

SVD, PSVD  
software  
issues

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Z. Bujanović,  
K. Veselić

Jacobi SVD

LAPACK style  
software

QR+Businger–  
Golub  
CP

PSVD

Conclusion

# Reliability issues in SVD and PSVD software

## A case study

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# Outline

New Jacobi SVD

LAPACK style software

QR+Businger–Golub CP

Product SVD

Conclusion



## New Jacobi SVD

Why is Jacobi SVD attractive?

How the new Jacobi works

LAPACK style software

QR+Businger–Golub CP

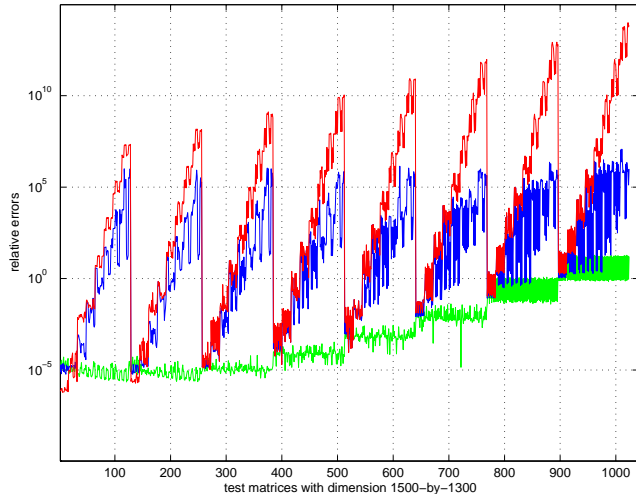
Product SVD

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SVD, PSVD  
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$$\text{Accuracy: } \max_j \frac{|\tilde{\sigma}_j - \sigma_j|}{\sigma_j}$$

relative errors: SGEPVD (green) vs. SGESVD (blue) and SGESDD (red)



Relative error:  $A = BD$ : Jacobi, SGESVD, SGESDD

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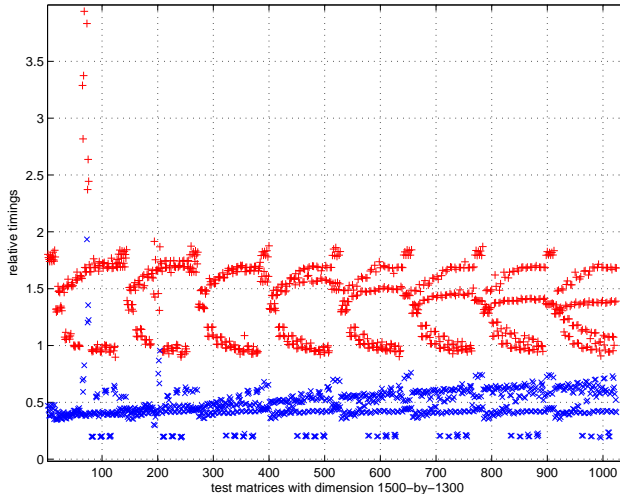
PSVD

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# Improved efficiency

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relative timings: SGEPVD vs. SGESVD (x) and SGESDD (+)



Timings: **Jacobi/SGESVD**, **Jacobi/SGESDD**

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## QRCP as preconditioner

$$AP = Q \begin{pmatrix} R \\ 0 \end{pmatrix}; \quad A = \begin{pmatrix} \blacksquare \\ \blacksquare \\ \blacksquare \end{pmatrix}, \quad R = (\blacksquare)$$

$$\text{SVD}(R) \leftrightarrow \text{SVD}(A), \quad \text{SVD}(R^T) \leftrightarrow \text{SVD}(A)$$

- $P^T A^T A P = R^T R$ 
  - $X = R$ , diagonalize  $X^T X = R^T R$ ;
  - $X \underbrace{J_1 J_2 \cdots J_\infty}_{V_x} = U_x \Sigma \implies R \equiv X = U_x \Sigma V_x^T$
  
- $AA^T = Q \begin{pmatrix} RR^T & 0 \\ 0 & 0 \end{pmatrix} Q^T$ 
  - $X = R^T$ , diagonalize  $X^T X = RR^T$ ;
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## Businger–Golub pivoting

$$AP = Q \begin{pmatrix} R \\ 0 \end{pmatrix}, \quad R = \begin{pmatrix} \blacksquare & \blacksquare & \blacksquare & \blacksquare & \blacksquare & \blacksquare \\ 0 & \blacksquare & \blacksquare & \blacksquare & \blacksquare & \blacksquare \\ 0 & 0 & \color{red}\blacksquare & \bullet & \color{blue}\blacksquare & \color{blue}\blacklozenge \\ 0 & 0 & 0 & \bullet & \color{blue}\blacksquare & \color{blue}\blacklozenge \\ 0 & 0 & 0 & 0 & \color{blue}\blacksquare & \color{blue}\blacklozenge \\ 0 & 0 & 0 & 0 & 0 & \color{blue}\blacklozenge \end{pmatrix}$$

