IMAGE QUALITY TRANSFER

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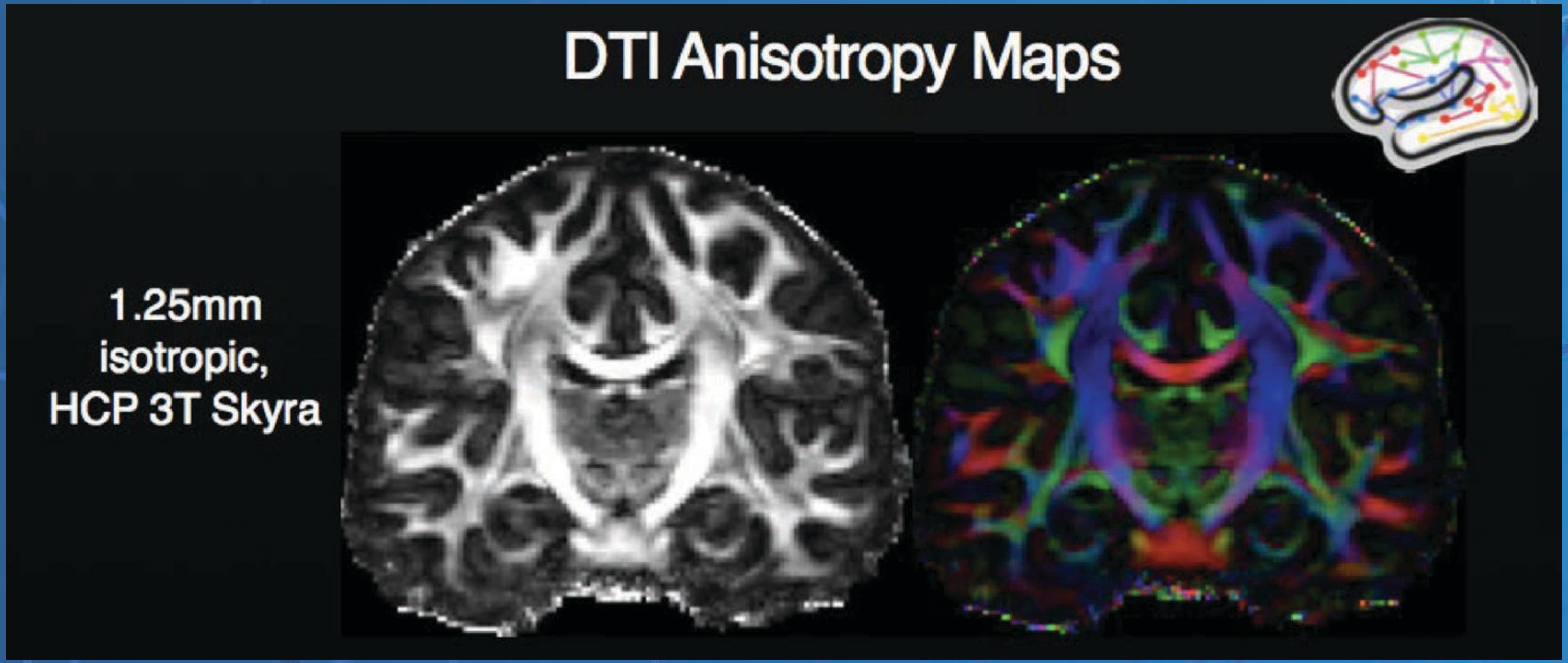
CENTRE FOR MEDICAL IMAGE COMPUTING, UNIVERSITY COLLEGE LONDON

COBCOM WINTER SCHOOL 2017, JUAN-LES-PINS, FRANCE

MOTIVATION

Human Connectome Project (HCP)



Research Scanner

- High resolution and SNR
- Long acquisition times
  - Expensive

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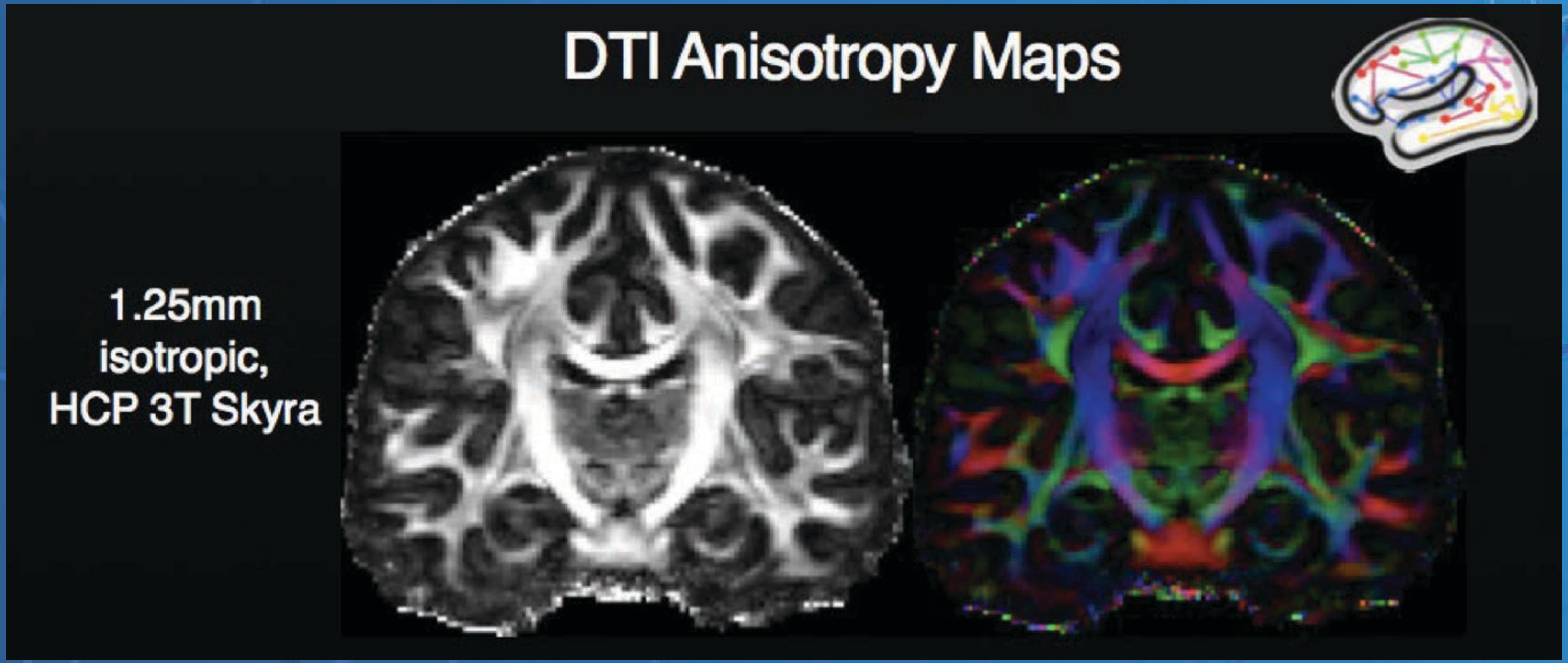
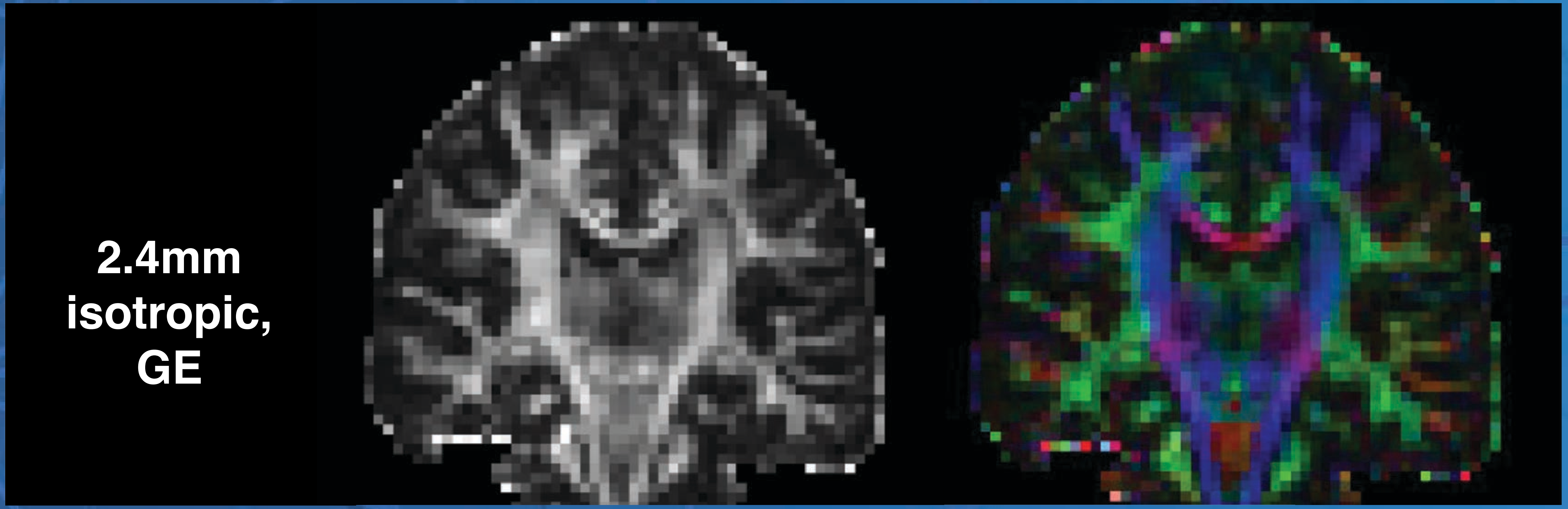


Hospital Scanner



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Clinical Scanners

- Low resolution and SNR
- Time and cost pressure
- Subsequent analysis affected

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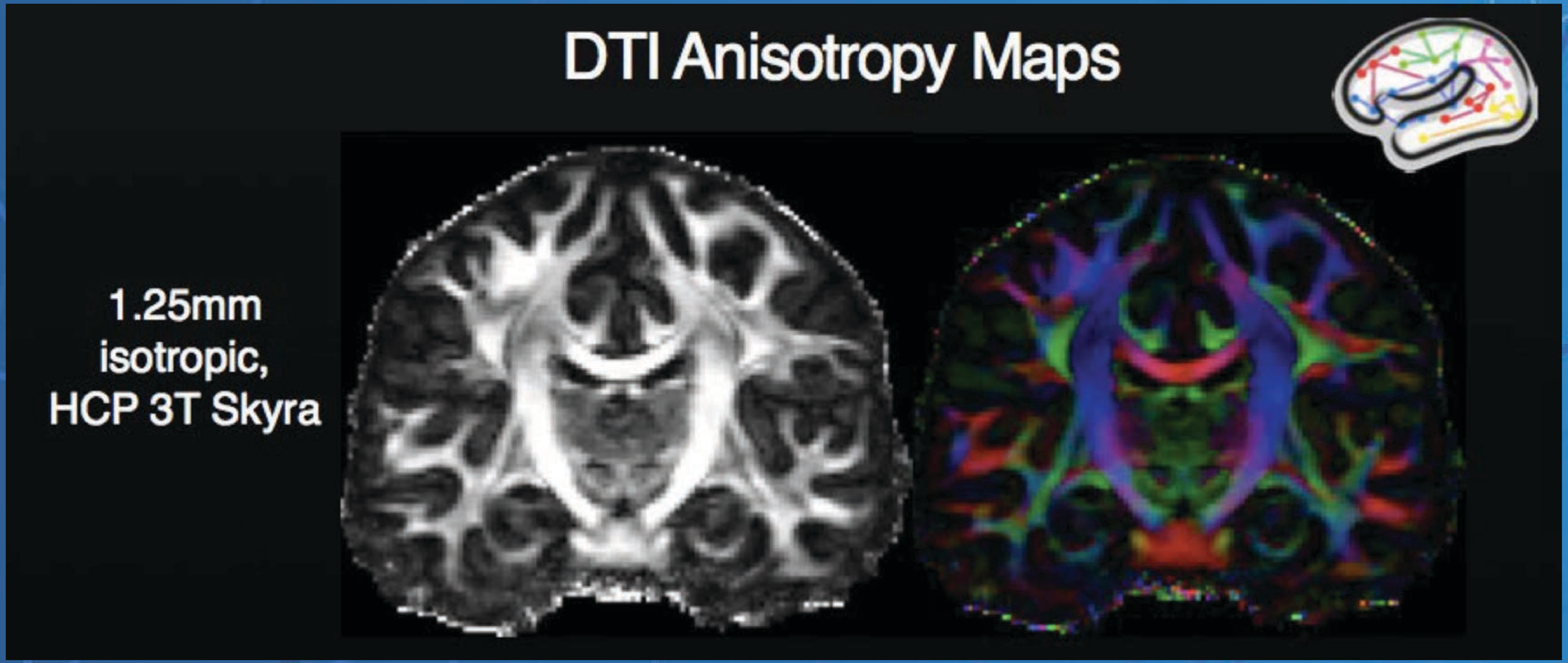

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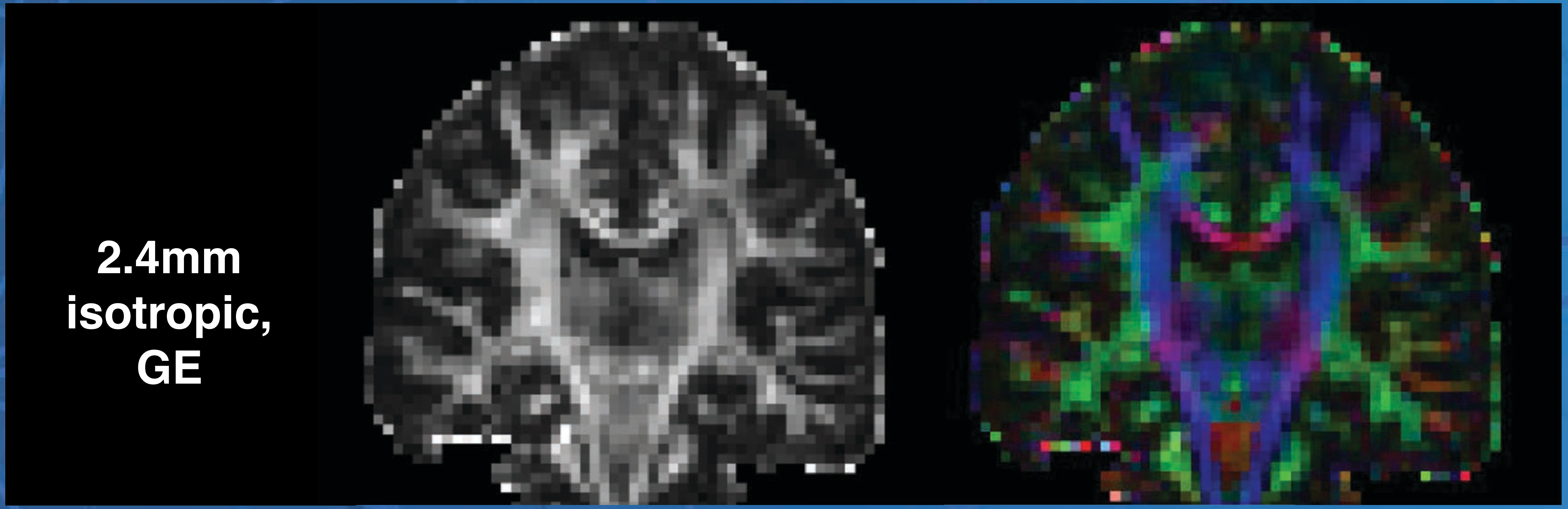

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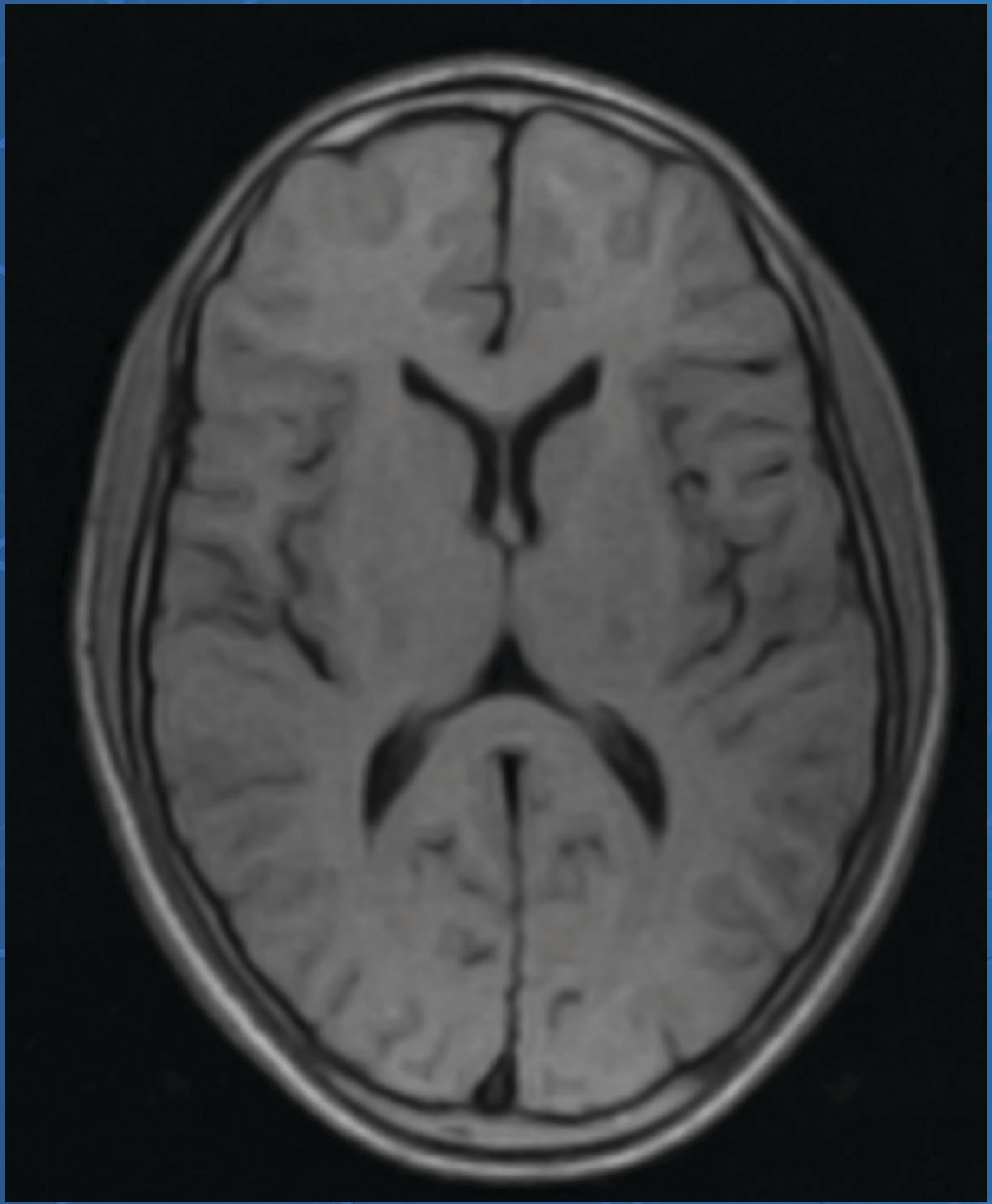
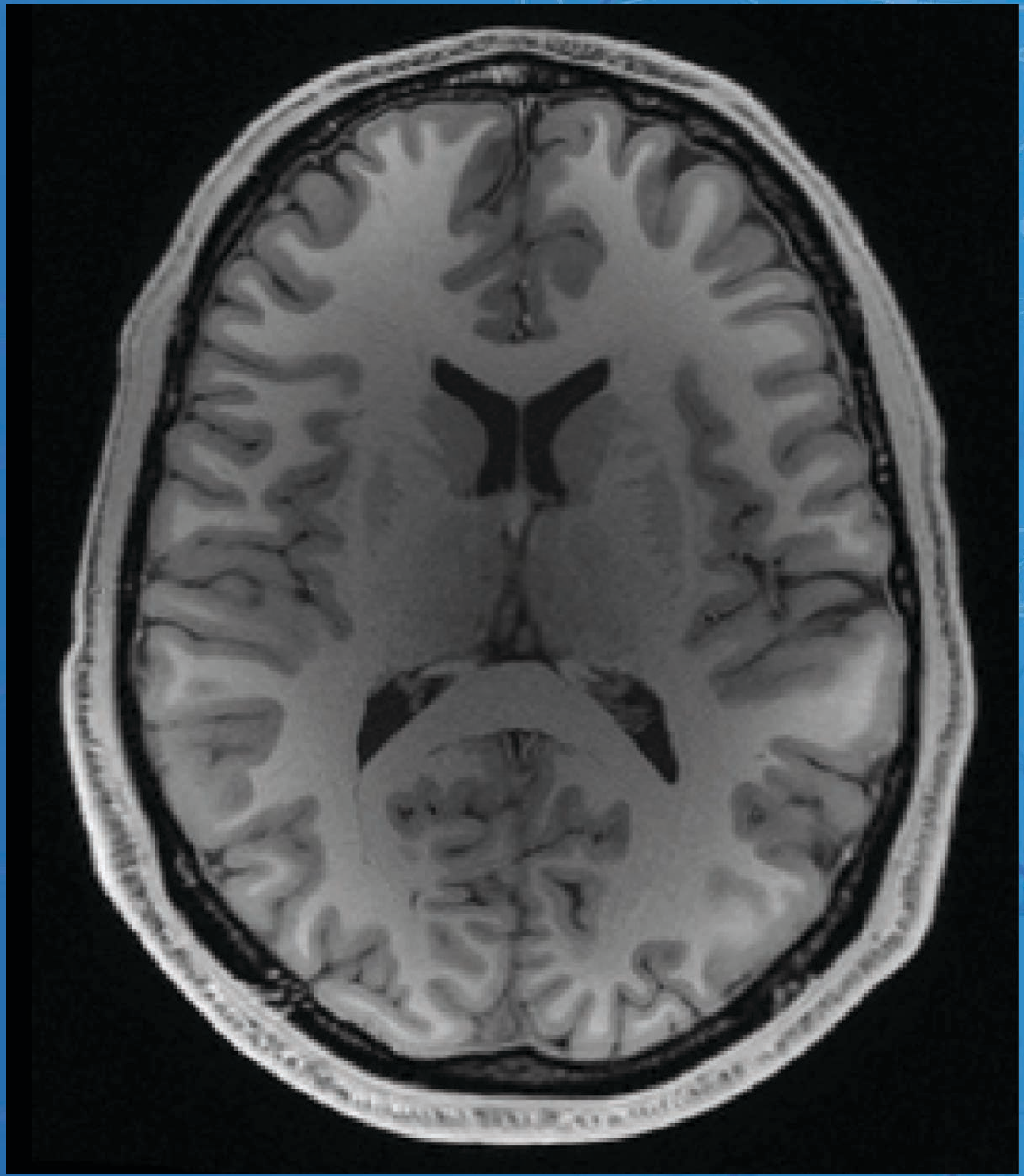
IQT: Machine Learning + Information propagation

ENHANCE DECISIONS IN DEVELOPING NATIONS

- Developing nations *(80% of world's population)* rely on older low-field MRI

ENHANCE DECISIONS IN DEVELOPING NATIONS

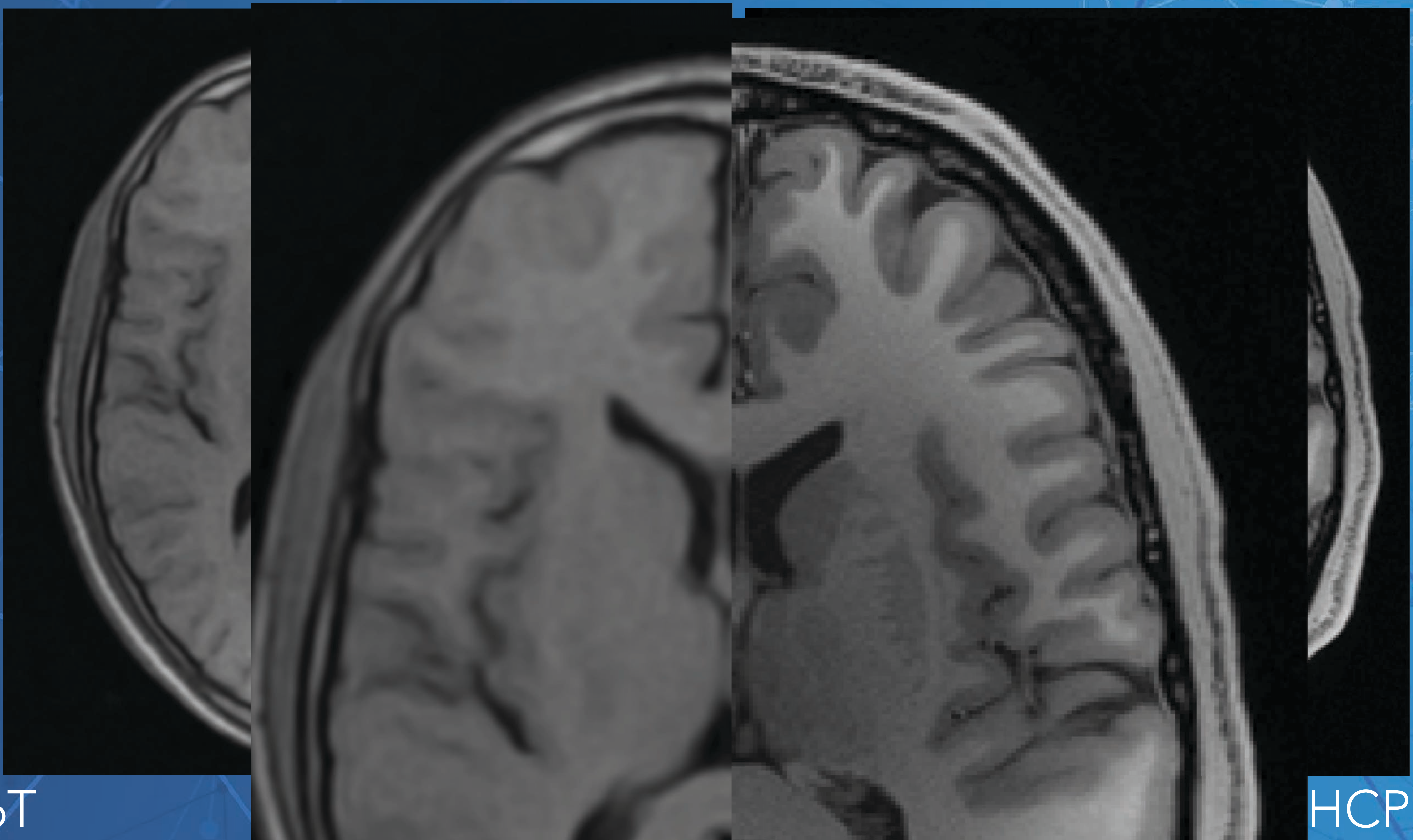




0.36T

HCP (3T-7T)

ENHANCE DECISIONS IN DEVELOPING NATIONS



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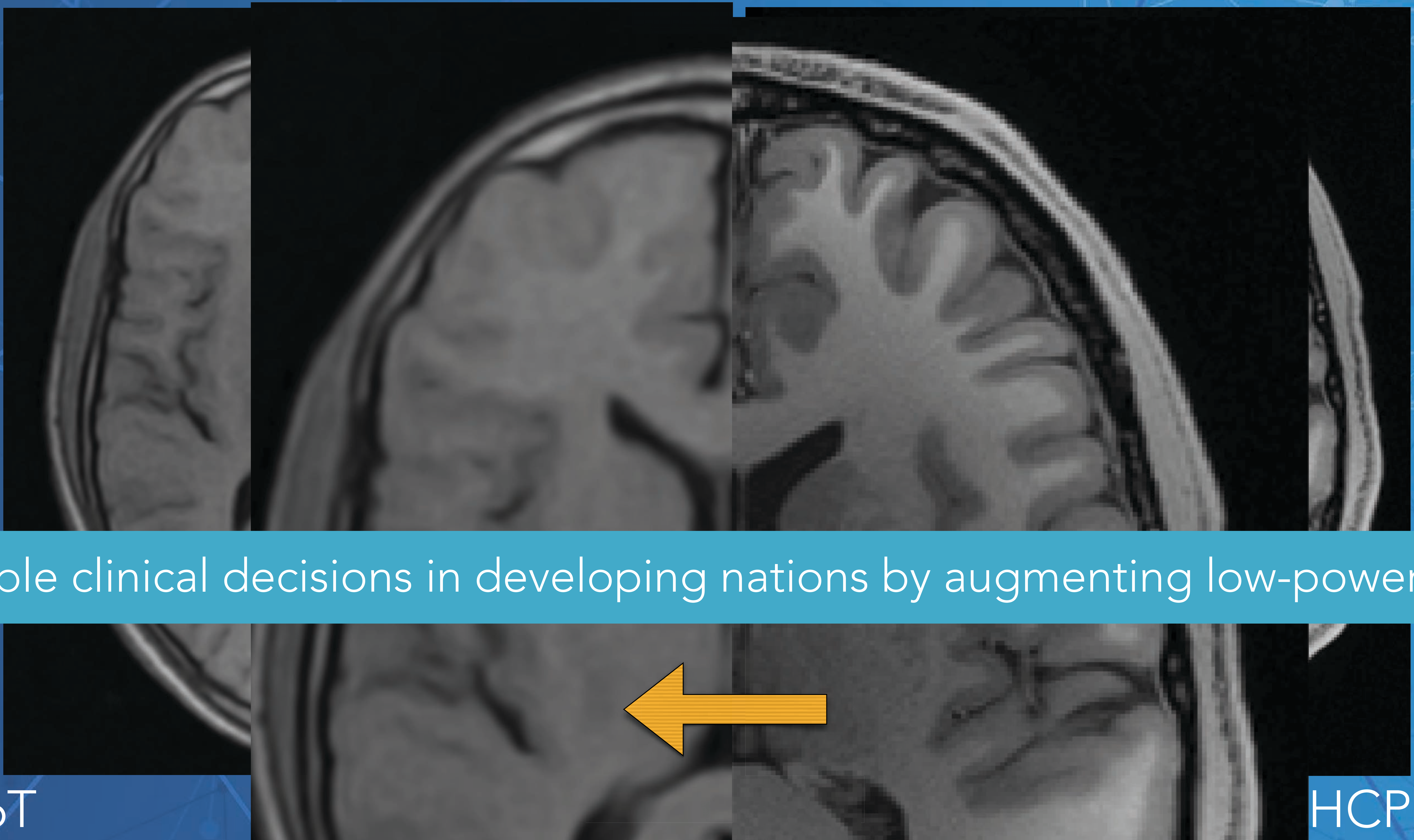
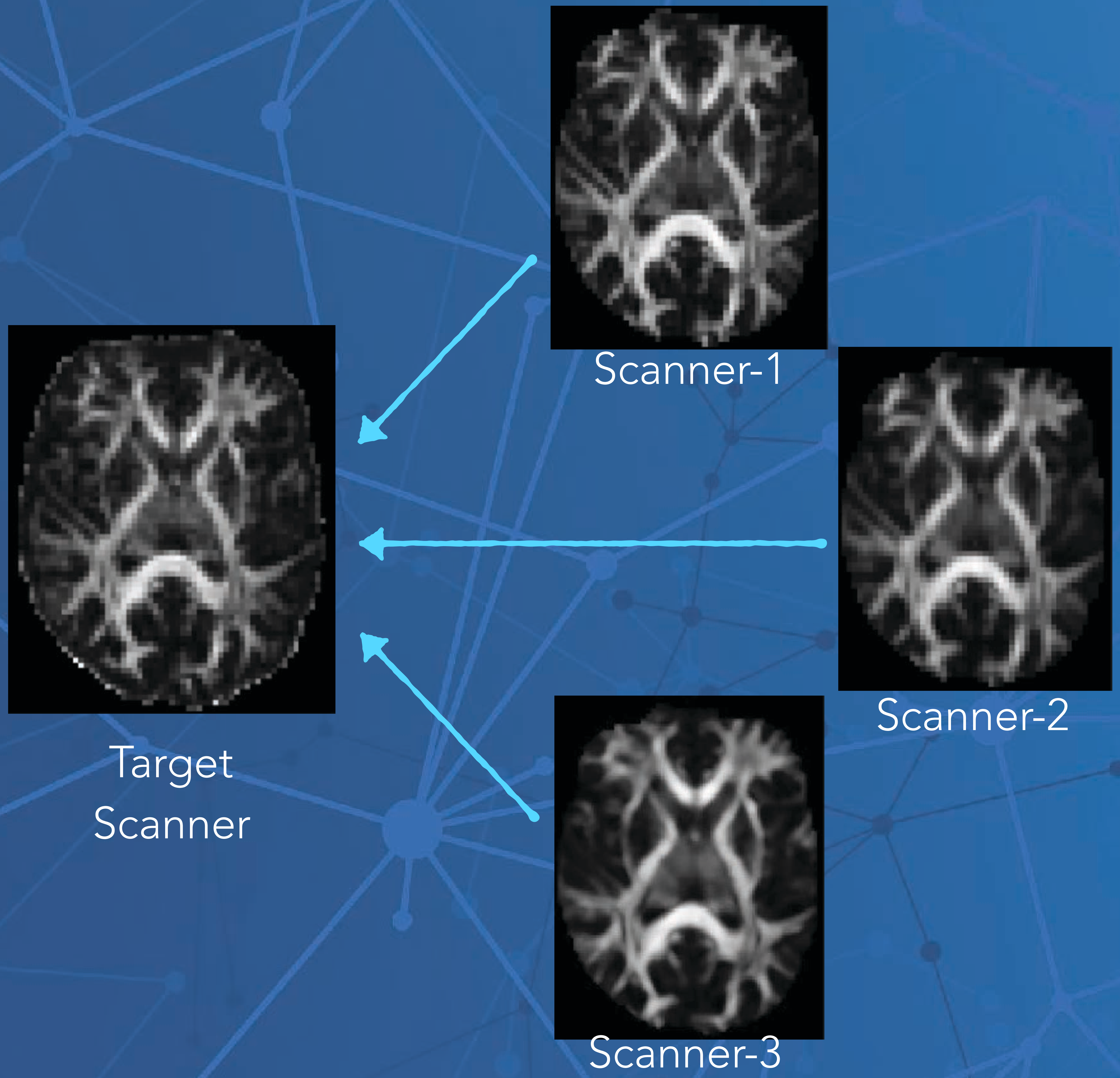


