Pseudoinverse and Least Squares

```
In [1]:
```

```
#keep
import numpy as np
import numpy.linalg as la

np.set_printoptions(precision=4, linewidth=100)
```

```
In [2]:
```

```
#keep
A = np.random.randn(5, 3)
```

Now compute the SVD of A. Note that numpy.linalg.svd returns $V^T\colon$

```
In [3]:
```

```
U, singval, VT = la.svd(A)
V = VT.T
```

Let's first understand the shapes of these arrays:

```
In [4]:
```

```
#keep
print(U.shape)
print(singval.shape)
print(V.shape)
```

```
(5, 5)
(3,)
(3, 3)
```

Check the orthogonality of U and V:

```
In [5]:
U.T.dot(U)
Out[5]:
array([[ 1.0000e+00, -1.6053e-16,
                                    -1.9500e-16,
                                                    2.1064e-17,
                                                                   0.
0000e+00],
       [ -1.6053e-16, 1.0000e+00,
                                    -8.5663e-17,
                                                    7.0205e-18,
                                                                   1.
1102e-16],
       [ -1.9500e-16, -8.5663e-17, 1.0000e+00,
                                                    1.2369e-18,
                                                                   0.
0000e+00],
                                                    1.0000e+00,
         2.1064e-17, 7.0205e-18, 1.2369e-18,
                                                                   2.
7756e-17],
         0.0000e+00, 1.1102e-16, 0.0000e+00,
                                                                   1.
                                                    2.7756e-17,
0000e+00]])
In [6]:
V.T.dot(V)
Out[6]:
array([[ 1.0000e+00, -3.4694e-17, -7.8063e-18],
       [ -3.4694e-17, 1.0000e+00, -5.5511e-17],
       [ -7.8063e-18, -5.5511e-17, 1.0000e+00]])
Now build the matrix \Sigma:
In [7]:
Sigma = np.zeros(A.shape)
Sigma[:3, :3] = np.diag(singval)
Sigma
Out[7]:
array([[ 2.4071, 0. ,
                           0.
                                 ],
                  2.2117,
       [ 0.
                           0.
                                 ],
       [ 0.
                  0.
                           0.4908],
       [ 0.
                  0.
                           0.
                                 ],
                  0.
                           0.
       [ 0.
                                 ]])
```

Now piece A back together from the factorization:

```
U.dot(Sigma).dot(V.T) - A
Out[8]:
array([[ 2.2204e-16,
                       5.5511e-16, -2.4425e-15],
       [ 2.2204e-16, -6.1062e-16, 7.7716e-16],
       [ 0.0000e+00, 1.1102e-16, -4.1633e-16],
       [ -1.1102e-16, 6.9389e-17, 5.5511e-17],
       [ -1.1102e-16, 2.4980e-16, -1.6653e-16]])
Next, compute the pseudoinverse:
In [9]:
SigmaInv = np.zeros((3,5))
SigmaInv[:3, :3] = np.diag(1/singval)
SigmaInv
Out[9]:
array([[ 0.4154, 0. , 0. , 0.
                                                     ],
       [ 0. , 0.4521, 0. , 0. 
[ 0. , 0. , 2.0373, 0.
                                              0.
                                                     ],
                                                     ]])
In [10]:
A pinv = V.dot(SigmaInv).dot(U.T)
Now use the pseudoinverse to "solve" Ax = b for our tall-and-skinny A:
In [11]:
#keep
b = np.random.randn(5)
In [12]:
A_pinv.dot(b)
Out[12]:
array([ 0.504 , -0.3182, 0.9697])
```

In [8]: