

Statistics 581, Problem Set 8 Solutions

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1. Suppose that $\theta = (\theta_1, \theta_2) \in \Theta \subset R^k$ where $\theta_1 \in R$ and $\theta_2 \in R^{k-1}$. Show that:
- A. $l_1^* = \dot{l}_1 - I_{12}I_{22}^{-1}\dot{l}_2$ is orthogonal to $[\dot{l}_2] \equiv \{a'\dot{l}_2 : a \in R^{k-1}\}$ in $L_2(P_\theta)$.
- B. $I_{11.2} = \inf_{c \in R^{k-1}} E_\theta(\dot{l}_1 - c'\dot{l}_2)^2$ and that the minimum is achieved when $c' = I_{12}I_{22}^{-1}$.
- Thus

$$I_{11.2} = E_\theta(\dot{l}_1 - I_{12}I_{22}^{-1}\dot{l}_2)^2 = E_\theta[(l_\theta^*)^2].$$

C. Prove the formulas (16) and (17) on page 17 and of the Chapter 3 notes and interpret these formulas geometrically.

Solution: A. Note that for any $a \in R^{k-1}$ we have

$$\begin{aligned} E_\theta[l_1^* \dot{l}_2^T a] &= E_\theta \left\{ (\dot{l}_1 - I_{12}I_{22}^{-1}\dot{l}_2) \dot{l}_2^T a \right\} \\ &= \left\{ E_\theta \left\{ \dot{l}_1 \dot{l}_2^T \right\} - I_{12}I_{22}^{-1} E_\theta \left\{ \dot{l}_2 \dot{l}_2^T \right\} \right\} a \\ &= \{I_{12} - I_{12}\} a = 0. \end{aligned}$$

Thus l_1^* is orthogonal to $[\dot{l}_2]$ in $L_2(P_\theta)$.

B. Note that for any $c \in R^{k-1}$ we have

$$\begin{aligned} E_\theta(\dot{l}_1 - c'\dot{l}_2)^2 &= E_\theta(\dot{l}_1 - I_{12}I_{22}^{-1}\dot{l}_2 + I_{12}I_{22}^{-1}\dot{l}_2 - c'\dot{l}_2)^2 \\ &= E_\theta(\dot{l}_1 - I_{12}I_{22}^{-1}\dot{l}_2)^2 + E_\theta((I_{12}I_{22}^{-1} - c')\dot{l}_2)^2 \\ &= I_{11} - I_{12}I_{22}^{-1}I_{21} + E_\theta((I_{12}I_{22}^{-1} - c')\dot{l}_2)^2 \\ &\geq I_{11.2} \end{aligned}$$

with equality if and only if $c' = I_{12}I_{22}^{-1}$. Here the second equality uses the orthogonality proved in A.

C. Formula (16) says that

$$\tilde{l}_1 = I_{11}^{-1}\dot{l}_1 - I_{11}^{-1}I_{12}\tilde{l}_2. \tag{0.1}$$

One way to derive this is as indicated on page 21: since $\tilde{l} = I^{-1}\dot{l}$ we have

$$\tilde{l}_1 = I^{11}\dot{l}_1 + I^{12}\dot{l}_2 \quad \text{and} \quad \tilde{l}_2 = I^{21}\dot{l}_1 + I^{22}\dot{l}_2.$$

Hence it follows that

$$\begin{aligned} \tilde{l}_1 + I_{11}^{-1}I_{12}\tilde{l}_2 &= I^{11}\dot{l}_1 + I^{12}\dot{l}_2 + I_{11}^{-1}I_{12}(I^{21}\dot{l}_1 + I^{22}\dot{l}_2) \\ &= I_{11}^{-1} \left\{ (I_{11}I^{11} + I_{12}I^{21})\dot{l}_1 + (I_{11}I^{12} + I_{12}I^{22})\dot{l}_2 \right\} \\ &= I_{11}^{-1} \left\{ Ident \cdot \dot{l}_1 + 0 \cdot \dot{l}_2 \right\} \\ &= I_{11}^{-1}\dot{l}_1. \end{aligned}$$

