Utilizing Baseline Information Addition to Task-Related Information in FMRI

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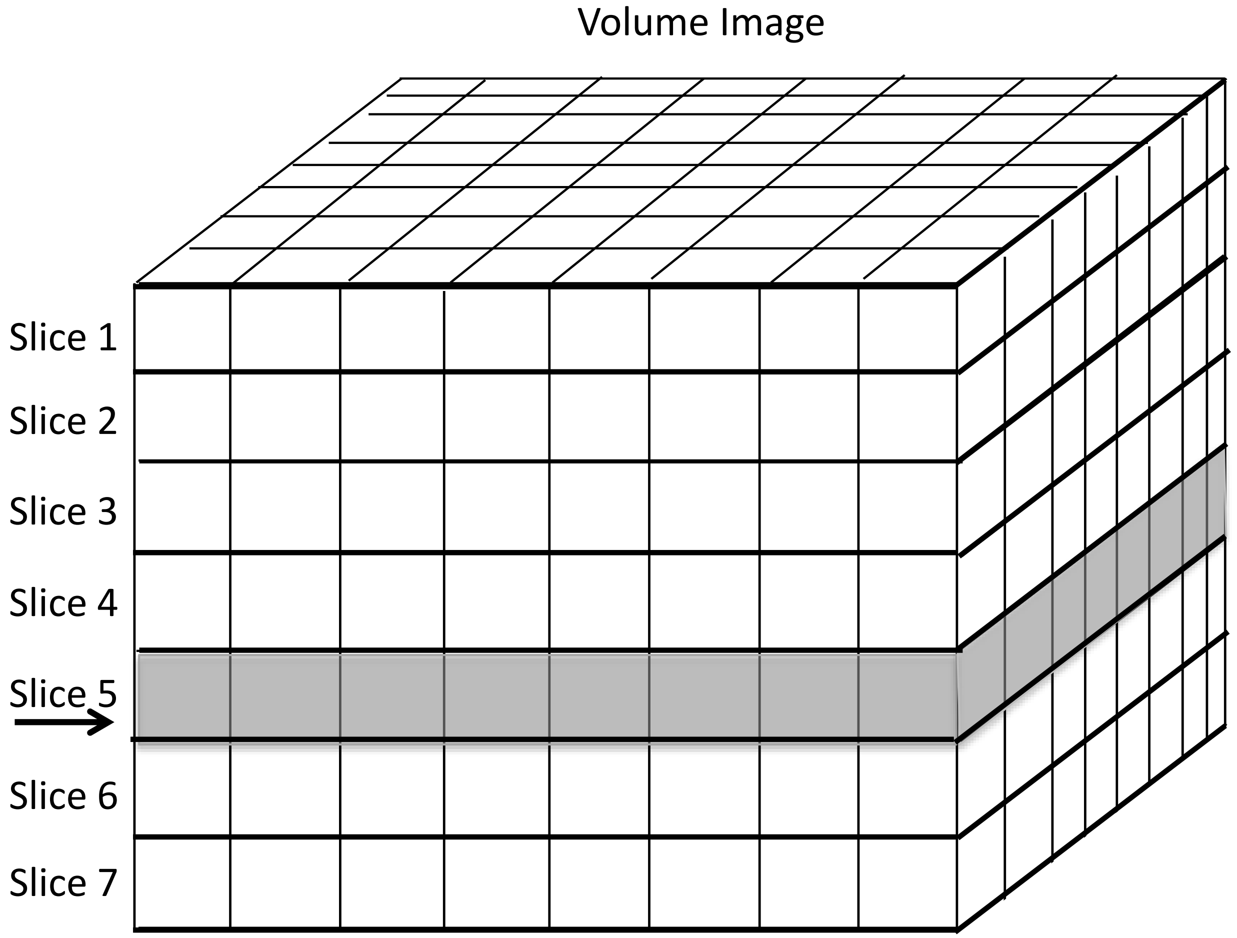
August 11, 2022

Outline

1. FMRI Problem
2. FMRI Data
3. FMRI Activation
4. FMRI Results
5. FMRI Discussion

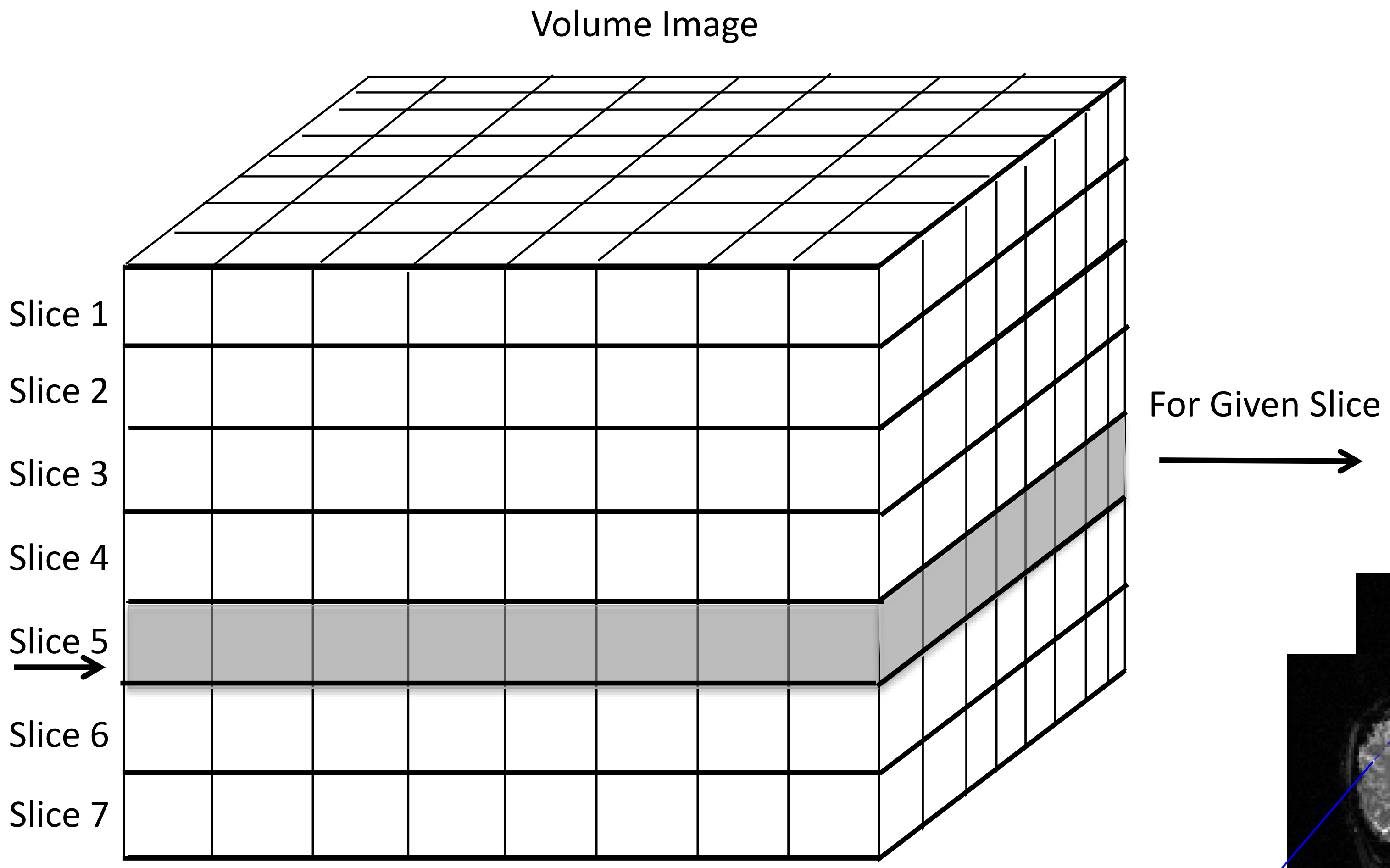
1. FMRI Problem

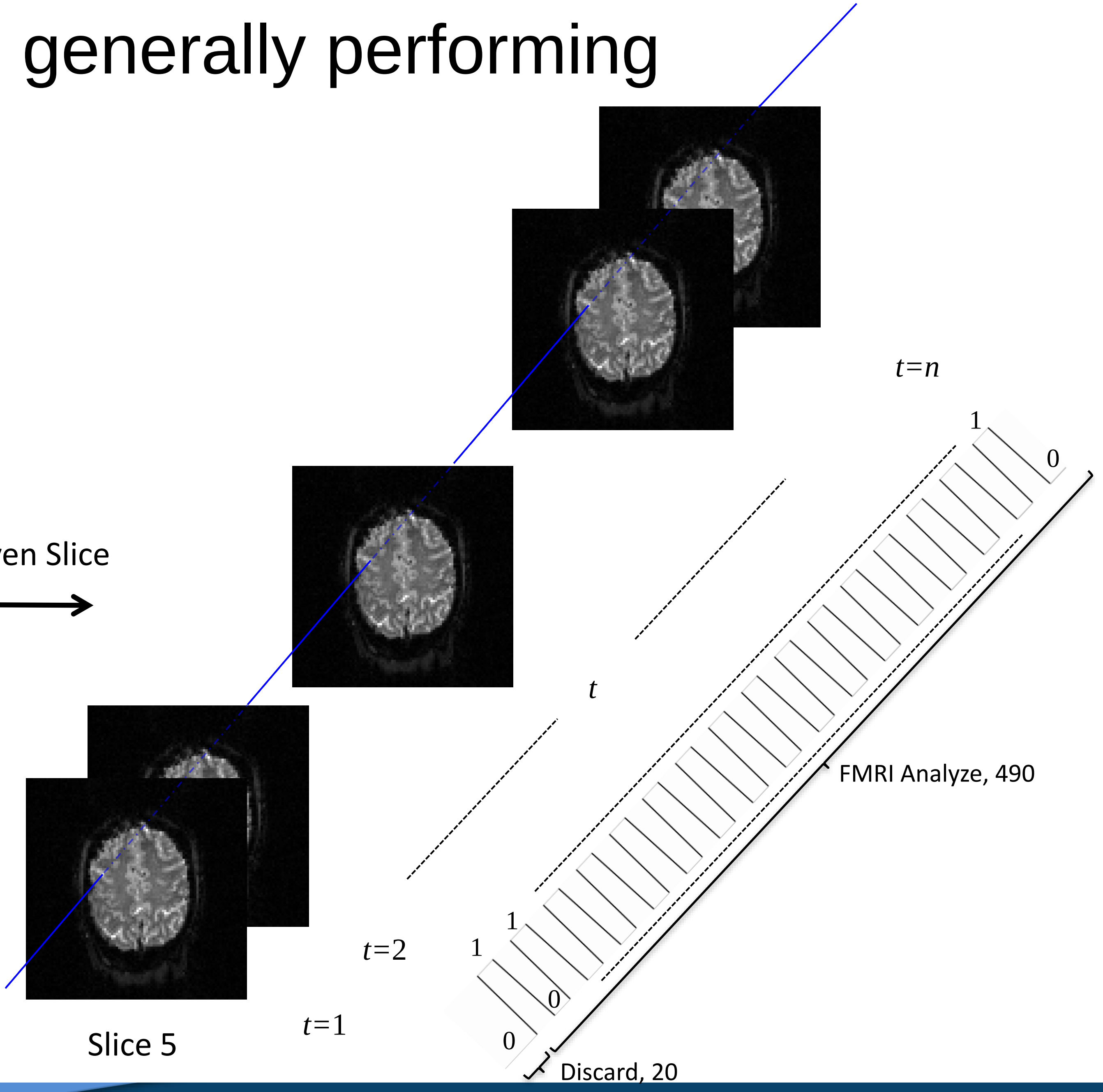
In fMRI, a subject is placed in the MRI machine and volume images of their brain measured



1. FMRI Problem

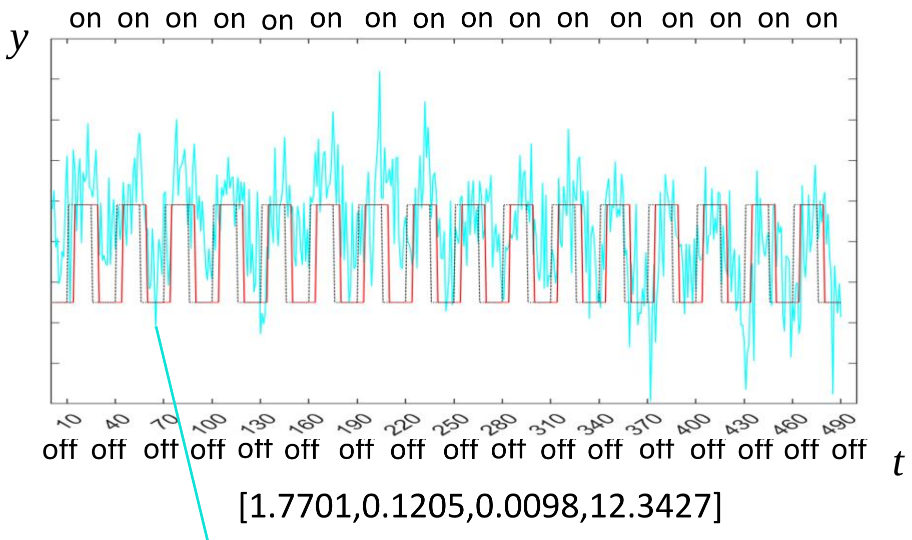
… at n time points while they are generally performing a designed cognitive task





1. FMRI Problem

We observe $n(=490)$, data points, $(x_1,y_1),\ldots,(x_n,y_n)$ and determine a statistically significant relationship between x (task design) an y (observed voxel value) as $y_t=\beta_0+\beta_1 x_t+\varepsilon_t$, assuming $\varepsilon_t\sim N(0,\sigma^2)$ for $t=1,\ldots,n$.



