

The Best Matrix
by
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In [1], p.24, while searching for the matrix A^* formed from a local model with the smallest principal eigenvalue λ , we considered two possibilities: The matrix A_e with equal main diagonal elements, and A_m , the matrix whose characteristic polynomial $\kappa(x)$ has minimum slope at $(1, \kappa(1))$. It can easily be shown that in two dimensions $A_e = A_m = A^*$.

However, in three dimensions this is not the case. In fact we showed in [1] that $A_m < A_e$ in the sense that A_m has a smaller eigenvalue than A_e . However, it was an open question whether it is the best. For dimensions greater than three, we did not even know that much. That is, until we finally obtained the minimax algorithm which is the content of this paper. Using it, we can definitely say that neither A_e or A_m is the best matrix except in very special cases.

The Minimax Algorithm

Theorem 6 in [1] specifies that if all the k 's are equal, then the best matrix is Ae . This will be our starting point. We will next consider the local model M defined in [2] on p.38:

$$M = \begin{bmatrix} 1 & w_1/w_2s_1 & w_1/w_3s_1 & \dots & w_1/w_ns_1 \\ w_2/w_1s_2 & 1 & w_2/w_3s_2 & \dots & w_2/w_ns_2 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ w_n/w_1s_n & w_n/w_2s_n & \dots & \dots & 1 \end{bmatrix}$$

where $s_i = k_i/(1-k_i)$ and $m_{ij} = w_i/w_js_i$, $i=1,2,\dots,n$. Notice that $m_{ij}m_{ji} = s_i s_j$ which depends only on the k 's. If all the k 's are equal, then $Ae(u)$ is the best matrix for any u , $0 < u < 1$.

If the k 's are not all the same, we find all the $(m_{ij}m_{ji})$, $i \neq j$. There are $n(n-1)$ of them. Let $r_{ij} = (m_{ij}m_{ji})^{1/2}$, $i \neq j$, and $(\prod_{j \neq i} r_{1j})^{1/(n-1)}$, $(\prod_{j \neq i} r_{2j})^{1/(n-1)}$, \dots , $(\prod_{j \neq i} r_{nj})^{1/(n-1)}$, i.e. the geometric mean of all the r_{ij} 's having the same i . Choose the smallest and largest of such numbers and call them g_s and g_l . Assume g_l is the largest. Let $l_s = (g_s/g_l)^{1/2}$. Then $u_s = l_s u$ and $u_l = u^2/u_s$, and all the other u_k 's are u .

We went through all of these details in order to justify how we arrived at u_s and u_l . A much easier way to calculate them is: $u_s = (\prod_{k \neq s} m_{sk}m_{ks} / \prod_{k \neq l} m_{lk}m_{kl})^{1/(4(n-1))} u$ and $u_l = u^2/u_s$, $k \neq s, l$. These new values for the u 's bring us into the neighborhood of the best matrix. Once u_s is given, we vary it by a small amount. If we decrease it, which means we increase u_l and get a smaller λ , we continue to decrease it until λ stops decreasing and starts to increase. If it gets larger right away, then we increase u_s by degrees until λ stops getting smaller.

Once this happens, we keep u_s and u_l fixed and do the same thing with the next two extreme values. If n is even the process eventually ends. If n is odd,

there is a u_k left over. We leave it as u .

The same algorithm can be applied to any mold M as defined in [2], p.19. Thus we have a way of finding the best matrix for any $\text{Pop}(u)$ from any mold M .

Example

In [2], p.38 a local model was given which depended on the worst vector $P_w(624.3 \ 476.74 \ 280.02 \ 210.39)$, and the k 's:

$k_1=.1723 \ k_2=.14995 \ k_3=.2001 \ k_4=.2401$. From these and $s_i=k_i/(1-k_i)$ we get $s_1=.20817 \ s_2=.1764 \ s_3=.25016 \ s_4=.31596$ and the model

$$M = \begin{bmatrix} 1 & .2726 & .4641 & .6177 \\ .1347 & 1 & .3003 & .3997 \\ .1122 & .1469 & 1 & .33295 \\ .1065 & .1394 & .2374 & 1 \end{bmatrix}$$

From this, we obtain

$$A_e(.3) = \begin{bmatrix} .7 & .08178 & .13923 & .1853 \\ .04041 & .7 & .09009 & .11991 \\ .03366 & .04407 & .7 & .099885 \\ .03195 & .04182 & .07122 & .7 \end{bmatrix}$$

and from this matrix, $\lambda_e=.9113433$.

We next find matrix A_m . For that we need to calculate $\delta_i = (1 - \sum_{j \neq i} k_j)(1 - k_i)$. Thus $\delta_1=.33923 \ \delta_2=.32939 \ \delta_3=.35008 \ \delta_4=.36297$, $\delta = (\prod \delta_i)^{1/4}$, and $u_i = .3/\delta \delta_i$. Therefore $u_1=.29482 \ u_2=.28627 \ u_3=.30425 \ u_4=.31544$, and

$$A_m = \begin{bmatrix} .70513 & .080368 & .136826 & .1821103 \\ .038561 & .71373 & .08596 & .114422 \\ .034137 & .044694 & .69575 & .1013 \\ .033595 & .043973 & .074886 & .6845564 \end{bmatrix}$$

which yields $\lambda_m=.91109333$. Thus we have $A_m < A_e$ in this case. It is quite possible that it is true in all cases except when $n=2$, where they are equal.

We next move on to the minimax algorithm. For that, we shall need $m_{12}m_{21}m_{13}m_{31}m_{14}m_{41}, m_{21}m_{12}m_{23}m_{32}m_{24}m_{42}$, etc. This gives us $1.2513 \times 10^{-4}, 9.025422 \times 10^{-5}, 1.99707 \times 10^{-4}, 2.958322 \times 10^{-4}$.

Thus $(9.025422/29.58322)^{1/12} \cdot 3 = .2717$. Letting $u_1=.3 \ u_2=.2717 \ u_3=.3 \ u_4=.3312477$, we get $\lambda=.911063519$, which is already better than A_m .

Continuing with the algorithm, we get the smallest eigenvalue keeping the first and third coordinate fixed at .3. This is $u_1=.3$ $u_2=.275$ $u_3=.3$ $u_4=.327272$

and $\lambda=.9110593859$. Keeping those coordinates fixed and varying the other two leads us to our best matrix

$A*(.292 .275 .308219 .3272727)=$

.708	.0795992	.1355172	.1803684
.0370425	.725	.0825835	.1099175
.034582	.0452774	.6917808	.1026216
.034854	.0456218	.0776945	.67267267

In this case, $\lambda=.911029867$.

Reference

- [1] Barsky, M. (1986) "A Matrix Method For Decision Making and Forecasting", Penn State U., Ogontz Campus, Abington, Pa.
 - [2] Barsky, M. (2019) "The Mathematics of Continuously changing Objects", Princeton, N.J.
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