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### AGGREGATE SMOOTHNESS

#### IN MULTI-DIMENSIONAL

### WHITTAKER-HENDERSON GRADUATION by Ronald Dubson

### abstract

A set of crude rates u" determined by D independent variables can be thought of as a discrete surface of dimension D. Let W, F,  $K_i$ , and  $S_i$  have their usual meaning in multi-dimensional Whittaker-Henderson graduation. Let  $t_1, \ldots, t_D$  be non-negative smoothness parameters, let

$$A = W + \sum_{i=1}^{D} t_{i} K_{i}^{T} K_{i}, \quad u = u(t_{i}) = A^{-1} W u^{n},$$

let  $\eta$  be the surface determined by limit  $(u - \eta)^T W(u - \eta) = 0$ , and  $t_{i \to \infty}$ let  $\sigma^2 > 0$  be some desired level of the fit F (e.g., its expected value). Then the point  $(t_i)$  at which  $(u - \eta)^T W(u - \eta)$  attains a minimum when subject to the constraint  $F(u) = \sigma^2$  is determined by the simultaneous equations

$$\frac{\partial F}{\partial t_i} = \lambda S_i \qquad (i = 1, \dots, D)$$

where  $\lambda$  depends on  $\sigma^2$ .

If C is any smooth curve in the region  $\{(t_i): t_i \ge 0\}$  with initial point  $(0, \ldots, 0)$  and end-point  $(t_i)$ , then

$$F + \sum_{i=1}^{D} t_i S_i = \int_{C} \sum_{i=1}^{D} S_i dt_i .$$

1. Given a set of crude motality rates  $u_x^*$  to be graduated by the Whittaker-Henderson method, one may ask under what conditions there exists a statistical estimator for the fit  $F = \sum w_x (u_x - u_x^*)^2$ . If the graduated rates  $u_x$  are considered to be random variables with expectation  $u_x^*$  and variance  $\sigma_x^2$ , then the expected value of F is

 $\mathbb{E}\{\mathbf{F}\} = \sum \mathbf{w}_{\mathbf{x}} \mathbb{E}\{(\mathbf{u}_{\mathbf{x}} - \mathbf{u}_{\mathbf{x}})^2\} = \sum \mathbf{w}_{\mathbf{x}} \sigma_{\mathbf{x}}^2 \quad .$ 

In the case of rates  $q_x = \theta_x / E_x$  based on the number of lives or number of policies, it is well known that  $\sigma_x^2 = q_x (1 - q_x) / E_x = p_x q_x / E_x$ .

For the so-called type B Whittaker-Henderson graduation, in which the weights  $w_x$  are the exposures  $E_x$ , one has

$$\mathbf{E} \{\mathbf{F}\} = \sum \mathbf{E}_{\mathbf{x}} (\mathbf{p}_{\mathbf{x}} \mathbf{q}_{\mathbf{x}} / \mathbf{E}_{\mathbf{x}}) = \sum \mathbf{p}_{\mathbf{x}} \mathbf{q}_{\mathbf{x}}$$

In multidimensional WH graduation where the subscript x is an ordered pair, or more generally, a lattice point  $(k_1, ..., k_D)$ , there is an infinite number of different values for the smoothness parameters which yield different graduated rates but the same fit. These considerations suggest the following problem:

For a given level of fit, how are the smoothness parameters to be chosen so that the graduated rates form, in some natural sense, the smoothest discrete surface?

In the one-dimensional case this is not an issue, as the fit determines the single smoothness parameter, and *vice versa*. Although this is a mathematical rather than an actuarial problem, it should not be without some interest to actuaries, since a solution would provide a standard against which to compare graduated rates that emphasize smoothness along a particular axis or axes. 2. We will use Knorr's notation [1], with the exception that the smoothness parameters will be denoted by  $t_i$  (i = 1, ..., D).

