

**Perturbation Theory for  
Simultaneous Bases of  
Singular Subspaces  
and  
Numerical Applications**

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## Setting the Problem

Let  $A$  and  $\tilde{A}$  be complex  $m \times n$  ( $m \geq n$ ) matrices with partitioned singular value decompositions (SVD):

$$A = \begin{matrix} & U_1 & U_2 & U_3 \end{matrix} \begin{pmatrix} \Sigma_1 & 0 \\ 0 & \Sigma_2 \\ 0 & 0 \end{pmatrix} \begin{matrix} V_1 & V_2 \end{matrix}^*,$$

$$\tilde{A} = \begin{matrix} & \tilde{U}_1 & \tilde{U}_2 & \tilde{U}_3 \end{matrix} \begin{pmatrix} \tilde{\Sigma}_1 & 0 \\ 0 & \tilde{\Sigma}_2 \\ 0 & 0 \end{pmatrix} \begin{matrix} \tilde{V}_1 & \tilde{V}_2 \end{matrix}^*$$

- where  $\Sigma_1$  and  $\tilde{\Sigma}_1$  are  $k \times k$  matrices,
- $( )^*$  denotes the conjugate transpose matrix,
- No special order is assumed on the singular values.

**How to bound the variation of left/right singular vectors ( $U_1, \tilde{U}_1$  and  $V_1, \tilde{V}_1$ ) using the difference  $A - \tilde{A}$**

## Well-known answer: $\sin \Theta$ theorems for subspaces

Let the following *residuals and gaps* be defined:

$$R = A\tilde{V}_1 - \tilde{U}_1\tilde{\Sigma}_1 = (A - \tilde{A})\tilde{V}_1$$

$$S = A^*\tilde{U}_1 - \tilde{V}_1\tilde{\Sigma}_1 = (A^* - \tilde{A}^*)\tilde{U}_1.$$

$$\text{gap} = \min_{\tilde{\mu} \in \sigma(\tilde{\Sigma}_1), \mu \in \sigma_{\text{ext}}(\Sigma_2)} |\tilde{\mu} - \mu|$$

where, for any matrix  $B$ ,  $\sigma(B)$  denotes the set of its singular values and  $\sigma_{\text{ext}}(\Sigma_2) \equiv \sigma(\Sigma_2) \cup \{0\}$  if  $m > n$  and  $\sigma_{\text{ext}}(\Sigma_2) \equiv \sigma(\Sigma_2)$  if  $m = n$ .

**Theorem in Frobenius norm** (Wedin, 1972):

If  $\text{gap} > 0$  then

$$\begin{aligned} & \sqrt{\|\sin \Theta(U_1, \tilde{U}_1)\|_F^2 + \|\sin \Theta(V_1, \tilde{V}_1)\|_F^2} \leq \\ & \leq \frac{\sqrt{\|R\|_F^2 + \|S\|_F^2}}{\text{gap}} \leq \frac{\sqrt{2}\|A - \tilde{A}\|_F}{\text{gap}} \end{aligned}$$

$\sin \Theta(V_1, \tilde{V}_1)$  are the singular values of  $\tilde{V}_2^* V_1$ .

## A drawback of $\sin \Theta$ theorems

When  $m > n$  the left singular subspaces may be much more sensible than the right singular subspaces: the zero appearing in  $\sigma_{\text{ext}}(\Sigma_2) \equiv \sigma(\Sigma_2) \cup \{0\}$  only affects to left singular subspaces.

$$\text{gap} = \min \left\{ \min_{\tilde{\mu} \in \sigma(\tilde{\Sigma}_1), \mu \in \sigma(\Sigma_2)} |\tilde{\mu} - \mu|, \sigma_{\min}(\tilde{\Sigma}_1) \right\}$$

**EXAMPLE:**

$$A = \begin{pmatrix} \epsilon & 0 \\ 0 & 1 \\ 0 & 0 \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} \epsilon & 0 \\ 0 & 1 \end{pmatrix}$$

$$\tilde{A} = \begin{pmatrix} \epsilon & 0 \\ 0 & 1 \\ \epsilon & 0 \end{pmatrix} = \begin{pmatrix} \frac{1}{\sqrt{2}} & 0 \\ 0 & 1 \\ \frac{1}{\sqrt{2}} & 0 \end{pmatrix} \begin{pmatrix} \sqrt{2}\epsilon & 0 \\ 0 & 1 \end{pmatrix}$$

**$\sin \Theta$  bound:**

$$\sqrt{\|\sin \Theta(U_1, \tilde{U}_1)\|_F^2 + \|\sin \Theta(V_1, \tilde{V}_1)\|_F^2} \leq \frac{\sqrt{2}\epsilon}{\sqrt{2}\epsilon} = 1$$