Enable clinical decisions in developing nations by augmenting low-power MRIs

0.36T

HCP (3T-7T)

DATA HARMONISATION

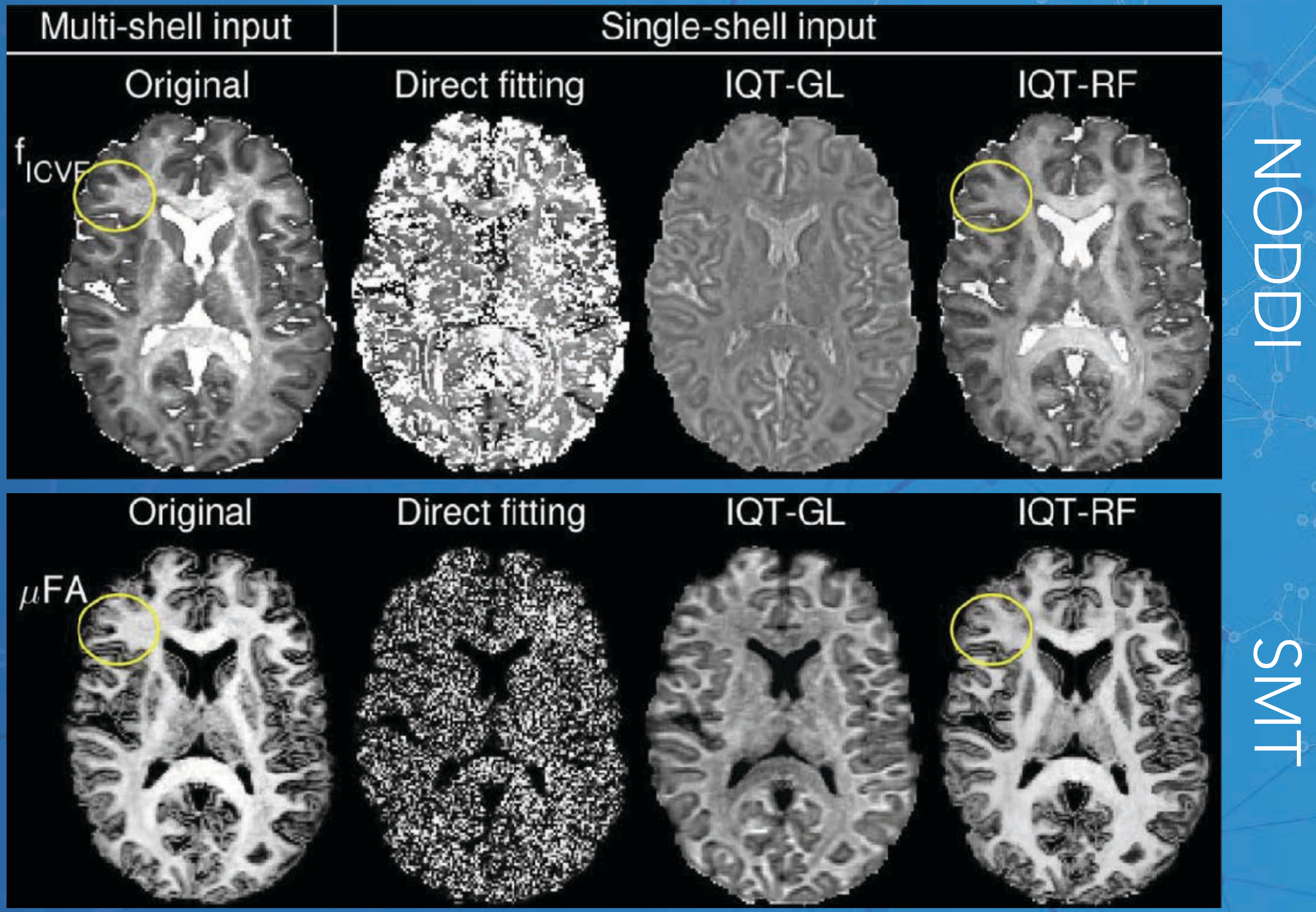


- Enable large scale multi-centre studies and acquisitions
    - Normalise data across various scanner models, makes and acquisition parameters
- Enable re-use of old data from phased out scanners
    - Facilitate longitudinal studies

PARAMETER MAPPING

- Estimate multi-shell model parameters from single-shell data
  - faster acquisition
  - apply on historical single-shell datasets

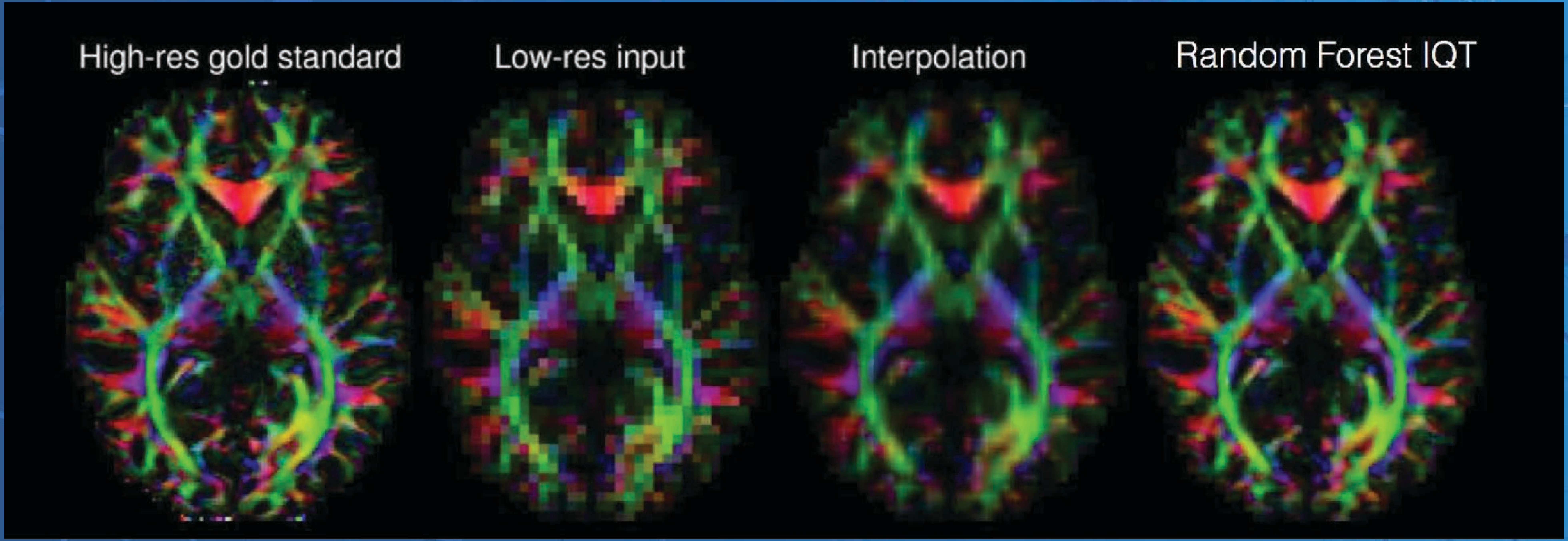
[ALEXANDER ET AL 2014, 2017]



SUPER-RESOLUTION

- Enhancing diffusion MRI maps: DTI, MAP-MRI, Tractography

[ALEXANDER ET AL 2014, 2017]



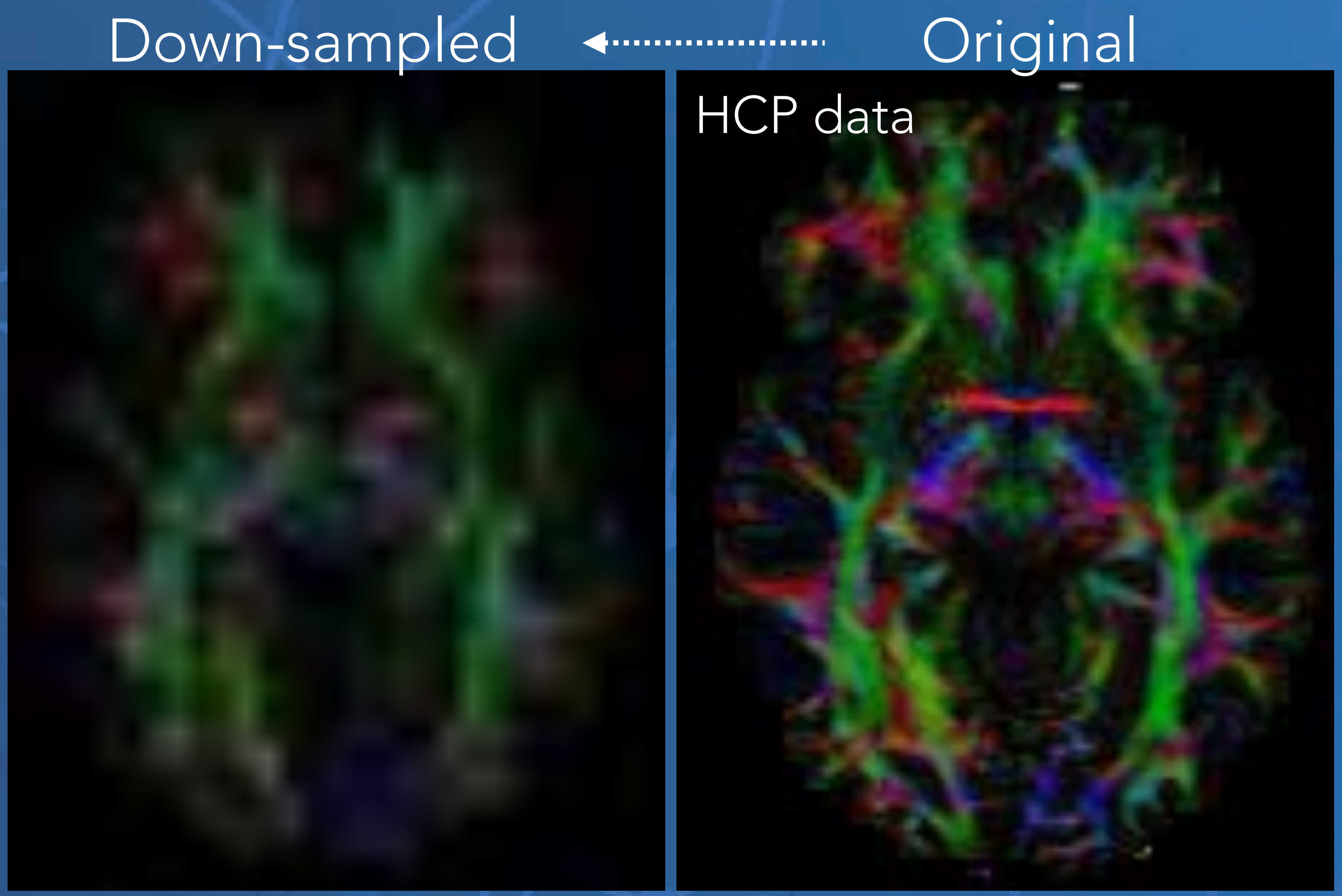
SUPER RESOLUTION

- Random Forest IQT
- Bayesian RF IQT: Introducing Uncertainty
- Deep Learning IQT with Uncertainty

PIPELINE OVERVIEW

- Training:
  - Begin with HIGH-quality data (HCP dataset)
  - Synthetically downsample to create paired low-quality / high-quality dataset
  - Learn mapping from low-quality —> high-quality
- Testing:
  - Apply mapping to test (low-quality) data to enhance quality

PATCH BASED REGRESSION



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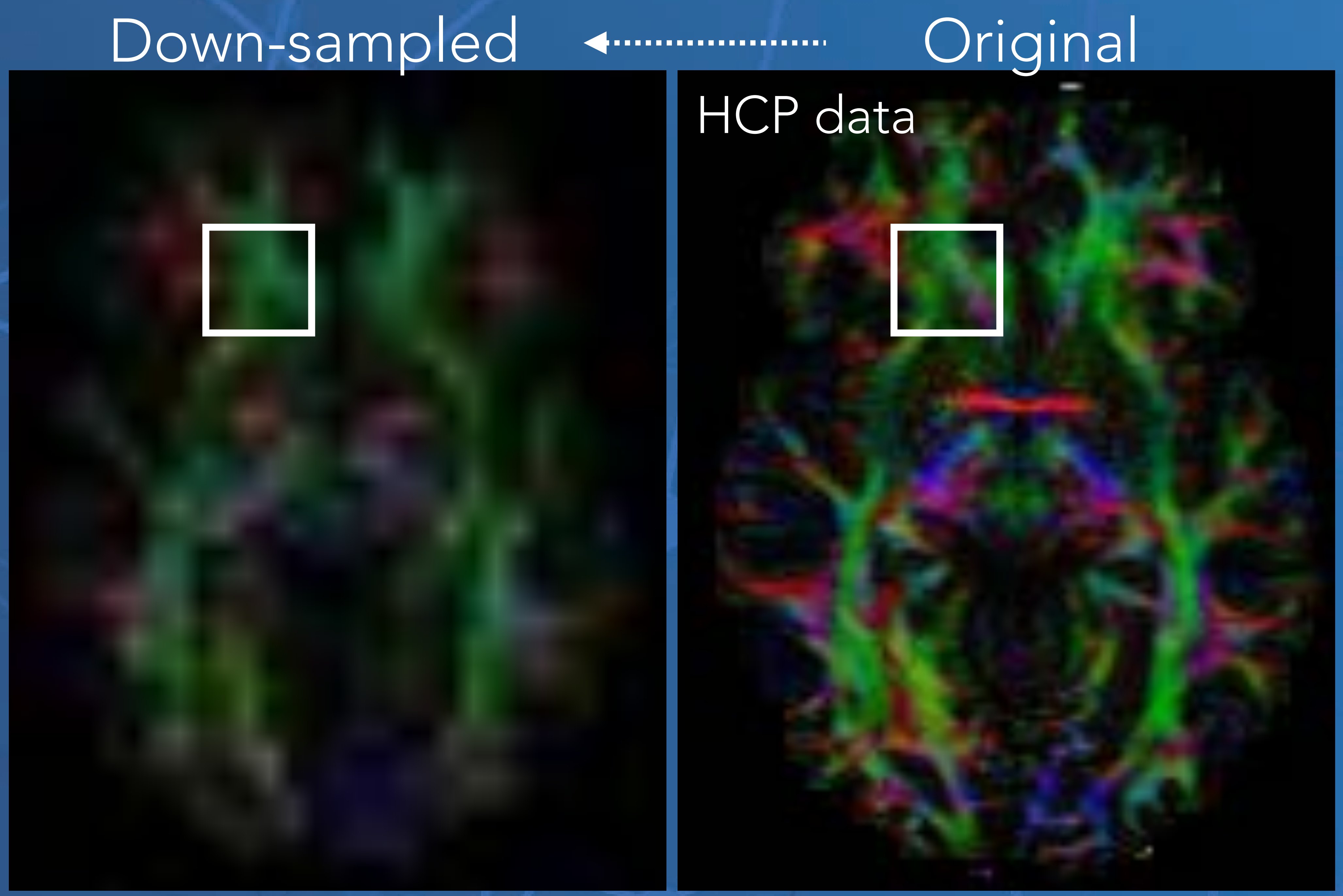

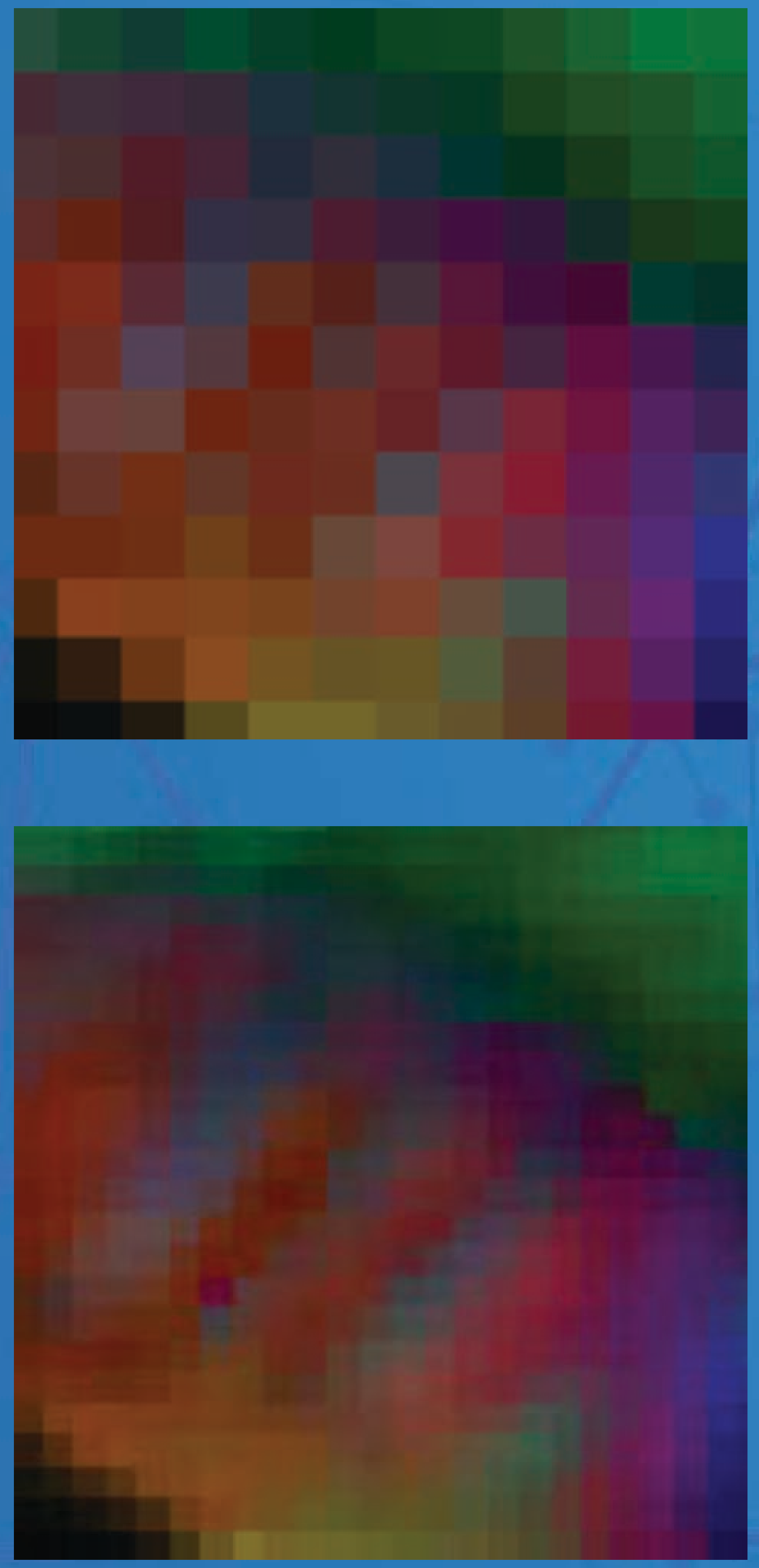

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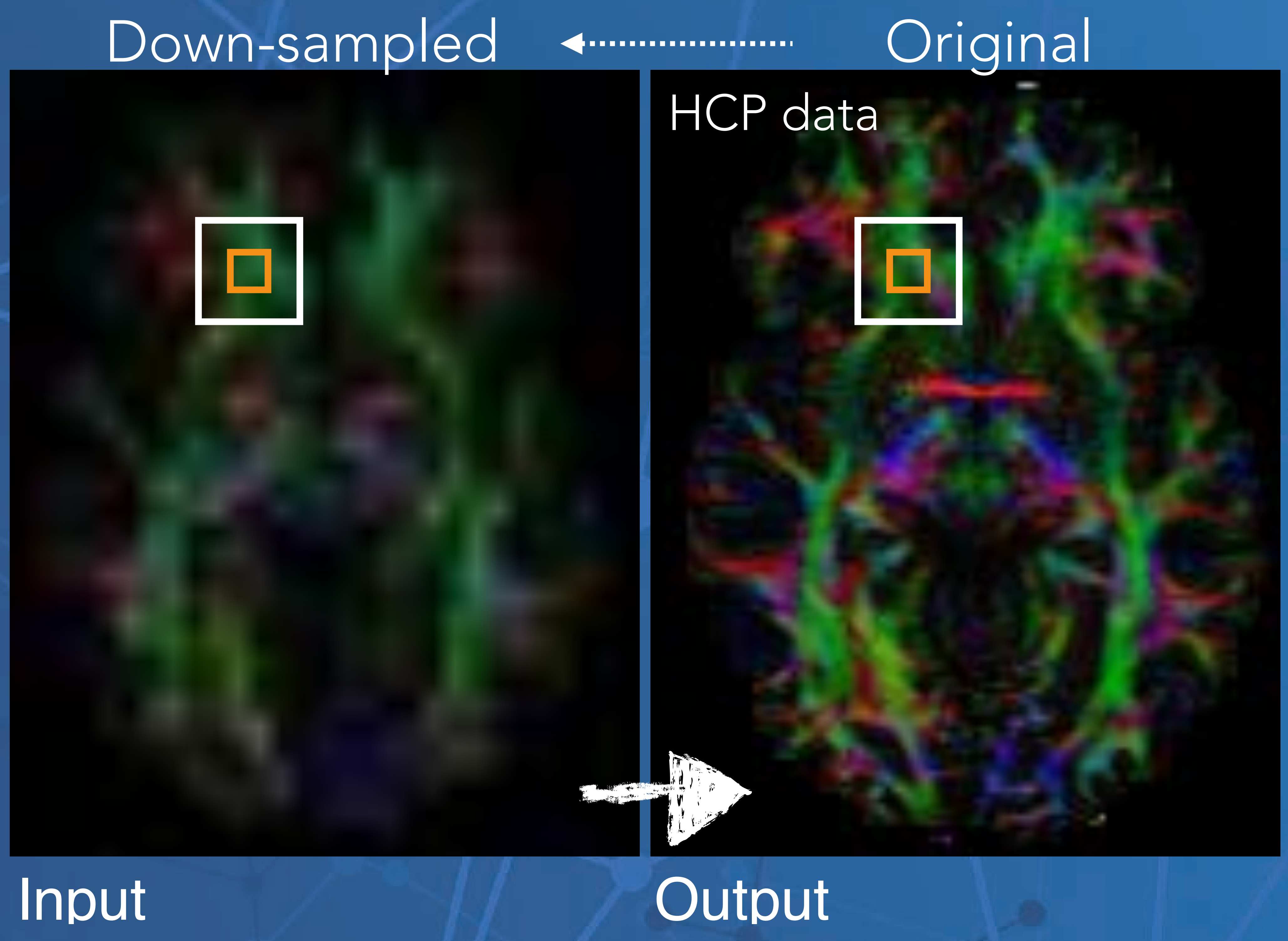

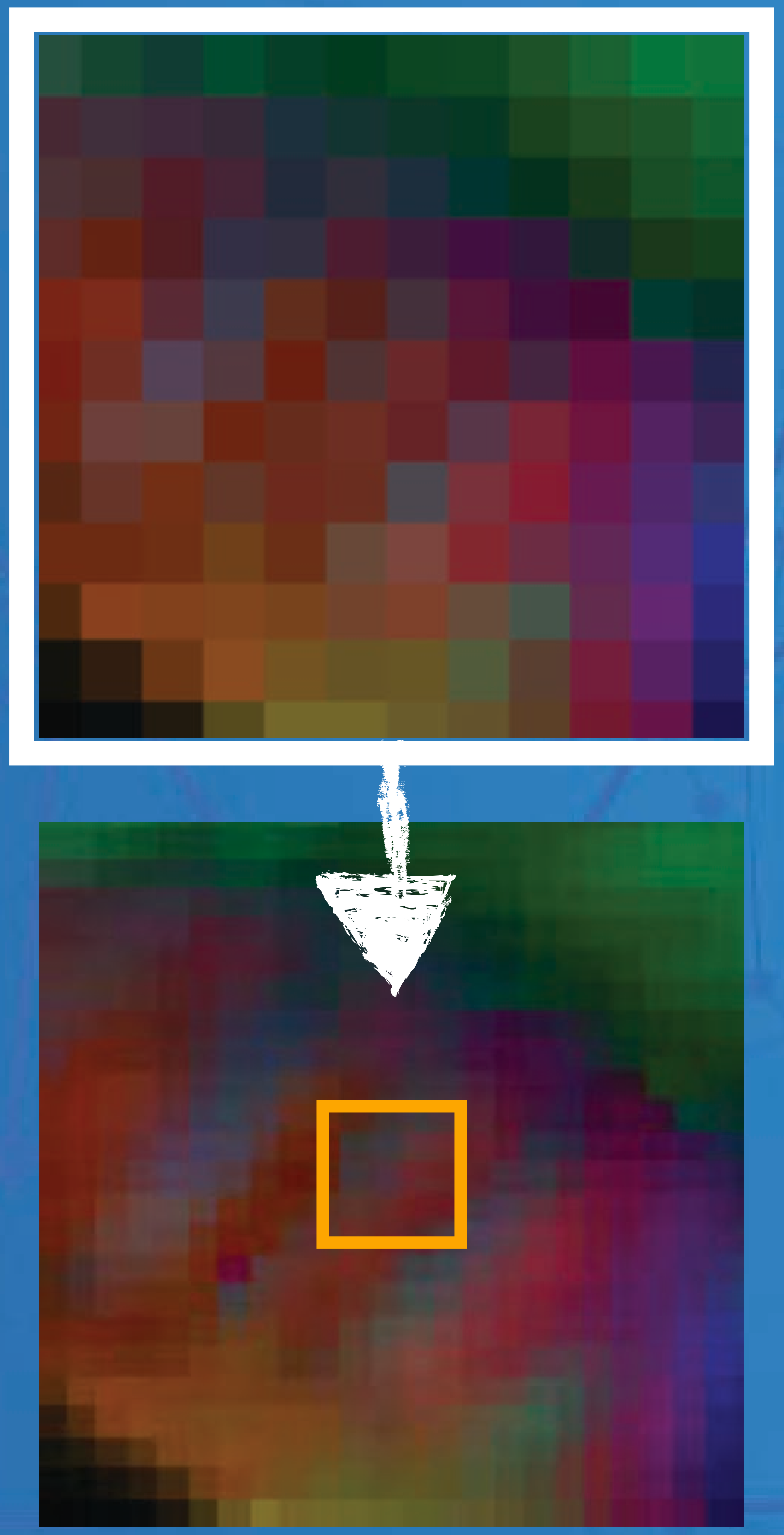

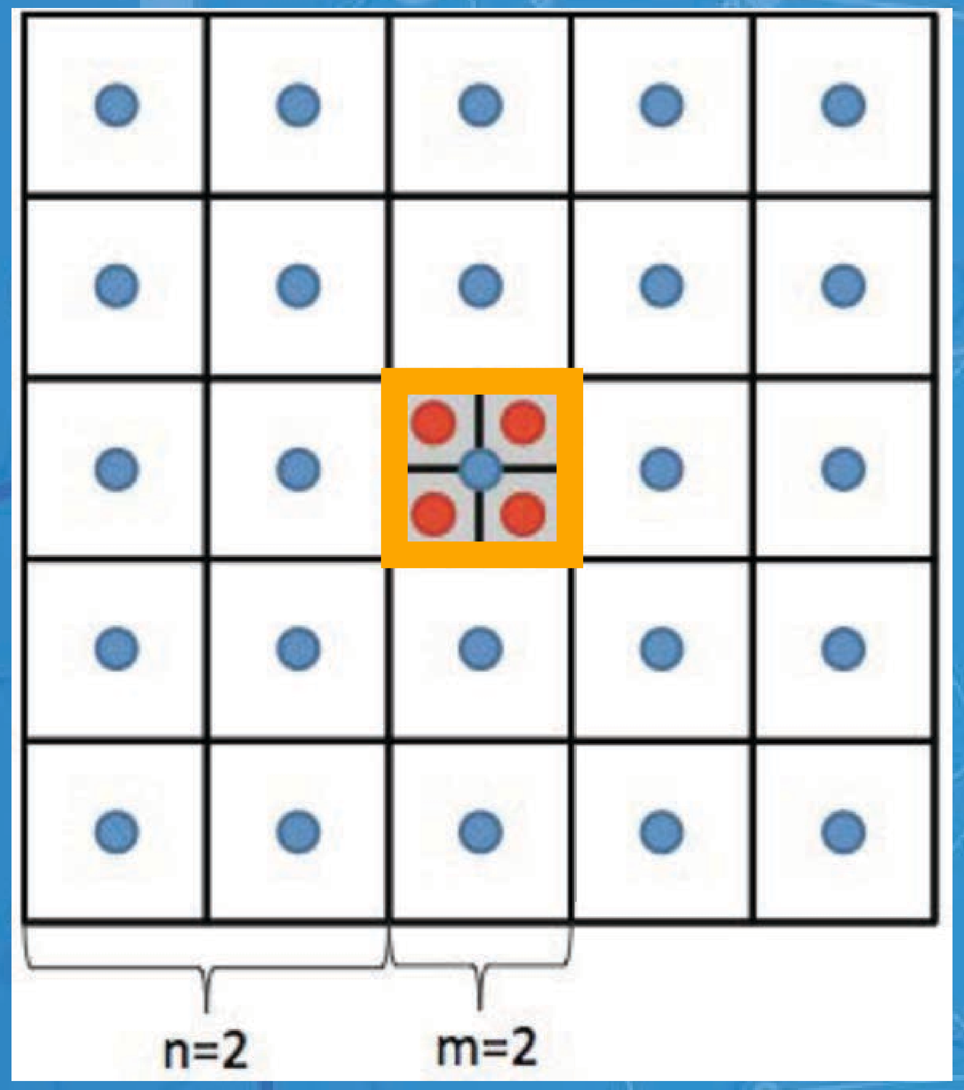

$$\mathbf{x} \in \mathbb{R}^{N_l p_l} \rightarrow \mathbf{y}(\mathbf{x}) \in \mathbb{R}^{N_h p_h}$$

