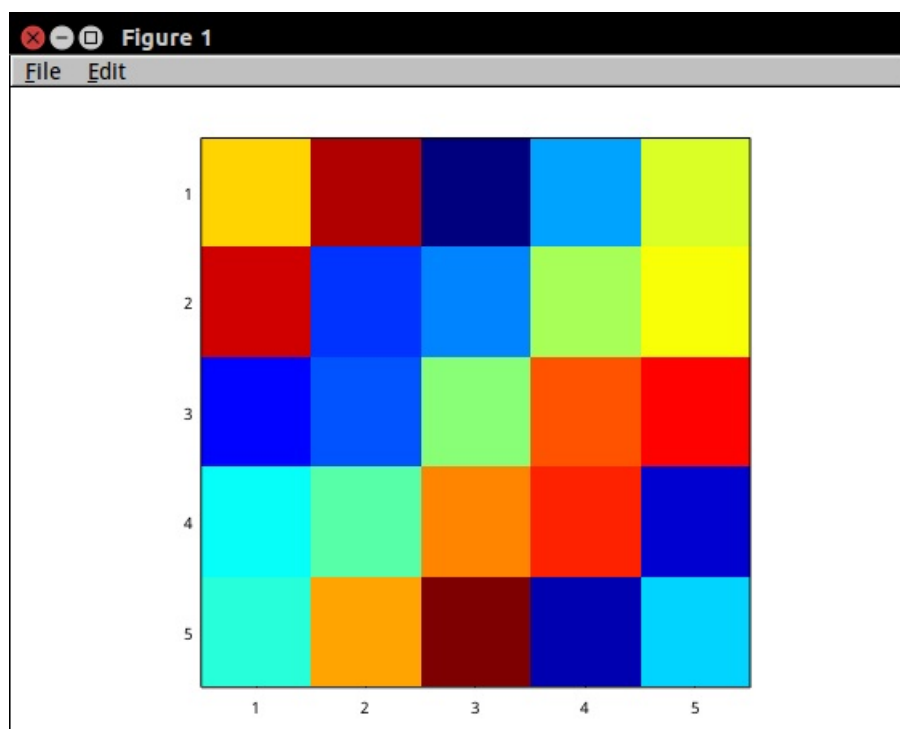
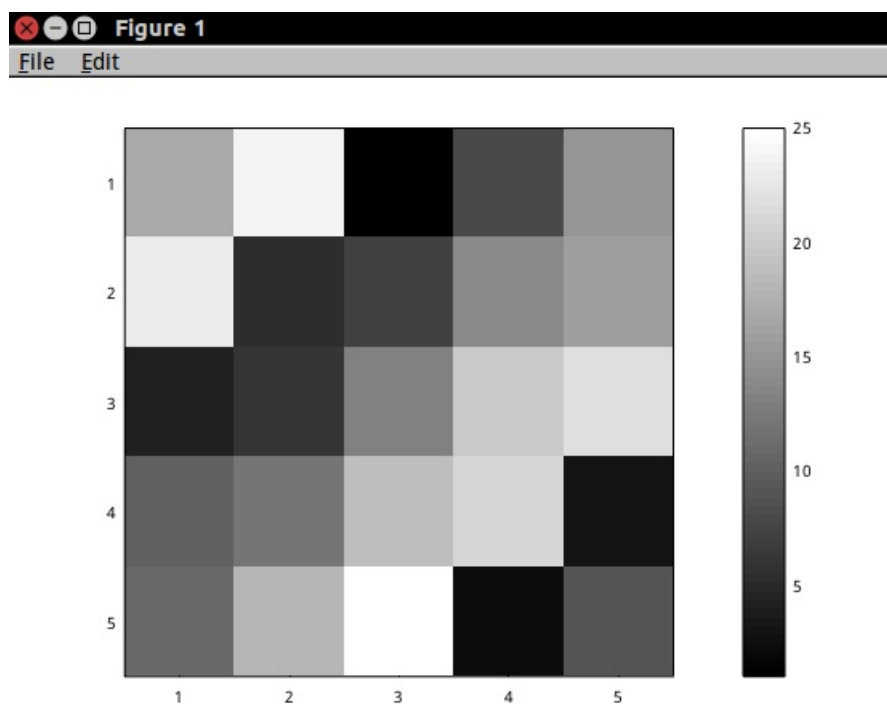