In each voxel

$$W=(X'X)^{-1}$$

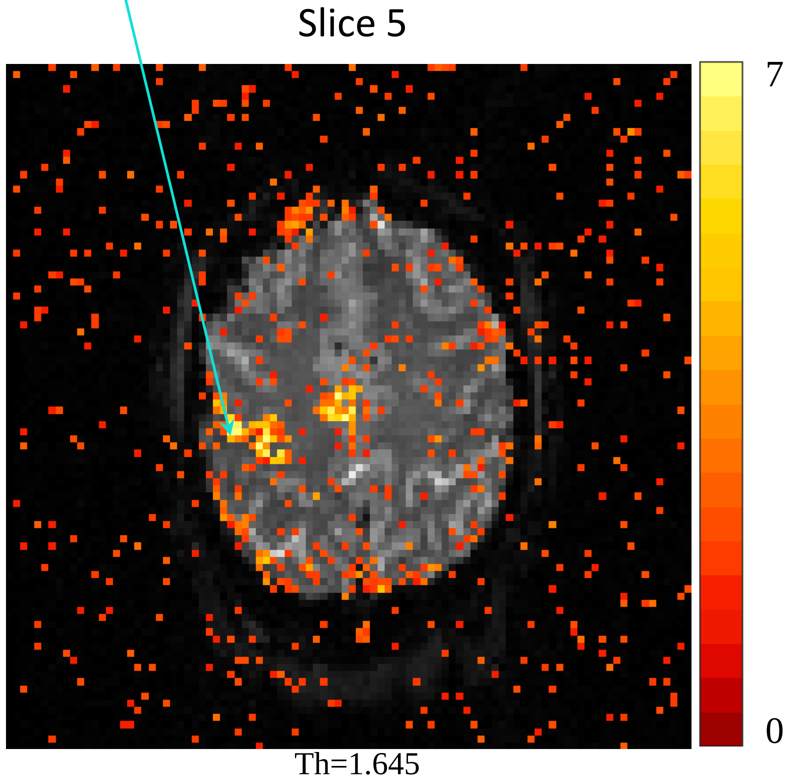
$$W=\begin{pmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{pmatrix}$$

$$SE(\hat{\beta}_1)=s\sqrt{w_{22}}$$

$$\hat{\beta}=(X'X)^{-1}X'y$$

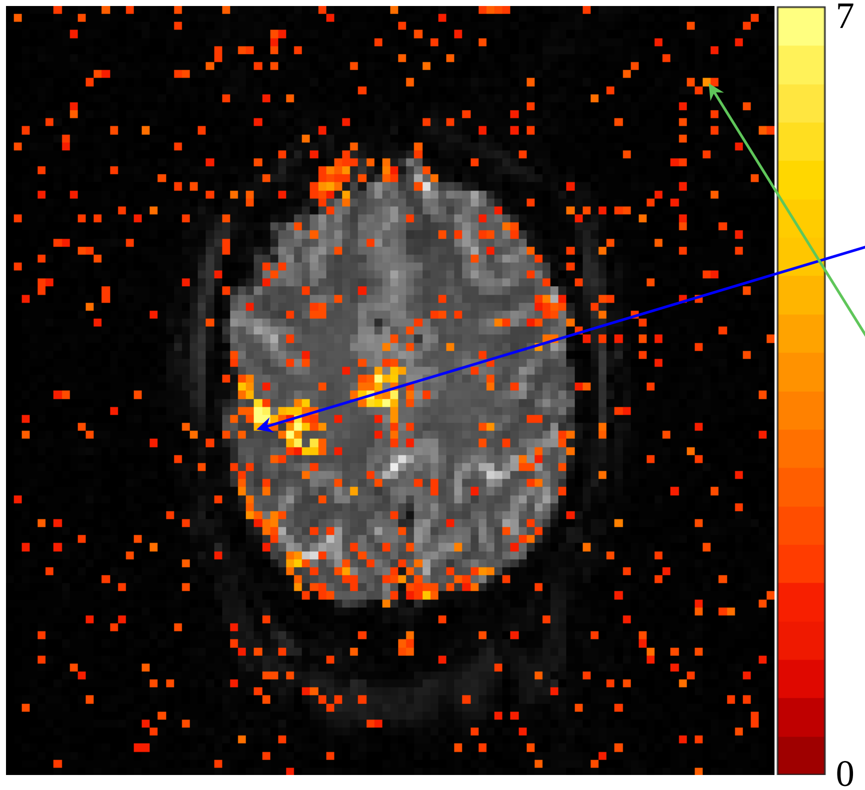
$$t=\frac{\hat{\beta}_1}{SE(\hat{\beta}_1)}$$

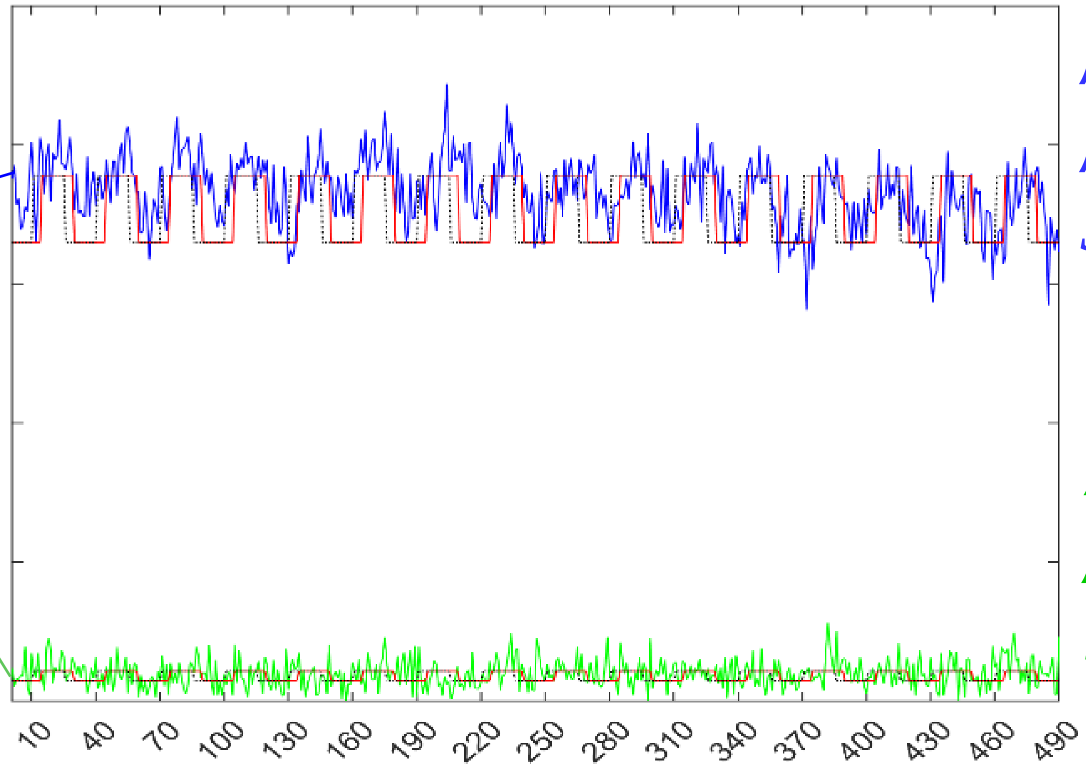
As you can see there are many “false positives.”



1. FMRI Problem

The issue is that we can have two voxels that have the same β_1 "activation" level, but different baselines, β_0.





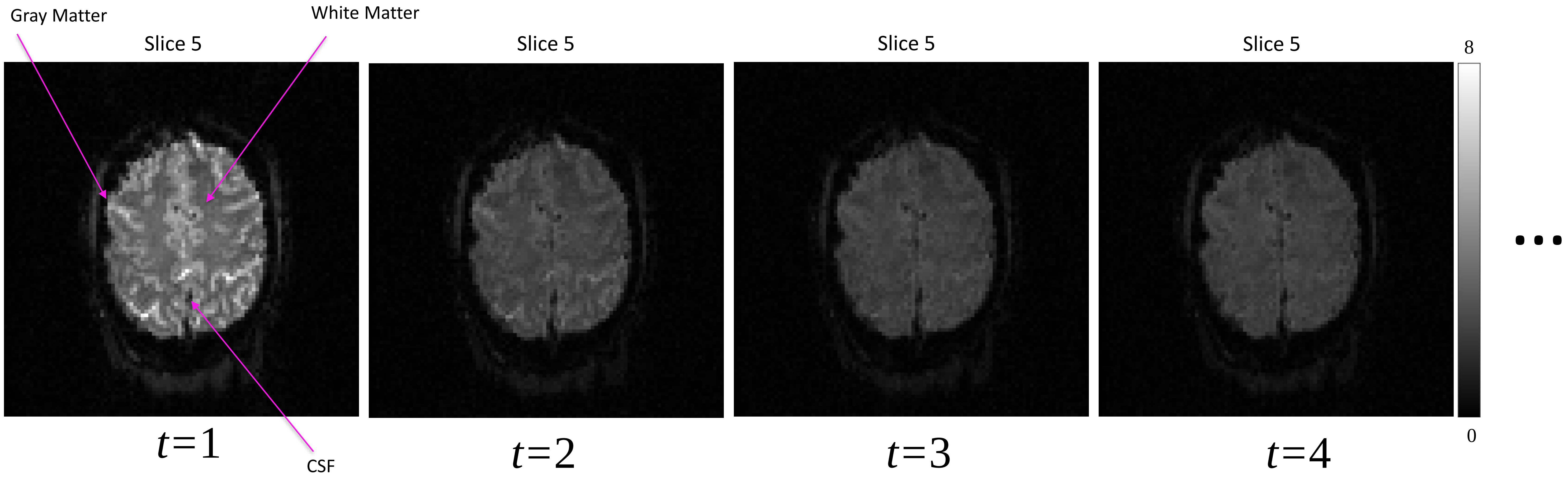
$\hat{\beta}_0 = 2.0989$
$\hat{\beta}_1 = 0.0311$
$SE(\hat{\beta}_1) = 0.0084$
$t = 3.7150$

$\hat{\beta}_0 = 0.0919$
$\hat{\beta}_1 = 0.0170$
$SE(\hat{\beta}_1) = 0.0046$
$t = 3.6844$

We don't use the β_0 information that we have.

2. FMRI Data

For FMRI Data, these are what the slice images look like over time.

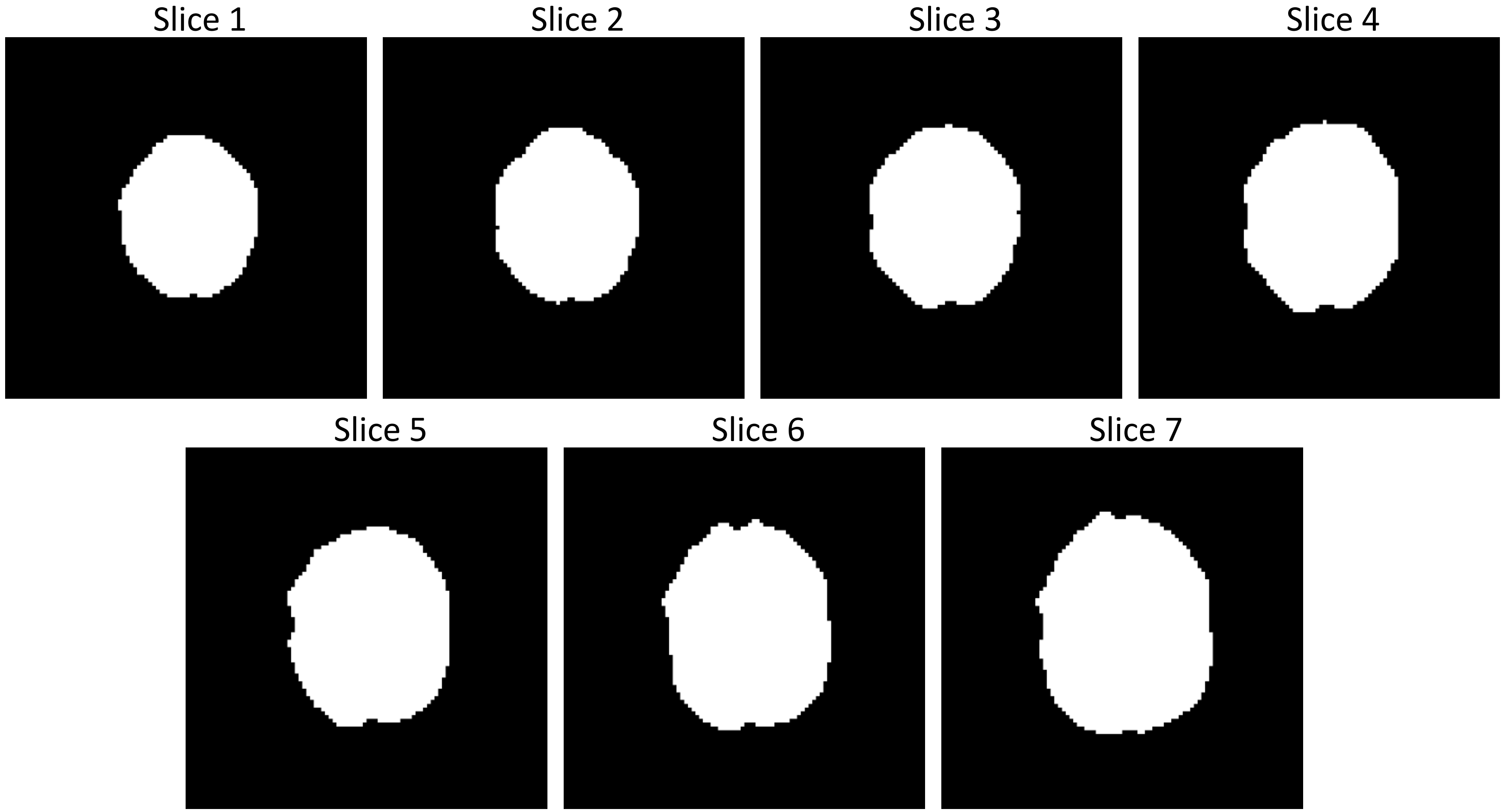


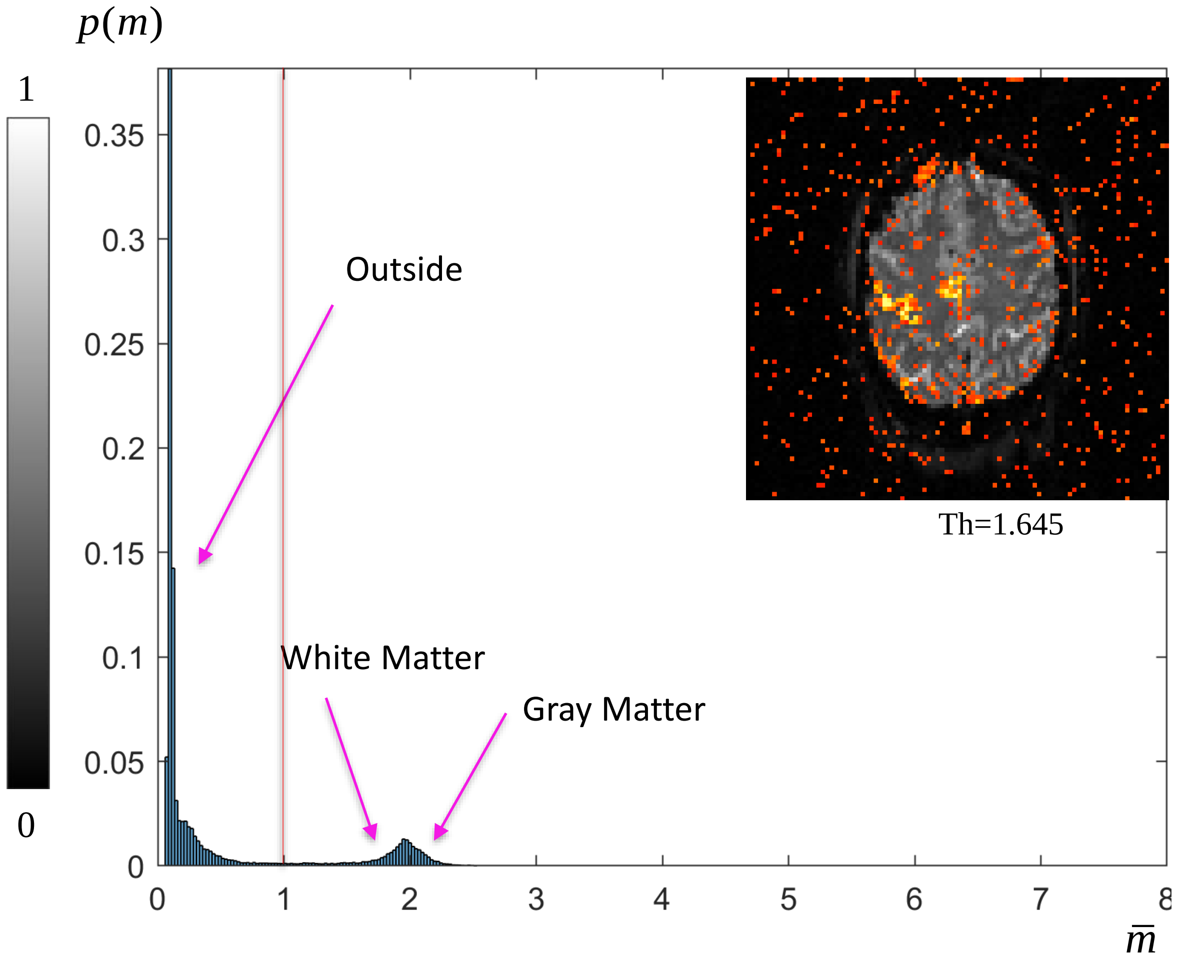
T_2* weighted images

Signal equilibration effect. Most never see these after “preprocessing.”

