



# 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  $N(0, I)$ 
rd_std_vec = randn([1, rd_num])*rd_std;
for k = 1:rd_num 执行500次
    rd_data(:, k) = rd*rd_std_vec(k); id为k随机变量和单位向量相乘
end
noi_data = randn([length(rd), rd_num])*noi_std;
ob_data = rd_data + noi_data;

```

生成一个  $1 \times 500$  行向量, 每一个元素服从  $N(0, 1.5)$

$rd\_data$  列表, 存入第 k 列

$\downarrow$   $2 \times 500 N(0, 0.05)$  列

$(\frac{z_1}{\sqrt{2}}, \frac{z_2}{\sqrt{2}}) + (z_3, z_4)$

⇒

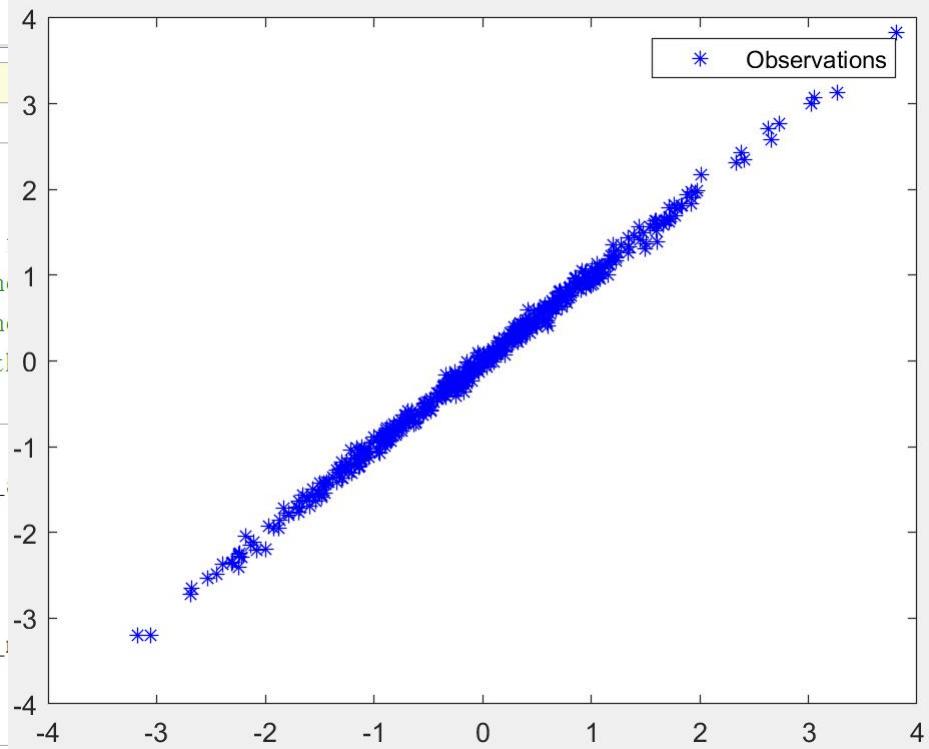
# Data Simulation

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

%% 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')

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



>> PCA\_demo  
The direction of the data distribution:  
0.7071  
0.7071

添加图形  
创建绘图窗口  
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

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

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

disp('The singular values are given:');
disp(singular_vec(1:2));
% The estimations of std:
disp(singular_vec(1:2)/sqrt(rd_num))
```

The eigenvectors:

-0.7065	0.7077
-0.7077	-0.7065

The singular values are given:

33.6941

1.0605

The estimations of std:

$$\Rightarrow 6_i = \frac{\sqrt{\lambda_i} N}{\sqrt{N}}$$

1.5068

>> PCA\_demo

The direction of the data distribution:

0.7071
--------

0.7071
--------

# 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))
```

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
```

```
%% 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
```

# Diagonal decomposition of the correlation matrix

```
%% Diagonal decomposition of the correlation matrix
R_Mat = ob_data*ob_data'
disp('The correlation matrix of the data is given:');
dinp(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)))
```

*Annotations:*  
R\_Mat = ob\_data\*ob\_data'  
The correlation matrix of the data is given:  
[V, D] = eig(R\_Mat);  
The eigenvectors are given:  
The eigenvalues are given:  
The singular vaules are given in another form:

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

```
%> Diagonal decomposition of the correlation matrix  
R_Mat = 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))  
dis The eigenvectors: r form:  
dis [-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:

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