Rearranging yields (0.1). Note that this identity decomposes the efficient influence function \tilde{l}_1 in the larger model with both θ_1 and θ_2 unknown into its projection onto the efficient influence function in the sub-model when θ_2 is known, namely $I_{11}^{-1}\dot{l}_1$, and a term which is orthogonal to $[\dot{l}_1]$. Formula (17) follows immediately from (16) in view of orthogonality of the two terms:

$$\begin{aligned} I_{11\cdot 2}^{-1} &= E[\tilde{l}_1 \tilde{l}_1^T] = E[I_{11}^{-1} \dot{l}_1 \dot{l}_1^T I_{11}^{-1}] + I_{11}^{-1} I_{12} E[\tilde{l}_2 \tilde{l}_2^T] I_{21} I_{11}^{-1} \\ &= I_{11}^{-1} + I_{11}^{-1} I_{12} I_{22\cdot 1}^{-1} I_{21} I_{11}^{-1} \end{aligned}$$

2. Suppose that $(Y|Z) \sim \text{Weibull}(\lambda^{-1}e^{-\gamma Z}, \beta)$, and $Z \sim G_\eta$ on R with density g_η with respect to some dominating measure μ . Thus the conditional cumulative hazard function $\Lambda(t|z)$ is given by

$$\Lambda_{\gamma, \lambda, \beta}(t|z) = (\lambda e^{\gamma Z} t)^\beta = \lambda^\beta e^{\beta \gamma Z} t^\beta$$

and hence

$$\lambda_{\gamma, \lambda, \beta}(t|z) = \lambda^\beta e^{\beta \gamma Z} \beta t^{\beta-1}.$$

(Recall that $\lambda(t) = f(t)/(1 - F(t))$ and

$$\Lambda(t) \equiv \int_0^t \lambda(s) ds = \int_0^t (1 - F(s))^{-1} dF(s) = -\log(1 - F(t))$$

if F is continuous.) Thus it makes sense to reparametrize by defining $\theta_1 \equiv \beta \gamma$ (this is the parameter of interest since it reflects the effect of the covariate Z), $\theta_2 \equiv \lambda^\beta$, and $\theta_3 \equiv \beta$. This yields

$$\lambda_\theta(t|z) = \theta_3 \theta_2 \exp(\theta_1 z) t^{\theta_3-1}$$

You may assume that

$$a(z) \equiv (\partial/\partial \eta) \log g_\eta(z)$$

exists and $E\{a^2(Z)\} < \infty$. Thus Z is a ‘‘covariate’’ or ‘‘predictor variable’’, θ_1 is a ‘‘regression parameter’’ which affects the intensity of the (conditionally) Exponential variable Y , and $\theta = (\theta_1, \theta_2, \theta_3, \theta_4)$ where $\theta_4 \equiv \eta$.

- (a) Derive the joint density $p_\theta(y, z)$ of (Y, Z) for the re-parametrized model.
- (b) Find the information matrix for θ . What does the structure of this matrix say about the effect of $\eta = \theta_4$ being known or unknown about the estimation of $\theta_1, \theta_2, \theta_3$?
- (c) Find the information and information bound for θ_1 if the parameters θ_2 and θ_3 are known?
- (d) What is the information bound for θ_1 if just θ_3 is known to be equal to 1?
- (e) Find the efficient score function and the efficient influence function for estimation of θ_1 when θ_3 is known.
- (f) Find the information $I_{11\cdot(2,3)}$ and information bound for θ_1 if the parameters θ_2 and θ_3 are unknown. (Here both θ_2 and θ_3 are in ‘‘the second block’’.)
- (g) Find the efficient score function and the efficient influence function for estimation of θ_1 when θ_2 and θ_3 are unknown.

