

```
# Singular-value decomposition :  
# =====
```

<https://machinelearningmastery.com/singular-value-decomposition-for-machine-learning/>

```
from numpy import array  
from scipy.linalg import svd
```

```
# define a matrix  
A = array([[1, 2], [3, 4], [5, 6]])  
print("A : {}".format(A))
```

```
# SVD  
U, s, V = svd(A)  
print("U : {}".format(U))  
print("S : {}".format(s))  
print("V : {}".format(V))
```

Result :  
=====

```
A : [[1 2]  
      [3 4]  
      [5 6]]
```

```
U : [[-0.2298477  0.88346102  0.40824829]  
      [-0.52474482  0.24078249 -0.81649658]  
      [-0.81964194 -0.40189603  0.40824829]]
```

```
S : [9.52551809 0.51430058]
```

```
V : [[-0.61962948 -0.78489445]  
      [-0.78489445  0.61962948]]
```

```
=====
```

## Calculate Singular-Value Decomposition

The SVD can be calculated by calling the `svd()` function.

The function takes a matrix and returns the U, Sigma and  $V^T$  elements. The Sigma diagonal matrix is returned as a vector of singular values. The V matrix is returned in a transposed form, e.g.  $V^T$ .

The example below defines a  $3 \times 2$  matrix and calculates the Singular-value decomposition.

```
1 # Singular-value decomposition
2 from numpy import array
3 from scipy.linalg import svd
4 # define a matrix
5 A = array([[1, 2], [3, 4], [5, 6]])
6 print(A)
7 # SVD
8 U, s, VT = svd(A)
9 print(U)
10 print(s)
11 print(VT)
```

Running the example first prints the defined  $3 \times 2$  matrix, then the  $3 \times 3$  U matrix, 2 element Sigma vector, and  $2 \times 2$   $V^T$  matrix elements calculated from the decomposition.

```
1 [[1 2]
2  [3 4]
3  [5 6]]
4
5 [[-0.2298477  0.88346102  0.40824829]
6  [-0.52474482  0.24078249 -0.81649658]
7  [-0.81964194 -0.40189603  0.40824829]]
8
9 [ 9.52551809  0.51430058]
10
11 [[-0.61962948 -0.78489445]
12  [-0.78489445  0.61962948]]
```

=====

=====