2. FMRI Data

For FMRI Data, a spatial mask based upon intensity can be generated.



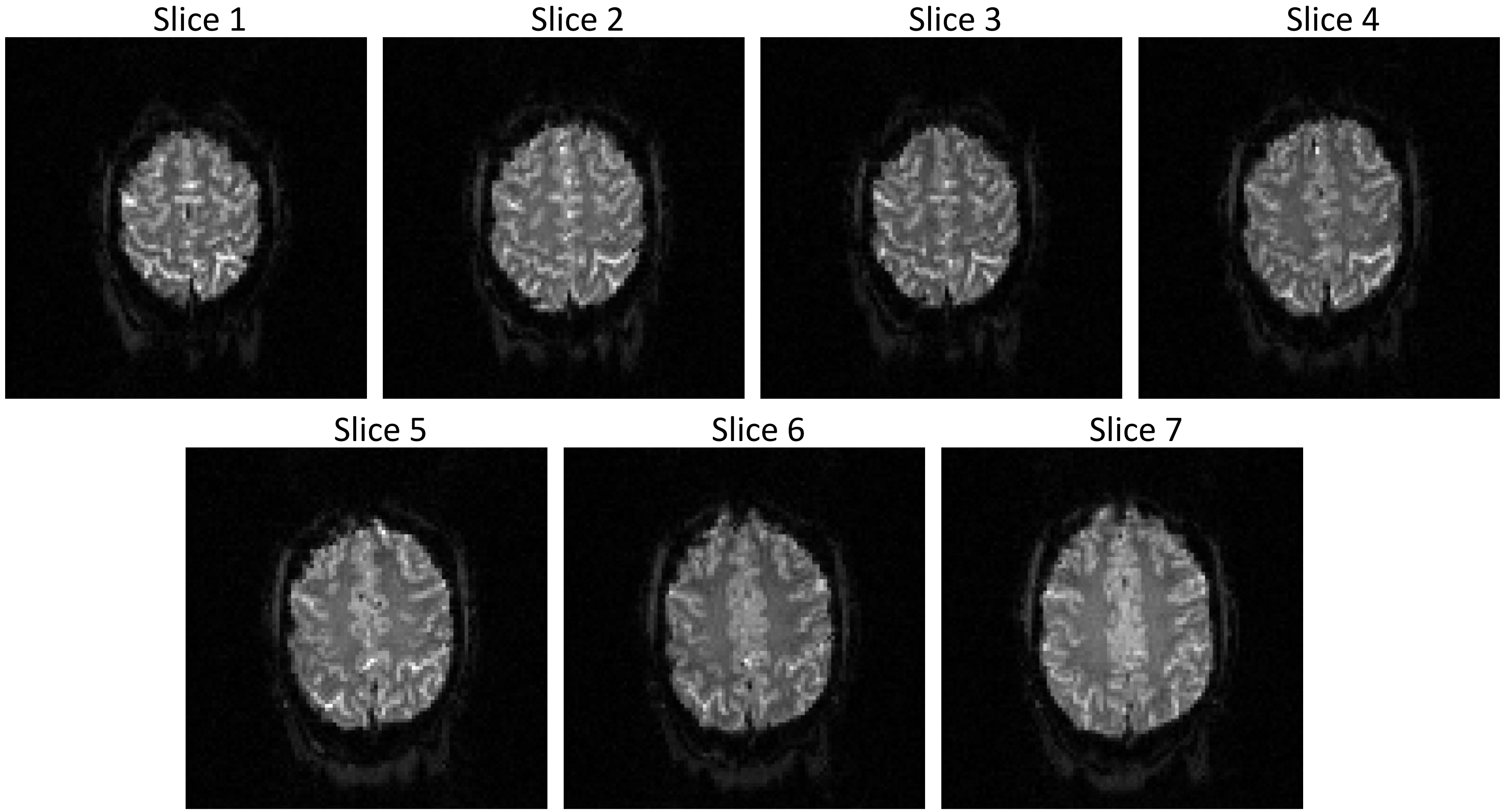


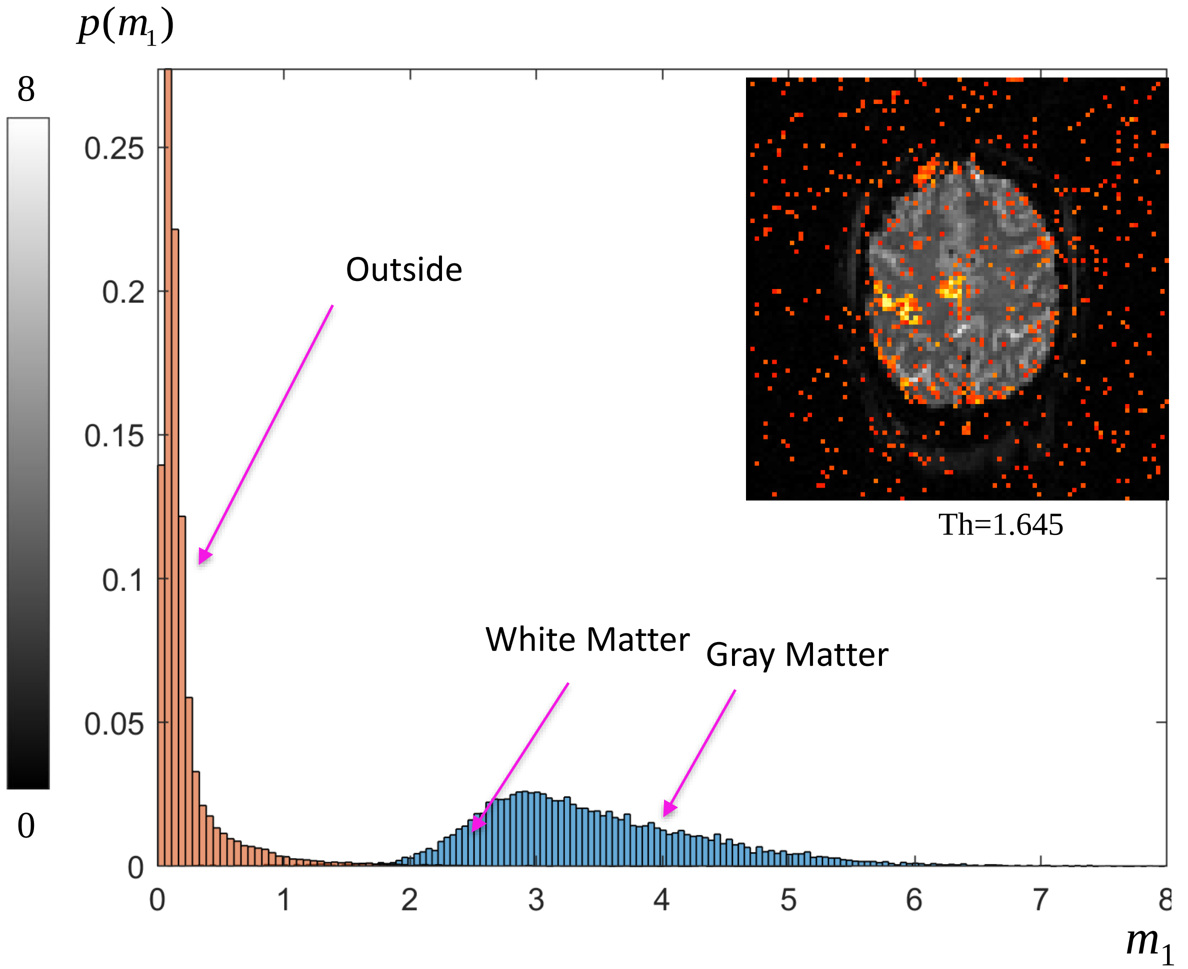
$n_y n_x n_z$=64512

1. Averaged $n_{del}+,\ldots,n$ images.
2. Smoothed with 5×5 mean filter.
3. Pixel intensities >1 in mask.

2. FMRI Data

For FMRI Data, these are what the first time point slice images look like.





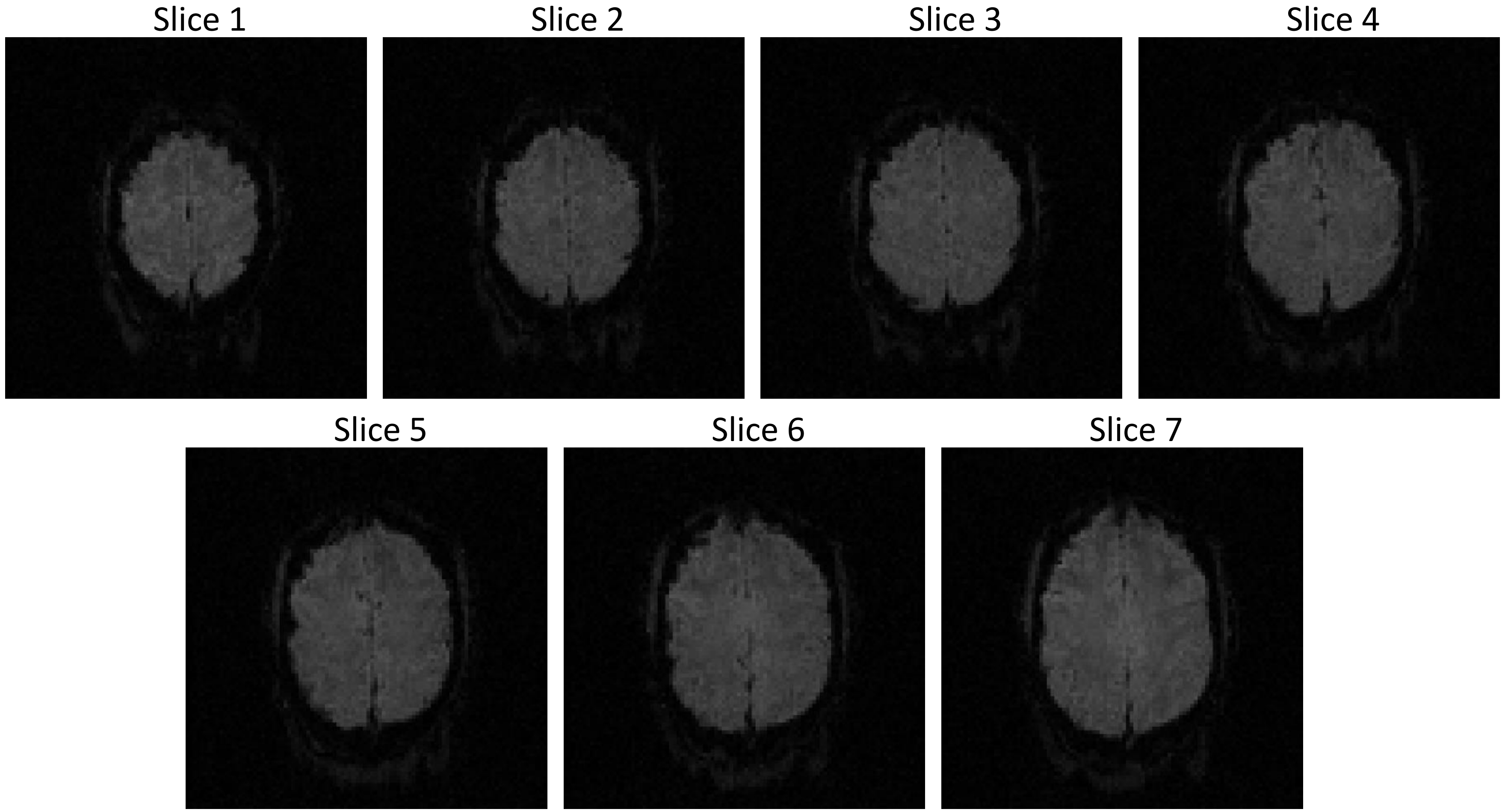
Usually Discarded $t=1$

$n_y n_x n_z$=64512

T_2* weighted images

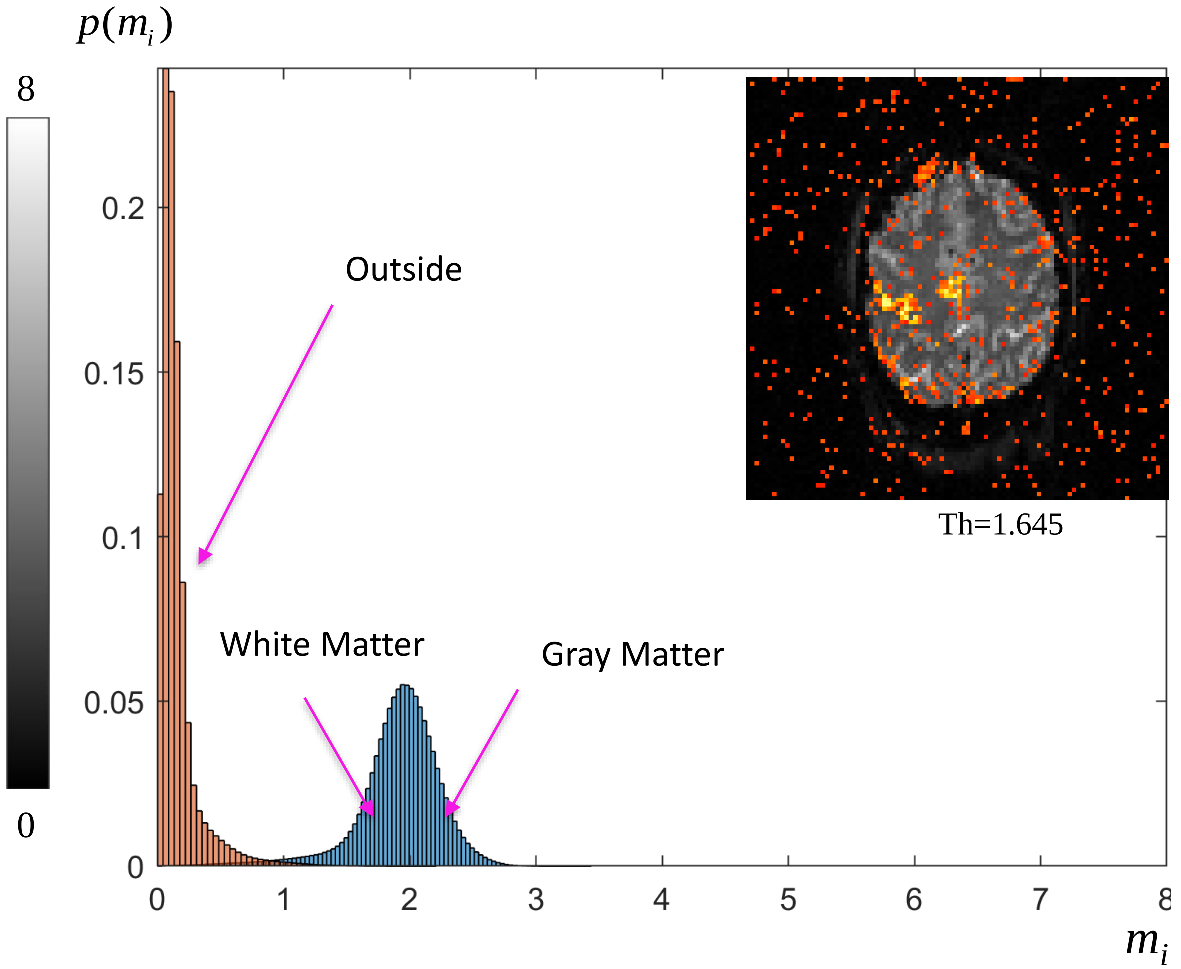
2. FMRI Data

For FMRI Data, these are what the after discarded slice images look like.