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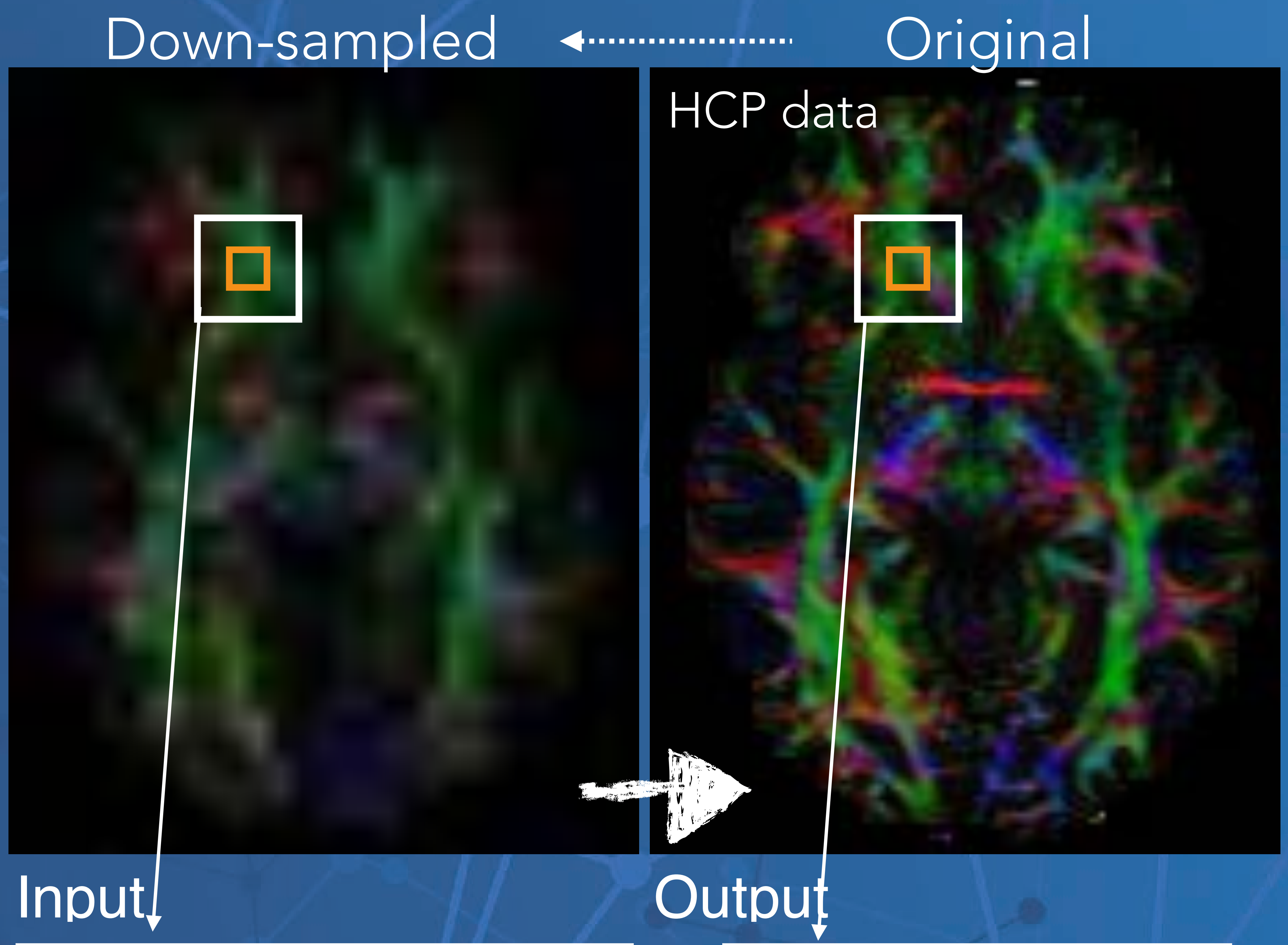
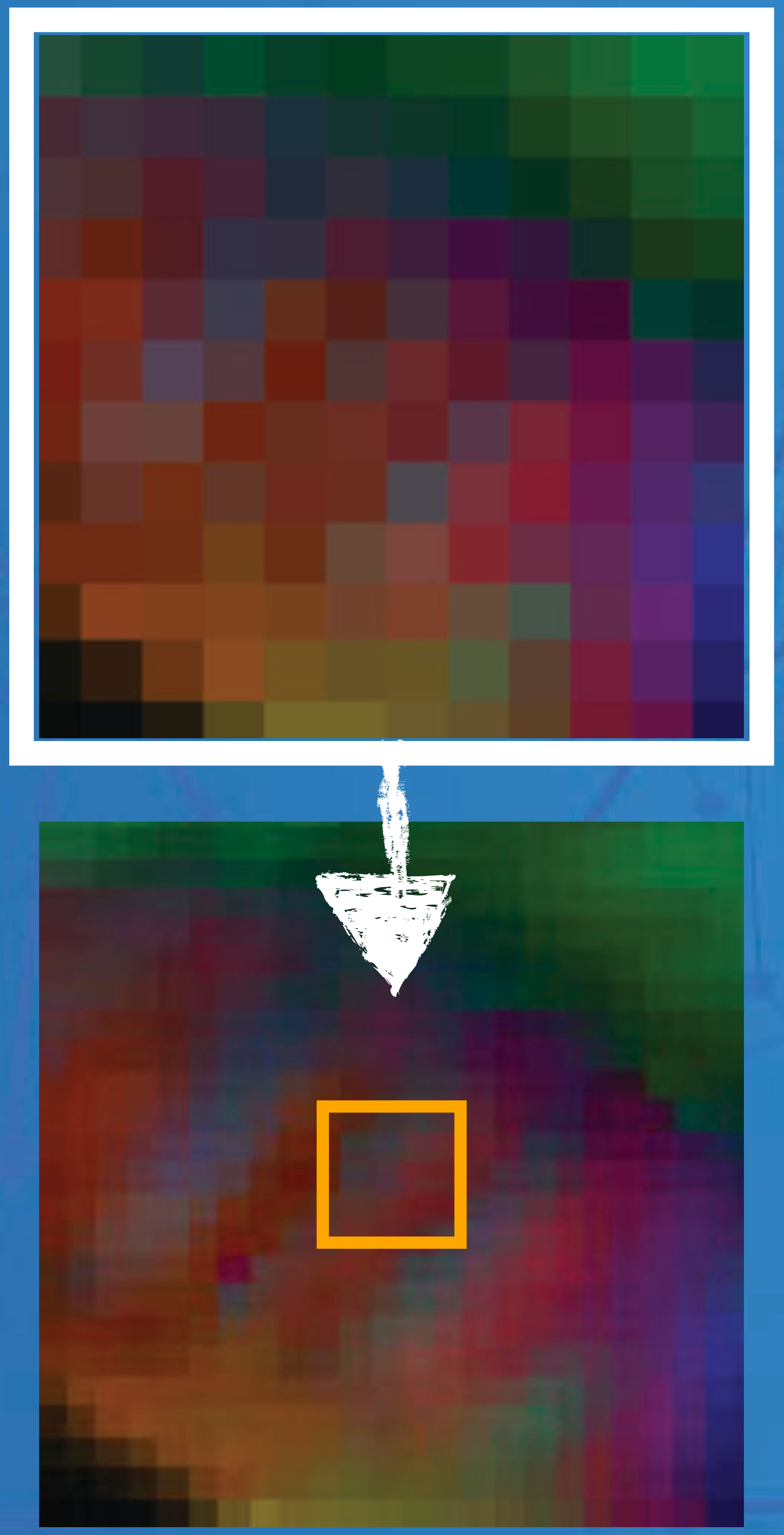
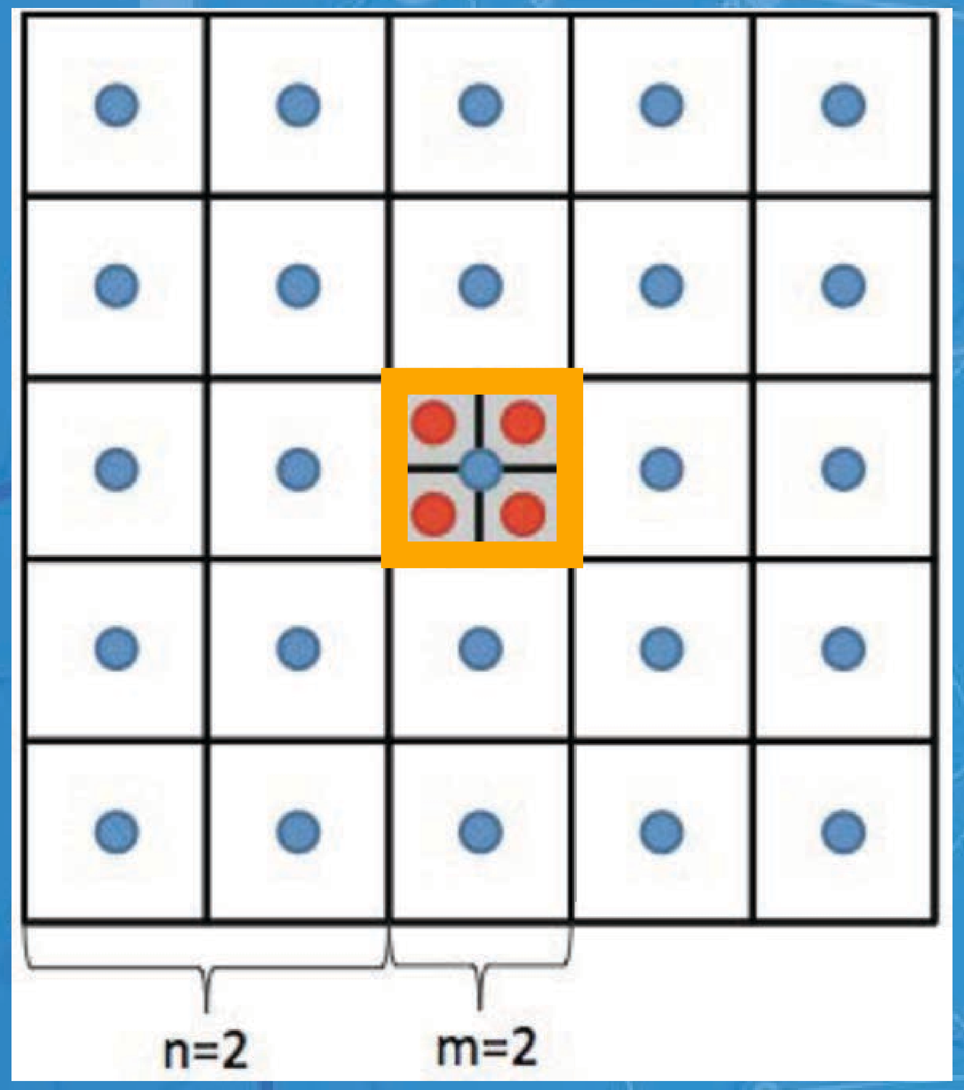


$6 \times (2n+1)^3$

$6 \times m^3$





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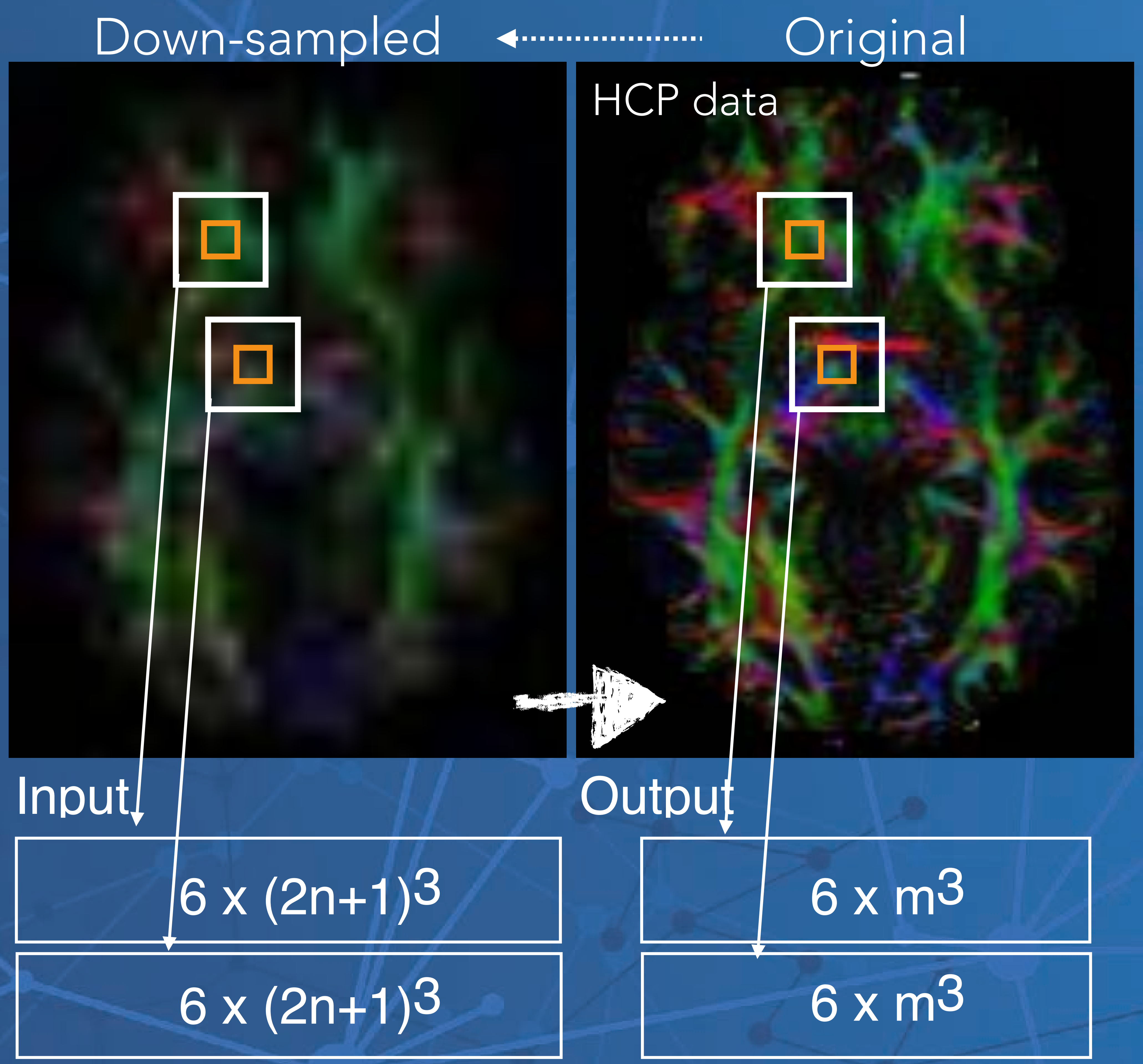

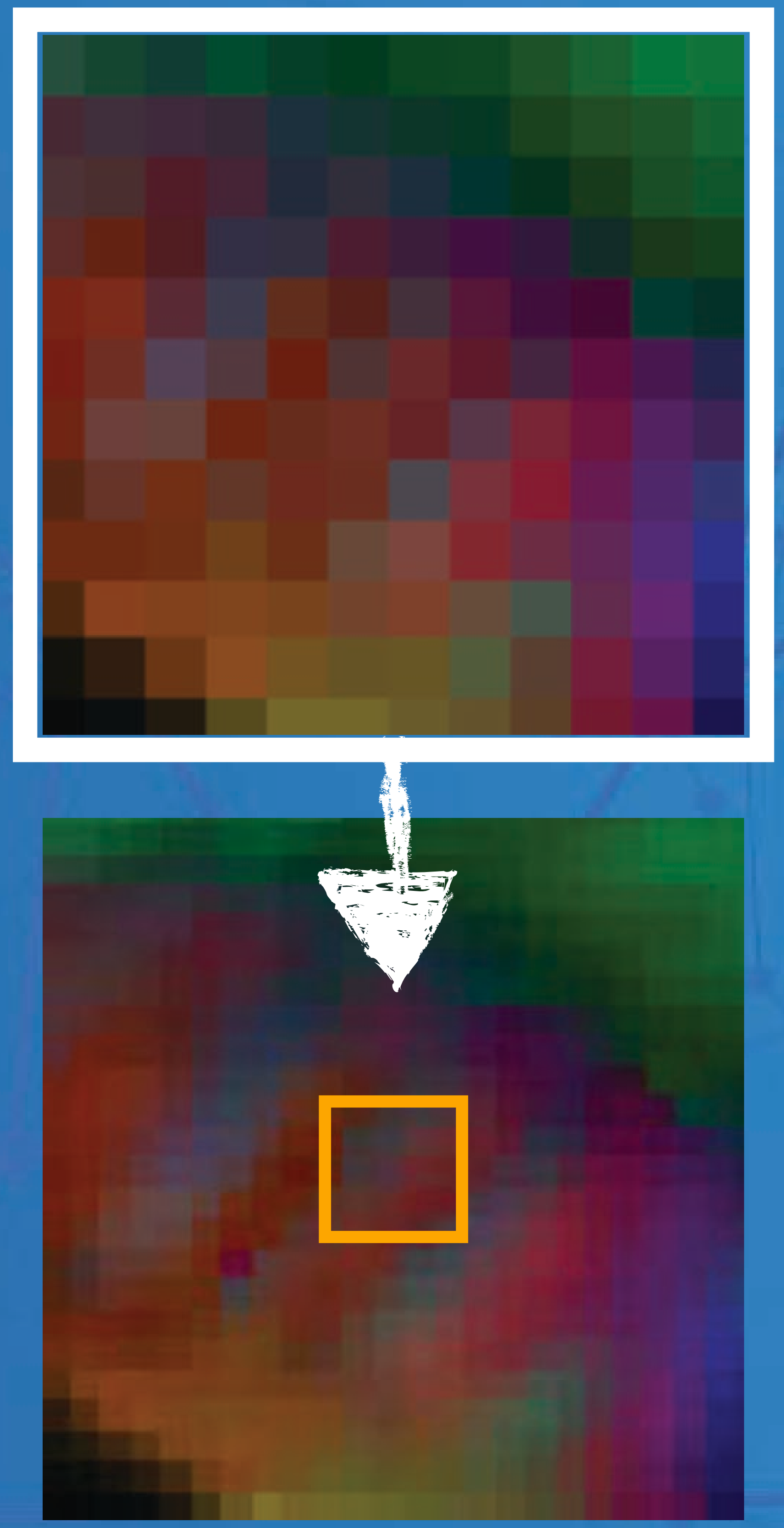

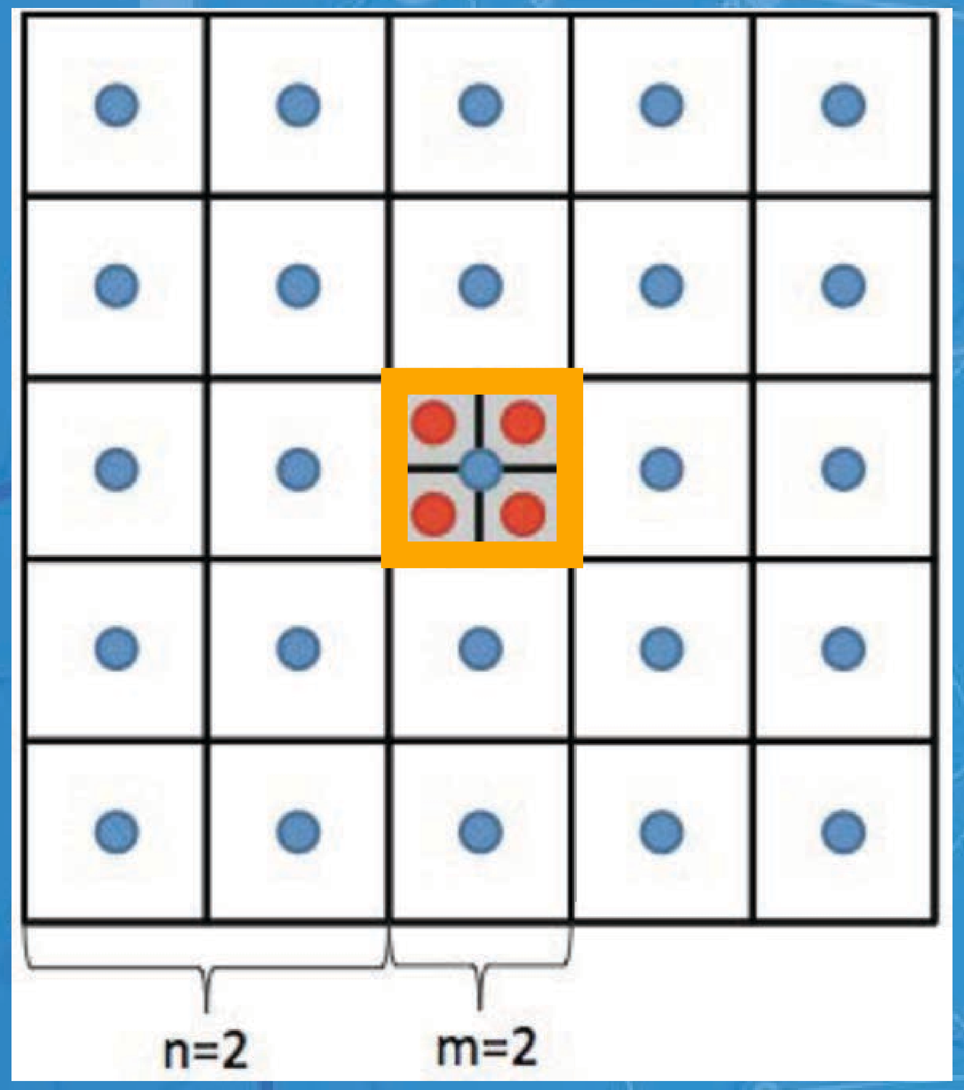

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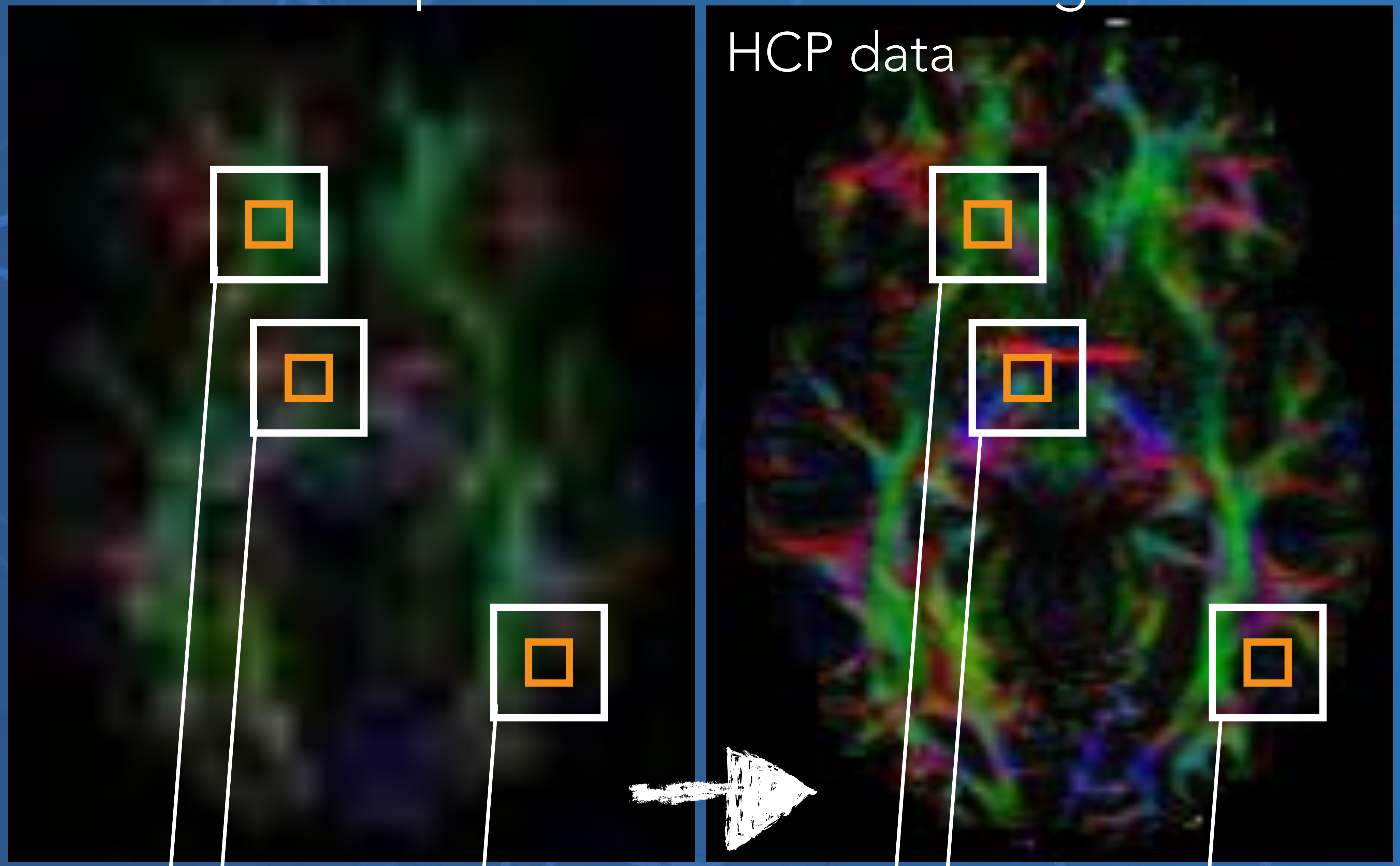

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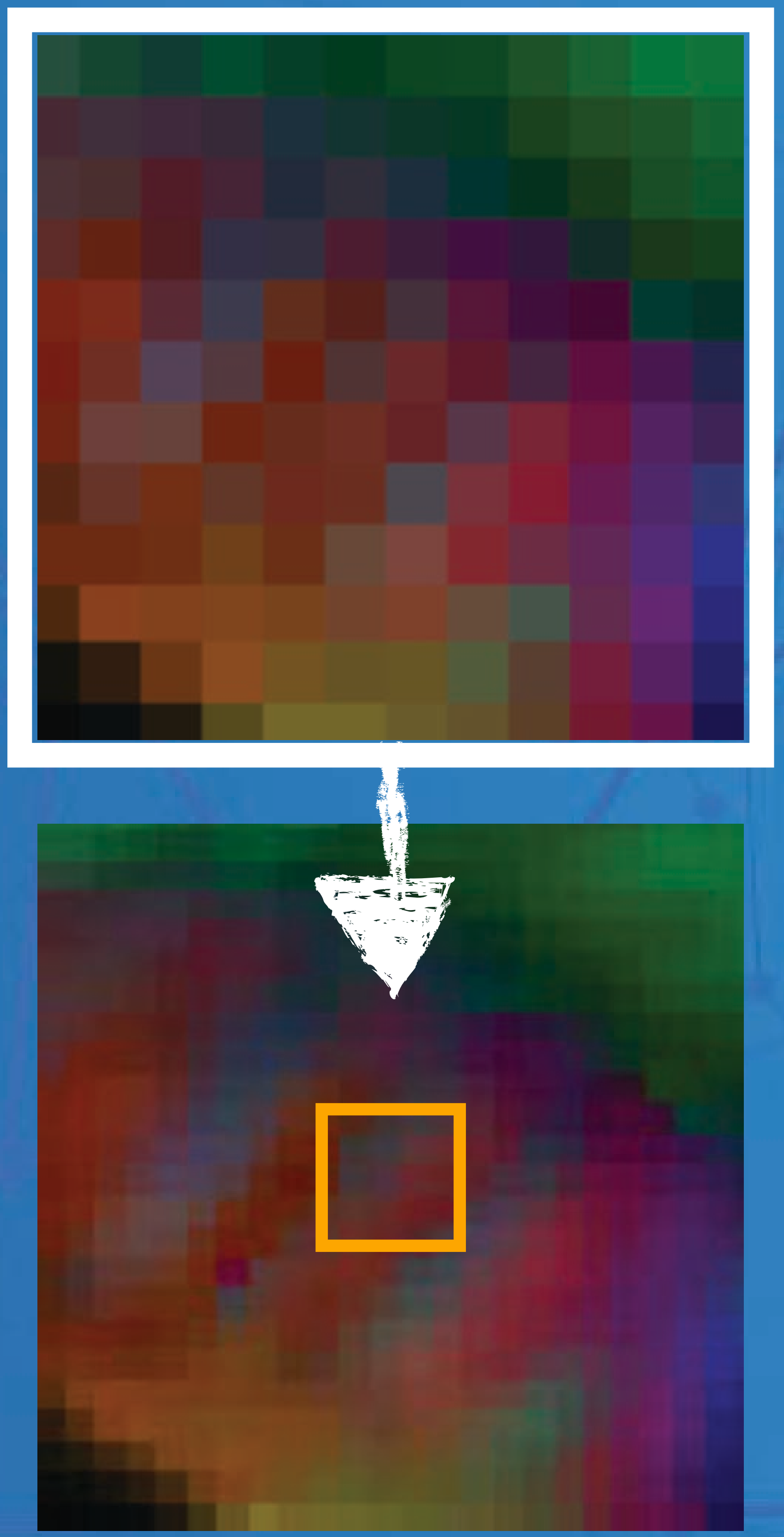
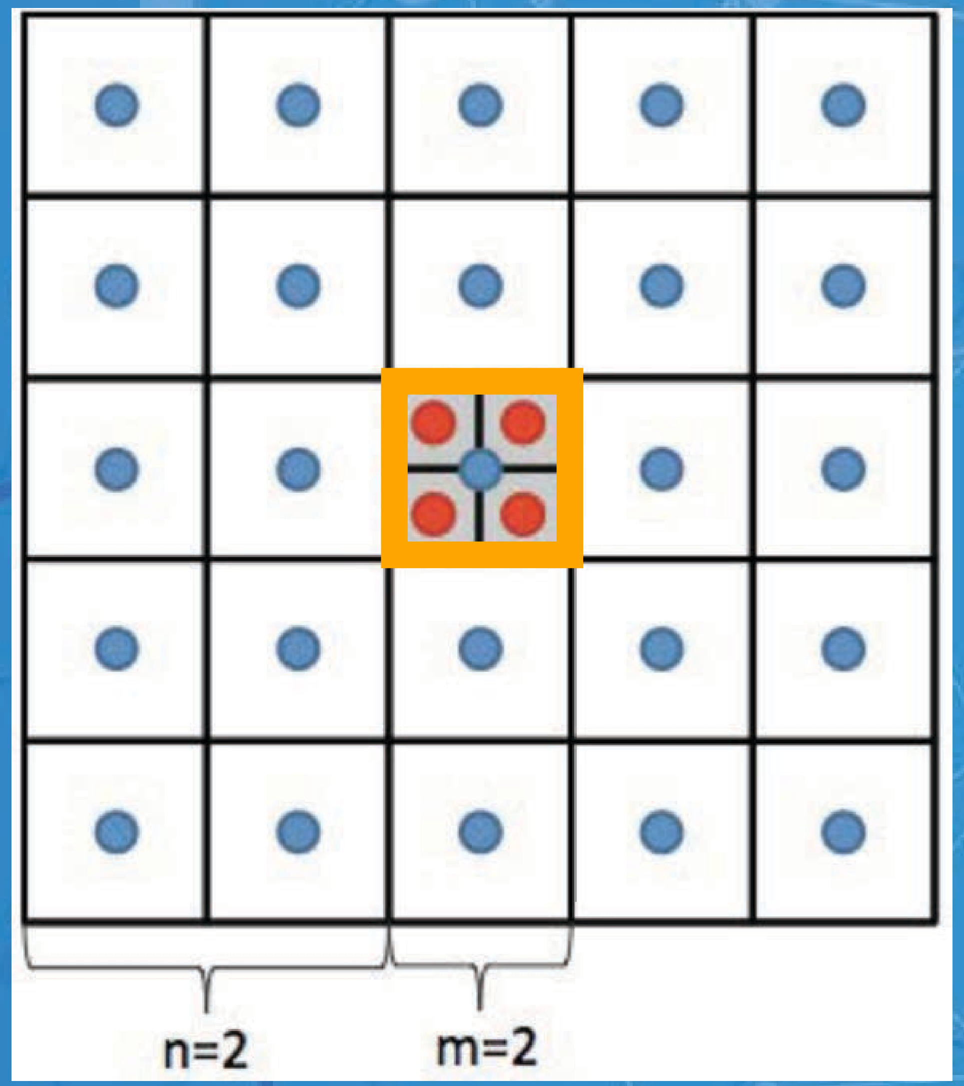
Output

6 x m^3

6 x m^3

6 x m^3





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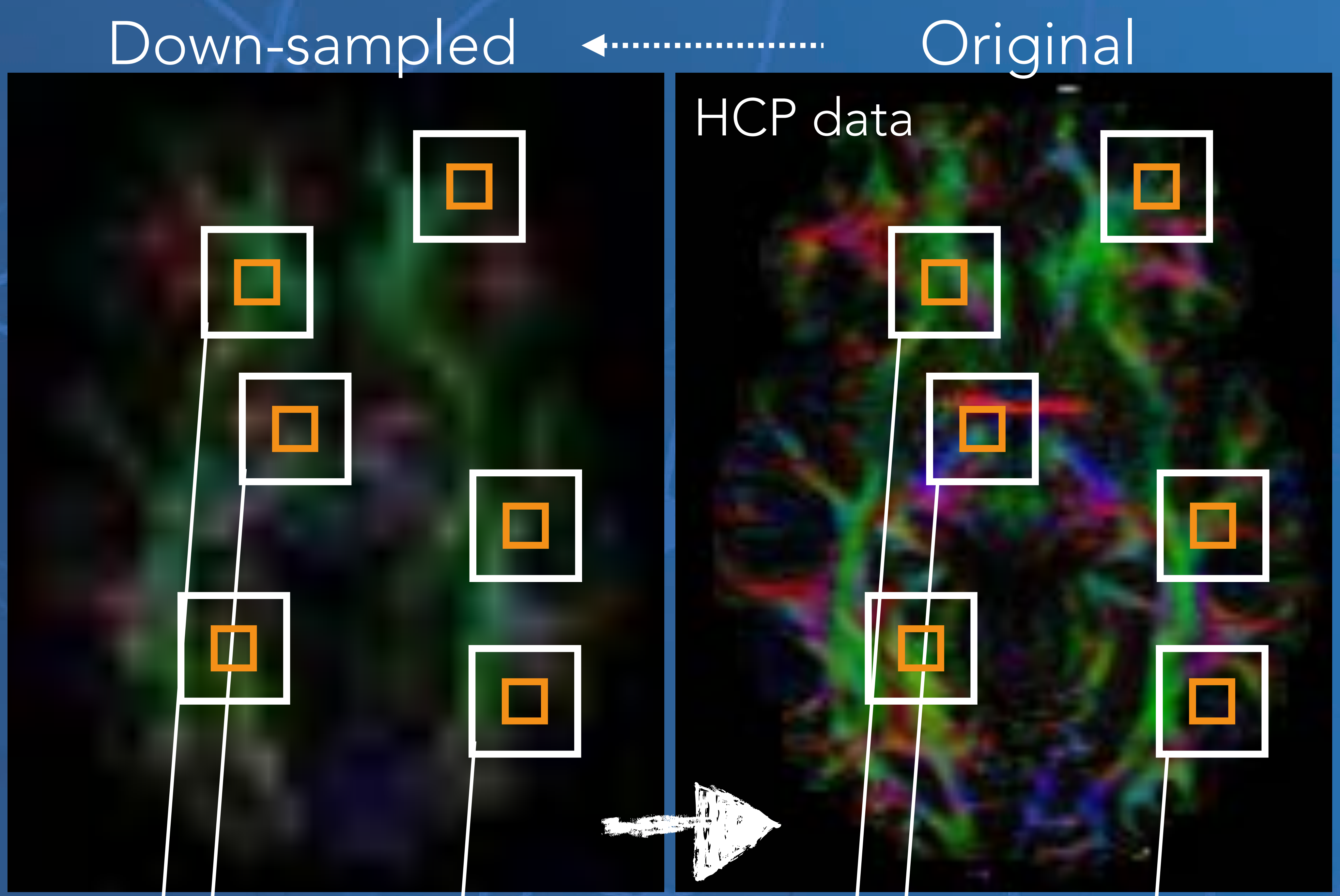

