# Contents

# Chapter 1

# Introduction to Machine Learning

Machine Learning is undeniably one of the most influential and powerful technologies in today's world. It is a tool for turning information into knowledge. In the past 50 years, there has been an explosion of data. This mass of data is useless unless we analyse it and find the patterns hidden within. Machine learning techniques are used to automatically find the valuable underlying patterns within complex data that we would otherwise struggle to discover. The hidden patterns and knowledge about a problem can be used to predict future events and perform all kinds of complex decision making.

There are multiple forms of Machine Learning; supervised, unsupervised , semi-supervised and reinforcement learning. Each form of Machine Learning has differing approaches, but they all follow the same underlying process and theory. I'll cover supervised and unsupervised learning for my report.

## 1.1 Supervised and Unsupervised Learning

The most basic thing to remember is that we already know what out correct output should look like in Supervised Learning. But, we have little or no idea about what out results should look like.

**Supervised Learning:**

- Classification: Spam/Not-spam.
- Regression: Predicting age.

**Unsupervised Learning:**

- Clustering: Grouping based on different variables.
- Non Clustering: Finding structue in chaotic environment.

# Chapter 2

# Linear Regression

## 2.1 Linear Regression with one variable

Regression being a part of Supervised Learning is used for estimatng data (Real-valued output).

### 2.1.1 Cost Function

This function measures the performance of a Machine Learning model for given data.

**Hypothesis**: $h_\theta(x) = \theta_0 + \theta_1 x$

**Parameters:** $\theta_0, \theta_1$

**Cost Function:**

$$J(\theta_0, \theta_1) = 1/2m \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)})^2 \tag{2.1}$$

**Goal:** Minimize cost function with $\theta_0, \theta_1$ as parameters.

### 2.1.2 Gradient Descent

**Basic idea:**

- Start with some $\theta_0, \theta_1$
- Keep changing $\theta_0, \theta_1$ to reduce $J(\theta_0, \theta_1)$ until we end up at minima.

**Algorithm:** repeat until convergence:

$$\theta_j := \theta_j - \alpha \frac{\partial J(\theta_0, \theta_1)}{\partial \theta_j} \tag{2.2}$$

(for $j = 0, 1$ ,here).

**Intution:** If $\alpha$ is too small, descent can be slow and if too large, descent may fail to converge or even diverge. Gradient descent can converge to a local minimum, even with fixed learning rate $\alpha$. As we approach local mimimum, gradient descent will automatically take smaller steps. So, no need to decrease $\alpha$ over time.

### 2.1.3 Gradient Descent for linear regression

Combining gradient descent algorithm with linear regression model, we get:

$$j = 0 : \frac{\partial J(\theta_0, \theta_1)}{\partial \theta_0} = 1/2 \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)}) \tag{2.3}$$

$$j = 1 : \frac{\partial J(\theta_0, \theta_1)}{\partial \theta_1} = 1/2 \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)}).x^{(i)} \tag{2.4}$$

Now, we can repeat 2.3 and 2.4 until convergence to obtain the minima.

"Batch" gradient descent: Each step of gradient descent uses all the training examples. For eq. "m" batches in equation 2.1.

## 2.2 Multivariate Linear Regression

Linear regression involving more than one variable. For eq., Predicting price of a house based on parameters "Plot Area", "No. of Floors", "Connectivity with markets", etc.

### 2.2.1 Multiple Features

The multivariable form of the hypothesis is as follows:

$$h_\theta(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 + ... + \theta_n x_n. \tag{2.5}$$

This hypothesis funtion can be concisely represented as:

$$h_\theta(x) = \theta^T x \tag{2.6}$$

where, $\theta^T$ is a 1xn matrix consisting of $\theta_0, \theta_1, \theta_2 ... \theta_n$.

### 2.2.2 Gradient Descent for Multiple Variables

Gradient descent formula for Multiple variable will be similar to that of single variable.

$$\theta_j = \theta_j - \alpha \frac{1}{m} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)}).x_j^{(i)} \tag{2.7}$$

Repeating this equation until convergence will give the minima. [1]

[1] $x_0 = 1$ in equation 2.7

**Feature Scaling**

Feature Scaling is used to reduce the number of iterations in Gradient Descent. Basic idea of feature scaling is to bring all the features on the same scale. (in general we try to approximate every feature in the range $-1 < x_i < 1$)

Reducing the number of iteration doesn't mean making computation of each step easier. And also it does not effect comtational efficiency of Normal Equation.