1.

```
1. octave:109> A = magic(5)
2. A =
3.
4.      17      24       1       8      15
5.      23       5       7      14      16
6.       4       6      13      20      22
7.      10      12      19      21       3
8.      11      18      25       2       9
9.
10. octave:110> imagesc(A)
```



```
1. octave:111> imagesc(A), colorbar, colormap gray;
```



2. for, while, if.

```
1. octave:114> v = rand(5, 1)
2. v =
3.
4.     0.462886
5.     0.242023
6.     0.042883
7.     0.639265
8.     0.725329
9.
10. octave:115> for i = v
11. > disp(i)
12. > end
13.     0.462886
14.     0.242023
15.     0.042883
16.     0.639265
17.     0.725329
18. octave:116>
```

3. 向量化：

Vectorization example.

$$\begin{aligned} \rightarrow h_{\theta}(x) &= \sum_{j=0}^n \theta_j x_j \\ &= \theta^T x \end{aligned}$$

$$\theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \end{bmatrix} \quad x = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \end{bmatrix}$$

Handwritten labels: θ_0 is labeled $\theta(1)$, θ_1 is labeled $\theta(2)$, and θ_2 is labeled $\theta(3)$.

Unvectorized implementation

```
 $\rightarrow$  prediction = 0.0;
 $\rightarrow$  for j = 1:n+1,
    prediction = prediction +
        theta(j) * x(j)
end;
```

θ 以及 x

Vectorized implementation

```
 $\rightarrow$  prediction = theta' * x;
```

Vectorization example.

$$h_{\theta}(x) = \sum_{j=0}^n \theta_j x_j$$

$$= \theta^T x$$

Unvectorized implementation

```
→ double prediction = 0.0;
→ for (int j = 0; j <= n; j++)
    prediction += theta[j] * x[j];
```

Vectorized implementation

```
double prediction
= theta.transpose() * x;
```

你只需要在 C++ 中将两个向量相乘

$$\begin{aligned} \theta_0 &:= \theta_0 - \alpha \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)}) x_0^{(i)} \\ \theta_1 &:= \theta_1 - \alpha \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)}) x_1^{(i)} \\ \theta_2 &:= \theta_2 - \alpha \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)}) x_2^{(i)} \\ (n=2) \end{aligned}$$

Vectorized implementation:

$$\Theta := \Theta - \alpha \delta$$

$$\text{where } \delta = \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)}) x^{(i)}$$

$$\delta = \begin{bmatrix} \delta_0 \\ \delta_1 \\ \delta_2 \end{bmatrix} \rightarrow \delta_0 = \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)}) x_0^{(i)}$$

成一个步骤

$$\rightarrow u(j) = 2v(j) + 5w(j) \quad (\text{for all } j)$$

$$\rightarrow u = 2v + 5w$$

$$(h_{\theta}(x^{(1)}) - y^{(1)}) x^{(1)} + (h_{\theta}(x^{(2)}) - y^{(2)}) x^{(2)} + \dots$$

$$x^{(i)} = \begin{bmatrix} x_0^{(i)} \\ x_1^{(i)} \\ \vdots \\ x_n^{(i)} \end{bmatrix}$$

4. 正规方程方法不可逆情况，也即 $X^T X$ 不可逆：

pinv - 即使矩阵不可逆也可以求出来。 - 伪逆

inv - 矩阵必须是可逆的。

$X^T X$ 不可逆是因为：特征中存在冗余特征，或者特征数大于样本数。例如：

What if $X^T X$ is non-invertible?

- Redundant features (linearly dependent).

E.g. x_1 = size in feet²

x_2 = size in m²

$$1\text{m} = 3.28\text{ feet}$$

$$\underline{x_1 = (3.28)^2 x_2}$$

$$\rightarrow \underline{m=10}$$

$$\rightarrow n=100$$

- Too many features (e.g. $m \leq n$).

$$\Theta \in \underline{\mathbb{R}^{101}}$$

- Delete some features, or use regularization.

通常 我们会使用一种叫做正则化的线性代数方法