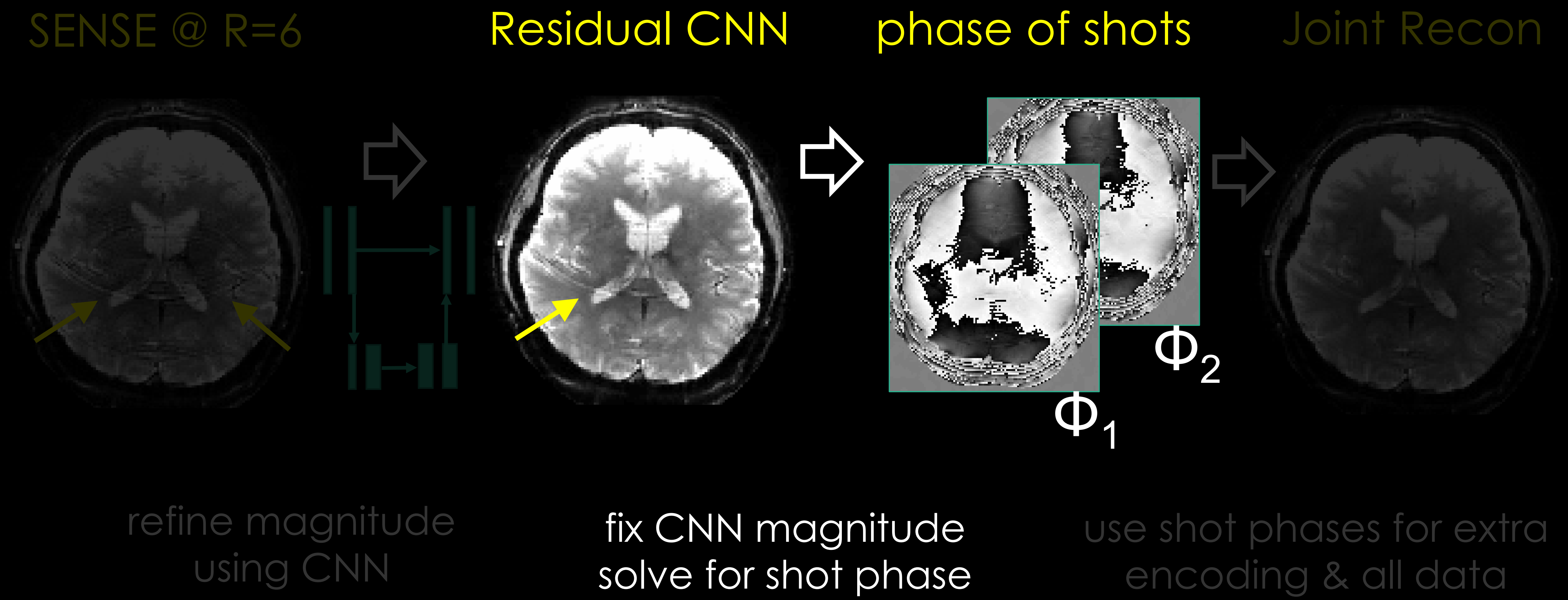
Deep Residual CNN

- Why Deep
- More layers describe complex interactions between many variables



Each output has contribution from 5 voxels

NEATR allows R=6 msEPI from 2-shots



Shot phase estimation

- Fix U-Net magnitude: m_{unet}
- Solve for phase of shot t [1]: ϕ_t

$$\min_{\phi_t} \left\| \mathrm{F_t} C e^{i\phi_t} m_{unet} - k_t \right\|_2^2 + \alpha \left\| \Psi \phi_t \right\|_1$$

[1] F Ong, MRM'18

Shot phase estimation

- Fix U-Net magnitude: m_{unet}
- Solve for phase of shot t [1]: ϕ_t

$$\min_{\phi_t} \left\| \mathrm{F}_\mathrm{t} \mathrm{C} e^{i\phi_t} m_{unet} - k_t \right\|_2^2 + \alpha \left\| \Psi \phi_t \right\|_1$$

sensitivity encoding | fixed | k-space | wavelet

[1] F Ong, MRM'18

Shot phase estimation

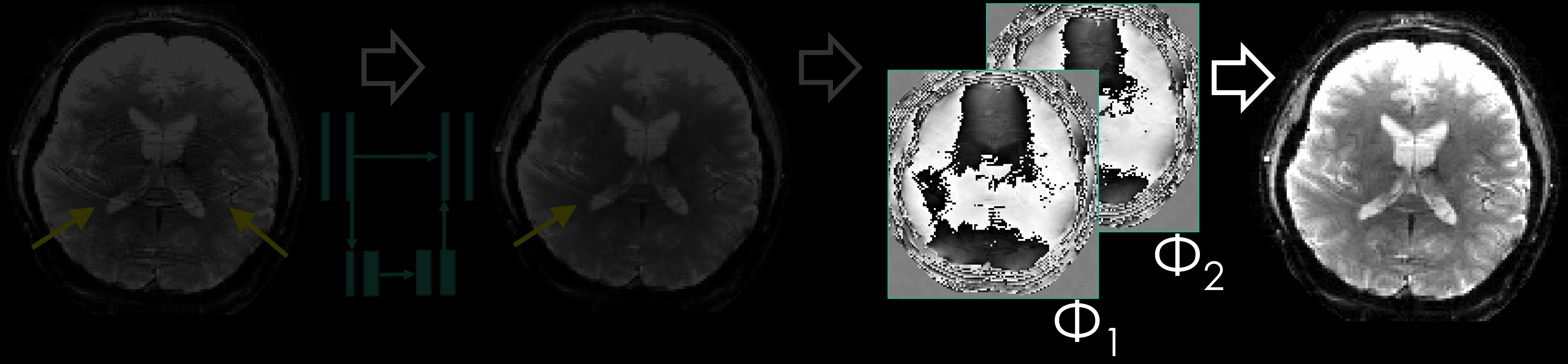
- Fix U-Net magnitude: m_{unet}
- Solve for phase of shot t [1]: ϕ_t