(h) Specialize the calculations in (d) - (g) to the case when $Z \sim \text{Bernoulli}(\theta_4)$ and compare the information bounds.

Solution: (a) Integrating $\lambda_\theta(t|z)$ with respect to t gives

$$\Lambda_\theta(t|z) = \theta_2 \exp(\theta_1 z) t^{\theta_3},$$

and hence the conditional survival function $1 - F_\theta(t|z)$ is given by

$$1 - F_\theta(t|z) = \exp(-\Lambda_\theta(t|z)) = \exp(-\theta_2 \exp(\theta_1 z) t^{\theta_3}). \quad (0.2)$$

It follows that

$$f_\theta(t|z) = \theta_2 \theta_3 e^{\theta_1 z} t^{\theta_3-1} \exp(-\theta_2 e^{\theta_1 z} t^{\theta_3}),$$

and hence that

$$\begin{aligned} p_\theta(y, z) &= f_\theta(y|z) g_\eta(z) = \theta_2 \theta_3 e^{\theta_1 z} t^{\theta_3-1} \exp(-\theta_2 e^{\theta_1 z} t^{\theta_3}) g_\eta(z) \\ &= \theta_2 \theta_3 e^{\theta_1 z} t^{\theta_3-1} \exp(-\theta_2 e^{\theta_1 z} t^{\theta_3}) g_{\theta_4}(z). \end{aligned}$$

(b) We first calculate the scores for θ . Note that the random variable $W \equiv \theta_2 \exp(\theta_1 Z) Y^{\theta_3}$ has, conditionally on Z , a standard Exponential(1) distribution:

$$P_\theta(W > w|Z) = P_\theta(\theta_2 \exp(\theta_1 Z) Y^{\theta_3} > w|Z) = e^{-w}$$

by (0.2). We calculate

$$\begin{aligned} l(\theta|Y, Z) &= \log p_\theta(Y, Z) \\ &= \log \theta_2 + \log \theta_3 + \theta_1 Z + (\theta_3 - 1) \log Y - \theta_2 e^{\theta_1 Z} Y^{\theta_3} + \log g_{\theta_4}(Z), \\ \dot{\mathbf{i}}_1(Y, Z) &= Z - Z \theta_2 e^{\theta_1 Z} Y^{\theta_3} = Z(1 - W), \\ \dot{\mathbf{i}}_2(Y, Z) &= \frac{1}{\theta_2} - \frac{\theta_2 e^{\theta_1 Z} Y^{\theta_3}}{\theta_2} = \frac{1}{\theta_2} (1 - W), \\ \dot{\mathbf{i}}_3(Y, Z) &= \frac{1}{\theta_3} + \log Y - \theta_2 e^{\theta_1 Z} Y^{\theta_3} \log Y \\ &= \frac{1}{\theta_3} + \log Y \{1 - \theta_2 e^{\theta_1 Z} Y^{\theta_3}\} \\ &= \frac{1}{\theta_3} \left\{ 1 + \log \frac{\theta_2 e^{\theta_1 Z} Y^{\theta_3}}{\theta_2 e^{\theta_1 Z}} \{1 - W\} \right\} \\ &= \frac{1}{\theta_3} \{1 + \{\log W - \log(\theta_2 e^{\theta_1 Z})\} \{1 - W\}\} \\ &= \frac{1}{\theta_3} \{[1 - (W - 1) \log W] + (W - 1) \log(\theta_2 e^{\theta_1 Z})\} \\ \dot{\mathbf{i}}_4(Y, Z) &= a(Z) = a(Z, \eta). \end{aligned}$$

