

A Users Guide to **panel**  
Technical Report 12  
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August 7, 2001

**Abstract**

Documentation for the R/Splus function **panel**. Included are installation instructions, a brief description of the problem and some problem solving hints. It is assumed that you know how to program R/Splus and some experience with the foreign function interface would be helpful-281/54c]TJ Olel

inspection times and the state of the individual at the inspection times. There are a great number of examples of such data, see for example Kalbfleisch and Lawless (1985), Gentleman, Lawless,

aware that it is a very strong assumption that is seldom met.

A multi-state model  $fY(t) : t \geq 0$  is Markov<sup>[1]</sup> if

with  $\mathbf{D} = diag(d_1; d_2; \dots; d_k)$ . Thus,

$$\mathbf{P}(t) = \mathbf{A} diag(e^{d_1 t}; e^{d_2 t}; \dots; e^{d_k t}) \mathbf{A}^{-1}, \quad (5)$$

where the dependence of  $\mathbf{Q}$ ,  $\mathbf{P}(t)$ ,  $\mathbf{A}$  and the  $d_v$ 's on  $t$  is suppressed for notational convenience. Once  $\mathbf{A}$  and  $\mathbf{D}$  are obtained, transition probabilities may be rapidly computed from (5). Additional



units you are using, **stage**, a vector of stages occupied by the individual at the corresponding inspection times, **cov**, a vector of covariate value(s) at the corresponding inspection times, and **len**, the length of the time vector.

```
function(indata, qmatf, gamma, qderivf, npar, nstage, ncov, verbose = F,
        tol = 0.001)
```

The arguments are as follows:

**indata** The data in the list structure described above.

**qmatf** A function which takes the parameter vector  $\underline{\gamma}$  as an argument and returns the **Q** matrix.

This is a three-way array. The first dimension codes the levels of the covariate and within each of these the two-way array is the **Q** matrix.

**gamma** The vector of parameter estimates. Recall that  $\gamma_i = \exp(\gamma_i)$





The appropriate versions of the `qfun` and `qderiv` functions are given below.

```
> qfun.m2 <- function(gamma)
```

```
rmat[4, 1, 3, 3] <- ( - theta[4])
rmat[4, 2, 3, 2] <- theta[4]
rmat[4, 2, 3, 3] <- ( - theta[4])
rmat[5, 1, 3, 3] <- ( - theta[5])
rmat[5, 1, 3, 4] <- theta[5]
rmat[6, 1, 2, 4] <- theta[6]
rmat[6, 1, 2, 2] <- ( - theta[6])
rmat[7, 2, 1, 1] <- ( - theta[7])
rmat[7, 2, 1, 2] <- theta[7]
rmat[8, 2, 2, 2] <- ( - theta[8])
```

```

qarr[2, 1, 1] <- qarr[2, 1, 1] * exp(gamma[7])
qarr[3, 1, 1] <- qarr[3, 1, 1] * exp(2 * gamma[7])
qarr[3, 1, 2] <- qarr[3, 1, 2] * exp(2 * gamma[7])
return(qarr)
}

> qderiv.ord <- function(gamma)
{
  rmat <- array(0, c(7, 3, 4, 4))
  theta <- exp(gamma)
  rmat[1, 1, 1, 1] <- ( - theta[1])
  rmat[1, 1, 1, 2] <- theta[1]
  rmat[1, 2, 1, 1] <- ( - theta[1] * exp(gamma[7]))
  rmat[1, 2, 1, 2] <- theta[1] * exp(gamma[7])
  rmat[1, 3, 1, 1] <- ( - theta[1] * exp(2 * gamma[7]))
  rmat[1, 3, 1, 2] <- theta[1] * exp(2 * gamma[7])
  rmat[2, , 2, 1] <- theta[2]
  rmat[2, , 2, 2] <- ( - theta[2])
  rmat[3, , 2, 2] <- ( - theta[3])
  rmat[3, , 2, 3] <- theta[3]
  rmat[4, , 2, 4] <- theta[4]
  rmat[4, , 2, 2] <- ( - theta[4])
  rmat[5, , 3, 3] <- ( - theta[5])
  rmat[5, , 3, 2] <- theta[5]
  rmat[6, , 3, 4] <- theta[6]
  rmat[6, , 3, 3] <- ( - theta[6])
  rmat[7, 2, 1, 1] <- ( - theta[1] * exp(gamma[7]))
  rmat[7, 2, 1, 2] <- theta[1] * exp(gamma[7])
  rmat[7, 3, 1, 1] <- (-2 * theta[1] * exp(2 * gamma[7]))
  rmat[7, 3, 1, 2] <- 2 * theta[1] * exp(2 * gamma[7])
  return(rmat)
}

```

Some simulated data from this model has been included and is in the file *simord.data*. The data

given by

$$\mathbf{Q} = \begin{smallmatrix} \circ \\ \mathbb{B} \\ @ \end{smallmatrix} q$$

```

rmat[1, 2, 3] <- theta[4]
rmat[2, 1, 1] <- ( - theta[1] * theta[6] - theta[2])
rmat[2, 1, 2] <- theta[1] * theta[6]
rmat[2, 1, 3] <- theta[2]
rmat[2, 2, 1] <- theta[3] * theta[8]
rmat[2, 2, 2] <- ( - theta[3] * theta[8] - theta[4])
rmat[2, 2, 3] <- theta[4]
rmat[3, 1, 1] <- ( - theta[1] * theta[5] - theta[2])
rmat[3, 1, 2] <- theta[1] * theta[5]
rmat[3, 1, 3] <- theta[2]
rmat[3, 2, 1] <- theta[3] * theta[7]
rmat[3, 2, 2] <- ( - theta[3] * theta[7] - theta[4])
rmat[3, 2, 3] <- theta[4]
rmat[4, 1, 1] <- ( - theta[1] * theta[5] * theta[6] - theta[2])
rmat[4, 1, 2] <- theta[1] * theta[5] * theta[6]
rmat[4, 1, 3] <- theta[2]
rmat[4, 2, 1] <- theta[3] * theta[7] * theta[8]
rmat[4, 2, 2] <- ( - theta[3] * theta[7] * theta[8] - theta[4])
rmat[4, 2, 3] <- theta[4]
return(rmat)
}

qderivs.kl<- function(gamma)
{
  rmat <- array(0, c(8, 4, 3, 3))
  theta <- exp(gamma)
  rmat[1, 1, 1, 1] <- ( - theta[1])
  rmat[1, 1, 1, 2] <- theta[1]
  rmat[1, 2, 1, 1] <- ( - theta[1] * theta[6])
  rmat[1, 2, 1, 2] <- theta[1] * theta[6]
  rmat[1, 3, 1, 1] <- ( - theta[1] * theta[5])
  rmat[1, 3, 1, 2] <- theta[1] * theta[5]
  rmat[1, 4, 1, 1] <- ( - theta[1] * theta[6] * theta[5])
  rmat[1, 4, 1, 2] <- theta[1] * theta[6] * theta[5]

```



### 3.3 Optimization Algorithms

To avoid some problems with the optimization rather than work with the  $\beta_i$ , directly they are transformed to  $\pi_i = \exp(\beta_i)$ . The main reason being that  $\beta_i$  are constrained to be positive (requiring constrained optimization) while the  $\pi_i$  are not constrained and standard Newton–Raphson c55 Tf92(be)]TJ -

always be positive while for other models some form of constrained estimation will be required.

large differences and it is worth amplifying these. At each observed failure time covariate informa-

Either there was one transition intensity that was several orders of magnitude different from the

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