D = dimension of the data set of crude rates,

 $N = n_1 n_2 \dots n_D$ , the total number of cells

$$u = \{u_{k_1 k_2 \dots k_D}: k_i = 1, \dots n_i; i = 1, \dots, D\}$$
 the "unraveled" graduated rates,

 $u = (u_1, ..., u_N)$  the "raveled" graduated rates,

 $u = (u_1, ..., u_N)$  the raveled crude rates

 $W = an N x N diagonal matrix with positive entries w_1, ..., w_N;$ 

 $K_i$  = the N x N matrix with binomial coefficients needed to determine  $\Delta_i^{z_i}$ ,  $K_i^{T}$  = the transpose of  $K_i$ ,

$$A = W + \sum_{i=1}^{D} t_i K_i^T K_i \quad (t_i > 0);$$
  
$$i = 1$$
  
$$F = (u \cdot u^*)^T W (u \cdot u^*);$$

$$\mathbf{S}_{i} = \mathbf{u}^{\mathrm{T}} \mathbf{K}_{i}^{\mathrm{T}} \mathbf{K}_{i} \mathbf{u}.$$

Note that  $\mathbf{u}^{\mathrm{T}} \mathbf{K}_{i}^{\mathrm{T}} \mathbf{K}_{i} \mathbf{u} = \sum_{i} (\mathbf{A}_{i}^{\mathbf{z}_{i}} \mathbf{u})^{2}$ ; e.g., for a two-dimensional data set with  $z_{1} = 3$ ,

$$u^{T}K_{1}^{T}K_{1}u = \sum_{i,j} (\Delta^{3} u_{i,j})^{2}$$
  
= 
$$\sum_{j=1}^{n_{2}} \sum_{i=1}^{n_{1}-3} (u_{i+3,j} - 3u_{i+2,j} + 3u_{i+1,j} - u_{i,j})^{2} .$$
  
= 
$$\sum_{j=1}^{n_{1}-3} \sum_{i=1}^{n_{1}-3} (u_{i+3,j} - 3u_{i+2,j} + 3u_{i+1,j} - u_{i,j})^{2} .$$

The vector u minimizes  $F+\sum t_i\,S_i$  when  $Au=Wu^*.$  As  $t_i \to \infty$ ,  $u \to \eta$ , the polynominal function of  $(k_1\,...,\,k_D)$  which minimizes F and whose partial derivatives  $\partial^{Z_i}/\partial k_i$  are zero. The vector  $\eta$  can also be charcterized as the orthogonal projection of u° onto the intersection of the null spaces of the  $K_i$ 's. This fact is used in appendix (i).

3. Let  $\sigma^2$  denote the desired level of fit. As the "smoothest"  $u (= A^{-1}Wu^*)$  for which  $F = \sigma^2$ , we propose the one which minimizes  $(u \cdot \eta)^T W (u - \eta)$ , the square of the distance to the ultimate smooth surface  $\eta$ .

In order to derive an equation for the  $(t_i)$  at which this condition is satisfied, it will be convenient to use the following notation:

$$\langle u, v \rangle = u^{T}Wv$$
,  $|u|^{2} = \langle u, u \rangle$ ; hence,  $F = |u - u^{r}|^{2}$  and  
 $(u - n)^{T}W(u - n) = |u - n|^{2}$ .

It is shown in appendix (i) that

$$|\mathbf{u} - \eta|^2 = 2 < \mathbf{u}, \mathbf{u}^* > + \mathbf{F} - |\mathbf{u}^*|^2 - |\eta|^2,$$

from which it follows that, when  $F = \sigma^2$ ,  $|u - \eta|^2$  and 2 < u,  $u^* >$  differ by a constant. Hence,  $< u, u^* >$  attains a minimum, say  $\mu$ , at the same point  $(t_i)$  as does  $|u - \eta|^2$ . By Lagrange's Theorem [2], there is a real number  $\lambda$ , depending on  $(t_i)$ , such that

(1)  $\partial \langle u, u^* \rangle / \partial t_i = \lambda \partial F / \partial t_i$ , i = 1, ..., D

at the point on the submanifold  $\{F = \sigma^2\}$  where  $\langle u, u^* \rangle = \mu$ . Geometrically speaking, this says that  $(t_i)$  is the point of tangency between the two submanifolds  $\{F = \sigma^2\}$  and  $\{\langle u, u^* \rangle = \mu\}$ . Replacing  $\lambda$  by  $-1/\lambda$  in equation (1) and using the fact that  $\partial \langle u, u^* \rangle / \partial t_i = -S_i$  [appendix (ii)], one obtains

1a)  $\partial F / \partial t_i = \lambda S_i$ , i = 1, ..., D.

Note that  $\partial F / \partial ti = 2 < u^{r} - u$ ,  $A^{-1} K_{i}^{T} K_{i} u > [appendix (iii)]$ . Since  $u = u^{r}$  at  $t_{i} = 0$ ,  $\partial F / \partial t_{i} = 0$  at  $t_{i} = 0$ . Hence, if  $S_{i} (u^{r}) > 0$  for some i, then  $\lambda = 0$  at  $t_{i} = 0$ .

