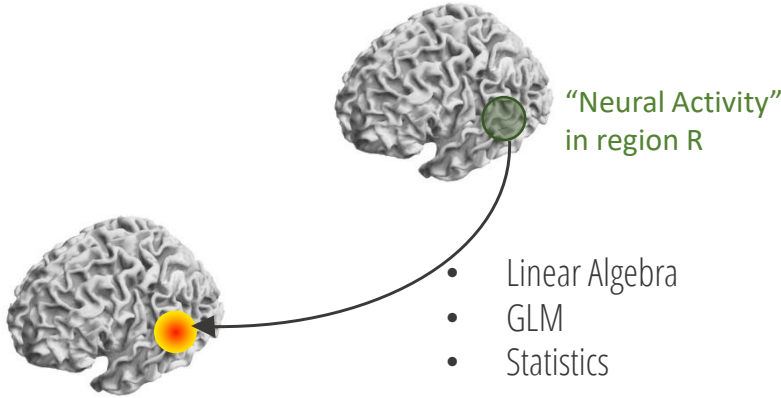


Cheat Sheet: From Linear Algebra to Significance

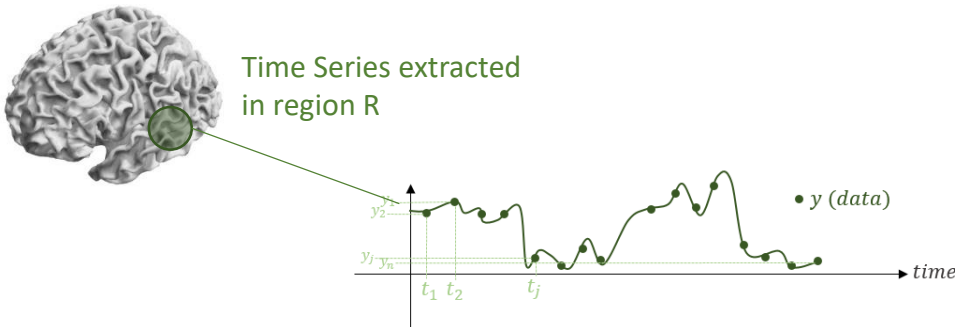


Glossary:

β	Scalar Values
\vec{x}	Vector
X	Matrix
X^T	Matrix transpose
$\vec{\epsilon}$	i.i.d. noise vector
n, m	dimensions

“...significant decrease in activation ($p < 0.05$) in region R during presentation of ...”

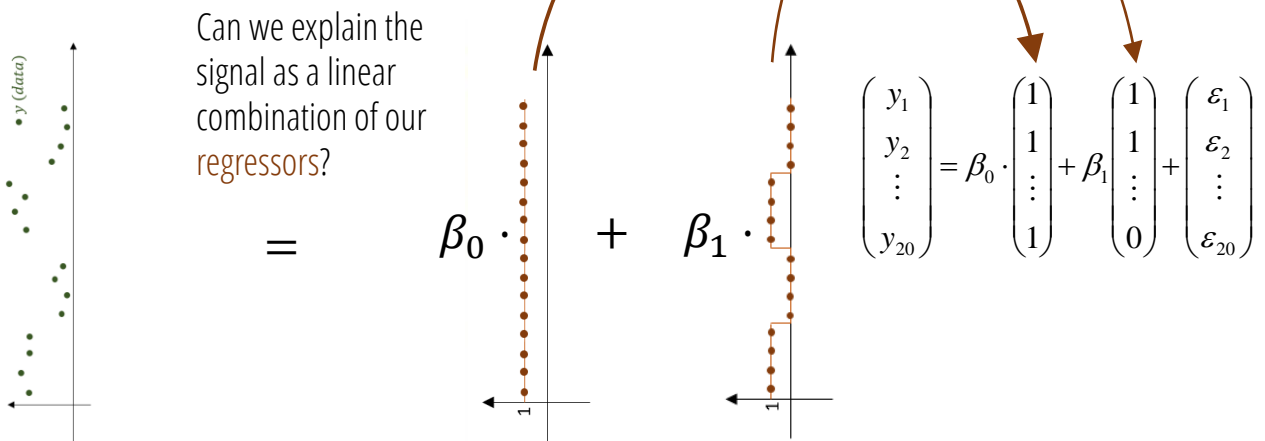
What fMRI data has to do with Linear Algebra



Note:


We don't really measure a continuous signal, but sample the data at discrete timepoints t_1, t_2, \dots, t_n . Since at these times, we measure discrete signal values y_1, y_2, \dots, y_n , we can nicely represent them in an n -dimensional vector \vec{y} .

How do we test for an effect of experimental factors?



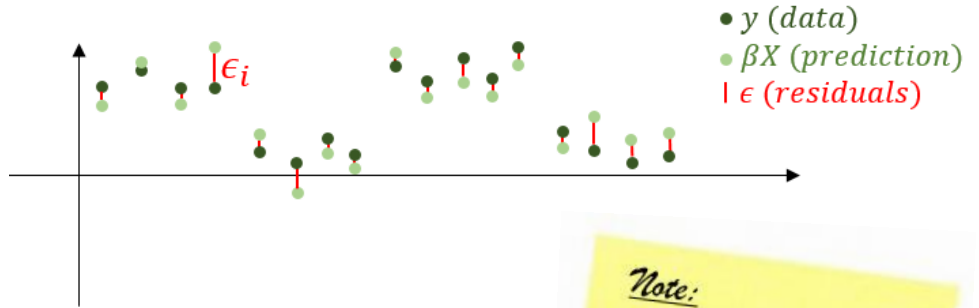
Generalized Linear Model (GLM)

$$\vec{y} = \beta_0 \cdot \vec{x}_0 + \beta_1 \cdot \vec{x}_1 + \vec{\epsilon} = X \cdot B + \vec{\epsilon}$$

$X = [\vec{x}_0, \vec{x}_1]$ "Design Matrix"
 $X = \begin{pmatrix} 1 & 1 \\ 1 & 1 \\ \vdots & \vdots \\ 1 & 0 \\ 1 & 0 \end{pmatrix} =$


$B = \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix}$

How to find the β -Values?



