



# A BRIEF ILLUSTRATION OF PCA

INT301 Bio-computation, Week 10, 2025



# Data Simulation

```

%% generate the data
%% define the direction of the real data
rd = [1;1];
rd = rd/norm(rd); %normalize the data direction
rd_std = 1.5; %define the standard deviation of the real data
rd_num = 500; %define the number of data
noi_std = 0.05; %define the standard deviation of the noise

%% simulate the observations
rd_std_vec = randn([1,rd_num])*rd_std;
for k = 1:rd_num
    rd_data(:,k) = rd*rd_std_vec(k);
end
noi_data = randn([length(rd),rd_num])*noi_std;
ob_data = rd_data + noi_data;

%% show the data
figure;
plot(ob_data(1,:), ob_data(2,:), 'b*')
legend('Observations')
disp('The direction of the data distribution:')
disp(rd)

```

向量(!)

归一化 →  $(\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}})$

→ std (data)  
→ num (data)  
→ 噪声 std

$N(0,1)$

生成一个  $1 \times 500$  行向量, 每个元素服从  $N(0, 1.5)$

执行 500 次

id 为 k 随机变量和单位向量相乘

rd\_data 列表, 存入第 k 列

↓  $2 \times 500$   $N(0, 0.05)$  矩阵

$(\frac{z_1}{\sqrt{2}}, \frac{z_1}{\sqrt{2}}) + (z_2, z_2)$

⇒

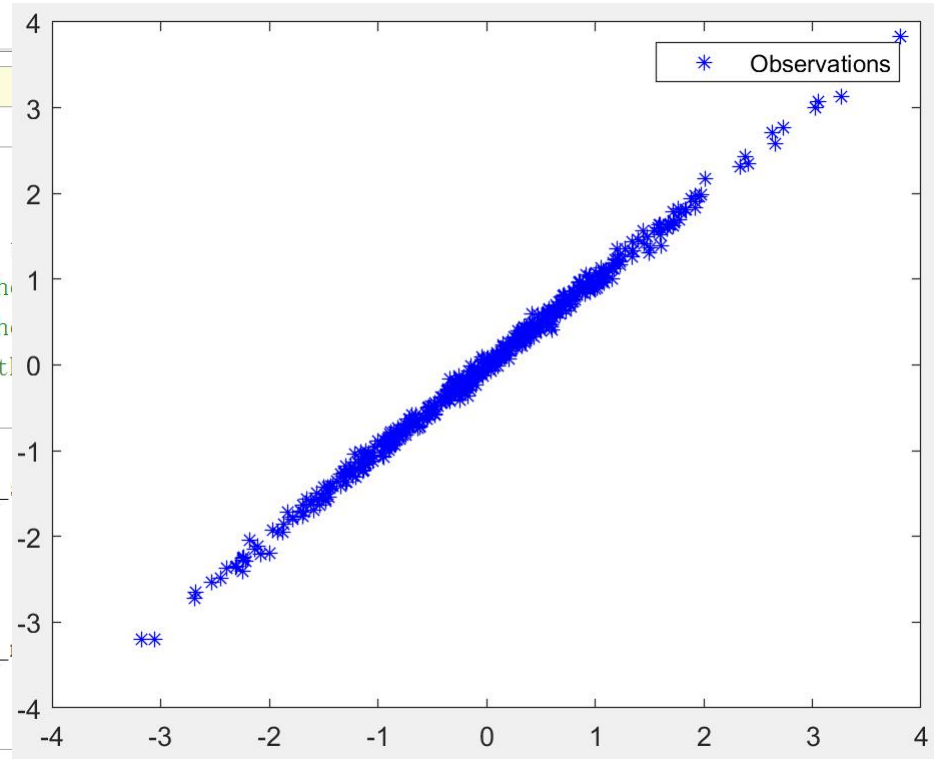


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legend('Observations')
disp('The direction of the data distribution:')
disp(rd)
```



```
>> PCA_demo
```

The direction of the data distribution:

0.7071

0.7071

添加图例  
创建绘图窗口  
blue  
命令行显示

# SVD

```
%% SVD analysis
[U, S, V] = svd(ob_data);
singular_vec = diag(S);
disp('The eigenvectors:')
disp(U)

disp('The singular values are given:')
disp(singular_vec(1:2))

disp('The estimations of std:')
disp(singular_vec(1:2)/sqrt(rd_num))
```

# SVD

$2 \times 2$   $2 \times 500$   $500 \times 500$   $2 \times 500$