```
%> Diagonal decomposition of the correlation matrix  
R_Mat = 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');  
disp(sqrt(diag(D)))
```

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:

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

# Projection and reconstruction

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

# Projection and reconstruction

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

the std of the projections  
33.7202

The eigenvectors:  
-0.7065 0.7077  
-0.7077 -0.7065

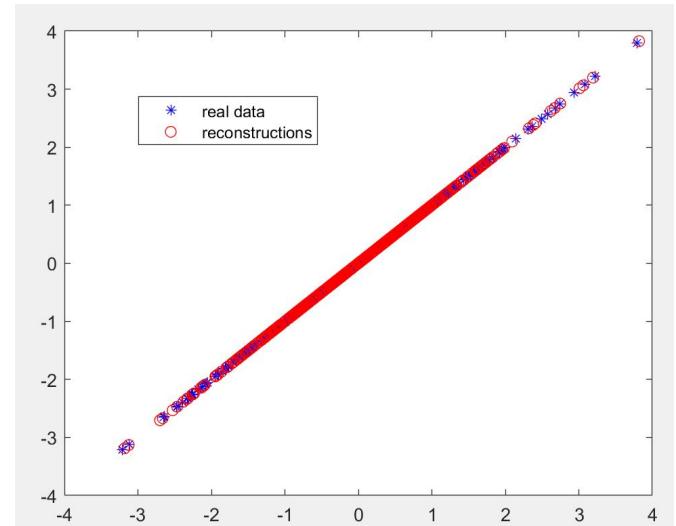
The singular values are given:  
33.6941  
1.0605

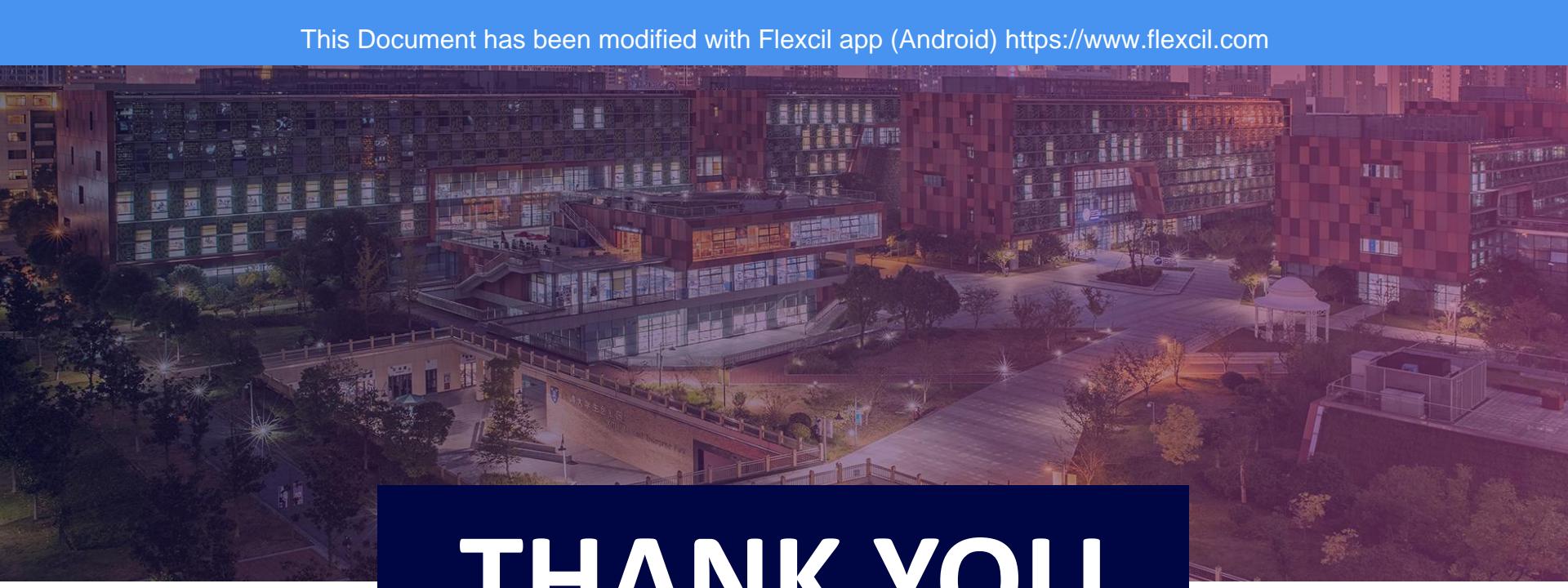
The estimations of std:  
1.5068  
0.0474

# Projection and reconstruction

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



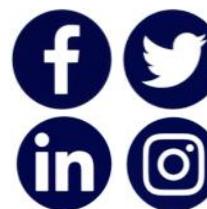


THANK YOU



**VISIT US**

[WWW.XJTLU.EDU.CN](http://WWW.XJTLU.EDU.CN)



**FOLLOW US**

@XJTLU



Xi'an Jiaotong-Liverpool University  
西交利物浦大学