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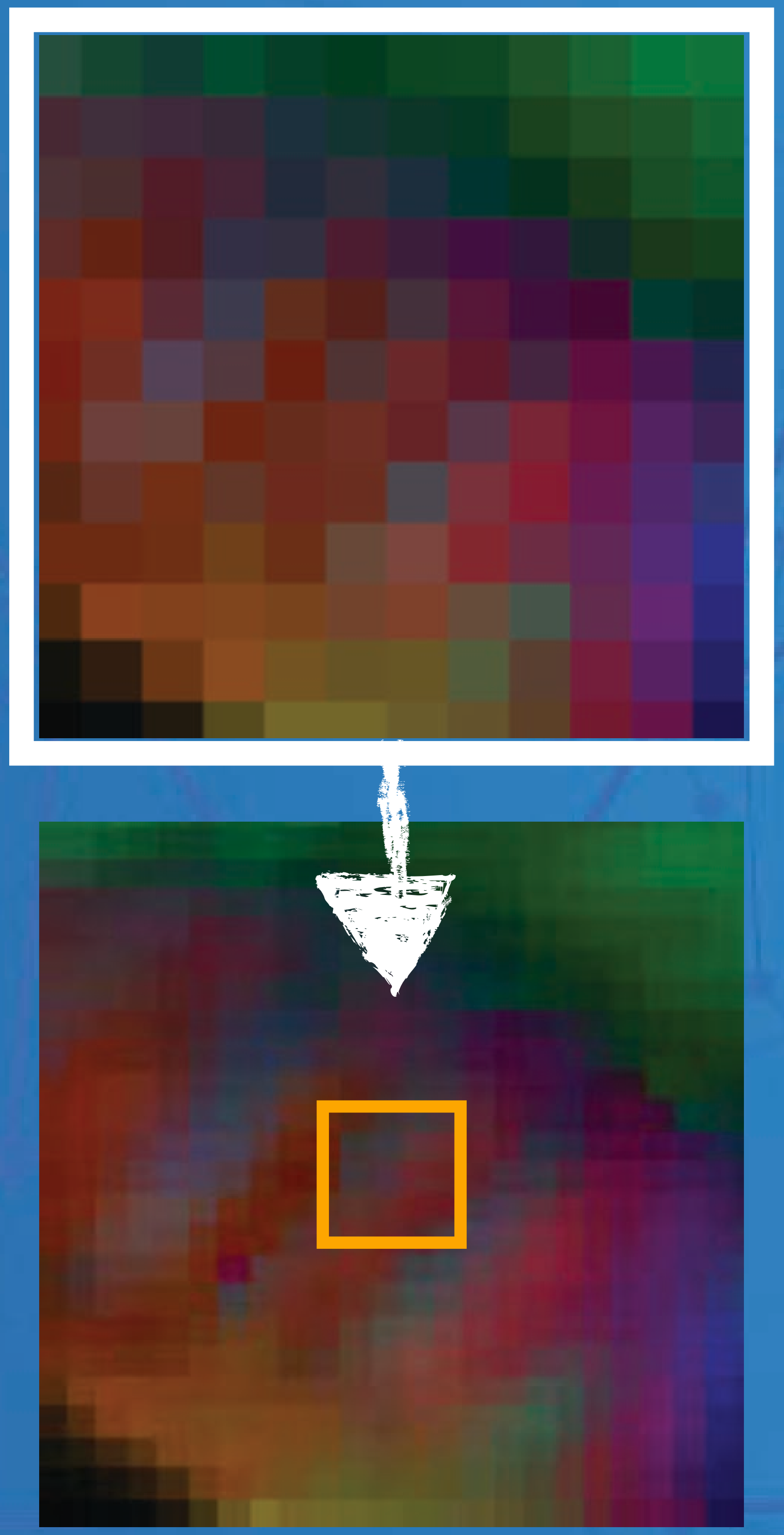

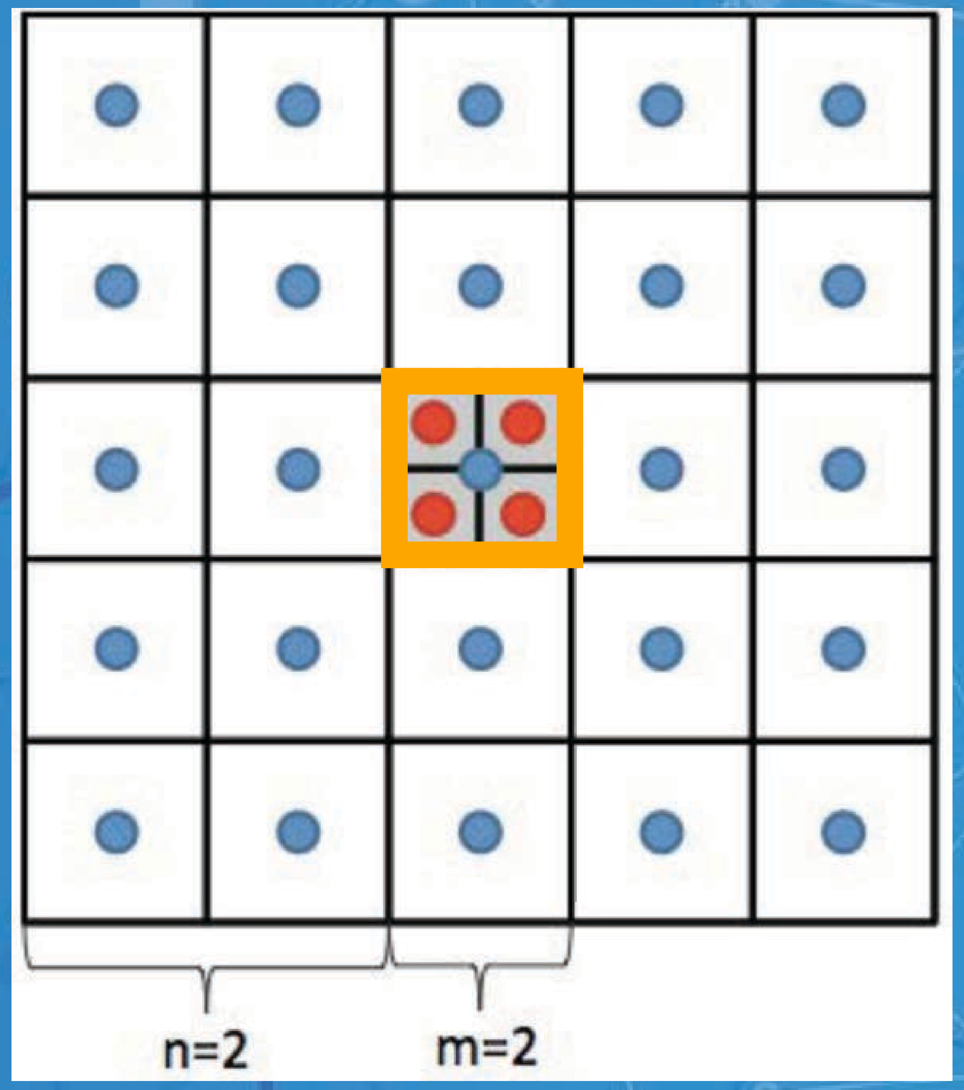

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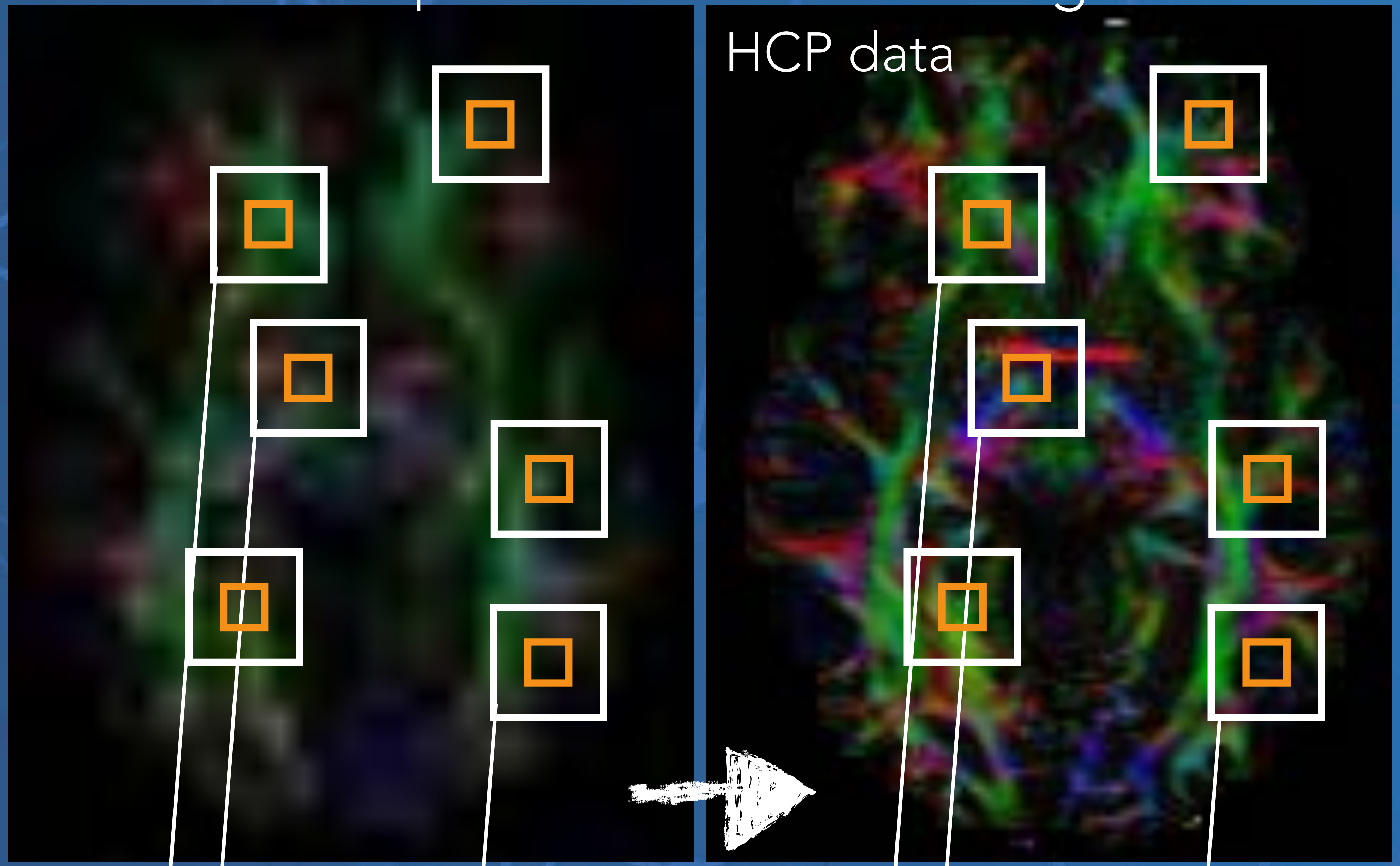

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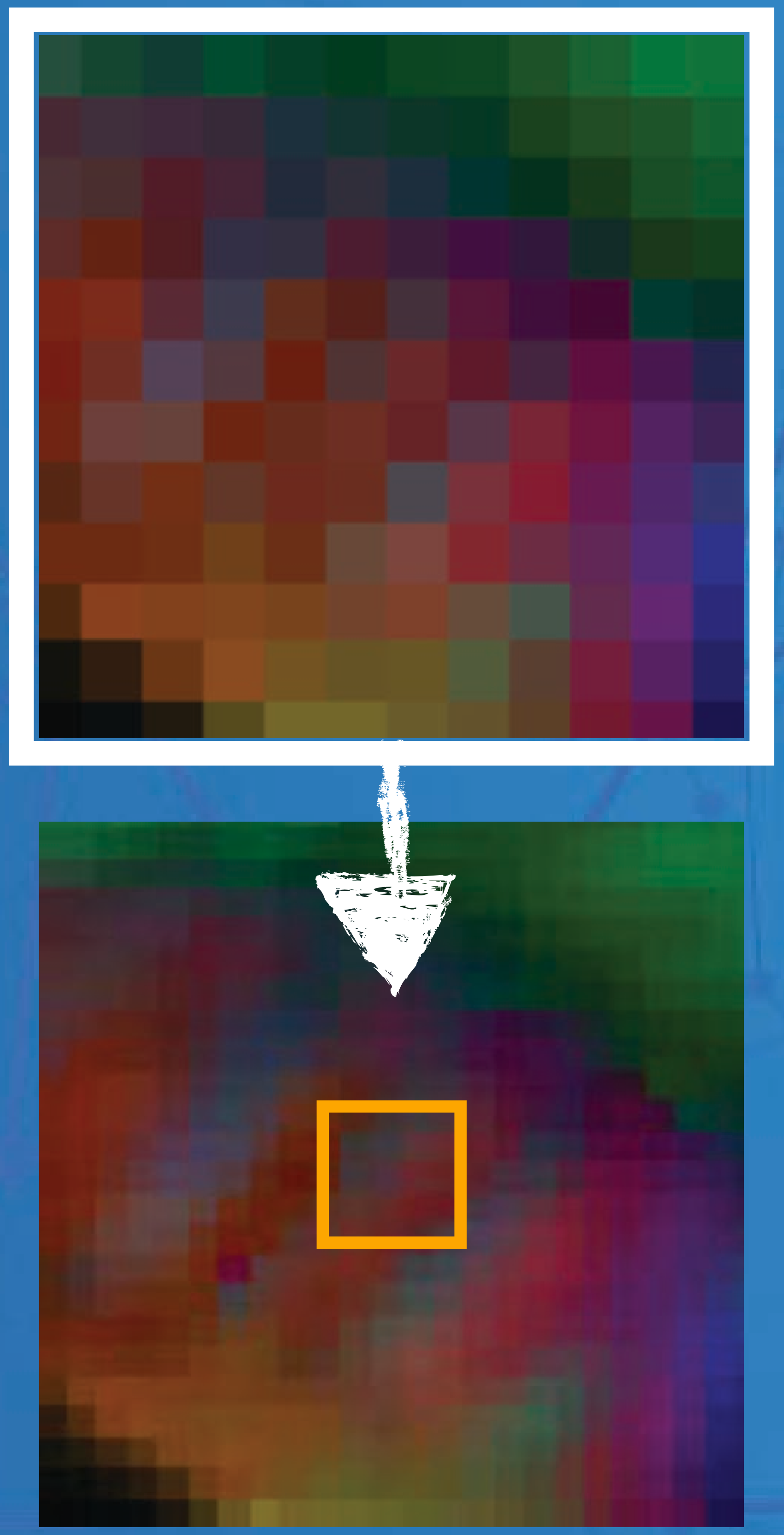

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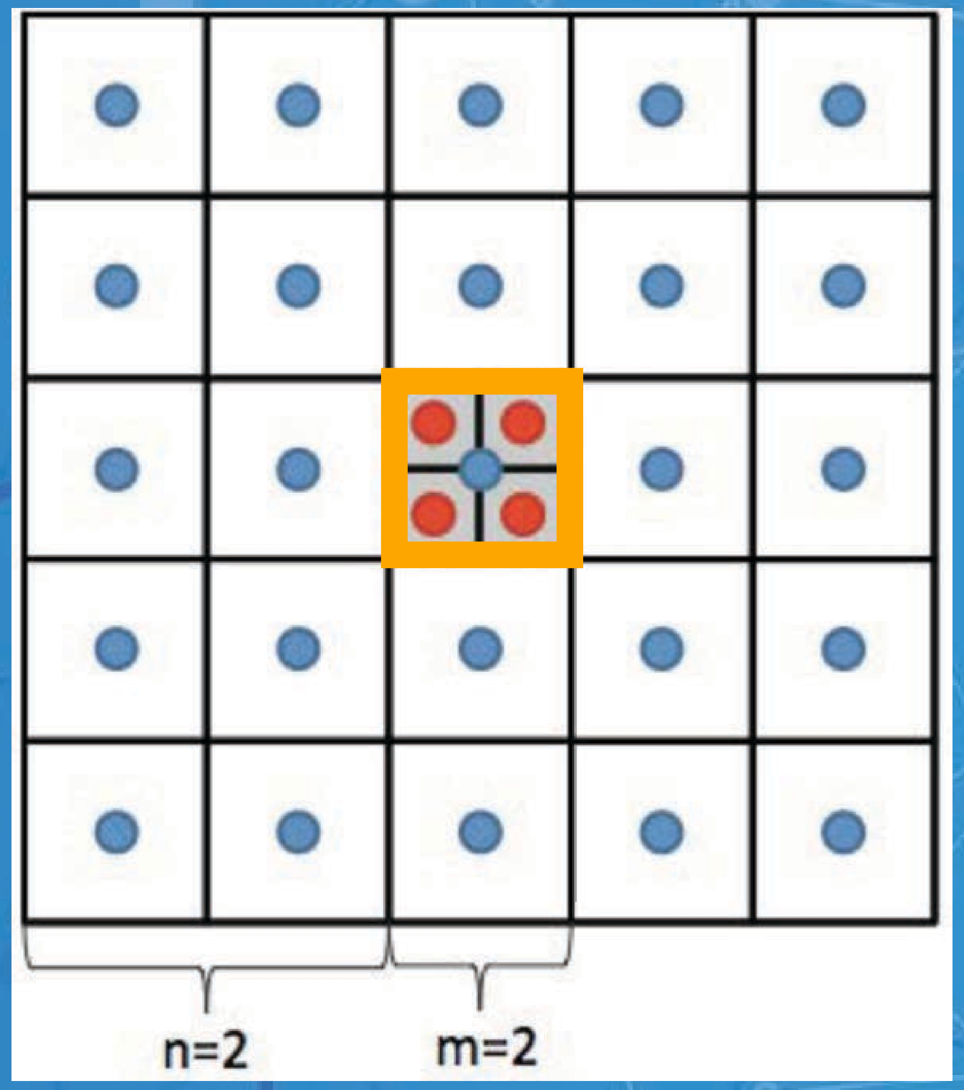

Regression:

- Random Forest [ALEXANDER 2017]
- Deep Learning [TANNO MICCAI 2017]

RANDOM FOREST IQT

https://github.com/ucl-mig/iqt

RANDOM FOREST IQT [ALEXANDER 2014, 2017]

- Decision Tree

RANDOM FOREST IQT [ALEXANDER 2014, 2017]

- Decision Tree

$$
\begin{aligned}
\mathcal{D} &= \{\mathbf{x}_i, \mathbf{y}_i\}_{|\mathcal{D}|} \\
&= \mathcal{D}_T \cup \mathcal{D}_V
\end{aligned}
$$

RANDOM FOREST IQT [ALEXANDER 2014, 2017]

$$\mathcal{D} = \{\mathbf{x}_i, \mathbf{y}_i\}_{|\mathcal{D}|} = \mathcal{D}_T \cup \mathcal{D}_V \qquad MX = Y$$

- Decision Tree

M

(Global Linear)

RANDOM FOREST IQT [ALEXANDER 2014, 2017]

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$$\begin{cases} \text{Features:} & F_1, F_2, ..., F_j \quad \in \mathbb{R} \\ \text{Thresholds:} & \tau_1, \tau_2, ..., \tau_j \quad \in \mathbb{R} \end{cases}$$

$\mathcal{D}_L$ $\mathcal{D}_R$

RANDOM FOREST IQT [ALEXANDER 2014, 2017]

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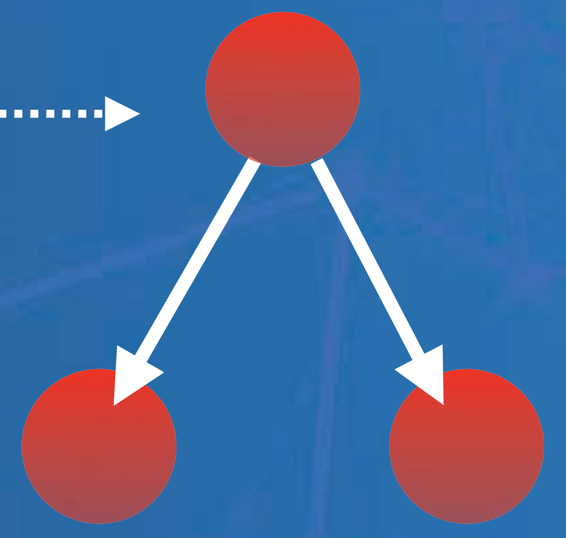

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Information Gain (training):

$$I_0 - I_L - I_R, \quad I_0 = 2|T| \log \det(S)$$
$$S = (Y - MX)^T (Y - MX)$$

RANDOM FOREST IQT [ALEXANDER 2014, 2017]

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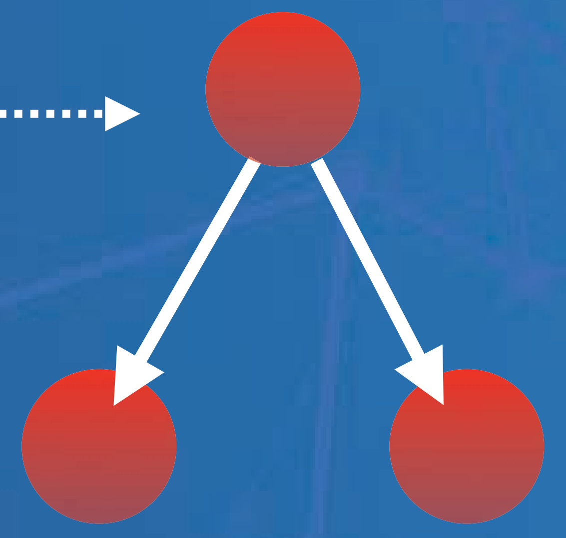

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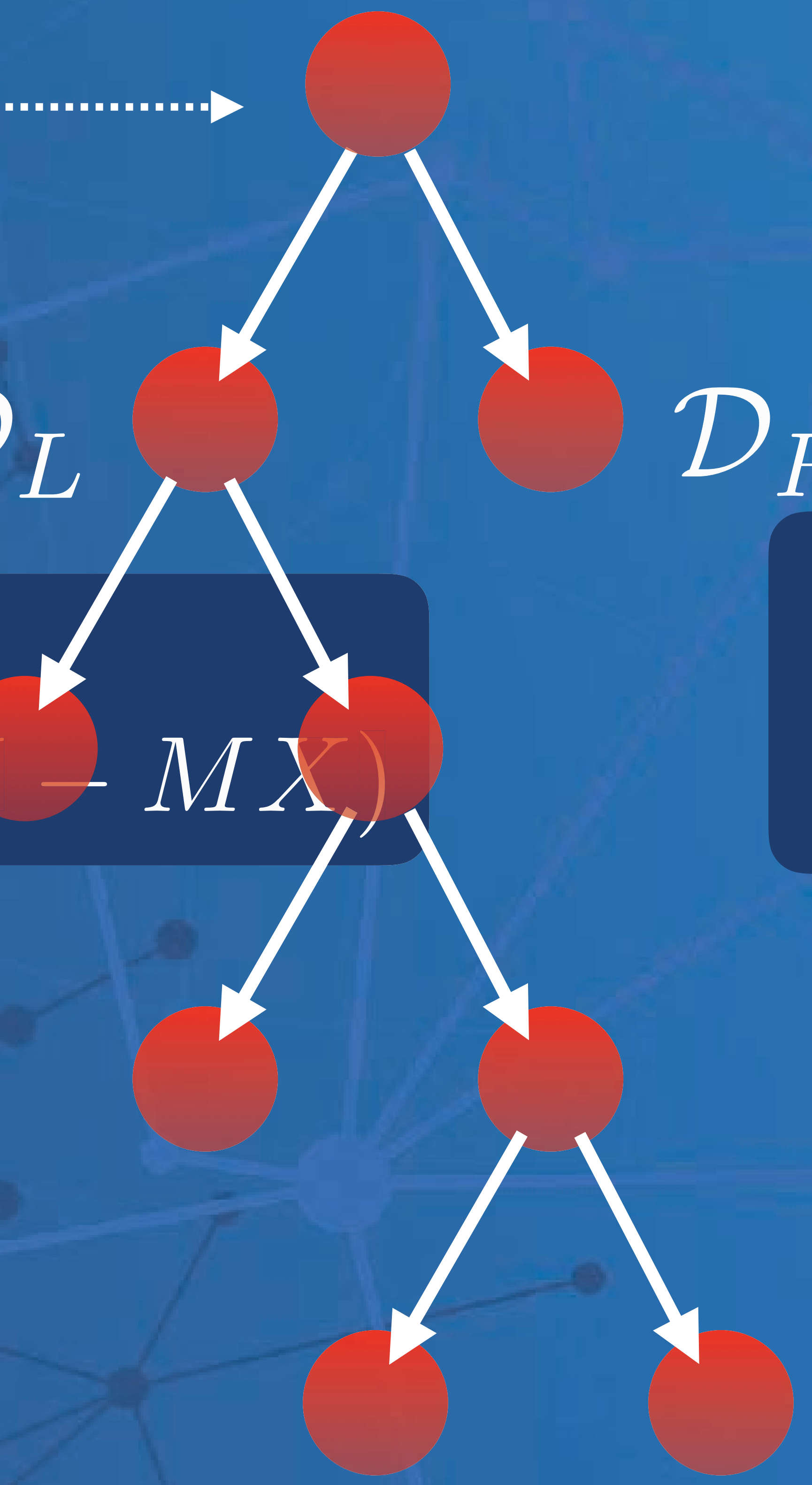

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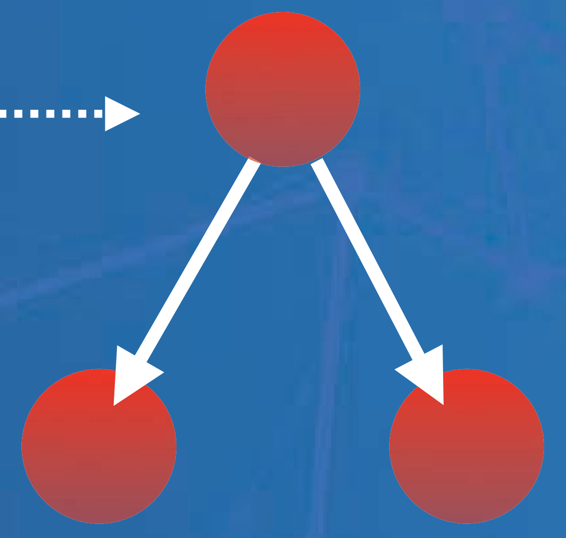

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- Random Forest: 8+ decision trees

(Patch library from 8 subjects)

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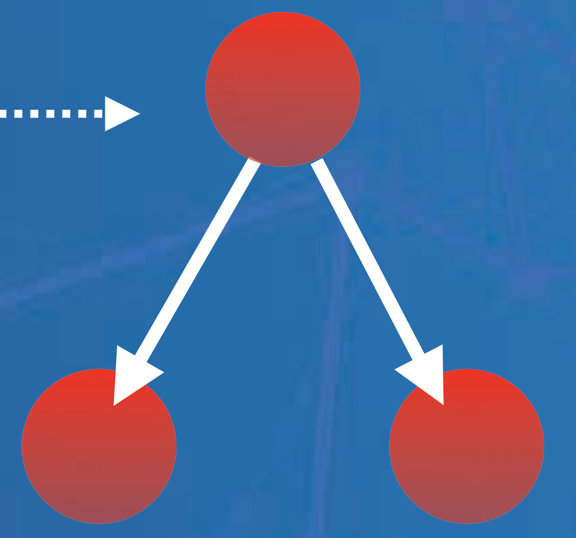

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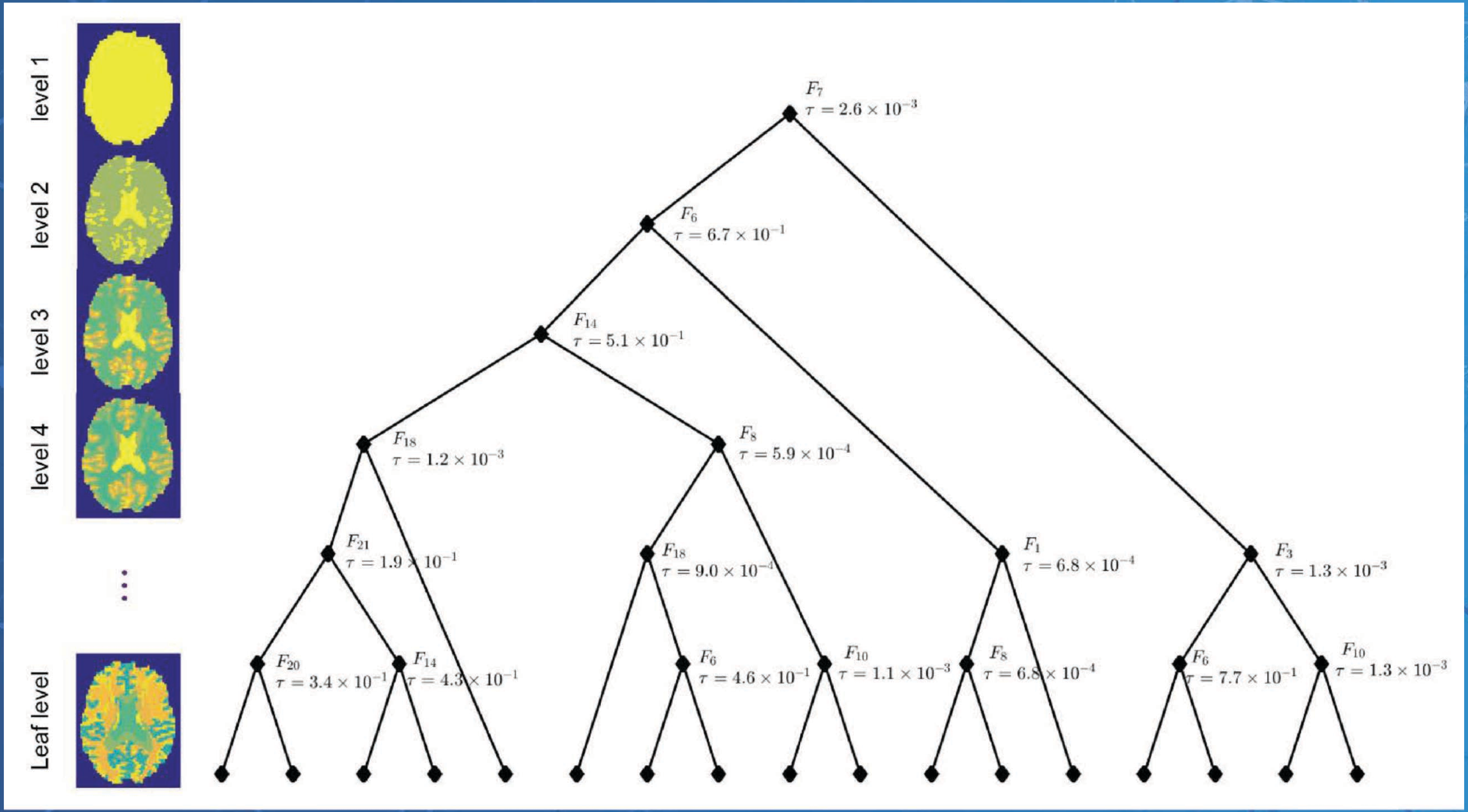
- Random Forest: 8+ decision trees

(Patch library from 8 subjects)

- Features up to 23 (DTI):
  - Eigenvalues of diffusion tensor
  - linearity, planarity, sphericity
  - Means of the features over patch