$$\min_{\phi_t} \left\| \mathrm{F_t} C e^{i\phi_t} m_{unet} - k_t \right\|_2^2 + \alpha \left\| \Psi \phi_t \right\|_1$$

[1] F Ong, MRM'18

NEATR allows R=6 msEPI from 2-shots

SENSE @ R=6 | Residual CNN | phase of shots | Joint Recon



refine magnitude
using CNN

fix CNN magnitude
solve for shot phase

use shot phases for extra
encoding & all data

Joint physics recon

- Once shot phases are estimated, solve for magnitude m

data from all shots

joint recon

$$\min_m \sum_t \left\| \left[F_t C e^{i\phi_t} \right] m - \left[k_t \right] \right\|_2^2$$

sum over shots

Joint physics recon

- Once shot phases are estimated, solve for magnitude m

data from all shots *joint recon*
virtual coil [1] *real-valued m*

$$\min_m \sum_t \left\| \begin{bmatrix} \mathrm{F_t C} e^{i\phi_t} \\ \mathrm{F_{-t} C^*} e^{-i\phi_t} \end{bmatrix} m - \begin{bmatrix} k_t \\ k^*_{-t} \end{bmatrix} \right\|_2^2$$

[1] M Blaimer, MRM'09

Joint physics recon

- Once shot phases are estimated, solve for magnitude m

data from all shots
virtual coil [1]

joint recon
real-valued m

$$\min_m \sum_t \left\| \begin{bmatrix} \mathrm{F}_t \mathrm{C} e^{i\phi_t} \\ \mathrm{F}_{-t} \mathrm{C}^* e^{-i\phi_t} \end{bmatrix} m - \begin{bmatrix} k_t \\ k_{-t}^* \end{bmatrix} \right\|_2^2 + \beta \|m\|_2^2$$

[1] M Blaimer, MRM'09

Data acquisition

- SAGE msEPI with 2-shots at **R=3**
- Six volunteers scanned

  three for training, three for test
- 1.5 x 1.5 mm^2 in-plane, 3 mm slice thickness
- Four echoes TE = 27 / 74 / 122 / 169 ms