## Solving the drawback

$$A = \begin{pmatrix} \epsilon & 0 \\ 0 & 1 \\ 0 & 0 \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} \epsilon & 0 \\ 0 & 1 \end{pmatrix}$$

$$\tilde{A} = \begin{pmatrix} \epsilon & 0 \\ 0 & 1 \\ \epsilon & 0 \end{pmatrix} = \begin{pmatrix} \frac{1}{\sqrt{2}} & 0 \\ 0 & 1 \\ \frac{1}{\sqrt{2}} & 0 \end{pmatrix} \begin{pmatrix} \sqrt{2}\epsilon & 0 \\ 0 & 1 \end{pmatrix}$$

**FIRST WAY:** Use  $\sin \Theta$  theorem on  $U_2$  and  $V_2$ ,

$$\sqrt{\|\sin \Theta(U_2, \tilde{U}_2)\|_F^2 + \|\sin \Theta(V_2, \tilde{V}_2)\|_F^2} \leq \frac{\sqrt{2}\epsilon}{1 - \epsilon}$$

## Relative $\sin \Theta$ theorems

Results for multiplicative perturbations are the most relevant in high relative accuracy algorithms for SVD.

These have been developed by several authors (Eisenstat, Ipsen, Li,...).

**Theorem** (R.C. Li 1999) *Let  $A$  and  $\tilde{A} = D_1^* A D_2$  where  $D_1, D_2$  are nonsingular matrices. Define the relative gap*

$$\text{relgap} = \min_{\mu \in \sigma(\Sigma_1), \tilde{\mu} \in \sigma_{\text{ext}}(\tilde{\Sigma}_2)} \frac{|\mu - \tilde{\mu}|}{\tilde{\mu}}$$

*If  $\text{relgap} > 0$  then*

$$\begin{aligned} & \sqrt{\|\sin \Theta(U_1, \tilde{U}_1)\|_F^2 + \|\sin \Theta(V_1, \tilde{V}_1)\|_F^2} \leq \\ & \sqrt{\|(I - D_1^*)U_1\|_F^2 + \|(I - D_2^*)V_1\|_F^2} \\ & + \frac{\sqrt{\|(D_1^* - D_1^{-1})U_1\|_F^2 + \|(D_2^* - D_2^{-1})V_1\|_F^2}}{\text{relgap}} \end{aligned}$$

## Are these results enough?

A simple example:

$$A = \begin{pmatrix} \epsilon & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{pmatrix} \quad \text{and} \quad \tilde{A} = \begin{pmatrix} -\epsilon & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{pmatrix}$$

where  $\epsilon > 0$  is small enough.  $\tilde{A}$  is a small additive normwise perturbation of  $A$ , but not small in a multiplicative sense. So **Wedin's theorem** applies to the singular subspaces associated with  $\epsilon$ :

$$\|R\|_F = \|S\|_F = 2\epsilon \quad \text{and} \quad \text{gap} = 1 - \epsilon$$

Thus

$$\sqrt{\|\sin \Theta(U_1, \tilde{U}_1)\|_F^2 + \|\sin \Theta(V_1, \tilde{V}_1)\|_F^2} \leq \frac{2\sqrt{2}\epsilon}{1 - \epsilon}$$

**This is right!!**, because the left/right singular subspaces of  $A$  and  $\tilde{A}$  are equal.

## Simple example (continued)

$$A = \begin{pmatrix} \epsilon & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{pmatrix} \quad \text{and} \quad \tilde{A} = \begin{pmatrix} -\epsilon & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{pmatrix}$$

But the **SIMULTANEOUS** left and right singular vectors of  $A$ ,  $\tilde{A}$  corresponding to  $\epsilon$  are

$$u_1 = (1, 0, 0)^T \quad \text{and} \quad v_1 = (1, 0, 0)^T$$

$$\tilde{u}_1 = (1, 0, 0)^T \quad \text{and} \quad \tilde{v}_1 = (-1, 0, 0)^T$$

and, **NO MATTER THE SIZE OF  $\epsilon$  THE PAIR  $(u_1, v_1)$  IS VERY FAR FROM  $(\tilde{u}_1, \tilde{v}_1)$ .**

Huge differences between  $u_1^T v_1$  ( $u_1 v_1^T$ ) and  $\tilde{u}_1^T \tilde{v}_1$  ( $\tilde{u}_1 \tilde{v}_1^T$ ).