$$t = n_{del} + 1, \ldots, n$$

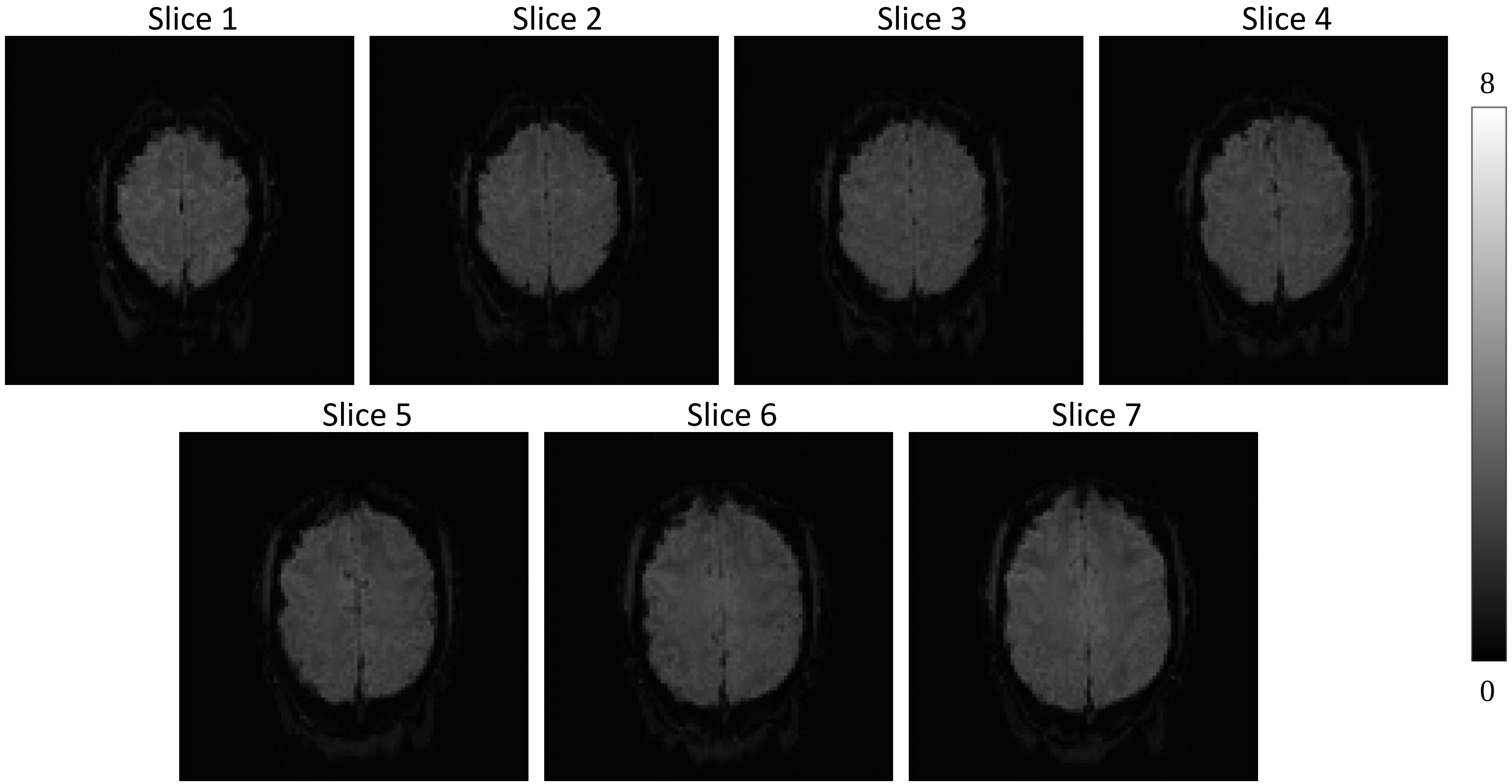
T_2* weighted images

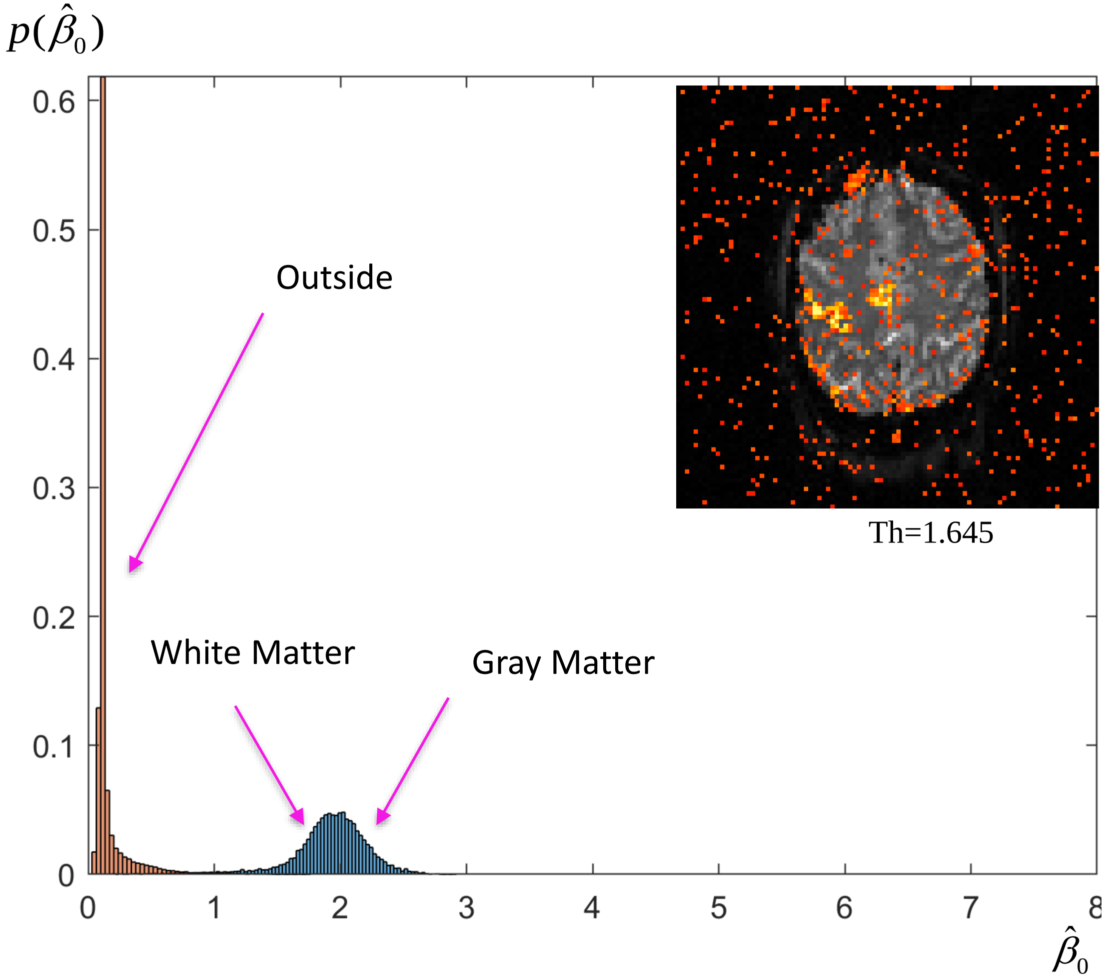


$n_y n_x n_z n_t$=31610880

2. FMRI Data

For FMRI Data, these are what the β_0 coefficients look like.





$$t = n_{del} + 1, \ldots, n$$

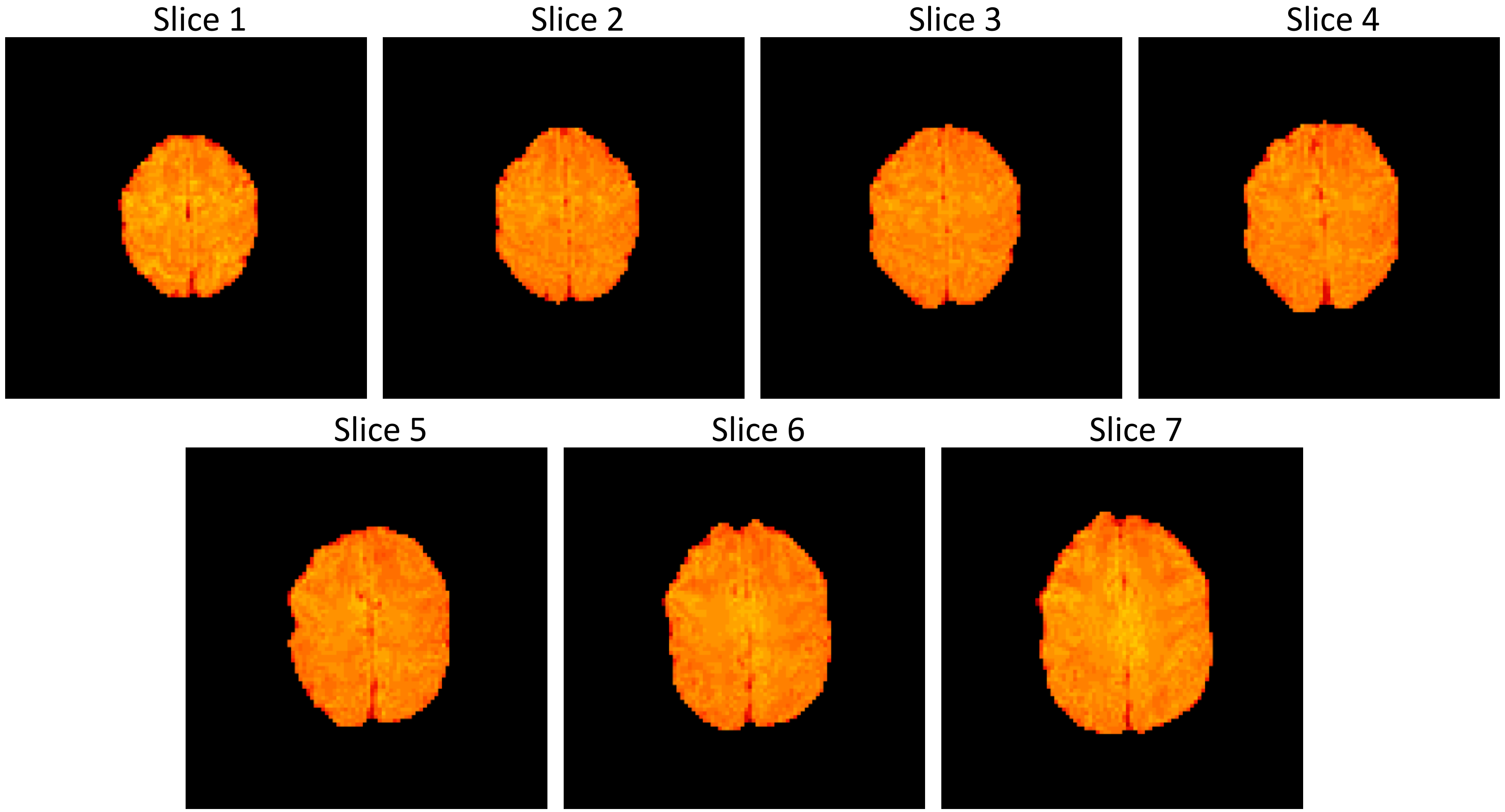
$n_y n_x n_z = 64512$

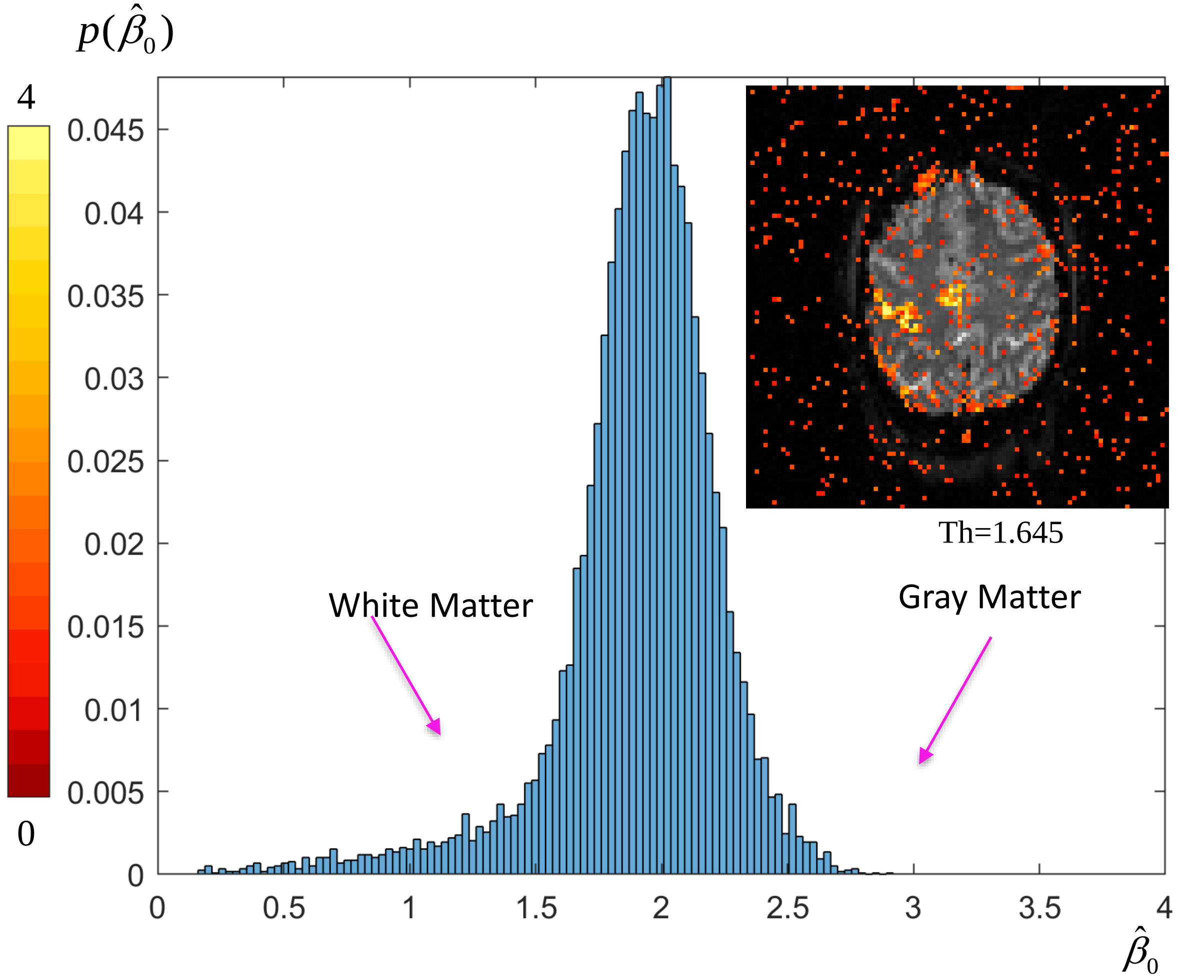
T_2* weighted images

3. FMRI Activation

$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t$

For FMRI Data, we can limit ourselves to within mask β_0 voxels.