TREE VISUALISED



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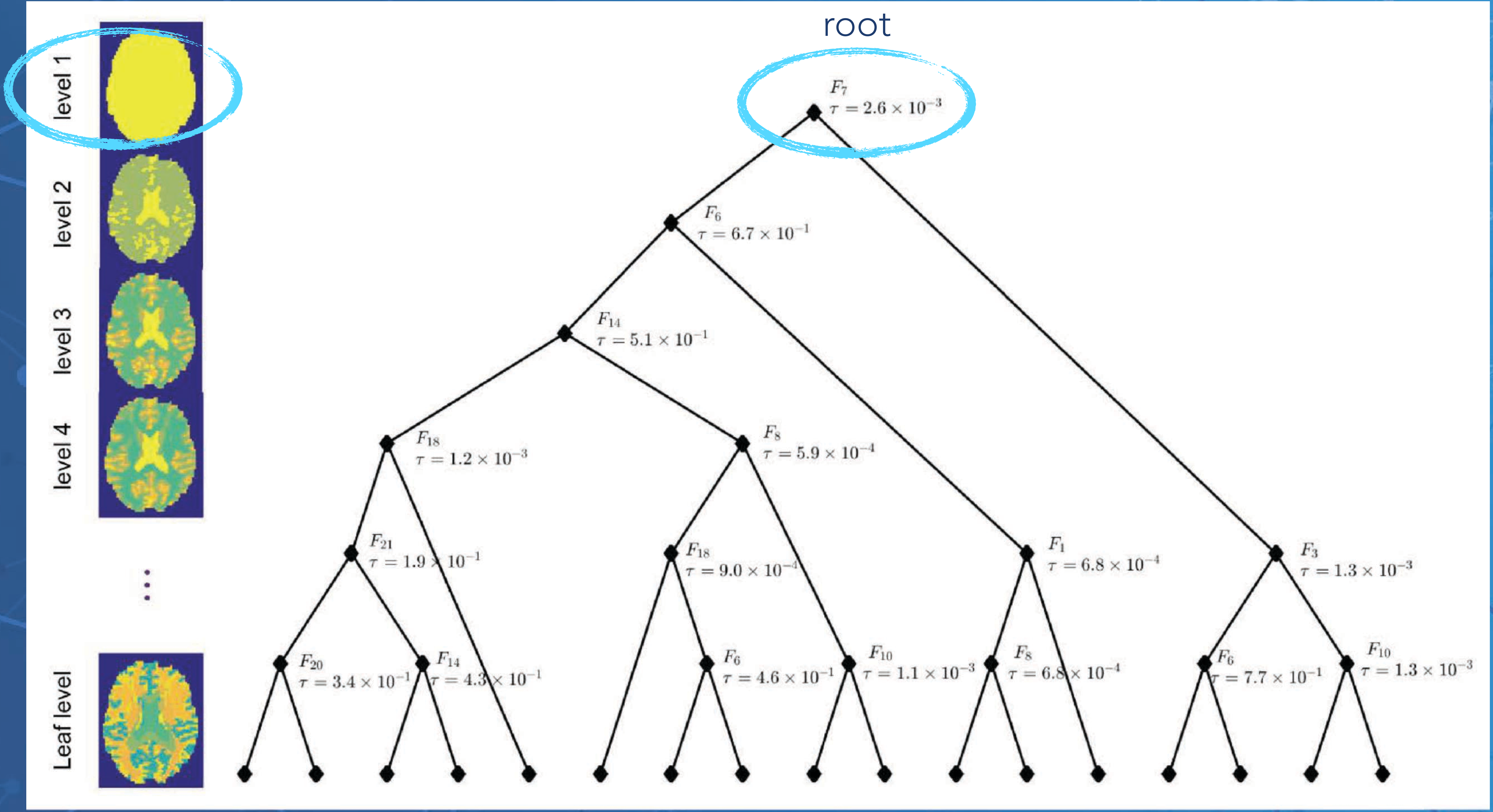

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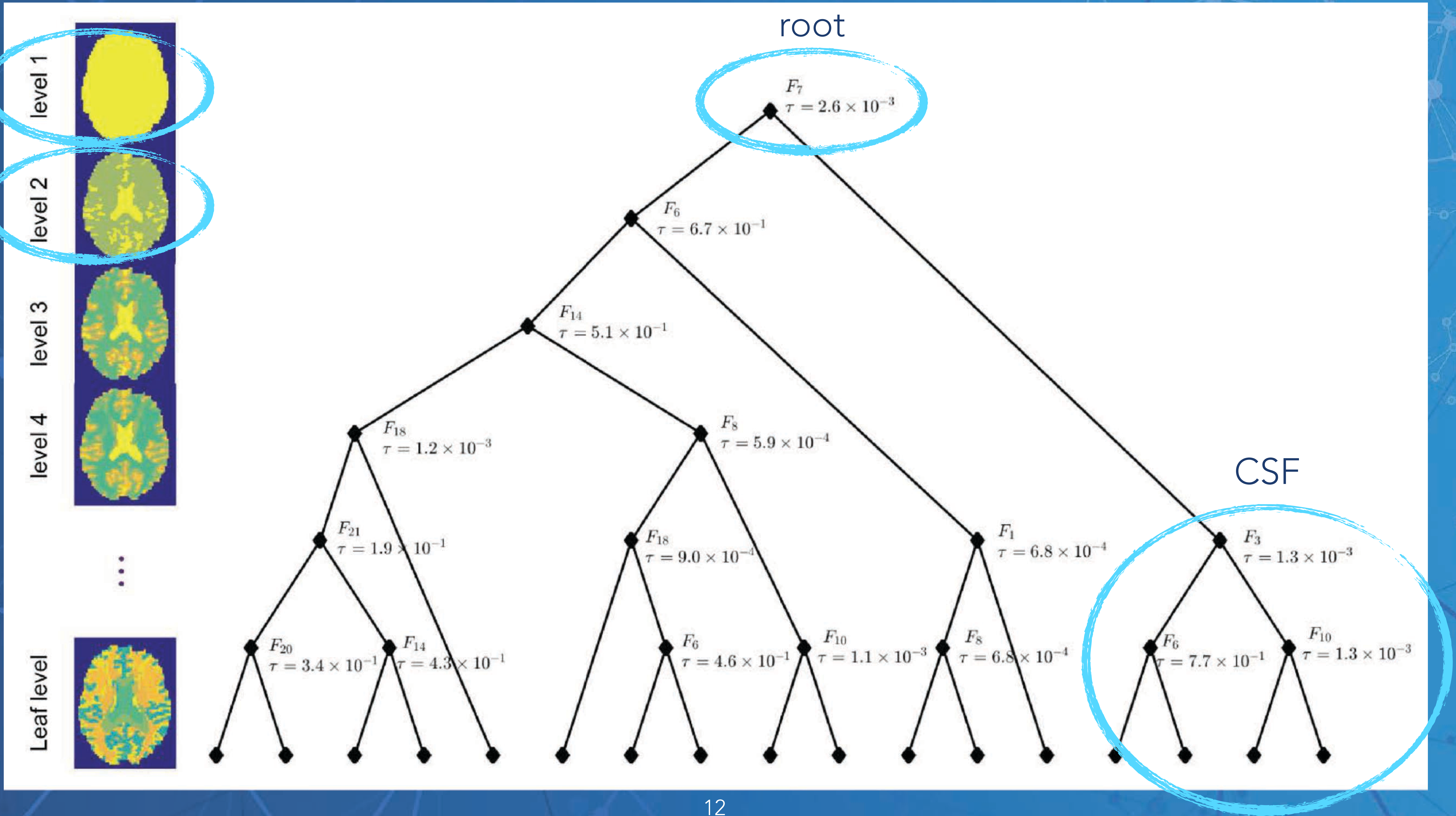

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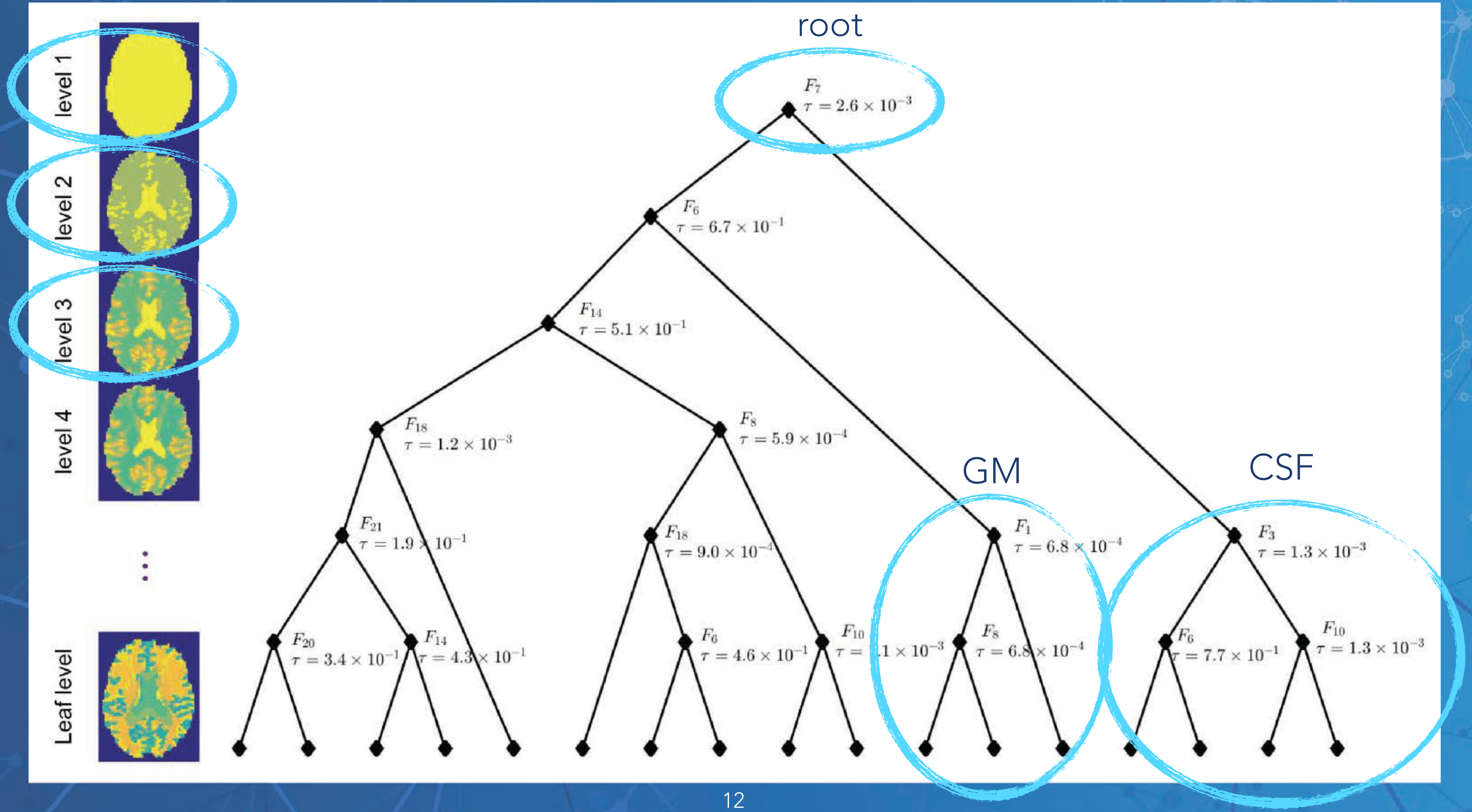

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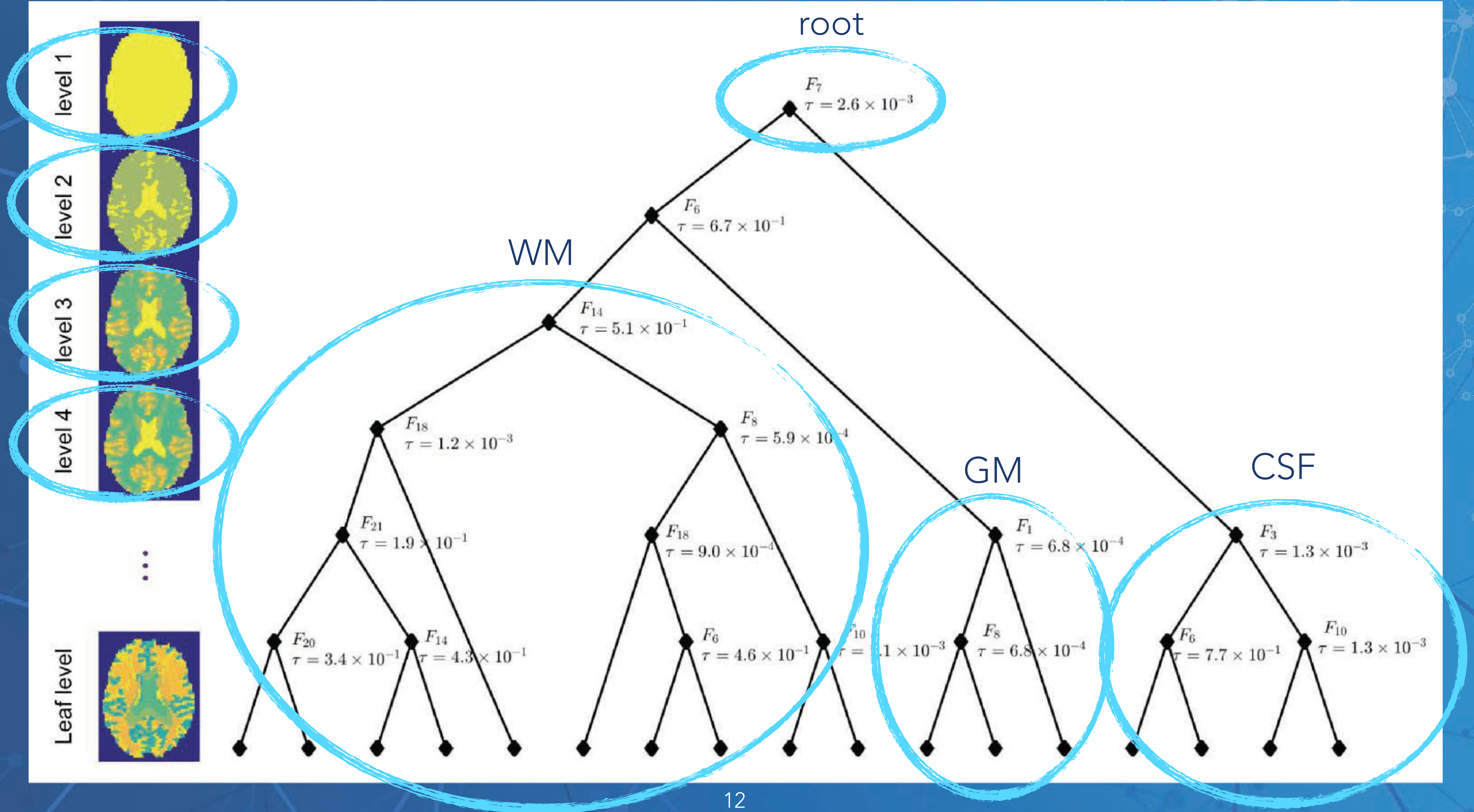

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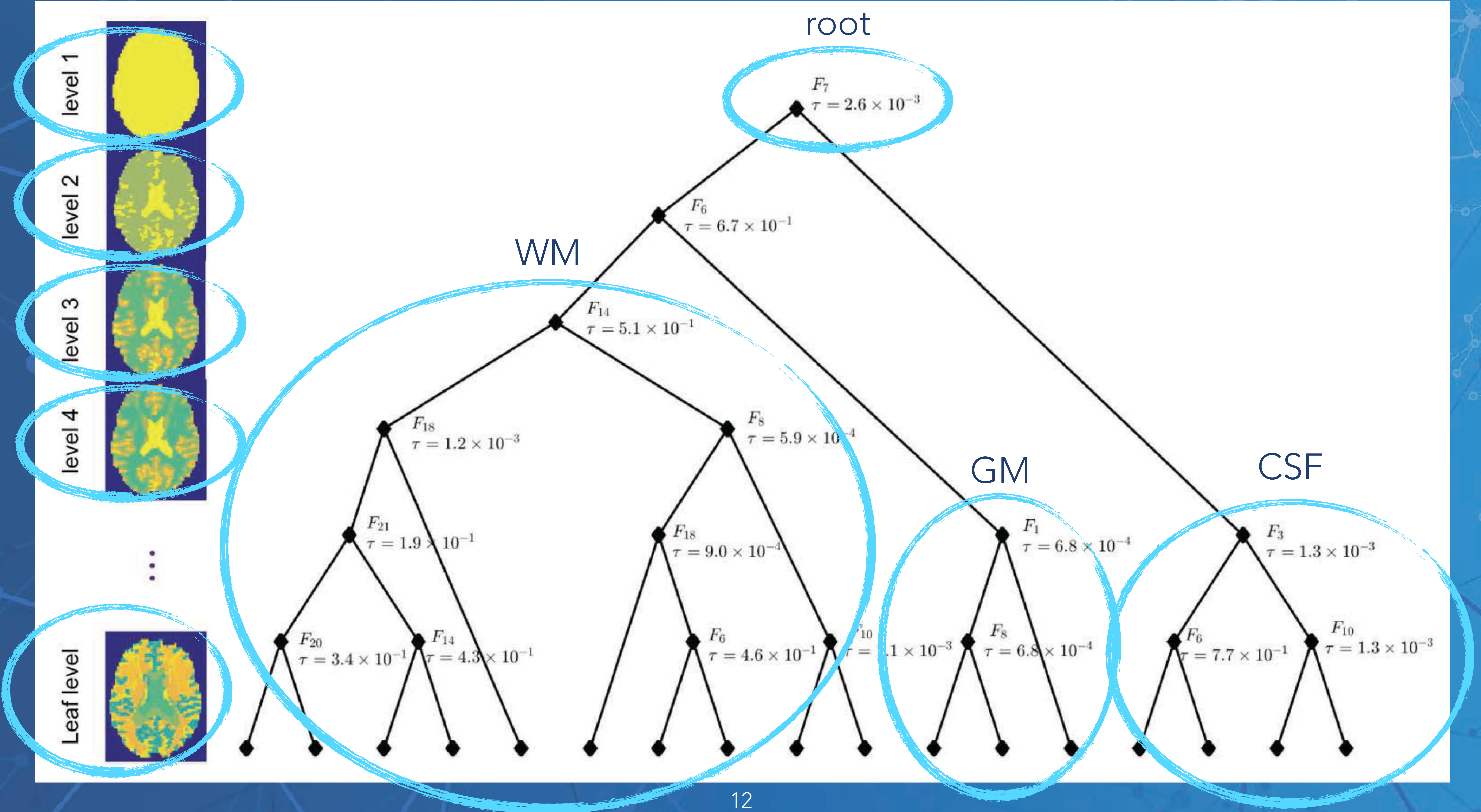

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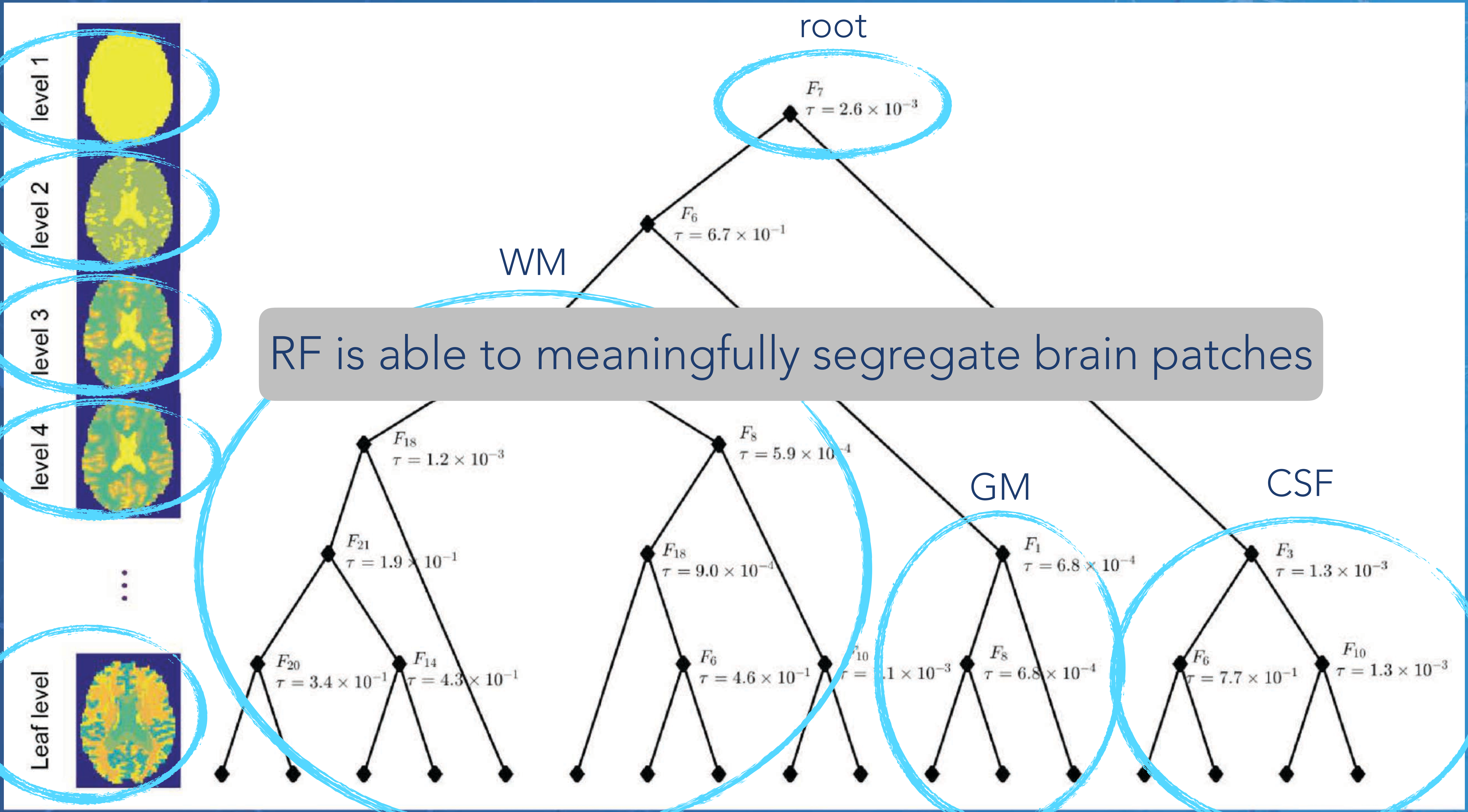
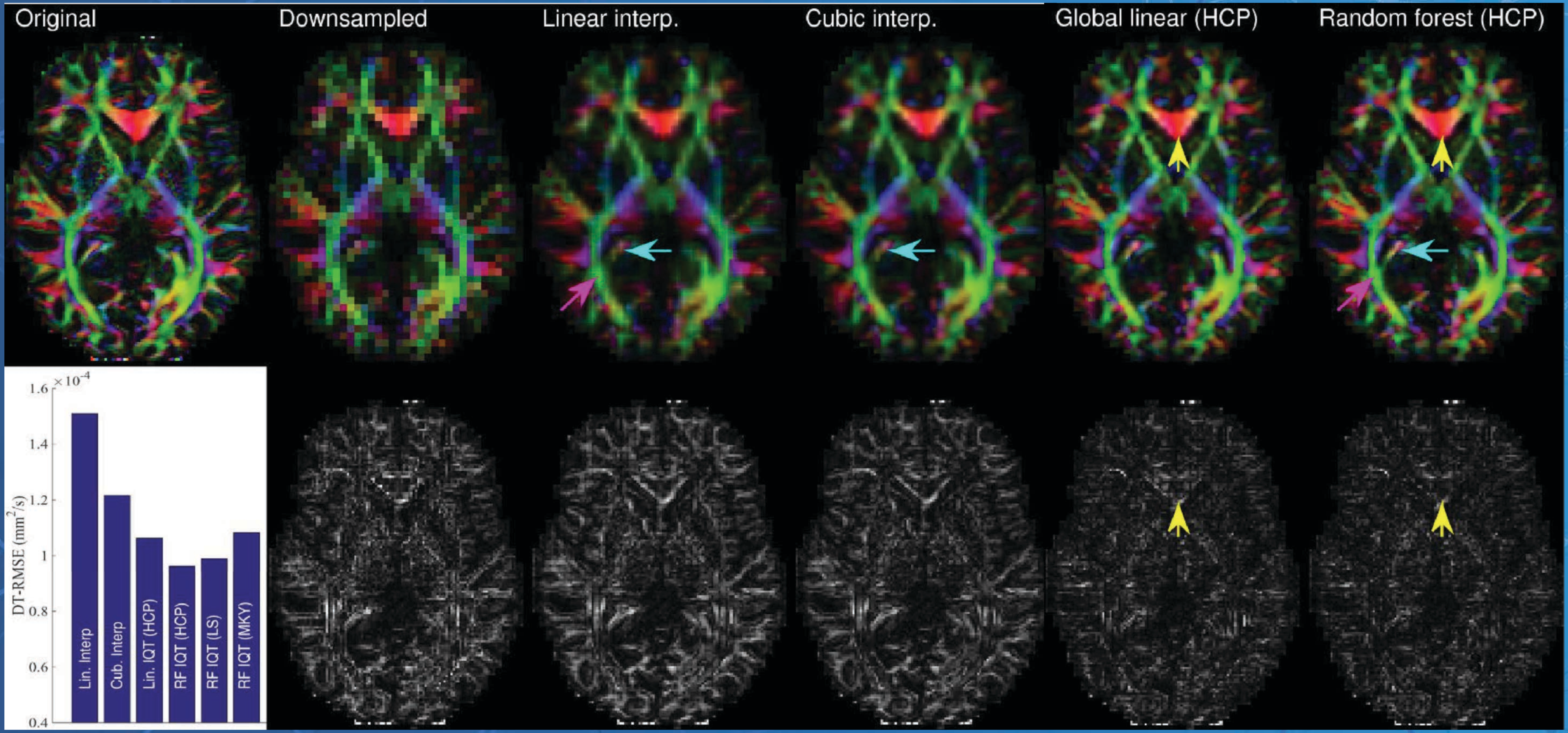


RF is able to meaningfully segregate brain patches

RESULTS — SUPER-RESOLUTION [ALEXANDER 2017]



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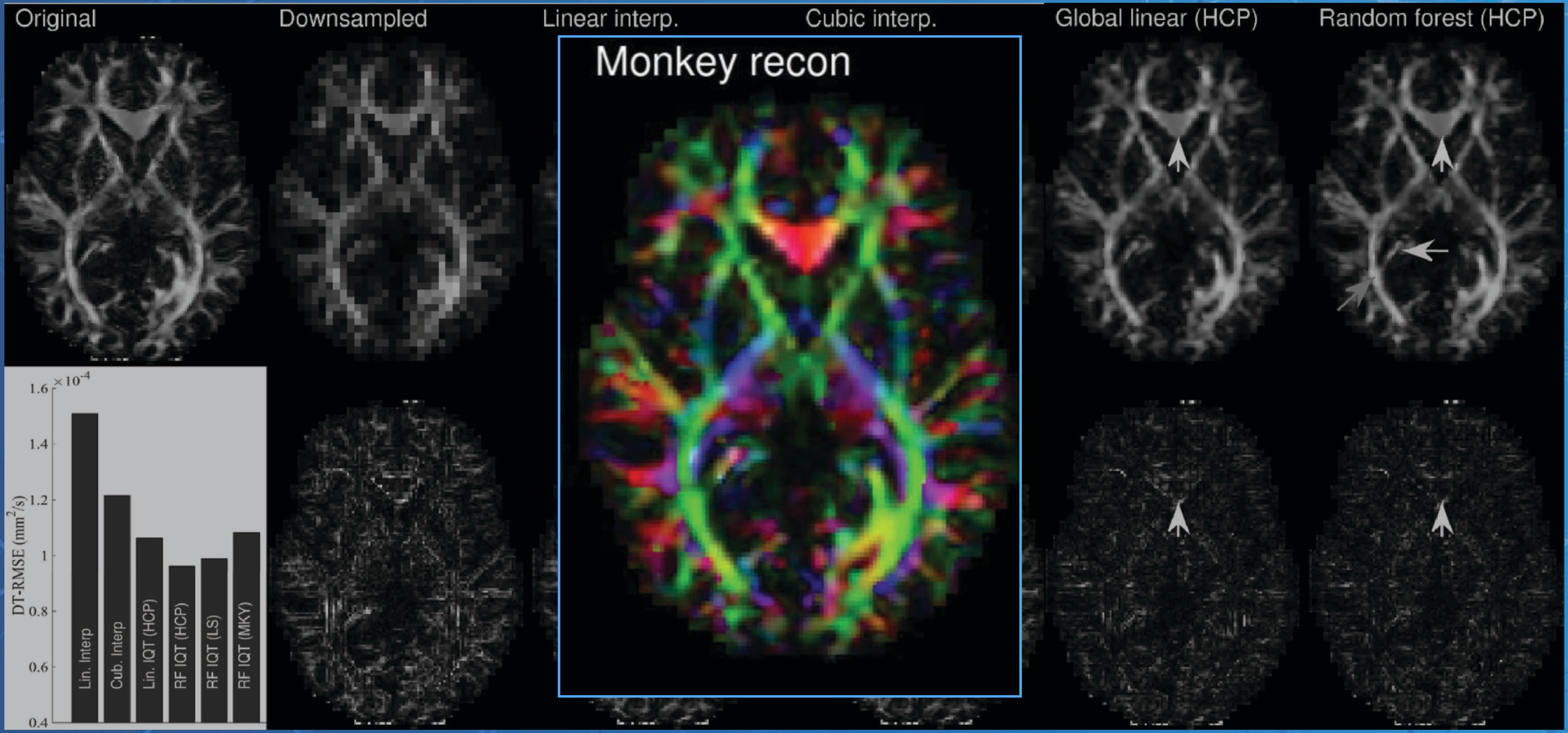
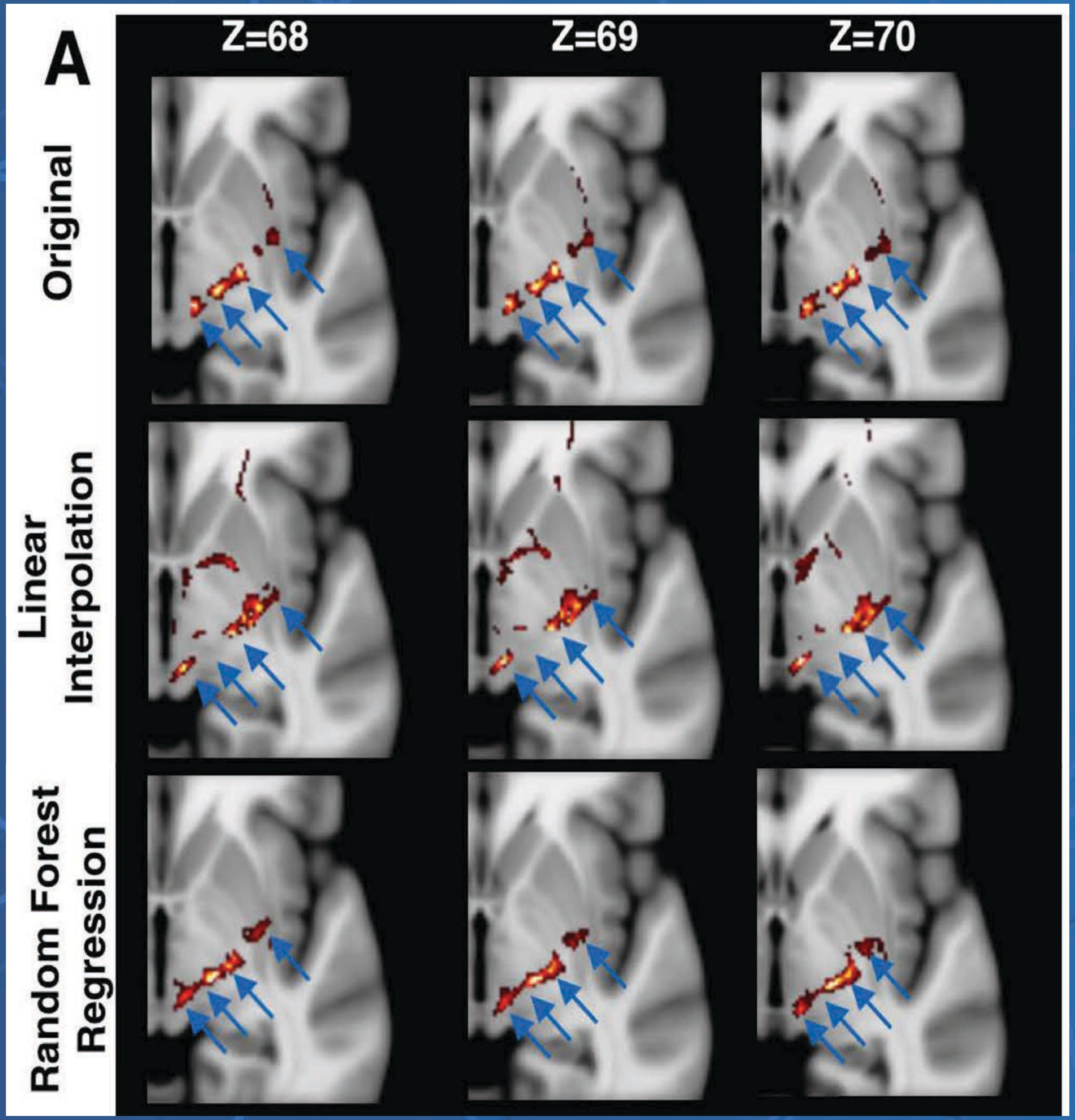
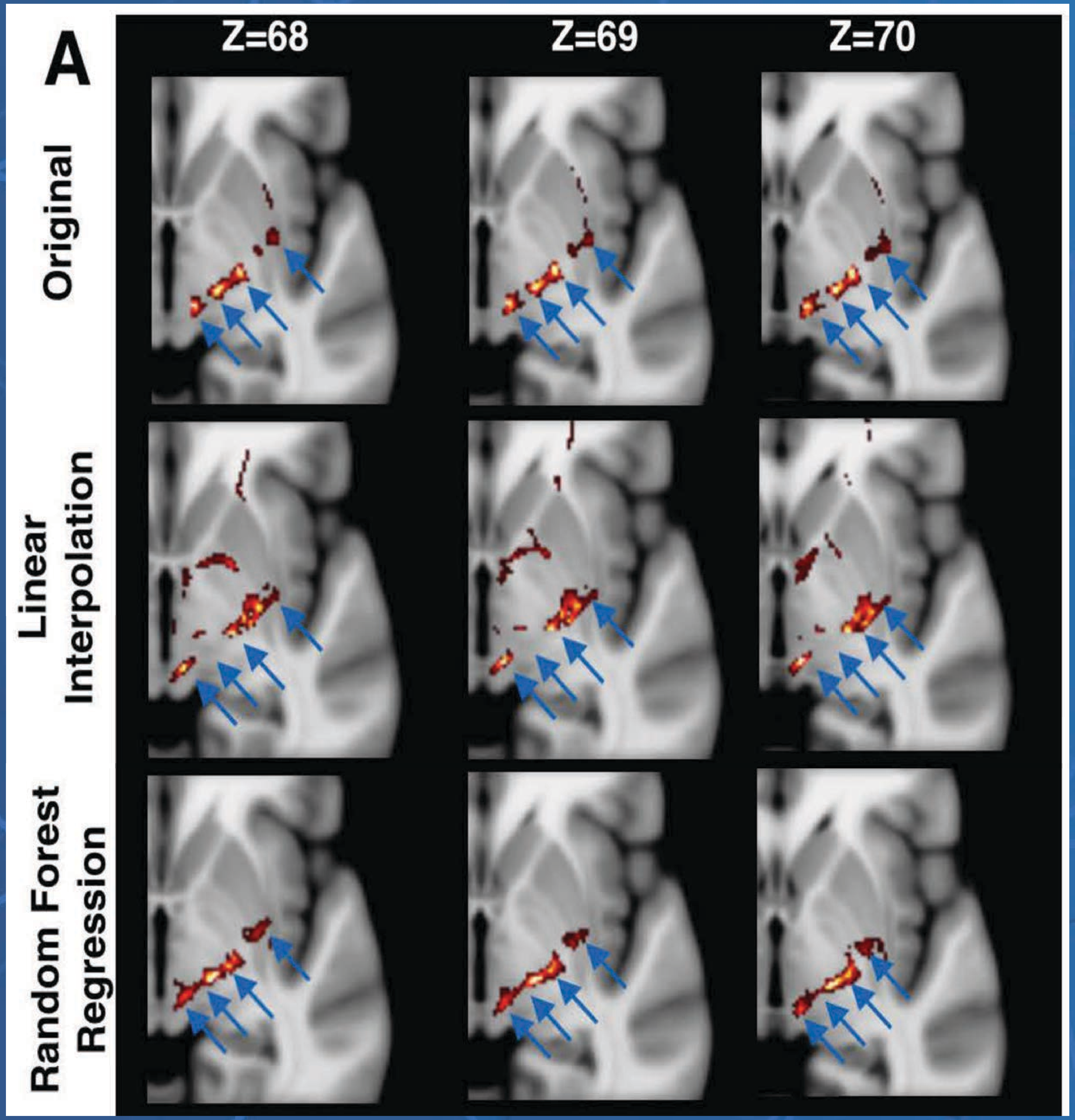


