

## Jacobian

$d$  = difference vector of length  $m \equiv \begin{matrix} \# \text{ states } s \\ \# \text{ characteristics } k \end{matrix}$

$\beta$  = parameters vector of length  $n \equiv m$

$$J = \begin{bmatrix} \frac{\partial d_1}{\partial \beta_1} & \dots & \frac{\partial d_1}{\partial \beta_n} \\ \dots & \dots & \dots \\ \frac{\partial d_m}{\partial \beta_1} & \dots & \frac{\partial d_m}{\partial \beta_n} \end{bmatrix}$$

$$d_i = \begin{matrix} \text{actual target} \\ t_i \\ \text{(constant)} \end{matrix} - \begin{matrix} \text{calculated} \\ \text{target } i \\ ct_i \end{matrix}$$

In computer programs,  $d$ ,  $t$ , and  $ct$  have been  $s \times k$  matrices. For example, with 3 states and 2 characteristics, we might have

$$t = \begin{bmatrix} 10 & 20 \\ 30 & 40 \\ 50 & 60 \end{bmatrix}$$

constant

$$ct = \begin{bmatrix} 8 & 24 \\ 27 & 41 \\ 50 & 59 \end{bmatrix}$$

calculated with  
a given set of  
estimated weights

$$d = \begin{bmatrix} 2 & -4 \\ 3 & -1 \\ 0 & 1 \end{bmatrix}$$

In this exercise we need to convert these to vectors with all of 1 characteristics of one state, then the next, then the next, so that we express this as

$$t = (10, 30, 50, 20, 40, 60)$$

$$ct = (8, 27, 50, 24, 41, 59)$$

$$d = (2, 3, 0, -4, -1, 1)$$

Similarly,  $\beta$  (I am making this up) might be estimated as:

$$\beta \approx \begin{bmatrix} 1 & 2 \\ 3 & 4 \\ 5 & 6 \end{bmatrix}$$

and so for purposes of calculating the Jacobian we would express

$\beta$  as

$$\beta \approx (1, 3, 5, 2, 4, 6)$$

The Jacobian is  $\left[ \frac{\partial d}{\partial \beta} \right]$  which is a  $6 \times 6$  symmetric matrix, It always will have dimension  $(s \cdot k) \times (s \cdot k)$ .

It's useful to think about how to map the  $s, k$  indexes to the  $i \equiv j$  indexes in this example

<u><math>i, j</math></u>	<u><math>s</math></u>	<u><math>k</math></u>
1	1	1
2	2	1
3	3	1
4	1	2
5	2	2
6	3	2

We want an analytic expression, ultimately in matrix notation, for  $J$ .

We can start by deriving the partial derivative of any single difference  $d_i$  with respect to any  $\beta_j$  ..

for example  $\frac{\partial d_1}{\partial \beta_2}$ , and then generalizing it.

Let's say, as above,  $k=2$  and  $s=3$  and  $h=4$ ,

Then for  $\frac{\partial d_1}{\partial \beta_2}$

	map of indexes		
	index	s	k
$d_1$	1	1	1
$\beta_2$	2	2	1

$$d_1 = \underbrace{z_1}_{\substack{\{s=1\} \\ \{k=1\}}} - \sum_{h=1}^4 w_{h,s=1} X_h^{s=1}$$

$$\frac{\partial d_1}{\partial \beta_2} = - \sum_{h=1}^4 w_{h,s=1} X_h^{s=1}$$

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Let's look just at  $h=1$  --  
one household, Then we have

$$w_{h=1, s=1} \cdot \prod_{h=1}^{s=1}$$

as one of the 4 elements in  
the second term of the RHS  
of  $d_1$ . We need

$$\frac{\partial}{\partial \beta_2} w_{h=1, s=1} \cdot \prod_{h=1}^{s=1} \left\{ \begin{matrix} s=2 \\ k=1 \end{matrix} \right\}$$

which is

$$\prod_{h=1}^{s=1} \frac{\partial}{\partial \beta_2} \left( w_{h=1, s=1} \right)$$

because  $x$  is constant

(after we get this we need  
to add the results for the  
4 households to get  $\frac{\partial d_1}{\partial \beta_2}$ )

So we need

$$\frac{\partial}{\partial \beta_{\sim}} \left( w_{h=1, s=1} \right)$$

(s=2)  
k=1

where

$$w_{h=1, s=1} = e^{\beta_{\sim} \cdot \sum_{k=1}^{K=1} X_{h=1}^{k=1} + \beta_{\sim} \cdot \sum_{k=2}^{K=2} X_{h=1}^{k=2} + \delta_{h=1}}$$

(s=1)  
k=1

(s=1)  
k=2

(s=4)  
k=2

where  $\delta_{h=1} = f(\beta)$

This is the part TPC left out of their paper,

as I read it, although their software might deal with it properly.

Re-express

$$W_{h=1, s=1} = e^{\underbrace{\left( \beta_{s=1, k=1} X_{h=1}^{k=1} + \beta_{s=1, k=2} X_{h=1}^{k=2} \right)}_f} \cdot \underbrace{e^{\delta}}_g \quad \delta = f(\beta)$$

By product rule:

$$\frac{\partial W_{h=1, s=1}}{\partial \beta_2} = f'g + fg'$$

$\left[ \begin{smallmatrix} s=2 \\ k=1 \end{smallmatrix} \right]$

This will not be zero  
on the diagonal

$$= 0 + f \cdot \frac{\partial g}{\partial \beta_2}$$

on the diagonal  
this will simplify  
 $X_{h=1}^{k=1} \cdot W_{h=1, s=1}$  I think