4. Let 
$$\phi = \begin{pmatrix} \partial_1 F & S_1 \\ \partial_2 F & S_2 \end{pmatrix}$$
  $(\partial_i = \partial / \partial t_i)$ 

In the case D = 2, the equations (1a) are equivalent to the single determinant equation  $\phi = 0$ , which determines a curve  $\Gamma$  with initial point (0,0). We have thus reduced our problem to locating the intersection of the two curves  $F = \sigma^2$  and  $\Gamma$ . An algorithm for approximating this point is the following:

(1) Calculate the slope  $m_1$  of  $\Gamma$  at the origin; it follows from what is shown in section 5 that

 $\mathbf{m}_{1} = \begin{vmatrix} \partial_{11} \mathbf{F} & \mathbf{S}_{1} \\ \partial_{12} \mathbf{F} & \mathbf{S}_{2} \end{vmatrix} \xrightarrow{+} \begin{vmatrix} \mathbf{S}_{1} & \partial_{21} \mathbf{F} \\ \mathbf{S}_{2} & \partial_{22} \mathbf{F} \end{vmatrix} ,$ 

where all functions are evaluated at (0,0). The straight line through the origin with slope  $m_1$  intersects  $F = \sigma^2$  at some point  $P_1$ ;

(2) the tangent line to  $F = \sigma^2$  at  $P_1$  has slope  $m_2 = -\partial_1 F(P_1) / \partial_2 F(P_1)$  and meets  $\Gamma$  at some point  $P_2$ ; namely, where  $\phi(P_2) = 0$ ;

(3) the straight line through the origin and  $P_2$  intersects  $F = \sigma^2$  at a point  $P_3$ ;

(4) repeat step (2) with  $P_3$  in place of  $P_1$  to obtain a point  $P_4$  on  $\Gamma$ . The sequence  $(P_n)$  converges to the intersection of  $F = \sigma^2$  and  $\Gamma$  (see figure). Finding  $P_1$ ,  $P_2$ ,  $P_3$  involves solving for  $t_1$ ,  $t_2$ ,  $t_3$  in the equations

$$F(t_1(1, m_1)) m = \sigma^2$$
,

 $\phi (\mathbf{P}_1 + \mathbf{t}_2 (1, \mathbf{m}_2)) = 0 ,$ 

F  $(t_3 (1, m_3)) = \sigma^2$ , where  $m_3 = \frac{m_1 t_1 + m_2 t_2}{t_1 + t_2}$ 

5. When the dimension D>2,  $F = \sigma^2$  is not a curve but a (D-1) – dimensional surface. This obviates the use of the preceding algorithm. We will show that  $\Gamma$  is an integral curve of a vector field V. Hence, any point of  $\Gamma$  can be approximated by numerical integration of V, starting at the origin. The modified Cauchy-Euler method [3] is an efficient algorithm for this purpose.



figure: Locating the intersection of  $F = \sigma^2$  and  $\phi = 0$ . (cf. para. 4)

Assume that the parameter  $\lambda$  in (1a) is monotone in a segment of  $\Gamma$  containing (t; ). Differentiating (1a) with respect to  $\lambda$  gives

$$(2a) \sum_{j} \partial_{j} (\partial_{i} F) \frac{dt_{j}}{d\lambda} = S_{i} + \lambda \sum_{j} (\partial_{j} S_{i}) \frac{dt_{j}}{d\lambda} , \quad (i = 1, ..., D) \text{ or}$$

$$(2b) (\partial^{2} F - \lambda \partial S) \frac{d\Gamma}{d\lambda} = S,$$

where the matrix  $\partial^2 F$  has entries  $\partial_i \partial_i F$  or  $\partial_{ji} F$ ,

 $\partial S$  has entries  $\partial_j S_i$ ,

the column vector  $d\Gamma/d\lambda$  has entries  $dt_i /d\lambda$ ,

and S has entries  $S_i$  .