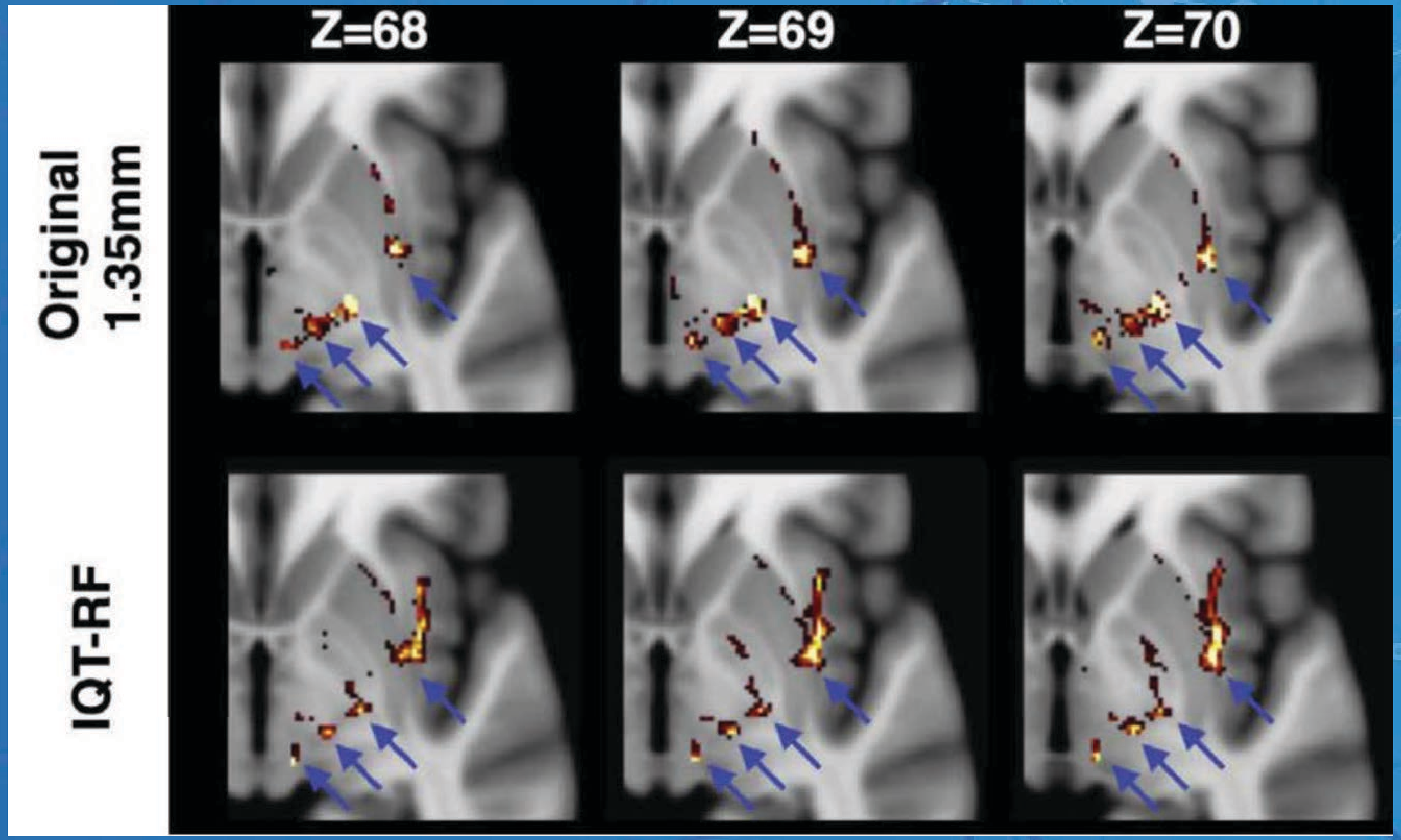
TRACTOGRAPHY [ALEXANDER 2017]



- Extension from DTI to MAP-MRI
- Tracing 4 pathways:
  cortical hand area to:
  - thalamus
  - brainstem
  - spinal cord
  - putamen
- Tractography separates tracts
  - in 1.25mm but not in low-res (2.5mm) or linear/cubic interpolation
  - **but again in IQT super-res**

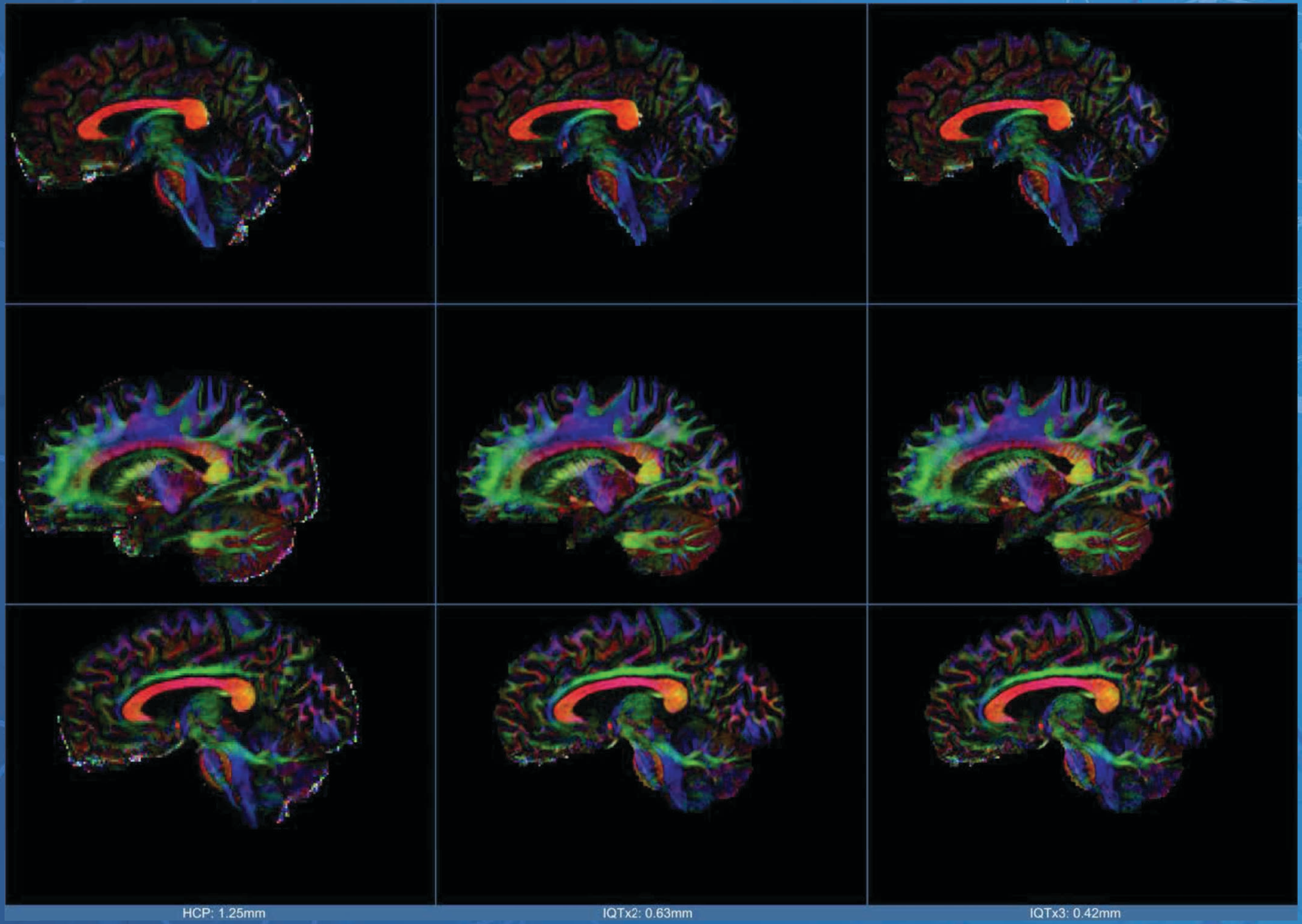
TRACTOGRAPHY [ALEXANDER 2017]

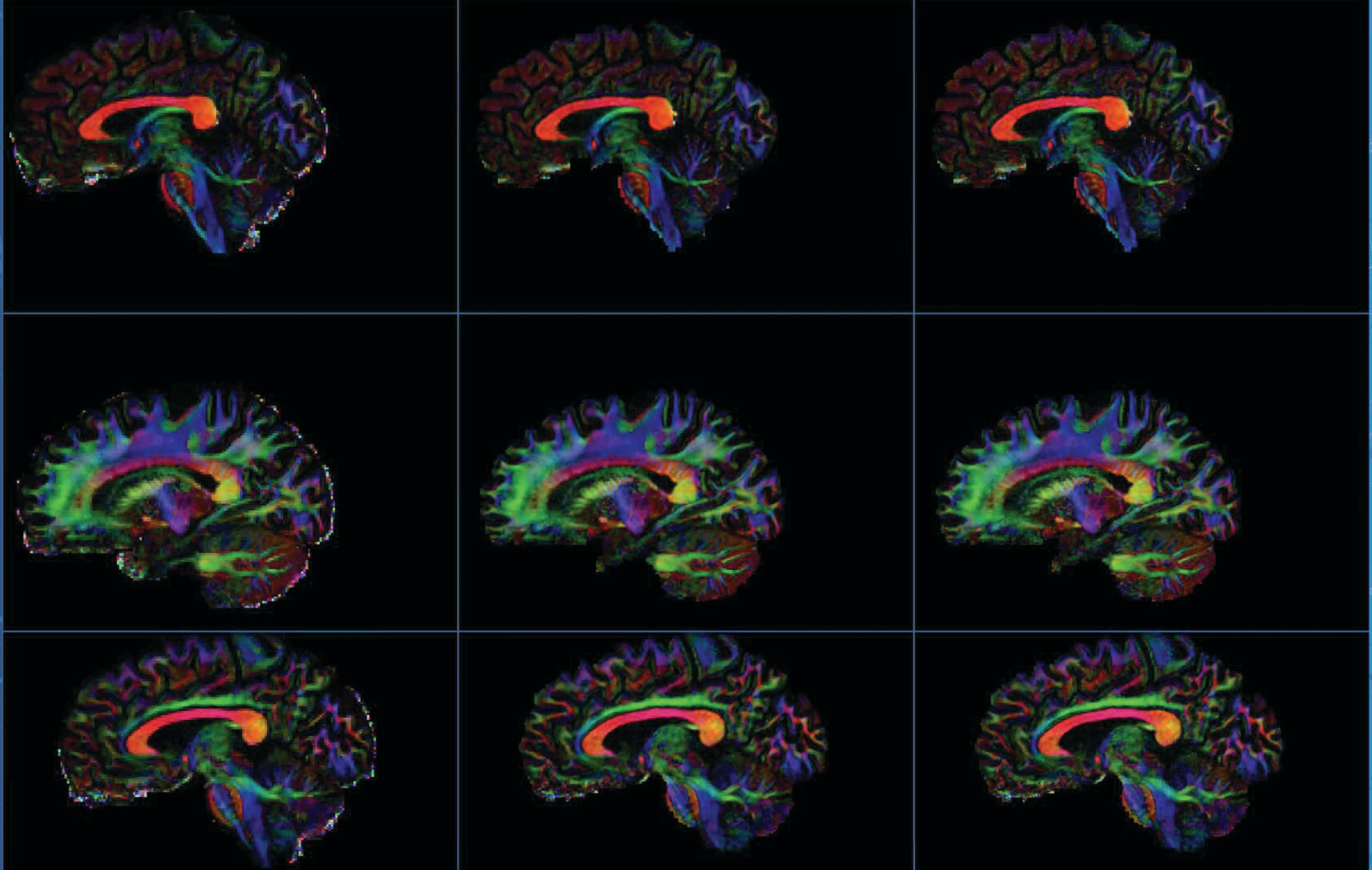




RESULTS — SUPER-RESOLUTION

[ALEXANDER 2017]





BAYESIAN RF IQT: INTRODUCING UNCERTAINTY

(LOCALLY) BAYESIAN RF IQT [TANNO 2016]

- Uncertainty estimation from a (locally) Bayesian inference
- Bayesian linear model at each node:

$$\mathbf{y} = M\mathbf{x} + \eta \qquad P(M_{|}|\alpha) = \mathcal{N}(M_{|}, \alpha^{-1}I)$$
$$P(\eta|\beta) = \mathcal{N}(\eta, \beta^{-1}I)$$

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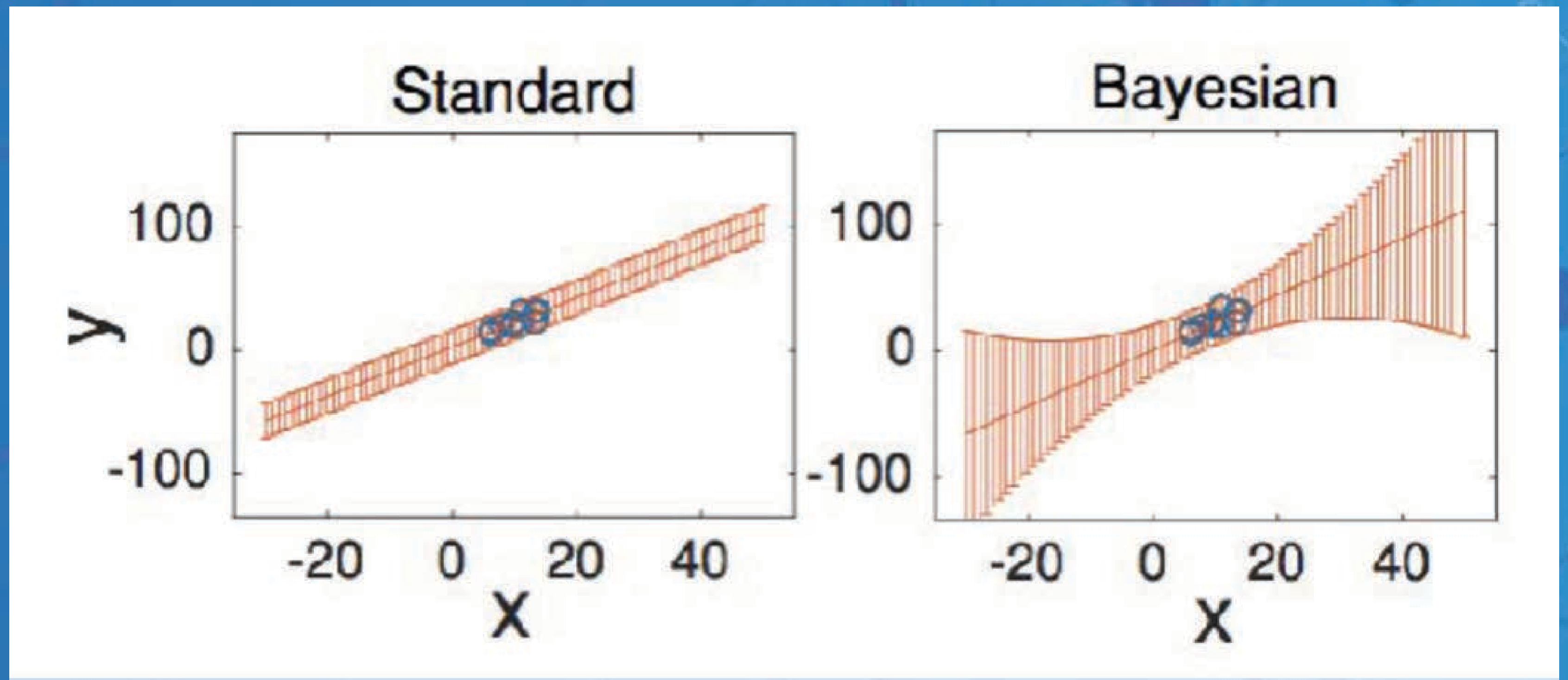
- Predictive variance for **uncertainty** quantification:

$$\sigma^2_{\text{Pred}}(\mathbf{x}^*) = \mathbf{x}^{*T}\mathbf{A}(\mathcal{D})\mathbf{x}^* + \beta^{-1}$$



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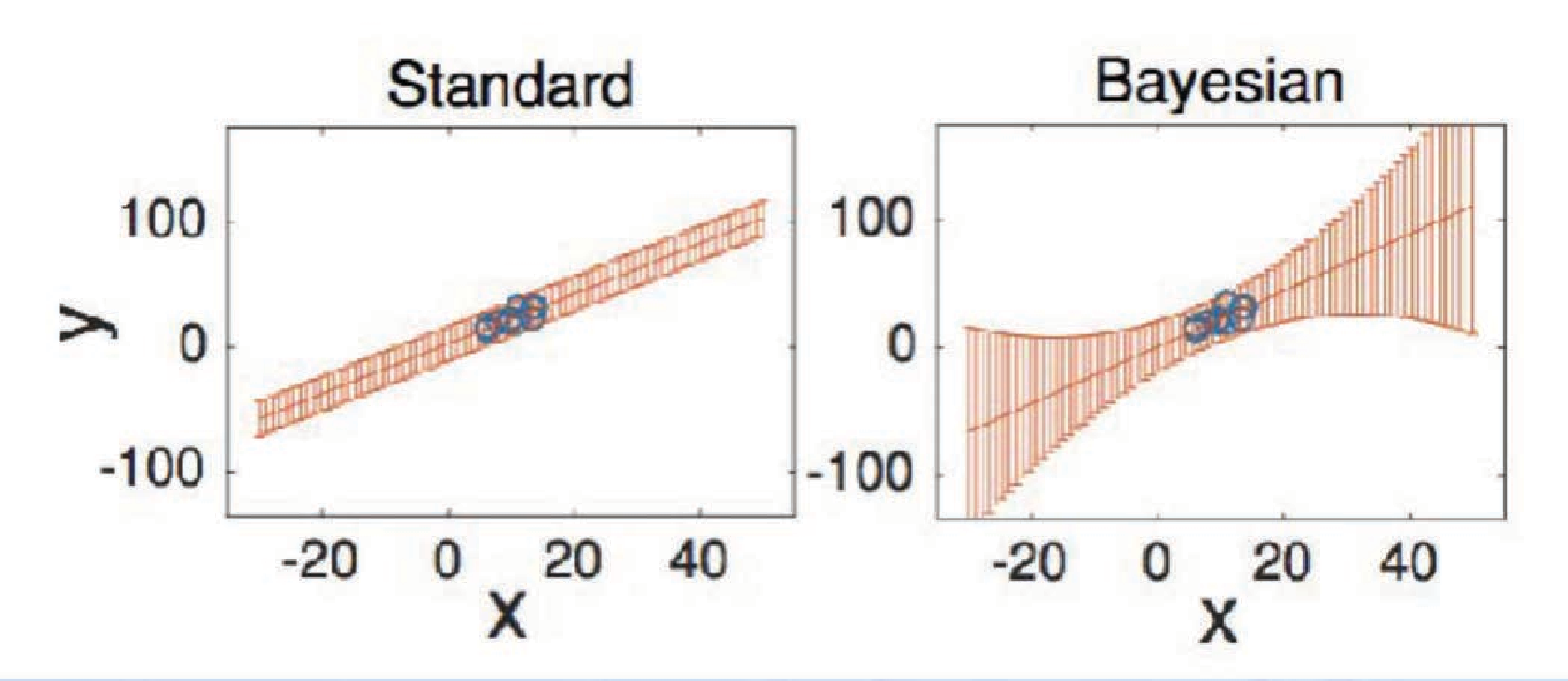
- Predictive variance for **uncertainty** quantification:

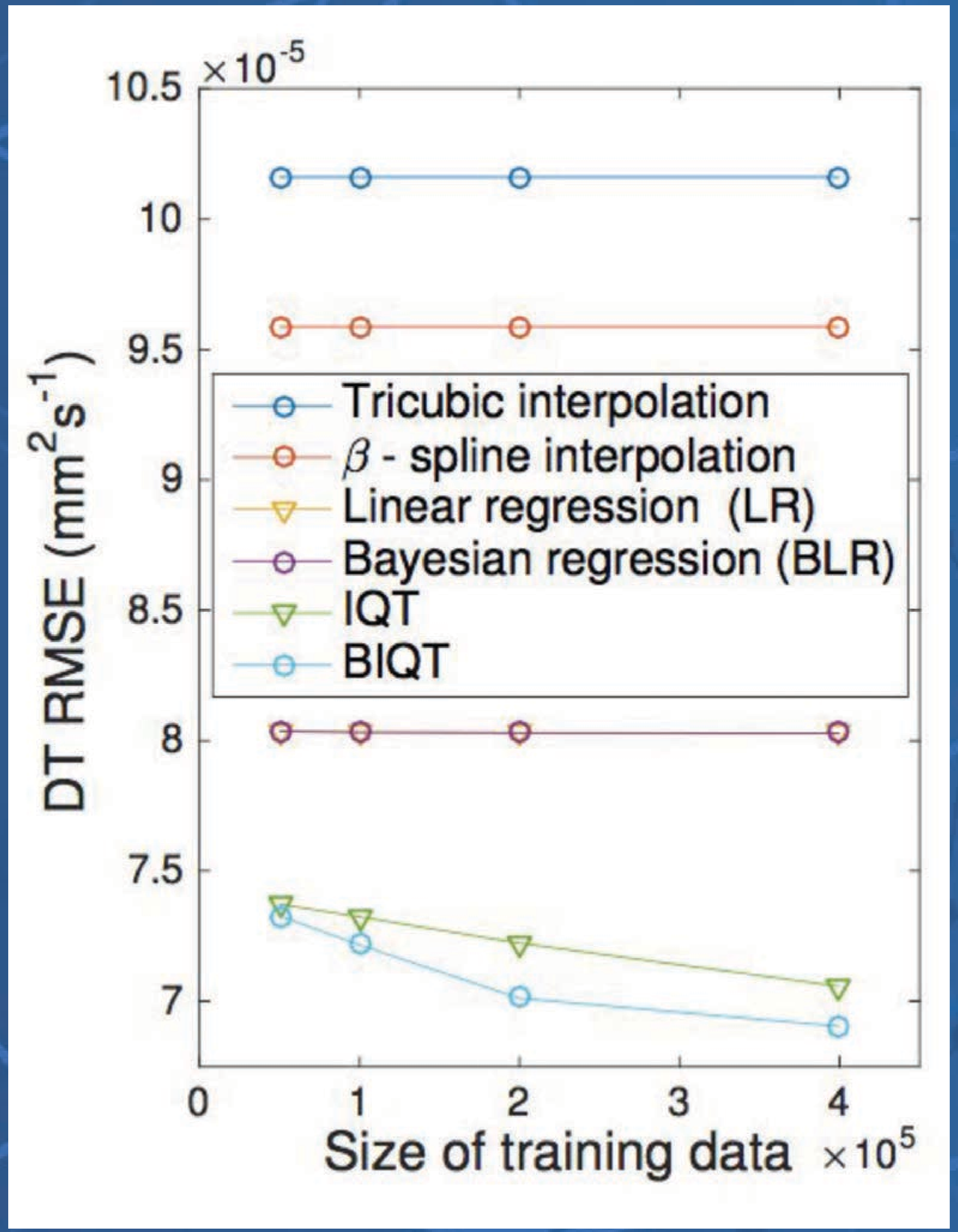
$$\sigma^2_{\text{Pred}}(\mathbf{x}^*) = \underbrace{\mathbf{x}^{*T}\mathbf{A}(\mathcal{D})\mathbf{x}^*}_{\text{Familiarity}} + \underbrace{\beta^{-1}}_{\text{Noise}}$$

Familiarity
distance from training data

Noise
variability in training data

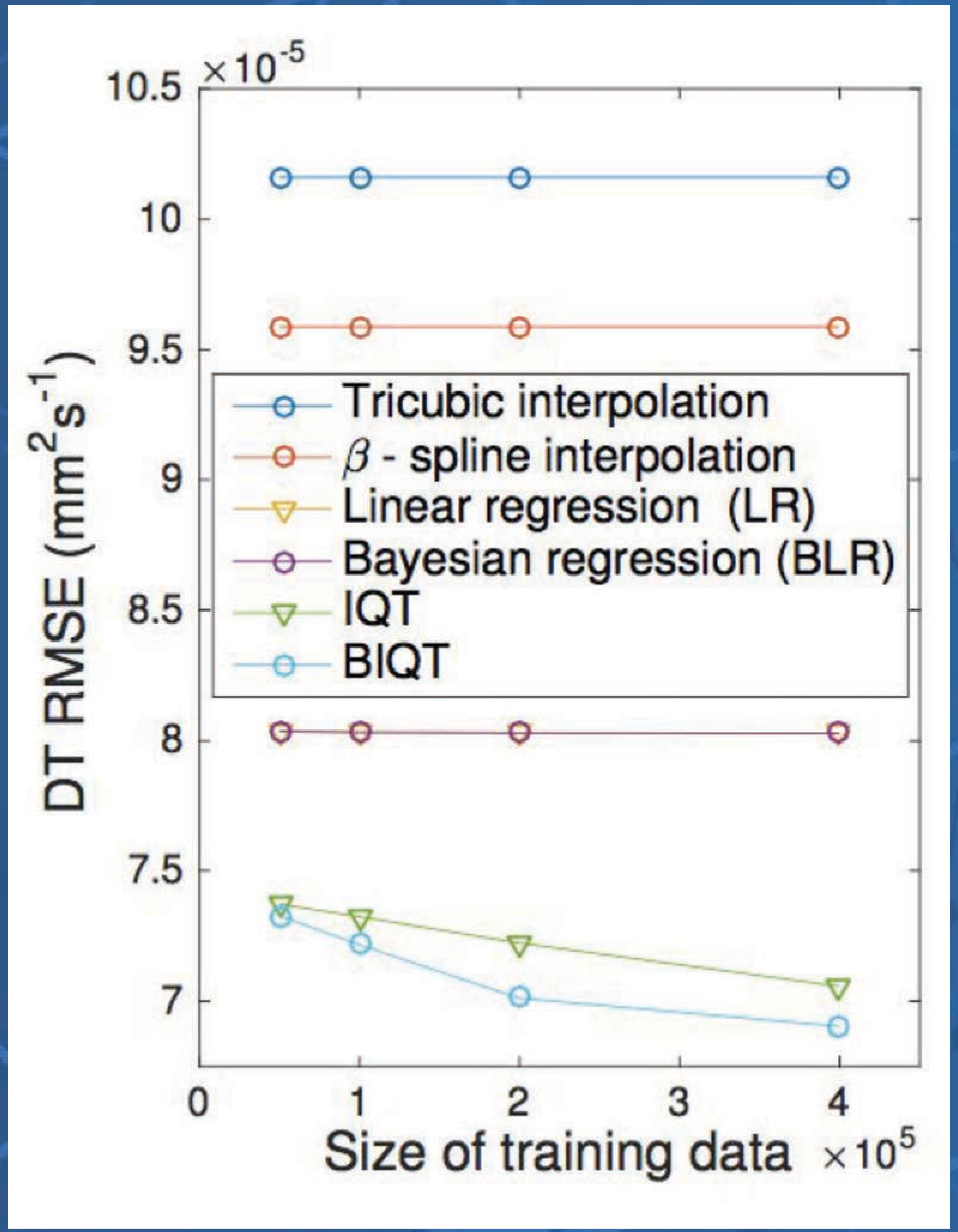


RESULTS



$\times 10^{-5}$
10.5
10
9.5
9
8.5
8
7.5
7
DT RMSE (mm^2s^{-1})
Tricubic interpolation
β - spline interpolation
Linear regression (LR)
Bayesian regression (BLR)
IQT
BIQT
0
1
2
3
4
Size of training data $\times 10^5$

