## Score Tests

Consider a statistical problem involving an unknown parameter  $\theta \in \mathbb{R}^p$ . Denote the loglikelihood  $\ell(\theta)$ , its gradient (vector of first derivatives) by  $U(\theta)$ , and its Hessian (matrix of second derivatives) by  $J(\theta)$ . Let  $\theta^*$  denote the true value of  $\theta$ . In the development below, all expectations and variances are computed under the distribution resulting from  $\theta^*$ . Recall that the Fisher information matrix is defined by  $\mathcal{I}(\theta) = -E[J(\theta)]$ . In typical settings, we have the following results:

$$E[U(\theta^*)] = 0, (1)$$

$$\operatorname{Cov}(U(\theta^*)] = \mathcal{I}(\theta^*), \tag{2}$$

$$U(\theta^*) \stackrel{\cdot}{\sim} N(0, \mathcal{I}(\theta^*)), \tag{3}$$

$$\mathcal{I}(\theta^*)^{-1}J(\theta^*) \xrightarrow{P} I,\tag{4}$$

$$U(\theta^*) \stackrel{\cdot}{\sim} N(0, J(\theta^*)). \tag{5}$$

Suppose we want to test the hypothesis  $H_0: \theta = \theta_0$  for some special value  $\theta_0$ . Define

$$S(\theta) = U(\theta)^T J(\theta)^{-1} U(\theta).$$
(6)

From equation (5) above we get that

$$S(\theta_0) \stackrel{\cdot}{\sim} \chi_p^2 \quad \text{under } H_0.$$
 (7)

We can thus use  $S(\theta_0)$  as a test statistic for testing  $H_0$ . This test is called the "score test."

We can extend the development to testing a subset of the elements of  $\theta$  while estimating the others. Let us partition  $\theta$  as  $\theta = (\phi, \psi)$ , where  $\phi \in \mathbb{R}^q$  is the vector of parameters of interest and  $\psi \in \mathbb{R}^{p-q}$  is the vector of remaining parameters (so-called "nuisance parameters"). Partition U correspondingly as  $U(\phi, \psi) = [U_{\phi}(\phi, \psi) \ U_{\psi}(\phi, \psi)]$ , partition  $\mathcal{I}$  as

$$\mathcal{I}(\phi,\psi) = \begin{bmatrix} \mathcal{I}_{\phi\phi}(\phi,\psi) & \mathcal{I}_{\phi\psi}(\phi,\psi) \\ \mathcal{I}_{\psi\phi}(\phi,\psi) & \mathcal{I}_{\psi\psi}(\phi,\psi) \end{bmatrix},$$

and partition J similarly. Note that  $\mathcal{I}_{\psi\phi} = \mathcal{I}_{\phi\psi}^T$  and similarly for J. Denote the true values of  $\phi$  and  $\psi$  by  $\phi^*$  and  $\psi^*$ .

Denote by  $\hat{\psi}(\phi)$  the MLE of  $\psi$  with  $\phi$  held fixed at the specified value. We have that  $\hat{\psi}(\phi)$  is the solution to the equation

$$U_{\psi}(\phi, \hat{\psi}(\phi)) = 0. \tag{8}$$

By the same kind of standard Taylor expansion argument as is used to develop the asymptotic properties of the MLE in general, we have

$$\hat{\psi}(\phi^*) - \psi^* \doteq -J_{\psi\psi}(\phi^*, \psi^*)^{-1} U_{\psi}(\phi^*, \psi^*).$$
(9)

Now, suppose we want to test  $H_0: \phi = \phi_0$ . We can build a test statistic based on  $U_{\phi}(\phi_0, \hat{\psi}(\phi_0))$ . We need to work out the asymptotic distribution of this quantity under  $H_0$ . Assume for now that  $H_0$  holds. We then have

$$U_{\phi}(\phi_{0},\hat{\psi}(\phi_{0})) \doteq U_{\phi}(\phi_{0},\psi^{*}) + J_{\phi\psi}(\psi_{0},\psi^{*})(\hat{\psi}(\phi_{0}) - \psi^{*})$$
$$\doteq U_{\phi}(\phi_{0},\psi^{*}) - \mathcal{I}_{\phi\psi}(\phi_{0},\psi^{*})\mathcal{I}_{\psi\psi}(\phi_{0},\psi^{*})^{-1}U_{\psi}(\phi_{0},\psi^{*}),$$
(10)

where the first step is based on a Taylor expansion and the second step is based on (4) and (9). Using the results (1)-(3), we find that  $U_{\phi}(\phi_0, \hat{\psi}(\phi_0))$  is asymptotically mean-zero multivariate normal with covariance matrix given as follows (where  $U_{\phi}$ ,  $U_{\psi}$ , and the various blocks of the matrix  $\mathcal{I}$  are all evaluated at  $(\phi_0, \psi^*)$ , but we omit these arguments for brevity):

$$\Omega = \operatorname{Cov}(U_{\phi}, U_{\phi}) - \operatorname{Cov}(U_{\phi}, U_{\psi})\mathcal{I}_{\psi\psi}^{-1}\mathcal{I}_{\phi\psi}^{T} - \mathcal{I}_{\phi\psi}\mathcal{I}_{\psi\psi}^{-1}\operatorname{Cov}(U_{\psi}, U_{\phi}) + \mathcal{I}_{\phi\psi}\mathcal{I}_{\psi\psi}^{-1}\operatorname{Cov}(U_{\psi}, U_{\psi})\mathcal{I}_{\psi\psi}^{-1}\mathcal{I}_{\phi\psi}^{T}$$
$$= \mathcal{I}_{\phi\phi} - \mathcal{I}_{\phi\psi}\mathcal{I}_{\psi\psi}^{-1}\mathcal{I}_{\phi\psi}^{T} - \mathcal{I}_{\phi\psi}\mathcal{I}_{\psi\psi}^{-1}\mathcal{I}_{\psi\phi} + \mathcal{I}_{\phi\psi}\mathcal{I}_{\psi\psi}^{-1}\mathcal{I}_{\phi\psi}\mathcal{I}_{\psi\psi}^{-1}\mathcal{I}_{\psi\psi}\mathcal{I}_{\psi\psi}\mathcal{I}_{\psi\psi}\mathcal{I}_{\phi\psi}\mathcal{I}_{\phi\psi}$$
$$= \mathcal{I}_{\phi\phi} - \mathcal{I}_{\phi\psi}\mathcal{I}_{\psi\psi}^{-1}\mathcal{I}_{\psi\phi}.$$
(11)

We can form an estimate  $\hat{\Omega}(\phi_0)$  of  $\Omega$  by replacing  $\mathcal{I}(\phi_0, \psi^*)$  with  $J(\phi_0, \hat{\psi}(\phi_0))$  throughout. We then get the score statistic

$$S(\phi_0) = U_{\phi}(\phi_0, \hat{\psi}(\phi_0))^T \hat{\Omega}(\phi_0)^{-1} U_{\phi}(\phi_0, \hat{\psi}(\phi_0)),$$
(12)

for which we have

$$S(\phi_0) \stackrel{\cdot}{\sim} \chi_q^2 \quad \text{under } H_0.$$
 (13)

*Remark*: By the formula for the inverse of a partitioned matrix, the matrix  $\hat{\Omega}(\phi_0)^{-1}$  is equal to the  $\phi\phi$  block of  $J(\phi_0, \hat{\psi}(\phi_0))^{-1}$ .