The matrix equation (2b) can be solved for  $d\Gamma/d\lambda$  by applying Cramer's Rule. Consider first the case D = 2. If  $\Delta$  is the determinant of  $\partial^2 S - \lambda \partial S$ , then

$$\Delta \frac{dt_{i}}{d\lambda} = \begin{vmatrix} S_{i} & \partial_{21}F - \lambda \partial_{2}S_{i} \\ S_{2} & \partial_{22}F - \lambda \partial_{2}S_{2} \end{vmatrix}$$
$$= \begin{vmatrix} S_{i} & \partial_{21}F \\ S_{2} & \partial_{12}F \end{vmatrix} - \begin{vmatrix} S_{i} & \lambda \partial_{2}S_{i} \\ S_{2} & \lambda \partial_{2}S_{2} \end{vmatrix}$$
$$= \begin{vmatrix} S_{i} & \partial_{21}F \\ S_{2} & \partial_{21}F \\ S_{2} & \partial_{21}F \end{vmatrix} - \begin{vmatrix} \lambda S_{i} & \partial_{2}S_{i} \\ \lambda S_{2} & \partial_{1}S_{2} \end{vmatrix}$$
$$(3a) = \begin{vmatrix} S_{i} & \partial_{21}F \\ S_{2} & \partial_{22}F \end{vmatrix} - \begin{vmatrix} \partial_{i}F & \partial_{2}S_{i} \\ \lambda S_{2} & \partial_{1}S_{2} \end{vmatrix} = \varepsilon_{i},$$

and similarly,

$$(3b) \ \Delta \frac{dt_2}{d\lambda} = \begin{vmatrix} \partial_{11}F & S_1 \\ \partial_{12}F & S_2 \end{vmatrix} - \begin{vmatrix} \partial_1S_1 & \partial_1F \\ \partial_1S_2 & \partial_2F \end{vmatrix} = \varepsilon_2.$$

The vector field V defined by  $(\xi_i, \xi_1)$  depends only on  $(t_i)$  and not on  $\lambda$ . On the curve  $\Gamma$ , V is parallel to the tangent vector  $d\Gamma/d\lambda$ . At  $t_i = 0$ ,  $\partial_i F = 0$  [cf. section 3]; denoting the value of  $\xi_i$  at  $t_i = 0$ by  $\xi_i''$ , one therefore has

$$\begin{aligned} \boldsymbol{\varepsilon}_{1}^{"} &= \left| \begin{array}{c} \boldsymbol{S}_{1} & \boldsymbol{\partial}_{21} \boldsymbol{F} \\ \boldsymbol{S}_{2} & \boldsymbol{\partial}_{22} \boldsymbol{F} \end{array} \right| , \\ \boldsymbol{\varepsilon}_{2}^{"} &= \left| \begin{array}{c} \boldsymbol{\partial}_{11} \boldsymbol{F} & \boldsymbol{S}_{1} \\ \boldsymbol{\partial}_{12} \boldsymbol{F} & \boldsymbol{S}_{2} \end{array} \right| , \end{aligned}$$

where all functions are evaluated at  $t_i = 0$ . Now  $(\mathcal{E}_{i-}^{\#}, \mathcal{E}_{1}^{\#}) \neq (0,0)$ if  $S_i \neq 0$  or  $S_2 \neq 0$  and

$$\begin{vmatrix} \partial_{11}F & \partial_{21}F \\ \partial_{12}F & \partial_{22}F \end{vmatrix} \neq 0.$$

If these conditions hold at  ${\tt t}_i=0,$  then one can solve the system of differential equations

$$\frac{dt_i}{dT} = \varepsilon_i , \quad \frac{dt_2}{dT} = \varepsilon_2$$

with initial conditions  $t_1(0) = 0$ ,  $t_2(0) = 0$ ;  $\xi_1$ ,  $\xi_2$  are given in equations (3a) and (3b). In particular, one can solve for the point  $(t_1^c)$  on  $\Gamma$  where  $F = \sigma^2$ .

For the case D > 2 the equation (2b) cannot be solved so neatly, but the principle is the same. Replacing  $\lambda$  by  $\partial_i F/S_i$  in equation (2a), one obtains

(2c) 
$$\sum_{j} \left[ \partial_{ji} F - \partial_{i} F \partial_{j} S_{i} / S_{i} \right] \frac{dt_{j}}{d\lambda} = S_{i},$$

which at  $t_i = 0$  reduces to

$$\sum_{j} \partial_{ji} F \frac{dt_{j}}{d\lambda} = S_{i} , \qquad (i=1, \ldots, D)$$

where  $S_i = u^{*T} K_i^T K_i u^{*}$ 

and 
$$\partial_{ji} F = 2 u^{nT} K_j^T K_j W' K_i^T K_i u^{m}$$

[cf. appendix (iii)].

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The author wishes to thank Arthur Cragoe for calling his attention to Mr. Knorr's article and for encouraging the work many years ago which led to this paper.