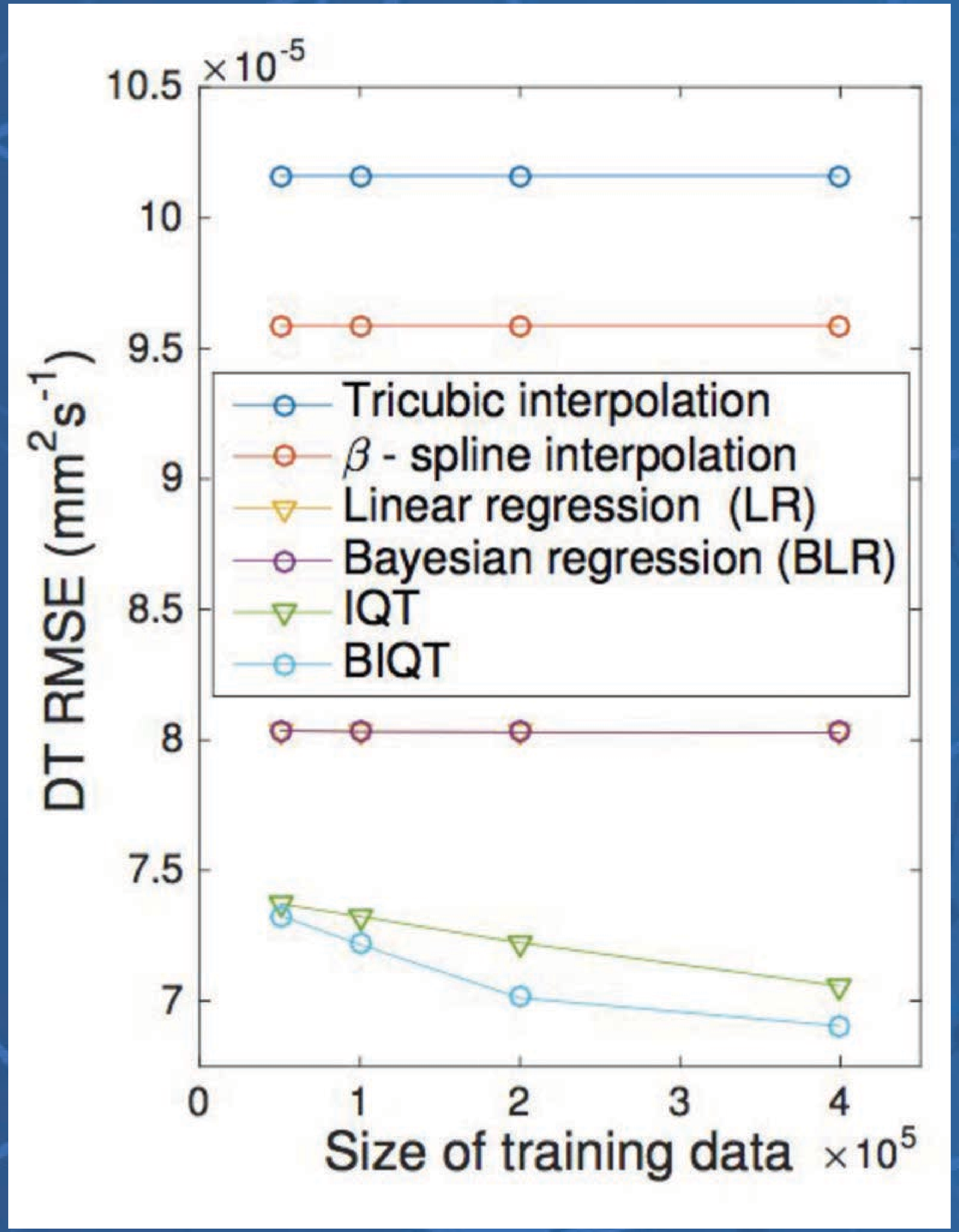
RESULTS

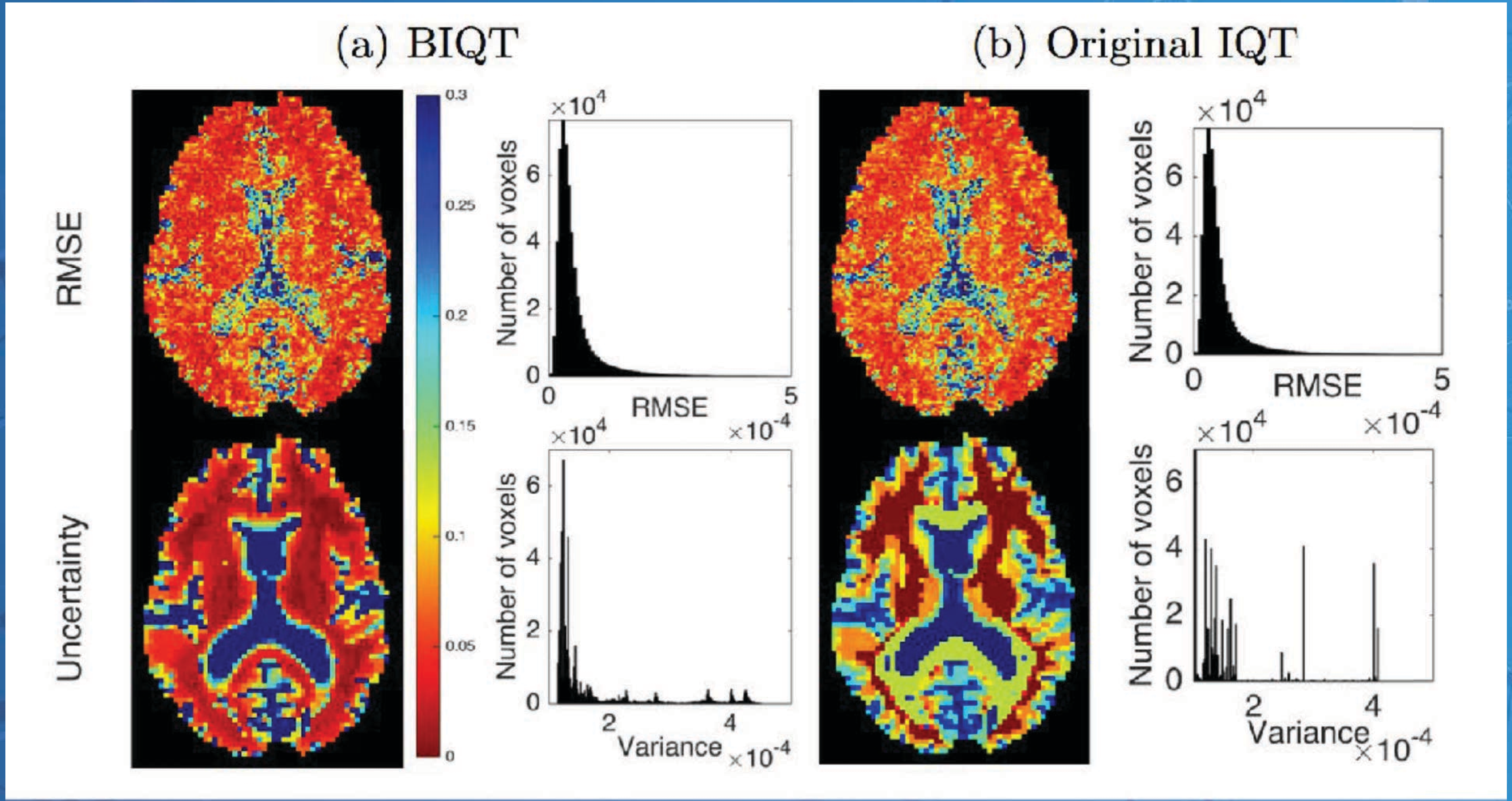


$$M = YX^T\left(XX^T + \frac{\alpha}{\beta}I\right)^{-1}$$

RESULTS

Uncertainty

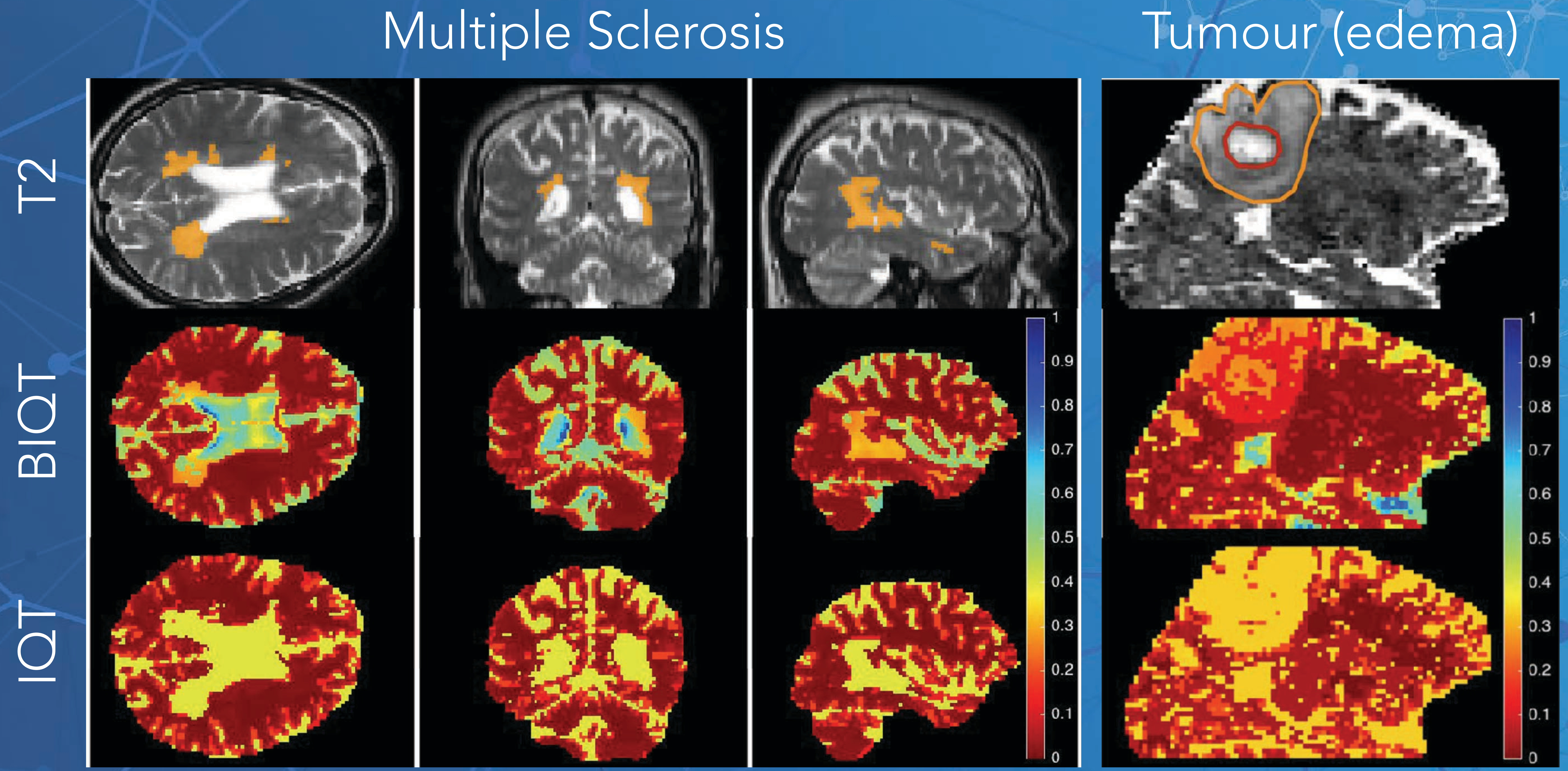




$$M = YX^T\left(XX^T + \frac{\alpha}{\beta}I\right)^{-1}$$

Uncertainty correlates with accuracy

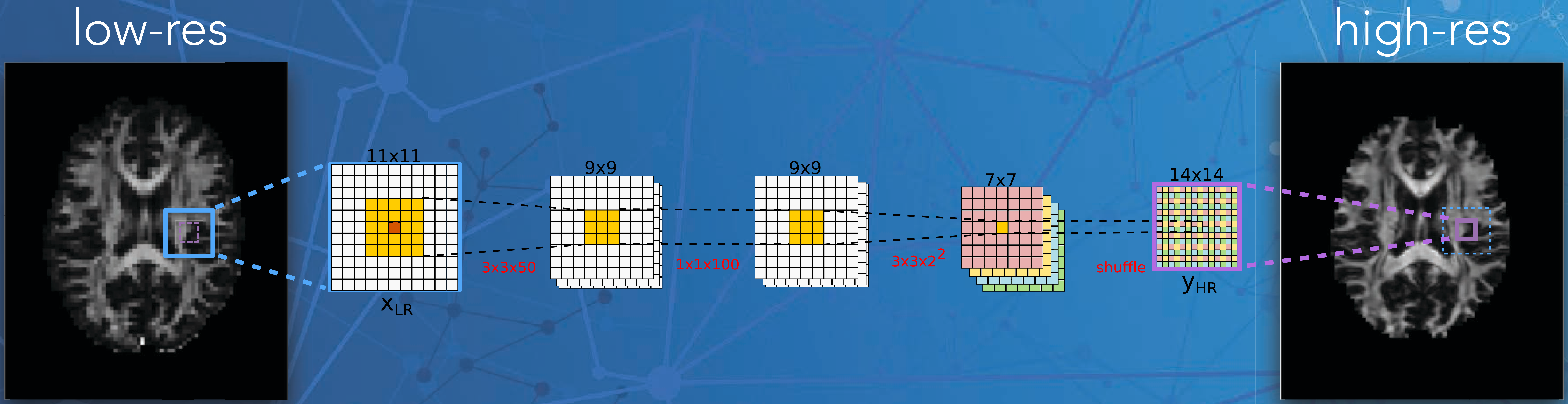
UNCERTAINTY



DEEP LEARNING IQT WITH UNCERTAINTY

BASELINE NETWORK [TANNO MICCAI 2017]

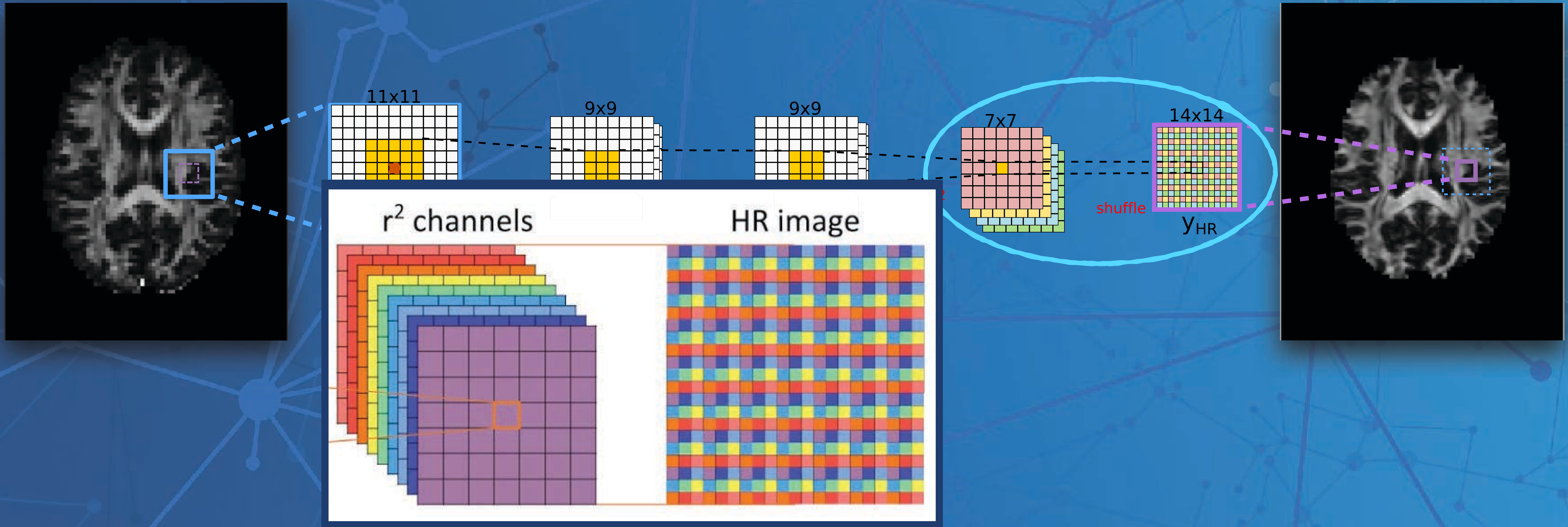
ESPCN = Efficient Subpixel Convolutional Network [SHI CVPR 2016]



BASELINE NETWORK [TANNO MICCAI 2017]

ESPCN = Efficient Subpixel Convolutional Network [SHI CVPR 2016]

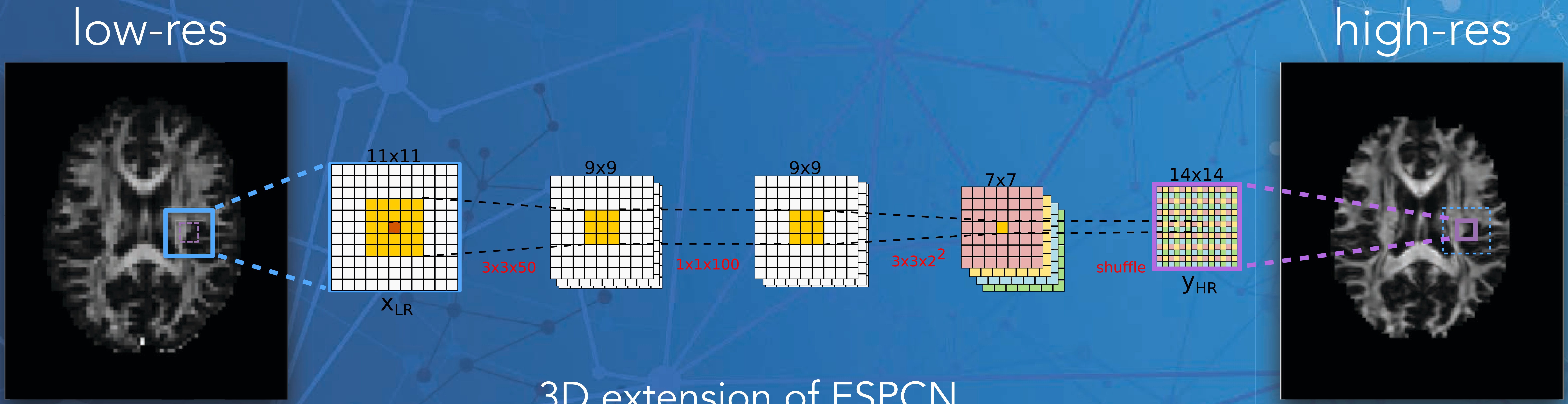
low-res high-res



Conv + Shuffle = deconvolution (learned)

BASELINE NETWORK [TANNO MICCAI 2017]

ESPCN = Efficient Subpixel Convolutional Network [SHI CVPR 2016]



3D extension of ESPCN

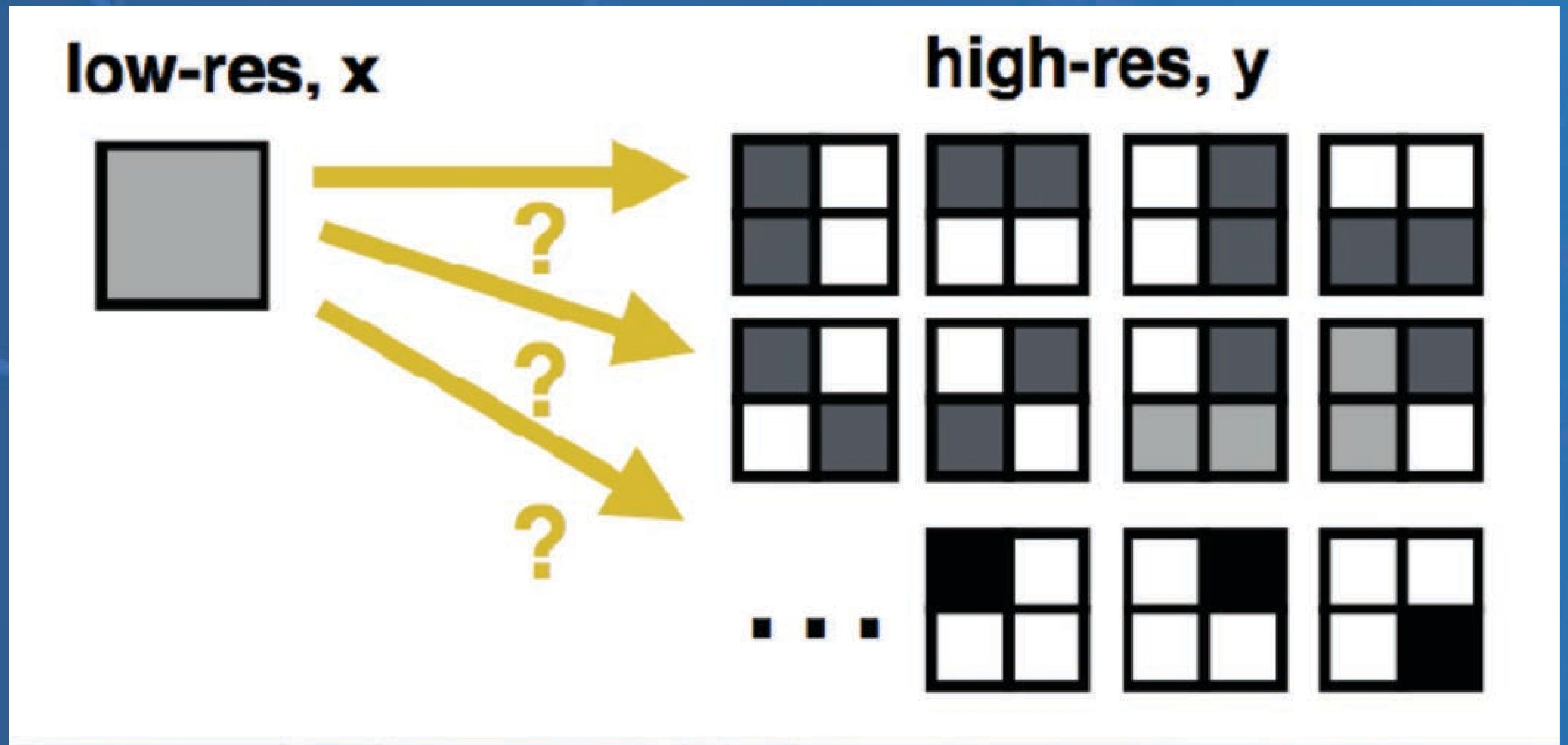
layers:

(3,3,3,50) —> (1,1,1,100) —> (3,3,3,r.r.r.c)

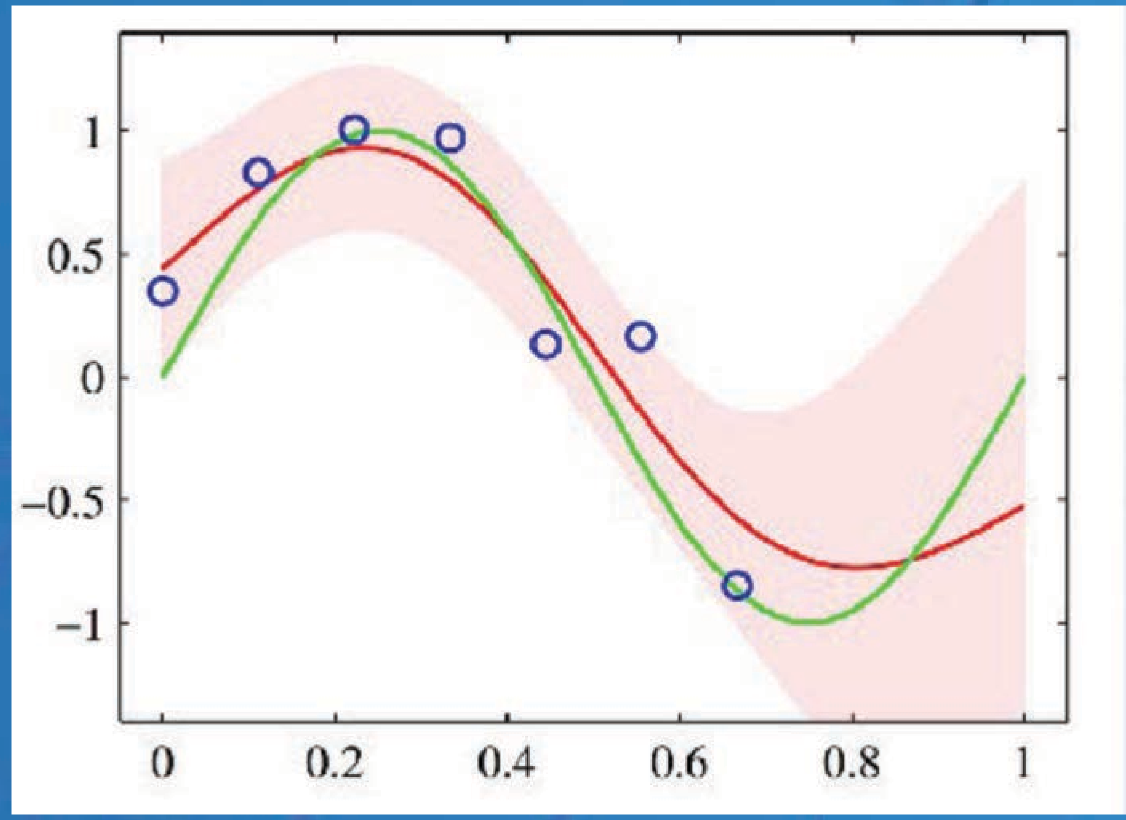
(width, height, depth, channels)

UNCERTAINTY [TANNO MICCAI 2017]

Intrinsic Uncertainty



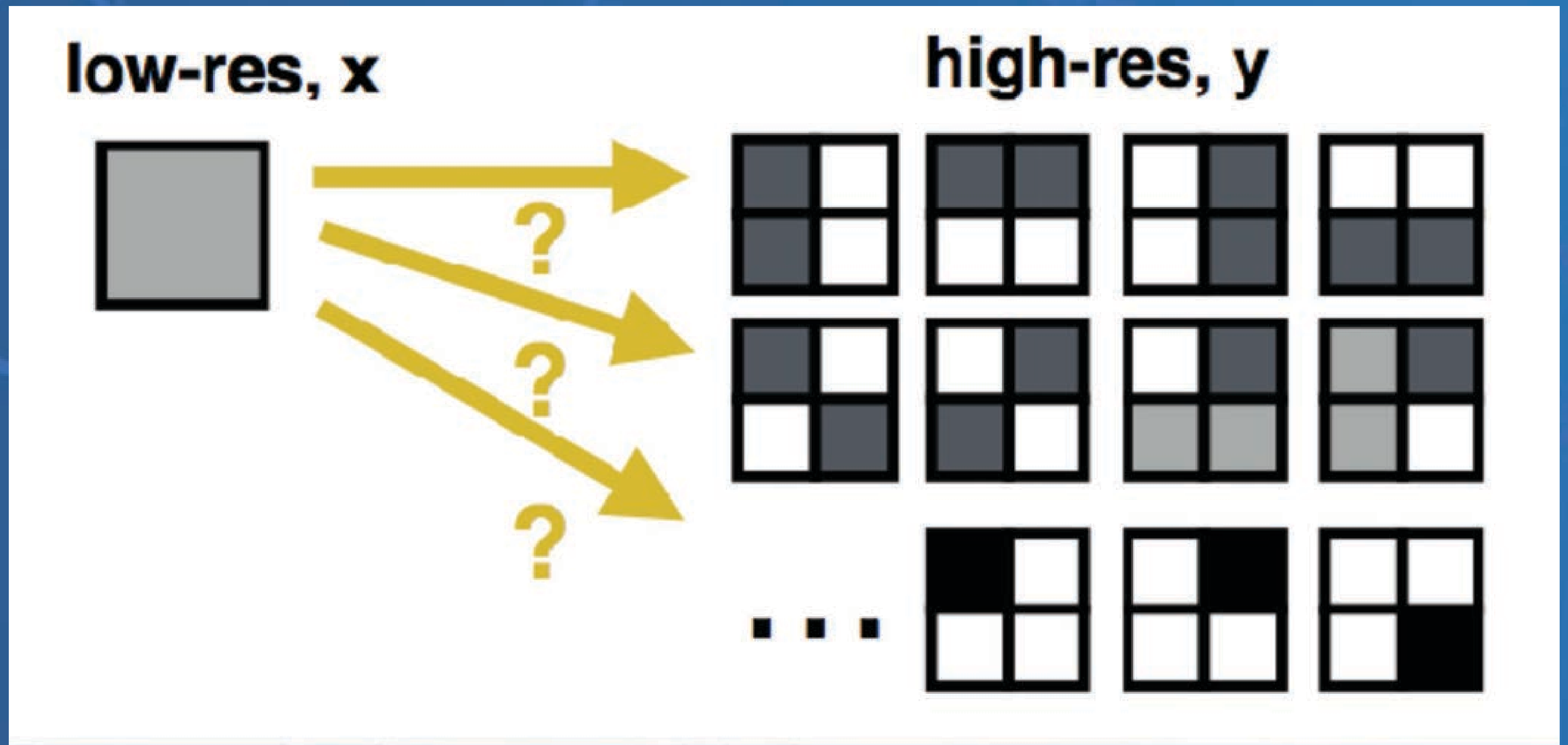
Parameter Uncertainty

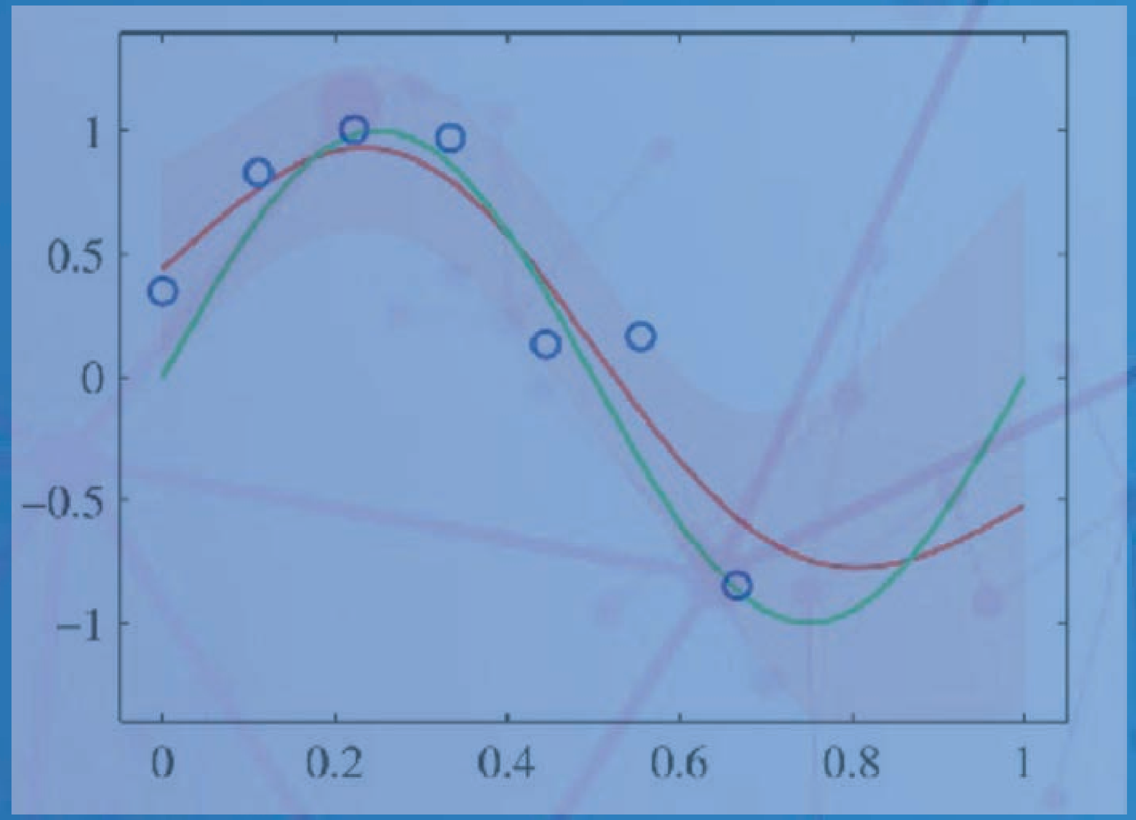


UNCERTAINTY [TANNO MICCAI 2017]

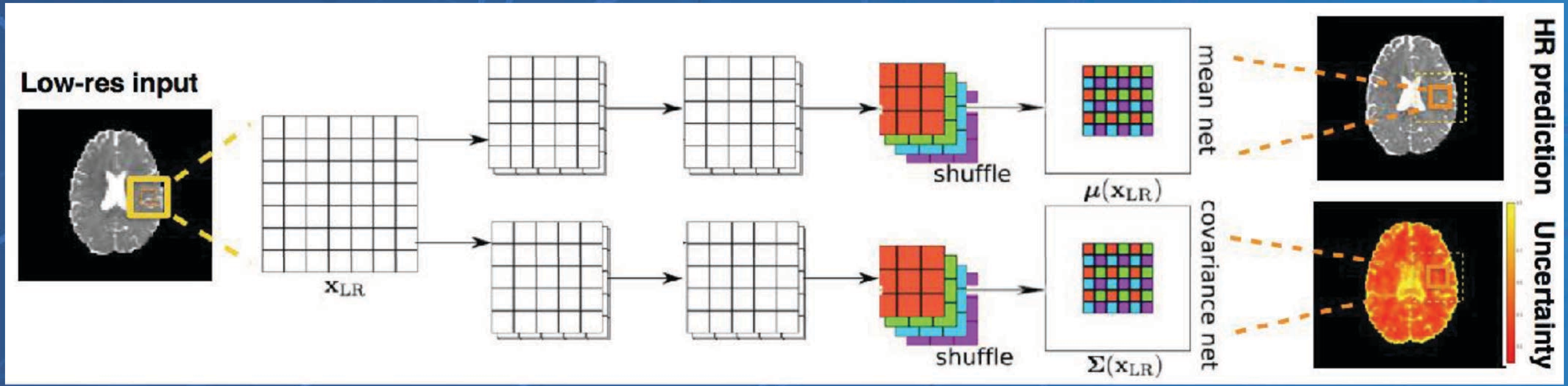
Intrinsic Uncertainty

Parameter Uncertainty





Heteroscedastic noise model (no parameter sharing)

