Updating Strategies and Speed/Accuracy trade-offs in Variable Selection Algorithms for Multivariate Data Analysis

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Speed and Accuracy in Variable Selection <u>OUTLINE</u>

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Speed and Accuracy in Variable Selection LINEAR MODELS WITH MULTIPLE RESPONSES Y = X B + U $T = S_{xx} E = S_{xy} S_{yy}^{-1} S_{yx} H = T - E$ $\operatorname{ccr}_{i}^{2} = \operatorname{Eigval}_{i}(T^{-1}H)$ (i = 1, ..., r) r = rank(H) = min (ncol(X), ncol(Y)) **Comparison Criteria: Multivariate Indices** $\mathbf{CCr}_1^2 = \frac{\lambda_1}{1+\lambda_1}$ $\varsigma^{2} = 1 - \frac{\mathbf{r}}{\sum_{i=1}^{r} \left(-\operatorname{ccr}_{i}^{2} \right)^{2}} = \frac{\mathbf{v}}{\mathbf{r} + \mathbf{v}}$ ($max \operatorname{ccr}_1^2 \Leftrightarrow max \lambda_1 = \operatorname{Eigval}_1 (T^{-1}E)$) (max $\varsigma^2 \Leftrightarrow$ max $v = tr E^{-1}H$) \rightarrow Roy criterion \rightarrow Lawley-Hotelling criterion $\tau^{2} = 1 - \left(\prod_{i=1}^{r} (1 - ccr_{i}^{2})\right)^{1/r} = 1 - \Lambda^{1/r}$ $\xi^2 = \frac{\sum \operatorname{ccr}_i^2}{1 = 1} = \frac{u}{r}$ $\left(\max \tau^2 = \min \Lambda = \frac{\det(W)}{\det(T)}\right)$ (max $\xi^2 \Leftrightarrow$ max $u = tr T^{-1}H$) \rightarrow Wilks criterion \rightarrow Bartlett-Pillai criterion

A LINEAR HYPOTHESIS FRAMEWORK

 $X = A \Psi + U \qquad H0: C \Psi = 0$

→ SELECT COLUMNS OF X IN ORDER TO EXPLAIN H1 PARTICULAR CASES: (i) LINEAR DISCRIMINANT ANALYSIS

 $\mathbf{A} = \begin{bmatrix} \mathbf{1}_{g} \end{bmatrix} \quad \Psi = \begin{bmatrix} \mu_{g} \end{bmatrix} \qquad \mathbf{C} = \begin{bmatrix} 1 & -1 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 1 & 0 & \dots & -1 \end{bmatrix}$

(ii) MULTI-WAY MANOVA/MANCOVA EFFECTS

$$\begin{split} \Omega &= \mathcal{R}(A) \quad \omega = \mathcal{R}(A) \cap \mathcal{M}(C) \quad \mathbf{r} = \dim(\Omega) - \dim(\omega) \\ \operatorname{ccr}_{i}^{2} &= \operatorname{Eigval}_{i}(\mathbf{T}^{-1}\mathbf{H}) \quad \mathbf{T} = \mathsf{X}'(\mathbf{I} - \mathsf{P}_{\omega}) \mathsf{X} \qquad \mathbf{H} = \mathsf{X}'(\mathsf{P}_{\Omega} - \mathsf{P}_{\omega}) \mathsf{X} \end{split}$$

Speed and Accuracy in Variable Selection ALGORITHMS BASED ON SSCP MATRICES

FURNIVAL'S ALGORITHM FOR LINEAR REGRESSION (1971):

min $s_e^2 = s_v^2 - S_{vX} S_{XX}^{-1} S_{Xv}$ $\mathbf{y} = \mathbf{X}' \hat{\boldsymbol{\beta}} + \mathbf{e}$ $\mathbf{A} = \begin{bmatrix} \mathbf{S}_{\mathbf{X}\mathbf{X}} & \mathbf{S}_{\mathbf{X}\mathbf{y}} \\ \mathbf{S}_{\mathbf{X}\mathbf{v}} & \mathbf{s}_{\mathbf{v}}^{2} \end{bmatrix} = \begin{bmatrix} \mathbf{S}_{11} & \mathbf{S}_{12} & \mathbf{S}_{1y} \\ \mathbf{S}_{21} & \mathbf{S}_{22} & \mathbf{S}_{2y} \\ \mathbf{S}_{21} & \mathbf{S}_{22} & \mathbf{S}_{2y} \\ \mathbf{S}_{21} & \mathbf{S}_{22} & \mathbf{S}_{2y}^{2} \end{bmatrix}$ GAUSSIAN **FI TMTNATTON** $\mathbf{X} = [\mathbf{X}_1 \mid \mathbf{X}_2]$ **PIVOTS** $\begin{array}{|c|c|c|c|c|c|c|} & & & -S_{11}^{-1}S_{12} & & -S_{11}^{-1}S_{1y} \\ \hline & -S_{21}S_{11}^{-1} & S_{22} - S_{21}S_{11}^{-1}S_{12} & S_{2y} - S_{21}S_{11}^{-1}S_{1y} \\ \hline & -S_{y1}S_{11}^{-1} & S_{y2} - S_{y1}S_{11}^{-1}S_{12} & \mathbf{s_{y}^{2}} - \mathbf{S_{y1}S_{11}^{-1}S_{1y}} \\ \hline & & \\ \hline & & \\ \end{array} \right)$