  TR = 12.6 sec

code / data: martinos.org/~berkin

Training & reconstruction

- SAGE msEPI with 2-shots at **R=3**

  pRx recon @ R=3 provided “clean” target for training

- Data were retrospectively undersampled by **R=6**

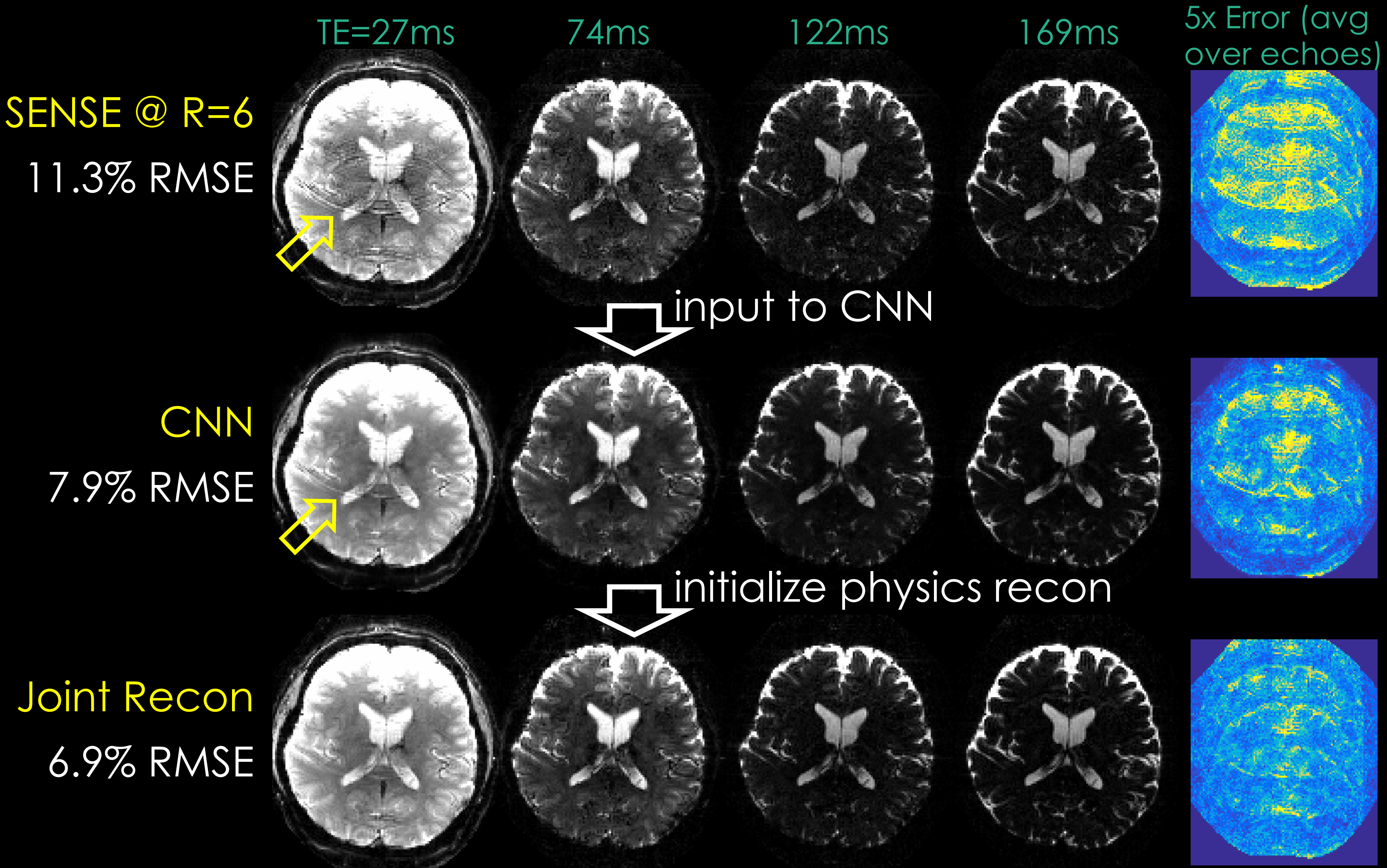
- Each shot was reconed with SENSE @ R=6

