
Singular Value Decomposition

An Example

Calculating a singular value decomposition

Consider the following matrix:
(Lay 7.4, Example 3)

```
Clear[a, aT a, evals, evecs,  $\Lambda$ , V, v1, v2, v3,  $\Sigma$ ,  $\sigma_1$ ,  $\sigma_2$ , U, u1, u2]

a =  $\begin{pmatrix} 4 & 11 & 14 \\ 8 & 7 & -2 \end{pmatrix}$ ;
```

■ Find the eigendata for $A^T A$.

```
aT a = Transpose[a] . a;

evals = Eigenvalues[aT a];
 $\Lambda$  = DiagonalMatrix[evals];
% // MatrixForm

 $\begin{pmatrix} 360 & 0 & 0 \\ 0 & 90 & 0 \\ 0 & 0 & 0 \end{pmatrix}$ 
```

```
evecs = Eigenvectors[aT a];
% // MatrixForm

 $\begin{pmatrix} 1 & 2 & 2 \\ -2 & -1 & 2 \\ 2 & -2 & 1 \end{pmatrix}$ 
```

■ Construct V.

The columns of the matrix V are the orthonormal eigenvectors of $A^T A$, taken in the proper order.

```

v1 = evecs[[1]] / Norm[evecs[[1]]];
v2 = evecs[[2]] / Norm[evecs[[2]]];
v3 = evecs[[3]] / Norm[evecs[[3]]];

V = Transpose[{v1, v2, v3}];
% // MatrixForm

```

$$\begin{pmatrix} \frac{1}{3} & -\frac{2}{3} & \frac{2}{3} \\ \frac{2}{3} & -\frac{1}{3} & -\frac{2}{3} \\ \frac{2}{3} & \frac{2}{3} & \frac{1}{3} \end{pmatrix}$$

Check that the columns of V are orthonormal.

```

Transpose[V].V;
% // MatrixForm

```

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

Check the diagonalization.

```

aTa == V.A.Inverse[V]

```

True

■ Construct Σ .

```

<< LinearAlgebra`MatrixManipulation`

```

```
singularValues = {σ1, σ2, σ3} = √evals
```

```
Σ = ZeroMatrix[2, 3];
```

```
Σ[[1, 1]] = σ1;
```

```
Σ[[2, 2]] = σ2;
```

```
Σ // MatrixForm
```

```
{6 √10, 3 √10, 0}
```

$$\begin{pmatrix} 6\sqrt{10} & 0 & 0 \\ 0 & 3\sqrt{10} & 0 \end{pmatrix}$$

■ Construct U .

A has rank 2. The two columns of U are the normalized vectors A.v1 and A.v2.

```
u1 = (1 / σ1) a.v1;
```

```
u2 = (1 / σ2) a.v2;
```

```
U = Transpose[{u1, u2}];
```

```
% // MatrixForm
```

$$\begin{pmatrix} \frac{3}{\sqrt{10}} & \frac{1}{\sqrt{10}} \\ \frac{1}{\sqrt{10}} & -\frac{3}{\sqrt{10}} \end{pmatrix}$$

■ Check the singular value decomposition, $A == U.\Sigma.V^T$.

```
Print[a // MatrixForm, "=", U // MatrixForm,
      ".", Σ // MatrixForm, ".", Transpose[V] // MatrixForm];
```

```
a == U.Σ.Transpose[V]
```

$$\begin{pmatrix} 4 & 11 & 14 \\ 8 & 7 & -2 \end{pmatrix} = \begin{pmatrix} \frac{3}{\sqrt{10}} & \frac{1}{\sqrt{10}} \\ \frac{1}{\sqrt{10}} & -\frac{3}{\sqrt{10}} \end{pmatrix} \cdot \begin{pmatrix} 6\sqrt{10} & 0 & 0 \\ 0 & 3\sqrt{10} & 0 \end{pmatrix} \cdot \begin{pmatrix} \frac{1}{3} & \frac{2}{3} & \frac{2}{3} \\ -\frac{2}{3} & -\frac{1}{3} & \frac{2}{3} \\ \frac{2}{3} & -\frac{2}{3} & \frac{1}{3} \end{pmatrix}$$

```
True
```

■ Compare with *Mathematica's* singular value decomposition.