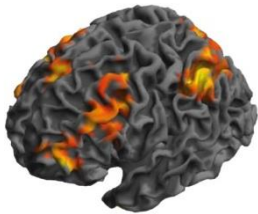
Minimize the error = explain the signal as good as possible! (Least squared error)

$$\hat{\beta} = \operatorname{argmin}_{\beta} ||\vec{y} - \beta X||^2 = \sum_{i=1}^n \epsilon_i^2$$

$$\rightarrow \hat{\beta} = (X^T X)^{-1} X^T \vec{y}$$

Note:
 β -values are a measure of 'how much' of an experimental factor is present in the signal, i.e. how much of the signal variance is explained by a regressor.

Is the effect significant?



"...significant decrease in activation ($p < 0.05$) in region R during presentation of ..."

Estimate $\hat{\beta}_i$

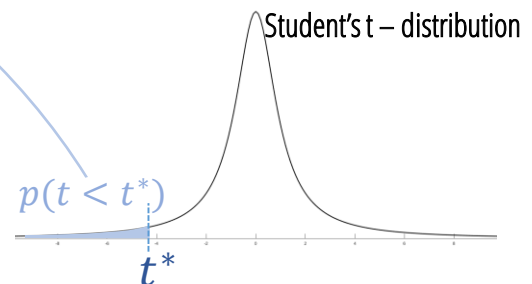
Standard error of estimate*

$$SEM_i = \frac{1}{\sqrt{\sigma^2 c_i^T (X^T X)^{-1} c_i}}$$

$c_i = \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{pmatrix}$ i^{th} entry

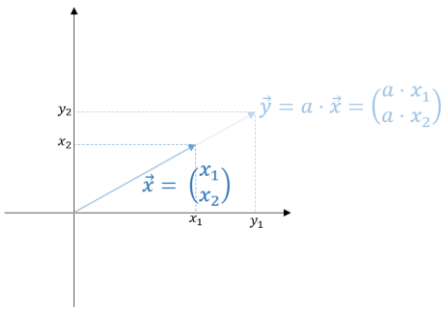
Test statistic

$$t^* = \frac{\hat{\beta}_i}{SEM_i}$$



Basics of Linear Algebra

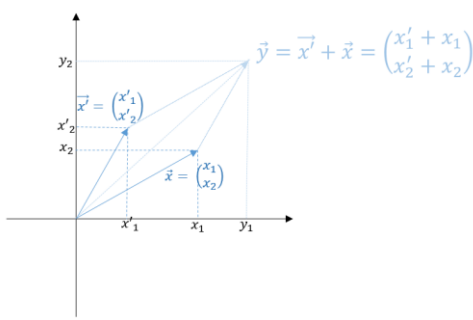
Multiplication with scalar $a \in \mathbb{R}$



$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = a \cdot \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} = \begin{pmatrix} a \cdot x_1 \\ a \cdot x_2 \\ \vdots \\ a \cdot x_n \end{pmatrix}$$

$y_j = a \cdot x_j$

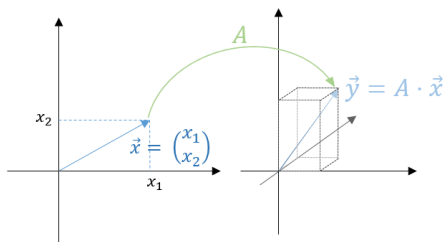
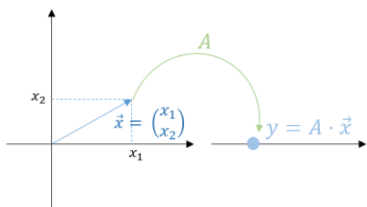
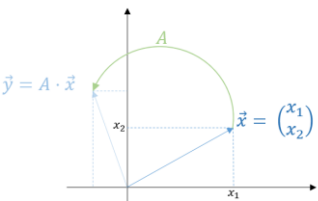
Vectoraddition $\vec{x}' \in \mathbb{R}$



$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} x'_1 \\ x'_2 \\ \vdots \\ x'_n \end{pmatrix} + \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} = \begin{pmatrix} x'_1 + x_1 \\ x'_2 + x_2 \\ \vdots \\ x'_n + x_n \end{pmatrix}$$

$y_j = x'_j + x_j$

Matrixmultiplication $A \in \mathbb{R}^{m \times n}$



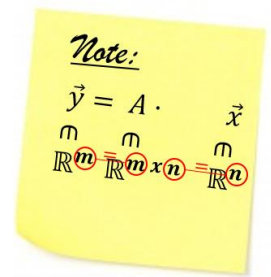
$$A: \mathbb{R}^n \rightarrow \mathbb{R}^m$$

m columns

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{pmatrix} \cdot \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}$$

n rows

$$\vec{y} = A \cdot \vec{x}$$



$$y_j = \begin{pmatrix} a_{j1} \\ a_{j2} \\ \vdots \\ a_{jn} \end{pmatrix} \cdot \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} = (a_{j1} \cdot x_1 + a_{j2} \cdot x_2 + \dots + a_{jn} \cdot x_n) = \sum_{k=1}^n a_{jk} \cdot x_k$$