  to provide “corrupt” input for U-Net

- U-Net: multi-contrast, augmented 16-fold

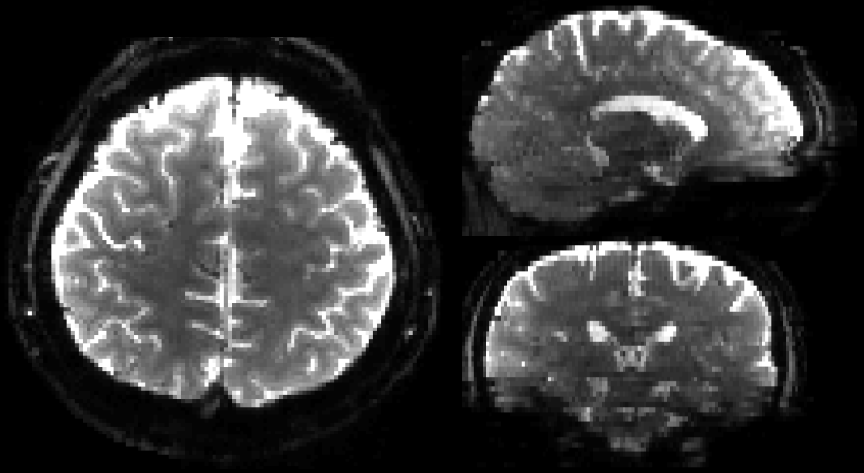
code / data: martinos.org/~berkin

SAGE msEPI: R=6 accl with 2-shots

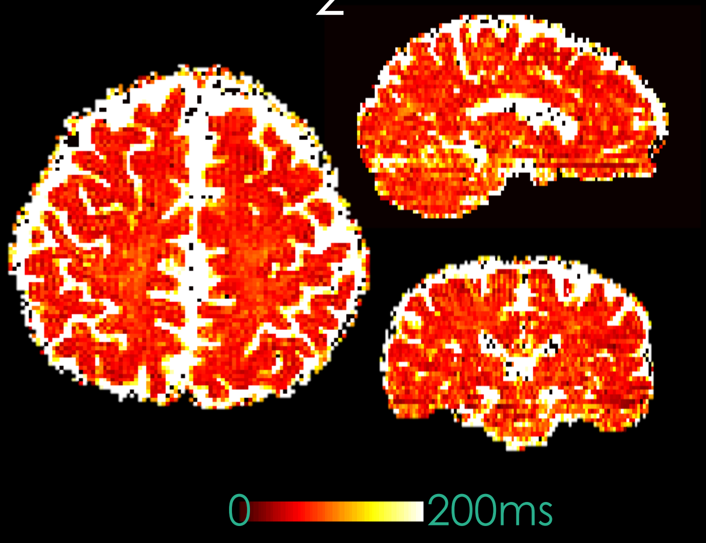


whole-brain msEPI in 25 sec @ R=6 with 2-shots

