

矩阵代数 Matlab 实验

丁广太等

上海大学计算机工程与科学学院

2020 年 4 月

目录

| | |
|---|----|
| Matlab 7.6 简单入门 | 1 |
| 1 启动 | 1 |
| 2 Matlab 的使用方式 | 1 |
| 3 交互方式的使用 | 1 |
| 4 Matlab 的程序工作方式 | 1 |
| 5 基本命令 | 2 |
| 6 基本函数 | 2 |
| 7 数据类型及运算 | 2 |
| 8 Matlab 程序控制流 | 3 |
| 实验一 矩阵的基本运算 | 5 |
| 1.1 矩阵的输入 | 5 |
| 1.2 矩阵的生成 | 5 |
| 1.3 矩阵的四则运算 | 8 |
| 1.4 矩阵与标量的运算 | 8 |
| 1.5 矩阵的函数运算 | 8 |
| 1.6 矩阵的引用 | 8 |
| 练习 | 9 |
| 思考 | 9 |
| 实验二 矩阵的性能指标和范数 | 10 |
| 2.1 矩阵相似 | 10 |
| 2.2 行列式 | 10 |
| 2.3 秩 | 10 |
| 2.4 二次型 | 10 |
| 2.5 特征值 | 10 |
| 2.6 迹 | 10 |
| 2.7 初等变换 | 11 |
| 2.8 向量的内积与范数 | 12 |
| 2.9 矩阵范数 | 16 |
| 实验三 特殊矩阵 | 1 |
| 3.1 三角阵和上三角阵的生成 | 1 |
| 3.2 基本矩阵和向量的外积 | 1 |
| 3.3 酉矩阵和正交矩阵 | 1 |
| 3.5 位移矩阵 | 1 |
| 3.6 傅里叶矩阵和范德蒙矩阵 | 1 |
| 3.7 各种对称矩阵 | 2 |
| 3.8 拓普利兹矩阵(Toeplitz matrix)和汉克矩阵(Hankel matrix) | 2 |
| 3.9 最小二乘拟合 | 2 |
| 3.10 Kronecker 积 | 3 |
| 实验四 矩阵分解 | 6 |
| 4.1 常用矩阵分解 | 6 |
| (1) 任意矩阵都与其等价标准型等价 | 6 |

| | |
|--|----|
| (2) 三角(LU)分解 | 6 |
| (3) Cholesky 分解(乔里斯基) | 6 |
| (4) C.Schur 分解(舒尔) | 6 |
| (5) QR 分解 | 6 |
| (6) 若当标准型 | 6 |
| (7) 特征值分解 | 6 |
| (8) 奇异值分解 | 7 |
| 4.2 案例 1: 图像压缩 | 7 |
| 4.3 条件数的计算 | 8 |
| 4.4 条件数与方程解的精度之间的关系 | 9 |
| 4.5 奇异值分解 (图像压缩) | 10 |
| 4.6 数字水印 | 11 |
| 4.7 主成分分析 | 12 |
| 4.8 城市生活指数排名 | 13 |
| 实验五 逆矩阵与矩阵方程求解 | 15 |
| 5.1 彭罗斯逆的奇异值分解(SVD)法 | 15 |
| 5.2 方程的普通最小二乘解 | 16 |
| 5.3 吉洪诺夫正则化方法 | 16 |
| 5.4 总体最小二乘法 | 16 |
| 5.5 稀疏矩阵方程求解 | 19 |
| 实验六 矩阵微积分 | 21 |
| 6.1 用 MATLAB 函数 logm() 计算 $\log(tA)$ 的导数 | 21 |
| 6.2 函数 $f(X)=a^T X b$ 的导函数 | 21 |
| 6.3 Tikhonov 方法的最速下降法实现 | 21 |
| 6.4 Tikhonov 方法的牛顿法实现 | 22 |

Matlab 7.6 简单入门

Matlab 是 Mathworks 公司推出的科技应用软件。

1 启动

点击 Matlab/bin/matlab.exe, 打开 Matlab 的工作窗(或指令窗)

2 Matlab 的使用方式

- ①指令行操作之直接交互工作方式;
- ②使用 Matlab 编程语言之程序设计方式。

3 交互方式的使用

在 Matlab 工作窗 (如图 1 所示, Command Window) 中一般输入以下三种指令行:

- ①命令
- ②表达式
- ③赋值语句: 变量=表达式

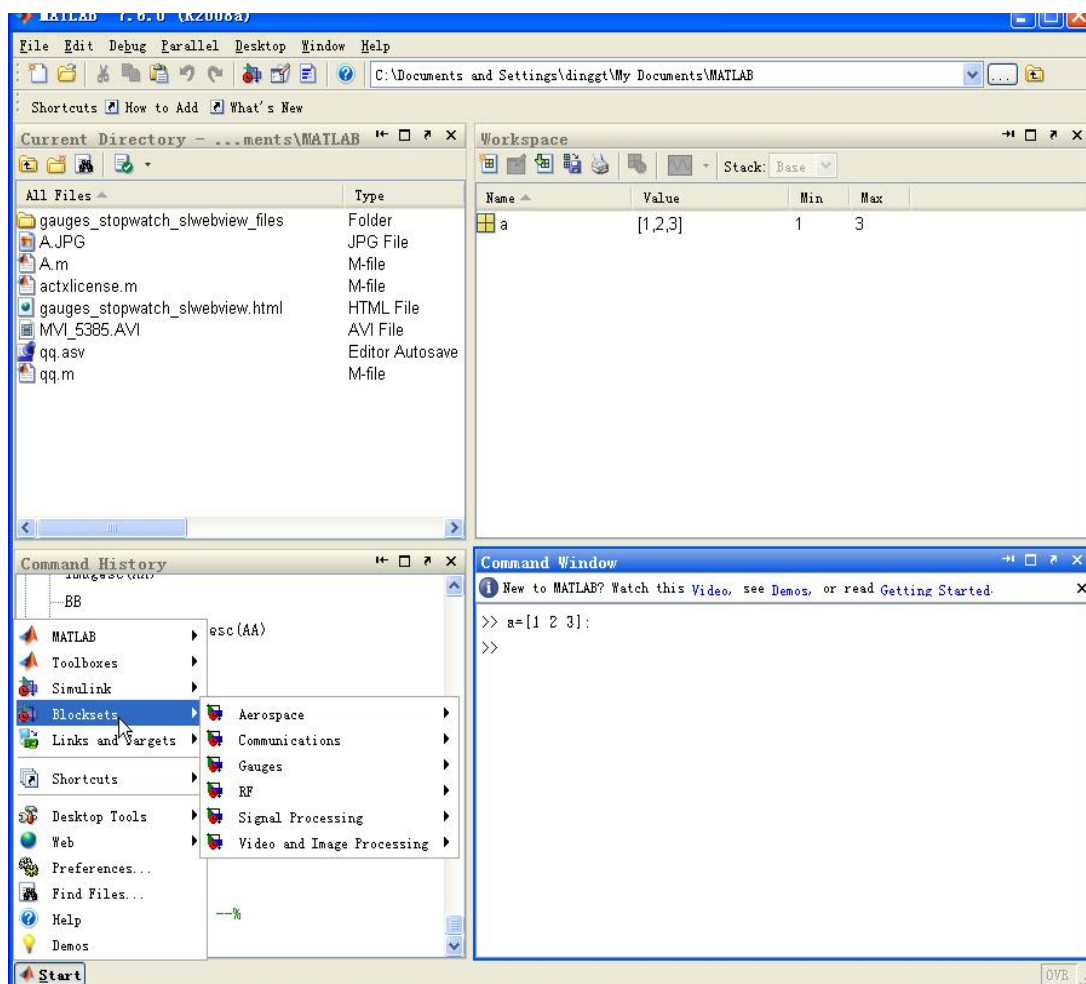


图 1 Matlab 工作窗

4 Matlab 的程序工作方式

- step 1. File→New→M-file %打开 Matlab 程序工作窗 Editor/Debugger
- step 2. 编写 Matlab 程序; Tools→Run

5 基本命令

| | |
|-------------|---------------|
| quit | %退出 Matlab |
| clc | %清除指令窗口 |
| clear | %从内存中清除变量和函数 |
| clf | %清除当前图 |
| pack | %合并工作内存中的碎块 |
| dir | %列出文件 |
| cd | %改变或显示当前工作目录 |
| disp | %显示矩阵和文字内容 |
| size | %确定矩阵的维数 |
| demo | %演示程序 |
| <u>help</u> | <u>%在线帮助</u> |
| delete | %删除文件 |
| whos | %列出工作内存中的变量细节 |
| xpimage | %图像处理性能的演示 |
| imagedemo | %同上 |