Speed and Accuracy in Variable Selection ALGORITHMS BASED ON SSCP MATRICES COMMENTS

(i) ONLY THE RIGHT-LOWER CORNER OF **A** NEEDS TO BE UPDATED AT EACH STEP

1/2 OF THE PIVOTS JUST HAVE TO COMPUTE s²_e

1/4 OF THE PIVOTS UPDATE (2*2) SYMMETRIC SUBMATRICES

ONE SINGLE PIVOT NEEDS TO UPDATE A (P*P) SYMMETRIC MATRIX

 \Rightarrow TOTAL NUMBER OF FLOATING POINT OPERATIONS:

 $\begin{array}{ll} 6(2^{p})-(1/2)p^{2}-(7/2)p-6 & multiplications/divisions \\ \underline{4(2^{p})-(1/2)p^{2}-(5/2)p-4} & additions/subtractions \\ 10(2^{p})-p^{2}-6p-10 & flops \end{array}$

Speed and Accuracy in Variable Selection ALGORITHMS BASED ON SSCP MATRICES COMMENTS

(ii) THE SAME PROCEDURE CAN BE APPLIED MOVING BACKWARDS



 \Rightarrow BRANCH AND BOUND ALGORITHMS (FURNIVAL AND WILSON 1974)

WORST CASE (NO PRUNING) TIME COMPLEXITY

- $6(2^p) + O(p^2)$ multiplications/divisions
- $\underline{4(2^p) + O(p^2)}$ additions/subtractions
- $10(2^p)+O(p^2) \qquad flops$

Speed and Accuracy in Variable Selection ALGORITHMS BASED ON SSCP MATRICES COMMENTS

(iil) AND REMAINS VALID ON APPLIED TO:

- QUADRATIC FORMS OF THE TYPE $v_1' \Phi_{11}^{-1} v_1$
- DETERMINANTS OF THE TYPE det(Φ_{11})
- SUMS AND RATIOS OF THE ABOVE CRITERIA

$$\Phi = \begin{bmatrix} \Phi_{11} & \Phi_{12} \\ \Phi_{21} & \Phi_{22} \end{bmatrix}$$

SYMMETRIC, NON-SINGULAR AND POSITIVE-DEFINITE

WORST CASE TIME COMPLEXITY:

$$v = tr \left(\mathbf{E}^{-1}\mathbf{H}\right) = tr \left[\mathbf{E}^{-1}\left(\sum_{i=1}^{r} \mathbf{h}_{i}\mathbf{h}_{i}'\right)\right] = \sum_{i=1}^{r} \mathbf{h}_{i}' \mathbf{E}^{-1}\mathbf{h}_{i} \qquad (5+5r)(2^{p}) + \mathbf{O}(p^{2}) \quad \text{flops}$$

→ Bartlett-Pillai criterion

 \rightarrow 1 awley-Hotelling criterion

$$u = tr \left(T^{-1}H \right) = tr \left[T^{-1} \left(\sum_{i=1}^{r} h_i h_i' \right) \right] = \sum_{i=1}^{r} h_i' T^{-1} h_i$$
(5+5r) (2^p) + O(p²) flops
 \rightarrow Wilks criterion