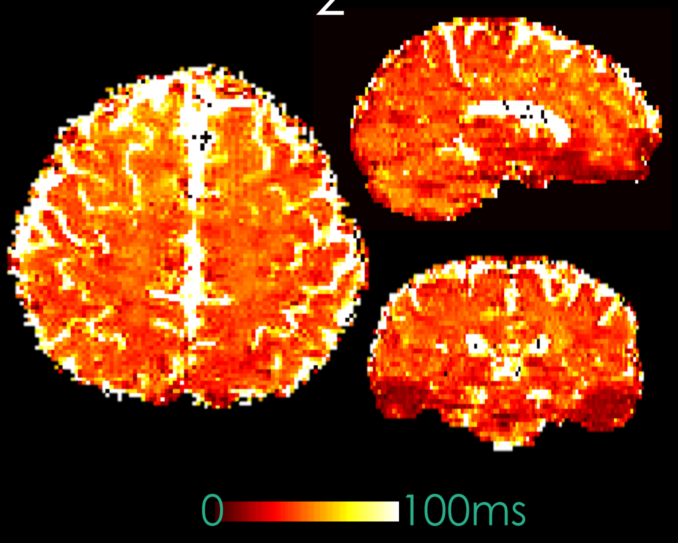
Avg over echoes



T_2



T_2*



code / data: martinos.org/~berkin

Will it generalize?

- Training was on Siemens Skyra

  TE = 98 ms (avg)

  TR = 12.6 sec

- Another test case from Prisma system

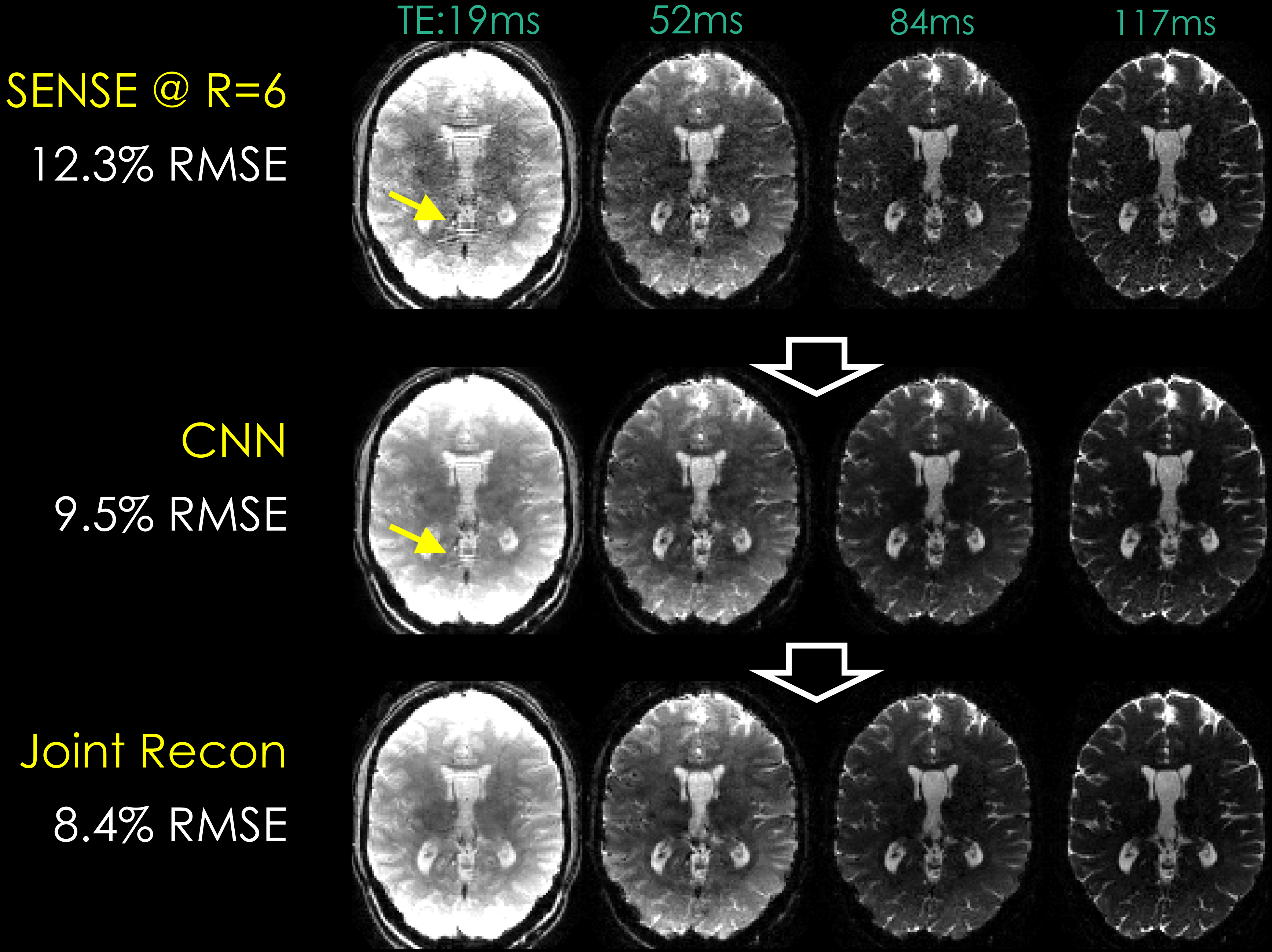
  TE = 68 ms (avg)