$t = n_{del}+1, \ldots, n$

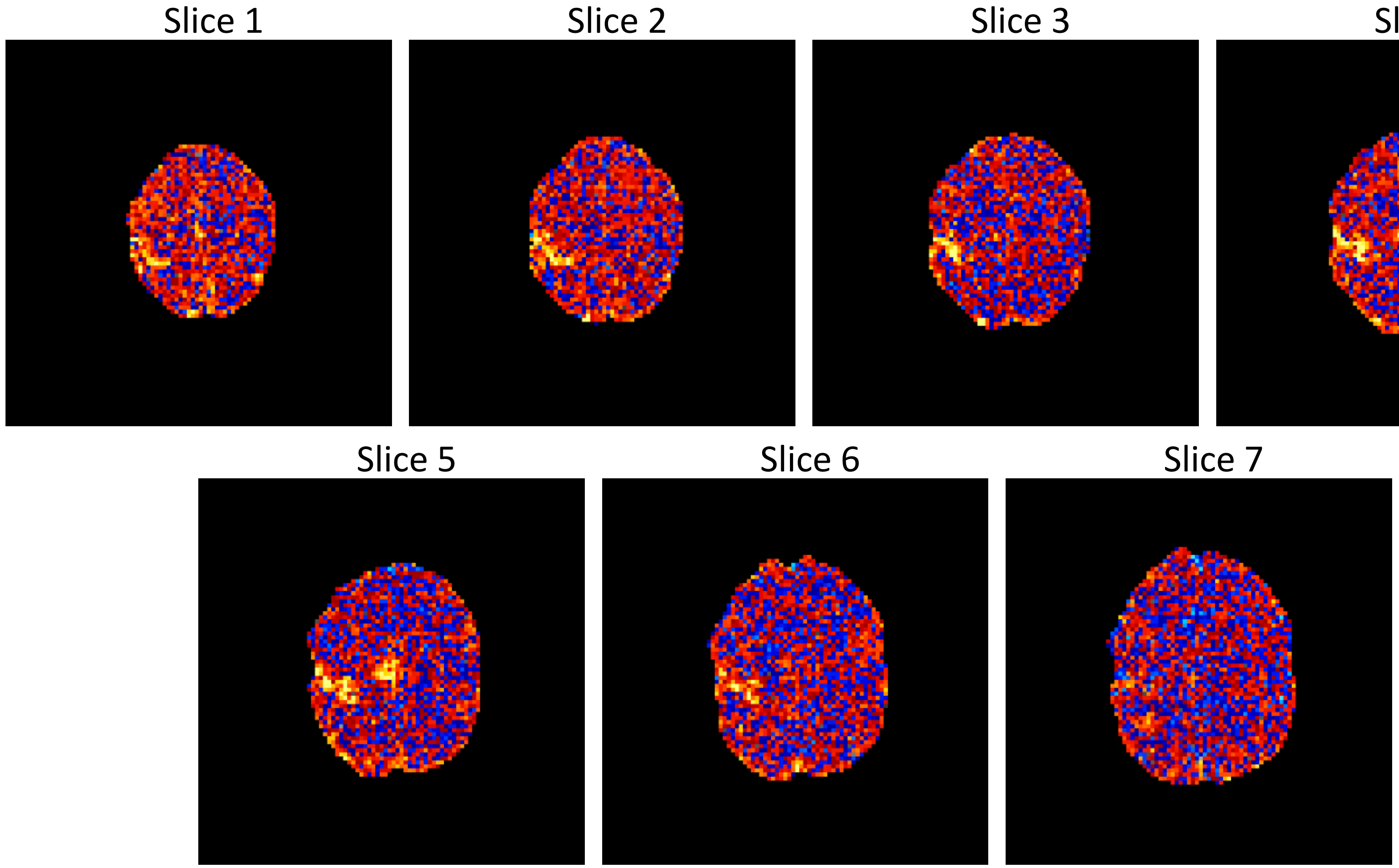
$n_y n_x n_z = 64512$

T_2* weighted images

3. FMRI Activation

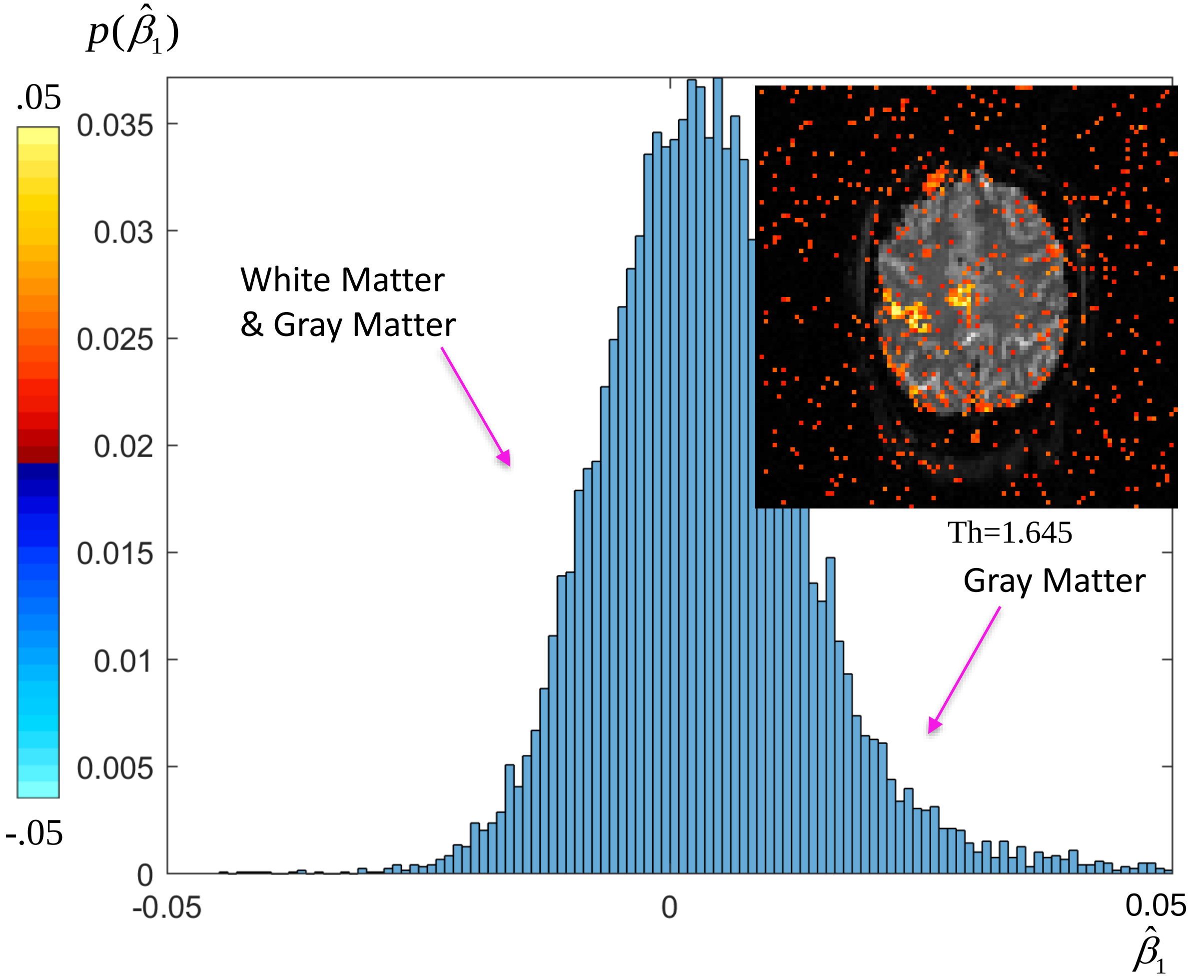
$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t$

For FMRI Data, we can limit ourselves to within mask β_1 voxels.



$t = n_{del}+1, \ldots, n$

T_2* weighted images

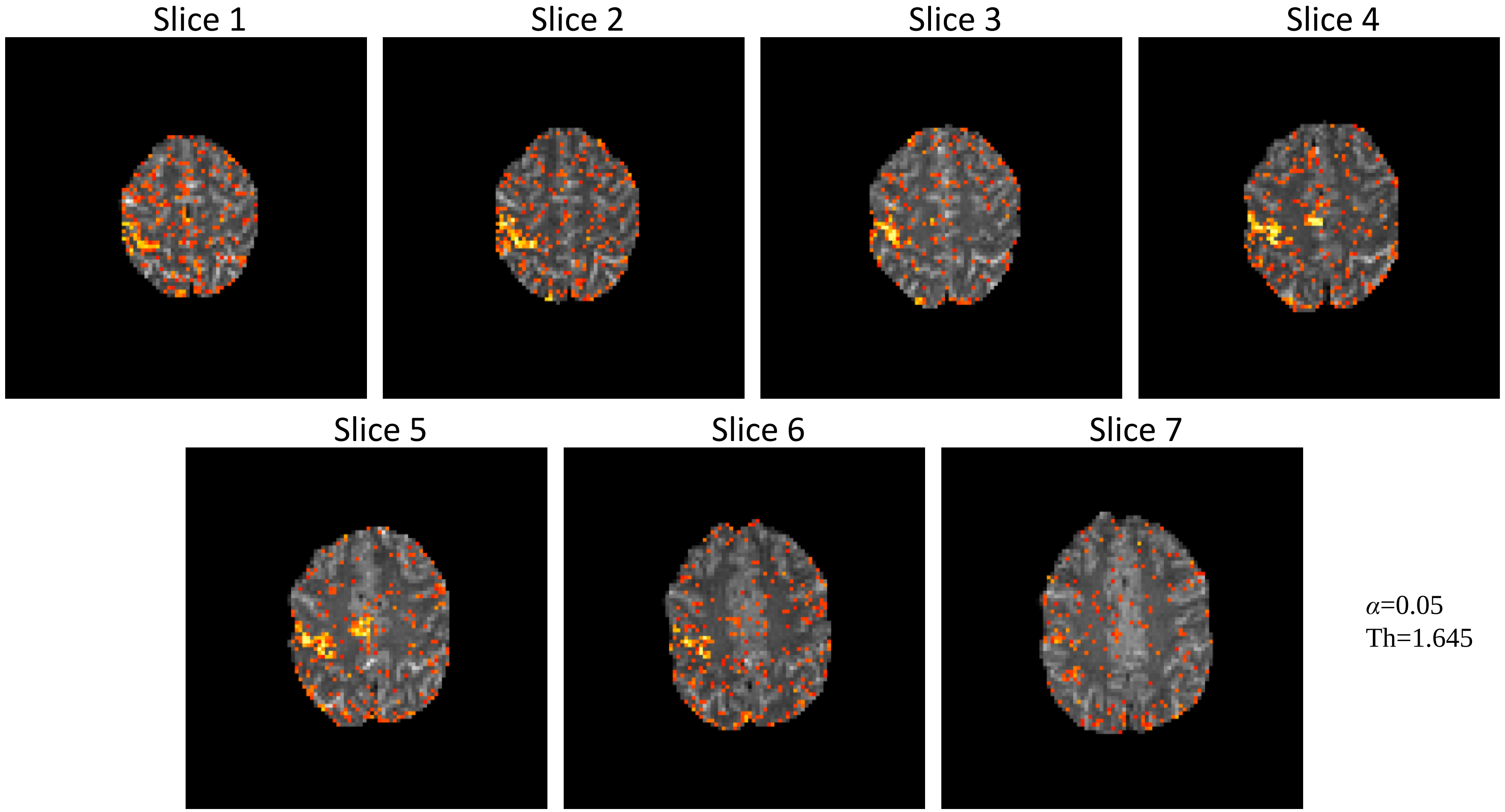


$n_y n_x n_z = 64512$

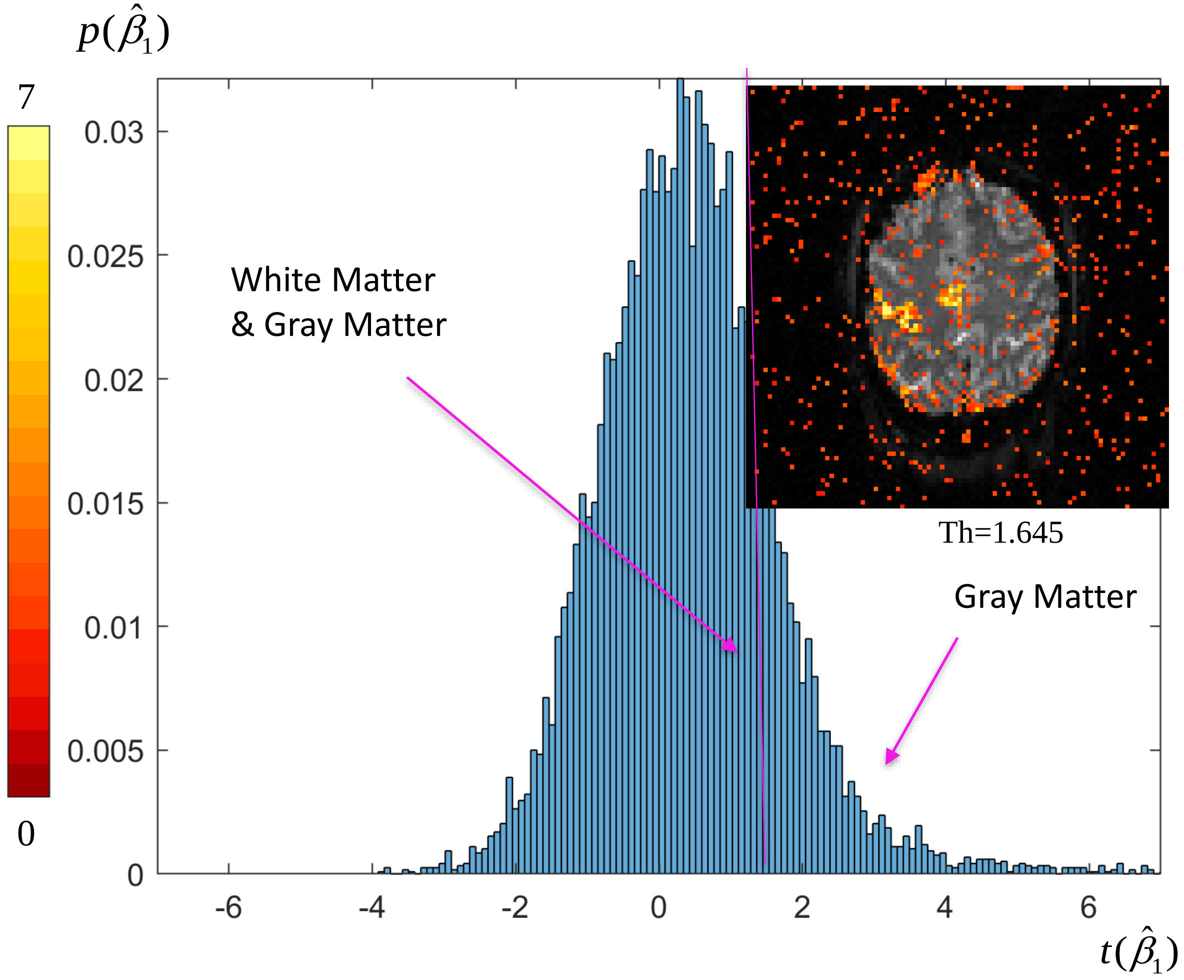
3. FMRI Activation

$y_t=\beta_0+\beta_1 x_t+\varepsilon_t$

For FMRI Data, we can limit ourselves to within mask $t(\beta_1)$ voxels.



