Title

fullsvd( ) — Full singular value decomposition

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Description

fullsvd(A, U, s, Vt) calculates the singular value decomposition of $m \times n$ matrix A, returning the result in U, s, and Vt. Singular values in s are sorted from largest to smallest.

fullsdiag(s, k) converts column vector s returned by fullsvd() into matrix S. In all cases, the appropriate call for this function is

S = fullsdiag(s, rows(A)-cols(A))

_fullsvd(A, U, s, Vt) does the same as fullsvd(), except that, in the process, it destroys A. Use of _fullsvd() in place of fullsvd() conserves memory.

_svd_la() is the interface to the LAPACK SVD routines and is used in the implementation of the previous functions. There is no reason you should want to use it. _svd_la() is similar to _fullsvd(). It differs in that it returns a real scalar equal to 1 if the numerical routines fail to converge, and it returns 0 otherwise. The previous SVD routines set s to contain missing values in this unlikely case.

Syntax

void	fullsvd(*numeric matrix A*, *U*, *s*, *Vt*)
numeric matrix	fullsdiag(*numeric colvector s*, *real scalar k*)
void	_fullsvd(*numeric matrix A*, *U*, *s*, *Vt*)
real scalar	_svd_la(*numeric matrix A*, *U*, *s*, *Vt*)

Remarks and examples

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Remarks are presented under the following headings:

Introduction
Relationship between the full and thin SVDs
The contents of s
Possibility of convergence problems

Documented here is the full SVD, appropriate in all cases, but of interest mainly when A: $m \times n$, $m < n$. There is a thin SVD that conserves memory when $m \geq n$; see [M-5] **svd()**. The relationship between the two is discussed in *Relationship between the full and thin SVDs* below.

Introduction

The SVD is used to compute accurate solutions to linear systems and least-squares problems, to compute the 2-norm, and to determine the numerical rank of a matrix.

The singular value decomposition (SVD) of A: $m \times n$ is given by

$$A = USV'$$

where

U:	$m \times m$ and orthogonal (unitary)
S:	$m \times n$ and diagonal
V:	$n \times n$ and orthogonal (unitary)

When A is complex, the transpose operator $'$ is understood to mean the conjugate transpose operator.

Diagonal matrix S contains the singular values and those singular values are real even when A is complex. It is usual (but not required) that S is arranged so that the largest singular value appears first, then the next largest, and so on. The SVD routines documented here do this.

The full SVD routines return U and $Vt = V'$. S is returned as a column vector s, and S can be obtained by

```
S = fullsdiag(s, rows(A)-cols(A))
```

so we will write the SVD as

```
A = U * fullsdiag(s, rows(A)-cols(A)) * Vt
```

Function `fullsvd(A, U, s, Vt)` returns the U, s, and Vt corresponding to A.

Relationship between the full and thin SVDs

A popular variant of the SVD is known as the thin SVD and is suitable for use when $m \geq n$. Both SVDs have the same formula,

$$A = USV'$$

but U and S have reduced dimensions in the thin version:

Matrix	Full SVD	Thin SVD
U:	$m \times m$	$m \times n$
S:	$m \times n$	$n \times n$
V:	$n \times n$	$n \times n$

When $m = n$, the two variants are identical.

The thin SVD is of use when $m > n$, because then only the first n diagonal elements of S are nonzero, and therefore only the first n columns of U are relevant in $A = USV'$. There are considerable memory savings to be had in calculating the thin SVD when $m \gg n$.

As a result, many people call the thin SVD the SVD and ignore the full SVD altogether. If the matrices you deal with have $m \geq n$, you will want to do the same. To obtain the thin SVD, see [M-5] **svd()**.

Regardless of the dimension of your matrix, you may wish to obtain only the singular values. In this case, see `svdsv()` documented in [M-5] **svd()**. That function is appropriate in all cases.

The contents of s

Given A: $m \times n$, the singular values are returned in s: $\min(m,n) \times 1$.