  TR = 9.1 sec

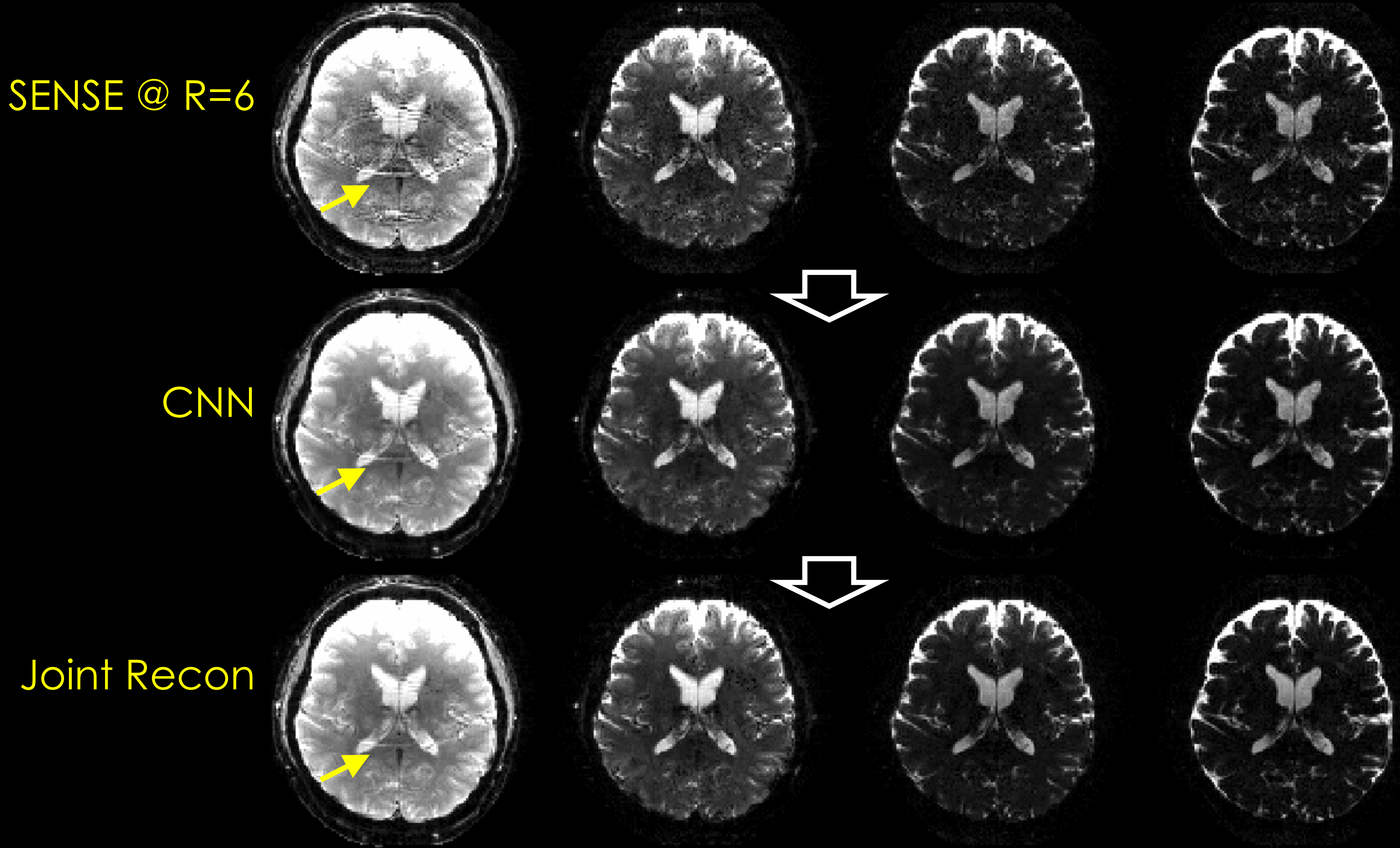
- **40% difference in TE & TR**

code / data: martinos.org/~berkin

R=6 with 2-shots: Another scanner & different parameters

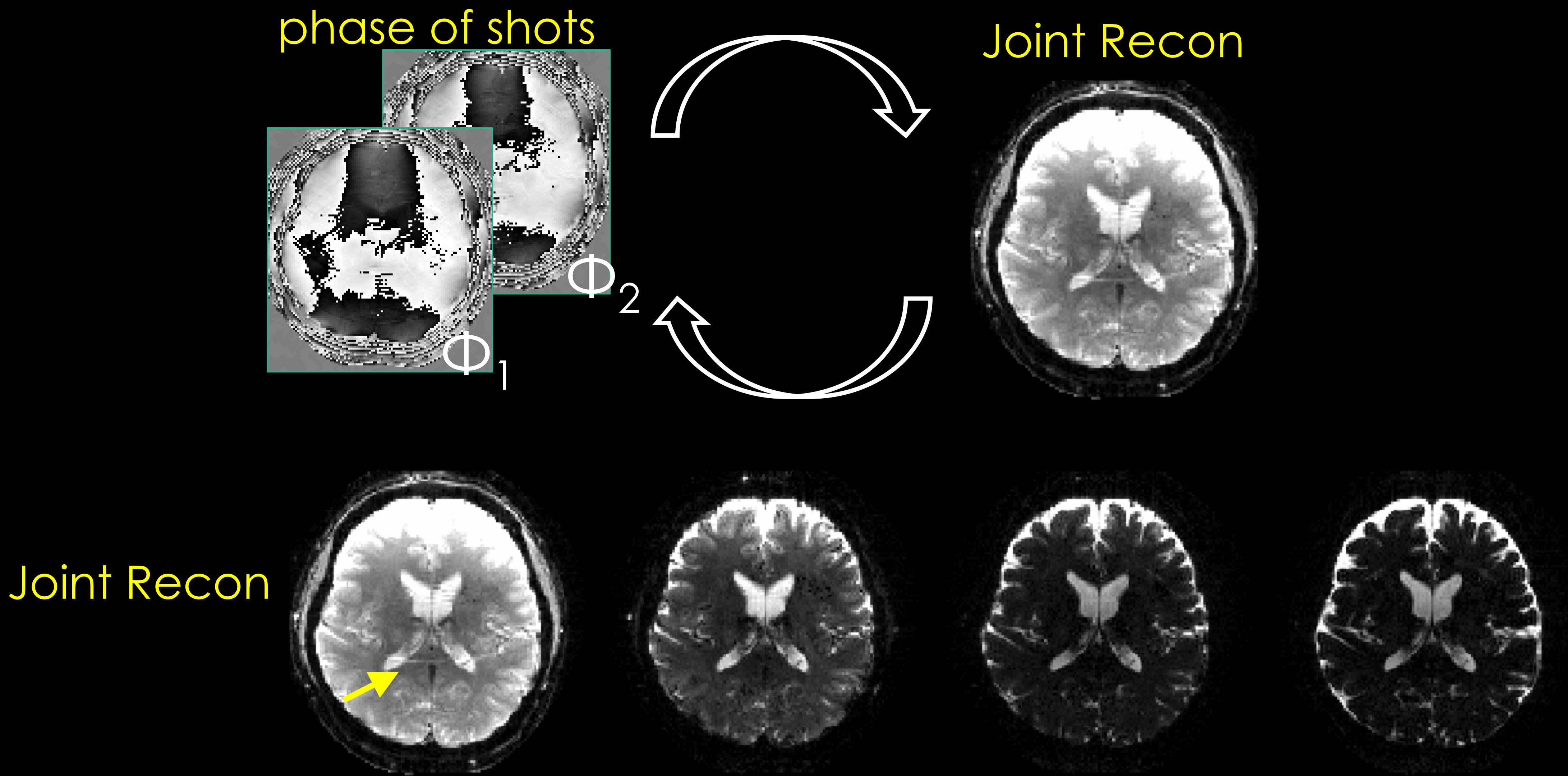


PROSPECTIVE R=6 with 2-shots



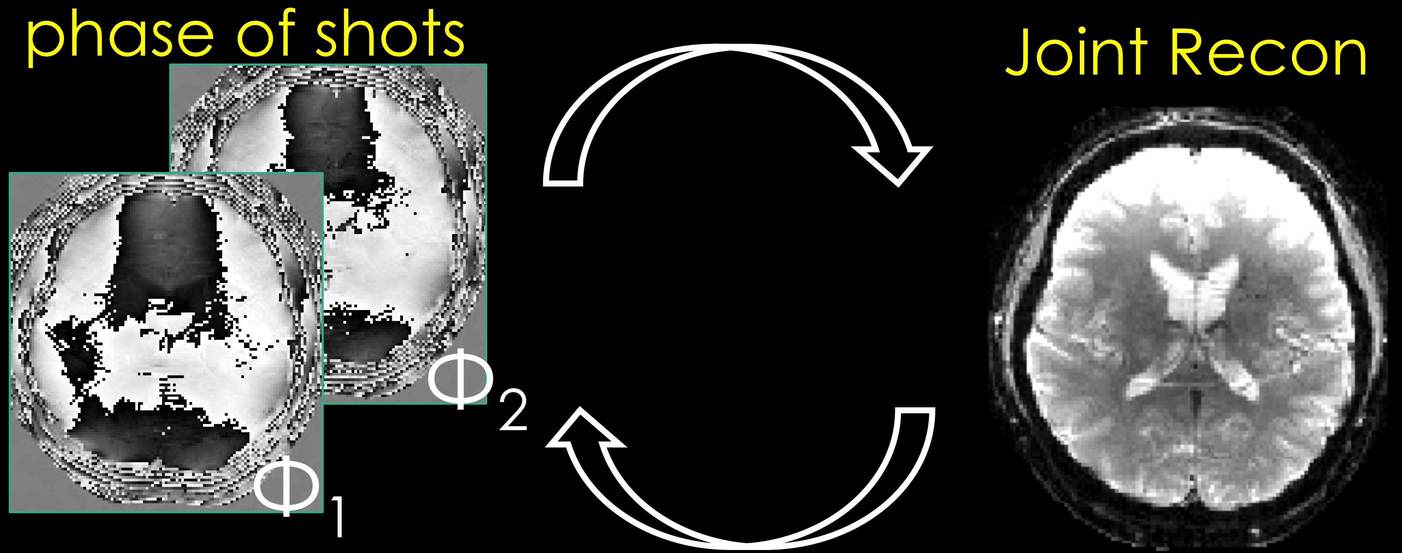
PROSPECTIVE R=6 with 2-shots