## APPENDIX

(i) Since K<sub>i</sub> η = 0, Aη = Wη and η = A<sup>-1</sup> Wη. As η is an orthogonal projection of u<sup>\*</sup>, it follows by definition that <u<sup>\*</sup> - η, η > = 0 or <u<sup>\*</sup>, η > = <η, η>; hence
<u, η> = <A<sup>-1</sup> Wu<sup>\*</sup>, η> = u<sup>\*T</sup>WA<sup>-1</sup>Wη = u<sup>\*T</sup> Wη = <u<sup>\*</sup>, η> = <η, η>; hence
| u - η |<sup>2</sup> = | u |<sup>2</sup> - 2 <u, η > + | η |<sup>2</sup>
= | u |<sup>2</sup> - | η |<sup>2</sup>
= | u - u<sup>\*</sup> |<sup>2</sup> + 2 < u, u<sup>\*</sup> > - | u<sup>\*</sup> |<sup>2</sup> - | η |<sup>2</sup>
(ii) Since Au = Wu<sup>\*</sup> = constant, 0 = ∂<sub>i</sub>Wu<sup>\*</sup> = ∂<sub>i</sub> (Au) = (∂<sub>i</sub> A) u + A ∂<sub>i</sub> u; ∂<sub>i</sub> A = K<sup>T</sup><sub>i</sub> K<sub>i</sub> now gives
∂<sub>i</sub> u = -A<sup>-1</sup> (∂<sub>i</sub> A) u = -A<sup>-1</sup> K<sub>i</sub><sup>T</sup> K<sub>i</sub> u; finally,

 $\begin{array}{l} \partial_i < u,\!u^* > = < u^*\!, \, \partial_i \, u > \\ = - u^{*T} \, W \, A^{-1} \, K^T_{\,\,i} \, K_i \, u \\ \end{array} > \\ = - u^{*T} \, W \, A^{-1} \, K^T_{\,\,i} \, K_i \, u \\ = - u^T \, K^T_{\,\,i} \, K_i \, u \\ \end{array}$ 

We note a striking identity which follows from this fact. Let C be any smooth curve in D-dimensional space with initial point (0, ..., 0) and endpoint  $(t_1, ..., t_D)$ . Then,  $Au = Wu^*$ ,

$$\begin{split} u^{T}Au &= u^{T}Wu^{*}, \\ u^{T}Wu + \sum t_{i} S_{i} &= u^{T}Wu^{*}, \text{ and} \\ \sum t_{i} S_{i} &= u^{T}W \; (u^{*} - u) = < u, \, u^{*} - u >; \text{ hence,} \\ F + \sum t_{i} S_{i} &= < u^{*} - u, \, u^{*} - u > + < u, \, u^{*} - u > \\ &= < u^{*}, \, u^{*} - u > \\ &= < u^{*}, \, u^{*} - u > \\ &= -\int_{c} \sum \vartheta_{i} < u, \, u^{*} > dt_{i} \\ &= \int_{c} \sum S_{i} \; dt_{i} \; . \end{split}$$

$$F + \sum t_i S_i = \underbrace{f}_{\Sigma} S_i dt_i$$

(iii) 
$$\partial_i F = \partial_i < u \cdot u^*, u \cdot u^* >$$
  
= 2 < u - u \*,  $\partial_i u >$   
= 2 < u \* - u,  $A^{-1} K^T_i K_i u >$ ;  $\partial_{ji} F =$   
 $\partial_j (\partial_i F) = 2 < -\partial_j u, A^{-1} K^T_i K_i u > + 2 < u^* - u, ... >$ ;

;

since, at  $t_i = 0$ ,  $u = u^*$  and A = W, we have

$$\hat{\theta}_{ji} \mathbf{F} \Big|_{t_i = 0} = 2 < \mathbf{A}^{-1} \mathbf{K}_j^{\mathrm{T}} \mathbf{K}_j \mathbf{u}, \ \mathbf{A}^{-1} \mathbf{K}_i^{\mathrm{T}} \mathbf{K}_i \mathbf{u} > \Big|_{t_i = 0}$$

$$= 2 \mathbf{u}^{*\mathrm{T}} \mathbf{K}_j^{\mathrm{T}} \mathbf{K}_j \mathbf{W}^{-1} \mathbf{K}_i^{\mathrm{T}} \mathbf{K}_i \mathbf{u}^{*}.$$

# **REFERENCES:**

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Kansas City, Missouri 1991