Mathematica's numerical result.

```

a =  $\begin{pmatrix} 4 & 11 & 14 \\ 8 & 7 & -2 \end{pmatrix}$ ;
{u, w, v} = SingularValueDecomposition[a];

Print[a // MatrixForm, "=", u // MatrixForm,
      ".", w // MatrixForm, ".", Transpose[v] // MatrixForm];
a == u.w.Transpose[v]

```

$$\begin{pmatrix} 4 & 11 & 14 \\ 8 & 7 & -2 \end{pmatrix} = \begin{pmatrix} -0.948683 & 0.316228 \\ -0.316228 & -0.948683 \end{pmatrix} \cdot \begin{pmatrix} 18.9737 & 0. & 0. \\ 0. & 9.48683 & 0. \end{pmatrix} \cdot \begin{pmatrix} -0.333333 & -0.666667 & -0.666667 \\ -0.666667 & -0.333333 & 0.666667 \\ -0.666667 & 0.666667 & -0.333333 \end{pmatrix}$$

```
True
```

Our numerical result.

These two results agree up to a sign change on some rows and columns.

```

Print[a // MatrixForm, "=", U // MatrixForm // N, ".",
      Σ // MatrixForm // N, ".", Transpose[V] // MatrixForm // N];

a == U.Σ.Transpose[V]

```

$$\begin{pmatrix} 4 & 11 & 14 \\ 8 & 7 & -2 \end{pmatrix} = \begin{pmatrix} 0.948683 & 0.316228 \\ 0.316228 & -0.948683 \end{pmatrix} \cdot \begin{pmatrix} 18.9737 & 0. & 0. \\ 0. & 9.48683 & 0. \end{pmatrix} \cdot \begin{pmatrix} 0.333333 & 0.666667 & 0.666667 \\ -0.666667 & -0.333333 & 0.666667 \\ 0.666667 & -0.666667 & 0.333333 \end{pmatrix}$$

```
True
```

The Four Fundamental Subspaces

Consider the matrix of the previous example, ...

```

a =  $\begin{pmatrix} 4 & 11 & 14 \\ 8 & 7 & -2 \end{pmatrix}$ ;

```

... and its singular value decomposition, $A = U \Sigma V^T$.

```
Print[a // MatrixForm, "=", U // MatrixForm,
      ".", Σ // MatrixForm, ".", Transpose[V] // MatrixForm];

a == U.Σ.Transpose[V]
```

$$\begin{pmatrix} 4 & 11 & 14 \\ 8 & 7 & -2 \end{pmatrix} = \begin{pmatrix} \frac{3}{\sqrt{10}} & \frac{1}{\sqrt{10}} \\ \frac{1}{\sqrt{10}} & -\frac{3}{\sqrt{10}} \end{pmatrix} \cdot \begin{pmatrix} 6\sqrt{10} & 0 & 0 \\ 0 & 3\sqrt{10} & 0 \end{pmatrix} \cdot \begin{pmatrix} \frac{1}{3} & \frac{2}{3} & \frac{2}{3} \\ -\frac{2}{3} & -\frac{1}{3} & \frac{2}{3} \\ \frac{2}{3} & -\frac{2}{3} & \frac{1}{3} \end{pmatrix}$$

```
True
```

a is an $m \times n$ matrix with rank r.

```
m = 2;
n = 3;
r = 2;
```

The **singular value decomposition** of a displays **orthogonal bases** for the **four fundamental subspaces** of a as follows:

(See Lay 7.4, p479)

```
(* α == [v1,v2] == [v1,...,vr] == basis for Row a *)
(* β == [v3] == [vr+1,...,vn] == basis for Nul a *)

(* γ == [u1,u2] == [u1,...,ur] == basis for Row a^T == Col a *)
(* δ == [] == [ur+1,...,um] == basis for Nul a^T *)
```