Let's consider the $m = n$ case first. A is $m \times m$ and the m singular values are returned in s, an $m \times 1$ column vector. If A were 3×3, perhaps we would get back

```
: s
              1
      +---------+
    1 |  13.47  |
    2 |    5.8  |
    3 |   2.63  |
      +---------+
```

If we needed it, we could obtain S from s simply by creating a diagonal matrix from s

```
: S = diag(s)

: S
[symmetric]
              1       2       3
      +-------------------------+
    1 |  13.47                  |
    2 |      0     5.8          |
    3 |      0       0    2.63  |
      +-------------------------+
```

although the official way we are supposed to do this is

```
: S = fullsdiag(s, rows(A)-cols(A))
```

and that will return the same result.

Now let's consider $m < n$. Let's pretend that A is 3×4. The singular values will be returned in 3×1 vector s. For instance, s might still contain

```
: s
              1
      +---------+
    1 |  13.47  |
    2 |    5.8  |
    3 |   2.63  |
      +---------+
```

The S matrix here needs to be 3×4, and `fullsdiag()` will form it:

```
: fullsdiag(s, rows(A)-cols(A))
              1       2       3       4
      +---------------------------------+
    1 |  13.47       0       0       0  |
    2 |      0     5.8       0       0  |
    3 |      0       0    2.63       0  |
      +---------------------------------+
```

The final case is $m > n$. We will pretend that A is 4×3. The s vector we get back will look the same

```
: s
            1
    +---------+
  1 |  13.47  |
  2 |    5.8  |
  3 |   2.63  |
    +---------+
```

but this time, we need a 4 × 3 rather than a 3 × 4 matrix formed from it.

```
: fullsdiag(s, rows(A)-cols(A))
            1        2        3
    +--------------------------+
  1 |  13.47        0        0 |
  2 |      0      5.8        0 |
  3 |      0        0     2.63 |
  4 |      0        0        0 |
    +--------------------------+
```

Possibility of convergence problems

See *Possibility of convergence problems* in [M-5] **svd()**; what is said there applies equally here.

Conformability

`fullsvd(`*A*`,` *U*`,` *s*`,` *Vt*`)`:

input:

A:	$m \times n$

output:

U:	$m \times m$
s:	$\min(m, n) \times 1$
Vt:	$n \times n$
result:	*void*

`fullsdiag(`*s*`,` *k*`)`:

input:

s:	$r \times 1$
k:	1×1

output:

result:	$r + k \times r$,	if k ≥ 0
	$r \times r - k$,	otherwise

`_fullsvd(`*A*`,` *U*`,` *s*`,` *Vt*`)`:

input:

A:	$m \times n$

output:

A:	0×0
U:	$m \times m$
s:	$\min(m, n) \times 1$
Vt:	$n \times n$
result:	*void*

`_svd_la(`A`,` U`,` s`,` Vt`)`:

input:

A:	$m \times n$	

output:

A:	$m \times n$,	but contents changed
U:	$m \times m$	
s:	$\min(m,n) \times 1$	
Vt:	$n \times n$	
result:	1×1	

Diagnostics

`fullsvd(`A`,` U`,` s`,` Vt`)` and `_fullsvd(`A`,` s`,` Vt`)` return missing results if A contains missing. In all other cases, the routines should work, but there is the unlikely possibility of convergence problems, in which case missing results will also be returned; see *Possibility of convergence problems* in [M-5] **svd( )**.

`_fullsvd()` aborts with error if A is a view.

Direct use of `_svd_la()` is not recommended.

Also see

[M-5] **norm( )** — Matrix and vector norms

[M-5] **pinv( )** — Moore–Penrose pseudoinverse

[M-5] **rank( )** — Rank of matrix

[M-5] **svd( )** — Singular value decomposition

[M-5] **svsolve( )** — Solve AX=B for X using singular value decomposition

[M-4] **Matrix** — Matrix functions