 $\Lambda = \det(E) / \det(T) \qquad 12 (2^p) + O(p^2) \quad \text{flops}$

Speed and Accuracy in Variable Selection ALGORITHMS BASED ON SSCP MATRICES L D L' DECOMPOSITIONS OF SYMMETRIC \Leftrightarrow positive-defenite matrices, M_{11} , by **BASIC ALGORITHM GAUSSIAN ELIMINATION** $v_1' \Phi_{11}^{-1} v_1 = \alpha - D_{11}(k+1,K+1)$ IF # $X_1 = K \rightarrow$ $det(\Phi_{11}) = det(M_{11}) = \coprod^{k} D_{ii}$ ERROR ANALYSIS COMPUTED $\hat{\mathbf{L}} \ \hat{\mathbf{D}} \ \hat{\mathbf{L}}' = \mathbf{M}_{11} + \Delta \ \mathbf{M}_{11}$ $\|\Delta \mathbf{M_{11}}\|_{2} \le \gamma_{k} \| |\hat{\mathbf{L}}| \hat{\mathbf{D}} |\hat{\mathbf{L}}'| \|_{2}$ $\gamma_l \leq \frac{l \ u}{1-l \ u}$ $l = \dim(M_{11})$ u: = unit roundoff**AND** $\| \mathbf{D} - \hat{\mathbf{D}} \|_{\mathbf{F}} \le \frac{\| \mathbf{M}_{11} \|_2 \| \mathbf{M}_{11}^{-1} \|_2 \| \Delta \mathbf{M}_{11} \|_{\mathbf{F}}}{1 - \| \mathbf{M}_{11}^{-1} \|_2 \| \Delta \mathbf{M}_{11} \|_2}$ (BARRLUND 1991) $\implies |\mathbf{D}(\mathbf{j}) - \hat{\mathbf{D}}(\mathbf{j})| \leq \frac{k^{3/2} \gamma_k (1 - k \gamma_k)^{-1} \kappa_2 (\mathbf{M}_{11}) \|\mathbf{M}_{11}\|_2}{1 - k (1 - k \gamma_k)^{-1} \kappa_2 (\mathbf{M}_{11})}$ $\kappa_2(M_{11}) = ||M_{11}||_2 ||M_{11}^{-1}||_2$

ALGORITHMS BASED ON SSCP MATRICES

ERROR ANALYSIS

Lawley-Hotelling criterion

$$\begin{split} |v - \hat{v}| &\leq \frac{(p+1)^{3/2} \gamma_{p+1}}{1 - (p+1)\gamma_{p+1}} \sum_{i=1}^{r} \frac{\kappa_2(M_i) \|M_i\|_2}{1 - (p+1)(1 - (p+1)\gamma_{p+1})^{-1} \kappa_2(M_i)} \\ M_i &= \begin{bmatrix} E & h_i \\ h_i' & \alpha_i \end{bmatrix} \quad \text{or} \quad \begin{bmatrix} -E^{-1} & -E^{-1}h_i \\ -h_i'E^{-1} & \alpha_i - h_i'E^{-1}h_i \end{bmatrix} \end{split}$$

Bartlett-Pillai criterion

$$\begin{split} | u - \hat{u} | &\leq \frac{(p+1)^{3/2} \gamma_{p+1}}{1 - (p+1) \gamma_{p+1}} \sum_{i=1}^{r} \frac{\kappa_2(N_i) \|N_i\|_2}{1 - (p+1) (1 - (p+1) \gamma_{p+1})^{-1} \kappa_2(N_i)} \\ N_i &= \begin{bmatrix} T & h_i \\ h_i' & \beta_i \end{bmatrix} \quad \text{or} \quad \begin{bmatrix} -T^{-1} & -T^{-1} h_i \\ -h_i' E^{-1} & \beta_i - h_i' T^{-1} h_i \end{bmatrix} \end{split}$$

ALGORITHMS BASED ON SSCP MATRICES

ERROR ANALYSIS

Wilks criterion

$$\begin{split} |\Lambda - \hat{\Lambda}| &\leq \frac{p^{3/2} \gamma_p}{1 - p \gamma_p} \frac{\kappa_2(M) \kappa_2(N) \|M\|_2 \|N\|_2}{1 - p (1 - p \gamma_p)^{-1} \langle \langle \chi_2(M) + \kappa_2(N) \rangle + \kappa_2(M) \kappa_2(N)} \\ &* \sum_{i=1}^r \left(\frac{1}{Egval_i(M)} + Egval_i(N) \right) + O(u^2) \end{split}$$

 $M = E \text{ or } -E^{-1} \qquad N = T \text{ or } -T^{-1}$

AN ALGORITHM BASED ON THE ORIGINAL DATA

 $X = A \Psi + U \qquad H0: C \Psi = 0$

 $\Omega = \mathcal{R}(A) \qquad \omega = \mathcal{R}(A) \cap \mathcal{M}(C) \qquad r = \dim(\Omega) - \dim(\omega)$