Moreover,

$$\begin{aligned} \ddot{\mathbf{i}}_{13}(Y, Z) &= -Z \theta_2 e^{\theta_1 Z} Y^{\theta_3} \log Y = -Z \frac{1}{\theta_3} \theta_2 e^{\theta_1 Z} Y^{\theta_3} \log \left(\frac{\theta_2 e^{\theta_1 Z} Y^{\theta_3}}{\theta_2 e^{\theta_1 Z}} \right) \\ &= -\frac{Z}{\theta_3} W \{\log W - \log(\theta_2 e^{\theta_1 Z})\} \end{aligned}$$

$$\begin{aligned}
&= -\frac{z}{\theta_3}W\{\log W - \log(\theta_2) - \theta_1 Z\} \\
\ddot{\mathbf{I}}_{23}(Y, Z) &= -e^{\theta_1 Z}Y^{\theta_3} \log Y = -\frac{1}{\theta_2\theta_3}\theta_2 e^{\theta_1 Z}Y^{\theta_3} \log\left(\frac{\theta_2 e^{\theta_1 Z}Y^{\theta_3}}{\theta_2 e^{\theta_1 Z}}\right) \\
&= -\frac{1}{\theta_2\theta_3}W\{\log W - \log(\theta_2 e^{\theta_1 Z})\} \\
&= -\frac{1}{\theta_2\theta_3}W\{\log W - \log(\theta_2) - \theta_1 Z\}, \\
\ddot{\mathbf{I}}_{33}(Y, Z) &= -\frac{1}{\theta_3^2}\{1 + W[\log W - \log(\theta_2 e^{\theta_1 Z})]^2\}.
\end{aligned}$$

Thus we calculate easily:

$$\begin{aligned}
I_{11}(\theta) &= E_\theta(\dot{\mathbf{I}}_1(Y, Z)^2) = E_\theta\{E[Z^2(1-W)^2|Z]\} \\
&= E\{Z^2 E[(1-W)^2|Z]\} = E(Z^2), \\
I_{22}(\theta) &= E_\theta(\dot{\mathbf{I}}_2(Y, Z)^2) = E_\theta\{E[\theta_2^{-2}(1-W)^2|Z]\} = \theta_2^{-2}, \\
I_{33}(\theta) &= \theta_3^{-2}\{1 + E[W(\log W)^2] - 2E(W \log W)\{\log \theta_2 + \theta_1 E(Z)\} \\
&\quad + E\{(\log \theta_2 + \theta_1 Z)^2\}\} \\
&= \theta_3^{-2}\{1 + B^2 - 2A\{\log \theta_2 + \theta_1 E(Z)\} + E\{(\log \theta_2 + \theta_1 Z)^2\}\} \\
I_{12}(\theta) &= E_\theta(\dot{\mathbf{I}}_1(Y, Z)\dot{\mathbf{I}}_2(Y, Z)) = E_\theta\{E[Z\theta_2^{-1}(1-W)^2|Z]\} = \theta_2^{-1}E(Z), \\
I_{13}(\theta) &= -E_\theta\{\ddot{\mathbf{I}}_{13}(Y, Z)\} \\
&= \theta_3^{-1}\{E(Z)[A - \log \theta_2] - \theta_1 E(Z^2)\}, \\
I_{23}(\theta) &= -E_\theta\{\ddot{\mathbf{I}}_{23}(Y, Z)\} \\
&= (\theta_2\theta_3)^{-1}\{A - \log \theta_2 - \theta_1 E(Z)\}
\end{aligned}$$

where

$$\begin{aligned}
A &\equiv E\{W \log W\} = \int_0^\infty (w \log w) \exp(-w)dw = 1 - \gamma, \\
B^2 &\equiv E\{W(\log W)^2\} = \pi^2/6 + (1 - \gamma)^2 - 1.
\end{aligned}$$

Note that since $\dot{\mathbf{I}}_4(y, z) = a(z)$ is just a function of Z , it follows easily that for $j = 1, 2, 3$ we also have

$$\begin{aligned}
I_{j4}(\theta) &= E_\theta\{\dot{\mathbf{I}}_j(Y, Z)\dot{\mathbf{I}}_4(Y, Z)\} \\
&= E\{g_j(W, Z)a(Z)\} = E\{E[g_j(W, Z)a(Z)|Z]\} \\
&= E\{a(Z)E[g_j(W, Z)|Z]\} = E\{a(Z) \cdot 0\} = 0,
\end{aligned}$$

Because of this orthogonality, the information bounds for $(\theta_1, \theta_2, \theta_3)$ are the same when $\theta_4 = \eta$ is unknown as when it is known.