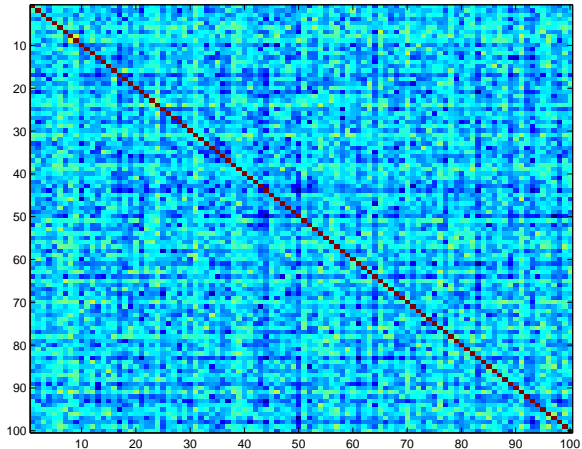
$$\star \quad |R_{ij}| \geq \sqrt{\sum_{k=i}^j |R_{kj}|^2}, \quad \text{for all } 1 \leq i \leq j \leq n.$$

$$|R_{11}| \geq |R_{22}| \geq \cdots \geq |R_{nn}|$$

$\star$  may not be rank revealing



## QRCP as preconditioner



$$AP = Q \begin{pmatrix} R \\ 0 \end{pmatrix}; P^T A^T AP = R^T R$$

# QRCP as preconditioner

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## Jacobi SVD

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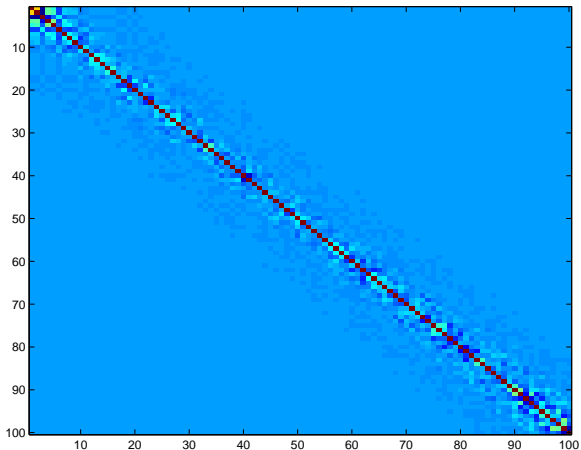
How the new Jacobi  
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$$AP = Q \begin{pmatrix} R \\ 0 \end{pmatrix}; AA^T = Q \begin{pmatrix} RR^T & 0 \\ 0 & 0 \end{pmatrix} Q^T$$

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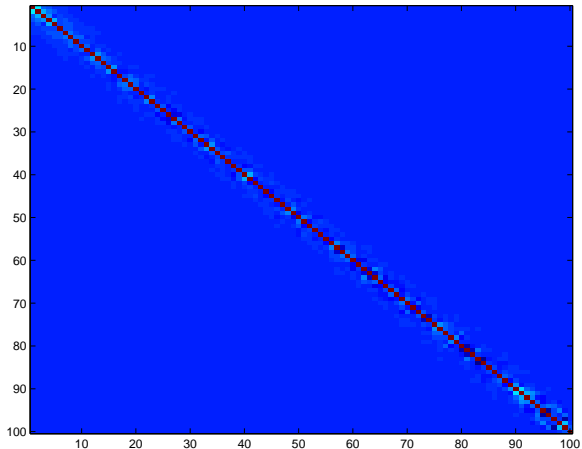
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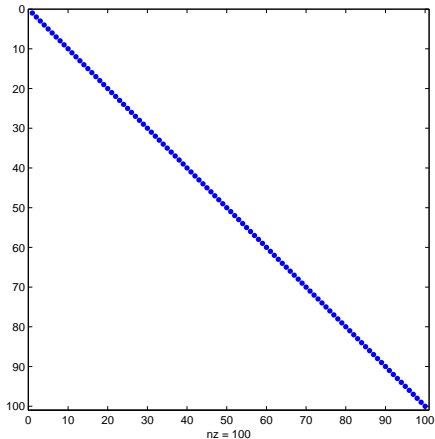
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## QRCP as preconditioner



$$R^T P_1 = Q_1 R_1; R^T R = Q_1 R_1 R_1^T Q_1^T$$

## QR as preconditioner



spy(P1)