 $\operatorname{ccr}_{i}^{2} = \operatorname{Eigval}_{i}(\mathbf{T}^{-1}\mathbf{H})$ $\mathbf{T} = \mathbf{X}'(\mathbf{I} - \mathbf{P}_{\omega})\mathbf{X}$ $\mathbf{H} = \mathbf{X}'(\mathbf{P}_{\Omega} - \mathbf{P}_{\omega})\mathbf{X}$

KEY INSIGHT:

THE COMPUTATION OF ccr_i² CAN ALWAYS BE BASED ON A GENERALIZED SINGULAR VALUE PROBLEM

WRITING: $H = X_{H}' X_{H}$ $E = X_{E}' X_{E}$ $X_{H} = U_{H} R_{H} Q'$ $X_{E}' = U_{E} R_{E} Q'$ $R_{H} = D_{H/E} R_{E}$ THEN $ccr_{i}^{2} = (D_{H/E}(i,i))^{2} / [1 + (D_{H/E}(i,i))^{2}]$

AN ALGORITHM BASED ON THE ORIGINAL DATA

INITIALIZATION STEP

FIND X_H AND X_E DIRECTLY FROM X, A AND C

FROM THE SVD's

$$\mathbf{A} = \mathbf{U} \Sigma \mathbf{V}' = \mathbf{U}_{\mathbf{S}} \widetilde{\mathbf{U}}_{\mathbf{\Sigma}} \mathbf{V}_{\mathbf{S}} \widetilde{\mathbf{V}}_{\mathbf{S}}'$$

 $\mathbf{C} \mathbf{V}_{s} \Sigma_{s}^{2} \mathbf{V}'_{s} \mathbf{C}' = \mathbf{F} \mathbf{D} \mathbf{F}'$

WE GET

$$X_E = \tilde{U}' X$$

$$X_{H} = D^{-1/2} F' C V_{S} \Sigma_{S}^{-1} U_{S}' X$$

AN ALGORITHM BASED ON THE ORIGINAL DATA

ITERATION STEP

AND

MIGHT NOT BE PARALLEL

 $\mathbf{R}_{\mathbf{E}} \mid \mathbf{U'}_{\mathbf{E}} \mathbf{X}_{\mathbf{E}}(.,\mathbf{k}+1)^{-}$

AN ALGORITHM BASED ON THE ORIGINAL DATA

ITERATION STEP

RESTORING TRIANGULAR STRUCTURE

- HOUSEHOLDER TRANSFORMATIONS ON

 $R_{H} | U'_{H} X_{H}(.,k+1)^{-}$ and $R_{E} | U'_{E} X_{E}(.,k+1)^{-}$

RESTORING PARALLELISM

- PAIGE'S (1986) ELEMENTARY 2*2 ROTATIONS

TIME COMPLEXITY OF EACH ITERATION:O(s*k + r*k + k²)TOTAL TIME COMPLEXITY:O(p² 2P)

FINAL REMARKS

NUMERICAL ACCURACY

IN MOST PRATICAL PROBLEMS THE DATA DOES NOT EXHIBIT A PATTERN OF MULTICORRELATION STRONG ENHOUGH TO MAKE THE STABILITY OF ANY OF THE ALGORITHMS A RELEVANT CONCERN

WHEN SEVERE MULTICORRELATION IS PRESENT NONE OF THE ALGORITHMS CAN GIVE RELIABLE RESULTS

OFTEN STATISTICAL REASONS RECOMMEND THAT MULTICOLINEAR SUBSETS SHOULD BE AVOID, LONG BEFORE NUMERICAL ACCURACY BECAMES AN ISSUE

FINAL REMARKS

COMPUTATIONAL EFFORT

WHEN THE NUMBER OF ORIGINAL VARIABLES IS MODERATE ALL ALGORITHMS ARE FAST ENOUGH SO THAT COMPUTATIONAL EFFORT IS NOT A RELEVANT CONCERN

WHEN THE NUMBER OF ORIGINAL VARIABLES IS LARGE NONE OF THE ALGORITHMS CAN PROVE OPTIMAL RESULTS IN A REASONABLE TIME

WHEN TRUE OPTIMALITY CANNOT BE PROVEN THERE ARE NEVERTHELESS MANY HEURISTIC METHODS THAT ARE ABLE TO QUICKLY IDENTIFY GOOD (OFTEN THE BEST) VARIABLE SUBSETS EVEN IN PROBLEMS WITH A VERY LARGE NUMBER OF ORIGINAL VARIABLES

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