The Moore-Penrose Inverse and Least-Squares Solutions

Consider the matrix of the previous example, ...

$$\mathbf{a} = \begin{pmatrix} 4 & 11 & 14 \\ 8 & 7 & -2 \end{pmatrix};$$

... and its singular value decomposition, $\mathbf{A} = \mathbf{U} \cdot \mathbf{\Sigma} \cdot \mathbf{V}^T$.

```
Print[a // MatrixForm, "=", U // MatrixForm,
      ".", Σ // MatrixForm, ".", Transpose[V] // MatrixForm];

a == U.Σ.Transpose[V]
```

$$\begin{pmatrix} 4 & 11 & 14 \\ 8 & 7 & -2 \end{pmatrix} = \begin{pmatrix} \frac{3}{\sqrt{10}} & \frac{1}{\sqrt{10}} \\ \frac{1}{\sqrt{10}} & -\frac{3}{\sqrt{10}} \end{pmatrix} \cdot \begin{pmatrix} 6\sqrt{10} & 0 & 0 \\ 0 & 3\sqrt{10} & 0 \end{pmatrix} \cdot \begin{pmatrix} \frac{1}{3} & \frac{2}{3} & \frac{2}{3} \\ -\frac{2}{3} & -\frac{1}{3} & \frac{2}{3} \\ \frac{2}{3} & -\frac{2}{3} & \frac{1}{3} \end{pmatrix}$$

```
True
```

a is an $m \times n$ matrix with rank r.

```
m = 2;
n = 3;
r = 2;
```

The **Moore-Penrose Inverse**, A^+ , or **pseudoinverse** of A is computed from its singular value decomposition, $A = U \cdot \Sigma \cdot V^T$, as follows:
(See Lay 7.4, p479)

```
Ur = U[[All, {1, 2}]];
Dr = DiagonalMatrix[{σ1, σ2}];
Vr = V[[All, {1, 2}]];

aPlus = Vr.Inverse[Dr].Transpose[Ur];

Print[aPlus // MatrixForm, " == ", Vr // MatrixForm, ".",
      Inverse[Dr] // MatrixForm, ".", Transpose[Ur] // MatrixForm];
```

$$\begin{pmatrix} -\frac{1}{180} & \frac{13}{180} \\ \frac{1}{45} & \frac{2}{45} \\ \frac{1}{18} & -\frac{1}{18} \end{pmatrix} = \begin{pmatrix} \frac{1}{3} & -\frac{2}{3} \\ \frac{2}{3} & -\frac{1}{3} \\ \frac{2}{3} & \frac{2}{3} \end{pmatrix} \cdot \begin{pmatrix} \frac{1}{6\sqrt{10}} & 0 \\ 0 & \frac{1}{3\sqrt{10}} \end{pmatrix} \cdot \begin{pmatrix} \frac{3}{\sqrt{10}} & \frac{1}{\sqrt{10}} \\ \frac{1}{\sqrt{10}} & -\frac{3}{\sqrt{10}} \end{pmatrix}$$

Suppose we wish to solve the least-squares problem $A \cdot x = b$.

```
(* a.x == b *)
```

Let

```
(* xHat = aPlus.b *)
```

Then,

$$(* \mathbf{a} \cdot \mathbf{xHat} == (\mathbf{Ur} \cdot \mathbf{D} \cdot \mathbf{Vr}^T) \cdot (\mathbf{Vr} \cdot \mathbf{D}^{-1} \cdot \mathbf{Ur}^T \cdot \mathbf{b}) == (\mathbf{Ur} \cdot \mathbf{D} \cdot \mathbf{D}^{-1} \cdot \mathbf{Ur}^T \cdot \mathbf{b}) == \mathbf{Ur} \cdot \mathbf{Ur}^T \cdot \mathbf{b} == \mathbf{bHat} *)$$

where \mathbf{bHat} is the orthogonal projection of \mathbf{b} onto $\text{Col } A == \text{Col } \mathbf{Ur}$.

Therefore, \mathbf{xHat} is a **least squares solution** of $\mathbf{A} \cdot \mathbf{x} == \mathbf{b}$.

It can be shown that this \mathbf{xHat} , obtained via the Moore-Penrose inverse of A , is the **shortest least-squares solution** of $\mathbf{A} \cdot \mathbf{x} == \mathbf{b}$

(See Lay 7.4, p480)

Another Example

Calculating another singular value decomposition

Consider the following matrix:

(Lay 7.4, Example 4)

```
Clear[a, aTa, evals, evecs, Λ, V, v1, v2, v3, Σ, σ1, σ2, U, u1, u2]
```

$$\mathbf{a} = \begin{pmatrix} 1 & -1 \\ -2 & 2 \\ 2 & -2 \end{pmatrix};$$

- Find the eigendata for $\mathbf{A}^T \mathbf{A}$.

```
aTa = Transpose[a] . a;
```

```
evals = Eigenvalues[aTa];
Λ = DiagonalMatrix[evals];
% // MatrixForm
```

$$\begin{pmatrix} 18 & 0 \\ 0 & 0 \end{pmatrix}$$

```
evecs = Eigenvectors[aTa];
% // MatrixForm
```

$$\begin{pmatrix} -1 & 1 \\ 1 & 1 \end{pmatrix}$$

■ Construct V .

The columns of the matrix V are the orthonormal eigenvectors of $A^T A$, taken in the proper order.

```
v1 = evecs[[1]] / Norm[evecs[[1]]];
v2 = evecs[[2]] / Norm[evecs[[2]]];

V = Transpose[{v1, v2}];
% // MatrixForm
```

$$\begin{pmatrix} -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{pmatrix}$$

Check that the columns of V are orthonormal.

```
Transpose[V].V;
% // MatrixForm
```

$$\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

Check the diagonalization.

```
aTa == V.A.Inverse[V]
```

```
True
```

■ Construct Σ .

```
<< LinearAlgebra`MatrixManipulation`
```

```
singularValues = {σ1, σ2} = √evals
```

```
Σ = ZeroMatrix[3, 2];
```

```
Σ[[1, 1]] = σ1;
```

```
Σ // MatrixForm
```

```
{3 √2, 0}
```

$$\begin{pmatrix} 3\sqrt{2} & 0 \\ 0 & 0 \\ 0 & 0 \end{pmatrix}$$

■ Construct U .

Calculate u1

```
u1 = (1 / σ1) a.v1
```

```
{-1/3, 2/3, -2/3}
```

Extend {u1} to an orthonormal basis of R³.

```
u1 = (1 / σ1) a.v1;
```

```
e1 = {1, 0, 0};
```

```
f1 = (e1 - e1.u1 u1);
```

```
u2 = f1 / Norm[f1];
```

```
e2 = {0, 1, 0};
```

```
f2 = (e2 - e2.u1 u1 - e2.u2 u2);
```

```
u3 = f2 / Norm[f2];
```

```
U = Transpose[{u1, u2, u3}];
```

```
% // MatrixForm
```

$$\begin{pmatrix} -\frac{1}{3} & \frac{2\sqrt{2}}{3} & 0 \\ \frac{2}{3} & \frac{1}{3\sqrt{2}} & \frac{1}{\sqrt{2}} \\ -\frac{2}{3} & -\frac{1}{3\sqrt{2}} & \frac{1}{\sqrt{2}} \end{pmatrix}$$

Check that the columns of U are orthonormal.

```
Transpose[U].U;
% // MatrixForm
```

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

■ Check the singular value decomposition, $A == U.\Sigma.V^T$.

```
Print[a // MatrixForm, "=", U // MatrixForm,
      ".", \Sigma // MatrixForm, ".", Transpose[V] // MatrixForm];
a == U.\Sigma.Transpose[V]
```

$$\begin{pmatrix} 1 & -1 \\ -2 & 2 \\ 2 & -2 \end{pmatrix} = \begin{pmatrix} -\frac{1}{3} & \frac{2\sqrt{2}}{3} & 0 \\ \frac{2}{3} & \frac{1}{3\sqrt{2}} & \frac{1}{\sqrt{2}} \\ -\frac{2}{3} & -\frac{1}{3\sqrt{2}} & \frac{1}{\sqrt{2}} \end{pmatrix} \cdot \begin{pmatrix} 3\sqrt{2} & 0 \\ 0 & 0 \\ 0 & 0 \end{pmatrix} \cdot \begin{pmatrix} -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{pmatrix}$$

```
True
```

■ Compare with *Mathematica's* singular value decomposition.