α=0.05
Th=1.645



$$t=n_{del}+1,\ldots,n$$

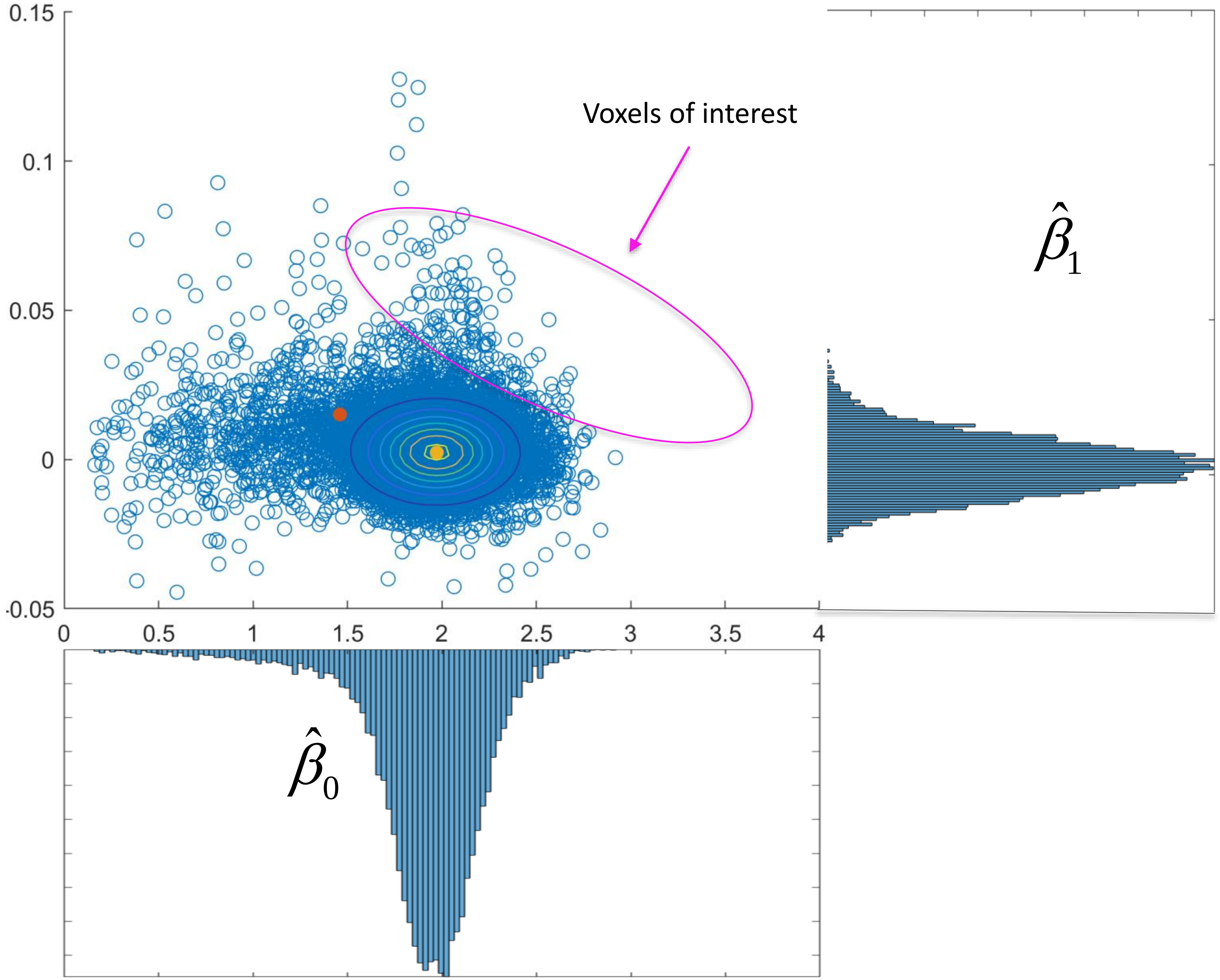
$n_y n_x n_z$=64512

T_2* weighted images

3. FMRI Activation

$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t$

For FMRI Data, we can plot within mask β_0 and β_1 coefficients.



Fit a 2 population bivariate Normal Mixture model.

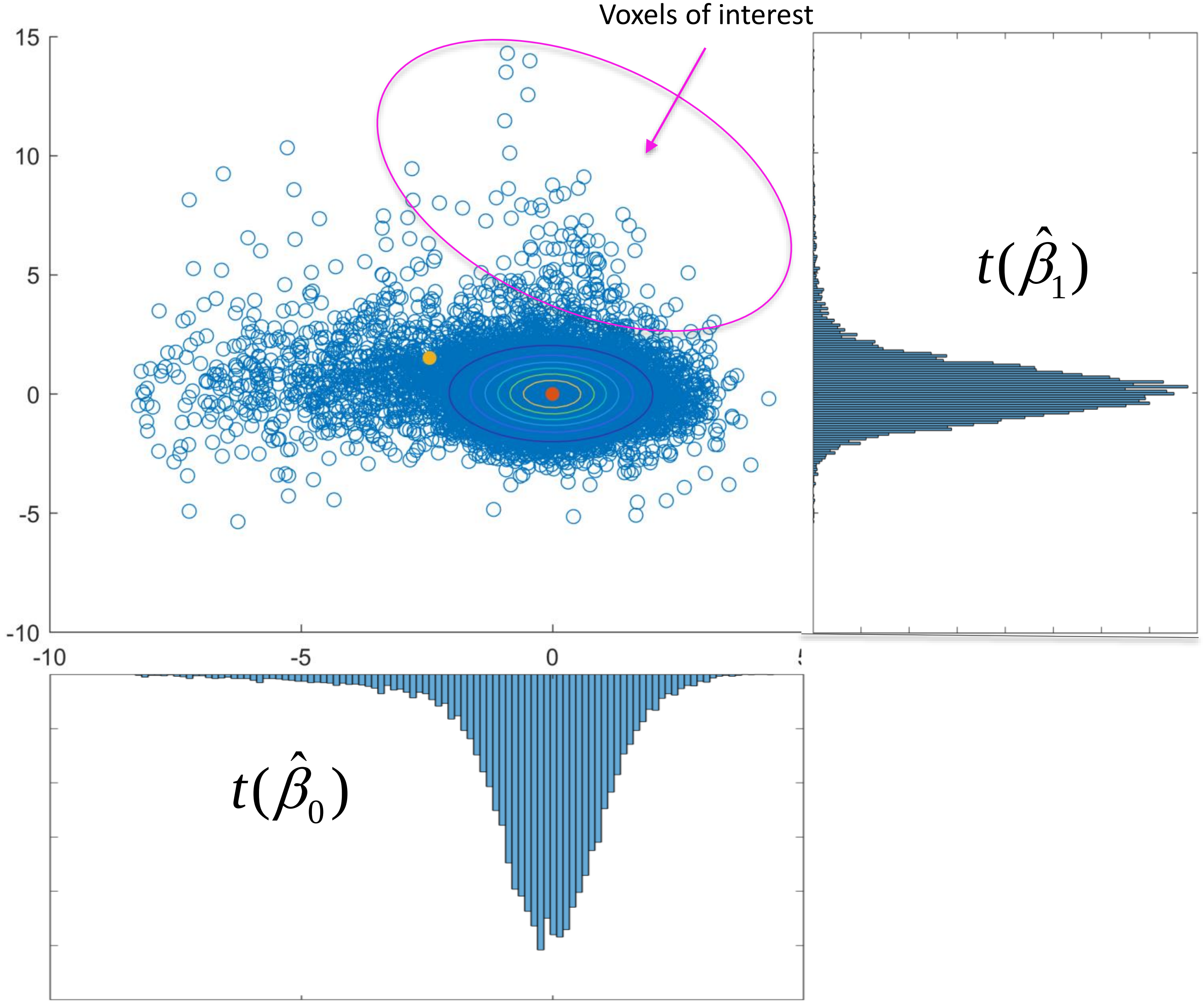
$$\mu_1 = \begin{bmatrix} 1.4611 \\ 0.0151 \end{bmatrix} \qquad \Sigma_1 = \begin{bmatrix} 0.2834 & 0.0026 \\ 0.0026 & 0.0004 \end{bmatrix}$$

$$\mu_2 = \begin{bmatrix} 1.9735 \\ 0.0024 \end{bmatrix} \qquad \Sigma_2 = \begin{bmatrix} 0.0484 & 0.0000 \\ 0.0000 & 0.0001 \end{bmatrix}$$

3. FMRI Activation

$y_t=\beta_0+\beta_1 x_t+\varepsilon_t$

For FMRI Data, we can plot within mask $t(\beta_0)$ and $t(\beta_1)$ coefficients.



Fit a 2 population bivariate Normal Mixture model.

$$\mu_1=\begin{bmatrix}-2.3245\\1.4548\end{bmatrix}\qquad \Sigma_1=\begin{bmatrix}5.8613 & 1.3268\\1.3268 & 5.4182\end{bmatrix}$$

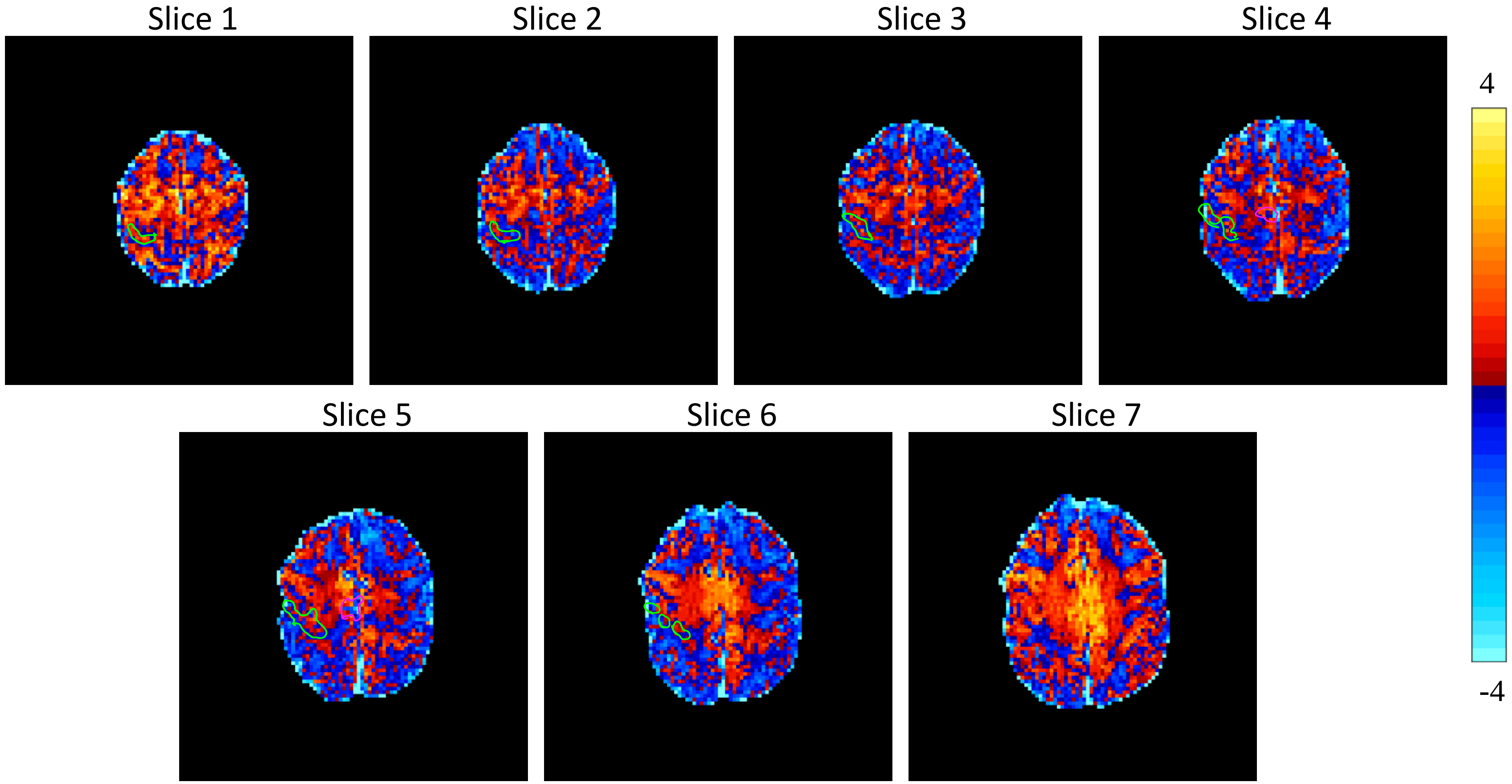
$$\mu_2=\begin{bmatrix}0.0000\\-0.0001\end{bmatrix}\qquad \Sigma_2=\begin{bmatrix}0.9995 & -0.0076\\-0.0076 & 0.9996\end{bmatrix}$$

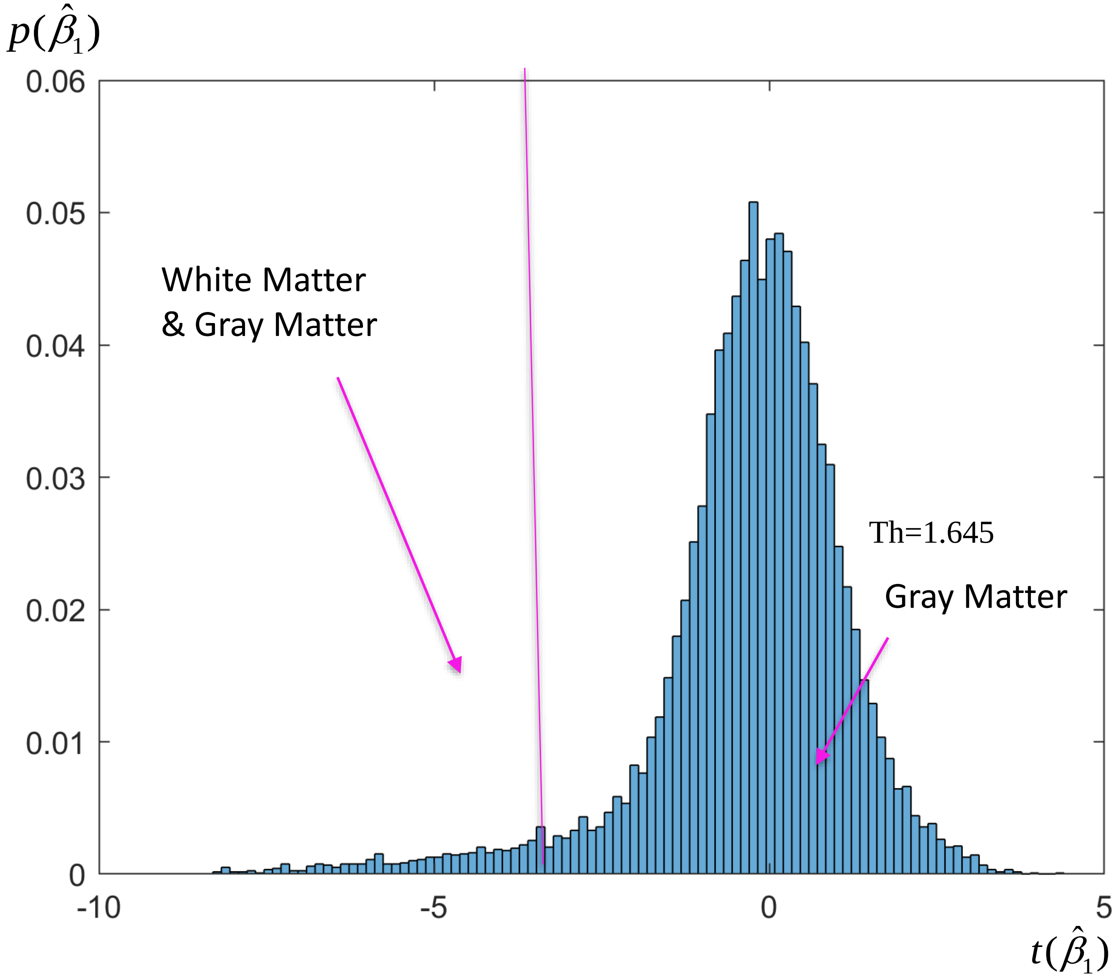
Formed t-statistics using main fitted PDF.

3. FMRI Activation

$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t$

For FMRI Data, we can limit ourselves to within mask $t(\beta_0)$ voxels.