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- $(\Pi A)P = Q \begin{pmatrix} R \\ 0 \end{pmatrix}$ ;  $\rho = \text{rank}(R)$  ( $A = D_1 B D_2$ )
  - $R(1 : \rho, 1 : n)^T = Q_1 \begin{pmatrix} R_1 \\ 0 \end{pmatrix}$ ;
  - $X = R_1^T = \begin{pmatrix} \blacksquare & 0 \\ \blacksquare & \blacksquare \end{pmatrix}$ ;  $X^T X - \xi I$  quasi-definite
    - $X_\infty \equiv U_x \Sigma = X \underbrace{\langle J_1 J_2 \cdots J_\infty \rangle}_{V_x}$
    - $V_x = R_1^{-T}(X_\infty)$
- $U = \Pi^T Q \begin{pmatrix} U_x & 0 \\ 0 & I_{m-\rho} \end{pmatrix}$ ;  $V = P Q_1 \begin{pmatrix} V_x & 0 \\ 0 & I_{n-\rho} \end{pmatrix}$
- if  $\rho = n$ ,  $Q_1 V_x = R^{-1} X_\infty$

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New Jacobi SVD

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# Testing the new software

- Our tests are rigorous

- full range,  $\sigma_i \in (\text{small}, \text{BIG})$
- two levels of accuracy
  - $|\tilde{\sigma}_i - \sigma_i| \leq K \cdot \epsilon \cdot \|A\|_2$  for all  $i$
  - $|\tilde{\sigma}_i - \sigma_i| \leq C \cdot \epsilon \cdot \sigma_i$  for all  $i$
- theoretical bounds attained
- no surprises

- All passed.
- Then we started looking for trouble. That is our job.

And we found trouble. We got surprised.

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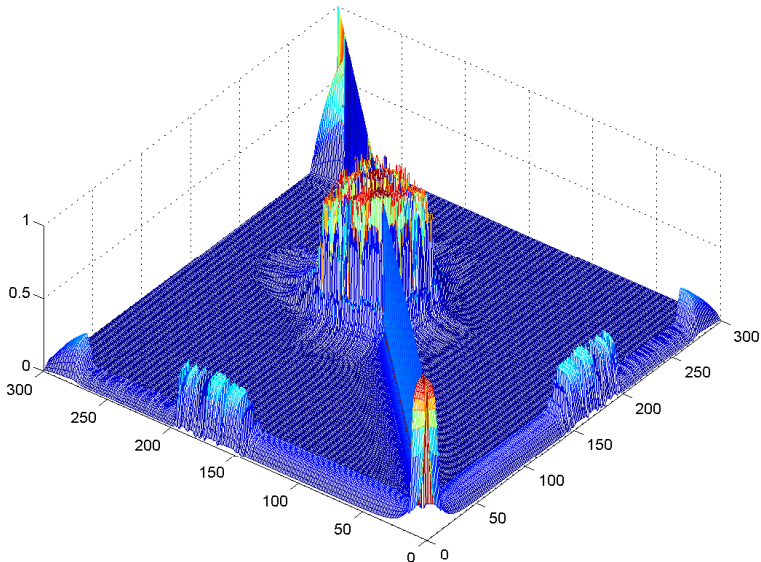
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$\mathfrak{K} = \text{Kahan}(n, c); A = \mathfrak{K} + \mathfrak{K}^T$ .  $RR^T$ . The ill-conditioned  
"tower" is a result of wrong pivot choices.

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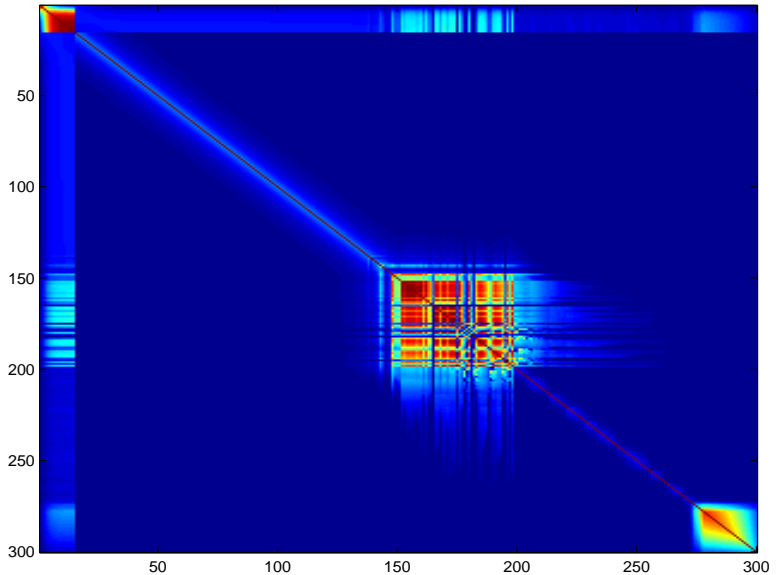
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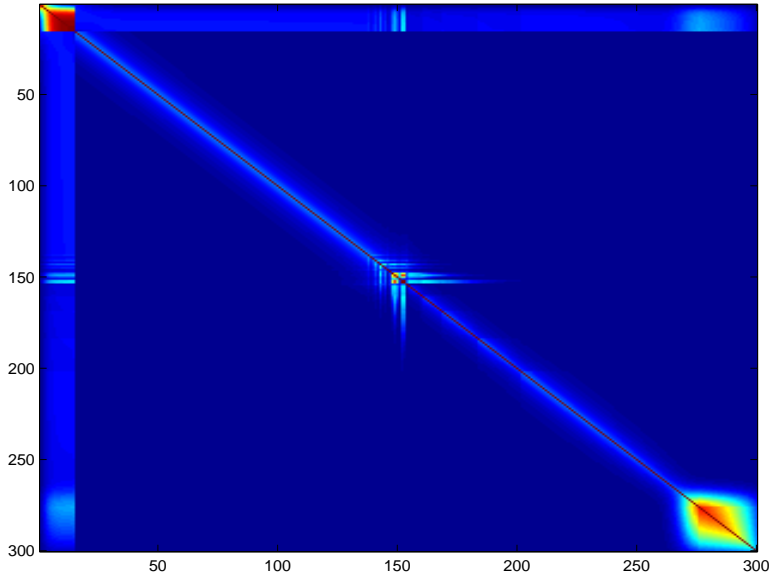
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$$\mathfrak{K} = \text{Kahan}(n, c \cdot (1 + \epsilon)); A = \mathfrak{K} + \mathfrak{K}^T. \text{RR}^T.$$