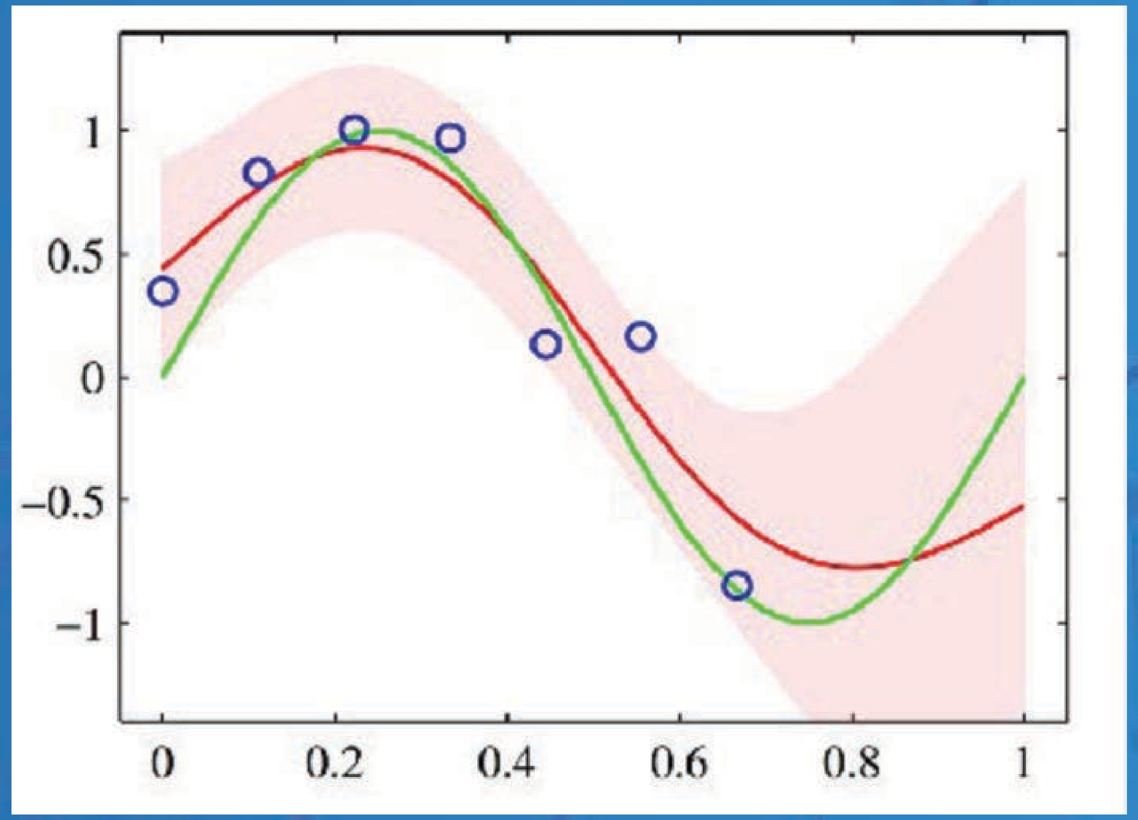


$$\frac{1}{N}\sum_i^N ||\mathbf{y}_i - \mu_{\theta_1}(\mathbf{x}_i)||^2_{\Sigma^{-1}_{\theta_2}(\mathbf{x}_i)}$$
$$+$$
$$\frac{1}{N}\sum_i^N \log\det \Sigma_{\theta_2}(\mathbf{x}_i)$$

UNCERTAINTY [TANNO MICCAI 2017]

Intrinsic Uncertainty

Parameter Uncertainty



- Approximate (intractable) posterior with a factored Gaussian distribution

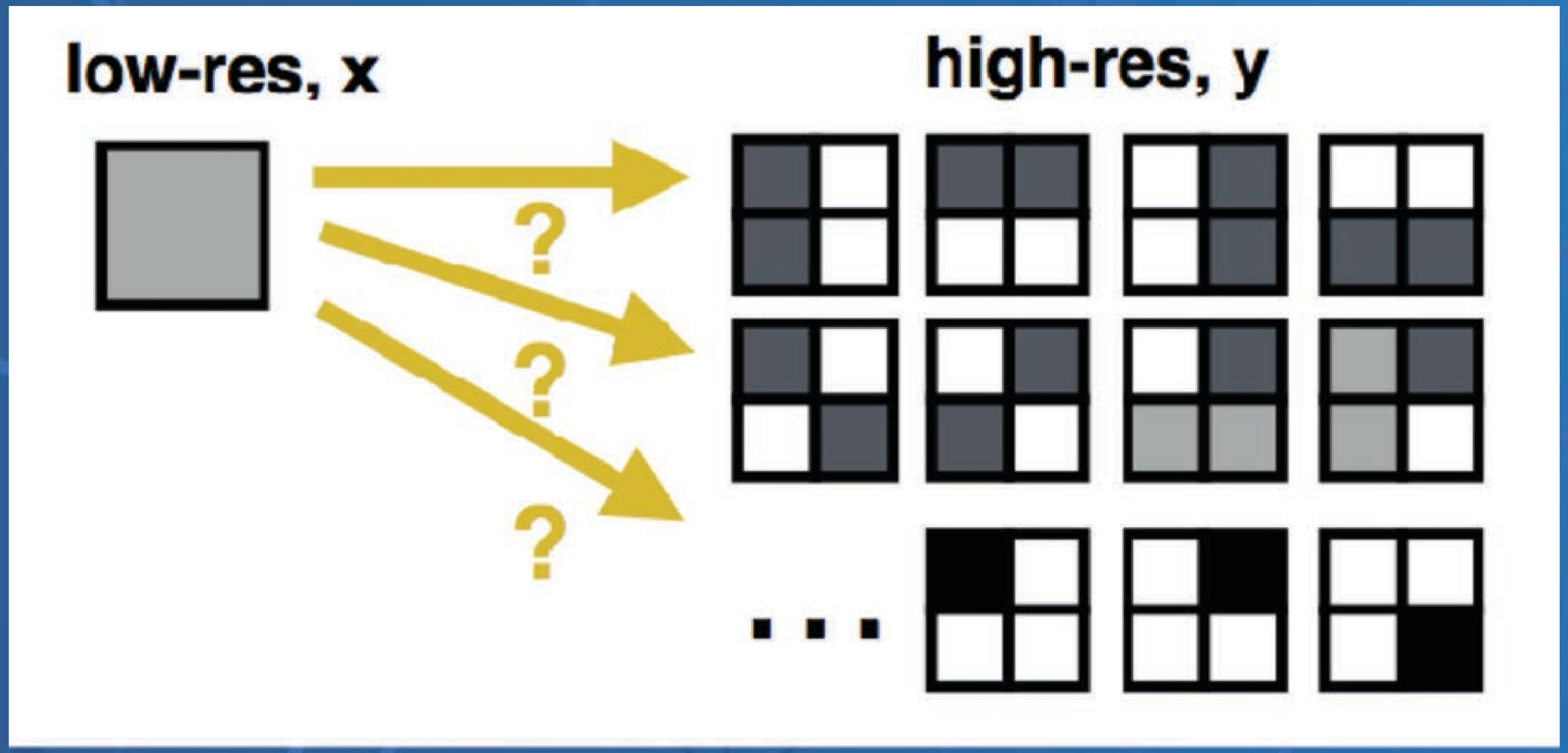
$$p(\theta|\mathcal{D}) \sim q_\phi(\theta)$$

[KINGMA 2015]

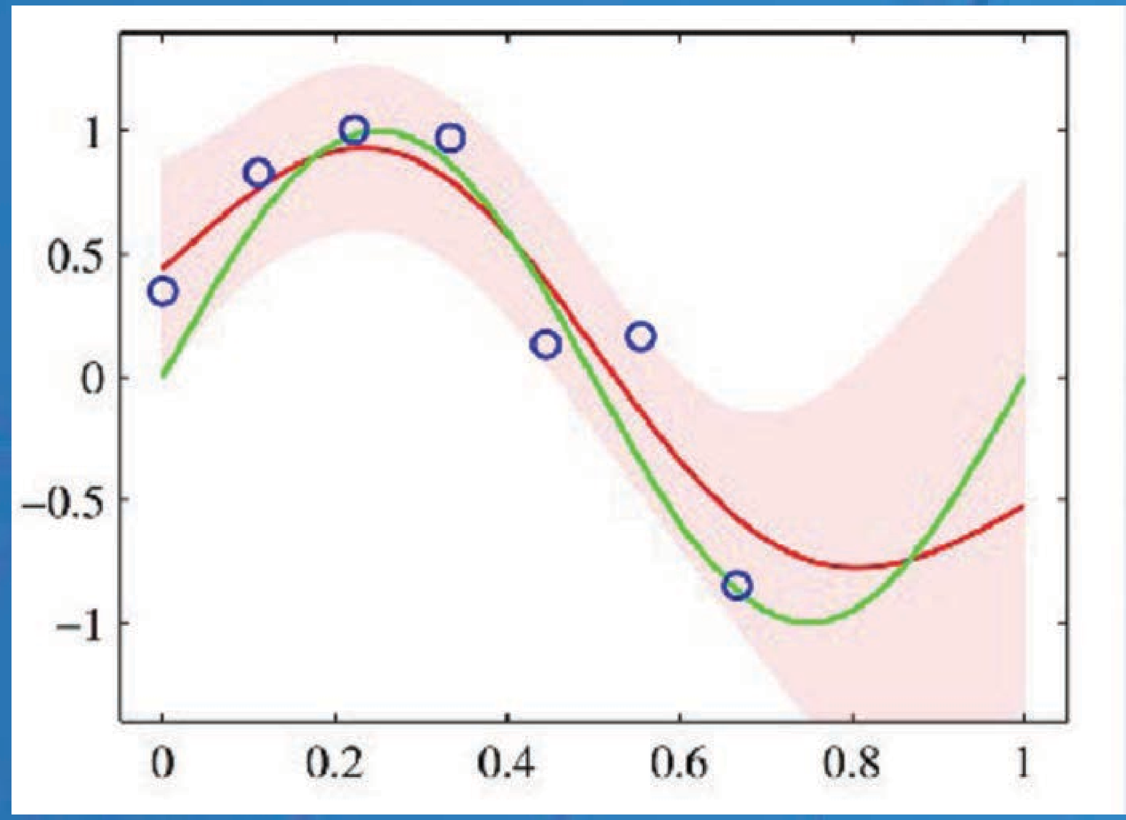
using **variational dropout** where dropout rates are learned

UNCERTAINTY [TANNO MICCAI 2017]

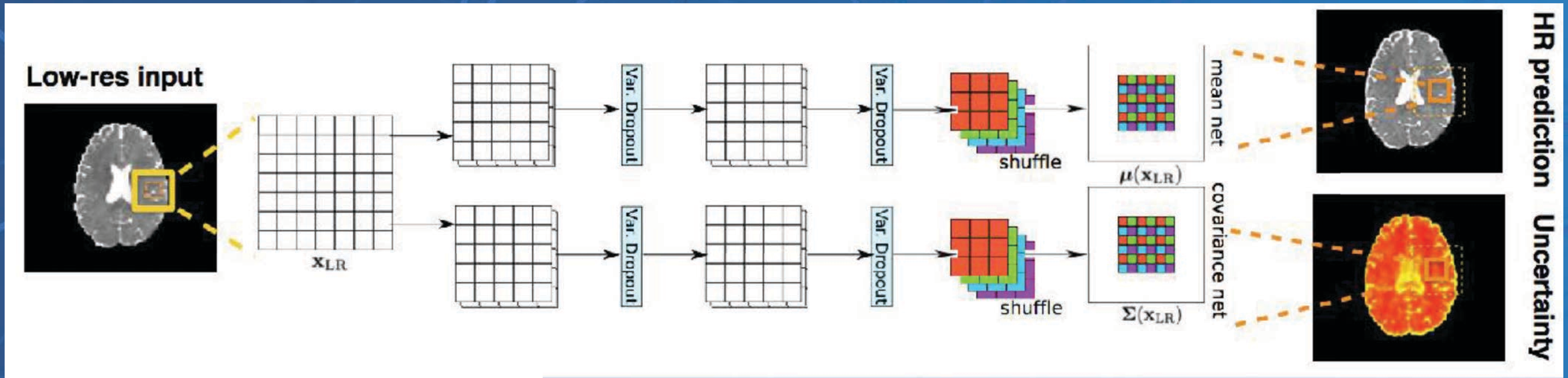
Intrinsic Uncertainty



Parameter Uncertainty



Heteroscedastic + Variational dropout

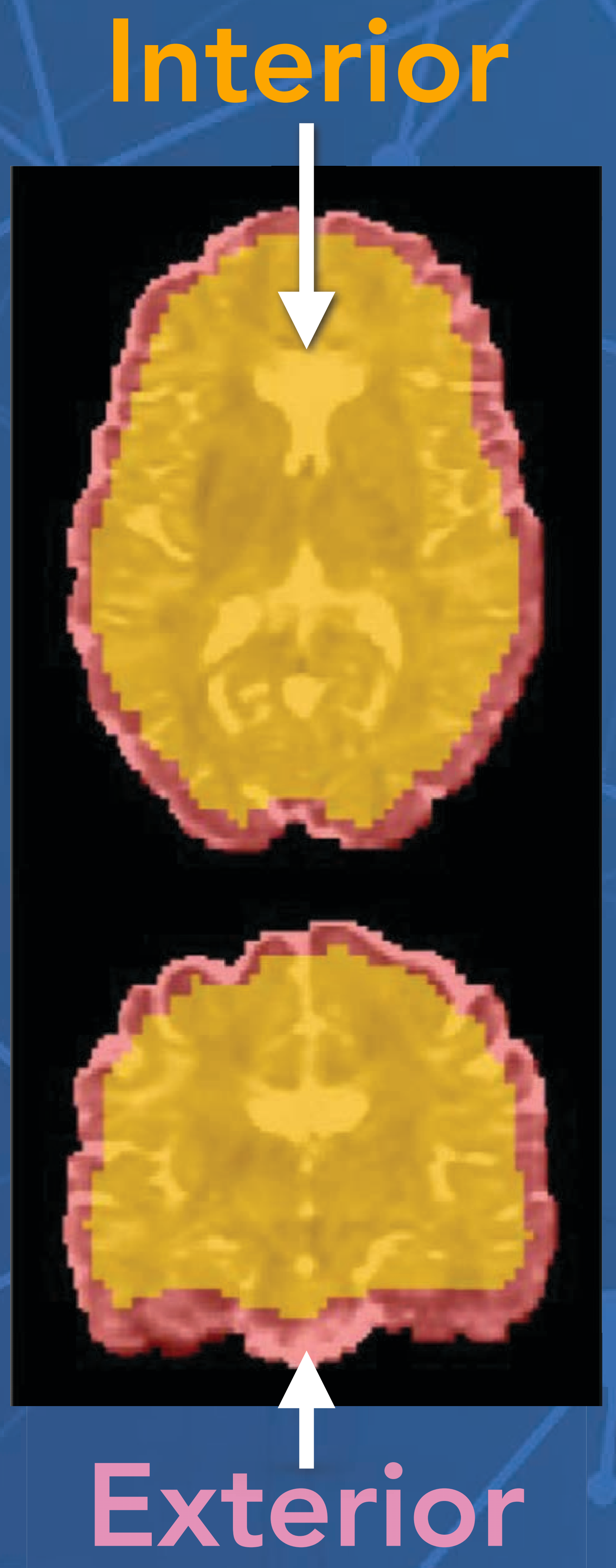


- Predictive distribution:

$$\int \mathcal{N}(\mathbf{y}; \mu_{\theta_1}, \Sigma_{\theta_2}(\mathbf{x})) \cdot q_\phi(\theta) d\theta$$

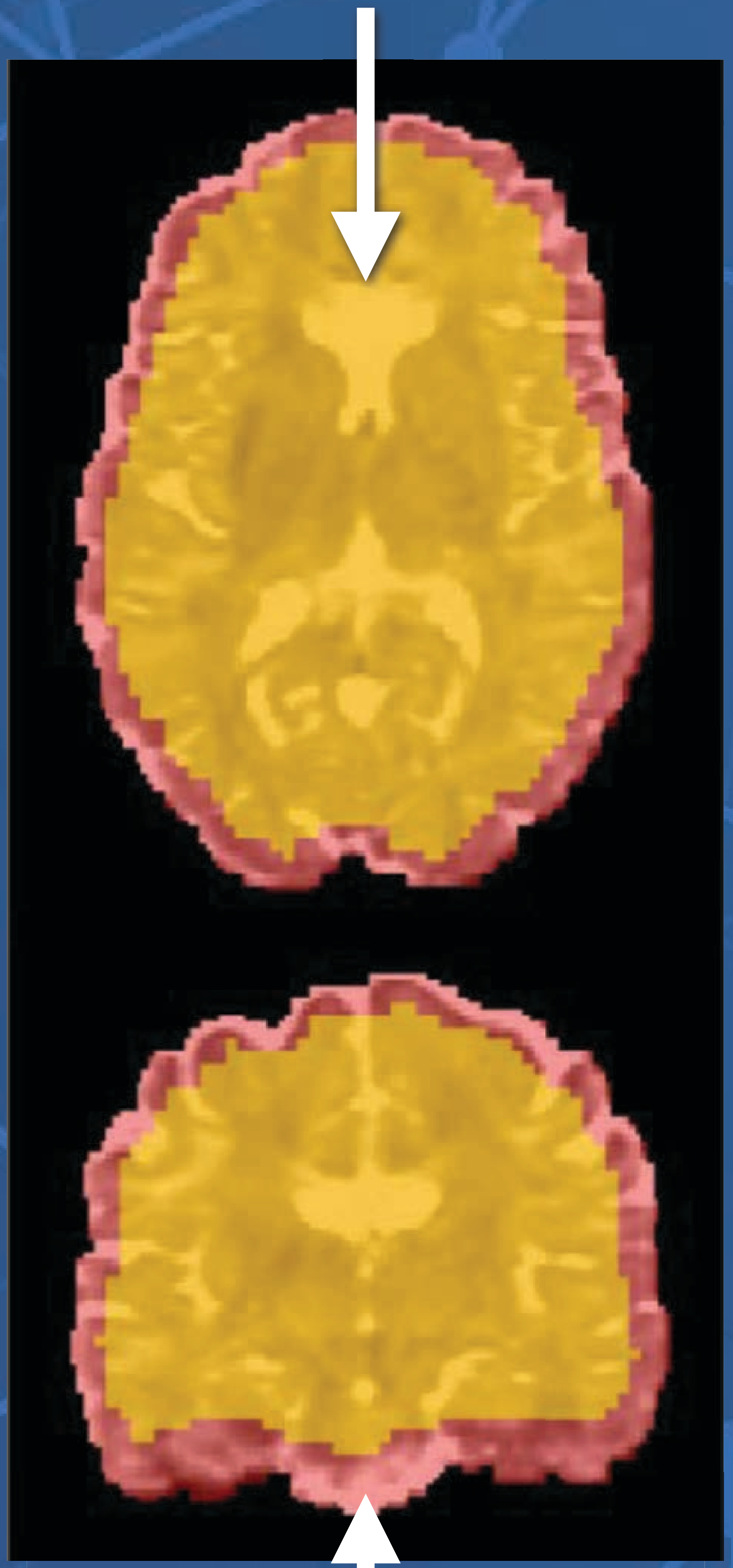
- Mean & Uncertainty (variance) from dropout sampling

RESULTS



RESULTS

Interior



Exterior

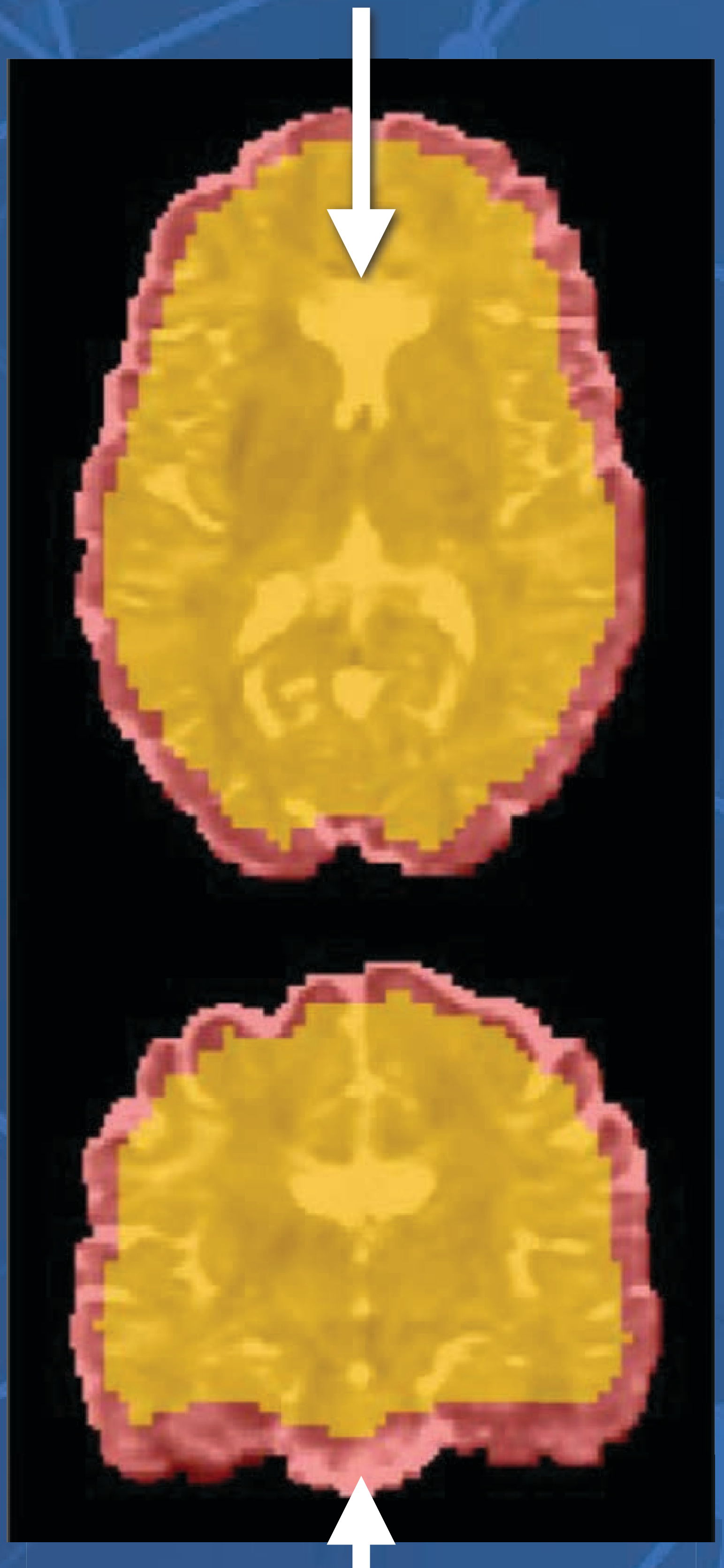
Unseen HCP cohort:
similar
demographics, protocol

Unseen Lifespan cohort:
different
demographics, protocol

Models	HCP (interior)	HCP (exterior)	Life (interior)	Life (exterior)
CSpline	$10.069 \pm$ n/a	$31.738 \pm$ n/a	$32.483 \pm$ n/a	$49.066 \pm$ n/a
IQT-RF	6.974 ± 0.024	23.139 ± 0.351	10.038 ± 0.019	25.166 ± 0.328
BIQT-RF	6.972 ± 0.069	23.110 ± 0.362	9.926 ± 0.055	25.208 ± 0.290
3D-ESPCN(baseline)	6.378 ± 0.015	13.909 ± 0.071	8.998 ± 0.021	16.779 ± 0.109

RESULTS

Interior



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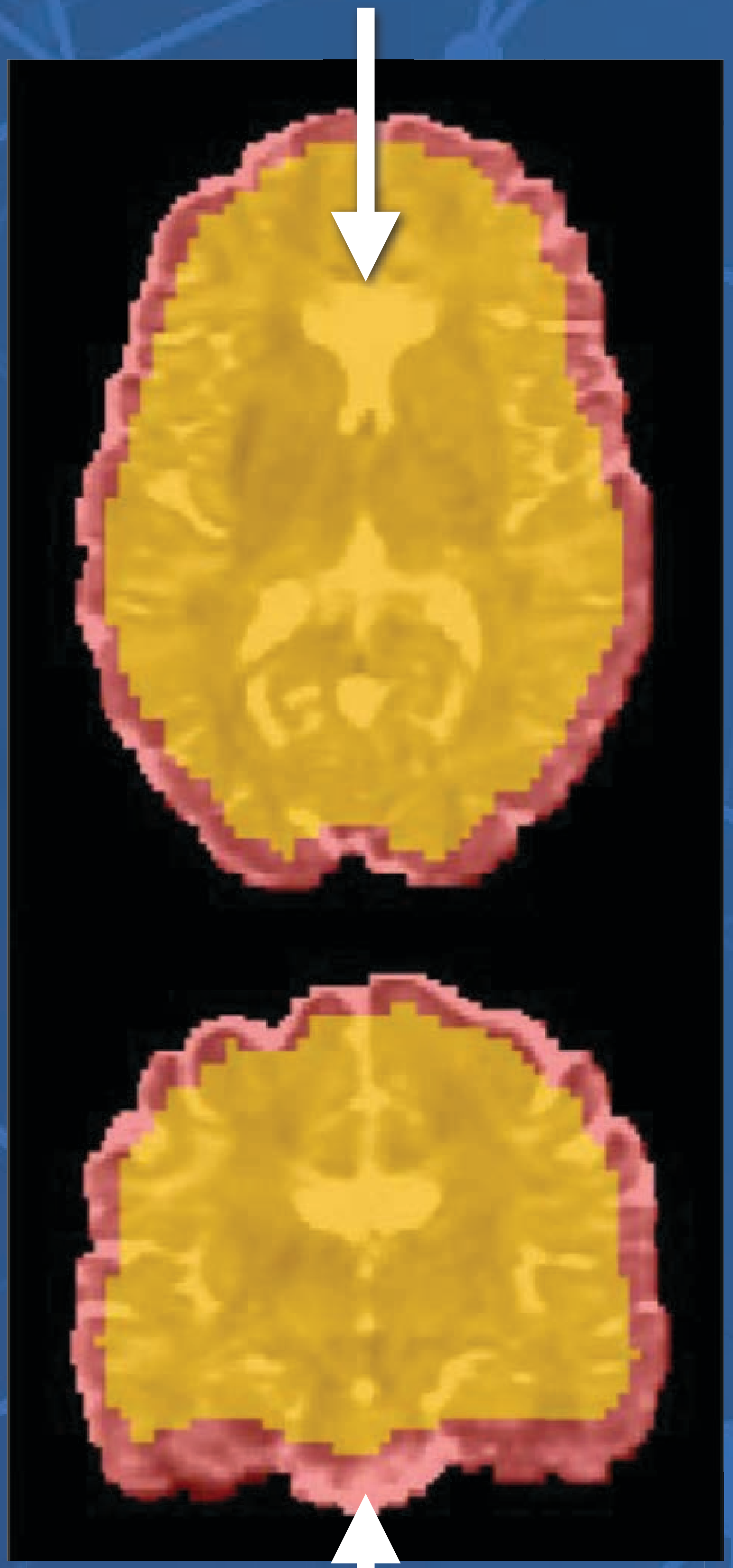
3D-ESPCN(baseline)	6.378 ± 0.015	13.909 ± 0.071	8.998 ± 0.021	16.779 ± 0.109
Improvement	9%	43%	10%	33%

Faster!

RESULTS

Interior



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Hetero-CNN	6.294 ± 0.029	15.569 ± 0.273	8.985 ± 0.051	17.716 ± 0.277
Var.(I)-CNN	6.354 ± 0.015	$\mathbf{13.824 \pm 0.031}$	8.973 ± 0.024	$\mathbf{16.633 \pm 0.053}$
Var.(II)-CNN	6.356 ± 0.008	13.846 ± 0.017	8.982 ± 0.024	16.738 ± 0.073
Hetero+Var.(I)	6.291 ± 0.012	13.906 ± 0.048	$\mathbf{8.944 \pm 0.044}$	16.761 ± 0.047
Hetero+Var.(II)	$\mathbf{6.287 \pm 0.029}$	13.927 ± 0.093	8.955 ± 0.029	16.844 ± 0.109

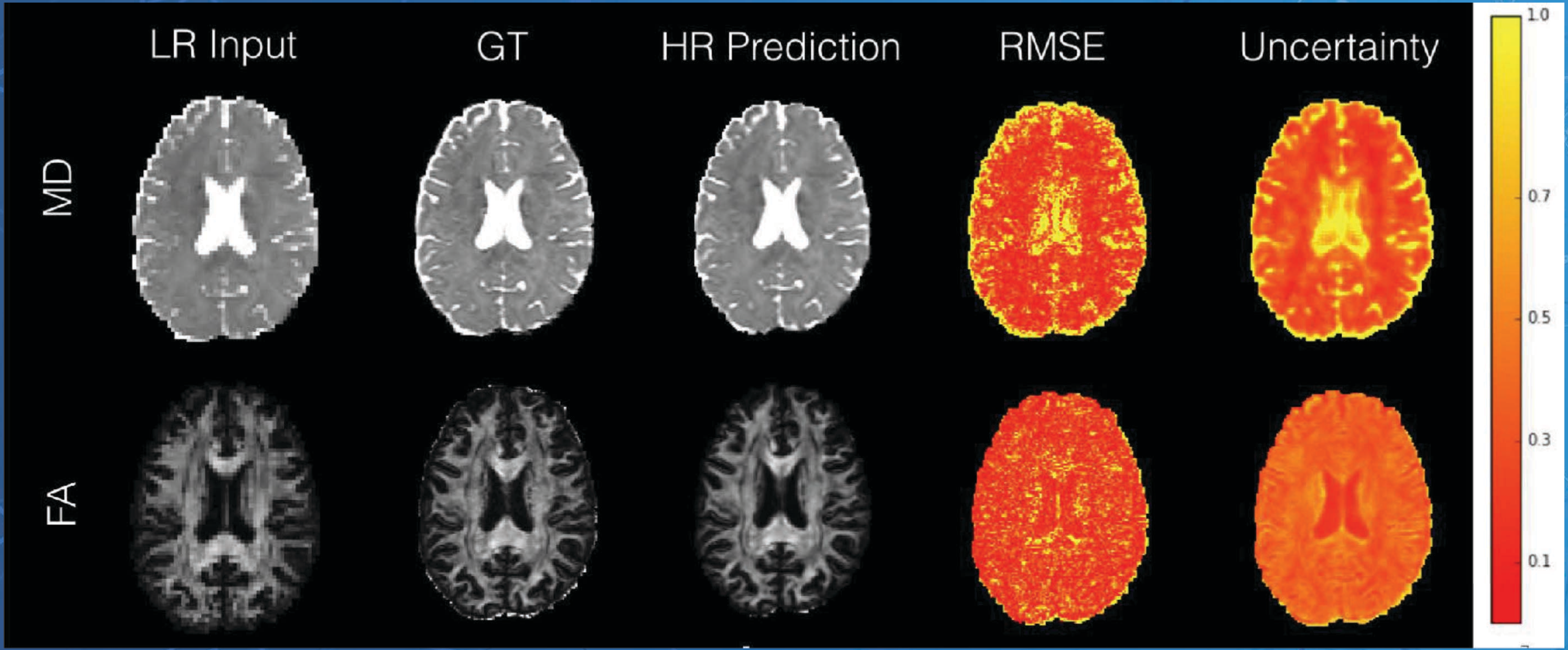
CNN based

Best

Second

Top models quantify uncertainty

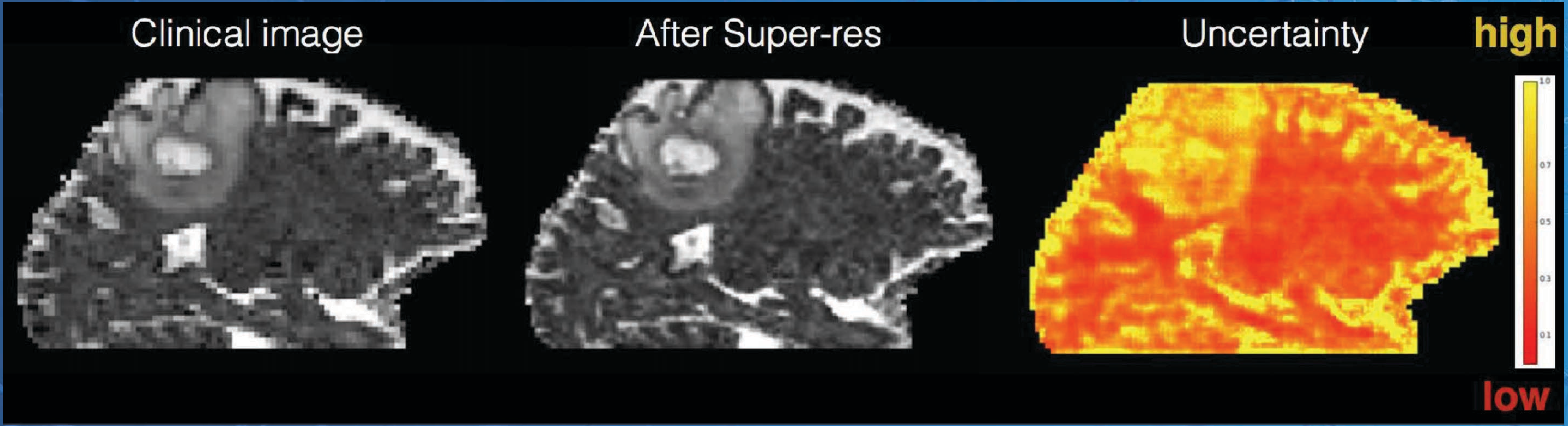
UNCERTAINTY PROPAGATION



Model: Hetero + Var (I)

200 samples of predicted DTI

UNCERTAINTY IN PATHOLOGY



Uncertainty correlates with pathology

CONCLUSION

TAKE AWAYS - 1

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- RF IQT:

TAKE AWAYS - 1

- RF IQT:
  - Patch based regression

TAKE AWAYS - 1

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  - Better reconstruction accuracy than regular RF IQT

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- Locally Bayesian RF IQT:
  - Better reconstruction accuracy than regular RF IQT
  - Uncertainty correlates well with reconstruction error
  - Uncertainty flags pathology (MS, tumour) consistently

TAKE AWAYS - 2

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- Deep Learning IQT:

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- Perspectives and Challenges:
  - Quantify performance in abnormal tissue (comparison with other methods requires data)
  - Explore other problems (parameter mapping, data harmonisation, etc…)

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  MICCAI 2016 pp 265-273, 2016

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  NeuroImage Volume 152, 15 May 2017, Pages 283–298

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  MICCAI 2017

THANK YOU

https://github.com/ucl-mig/iqt