(c) If θ_2 and θ_3 are known, then the information bound for estimation of θ_1 is just $I_{11}^{-1}(\theta) = 1/E(Z^2)$. It follows that the information matrix for θ is of the following form:

$$I(\theta) = \begin{pmatrix} E(Z^2) & \theta_2^{-1}E(Z) & \theta_3^{-1}C & 0 \\ \theta_2^{-1}E(Z) & \theta_2^{-2} & (\theta_2\theta_3)^{-1}D & 0 \\ \theta_3^{-1}C & (\theta_2\theta_3)^{-1}D & \theta_3^{-2}E & 0 \\ 0 & 0 & 0 & Ea^2(Z) \end{pmatrix}$$

where

$$\begin{aligned} C &= E(Z)(A - \log \theta_2) - \theta_1 E(Z^2) \\ D &= A - \log \theta_2 - \theta_1 E(Z) \\ E &= 1 + B^2 - 2A(\log \theta_2 + \theta_1 E(Z)) + E(\log \theta_2 + \theta_1 Z)^2. \end{aligned}$$

(d) If $\theta_3 = 1$ is known, then the information bound for θ_1 is $I_{11.2}^{-1}$ where

$$\begin{aligned} I_{11.2}(\theta) &= I_{11} - I_{12}I_{22}^{-1}I_{21} \\ &= E(Z^2) - (E(Z)/\theta_2)^2\theta_2^2 = E(Z^2) - (EZ)^2 = Var(Z). \end{aligned}$$

Thus $I_{11.2}^{-1} = 1/Var(Z)$.

(e) When θ_3 is known, the efficient score function and the efficient influence function for estimation of θ_1 are given by

$$\begin{aligned} \dot{\mathbf{i}}_1^*(Y, Z) &= \dot{\mathbf{i}}_1 - I_{12}I_{22}^{-1}\dot{\mathbf{i}}_2 \\ &= Z(1 - W) - \theta_2^{-1}E(Z)\theta_2^2\frac{1}{\theta_2}(1 - W) \\ &= Z(1 - W) - E(Z)(1 - W) = (Z - E(Z))(1 - W), \end{aligned}$$

and

$$\begin{aligned} \tilde{\mathbf{I}}_1(Y, Z) &= I_{11.2}^{-1}\dot{\mathbf{i}}_1^*(Y, Z) \\ &= \frac{1}{Var(Z)}(Z - E(Z))(1 - W). \end{aligned}$$

(f) When both the parameters θ_2 and θ_3 are unknown, the information $I_{11.(2,3)}$ is given by

$$\begin{aligned} I_{1.(2,3)} &\equiv I_{11.2} \quad \text{where the "second block" contains both } \theta_2, \theta_3 \\ &= I_{11} - I_{12}I_{22}^{-1}I_{21} \end{aligned} \tag{0.3}$$

where

$$\begin{aligned} I_{12} &= (\theta_2^{-1}E(Z), \theta_3^{-1}C), \\ I_{22}^{-1} &= \begin{pmatrix} \theta_2^2 E & -\theta_2 \theta_3 D \\ -\theta_2 \theta_3 D & \theta_3^2 \end{pmatrix} \frac{1}{E - D^2}. \end{aligned}$$