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★  $|R_{ij}| \geq \sqrt{\sum_{k=i}^j |R_{kj}|^2}$ , for all  $1 \leq i \leq j \leq n$ .

$|R_{11}| \geq |R_{22}| \geq \dots \geq |R_{nn}|$

★ may not be rank revealing but it must be guaranteed by the software (xGEQPF, xGEQP3)

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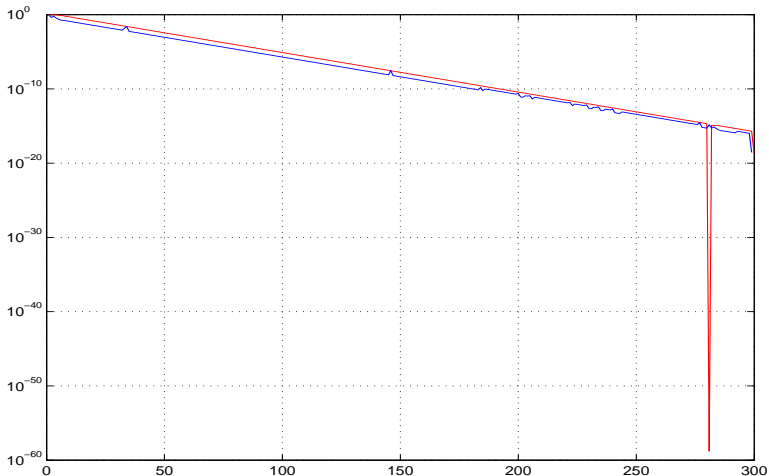
$$AP = Q \begin{pmatrix} R \\ 0 \end{pmatrix}, \quad R = \begin{pmatrix} \blacksquare & \blacksquare & \blacksquare & \blacksquare & \blacksquare & \blacksquare \\ 0 & \blacksquare & \blacksquare & \blacksquare & \blacksquare & \blacksquare \\ 0 & 0 & \color{red}\blacksquare & \bullet & \color{blue}\blacksquare & \color{blue}\blacklozenge \\ 0 & 0 & 0 & \bullet & \color{blue}\blacksquare & \color{blue}\blacklozenge \\ 0 & 0 & 0 & 0 & \color{blue}\blacksquare & \color{blue}\blacklozenge \\ 0 & 0 & 0 & 0 & 0 & \color{blue}\blacklozenge \end{pmatrix}$$

★  $|R_{ij}| \geq \sqrt{\sum_{k=i}^j |R_{kj}|^2}$ , for all  $1 \leq i \leq j \leq n$ .

$|R_{11}| \geq |R_{22}| \geq \dots \geq |R_{nn}|$

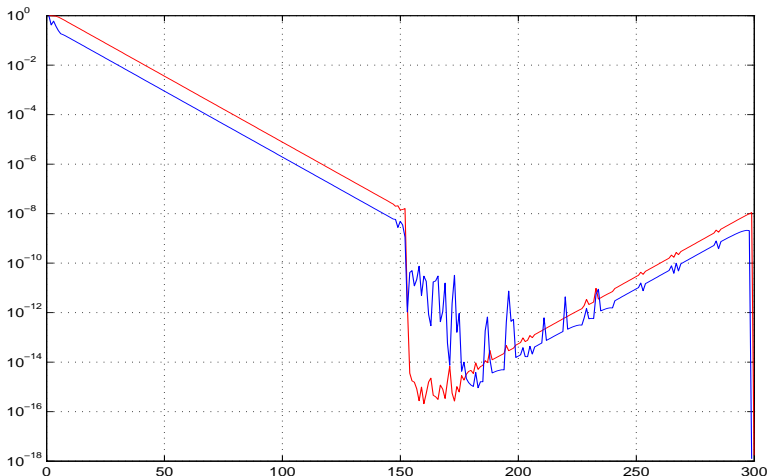
★ may not be rank revealing but it must be guaranteed by the software (xGEQPF, xGEQP3)

