

VE472 HW5

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EX 1

1.

If we do not increase the precision, there will be an error with a single data. Whatever small error it may be, when the data becomes huge, the error will increase with the data amount and finally becomes a huge error to the result.

2.

```
1 clear; clearvars;
2 matrices = cell(1, 100);
3 for i = 1 : 100
4     matrices{i} = rand(1000,100);
5 end
6 disp('a')
7 tic;
8 for i = 1 : 100
9     X = matrices{i};
10    [U,S,V] = svd(X);
11 end
12 toc;
13 disp('b')
14 tic;
15 for i = 1 : 100
16     X = matrices{i};
17     [U,S,V] = svd(X');
18 end
19 toc;
20 disp('c')
21 tic;
22 for i = 1 : 100
23     X = matrices{i};
24     e = eig(X*(X'));
25 end
26 toc;
27 disp('d')
28 tic;
29 for i = 1 : 100
30     X = matrices{i};
31     e = eig((X')*X);
32 end
33 toc;
```

3.

a)

```
1 x = [-9 11 -21 63 -252; 70 -69 141 -421 1684; -575 575 -1149 3451 -13801;  
2 3891 -3891 7782 -23345 93365; 1024 -1024 2048 -6144 24572];  
3 baseEig = eig(X);  
4 variations = zeros(5, 1);  
5 for i = 1 : 1000  
6     perturbations = eps(X) .* rand(5,5);  
7     e = eig(X + perturbations);  
8     variations = variations + (e - baseEig);  
9 end  
10 disp(variations);
```

b)

```
1 x = [-9 11 -21 63 -252; 70 -69 141 -421 1684; -575 575 -1149 3451 -13801;  
2 3891 -3891 7782 -23345 93365; 1024 -1024 2048 -6144 24572];  
3 baseSVD = svd(X);  
4 variations = zeros(5, 1);  
5 for i = 1 : 1000  
6     perturbations = eps(X) .* rand(5,5);  
7     svdValue = svd(X + perturbations);  
8     variations = variations + (svdValue - baseSVD);  
9 end  
10 disp(variations);
```

EX2

17:27 7月24日周六

Ex. 2

$$XX^T = \begin{pmatrix} 30 & 70 & 20 \\ 70 & 174 & 68 \\ 20 & 68 & 86 \end{pmatrix}$$

$$\det(XX^T - \lambda I) = 0$$

$$\Rightarrow -\lambda^3 + 290\lambda^2 - 13220\lambda + 75770 = 0$$

$$\begin{cases} \lambda_1 \approx 235.70 \\ \lambda_2 \approx 53.54 \\ \lambda_3 \approx 0.76 \end{cases} \Rightarrow \Sigma = \begin{pmatrix} \sqrt{\lambda_1} & 0 & 0 & 0 \\ 0 & \sqrt{\lambda_2} & 0 & 0 \\ 0 & 0 & \sqrt{\lambda_3} & 0 \end{pmatrix}$$

$$= \begin{pmatrix} 15.35 & 0 & 0 & 0 \\ 0 & 7.32 & 0 & 0 \\ 0 & 0 & 0.87 & 0 \end{pmatrix}$$

EX3

1.

PCA decreases the dimension of the data so that Krystor can see the relation between two sensors more directly (i mean with less data processing)

2.

```

1 import numpy as np
2 from sklearn.decomposition import PCA
3
4 if __name__ == '__main__':
5     sensor_mat = np.mat(np.loadtxt(open("cinema_sensors/sensors1.csv",
6     "rb"), delimiter=','))[:, :1000]
7     pca = PCA()
8     pca.fit(sensor_mat)
9
10    target = 0.9 * sum(pca.explained_variance_ratio_)
11    for N in range(1, 1001):
12        pca = PCA(n_components=N)
13        pca.fit(sensor_mat)
14        ret = sum(pca.explained_variance_ratio_)
15        if ret > target:
16            print(N)
17            break

```

N=3

3.

```
1 import numpy as np
2 from sklearn.decomposition import PCA
3 from sklearn.linear_model import LinearRegression
4
5 if __name__ == '__main__':
6     sensor_mat = np.mat(np.loadtxt(open("cinema_sensors/sensors1.csv",
7 "rb"), delimiter=','))[:, :1000]
8     y = sensor_mat[:, -1]
9     pca = PCA(n_components=3)
10    x = pca.fit_transform(sensor_mat[:, :1000])
11    print("data shape:", x.shape, y.shape)
12    reg = LinearRegression().fit(x, y)
13    print("R^2:", reg.score(x, y))
14    print("coefficient:", reg.coef_.flatten())
15    print("intercept:", reg.intercept_.flatten())
```

```
1 data shape: (10000, 3) (10000, 1)
2 R^2: 0.996039896320849
3 coefficient: [ 0.62564059  0.28116334 -0.36152544]
4 intercept: [761.0112442]
```

4.

For `sensor2.csv`

N=3

```
1 data shape: (100, 3) (100, 1)
2 R^2: 0.9950861037323646
3 coefficient: [ 0.59925067 -0.27709259 -0.38590096]
4 intercept: [731.15229]
```

I think sensor 2 contains the output of the sensors in the electric circuit of Reapor Rich's new cinema