- Iterate: physics recon & shot phase estimation



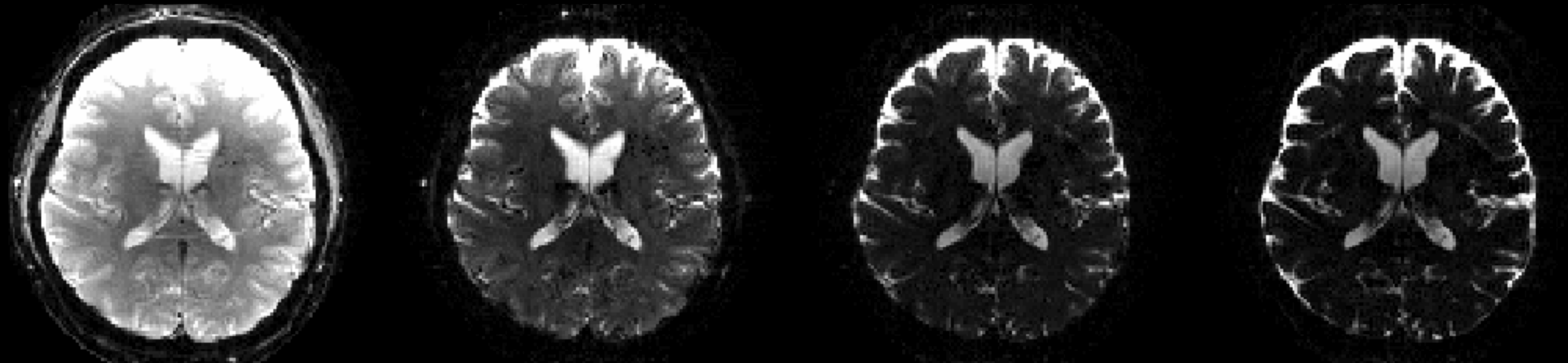
PROSPECTIVE R=6 with 2-shots

- Iterate: physics recon & shot phase estimation



Joint Recon

3 iters



PROSPECTIVE R=6 with 2-shots

- Iterate: physics recon & shot phase estimation

- Extension:
  - ❖ Joint pRx & joint sparsity across contrasts
  - ❖ wave-CAIPI for R ≥ 8

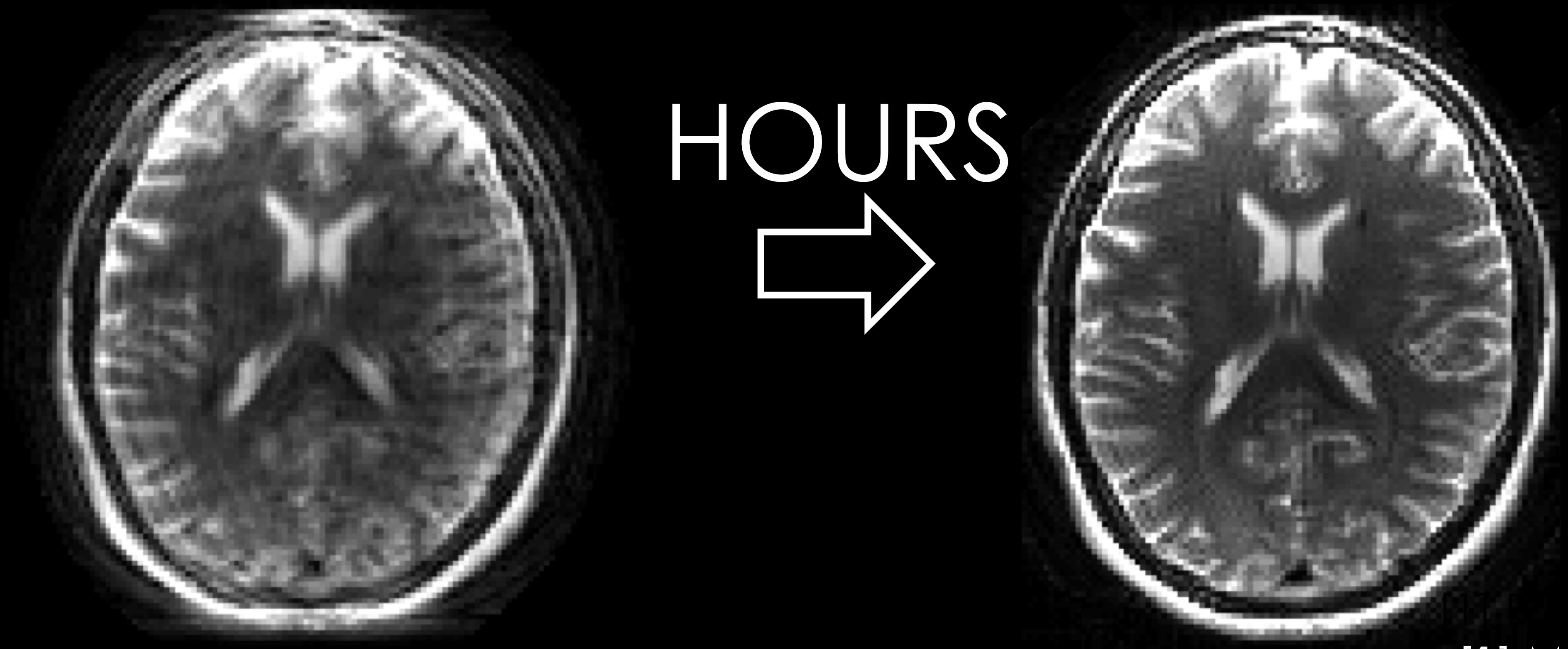
Joint Recon
3 iters

Motion Correction

- Physics recon: use redundancy in multi-channel coil

$$F \cdot \text{Coil} \cdot \underbrace{\text{Motion (image)}}_{\text{unknown}} = \underbrace{\text{k-space}}_{\text{corrupt}}$$

Physics-based[1]



[1] M Haskell, TMI'18

NEATER: in Motion Correction

- Residual learning: Jumpstart physics-recon
- Trained on Alzheimer's patients data

Minutes

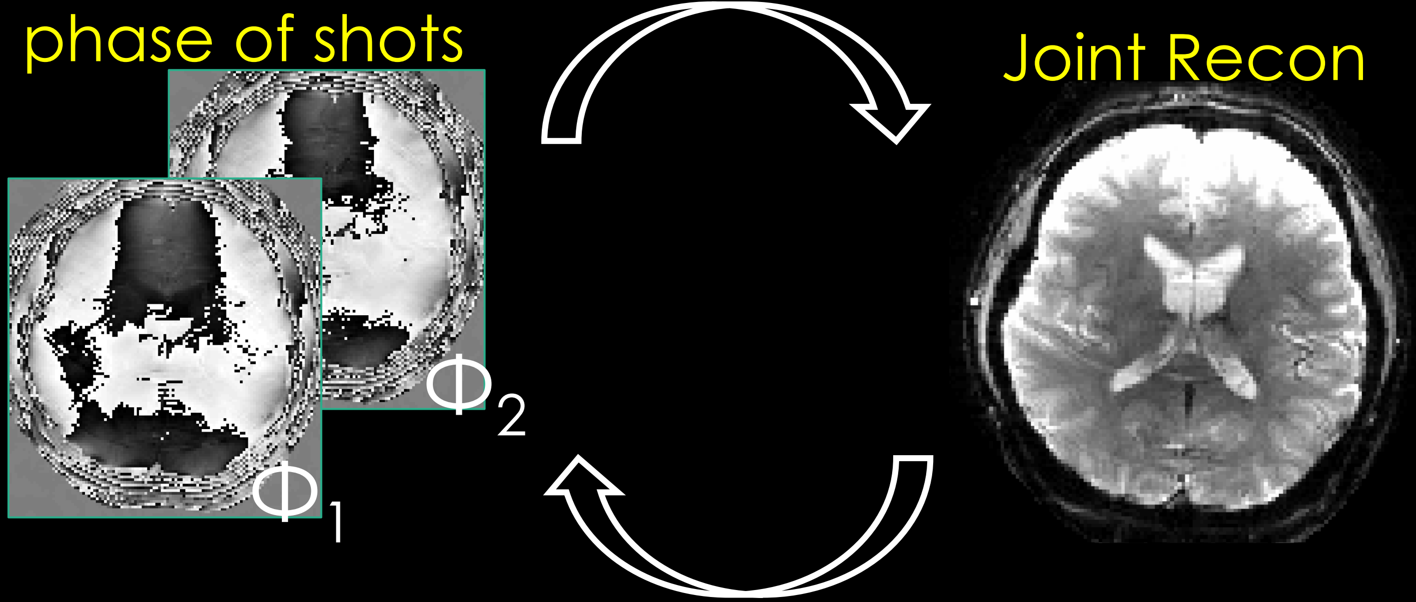
Residual learning[1]

Physics-based[1]

[1] B Bilgic, *ISMRM'18*
[2] M Haskell, TMI'18

Extensions

- Iterate: physics recon & shot phase estimation



code / data: martinos.org/~berkin

Extensions

- Iterate: physics recon & shot phase estimation
- Joint pRx & joint sparsity across contrasts for $R \geq 8$

code / data: martinos.org/~berkin

Summary

- NEATR: synergistic combo of Machine + Physics
  prevents black-box ML

- Physics recon keeps ML in check
  ML enables R=6 (not possible with pRx)

- NEATR reduced RMSE 1.6-fold over SENSE
  enabled fast, low-distortion,
  artifact- & nav-free imaging

code / data: martinos.org/~berkin

Thank you for your attention!

- Questions / comments:
  berkin@nmr.mgh.harvard.edu

- Recon code / data:
  martinos.org/~berkin