Thus the second term in (0.3) is

$$\{[E(Z)]^2 E - 2E(Z)CD + C^2\} / (E - D^2). \tag{0.4}$$

Now the denominator is

$$\begin{aligned} E - D^2 &= 1 + B^2 - 2A(\log \theta_2 + \theta_1 E(Z)) + E(\log \theta_2 + \theta_1 Z)^2 \\ &\quad - (A - \log \theta_2 - \theta_1 E(Z))^2 \\ &= 1 + B^2 - 2A(\log \theta_2 + \theta_1 E(Z)) + E(\log \theta_2 + \theta_1 Z)^2 \\ &\quad - [A^2 - 2A(\log \theta_2 + \theta_1 E(Z)) + (\log \theta_2 + \theta_1 E(Z))^2] \\ &= 1 + B^2 - A^2 + Var[\log \theta_2 + \theta_1 Z] \\ &= \pi^2/6 + \theta_1^2 Var(Z), \end{aligned}$$

and, upon noting that

$$\begin{aligned} C - E(Z)D &= E(Z)(A - \log \theta_2) - \theta_1 E(Z^2) - \{E(Z)(A - \log \theta_2) - \theta_1 [E(Z)]^2\} \\ &= -\theta_1 \text{Var}(Z), \end{aligned}$$

it follows that the numerator of (0.4) is

$$\begin{aligned} C^2 - 2E(Z)CD + [E(Z)]^2 E &= C^2 - 2E(Z)CD + [E(Z)]^2 D^2 + [E(Z)]^2 (E - D^2) \\ &= (C - E(Z)D)^2 + [E(Z)]^2 \{\pi^2/6 + \theta_1^2 \text{Var}(Z)\} \\ &= \theta_1^2 [\text{Var}(Z)]^2 + [E(Z)]^2 \{\pi^2/6 + \theta_1^2 \text{Var}(Z)\}. \end{aligned}$$

It follows that the information for θ_1 when θ_2 and θ_3 are unknown is equal to

$$\begin{aligned} I_{11 \cdot (2,3)} &= E(Z^2) - \frac{\theta_1^2 [\text{Var}(Z)]^2 + [E(Z)]^2 \{\pi^2/6 + \theta_1^2 \text{Var}(Z)\}}{\pi^2/6 + \theta_1^2 \text{Var}(Z)} \\ &= \frac{\pi^2/6}{\pi^2/6 + \theta_1^2 \text{Var}(Z)} \text{Var}(Z) \leq \text{Var}(Z) \leq E(Z^2) \end{aligned}$$

with equality in the first inequality if and only if $\theta_1 = 0$. Note that the information decreases as θ_1 increases, and it converges to $\pi^2/(6\theta_1^2)$ as $\text{Var}(Z) \rightarrow \infty$.

(g) When θ_2 and θ_3 are unknown the efficient score function for θ_1 is, with the “second block” containing both θ_2 and θ_3 ,

$$\begin{aligned} \mathbf{I}_1^* &= \dot{\mathbf{i}}_1 - I_{12} I_{22}^{-1} \dot{\mathbf{i}}_2 \\ &= \dot{\mathbf{i}}_1 - (\theta_2(E(Z)E - CD), \theta_3(C - DE(Z))) \dot{\mathbf{i}}_2 / (E - D^2) \\ &= Z(1 - W) - \frac{E(Z)E - CD}{E - D^2} (1 - W) \\ &\quad + \frac{\theta_1 \text{Var}(Z)}{\pi^2/6 + \theta_1^2 \text{Var}(Z)} \{[1 - (W - 1) \log W] + (W - 1) \log(\theta_2 e^{\theta_1 Z})\} \\ &= \left\{ Z - \frac{E(Z)E - CD + \log(\theta_2 e^{\theta_1 Z})}{\pi^2/6 + \theta_1^2 \text{Var}(Z)} \right\} (1 - W) \\ &\quad + \frac{\theta_1^2 \text{Var}(Z)}{\pi^2/6 + \theta_1^2 \text{Var}(Z)} \{1 - (W - 1) \log W\}. \end{aligned}$$

