

Multivariate Regression Generalized Likelihood Ratio Tests for fMRI Activation

$$\mathbf{a} \quad \mathbf{R}_v$$

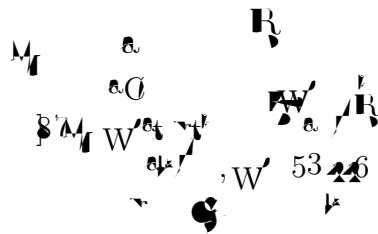
$$\mathbf{M}_T \quad \mathbf{a} \mathbf{G} \quad \begin{matrix} \mathbf{t} \mathbf{a} \mathbf{t} \\ \mathbf{W}' \end{matrix}$$

$$\mathbf{a} \quad \mathbf{R}_v \quad \mathbf{t}$$

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Abstract

In neuroscience, an important research question to be investigated, is whether a region or regions of the brain are being activated when a subject is presented a stimulus. A few methods are in use to address this question but they do not jointly take into account the spatial relationship among the set of voxels under consideration. Multivariate regression can determine whether the set of voxels in one, or several re-

2 UNIVARIATE MODEL

$$y_{ji} = \theta_j + \beta_{1j}X_{1i} + \dots + \beta_{qj}X_{qi} + \epsilon_{ji} \quad (2.1)$$

$$y_{ji} = (\beta_{1j}, \dots, \beta_{qj}) \begin{pmatrix} X_{1i} \\ \vdots \\ X_{qi} \end{pmatrix} + \epsilon_{ji} \quad (2.2)$$

$$\begin{pmatrix} y_{j1} \\ \vdots \\ y_{jn} \end{pmatrix} = \begin{pmatrix} X_{11} \\ \vdots \\ X_{1n} \\ \vdots \\ X_{q1} \\ \vdots \\ X_{qn} \end{pmatrix} \begin{pmatrix} \beta_{1j} \\ \vdots \\ \beta_{qj} \end{pmatrix} + \begin{pmatrix} \epsilon_{j1} \\ \vdots \\ \epsilon_{jn} \end{pmatrix} \quad (2.3)$$

$$p(Y_j | \beta_j, \sigma_j^2, X) = \frac{1}{(2\pi)^{n/2} \sigma_j^n} e^{-\frac{(Y_j - X\beta_j)'(Y_j - X\beta_j)}{2\sigma_j^2}} \quad (2.4)$$

$$\hat{\beta}_j = (X'X)^{-1}X'Y_j \quad (2.5)$$

$$\hat{\beta}_j \sim t(n - q - 1, \beta_j, (n - q - 1)\sigma_j^2(X'X)^{-1}) \quad (2.6)$$

$$(X'X)^{-1} g_j (Y_j - X_j' \hat{\beta}_j) (Y_j - X_j' \hat{\beta}_j)' W_{kk} \quad kk^{th} \quad W_j^2$$

$$H_0: C_j' \hat{\beta}_j > j \quad vs \quad H_1: C_j' \hat{\beta}_j / j > \quad (2.8)$$

where C_j is a $r \times (q+1)$ matrix, $r \times$ matrix

$$F = \frac{(C_j' \hat{\beta}_j - j)' C(X'X)^{-1} C_j^{-1} (C_j' \hat{\beta}_j - j)}{rg_j / (n - q - 1)} \quad (2.9)$$

where $n - q - 1$ is the degrees of freedom, C_j is a $r \times (q+1)$ matrix

under H_0 , k_j is a $1 \times (q+1)$ vector, C_j is a $r \times (q+1)$ matrix, k^{th} element

$$t_{kj} = \frac{\hat{k}_j - k_j}{W_{kk} g_j / (n - q - 1)^{1/2}} \quad (2.10)$$

$$F_{kj} = \frac{(\hat{k}_j - k_j)^2}{W_{kk} g_j / (n - q - 1)} \quad (2.11)$$

where $n - q - 1$ is the degrees of freedom, $n - q - 1$ is the degrees of freedom, g_j is a scalar, $(X'X)^{-1}$ is a $(q+1) \times (q+1)$ matrix, $n > q + 1$