$t = n_{del} + 1, \ldots, n$

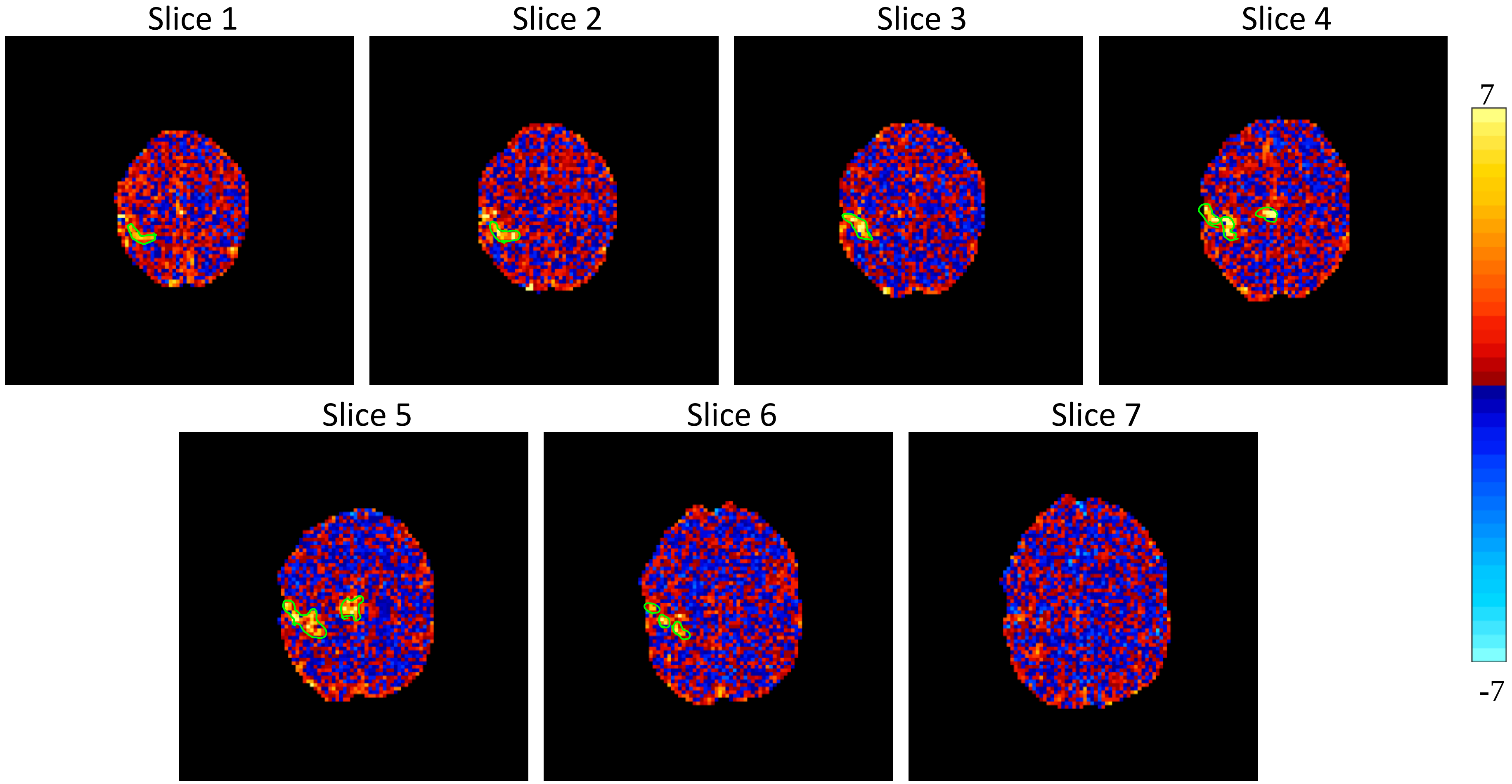
$n_y n_x n_z = 64512$

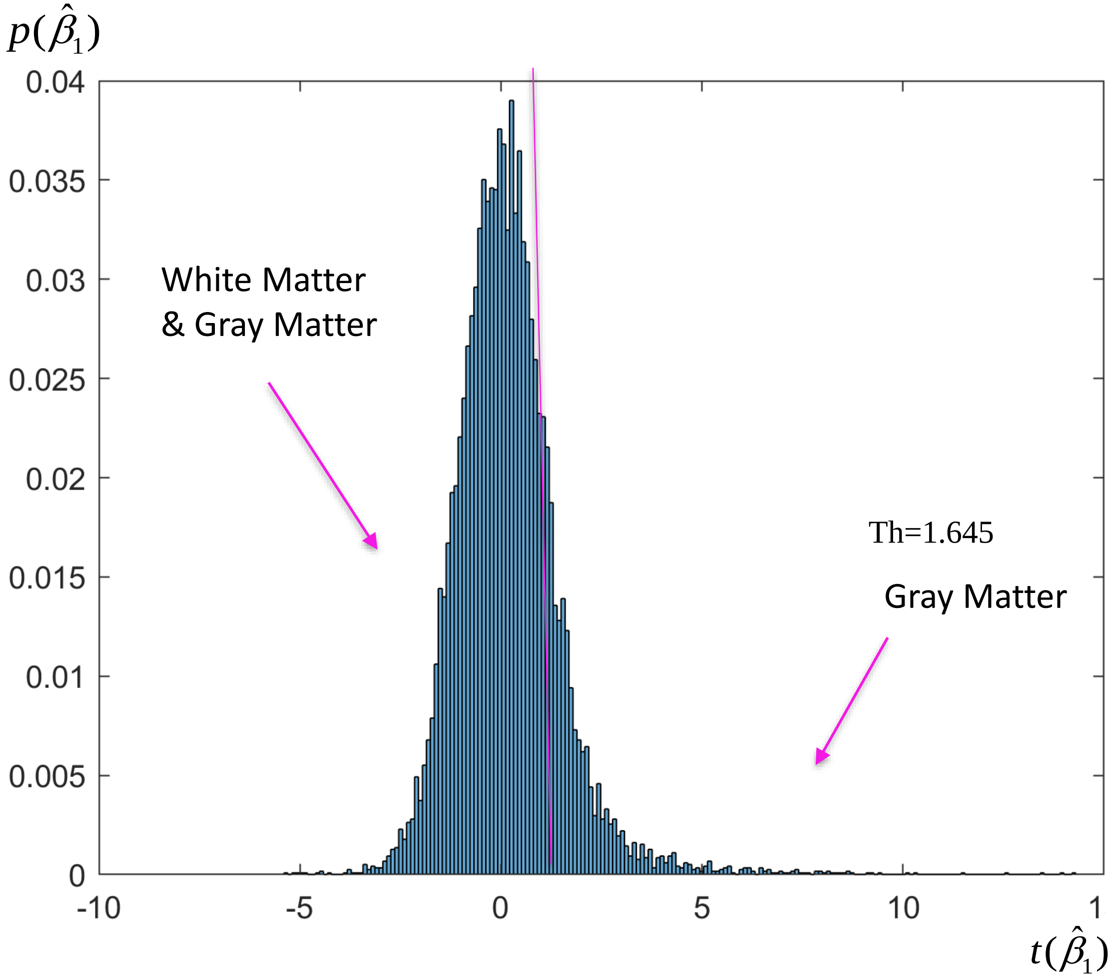
T_2* weighted images

3. FMRI Activation

$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t$

For FMRI Data, we can limit ourselves to within mask $t(\beta_1)$ voxels.





$t = n_{del}+1, \ldots, n$

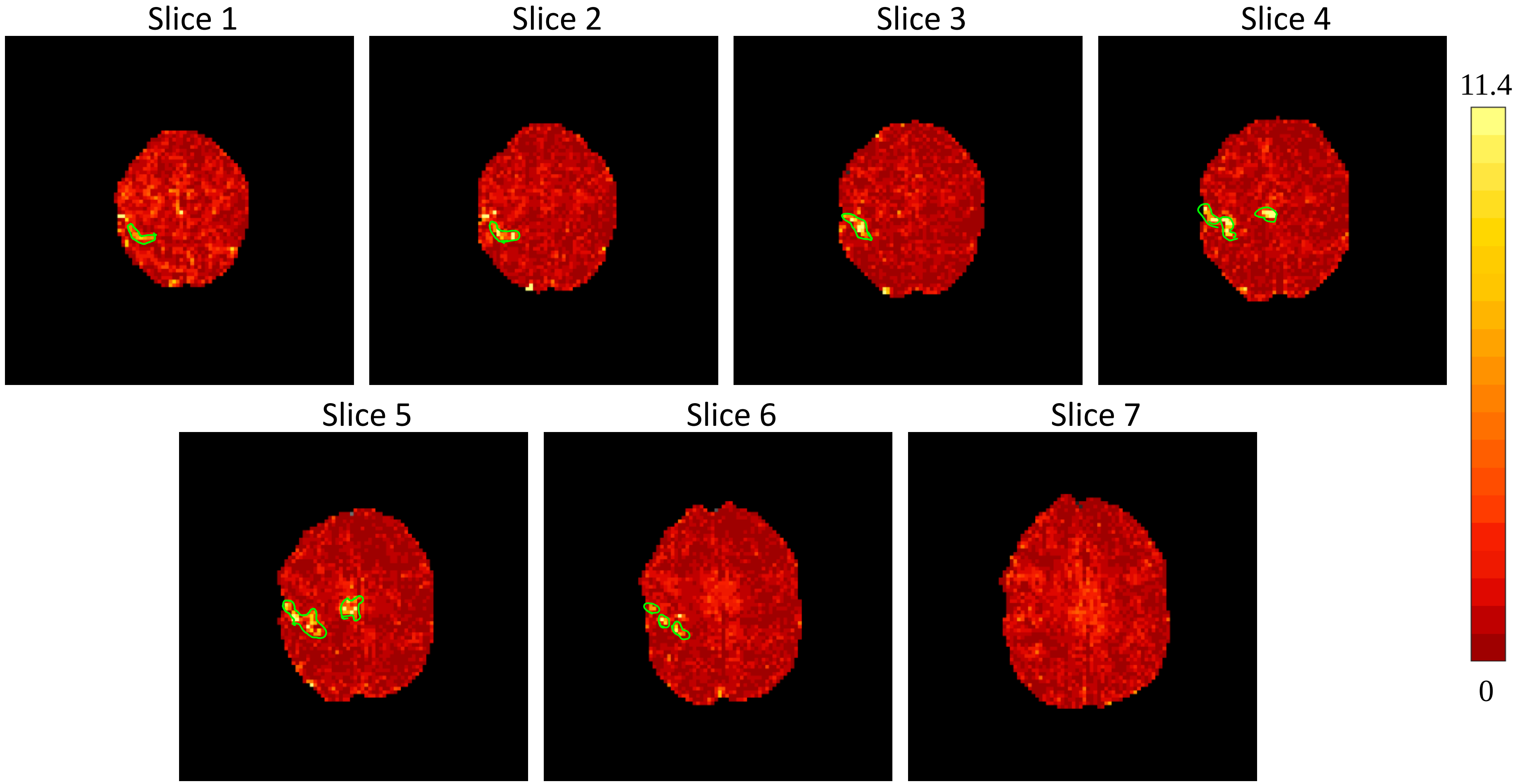
$n_y n_x n_z = 64512$

T_2* weighted images

4. FMRI Results

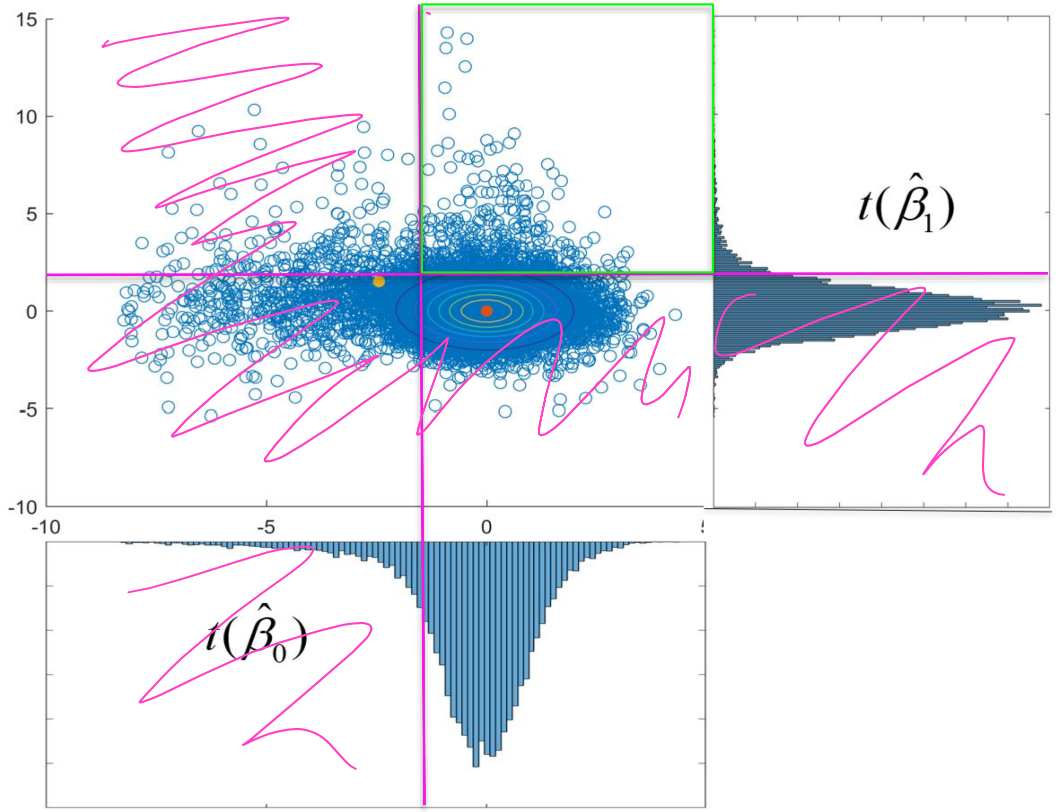
$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t$

We can multiply p-values together and display $-\log_{10}(p\text{-value})$.



$$t = n_{del} + 1, \ldots, n$$

T_2* weighted images

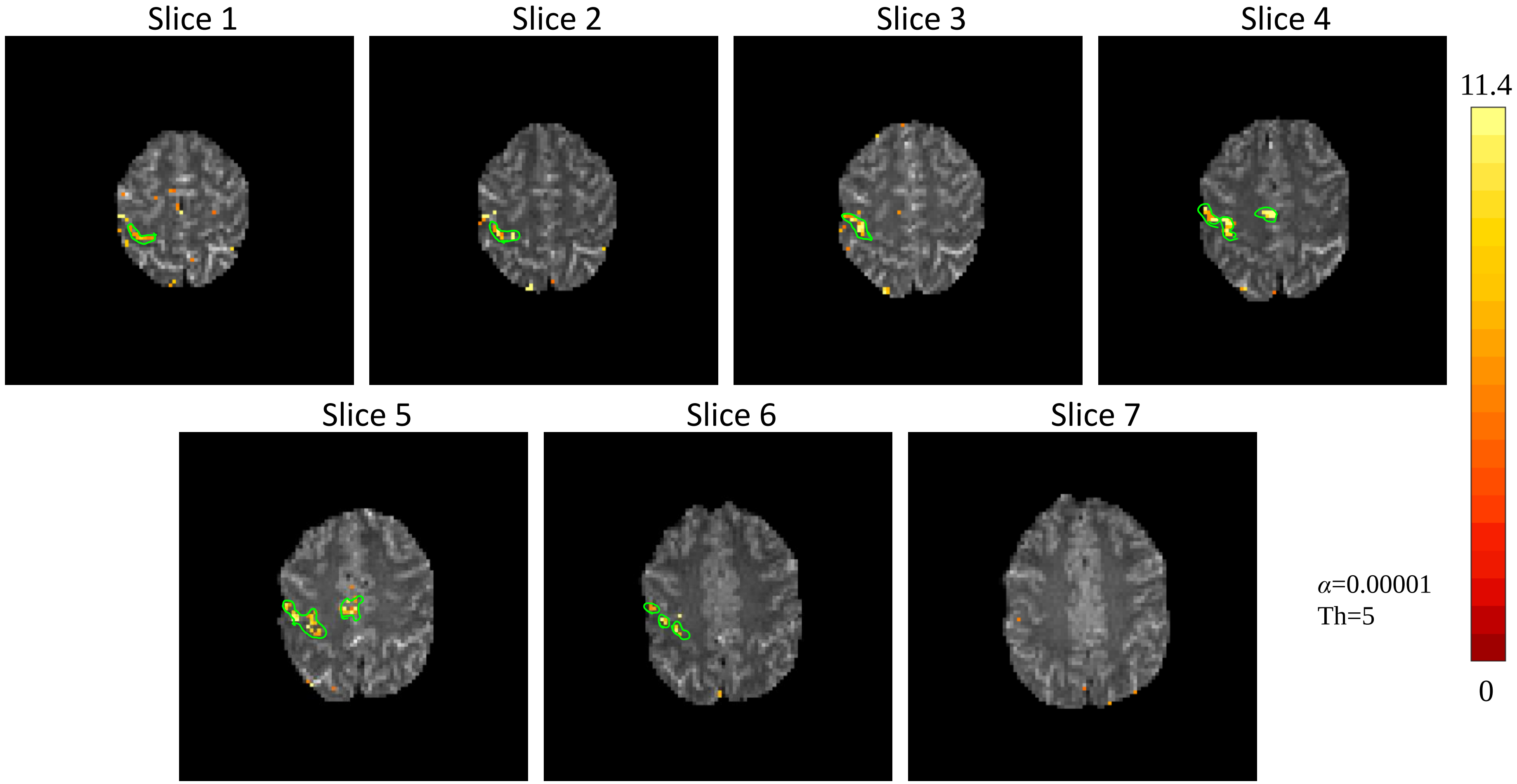


Multiplied of β_0 and of β_1 p-values together.