This fact happens for any choice of simultaneous left/right singular vectors. **The  $\sin \Theta$  theorems do not give any information about this fact.**



## How to define the magnitude to be bounded

Notice that if

$$A = \begin{matrix} & U_1 & U_2 & U_3 \end{matrix} \begin{pmatrix} \Sigma_1 & 0 \\ 0 & \Sigma_2 \\ 0 & 0 \end{pmatrix} \begin{matrix} V_1 & V_2 & * \end{matrix},$$

$$A = \begin{matrix} \hat{U}_1 & \hat{U}_2 & \hat{U}_3 \end{matrix} \begin{pmatrix} \Sigma_1 & 0 \\ 0 & \Sigma_2 \\ 0 & 0 \end{pmatrix} \begin{matrix} \hat{V}_1 & \hat{V}_2 & * \end{matrix}$$

are TWO SVD's OF THE SAME MATRIX  $A$ ,  $\Sigma_1$  is **not singular**, and  $\sigma(\Sigma_1) \cap \sigma(\Sigma_2) = \phi$  then there exists a unitary  $k \times k$  matrix  $Q$  such that

$$\hat{U}_1 = U_1 Q \quad \text{and} \quad \hat{V}_1 = V_1 Q.$$

This leads us to bound the following quantity

$$\min_{W \text{ unitary}} \sqrt{\|U_1 W - \tilde{U}_1\|_F^2 + \|V_1 W - \tilde{V}_1\|_F^2}$$

## Absolute perturbation theorem for bases

**Theorem** Define the “new” gap

$$\text{gap}_b = \min \left\{ \text{gap}, \sigma_{\min}(\tilde{\Sigma}_1) + \sigma_{\min}(\Sigma_1) \right\}$$

where  $\sigma_{\min}(\Sigma_1)$  and  $\sigma_{\min}(\tilde{\Sigma}_1)$  denote the minimum of the singular values of  $\Sigma_1$  and  $\tilde{\Sigma}_1$ . If  $\text{gap}_b > 0$  then

$$\begin{aligned} \min_{W \text{ unitary}} \sqrt{\|U_1 W - \tilde{U}_1\|_F^2 + \|V_1 W - \tilde{V}_1\|_F^2} &\leq \\ &\leq \sqrt{2} \frac{\sqrt{\|R\|_F^2 + \|S\|_F^2}}{\text{gap}_b} \leq \frac{2\|A - \tilde{A}\|_F}{\text{gap}_b} \end{aligned}$$

Moreover, the left hand side is minimized for

$W = Y Z^*$ , where  $Y S Z^*$  is any SVD of

$U_1^* \tilde{U}_1 + V_1^* \tilde{V}_1$ , and the equality can be attained.

**Remember that:**

$$\text{gap} = \min_{\tilde{\mu} \in \sigma(\tilde{\Sigma}_1), \mu \in \sigma_{\text{ext}}(\Sigma_2)} |\tilde{\mu} - \mu|$$

## Remarks

$$\text{gap}_b = \min \left\{ \text{gap}, \sigma_{\min}(\tilde{\Sigma}_1) + \sigma_{\min}(\Sigma_1) \right\}$$

$$\text{gap} = \min_{\tilde{\mu} \in \sigma(\tilde{\Sigma}_1), \mu \in \sigma_{\text{ext}}(\Sigma_2)} |\tilde{\mu} - \mu|$$

- If  $m > n$  then  $\text{gap}_b = \text{gap}$ . The relevant changes appear when  $m = n$ .
- If  $m = n$  then it may happen

$$\text{gap}_b \ll \text{gap}$$

when  $\Sigma_1$  contains the smallest singular values and these are “very small”.

**BAD NEWS!!:** simultaneous bases can be much more sensitive than singular subspaces for the smallest singular values.

## Simple example revisited

$$A = \begin{pmatrix} \epsilon & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{pmatrix} \quad \text{and} \quad \tilde{A} = \begin{pmatrix} -\epsilon & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{pmatrix}$$

$$\text{gap}_b = 2\epsilon$$

This implies

$$\begin{aligned} 2 &= \min_{W \text{ unitary}} \sqrt{\|U_1 W - \tilde{U}_1\|_F^2 + \|V_1 W - \tilde{V}_1\|_F^2} \leq \\ &\leq \sqrt{2} \frac{\sqrt{\|R\|_F^2 + \|S\|_F^2}}{\text{gap}_b} = 2 \end{aligned}$$