6 基本函数

| | |
|-----------|-----------------------|
| figure | %创建图形窗口 |
| image | %创建图形窗口 |
| imshow | %显示图像 |
| colormap | %设置配色图 |
| rgb2hsv | %将 rgb 图像转换成 hsv 图像 |
| hsv2rgb | %将 hsv 图像转换成 rgb 图像 |
| rgb2ycbcr | %将 rgb 图像转换成 ycbcr 图像 |
| ycbcr2rgb | %将 ycbcr 图像转换成 rgb 图像 |
| abs | %幅值 |
| fft2 | %二维快速 Fourier 变换 |
| ifft2 | %二维快速 Fourier 反变换 |
| log | %自然对数 |
| dct2 | %二维快速余弦变换 |
| idct2 | %二维快速余弦反变换 |
| image | %与 imshow 相似 |
| imfinfo | %显示图像参数 |

7 数据类型及运算

1) Matlab 的基本数据类型为矩阵(实数皆看成 1×1 的矩阵)，矩阵的基本运算同线性代数

| | |
|------|-----------|
| A+B | %矩阵相加 |
| A-B | %矩阵相减 |
| A*B | %矩阵相乘 |
| A.*B | %矩阵对应元素相乘 |

2) 标量与矩阵进行运算的规定

$$s+B=sE+B$$

$$s-B=sE-B$$

$$B-s=B-sE$$

$$s*B=sE*B$$

3) 其他运算

$$\text{inv}(B)=B^{-1}$$

$$A^n=A^n, \quad A.^n=(a_{ij})^n$$

$$\exp(A)=(\exp(a_{ij}))$$

$$\log(A)=(\log(a_{ij}))$$

$$f(A)=(f(a_{ij}))$$

$$A' = A'$$

4) 矩阵的输入

直接输入

```
A=[1 2 3;
    4 5 6;
    7 8 9]
```

矩阵编辑器

```
edit A
```

5) 指令行结果的输出

(有如下三个要点)

指令行后有分号，不输出结果

指令行后无分号，输出运算结果

表达式后按回车，则 ans=之后，给出结果

6) 冒号运算符

设 A 是 m*n 矩阵

$B=A(:, r)$ %由第 r 列元素组成的矩阵

$B=A(s, :)$ %由第 s 行元素组成的矩阵

$B=A(s1:s2, r1:r2)$ %取 A 的子矩阵

$B=A([1 \ 3 \ 5], :)$ %由 A 的 1, 3, 5 行组成的矩阵

7) 给矩阵作标志

$L=X \leq 0.5$; %标志矩阵 X 中其值小于 0.5 的元素的位置 (小于 0.5 的元素替换为 1, 其余为零, 作成一个新矩阵)

8) Laplacian 算子

del2() %五点离散拉普拉斯算子

8 Matlab 程序控制流

1) 注释

%号为串首元素的一行字符串

2) 循环结构

| for-end | while-end |
|--------------------------------------|---------------------------|
| for 循环变量=循环初值:增量值:循环终值 语句组 end | while 逻辑表达式 语句组 end |

3) 分支结构

| if-else-end | switch-case-end |
|---|---|
| if 逻辑表达式 语句体 1 else 语句体 2 end | switch 表达式 case value1 语句体 1 case valueN 语句体 N otherwise 语句体 N+1 end |

实验一 矩阵的基本运算

1.1 矩阵的输入

通过键盘输入数据创建一个矩阵。

```
A=[ 1 2 3 4;2 3 4 5;6 7 8 9];
```

```
disp(A)
```

```
>> A=[ 1 2 3 4;2 3 4 5;6 7 8 9];
```

```
disp(A)
```

```
1  2  3  4
2  3  4  5
6  7  8  9
```

```
B=[0.1 0.2 0.3
```

```
    -1 2 3
```

```
    1 1 1];
```

```
disp(B)
```

```
>> B=[0.1 0.2 0.3
```

```
    -1 2 3
```

```
    1 1 1];
```

```
disp(B)
```

```
0.1000 0.2000 0.3000
-1.0000 2.0000 3.0000
1.0000 1.0000 1.0000
```

注：蓝色表示在控制台运行的结果（命令行方式）

1.2 矩阵的生成

(1) 特殊矩阵

● 单位矩阵

```
I=eye(5)
```

```
I=eye(3,5)
```

```
>> I=eye(5)
```

```
I =
```

```
1  0  0  0  0
0  1  0  0  0
0  0  1  0  0
0  0  0  1  0
0  0  0  0  1
```

```
>> I=eye(3,5)
```

```
I =
```

```
1  0  0  0  0
0  1  0  0  0
0  0  1  0  0
```


eye 的帮助文档

>> help eye

EYE Identity matrix.

EYE(N) is the N-by-N identity matrix.

EYE(M,N) or EYE([M,N]) is an M-by-N matrix with 1's on the diagonal and zeros elsewhere.

EYE(SIZE(A)) is the same size as A.

EYE with no arguments is the scalar 1.

EYE(M,N,CLASSNAME) or EYE([M,N],CLASSNAME) is an M-by-N matrix with 1's

of class CLASSNAME on the diagonal and zeros elsewhere.

Note: The size inputs M and N should be nonnegative integers. Negative integers are treated as 0.

Example:

```
x = eye(2,3,'int8');
```

See also speye, ones, zeros, rand, randn.

Overloaded methods:

distributionReplicated/eye

distribution1d/eye

Reference page in Help browser

doc eye

● 零矩阵

```
A=zeros(n);
```

```
B=zeros(n,m);
```

```
>> A=zeros(3)
```

```
A =
```

```
0 0 0
```

```
0 0 0
```

```
0 0 0
```

```
>> B=zeros(3,3)
```

```
B =
```

```
0 0 0
```

```
0 0 0
```

```
0 0 0
```

```
>> C=zeros(1,3)
```

```
C =
```

```
0 0 0
```

● 元素全 1 的矩阵

```
A=ones(n);
```

```
B=ones(n,m);
```

语法同 zeros

● 稀疏单位矩阵

用表示稀疏数据的数据结构表示的单位阵

```
>> A=speye(4)
```

```
A =
```

```
(1,1) 1
```

```
(2,2) 1
```

```
(3,3) 1
```

```
(4,4) 1
```

```
>> whos
```

| Name | Size | Bytes | Class | Attributes |
|------|------|-------|--------|------------|
| A | 4x4 | 104 | double | sparse |
| B | 3x3 | 72 | double | |
| C | 1x3 | 24 | double | |
| I | 3x5 | 120 | double | |
| ans | 2x2 | 56 | double | sparse |

```
>> help speye
```

SPEYE Sparse identity matrix.

SPEYE(M,N) forms an M-by-N sparse matrix with 1's on the main diagonal. SPEYE(N) abbreviates SPEYE(N,N).

SPEYE(SIZE(A)) is a space-saving SPARSE(EYE(SIZE(A))).

See also spones, spdiags, spalloc, sprand, sprandn.

Overloaded methods:

distributionReplicated/speye

distribution1d/speye

Reference page in Help browser

doc speye

```
>> A(1,1)
```

```
ans =
```

1

>> A(1,2)

ans =

0

>> B=A

B =

(1,1) 1

(2,2) 1

(3,3) 1

(4,4) 1

(2) 随机矩阵

- 服从均匀分布的随机矩阵

rand(n);

rand(n,m)

- 服从标准正态分布的随机矩阵

randn(n);

randn(n,m)

1.3 矩阵的四则运算

A+B %矩阵相加

C-B %矩阵相减

A*B %矩阵相乘

A.*B %矩阵对应元素相乘

1.4 矩阵与标量的运算

s+B=sE+B

s-B=sE-B

B-s=B-sE

s*B=sE*B

1.5 矩阵的函数运算

inv(B)=B⁻¹Aⁿ=Aⁿ, A.ⁿ=(a_{ij})ⁿexp(A)=(exp(a_{ij}))log(A)=(log(a_{ij}))f(A)=(f(a_{ij}))

A'=A'

1.6 矩阵的引用

- 用位置标号引用

设 A 是 m*n 矩阵

B=A(i,j)

- 冒号运算符

设 A 是 m*n 矩阵

$B=A(:,r)$ %由第 r 列元素组成的矩阵
 $B=A(s,:)$ %由第 s 行元素组成的矩阵
 $B=A(s1:s2,r1:r2)$ %取 A 的子矩阵
 $B=A([1\ 3\ 5],:)$ %由 A 的 1,3,5 行组成的矩阵

练习

- (1) 生成随机矩阵 A, B
- (2) 计算 $A+A^2+A^3+A^4+A^5+A^6$
- (3) 计算 $\sin(A), \exp(A)$
- (4) 计算 $\sin.(A), \exp.(A)$

思考

引进矩阵这种数据对象，有何必要？目的何在？

（数学家，工程人员如何想？）

实验二 矩阵的性能指标和范数

2.1 矩阵相似

判断 $A \sim B$ ，只需求方程 $AX - XB = 0$ 是否有非奇异解。

`X=lyap(A,-B,0);`

`det(X)`

2.2 行列式

`det(A)`

2.3 秩

`rank(A)`

`conj(x)`: x 的共轭。

2.4 二次型

`quadprog`

2.5 特征值

`eig(A)`

例: $\text{eig}(A - cI) = \text{eig}(A) - c$

`A=rand(5,5);`

`c=20;`

`I=eye(5,5);`

`eig(A+c*I)`

`eig(A)`

`ans =`

`23.2146 + 0.0000i`

`20.3121 + 0.0000i`

`19.6940 + 0.0000i`

`19.4406 + 0.1624i`

`19.4406 - 0.1624i`

`ans =`

`3.2146 + 0.0000i`

`0.3121 + 0.0000i`

`-0.3060 + 0.0000i`

`-0.5594 + 0.1624i`

`-0.5594 - 0.1624i`

2.6 迹

`trace(A)`

例: 写出矩阵乘积 ABCD 的等迹关系式! (最好使用递归)

`i=0;`

`A=zeros(24,4);`

`for i1=1:4`

`for i2=1:4`

`for i3=1:4`

`for i4=1:4`

`if i1~=i2 && i1~=i3 && i1~=i4 && i2~=i3 && i2~=i4 && i3~=i4`

`i=i+1;`

`A(i,1)=i1;A(i,2)=i2;A(i,3)=i3;A(i,4)=i4;`

```

        disp(A(i,:));
    end
end
end
end
End

B=zeros(4,5,5);
for ii=1:4
    BB=rand(5,5);
    B(ii,:,:)=BB(:,:,);
    % C(:,:,)=B(ii,:,:);
    % disp(C);
End

for ii=1:24
    D1(:,:,)=B(A(ii,1),:,:);
    D2(:,:,)=B(A(ii,2),:,:);
    D3(:,:,)=B(A(ii,3),:,:);
    D4(:,:,)=B(A(ii,4),:,:);
    D=D1*D2*D3*D4;
    E(ii)=trace(D);
End

for ii=1:24
    for jj=(ii+1):24
        if abs(E(ii)-E(jj))<0.00001
            E(jj)=0;
        end
    end
end
for ii=1:24
    if E(ii)~=0
        F(ii)=E(ii);
    else
        break;
    end
end
disp(F);

```

2.7 初等变换

```

m=5;
I=eye(m,m);
A=randn(m,m);
%某行乘以常数倍-----
c=0.5;%常数
col=3;%行号
I1=I;
I1(col,col)=1*c;

%某两行互换-----
col1=2;%行号 1
col2=4;%行号 2
I2=I;

```

```

I2(col1,col1)=0;
I2(col2,col2)=0;
I2(col1,col2)=1;
I2(col2,col1)=1;

```

```

%一行乘以常数倍加另一行-----

```

```

c3=10;%常数

```

```

col3=1;%目标排行的行号

```

```

col4=4;%乘以常数倍的行

```

```

I3=I;

```

```

I3(col3,col4)=c3;

```

```

%-----

```

```

A1=I1*A;

```

```

A2=I2*A;

```

```

A3=I3*A;

```

```

disp(A)

```

```

disp(A1)

```

```

disp(A2)

```

```

disp(A3)

```

```

-1.0056 -0.4049 -0.3038 0.3970 0.5684
 0.4340 0.5279 -0.0087 -0.4828 -1.2060
 0.5201 -1.0070 0.5066 -0.2315 0.4331
-1.0922 1.0890 1.2033 0.6134 -0.0921
-0.2258 1.7849 0.5220 1.6829 -0.2441

```

```

-1.0056 -0.4049 -0.3038 0.3970 0.5684
 0.4340 0.5279 -0.0087 -0.4828 -1.2060
 0.2601 -0.5035 0.2533 -0.1157 0.2165
-1.0922 1.0890 1.2033 0.6134 -0.0921
-0.2258 1.7849 0.5220 1.6829 -0.2441

```

```

-1.0056 -0.4049 -0.3038 0.3970 0.5684
-1.0922 1.0890 1.2033 0.6134 -0.0921
 0.5201 -1.0070 0.5066 -0.2315 0.4331
 0.4340 0.5279 -0.0087 -0.4828 -1.2060
-0.2258 1.7849 0.5220 1.6829 -0.2441

```

```

-11.9280 10.4853 11.7288 6.5309 -0.3528
 0.4340 0.5279 -0.0087 -0.4828 -1.2060
 0.5201 -1.0070 0.5066 -0.2315 0.4331
-1.0922 1.0890 1.2033 0.6134 -0.0921
-0.2258 1.7849 0.5220 1.6829 -0.2441

```

2.8 向量的内积与范数

(1) 内积

dot

表示两个向量的内积

(2) 范数

norm(x, 1), norm(x, 2), norm(x, inf), norm(x, -inf), norm(x, p)

(3) 距离（相似性）

pdist2

[help pdist2](#)

[pdist2 - Pairwise distance between two sets of observations](#)

This MATLAB function returns the distance between each pair of observations in X and Y using the metric specified by Distance.

`D = pdist2(X,Y,Distance)`

`D = pdist2(X,Y,Distance,DistParameter)`

`D = pdist2(__,Name,Value)`

`[D,I] = pdist2(__,Name,Value)`

另请参阅 [ExhaustiveSearcher](#), [KDTreeSearcher](#), [createns](#), [knnsearch](#), [pdist](#)

[pdist2 的参考页](#)

[名为 pdist2 的其他函数](#)

```
d1 = pdist2(x,y,'Euclidean');
d2 = pdist2(x,y,'seuclidean');
d3 = pdist2(x,y,'mahalanobis');
d4 = pdist2(x,y,'cityblock');
d5 = pdist2(x,y,'minkowski',p);
d6 = pdist2(x,y,'chebychev');
d7 = pdist2(x,y,'cosine');
d8 = pdist2(x,y,'correlation');
d9 = pdist2(x,y,'hamming');
d10 = pdist2(x,y,'jaccard');
d11 = pdist2(x,y,'spearman');
```

[S=dist\(X,0\)](#)

▼ Distance Metrics

A distance metric is a function that defines a distance between two observations. `pdist2` supports various distance metrics: Euclidean distance, standardized Euclidean distance, Mahalanobis distance, city block distance, Minkowski distance, Chebychev distance, cosine distance, correlation distance, Hamming distance, Jaccard distance, and Spearman distance.

Given an $m \times n$ -by- n data matrix X , which is treated as $m \times (1\text{-by-}n)$ row vectors x_1, x_2, \dots, x_m , and an $m \times n$ -by- n data matrix Y , which is treated as $m \times (1\text{-by-}n)$ row vectors y_1, y_2, \dots, y_m , the various distances between the vector x_s and y_t are defined as follows:

- Euclidean distance

$$d_{st}^2 = (x_s - y_t)(x_s - y_t)'$$

The Euclidean distance is a special case of the Minkowski distance, where $p = 2$.

- Standardized Euclidean distance

$$d_{st}^2 = (x_s - y_t)V^{-1}(x_s - y_t)',$$

where V is the n -by- n diagonal matrix whose j th diagonal element is $(S(j))^2$, where S is a vector of scaling factors for each dimension.

- Mahalanobis distance

$$d_{st}^2 = (x_s - y_t)C^{-1}(x_s - y_t)',$$

where C is the covariance matrix.

- City block distance

$$d_{st} = \sum_{j=1}^n |x_{sj} - y_{tj}|.$$

The city block distance is a special case of the Minkowski distance, where $p = 1$.

- Minkowski distance

$$d_{st} = \sqrt[p]{\sum_{j=1}^n |x_{sj} - y_{tj}|^p}.$$

For the special case of $p = 1$, the Minkowski distance gives the city block distance. For the special case of $p = 2$, the Minkowski distance gives the Euclidean distance. For the special case of $p = \infty$, the Minkowski distance gives the Chebychev distance.

- Chebychev distance

$$d_{st} = \max_j \{|x_{sj} - y_{tj}|\}.$$

The Chebychev distance is a special case of the Minkowski distance, where $p = \infty$.

- Cosine distance

$$d_{st} = \left(1 - \frac{x_s y_t'}{\sqrt{(x_s x_s') (y_t y_t')}}\right).$$

- Correlation distance

$$d_{st} = 1 - \frac{(x_s - \bar{x}_s)(y_t - \bar{y}_t)'}{\sqrt{(x_s - \bar{x}_s)(x_s - \bar{x}_s)'} \sqrt{(y_t - \bar{y}_t)(y_t - \bar{y}_t)'}} ,$$

where

$$\bar{x}_s = \frac{1}{n} \sum_j x_{sj}$$

and

$$\bar{y}_t = \frac{1}{n} \sum_j y_{tj}.$$

- Hamming distance

$$d_{st} = (\#(x_{sj} \neq y_{tj})/n).$$

- Jaccard distance

$$d_{st} = \frac{\#[(x_{sj} \neq y_{tj}) \cap ((x_{sj} \neq 0) \cup (y_{tj} \neq 0))]}{\#[(x_{sj} \neq 0) \cup (y_{tj} \neq 0)]}.$$

- Spearman distance

$$d_{st} = 1 - \frac{(r_s - \bar{r}_s)(r_t - \bar{r}_t)'}{\sqrt{(r_s - \bar{r}_s)(r_s - \bar{r}_s)'} \sqrt{(r_t - \bar{r}_t)(r_t - \bar{r}_t)'}} ,$$

where

- r_{sj} is the rank of x_{sj} taken over $x_{1j}, x_{2j}, \dots, x_{mj}$, as computed by [tiedrank](#).
- r_{tj} is the rank of y_{tj} taken over $y_{1j}, y_{2j}, \dots, y_{mj}$, as computed by [tiedrank](#).
- r_s and r_t are the coordinate-wise rank vectors of x_s and y_t , i.e., $r_s = (r_{s1}, r_{s2}, \dots, r_{sn})$ and $r_t = (r_{t1}, r_{t2}, \dots, r_{tm})$.
- $\bar{r}_s = \frac{1}{n} \sum_j r_{sj} = \frac{(n+1)}{2}$.
- $\bar{r}_t = \frac{1}{n} \sum_j r_{tj} = \frac{(n+1)}{2}$.

Distance metric, specified as a character vector, string scalar, or function handle, as described in the following table.

| Value | Description |
|--------------------|--|
| 'euclidean' | Euclidean distance (default). |
| 'squaredeuclidean' | Squared Euclidean distance. (This option is provided for efficiency only. It does not satisfy the triangle inequality.) |
| 'seuclidean' | Standardized Euclidean distance. Each coordinate difference between observations is scaled by dividing by the corresponding element of the standard deviation, $S = \text{nanstd}(X)$. Use DistParameter to specify another value for S . |
| 'mahalanobis' | Mahalanobis distance using the sample covariance of X , $C = \text{nancov}(X)$. Use DistParameter to specify another value for C , where the matrix C is symmetric and positive definite. |
| 'cityblock' | City block distance. |
| 'minkowski' | Minkowski distance. The default exponent is 2. Use DistParameter to specify a different exponent P , where P is a positive scalar value of the exponent. |
| 'chebychev' | Chebychev distance (maximum coordinate difference). |
| 'cosine' | One minus the cosine of the included angle between points (treated as vectors). |
| 'correlation' | One minus the sample correlation between points (treated as sequences of values). |

| Value | Description |
|------------|---|
| 'hamming' | Hamming distance, which is the percentage of coordinates that differ. |
| 'jaccard' | One minus the Jaccard coefficient, which is the percentage of nonzero coordinates that differ. |
| 'spearman' | One minus the sample Spearman's rank correlation between observations (treated as sequences of values). |
| @distfun | <p>Custom distance function handle. A distance function has the form</p> <pre>function D2 = DISTFUN(ZI,ZJ) % calculation of distance ...</pre> <p>where ZI is a 1-by-n vector containing a single observation. ZJ is an m2-by-n matrix containing multiple observations. distfun must accept a matrix ZJ with an arbitrary number of observations. D2 is an m2-by-1 vector of distances, and D2(k) is the distance between observations ZI and ZJ(k, :). If your data is not sparse, you can generally compute distance more quickly by using a built-in distance instead of a function handle.</p> |

```

A=rand(4,5);
B=rand(4,5);
ab=dot(A,B);
X(:)=A(:,1);
Y(:)=B(:,1);
xy=dot(X,Y);
disp(ab);
disp(xy);
disp(['X=',num2str(X)]);
normX=norm(X);
normX1=norm(X,1);
normX2=norm(X,2);
normXinf=norm(X,Inf);
normXfro=norm(X,'fro');
disp(normX);
disp(normX1);
disp(normX2);
disp(normXinf);
disp(normXfro);

```

2.9 矩阵范数

列和范数: $\text{norm}(A, 1)$

行和范数: `norm(A, inf)`

谱范数: `norm(A, 2)`

Frobenius 范数: `norm(A, 'fro')`

Syntax

```
n = norm(v)
n = norm(v, p)
n = norm(X)
n = norm(X, p)
n = norm(X, 'fro')
```

Description

`n = norm(v)` returns the **Euclidean norm** of vector `v`. This **norm** is also called the **2-norm**, vector magnitude, or Euclidean length.

`n = norm(v, p)` returns the **generalized vector p-norm**.

`n = norm(X)` returns the **2-norm** or maximum singular value of matrix `X`, which is approximately `max(svd(X))`.

`n = norm(X, p)` returns the **p-norm** of matrix `X`, where `p` is 1, 2, or Inf:

If `p = 1`, then `n` is the **maximum absolute column sum** of the matrix.

If `p = 2`, then `n` is approximately `max(svd(X))`. This is equivalent to `norm(X)`.

If `p = Inf`, then `n` is the **maximum absolute row sum** of the matrix.

`n = norm(X, 'fro')` returns the **Frobenius norm** of matrix `X`.

```
A=rand(4,5);
B=rand(4,5);
ab=dot(A,B);
disp(ab);
%disp(['A=',num2str(A)]);
normA=norm(A);
normA1=norm(A,1);
normA2=norm(A,2);
normAinf=norm(A,Inf);
normAfro=norm(A,'fro');
disp(normA);
disp(normA1);
disp(normA2);
disp(normAinf);
disp(normAfro);
```

练习

(1) 生成一个矩阵 `A`, 求其行列式、迹、秩等。

(2) 研究 `quadprog`, 生成一个二次型问题, 并对其求解。

(3) 编写程序，实现矩阵的初等变换，三种类型都考虑。

思考

判断两个向量的相似性，用哪种距离函数最好？

实验三 特殊矩阵

3.1 三角阵和上三角阵的生成

diag, triu, chol

3.2 基本矩阵和向量的外积

$$a \wedge b = ab^T$$

3.3 酉矩阵和正交矩阵

傅里叶矩阵、Hadamard 矩阵是正交矩阵

3.4 矩阵的向量化

```
A = 1  2  3
     4  5  6
>> B=reshape(A,1,[])
B =
     1  4  2  5  3  6
>> C=reshape(B,2,3)
C =
     1  2  3
     4  5  6
```

3.5 位移矩阵

```
A=eye(3);
B=circshift(A,-1);
C=B*[ 10,11,12]'
```

3.6 傅里叶矩阵和范德蒙矩阵

```
clear all
N=4;
w=exp(-1i*2*pi/N);
V=zeros(1,N);
for ii=1:N
    V(ii)=w^(ii-1);
end
A=vander(V);
B=fliplr(A);
F=B;
for ii=1:N
    for jj=1:N
        k=((ii-1)*(jj-1));
        FF(ii,jj)=w^k;
    end
end
```

```
end
```

```
F-FF
```

```
C=real(F);
```

```
S=imag(F);
```

```
C*C+S*S
```

```
F*F
```

3.7 各种对称矩阵

对称矩阵、反对称矩阵、斜对称矩阵、中心对称矩阵

3.8 拓普利兹矩阵(Toeplitz matrix)和汉克矩阵(Hankel matrix)

```
>> help hankel
```

hankel - Hankel 矩阵

此 MATLAB 函数 返回其第一列是 c 并且其第一个反对角线下方的元素为零的

Hankel 方阵.

```
H = hankel(c)
```

```
H = hankel(c,r)
```

```
>> help toeplitz
```

toeplitz - Toeplitz matrix

This MATLAB function returns a nonsymmetric Toeplitz matrix with c as its first column and r as its first row.

```
T = toeplitz(c,r)
```

```
T = toeplitz(r)
```

3.9 最小二乘拟合

```
clear all
```

```
close all
```

```
N=7;%阶数, N+1 个系数
```

```
M=20;%数据采样点个数
```

```
x=rand(M,1);
```

```
a=zeros(1,2*N+1);y=sin(pi/2*x);%真实信号
```

```
K=0.02;%干扰信号的放大系数
```

```
errors=K*randn(M,1);%干扰信号
```

```
y=y+errors;%采样信号 (叠加了噪声, 加性噪声)
```

```
%y=y.*(1+errors) ;%采样信号 (叠加了噪声, 一种乘性噪声)
```

```
b=zeros(N+1,1);
```

```
for k=1:2*N+1
```

```
    for ii=1:M
```

```
        a(k)=a(k)+x(ii)^(k-1);
```

```
    end
```

```
end
```

```
for k=1:N+1
```

```

for ii=1:M
    b(k)=b(k)+y(ii)*x(ii)^(k-1);
end
end
H=zeros(N+1,N+1);
for ii=1:N+1
    for jj=1:N+1
        H(ii,jj)=a(ii+jj-1);
    end
end
disp(H); A=H\b; disp(A'); tt=0:0.01:1;
yy=zeros(1,length(tt));
for ii=1:length(tt)
    for jj=1:N+1
        yy(ii)=yy(ii)+A(jj)*tt(ii)^(jj-1);
    end
end
plot(tt,0.05+sin(tt*pi/2),'--','Color','b','LineWidth',1);
hold on
plot(tt,yy,'Color','r');
legend('真实信号','多项式拟合','Location','SouthEast');

```

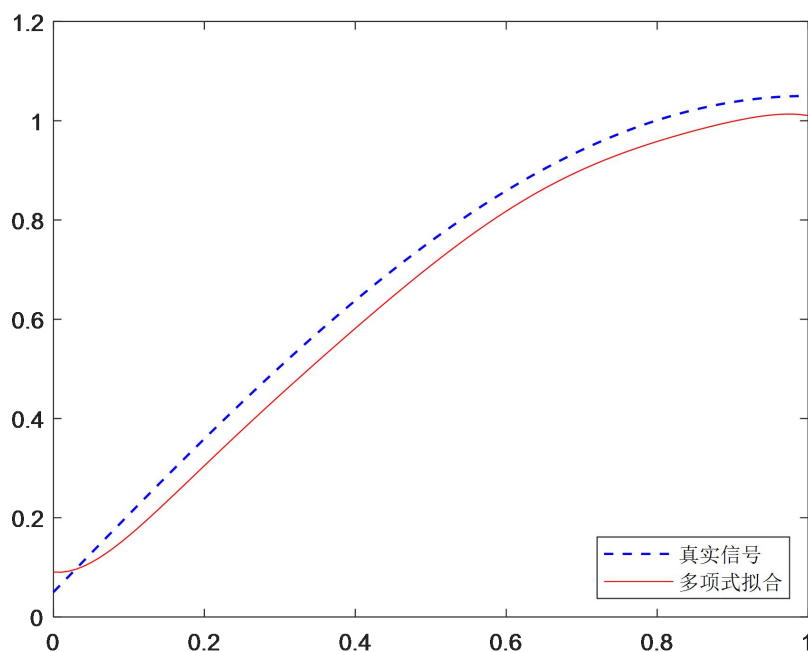


图 3.1 曲线拟合

3.10 Kronecker 积

验证 $K_{mn} \text{vec}(A) = \text{vec}(A^T)$ ，其中 $K_{mn} = \sum_{j=1}^n (e_j^T \otimes I_m \otimes e_j)$

```
function main()
clear all
n=3;
m=3;
K=comm(n,m);
disp(K)
A=rand(3,3);
B=vec(A);
C=vec(A');
D=K*B-C;
disp(D');
end
%子程序:
function V=vec(A) %向量化
    V=reshape(A,[],1);
end
function V=unvec(A,m,n)%反向量化
    V=reshape(A,m,n);
end
function K=comm(n,m)%生成交换矩阵
    I1=eye(n);
    I2=eye(m);
    K=zeros(m*n);
    for ii=1:n
        temp1(:)=I1(:,ii);
        e_ii=temp1';%列向量
        temp2=kron(e_ii,I2);
        K=K+kron(temp2,e_ii);
    end
end
end

>> main

1  0  0  0  0  0  0  0  0
0  0  0  1  0  0  0  0  0
0  0  0  0  0  0  1  0  0
0  1  0  0  0  0  0  0  0
0  0  0  0  1  0  0  0  0
0  0  0  0  0  0  0  1  0
0  0  1  0  0  0  0  0  0
```

0 0 0 0 0 1 0 0 0

0 0 0 0 0 0 0 0 1

0 0 0 0 0 0 0 0 0

练习

- (1) 验证酉矩阵的性质。
- (2) 研究最小二乘法曲线拟合问题。
- (3) 验证矩阵各种新运算是否满足：交换律、结合律、分配律。

思考

- (1) 如何随机生成正交矩阵？
- (2) 验证矩阵各种新运算是否满足：交换律、结合律、分配律。
- (3) 如何用增量采样数据，改进曲线拟合？

实验四 矩阵分解

4.1 常用矩阵分解

矩阵分解是矩阵分析的出发点。注：蓝色标注的矩阵分解是针对方阵的。

(1) 任意矩阵都与其等价标准型等价

$$A_{m \times n} = P_{m \times m} \begin{pmatrix} I_{r \times r} & O_{r \times (n-r)} \\ O_{(m-r) \times r} & O_{(m-r) \times (n-r)} \end{pmatrix} Q_{n \times n}, r = \text{rank}(A), Q, P \text{ 是非奇异的.}$$

(2) 三角(LU)分解

$$[L, U, P] = \text{l u}(A);$$

(3) Cholesky 分解(乔里斯基)

$$R = \text{chol}(X);$$

(4) C. Schur 分解(舒尔)

$$\begin{aligned} [U, R] &= \text{schur}(X, 'complex'); \\ [U, R] &= \text{schur}(X, 'real'); \end{aligned}$$

(5) QR 分解

$$\begin{aligned} [Q, R] &= \text{qr}(X); \\ [Q, R, E] &= \text{qr}(X); \end{aligned}$$

(6) 若当标准型

$$U^{-1}AU = J$$

$$J = \begin{pmatrix} J_1 & & O \\ & \ddots & \\ O & & J_p \end{pmatrix}, J_k = \begin{pmatrix} \lambda & 1 & & 0 \\ & \lambda & 1 & \\ & & \ddots & 1 \\ 0 & & & \lambda \end{pmatrix} \in C^{L_k \times L_k}$$

Jordan 标准型理论价值比较大。很多性质，都可基于 Jordan 标准型理论推导。

(7) 特征值分解

$$[V, D] = \text{eig}(X);$$

(8) 奇异值分解

$$[U, S, V] = \text{svd}(X);$$

4.2 案例 1：图像压缩

%读原图像

```
X=imread('test.jpg');
```

```
Y=rgb2gray(X);
```

```
figure(1);imshow(Y);
```

%将原图像整理为正方图像，宽高为 H

```
H=100;
```

```
S=size(Y);%得图像的宽和高
```

```
Z=zeros(H,H);
```

```
for ii=1:H
```

```
    for jj=1:H
```

```
        Z(ii,jj)=Y(fix((S(1)-1)/H*ii)+1,fix((S(2)-1)/H*jj)+1);
```

```
    end
```

```
end
```

```
figure(2); imshow(uint8(Z)); title('原图');
```

%特征分解

```
[U,D]=eig(double(Z));
```

```
M=zeros(H,H);
```

```
for LL=1:H/10-1;
```

```
    MM=M;
```

```
    for ii=1:(LL+1)*10
```

```
        MM(ii,ii)=1;
```

```
    end
```

%基于特征分解进行图像重建（还原）

```
GG=U*MM*D/U;
```

```
figure(3),subplot(3,3,LL),
```

```
imshow(uint8(abs(GG))); title(['LL=',num2str(LL*10+10)]);
```

```
end
```

```
ZZ=zeros(10,10);
```

```
flag=1;
```

```
for ii=1:10
```

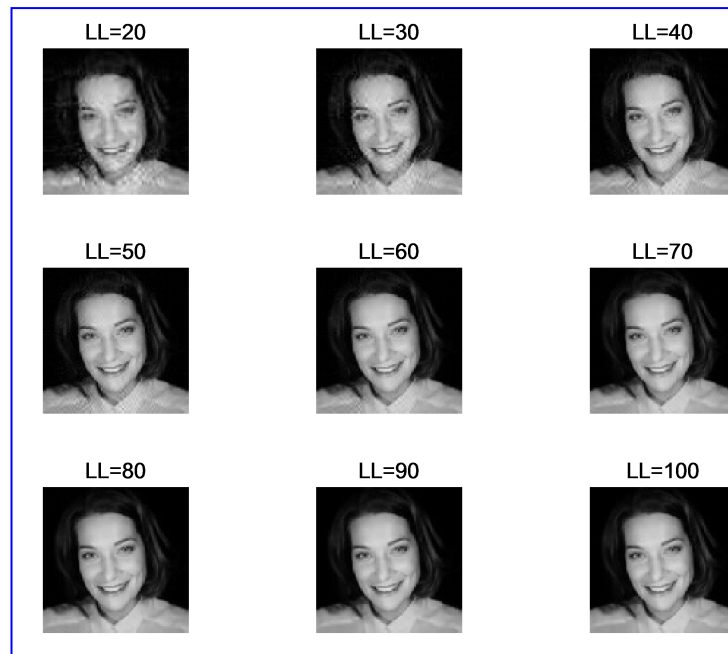
```
    for jj=1:10
```

```
        ZZ(ii,jj)=abs(D(flag,flag));
```

```

    flag=flag+1;
end
end
disp(ZZ);

```



4.3 条件数的计算

%设置一个 小参数

```
d=0.01;
```

%生成两个满秩矩阵

```
U=rand(4,4);
```

```
V=rand(4,4);
```

%基于 d 生成一个矩阵序列

```
for l=1:100
```

```
    dd=d*l;
```

```
    D=diag([4,3,2,dd]);
```

```
    A=U*D*V;
```

%计算矩阵条件数

```
    Y(l)=cond(A);
```

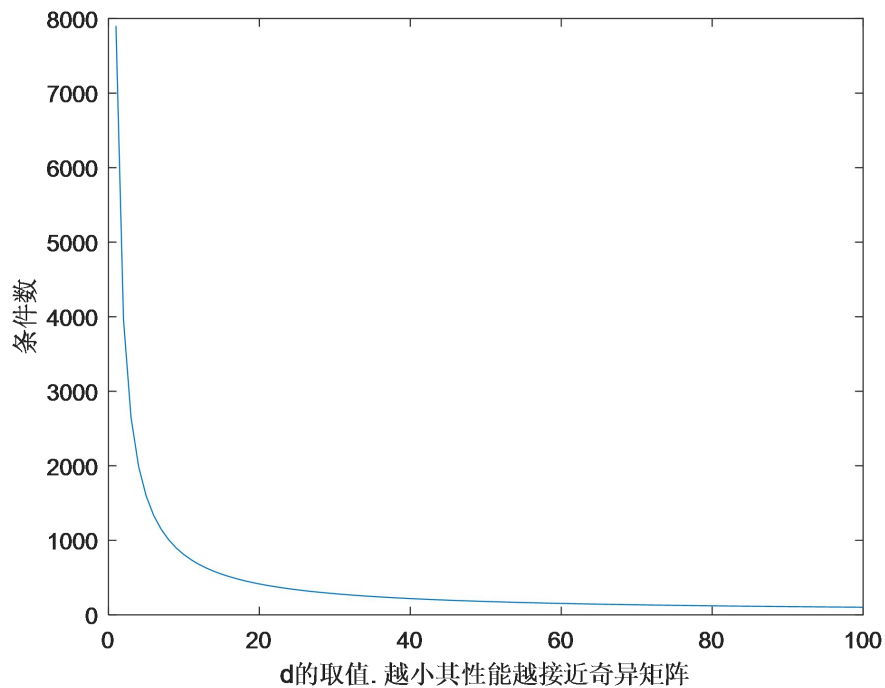
```
end
```

%画 Y 的函数图象

```
plot(Y);
```

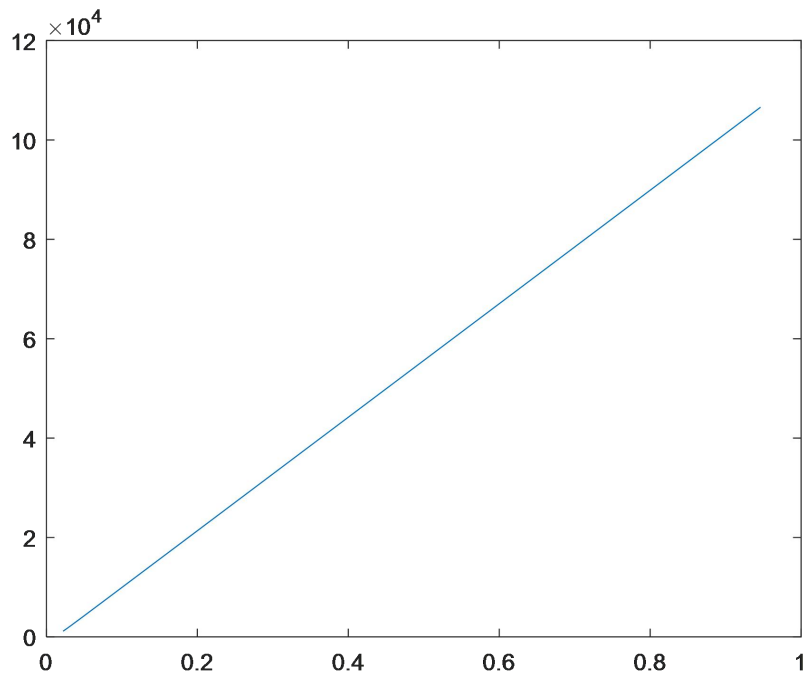
```
xlabel('d 的取值. 越小其性能越接近奇异矩阵');
```

```
ylabel('条件数');
```



4.4 条件数与方程解的精度之间的关系

```
clear all
dd=0.01;
b=rand(4,1);
dA=0.01*rand(4,4);
U=rand(4,4);
V=rand(4,4);
for l=1:100
    d=dd*l;
    D=diag([4,3,2,d]);
    A=U*D*V;
    Y(l)=cond(A);
    X=A\b;
    XX=(A+dA)\b;
    a1=norm(XX);
    a2=norm(XX-X);
    YY(l)=a2/a1;
end
whos
plot(YY,Y);
```



4.5 奇异值分解（图像压缩）

%读原图像

X=imread('test.jpg');

Y=rgb2gray(X);

figure(1);imshow(Y);

%奇异值分解

[U,D,V]=svd(double(Y));

SS=size(D);

M=zeros(SS(1),SS(2));

H=min(SS(1),SS(2));

dd=fix(H/9);

d=fix(sqrt(dd));

for L=1:d*d

MM=M;

for ii=1:(L)*9

MM(ii,ii)=1;

end

rho=SS(1)*SS(2)/((SS(1)+SS(2)+1)*L);

%基于特征值分解进行图像重建（还原）

GG=U*(MM.*D)*V';

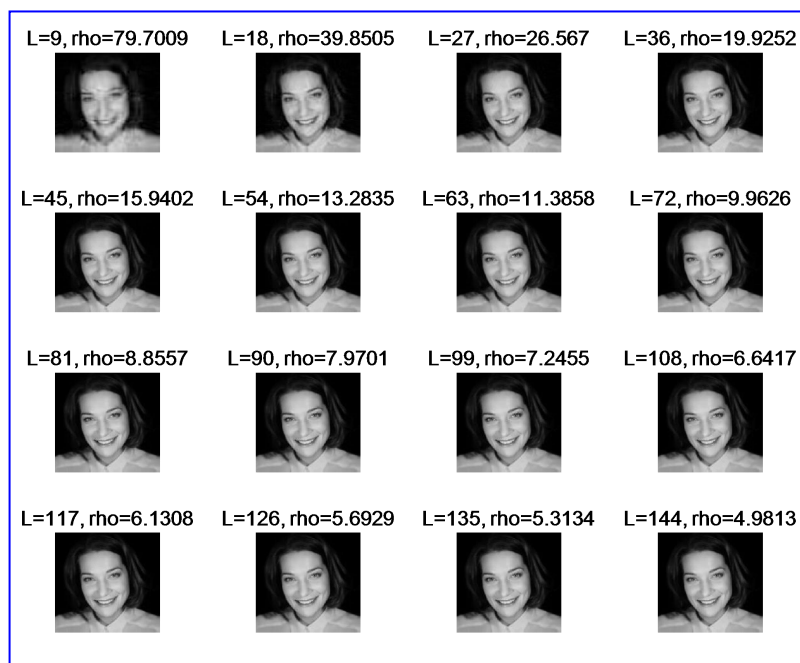
figure(3),subplot(d,d,L),

```

imshow(uint8(abs(GG)));
title(['L=',num2str(L*9),', rho=',num2str(rho)]);
end

ZZ=zeros(d,d);
flag=1;
for ii=1:d
    for jj=1:d
        ZZ(ii,jj)=abs(D(flag,flag));
        flag=flag+1;
    end
end
disp(ZZ);

```



4.6 数字水印

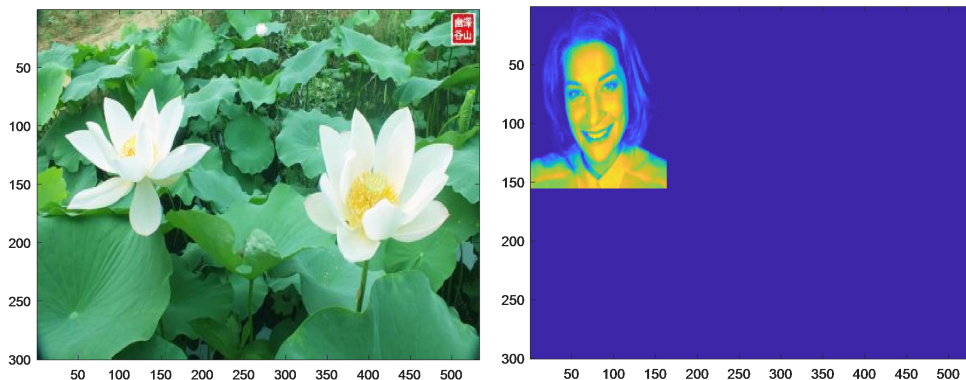
```

AA=imread('A.jpg'); %原图
WW=imread('test.jpg');%水印
A(:,:,1)=AA(:,:,1);
W=rgb2gray(WW);
SW=size(W);
figure(1),imagesc(AA);
[U,S,V]=svd(double(A));
SS=size(S);
WWW=zeros(SS(1),SS(2));
WWW(1:SW(1),1:SW(2))=W(:,:);
figure(2),imagesc(WWW);
a=0.1;

```



```
%嵌入数字水印
L=a*double(WWW)+S;
[U1,S1,V1]=svd(double(L));
AW=U*S1*V';
AA(:,1)=AW(:,1);
figure(3),imagesc(AA);
%提取数字水印
[Up,Sp,Vp]=svd(double(AW));
F=U1*Sp*V1';
WE=(F-S)/a;
figure(4),imagesc(WE);
```



4.7 主成分分析

```
load hald;
%用 Matlab 函数 pca() 进行主成分分析
[coeff,score,latent,tsquared,explained] =
pca(ingredients,'Algorithm','svd','Centered',true)
disp('--用 Matlab 函数 pca() 进行主成分分析---结束');
%自编程序验证 pca()
S=size(ingredients);%求数据维数
EX=zeros(1,S(2)); %用于存放数据期望值
% (1) 求期望值
for ll=1:S(1)
    EX=EX+ingredients(ll,:);
end
EX=EX/S(1);
% (2) 求协方差矩阵
DX=zeros(S(2),S(2));
for ll=1:S(1)
    DX=DX+(ingredients(ll,:)-EX)*(ingredients(ll,:)-EX);
end
DX=DX/(S(1)-1);
disp(EX);
```

```

disp('以上是数学期望-----');
disp(DX);
disp('以上是协方差矩阵-----');
% (3) 特征值分解或奇异值分解
[U,SS,V]=svd(DX);
%[U,SS]=eig(DX)
Y=U*(ingredients'-EX'*ones(1,S(1)));%Hotelling 变换
%coeff
disp('Coeff=');
disp(U);
%latent
disp('Latent=');
disp(diag(SS));
%score
disp('Score=');
disp(Y');
Explained=diag(SS);
Explained=100*Explained/sum(Explained);
%explained
disp('Explained=');
disp(Explained);
S1=DX;
n=S(2);
for II=1:S(1)
    X(II,:)=ingredients(II,:)-EX;
end
Tsquared=X*pinv(S1)*X';%Matlab 如此计算 Tsquared!!!
T2=diag(Tsquared);
%tsquared
disp('Tsquared=');
disp(T2);
disp('---自编程验证 pca()结束----');

```

4.8 城市生活指数排名

（此实例来自 Matlab 帮助）

```

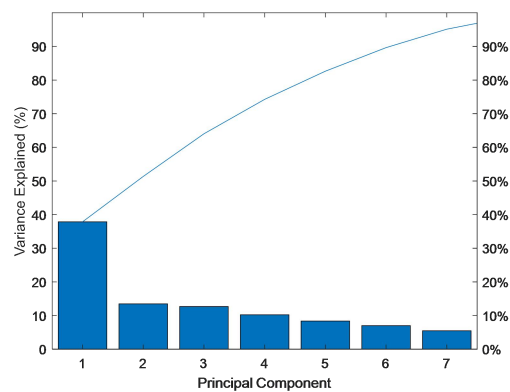
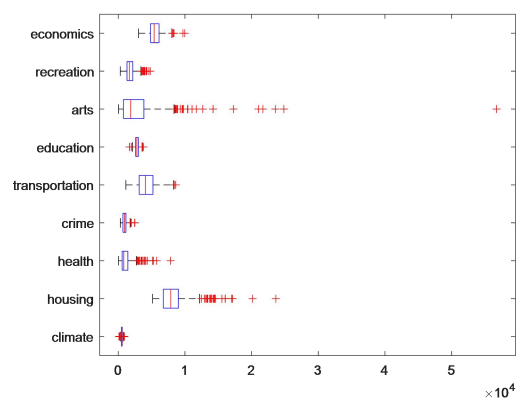
load cities
figure()
boxplot(ratings,'Orientation','horizontal','Labels',categories)
[wcoeff,score,latent,tsquared,explained] = pca(ratings,...
'VariableWeights','variance');

```

```

figure()
pareto(explained)
xlabel('Principal Component')
ylabel('Variance Explained (%)')
[st2,index] = sort(tsquared,'descend');
% sort in descending order
extreme = index(1);
names(extreme,:);
for ll=1:329
    extreme = index(ll);
    disp(names(extreme,:));
end

```



练习

- (1) 随机生成正交阵、酉矩阵、对称阵
- (2) 讨论条件数对矩阵分解精度的影响

思考

- (1) 使用 `pca` 函数进行主成分分析，算法可选择 `svd` 或 `eig`。算法选择是否影响数据分析结论？

实验五 逆矩阵与矩阵方程求解

5.1 彭罗斯逆的奇异值分解(SVD)法

$$A^+ = V\Sigma^+U^H$$

```

A=rand(3,4);
[U,S,V]=svd(A)
SS=size(S);
SSS=min(SS(1),SS(2));
S1=S;
for II=1:SSS
    if S(II,II)>eps
        S1(II,II)=1/S(II,II);
    end
end
PA=(U*S1*V')'
PA1=pinv(A)

U =
    -0.7350    -0.0625     0.6751
    -0.4743    -0.6643    -0.5778
    -0.4846     0.7449    -0.4586

S =
    1.9188         0         0         0
         0    0.7543         0         0
         0         0    0.2598         0

V =
    -0.6132     0.4201     0.4111    -0.5277
    -0.5262     0.1633     0.1102     0.8273
    -0.1764     0.4704    -0.8599    -0.0905
    -0.5621    -0.7587    -0.2818    -0.1702

PA =
    1.2685    -1.1327    -0.1561
    0.4745    -0.2589     0.0995
    -2.2061     1.5419     2.0271
    -0.4541     1.4337    -0.1099

PA1 =
    1.2685    -1.1327    -0.1561
    0.4745    -0.2589     0.0995
    -2.2061     1.5419     2.0271

```

-0.4541 1.4337 -0.1099

5.2 方程的普通最小二乘解

```
clear all
MU=1.5;
SIGMA=1;
A= normrnd(MU,SIGMA,3,4)
b= normrnd(MU,SIGMA,3,1)
XLS1=(A'*A)\(A'*b)
XLS2=pinv(A'*A)*(A'*b)
```

5.3 吉洪诺夫正则化方法

```
clear all
MU=1.5;
SIGMA=1;
A= normrnd(MU,SIGMA,4,3)
b= normrnd(MU,SIGMA,4,1)
l=1
T=(A'*A+l.*eye(3,3))\A'*b
l=2
T=(A'*A+l.*eye(3,3))\A'*b
l=10
T=(A'*A+l.*eye(3,3))\A'*b
l=100
T=(A'*A+l.*eye(3,3))\A'*b
```

5.4 总体最小二乘法

若增广矩阵 $B=[A,b]$ 的奇异值为 $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_{n+1}$, 则总体最小二乘解可表示为