(h) When $Z \sim \text{Bernoulli}(\eta)$, then

$$\begin{aligned} I_{11} &= E(Z^2) = \eta = \theta_4, \\ I_{11 \cdot 2} &= \text{Var}(Z) = \eta(1 - \eta) = \theta_4(1 - \theta_4), \\ I_{11 \cdot (2,3)} &= \frac{\pi^2/6}{\pi^2/6 + \theta_1^2 \text{Var}(Z)} \text{Var}(Z) \\ &= \frac{\pi^2/6}{\pi^2/6 + \theta_1^2 \eta(1 - \eta)} \eta(1 - \eta). \end{aligned}$$

The corresponding information bounds are given by the reciprocals of these quantities. See the following figures for comparisons of the information and information bounds.

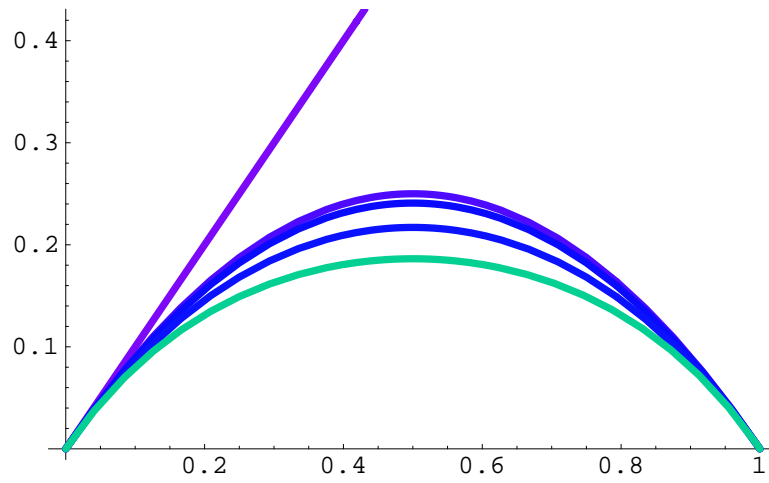


Figure 1: Plots of I_{11} , $I_{11,2}$, and $I_{11,(2,3)}$ as a function of $\eta = \theta_4$, and for $\theta_1 = .5, 1.0, 1.5$

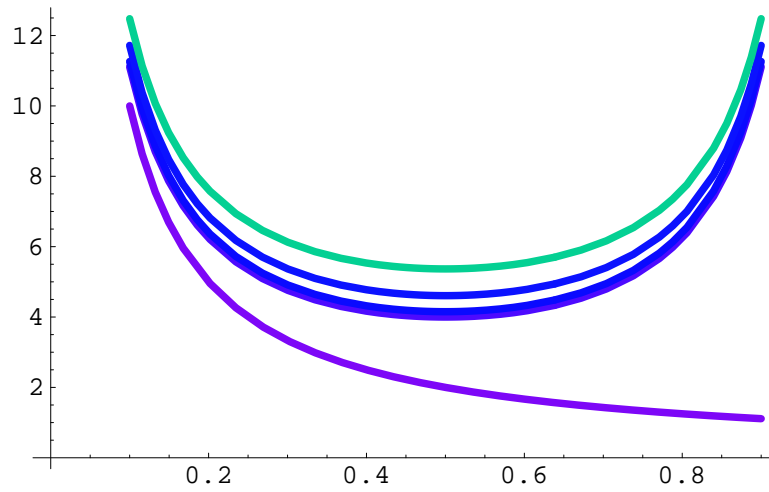


Figure 2: Plots of I_{11}^{-1} , $I_{11,2}^{-1}$, and $I_{11,(2,3)}^{-1}$ as a function of $\eta = \theta_4$, , and for $\theta_1 = .5, 1.0, 1.5$