## Examples of failure of ★



$$|R_{ii}|, \max_{j \geq i} \sqrt{\sum_{k=i}^j |R_{kj}|^2}$$

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# Examples of failure of ★

Jacobi SVD

LAPACK style  
software

QR+Businger–  
Golub  
CP

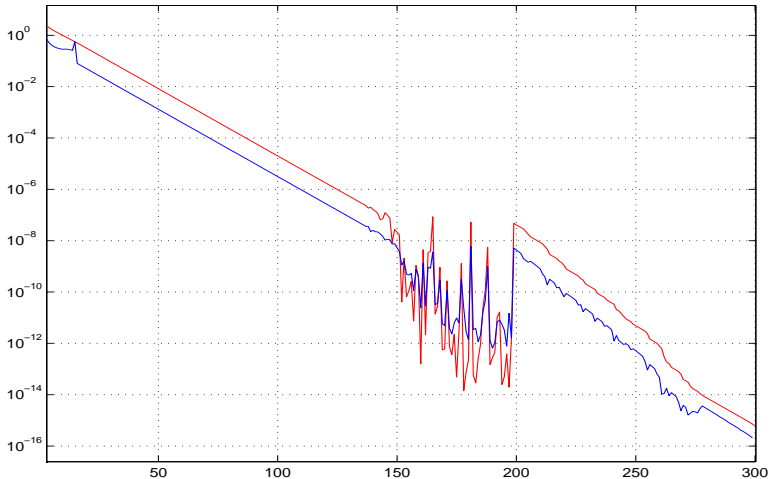
Examples

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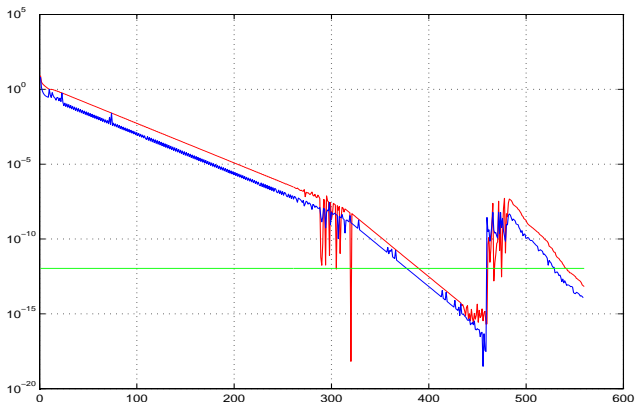


$$|R_{ii}|, \max_{j \geq i} \sqrt{\sum_{k=i}^j |R_{kj}|^2}$$

## Consequences

$$\|Ax - d\|_2 \rightarrow \min; x = A \setminus d$$

Warning: Rank deficient, rank = 304 tol =  
1.0994e-012.



rank(A, 1.0994e-12) returns 466

## Consequences

Any routine based on xQRDC (LINPACK) or xGEQPF, xGEQP3 (LAPACK) can catastrophically fail.

- xGEQPX (TOMS # 782, rank revealing QRF)
- xGELSX and xGELSY in LAPACK ( $\|Ax - b\|_2 \rightarrow \min$ )
- xGGSPV in LAPACK (GSVD of  $(A, B)$ )

$$U^T A Q = \begin{pmatrix} 0 & A_{12} & A_{13} \\ 0 & 0 & A_{23} \\ 0 & 0 & 0 \end{pmatrix}, \quad V^T B Q = \begin{pmatrix} 0 & 0 & B_{13} \\ 0 & 0 & 0 \end{pmatrix}.$$

- ... and many others ... long list. Need a new xGEQP3.



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## L(IN+A)PACK update

Zlatko Drmač,  
Z. Bujanović,  
K. Veselić

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$$A^{(k)}\Pi_k = \begin{pmatrix} \cdot & \cdot & \odot & \cdot & \oplus & \cdot \\ \cdot & \cdot & \odot & \cdot & \oplus & \cdot \\ & & \blacksquare & \circledast & \circledast & \circledast \\ \odot & * & * & * & * & * \\ \odot & * & * & * & * & * \\ \odot & * & * & * & * & * \end{pmatrix}, \quad \mathbf{a}_j^{(k)} = \begin{pmatrix} \oplus \\ \oplus \\ \circledast \\ * \\ * \\ * \end{pmatrix} \equiv \begin{pmatrix} \mathbf{x}_j^{(k)} \\ \mathbf{z}_j^{(k)} \end{pmatrix} \quad (1)$$