4. FMRI Results

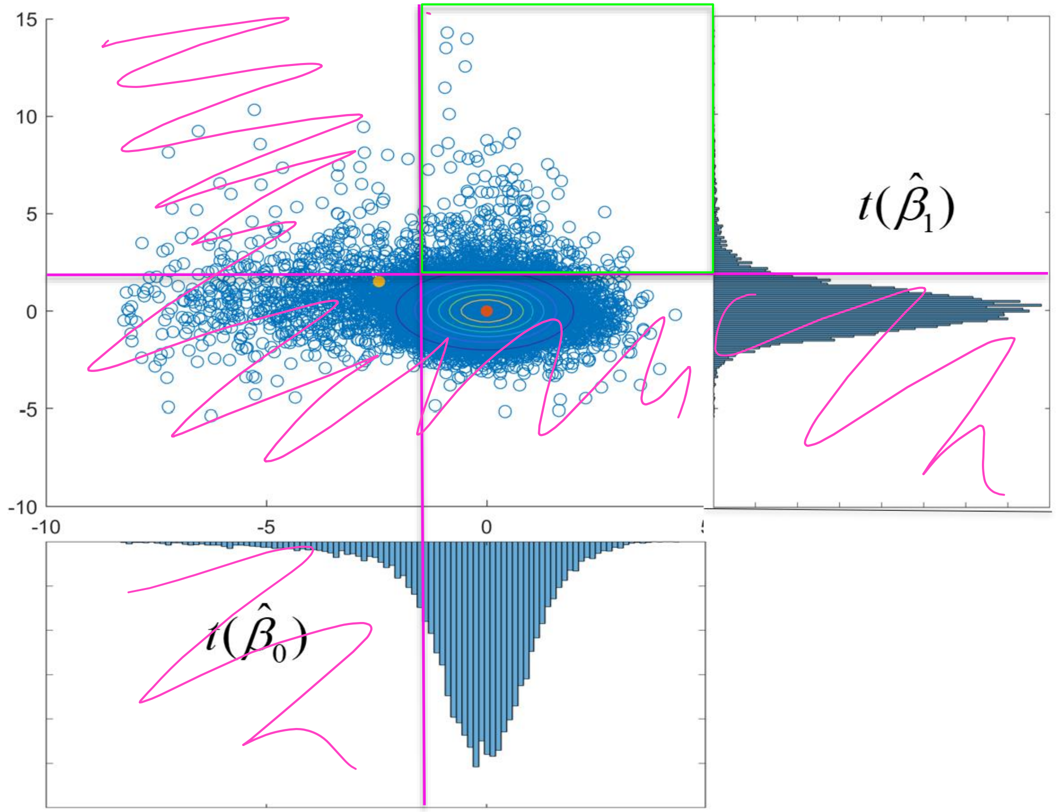
$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t$

We can eliminate lower probability of $t(\beta_0)$ and of $t(\beta_1)$.



$$t = n_{del} + 1, \ldots, n$$

T_2* weighted images

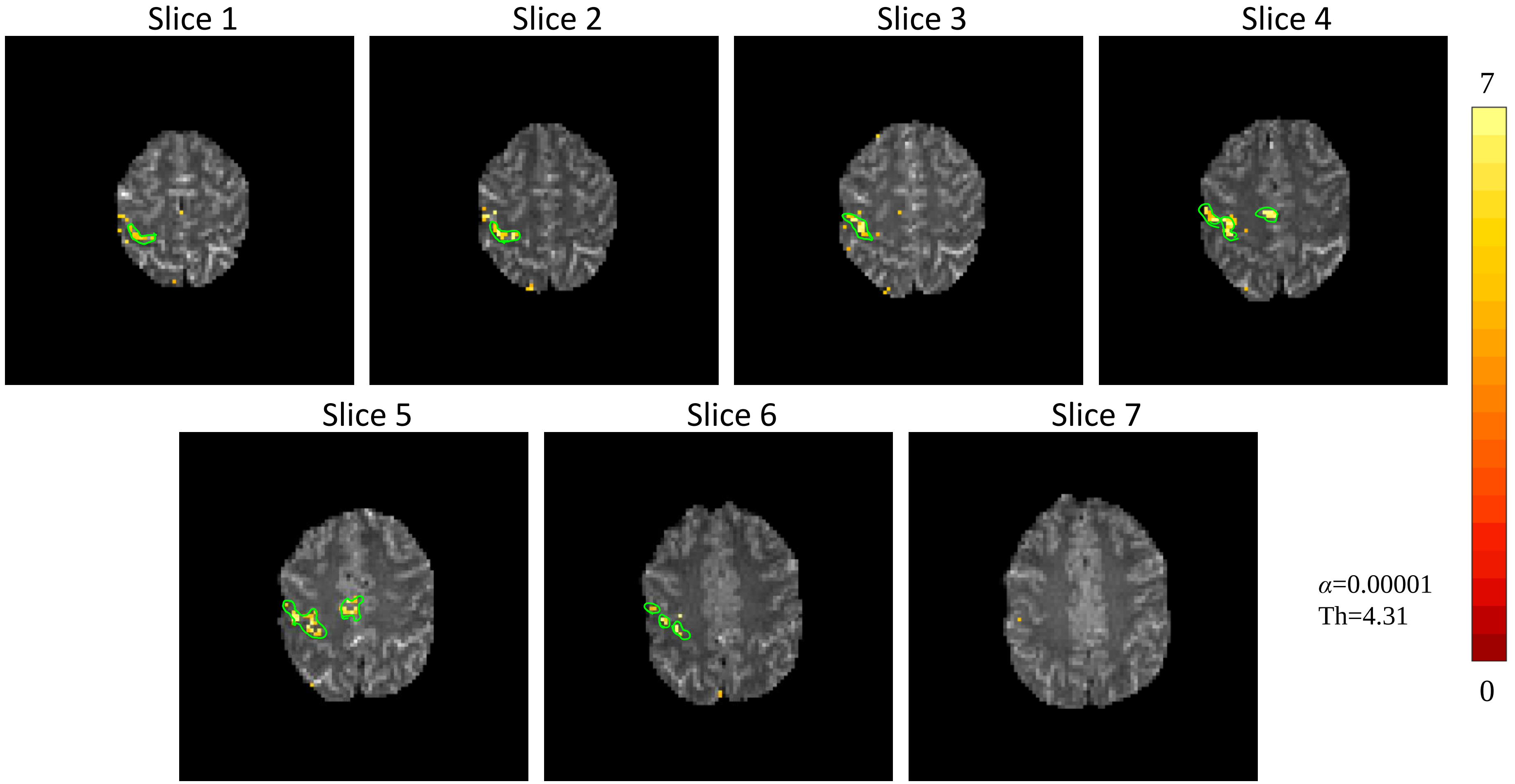


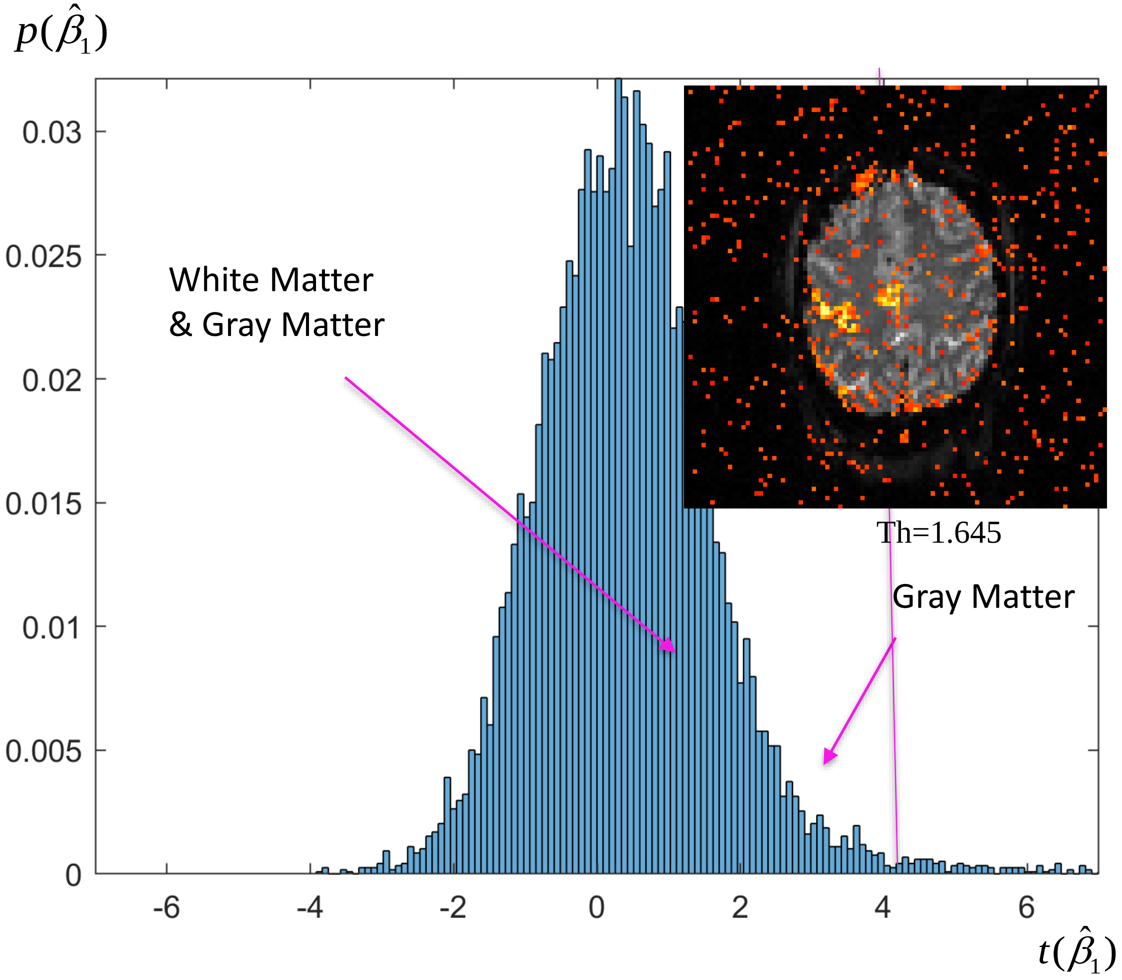
Multiplied of β_0 and of β_1 p-values together.

3. FMRI Activation

$y_t=\beta_0+\beta_1 x_t+\varepsilon_t$

For FMRI Data, we can limit ourselves to within mask $t(\beta_1)$ voxels.





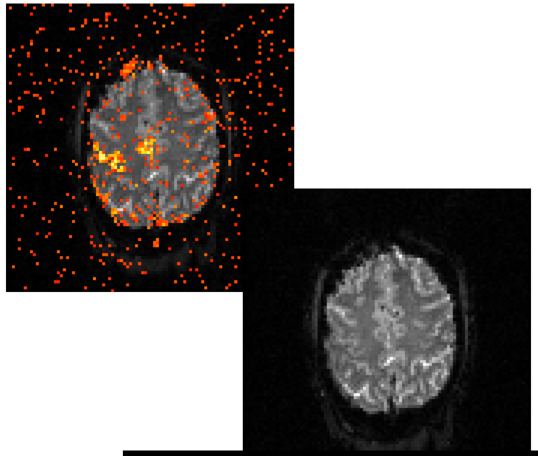
$t=n_{del}+1,\ldots,n$

$n_y n_x n_z=64512$

T_2* weighted images

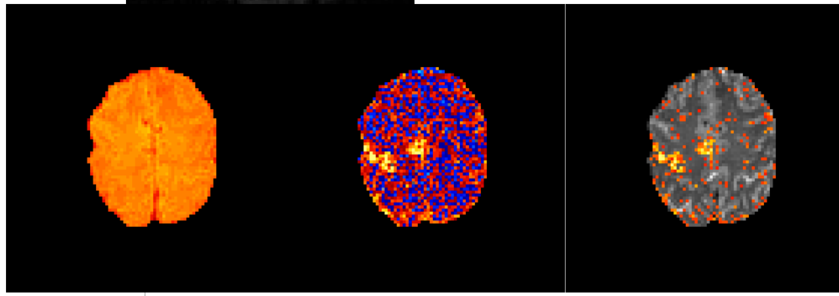
5. Discussion

Presented usual FMRI process with t-statistics of β_1.

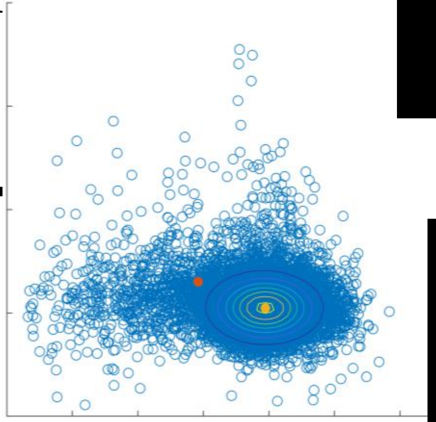


Presented usually discarded first images data.

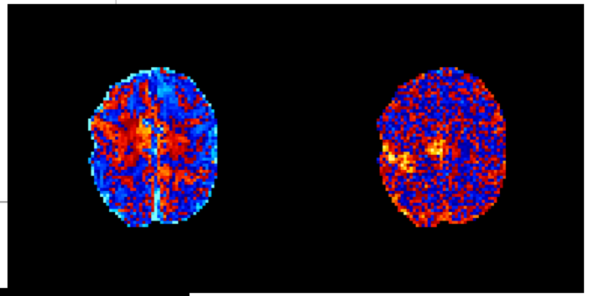
Presented of β_0 and of β_1 coefficients and of β_1 t-statistic.



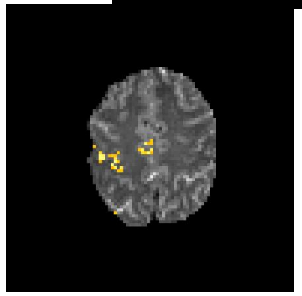
Presented bivariate distribution of β_0 and of β_1.



Presented new t-statistics of β_0 and of β_1.



Presented way to bivariate threshold on β_0 and of β_1.



Thank You

Questions?