3 MULTIVARIATE MODEL

Let y_i be a p vector, $i = 1, \dots, n$

$$\begin{pmatrix} y_{1i} \\ \vdots \\ y_{pi} \end{pmatrix} = \begin{pmatrix} \mu_{01} + \mu_{11}X_{1i} + \dots + \mu_{q1}X_{qi} \\ \vdots \\ \mu_{0p} + \mu_{1p}X_{1i} + \dots + \mu_{qp}X_{qi} \end{pmatrix} + \begin{pmatrix} \epsilon_{1i} \\ \vdots \\ \epsilon_{pi} \end{pmatrix} \quad (3)$$

$$\begin{pmatrix} y_{1i} \\ \vdots \\ y_{pi} \end{pmatrix} = \begin{pmatrix} x_{1i} \\ \vdots \\ x_{qi} \end{pmatrix} \begin{pmatrix} \beta_{0i} & \beta_{1i} & \cdots & \beta_{qi} \\ \beta_{0i} & \beta_{1i} & \cdots & \beta_{qi} \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{0i} & \beta_{1i} & \cdots & \beta_{qi} \end{pmatrix} + \begin{pmatrix} \epsilon_{1i} \\ \vdots \\ \epsilon_{pi} \end{pmatrix} \quad (3.2)$$

for $i = 1, \dots, n$

$$\begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} \begin{pmatrix} \beta_0 & \beta_1 & \cdots & \beta_p \\ \beta_0 & \beta_1 & \cdots & \beta_p \\ \vdots & \vdots & \ddots & \vdots \\ \beta_0 & \beta_1 & \cdots & \beta_p \end{pmatrix} + \begin{pmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{pmatrix} \quad (3.3)$$

Let $y = (y_1, \dots, y_n)'$, $X = (x_1, \dots, x_n)'$, $B = (\beta_0, \beta_1, \dots, \beta_p)$, and $E = (\epsilon_1, \dots, \epsilon_n)'$. Then the model can be written as $y = X\beta + E$. The matrix X is of order $n \times (q+1)$, y is of order $n \times 1$, B is of order $(q+1) \times p$, and E is of order $n \times 1$.

$$\hat{B}' = (X'X)^{-1}X'Y, \quad (3.4)$$

Let \hat{B} be the matrix of the estimated regression coefficients. Then $\hat{B} \sim t(n - q - 1, B, (n - q - 1)(X'X)^{-1}G)$, (3.5)

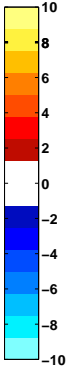
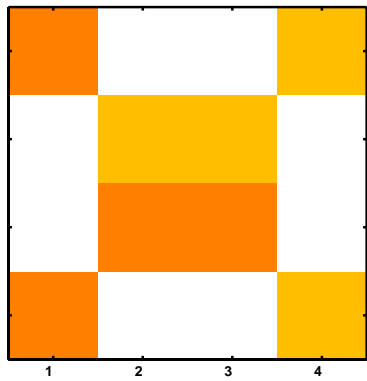
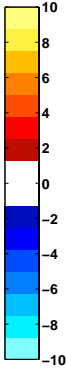
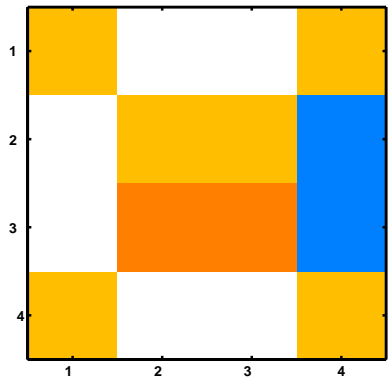
Let \hat{B}_k be the matrix of the estimated regression coefficients for the k th variable. Then $\hat{B}_k \sim t(n - q - p, B_k, (n - q - p)^{-1}W_{kk}G)$, (3.6)

Let \hat{g}_j be the estimated regression coefficient for the j th variable. Then $\hat{g}_j \sim t(n - q - p, g_j, (n - q - p)^{-1}g_j(X'X)^{-1})$, (3.7)

$$\hat{B}_{jk} \sim t$$

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A.2 Multivariate Likelihood Ratio

Suppose that Y is a $n \times 1$ vector of random variables, X is a $n \times p$ matrix of random variables, and B, Σ are $p \times 1$ and $p \times p$ matrices, respectively, of parameters. Let $\hat{B}, \hat{\Sigma}$ be the maximum likelihood estimates of B, Σ .