## Relative perturbation theorem for bases

**Theorem** *Let  $A$  and  $\tilde{A} = D_1^* A D_2$  where  $D_1$  and  $D_2$  are nonsingular matrices. Define the “new” relative gap*

$$\text{relgap}_b = \min \left\{ \text{relgap}, \left( \min_{\mu \in \sigma(\Sigma_1), \tilde{\mu} \in \sigma(\tilde{\Sigma}_1)} \frac{\mu + \tilde{\mu}}{\tilde{\mu}} \right) \right\}.$$

*If  $\text{relgap}_b > 0$  then*

$$\begin{aligned} \min_{W \text{ unitary}} & \sqrt{\|U_1 W - \tilde{U}_1\|_F^2 + \|V_1 W - \tilde{V}_1\|_F^2} \leq \\ & \sqrt{2} \sqrt{\|(I - D_1^*)U_1\|_F^2 + \|(I - D_2^*)V_1\|_F^2} \\ & + \frac{\sqrt{\|(D_1^* - D_1^{-1})U_1\|_F^2 + \|(D_2^* - D_2^{-1})V_1\|_F^2}}{\text{relgap}_b}. \end{aligned}$$

*Moreover the left hand sides is minimized for  $W = Y Z^*$ , where  $Y S Z^*$  is any SVD of  $U_1^* \tilde{U}_1 + V_1^* \tilde{V}_1$ .*

## Remarks and conclusions

$$\text{relgap}_b = \min \left\{ \text{relgap}, \min_{\mu \in \sigma(\Sigma_1), \tilde{\mu} \in \sigma(\tilde{\Sigma}_1)} \frac{\mu + \tilde{\mu}}{\tilde{\mu}} \right\}.$$

$$\frac{\mu + \tilde{\mu}}{\tilde{\mu}} \geq 1$$

## GOOD NEWS!!

**for small multiplicative perturbations** the sensitivity of simultaneous bases is similar to that of singular subspaces.

Important changes with respect to singular subspaces sensitivity results for arbitrary additive perturbations, **BUT NOT FOR MULTIPLICATIVE PERTURBATIONS.**

## Sketch of the proofs

**STEP 1:** Let us define

$$X_1 = \frac{1}{\sqrt{2}} \begin{pmatrix} U_1 \\ V_1 \end{pmatrix} \quad \text{and} \quad \tilde{X}_1 = \frac{1}{\sqrt{2}} \begin{pmatrix} \tilde{U}_1 \\ \tilde{V}_1 \end{pmatrix},$$

$$\begin{aligned} & \min_{W \text{ unitary}} \sqrt{\|U_1 W - \tilde{U}_1\|_F^2 + \|V_1 W - \tilde{V}_1\|_F^2} = \\ & = \sqrt{2} \min_{W \text{ unitary}} \|X_1 W - \tilde{X}_1\|_F \\ & = \sqrt{2} \sqrt{\|I - \cos \Theta(X_1, \tilde{X}_1)\|_F^2 + \|\sin \Theta(X_1, \tilde{X}_1)\|_F^2} \\ & \leq 2 \|\sin \Theta(X_1, \tilde{X}_1)\|_F. \end{aligned}$$

**STEP 2:** Apply absolute/relative  $\sin \Theta$  theorems to bound the sines of the canonical angles between

$$\text{col}(X_1) \quad \text{and} \quad \text{col}(\tilde{X}_1)$$

which are invariant subspaces of the Jordan-Wielandt matrices

$$\begin{pmatrix} 0 & A \\ A^* & 0 \end{pmatrix} \quad \text{and} \quad \begin{pmatrix} 0 & \tilde{A} \\ \tilde{A}^* & 0 \end{pmatrix}$$

## Numerical Experiments (I)

- MATLAB 5.3
- $A = S * Q$  real  $8 \times 8$  matrix.
- $Q$  random finite precision orthogonal  $8 \times 8$  matrix.
- $S = \text{diag}([\text{ones}(1, 6), 10^{-j}, 10^{-j}])$ .
- $j = 1 : 30$ .
- 20 matrices for each  $j$ .
- Well-determined TWO-dim. singular subspaces associated with the two smallest singular values.
- Compute  $\tilde{U}\tilde{\Sigma}\tilde{V}^T$  with
  1. MATLAB:  $A + E = \tilde{U}\tilde{\Sigma}\tilde{V}^T$ .
  2. Right-Jacobi:  $A(I + F) = \tilde{U}\tilde{\Sigma}\tilde{V}^T$ .
- Plot

$$\min_{W_{\text{unitary}}} \sqrt{\|U_1 W - \tilde{U}_1\|_F^2 + \|V_1 W - \tilde{V}_1\|_F^2} \quad \text{vs. } j$$

for singular vectors associated with the smallest singular values.