$$\mathbf{H}_k \mathbf{z}_k^{(k)} = \begin{pmatrix} R_{kk} \\ \mathbf{0} \end{pmatrix}, \quad \begin{pmatrix} \beta_j^{(k+1)} \\ \mathbf{z}_j^{(k+1)} \end{pmatrix}, \quad \omega_j^{(k)} = \|\mathbf{z}_j^{(k)}\| = \mathbf{H}_k \mathbf{z}_j^{(k)}. \quad (2)$$

$$\|\mathbf{z}_j^{(k+1)}\| \equiv \omega_j^{(k+1)} = \sqrt{(\omega_j^{(k)})^2 - (\beta_j^{(k+1)})^2}, \quad \text{provided that}$$

$$\text{computed} \left( 1 - \left( \frac{\tilde{\beta}_j^{(k+1)}}{\tilde{\omega}_j^{(k)}} \right)^2 \right) \cdot \left( \frac{\tilde{\omega}_j^{(k)}}{\tilde{v}_j} \right)^2 > \text{tol}, \quad \text{tol} \approx 20\epsilon,$$

## L(IN+A)PACK update

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## L(IN+A)PACK update

```
DO 30 J = I+1, N
  IF ( WORK( J ).NE.ZERO ) THEN
    TEMP = ONE - ( ABS( A( I, J ) ) / WORK( J ) )**2
    TEMP = MAX( TEMP, ZERO )
    TEMP2 = ONE + 0.05*TEMP*( WORK( J ) / WORK( N+J ) )**2
    WRITE(*,*) TEMP2
    IF ( TEMP2.EQ.ONE ) THEN
      IF( M-I.GT.0 ) THEN
        WORK( J ) = SNRM2( M-I, A( I+1, J ), 1 )
        WORK( N+J ) = WORK( J )
      ELSE
        WORK( J ) = ZERO
        WORK( N+J ) = ZERO
      END IF
    ELSE
      WORK( J ) = WORK( J )*SQRT( TEMP )
    END IF
  END IF
END IF
30 CONTINUE
```

`g77 -c -O -ffloat-store`

Critical part in the column norm update. (For the full source see <http://www.netlib.org/lapack/single/sgeqpf.f>)

## NEW update

$$A^{(k)} \Pi_k = \begin{pmatrix} \cdot & \cdot & \odot & \cdot & \oplus & \cdot \\ & \cdot & \odot & \cdot & \oplus & \cdot \\ & & \blacksquare & \otimes & \otimes & \otimes \\ & & \odot & * & * & * \\ & & \odot & * & * & * \\ & & \odot & * & * & * \end{pmatrix}, \quad \mathbf{a}_j^{(k)} = \begin{pmatrix} \oplus \\ \oplus \\ \otimes \\ * \\ * \\ * \end{pmatrix} \equiv \begin{pmatrix} \mathbf{x}_j^{(k)} \\ \mathbf{z}_j^{(k)} \end{pmatrix} \quad (3)$$

$$H_k \mathbf{z}_k^{(k)} = \begin{pmatrix} R_{kk} \\ \mathbf{0} \end{pmatrix}, \quad \begin{pmatrix} \beta_j^{(k+1)} \\ \mathbf{z}_j^{(k+1)} \end{pmatrix}, \quad \omega_j^{(k)} = \|\mathbf{z}_j^{(k)}\| = H_k \mathbf{z}_j^{(k)}. \quad (4)$$

$$\|\mathbf{a}_j^{(k)}\| = \alpha_j^{(k)} = \alpha_j^{(0)}; \quad \xi_j^{(k+1)} = \sqrt{(\xi_j^{(k)})^2 + (\beta_j^{(k+1)})^2}$$

$$\|\mathbf{z}_j^{(k+1)}\| \equiv \omega_j^{(k+1)} = \sqrt{(\alpha_j^{(0)})^2 - (\xi_j^{(k+1)})^2}$$

## NEW update

Z.D. and Z. Bujanović, Zagreb 2006

New code xGEQP3Z tested.

- Provably delivers Businger–Golub structured  $R$  (up to roundoff)
- Same efficiency as xGEQP3 (up to  $\pm 3 - 4$  %)
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SVD, PSVD  
software  
issues

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LAPACK style  
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New Jacobi SVD

LAPACK style software

QR+Businger–Golub CP

**Product SVD**

Conclusion



# PSVD

$A = BC^T = U\Sigma V^T$ ,  $B, C$  full column rank

$$BC^T = \begin{pmatrix} \blacksquare & \blacksquare & \blacksquare \\ \blacksquare & \blacksquare & \blacksquare \\ \blacksquare & \blacksquare & \blacksquare \\ \blacksquare & \blacksquare & \blacksquare \end{pmatrix} \begin{pmatrix} \blacksquare & \blacksquare & \blacksquare & \blacksquare \\ \blacksquare & \blacksquare & \blacksquare & \blacksquare \\ \blacksquare & \blacksquare & \blacksquare & \blacksquare \\ \blacksquare & \blacksquare & \blacksquare & \blacksquare \end{pmatrix}$$