$$\frac{\rho(Y|B, \Sigma, X)}{\rho(Y|\hat{B}, \hat{\Sigma}, X)} \quad (6)$$

$$\frac{\left(\frac{1}{2\pi} \right)^{-\frac{np}{2}} |\Sigma|^{-\frac{n}{2}} e^{-\frac{1}{2} \text{tr} \Sigma^{-1} (Y - XB')(Y - XB)'} \quad (7)}{\left(\frac{1}{2\pi} \right)^{-\frac{np}{2}} |\hat{\Sigma}|^{-\frac{n}{2}} e^{-\frac{1}{2} \text{tr} \hat{\Sigma}^{-1} (Y - X\hat{B})(Y - X\hat{B})'}}$$

$$= \frac{|(Y - XB')(Y - XB)'|}{|(Y - X\hat{B})(Y - X\hat{B})'|} \quad (8)$$

$$= |G + (\hat{B} - B)' X' X (\hat{B} - B)'| |G| \quad (9)$$

where $G = (Y - X\hat{B})(Y - X\hat{B})'$ and $\Lambda = \frac{2}{n} \text{tr} \Sigma^{-1} (Y - X\hat{B})(Y - X\hat{B})'$.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	71.9	23.4	12.3	-7.6	11.0	-7.0	8.4	-2.6	3.9	-2.0	3.8	-0.5	-16.1	-9.9	4.4	-3.7
2	23.4	59.9	7.8	-5.6	-7.4	14.5	1.1	1.1	8.3	4.4	-0.9	2.5	-4.2	-7.5	-4.4	-7.3
3	12.3	7.8	66.7	19.6	4.6	0.2	13.1	3.2	10.7	0.0	1.6	10.3	7.7	-2.2	1.0	-6.6
4	-7.6	-5.6	19.6	57.1	0.8	1.7	-1.0	15.4	-1.8	-4.1	3.1	17.3	2.4	-6.9	-6.0	-6.8
5	11.0	-7.4	4.6	0.8	55.9	18.6	3.3	-2.6	19.5	5.4	5.4	-10.7	-0.2	-5.6	2.0	-3.9
6	-7.0	14.5	0.2	1.7	18.6	57.3	16.9	2.7	11.7	17.5	1.7	-5.2	-0.9	4.7	-2.4	3.8
7	8.4	1.1	13.1	-1.0	3.3	16.9	55.3	23.3	7.0	2.3	19.5	4.7	-5.7	-3.1	3.5	4.2
8	-2.6	1.1	3.2	15.4	-2.6	2.7	23.3	57.8	-1.9	3.3	10.8	18.7	2.8	-3.0	9.2	3.5
9	3.9	8.3	10.7	-1.8	19.5	11.7	7.0	-1.9	76.5	28.9	1.8	-10.4	13.3	-4.2	-3.3	-3.3
10	-2.0	4.4	0.0	-4.1	5.4	17.5	2.3	3.3	28.9	71.5	25.0	-2.7	0.9	11.4	4.4	-3.5
11	3.8	-0.9	1.6	3.1	5.4	1.7	19.5	10.8	1.8	25.0	73.0	16.1	4.5	1.8	17.7	-0.6
12	-0.5	2.5	10.3	17.3	-10.7	-5.2	4.7	18.7	-10.4	-2.7	16.1	71.7	-6.1	1.1	-1.2	14.0
13	-16.1	-4.2	7.7	2.4	-0.2	-0.9	-5.7	2.8	13.3	0.9	4.5	-6.1	67.3	14.4	1.7	-0.9
14	-9.9	-7.5	-2.2	-6.9	-5.6	4.7	-3.1	-3.0	-4.2	11.4	1.8	1.1	14.4	59.2	15.9	5.6
15	4.4	-4.4	1.0	-6.0	2.0	-2.4	3.5	9.2	-3.3	4.4	17.7	-1.2	1.7	15.9	58.9	22.5
16	-3.7	-7.3	-6.6	-6.8	-3.9	3.8	4.2	3.5	-3.3	-3.5	-0.6	14.0	-0.9	5.6	22.5	60.9

References