$$X_{TLS} = (A^H A - \sigma_{n+1}^2 I)^{-1} A^H b.$$

若增广矩阵具有比较好的性质，则总体最小二乘解等价于特殊参数的吉洪诺夫反正则化方法 (deregularized method) 解。

```
clear all; rng default
N=7;%阶数, N+1 个系数
M=20;%数据采样点个数
x=rand(M,1);
alpha=0.1;
beta=0.05;
b=sin(pi/2*x)+randn*alpha;%取值有噪声!
a=zeros(N+1,1);
A=zeros(M,N+1);
```

```

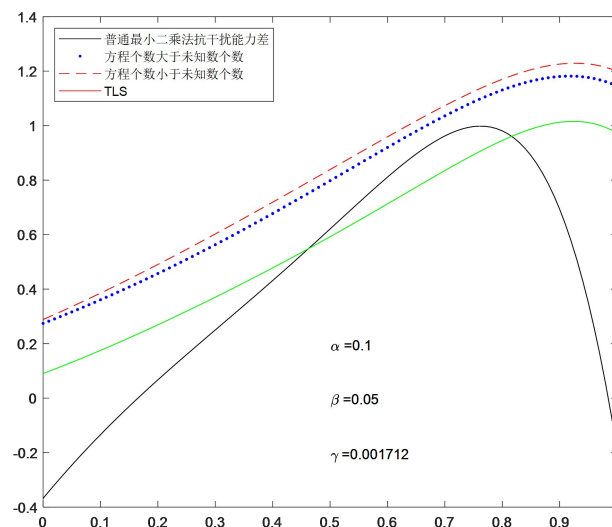
for ii=1:M
    for jj=1:N+1
        A(ii,jj)=x(ii)^(jj-1)+randn*beta;%有噪声!
    end
end
Bltn=A(1:N-1,:);
Beqn=A(1:N+1,:);
BgtN=A;
%%
%(1):方程个数等于未知数个数
B=Beqn;
bb=b(1:N+1); a=B\bb;
%a=(B'*B+.00012*eye(1+N,1+N))\B'*bb;
tt=0:0.01:1;
yy=zeros(1,length(tt));
for ii=1:length(tt)
    for jj=1:N+1
        yy(ii)=yy(ii)+a(jj)*tt(ii)^(jj-1);
    end
end
plot(tt,yy,'-k');
hold on
%%
%(2)方程个数大于未知数个数
B=BgtN;
bb=b;
a=(B'*B+.00012*eye(1+N,1+N))\B'*bb;
yy=zeros(1,length(tt));
for ii=1:length(tt)
    for jj=1:N+1
        yy(ii)=yy(ii)+a(jj)*tt(ii)^(jj-1);
    end
end
plot(tt,yy+0.1,'.b');
hold on
%%
%(3)方程个数小于未知数个数
B=Bltn;
bb=b(1:N-1);
a=(B'*B+.0012*eye(1+N,1+N))\B'*bb;

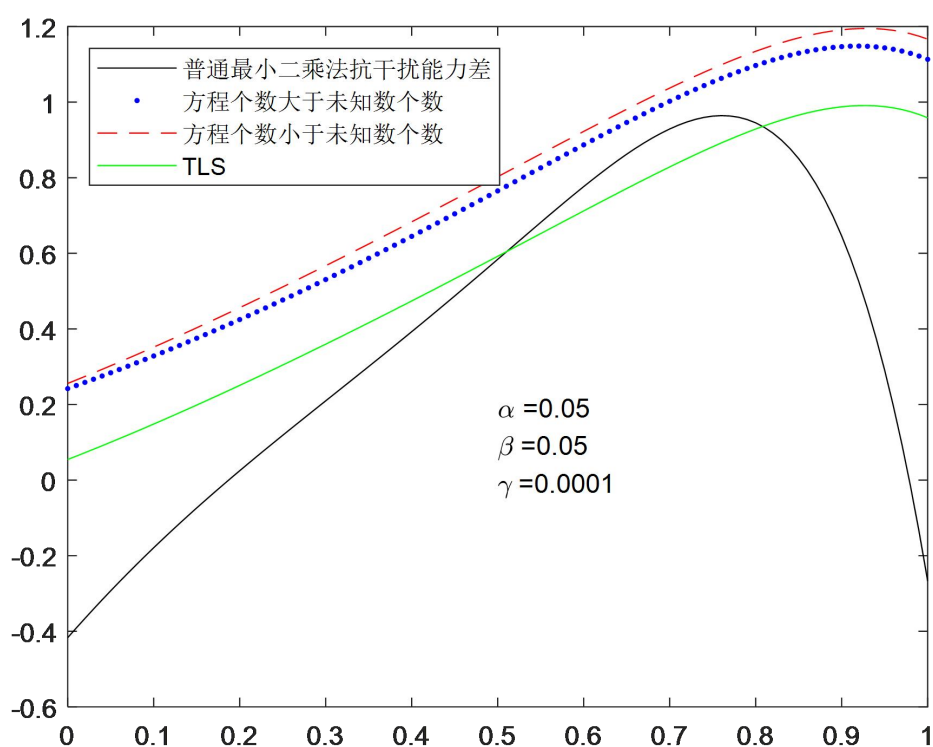
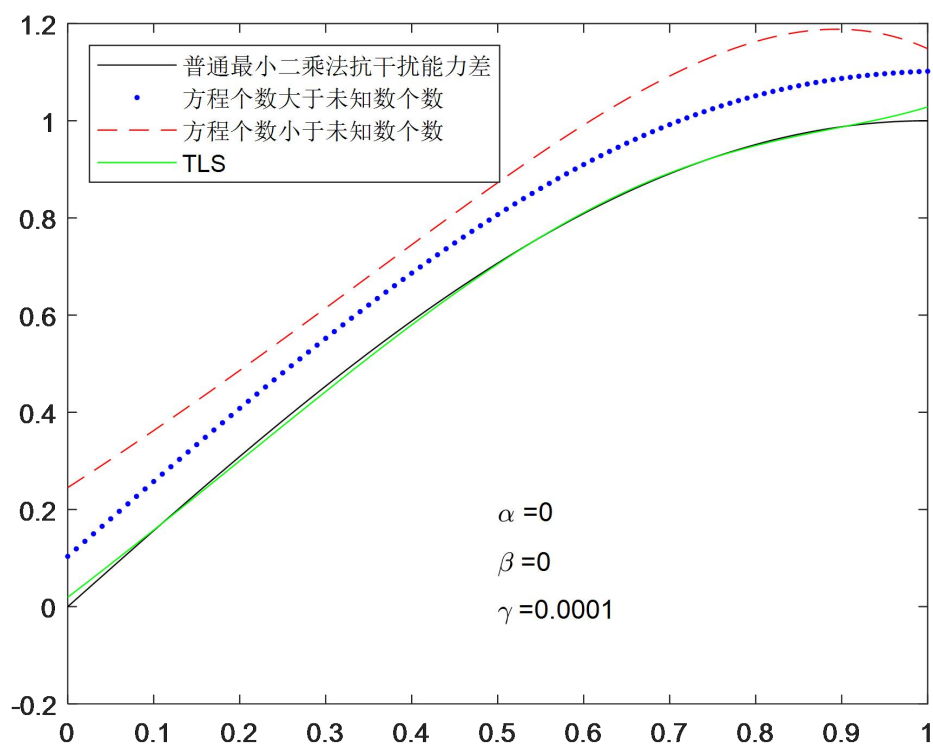
```

```

yy=zeros(1,length(tt));
for ii=1:length(tt)
    for jj=1:N+1
        yy(ii)=yy(ii)+a(jj)*tt(ii)^(jj-1);
    end
end
plot(tt,yy+0.2,'--r');
%%
%(4)方程个数小于未知数个数
B=Bltn;
bb=b(1:N-1);
%这是总体最小二乘法的简单处理方案，调整参数 gama
gamma=.001712;
a=(B'*B-gamma*eye(1+N,1+N))\B'*bb;
yy=zeros(1,length(tt));
for ii=1:length(tt)
    for jj=1:N+1
        yy(ii)=yy(ii)+a(jj)*tt(ii)^(jj-1);
    end
end
plot(tt,yy,'-g');
legend('普通最小二乘法抗干扰能力差','方程个数大于未知数个数','方程个数小于未知数个数','TLS','Location','NorthWest');
text(0.5,0.2,['\alpha =',num2str(alpha)]);
text(0.5,0,['\beta =',num2str(beta)]);
text(0.5,-0.2,['\gamma =',num2str(gamma)]);

```





5.5 稀疏矩阵方程求解

$X = \text{normrnd}(0, 1, 3, 5)$


```
Y=rand(3,1)
B=lasso(X,Y)
>> B(:,3)
ans =
    0
    0
    0.1941
    1.3347
    0
>> B(:,39)
ans =
    0
    0
    0
    0
    0
    0
>> B(:,33)
ans =
    0
    0
    0.1079
    0.3278
    0
>>
```

实验六 矩阵微积分

6.1 用 MATLAB 函数 logm() 计算 $\log(tA)$ 的导数

```
rng default;
A=rand(3,3);
disp(A);
t=3;
dt=0.001;
dA=logm((t+dt)*A)-logm(t*A);
B=dA/dt;
disp(B);
0.8147  0.9134  0.2785
0.9058  0.6324  0.5469
0.1270  0.0975  0.9575
0.3333 + 0.0000i  0.0000 - 0.0000i  -0.0000 + 0.0000i
0.0000 - 0.0000i  0.3333 + 0.0000i  0.0000 - 0.0000i
0.0000 + 0.0000i  0.0000 - 0.0000i  0.3333 + 0.0000i
```

6.2 函数 $f(X)=aTXb$ 的导函数

```
a=rand(1,5);
b=rand(1,5)';
X=rand(5,5);
delta=0.01;
Z=zeros(5,5);
for ii=1:5
    for jj=1:5
        XX=X;    XX(ii,jj)=XX(ii,jj)+delta;
        f=a*XX*b-a*X*b;
        Z(ii,jj)=f/delta;
    end
end
disp(Z);
disp(a*b');
```

6.3 Tikhonov 方法的最速下降法实现

```
A=rand(4,4);
b=rand(4,1);
X=zeros(4,1);
lamda=.2;
Xt=(A'*A+lamda*eye(4,4))\A'*b;
disp([0,Xt']);

lamda1=0.15;
```

```

Df=zeros(4,4);
jj=10;kk=1;
for ii=1:200
    df=2*(A*X-b)'*A+2*lamda*X';
    Df=-df';
    X=X+lamda1*Df;
    if jj==ii
        disp([ii,X']);
        kk=kk+1;
        jj=kk*40;
    end
end
disp([ii,X']);
lamda1=0.1 (迭代两百次，与理论值就基本相同了)
    0  0.1264 -0.0274  0.0519  0.0388
10.0000  0.0909  0.0032  0.0519  0.0436
80.0000  0.1262 -0.0273  0.0523  0.0385
120.0000  0.1264 -0.0274  0.0520  0.0387
160.0000  0.1264 -0.0274  0.0519  0.0387
200.0000  0.1264 -0.0274  0.0519  0.0388
200.0000  0.1264 -0.0274  0.0519  0.0388

```

6.4 Tikhonov 方法的牛顿法实现

```

A=rand(4,4);
b=rand(4,1);
X=zeros(4,1);
lamda=.2;
%Tikhonov 解
Xt=(A'*A+lamda*eye(4,4))\A'*b;
disp([0,Xt]);
lamda1=1.2;%学习率
Df=zeros(4,4);
jj=5;kk=1;
for ii=1:200
    df=2*(A*X-b)'*A+2*lamda*X';%协梯度
    Df=2*(A'*A+lamda*eye(4,4));%H 矩阵
    X=X-lamda1*Df\df';
    if jj==ii
        disp([ii,X']);
        kk=kk+1;
        jj=kk*5;
    end
end

```

```
end
disp([ii,X']);
lamda=.2, lamda1=1.2
0 -0.0838  0.2688  0.0570  0.1199
5 -0.0838  0.2687  0.0570  0.1198
10 -0.0838  0.2688  0.0570  0.1199
15 -0.0838  0.2688  0.0570  0.1199
20 -0.0838  0.2688  0.0570  0.1199
25 -0.0838  0.2688  0.0570  0.1199
5 步收敛到一个比较精确的值！
```