```

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[U, S, V] = svd(ob_data);
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disp(U)

disp('The singular values are given:')
disp(singular_vec(1:2))

disp('The estimations of std:')
disp(singular_vec(1:2)/sqrt(rd_num))
  
```

→ 提取特征值

接近  $(\frac{\sqrt{2}}{2}, \frac{\sqrt{2}}{2})$

The eigenvectors:

-0.7065	0.7077
-0.7077	-0.7065

The singular values are given:

33.6941  
1.0605

The estimations of std:

1.5068

$$\Rightarrow \sigma_i = \frac{\sqrt{\lambda_i} N}{\sqrt{N}}$$

>> PCA\_demo

The direction of the data distribution:

0.7071
0.7071

# SVD

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singular_vec = diag(S);
disp('The eigenvectors:')
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The eigenvectors:

```
-0.7065    0.7077
-0.7077   -0.7065
```

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33.6941
 1.0605
```

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```

# Diagonal decomposition of the correlation matrix

```
%% Diagonal decomposition of the correlation matrix
R_Mat 2x2 = ob_data*ob_data' = ob_data'
disp('the correlation matrix of the data is given:');
disp(R_Mat)
[V, D] = eig(R_Mat);
disp('The eigenvectors are given:');
disp(V)
disp('The eigenvalues are given:');
disp(diag(D))
disp('The singular vaules are given in another form:');
disp(sqrt(diag(D)))
```

the correlation matrix of the data is given:

```
567.1940  567.0836
567.0836  569.2243
```

The eigenvectors are given:

```
-0.7077    0.7065
 0.7065    0.7077
```

The eigenvalues are given:

```
1.0e+03 *
0.0011
1.1353
```

The singular vaules are given in another form:

```
1.0605
33.6941
```

# Diagonal decomposition of the correlation matrix

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%% Diagonal decomposition of the correlation matrix
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disp('the correlation matrix of the data is given:');  
disp(R_Mat)
```

```
[V, D] = eig(R_Mat);  
disp('The eigenvectors are given:');  
disp(V)  
disp('The eigenvalues are given:');  
disp(diag(D))
```

```
disp('The eigenvectors: r form:');  
disp([ -0.7065 0.7077  
       -0.7077 -0.7065])
```

```
The singular values are given:  
33.6941  
1.0605
```

```
The estimations of std:  
1.5068
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567.1940 567.0836  
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```



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disp('The eigenvalues are given:');  
disp(diag(D))  
disp('The singular vaules  
disp(sqrt(diag(D)))
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The eigenvectors:  
-0.7065 0.7077  
-0.7077 -0.7065

The singular values are given:  
33.6941  
1.0605

The estimations of std:  
1.5068

the correlation matrix of the data is given:

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567.1940 567.0836  
567.0836 569.2243
```

The eigenvectors are given:

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-0.7077 0.7065  
0.7065 0.7077
```

The eigenvalues are given:

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1.0e+03 *  
  
0.0011  
1.1353
```

The singular vaules are given in another form:

```
1.0605  
33.6941
```

# Projection and reconstruction

```
%% Reconstruction with eigenvectors
%% Projection with the maximum eignvalue related eigenvector
ob_pro          = V(:,2)'*ob_data; 降低
pro_std         = std(ob_pro)*sqrt(rd_num);
disp('the std of the projections');
disp(pro_std)

%% reconstructions with the maximum eignvalue related eigenvector
pro_data        = V(:,2)*V(:,2)'\ob_data; 重构
figure;
plot(rd_data(1,:), rd_data(2,:), 'b*')
hold on
plot(pro_data(1,:), pro_data(2,:), 'ro')
legend('real data', 'reconstructions')
```

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```

the std of the projections  
33.7202

The eigenvectors:

-0.7065	0.7077
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The singular values are given:

33.6941
1.0605

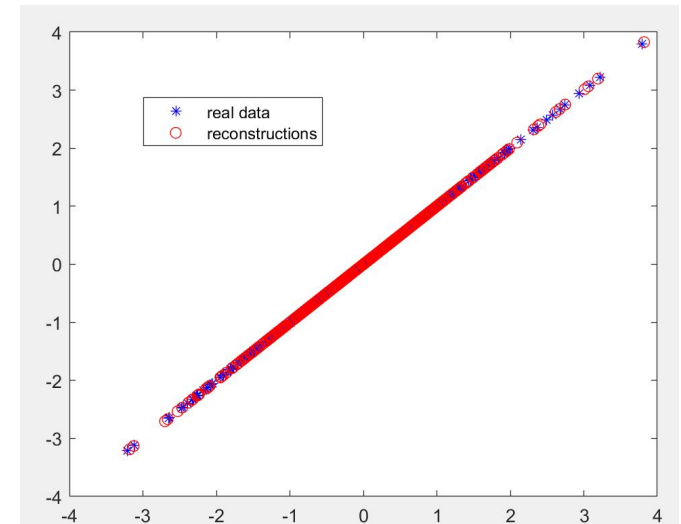
The estimations of std:

1.5068
0.0474

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# THANK YOU



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