- $A=yx$ GEMM( $B,C^T$ ) fastest matrix multiply
- CALL yxGESDD( $A$ ) fastest SVD
- $\begin{pmatrix} 1 & \epsilon \\ -1 & \epsilon \end{pmatrix} \begin{pmatrix} 2 & 2 \\ 2 & 1 \end{pmatrix} = \begin{pmatrix} 2+2\epsilon & 2+\epsilon \\ -2+2\epsilon & -2+\epsilon \end{pmatrix} \approx \begin{pmatrix} 2 & 2 \\ -2 & -2 \end{pmatrix}$
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Z.D. 1998., now improved

$$BC^T = \begin{pmatrix} \color{red}{\square} & \color{red}{\square} & \color{red}{\square} \\ \color{red}{\square} & \color{red}{\square} & \color{red}{\square} \\ \color{red}{\square} & \color{red}{\square} & \color{red}{\square} \\ \color{red}{\square} & \color{red}{\square} & \color{red}{\square} \end{pmatrix} \begin{pmatrix} \color{blue}{\square} & \color{blue}{\square} & \color{blue}{\square} & \color{blue}{\square} \\ \color{cyan}{\square} & \color{cyan}{\square} & \color{cyan}{\square} & \color{cyan}{\square} \\ \color{purple}{\square} & \color{purple}{\square} & \color{purple}{\square} & \color{purple}{\square} \end{pmatrix}$$

- $CP = Q \begin{pmatrix} R \\ 0 \end{pmatrix}$ ;  $BC^T = (BP) \begin{pmatrix} R^T & 0 \end{pmatrix} Q^T$ ;
- $A = (BP)R^T$ ;  $R^T = \begin{pmatrix} \color{darkblue}{\square} & & & \\ \color{yellow}{\square} & \color{blue}{\square} & & \\ \color{yellow}{\square} & \color{yellow}{\square} & \color{cyan}{\square} & \\ & & & \end{pmatrix}$
- $[U, \Sigma, V_1] = \text{SVD}(A)$ ;  $V = Q \begin{pmatrix} V_1 & 0 \\ 0 & I_{n-p} \end{pmatrix}$

## And what about $BPR^T$ ?

$$BPR^T \equiv \begin{pmatrix} \blacksquare & \blacksquare & \blacksquare \\ \blacksquare & \blacksquare & \blacksquare \\ \blacksquare & \blacksquare & \blacksquare \\ \blacksquare & \blacksquare & \blacksquare \end{pmatrix} \begin{pmatrix} \blacksquare & & & \\ \blacksquare & \blacksquare & & \\ \blacksquare & \blacksquare & \blacksquare & \\ \blacksquare & \blacksquare & \blacksquare & \blacksquare \end{pmatrix}$$

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## Backward stability

- $C = Q \begin{pmatrix} R \\ 0 \end{pmatrix};$ 
  - $C + \delta C = \tilde{Q} \begin{pmatrix} \tilde{R} \\ 0 \end{pmatrix};$
  - $\|\delta C(:, i)\| \leq \epsilon \|C(:, i)\|$ , for all columns  $i$
- $A = BR^T;$ 
  - $\tilde{A} = (B + \delta B)\tilde{R}^T,$
  - $\|\delta B(:, i)\| \leq \epsilon \|B(:, i)\|$ , for all columns  $i$
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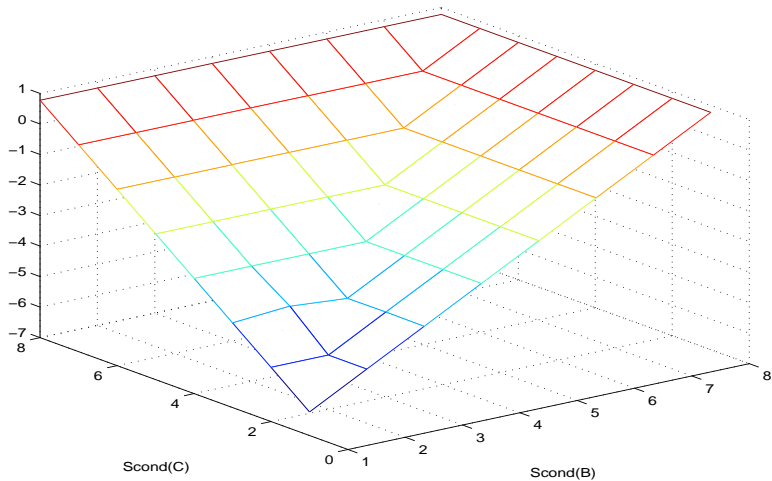
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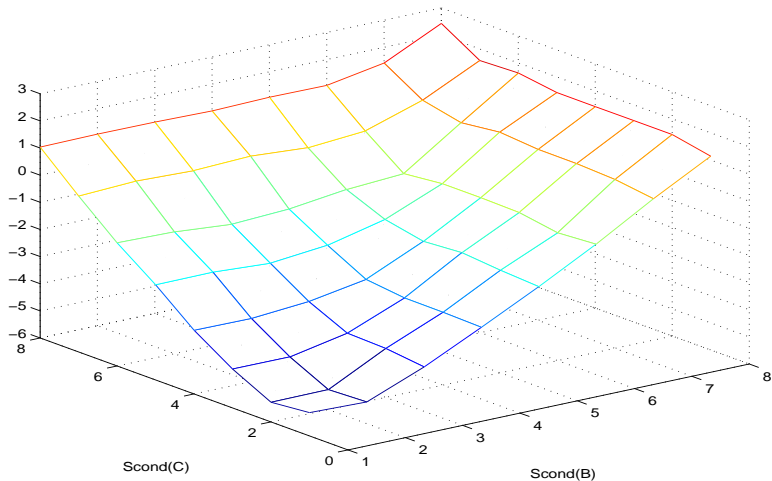
## Theoretical accuracy



theory:

$$\max_i \frac{|\tilde{\sigma}_i - \sigma_i|}{\sigma_i} \leq f(m, p, n) \cdot \epsilon \cdot \max\{\text{scnd}(B), \text{scnd}(C)\}$$

## Measured accuracy



theory: measured  $\max_i \frac{|\tilde{\sigma}_i - \sigma_i|}{\sigma_i}$ ; in  $(0.3, 46) \times$  theory

SVD, PSVD  
software  
issues

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Z. Bujanović,  
K. Veselić

Jacobi SVD

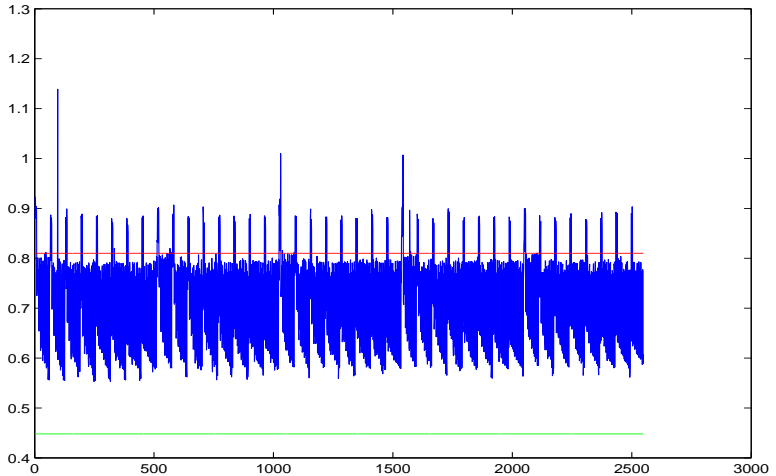
LAPACK style  
software

QR+Businger–  
Golub  
CP

PSVD

Conclusion

# Timings



$400 \times 350 \times 400$ , *PSVD*, *SGESDD*  $\circ$  *SGEMM*,  
*SGESVD*  $\circ$  *SGEMM*

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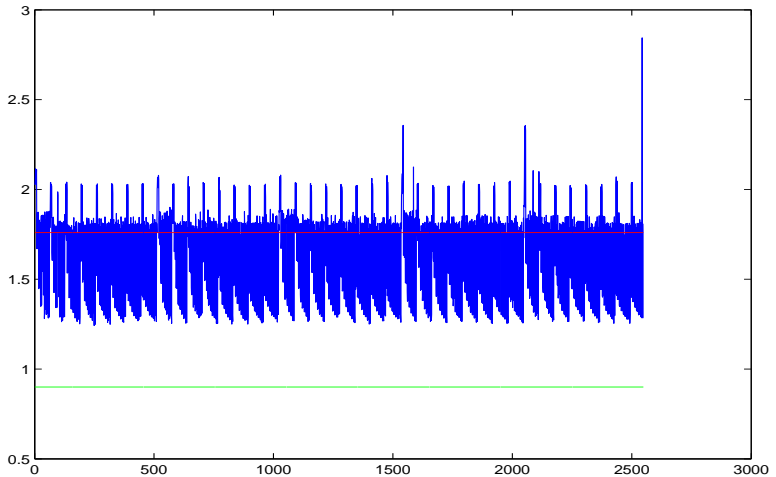
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New Jacobi SVD

LAPACK style software

QR+Businger–Golub CP

Product SVD

**Conclusion**

## Conclusion

- New implementation of Businger–Golub QRCP more reliable than xGEQP3 and equally efficient.  
**Recommended as replacement for xGEQP3.**
- Jacobi SVD code in final stage of testing.
- New Jacobi SVD code as basis for
  - SEVP  $Hx = x\lambda$ , SSVD
  - PSVD,  $HMx = x\lambda$ ,  $|\delta H_{ij}| \leq \epsilon \sqrt{H_{ij}H_{ij}}$
  - QSVD,  $Hx = Mx\lambda$
  - $(H, K)$ –SVD