Mathematica's numerical result.

```

a =  $\begin{pmatrix} 1. & -1 \\ -2 & 2 \\ 2 & -2 \end{pmatrix}$ ;

{u, w, v} = SingularValueDecomposition[a];

Print[a // MatrixForm, "=", u // MatrixForm,
      ".", w // MatrixForm, ".", Transpose[v] // MatrixForm];
a == u.w.Transpose[v]

```

$$\begin{pmatrix} 1. & -1 \\ -2 & 2 \\ 2 & -2 \end{pmatrix} = \begin{pmatrix} -0.333333 & 0.942809 & -7.40149 \times 10^{-17} \\ 0.666667 & 0.235702 & 0.707107 \\ -0.666667 & -0.235702 & 0.707107 \end{pmatrix} \\ \cdot \begin{pmatrix} 4.24264 & 0. \\ 0. & 0. \\ 0. & 0. \end{pmatrix} \cdot \begin{pmatrix} -0.707107 & 0.707107 \\ 0.707107 & 0.707107 \end{pmatrix}$$

True

Our numerical result.

These agree up to the precision of the computer arithmetic that is involved.

```

Print[a // MatrixForm, "=", U // MatrixForm // N, ".",
      Σ // MatrixForm // N, ".", Transpose[V] // MatrixForm // N];
a == U.Σ.Transpose[V]

```

$$\begin{pmatrix} 1. & -1 \\ -2 & 2 \\ 2 & -2 \end{pmatrix} = \begin{pmatrix} -0.333333 & 0.942809 & 0. \\ 0.666667 & 0.235702 & 0.707107 \\ -0.666667 & -0.235702 & 0.707107 \end{pmatrix} \\ \cdot \begin{pmatrix} 4.24264 & 0. \\ 0. & 0. \\ 0. & 0. \end{pmatrix} \cdot \begin{pmatrix} -0.707107 & 0.707107 \\ 0.707107 & 0.707107 \end{pmatrix}$$

True

The Four Fundamental Subspaces

Consider the matrix of the previous example, ...

$$\mathbf{a} = \begin{pmatrix} 1 & -1 \\ -2 & 2 \\ 2 & -2 \end{pmatrix};$$

... and its singular value decomposition, $\mathbf{A} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T$.

```
Print[a // MatrixForm, "=", U // MatrixForm,
      ".", Σ // MatrixForm, ".", Transpose[V] // MatrixForm];

a == U.Σ.Transpose[V]
```

$$\begin{pmatrix} 1 & -1 \\ -2 & 2 \\ 2 & -2 \end{pmatrix} = \begin{pmatrix} -\frac{1}{3} & \frac{2\sqrt{2}}{3} & 0 \\ \frac{2}{3} & \frac{1}{3\sqrt{2}} & \frac{1}{\sqrt{2}} \\ -\frac{2}{3} & -\frac{1}{3\sqrt{2}} & \frac{1}{\sqrt{2}} \end{pmatrix} \cdot \begin{pmatrix} 3\sqrt{2} & 0 \\ 0 & 0 \\ 0 & 0 \end{pmatrix} \cdot \begin{pmatrix} -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{pmatrix}$$

```
True
```

\mathbf{a} is an $m \times n$ matrix with rank r .

```
m = 3;
n = 2;
r = 1;
```

The **singular value decomposition** of \mathbf{a} displays **orthogonal bases** for the **four fundamental subspaces** of \mathbf{a} as follows:

(See Lay 7.4, p479)

```
(* α == [v1] == [v1, ..., vr] == basis for Row a *)
(* β == [v2] == [vr+1, ..., vn] == basis for Nul a *)

(* γ == [u1] == [u1, ..., ur] == basis for Row a^T == Col a *)
(* δ == [u2, u3] == [ur+1, ..., um] == basis for Nul a^T *)
```

The Moore-Penrose Inverse and Least-Squares Solutions

Consider the matrix of the previous example, ...

$$\mathbf{a} = \begin{pmatrix} 1 & -1 \\ -2 & 2 \\ 2 & -2 \end{pmatrix};$$

... and its singular value decomposition, $A = U \Sigma V^T$.

```
Print[a // MatrixForm, "=", U // MatrixForm,
      ".", Σ // MatrixForm, ".", Transpose[V] // MatrixForm];

a == U.Σ.Transpose[V]
```

$$\begin{pmatrix} 1 & -1 \\ -2 & 2 \\ 2 & -2 \end{pmatrix} = \begin{pmatrix} -\frac{1}{3} & \frac{2\sqrt{2}}{3} & 0 \\ \frac{2}{3} & \frac{1}{3\sqrt{2}} & \frac{1}{\sqrt{2}} \\ -\frac{2}{3} & -\frac{1}{3\sqrt{2}} & \frac{1}{\sqrt{2}} \end{pmatrix} \cdot \begin{pmatrix} 3\sqrt{2} & 0 \\ 0 & 0 \\ 0 & 0 \end{pmatrix} \cdot \begin{pmatrix} -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{pmatrix}$$

```
True
```

a is an $m \times n$ matrix with rank r .

```
m = 3;
n = 2;
r = 1;
```

The **Moore-Penrose Inverse**, A^+ , or **pseudoinverse** of A is computed from its singular value decomposition, $A = U \Sigma V^T$, as follows:
(See Lay 7.4, p479)

```
Ur = Map[List, U[[All, 1]]];
Dr = {{σ1}};
Vr = Map[List, V[[All, 1]]];

aPlus = Vr.Inverse[Dr].Transpose[Ur];

Print[aPlus // MatrixForm, " = ", Vr // MatrixForm, ".",
      Inverse[Dr] // MatrixForm, ".", Transpose[Ur] // MatrixForm];
```

$$\begin{pmatrix} \frac{1}{18} & -\frac{1}{9} & \frac{1}{9} \\ -\frac{1}{18} & \frac{1}{9} & -\frac{1}{9} \end{pmatrix} = \begin{pmatrix} -\frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{pmatrix} \cdot \left(\frac{1}{3\sqrt{2}} \right) \cdot \begin{pmatrix} -\frac{1}{3} & \frac{2}{3} & -\frac{2}{3} \end{pmatrix}$$

Suppose we wish to solve the least-squares problem $Ax = b$.

```
(* a.x == b *)
```

Let

```
(* xHat = aPlus.b *)
```

Then,

$$\begin{aligned} (* \mathbf{a} \cdot \mathbf{xHat} &= (\mathbf{Ur} \cdot \mathbf{D} \cdot \mathbf{Vr}^T) \cdot (\mathbf{Vr} \cdot \mathbf{D}^{-1} \cdot \mathbf{Ur}^T \cdot \mathbf{b}) = \\ &(\mathbf{Ur} \cdot \mathbf{D} \cdot \mathbf{D}^{-1} \cdot \mathbf{Ur}^T \cdot \mathbf{b}) = \mathbf{Ur} \cdot \mathbf{Ur}^T \cdot \mathbf{b} = \mathbf{bHat} *) \end{aligned}$$

where \mathbf{bHat} is the orthogonal projection of \mathbf{b} onto $\text{Col } A = \text{Col } \mathbf{Ur}$.

Therefore, \mathbf{xHat} is a **least squares solution** of $\mathbf{A} \cdot \mathbf{x} = \mathbf{b}$.

It can be shown that this \mathbf{xHat} , obtained via the Moore-Penrose inverse of A , is the **shortest least-squares solution** of $\mathbf{A} \cdot \mathbf{x} = \mathbf{b}$

(See Lay 7.4, p480)