## Numerical Experiments (II)

- Compare REAL and COMPLEX matrices which do not deserve high relative accuracy. Thus only MATLAB is used.
- $R = U * S * V'$  REAL  $50 \times 50$  matrix.
- $C = U_c * S * V_c'$  COMPLEX  $50 \times 50$  matrix.
- $S = \text{diag}([3 * \text{rand}(1, 49) + 1, 10^{-j}])$ .
- $U, V$  random finite precision REAL orthogonal.
- $U_c, V_c$  random finite precision COMPLEX unitary.
- $j = 1 : 0.5 : 25$ .
- 4 real matrices and 4 complex matrices for each  $j$ .
- Well-determined ONE-dim. singular subspaces associated with the least singular value.
- Plot

$$\min_{W_{\text{unitary}}} \sqrt{\|U_1 W - \tilde{U}_1\|_F^2 + \|V_1 W - \tilde{V}_1\|_F^2} \quad \text{vs.} \quad j$$

for singular vectors associated with the least singular value in REAL and COMPLEX case.

## Absolute perturbation theorem in real case

**Theorem** Let  $A$  and  $\tilde{A}$  be REAL and  $\boxed{\mathcal{M} = \mathcal{N}}$ .

Define

$$\sigma(\Sigma_1) = \{\sigma_1 \geq \dots \geq \sigma_k\}$$

$$\text{Rgap}_b = \min \left\{ \min_{\lambda \in \sigma(\Sigma_1), \mu \in \sigma(\Sigma_2)} |\lambda - \mu|, \sigma_k + \sigma_{k-1} \right\}$$

IF

$$\|A - \tilde{A}\|_2 < \frac{1}{2} \min \left\{ \min_{\lambda \in \sigma(\Sigma_1), \mu \in \sigma(\Sigma_2)} |\lambda - \mu|, 2\sigma_k \right\}$$

THEN

$$\begin{aligned} \min_{\text{Worthogonal}} \sqrt{\|U_1 W - \tilde{U}_1\|_F^2 + \|V_1 W - \tilde{V}_1\|_F^2} &\leq \\ &\leq -\frac{\|A - \tilde{A}\|_F}{\|A - \tilde{A}\|_2} \ln \left( 1 - \frac{2\|A - \tilde{A}\|_2}{\text{Rgap}_b} \right) \\ &= \frac{2\|A - \tilde{A}\|_F}{\text{Rgap}_b} + O(\|A - \tilde{A}\|_2^2) \end{aligned}$$

## One-dimensional real case

Moreover, if  $\Sigma_1$  is  $1 \times 1$  then

$$\text{Rgap}_b = \min_{\mu \in \sigma(\Sigma_2)} |\Sigma_1 - \mu|$$

and

$$\begin{aligned} \min_{w \in \{-1, 1\}} \sqrt{\|U_1 w - \tilde{U}_1\|_2^2 + \|V_1 w - \tilde{V}_1\|_2^2} &\leq \\ &\leq -\ln \left( 1 - \frac{2\|A - \tilde{A}\|_2}{\text{Rgap}_b} \right) \end{aligned}$$

### Remarks:

- For numerical algorithms only the one dimensional case is important. If  $k > 1$

$$2\sigma_k \approx \sigma_k + \sigma_{k-1}$$

if  $\Sigma_1$  is a “cluster” of singular values.

- The experiments show that the restriction on the size of the perturbation cannot be removed.
- Similar to perturbations results for the unitary polar factor (Kenney, Laub, Barrlund, Mathias, Li...).

## Ideas of the proof

1. Derivatives of orthogonal projectors on invariant subspaces of Jordan-Wielandt matrices are used.
2. For the one-dimensional case: Consider the Hermitian matrices  $B + tF$ ,  $t$  real parameter, and let  $x_1(t), \dots, x_n(t)$  be their orthonormal basis of eigenvectors.

$$x_k(t) = x_k + \sum_{i \neq k}^n \frac{x_i^* F x_k}{\lambda_k - \lambda_i} x_i + O(t^2)$$

### 3. Fundamental Fact:

$$[u_1^*, -v_1^*] \begin{bmatrix} 0 & E \\ E^* & 0 \end{bmatrix} \begin{bmatrix} u_1 \\ v_1 \end{bmatrix} \equiv 0$$

IN THE REAL CASE, BUT NOT IN THE COMPLEX CASE.

## and more...

### Other results have been obtained:

- Bounds in arbitrary unitarily invariant norms in the absolute setting.
- Bounds with other relgaps in the relative setting.
- There are also changes in the case  $m > n$ .

## Future work

- Relative results for ADDITIVE perturbations.
- Relative results for arbitrary unitarily invariant norms.