**Mean Normalisation**

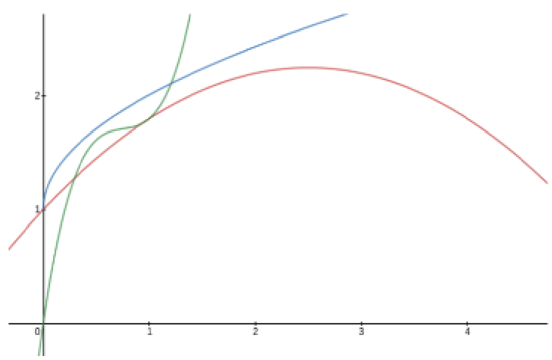
Mean Normalisation makes features to have approximately zero mean.

**Learning Rate**

If $\alpha$ is too small: slow convergence.
if $\alpha$ is too large: $J(\theta)$ may not decrease on every iteration, or may not converge.

**Polynomial Regression**

Selecting proper polynomial for fitting data is very important.




**Red:** Quadratic
**Blue:** Square root funtion $\theta_0 + \theta_1 x + \theta_2\sqrt{x}$
**Green:** Cubic function

## 2.3 Normal equation

Normal Equation is a method to solve for $\theta_T$ analytically, by creating a $m \times (n+1)$ matrix $X$ and another $m \times 1$ matrix $Y$.[2]

[2] Every element of first column of matrix $X$ is 1 and other are the feature's coefficient

Mathematically $\theta$ is given as:

$$\theta = (X^T X)^{-1} X^t y \tag{2.8}$$

| **Gradient Descent** | **Normal Equation** |
|---|---|
| Need to choose $\alpha$ | No need to choose $\alpha$ |
| Needs many iteration | Don't need to iterate |
| Works well with large n | Slow for large n |

**Reasons for non-invertiblity of $X^T X$**

- Redundant features (linear dependence) [3]
- Too many features (m <= n)

[3] Eg. Using both $m^2$ & $(feet)^2$ features

# Chapter 3

# Logistic Regression

## 3.1 Classification and Represention

### 3.1.1 Classification

The classification problem is just like the regression problem, except that the values we now want to predict take on onle a small number of discrete values. For now, we'll discuss binary classification problem.

### 3.1.2 Hypothesis Representation

We may use out old regression algorithm by classifying data on the basis of a threshold. But it will have very poor performance.

We will introduce "Sigmoid Function", also called the "Logistic Function":

$$h_\theta(x) = g(\theta^T x) \tag{3.1}$$

$$z = \theta^T x \tag{3.2}$$

$$g(z) = \frac{1}{1 + e^{-z}} \tag{3.3}$$

This is how the Sigmoid Function looks like:

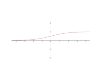


Figure 3.1: Sigmoid Funtion 3.3

### 3.1.3 Decesion Boundary

The decesion boundary is the line that separates the area where y=0 and where y=1. It is similar to the decesion boundary for linear regression, the only difference is distibution of values (linear and sigmoid)

## 3.2 Logistic Regression Model

### 3.2.1 Cost Function

Cost funtion for logistic regression looks like:

$$J(\theta) = \frac{1}{m} \sum_{i=1}^{m} Cost(h_\theta(x^{(i)}), y^{(i)}) \tag{3.4}$$

$Cost(h_\theta(x), y) = -\log\left(h_\theta(x)\right)$ if $y = 1$

$Cost(h_\theta(x), y) = -\log\left(1 - h_\theta(x)\right)$ if $y = 0$

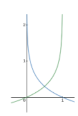


Figure 3.2: Cost Funtion

**Siplified Cost Funtion**

This cost funtion can be compressed into a single funtion:

$$Cost(h_\theta(x), y) = -y \log\left(h_\theta(x)\right) - (1 - y) \log\left(1 - h_\theta(x)\right) \tag{3.5}$$

A vectorised implementation is:

$h = g(X\theta)$
$J(\theta) = \frac{1}{m}.(-y^T \log h - (1-y)^T \log 1 - h)$

Vectorised implementation for Gradient Descent:

$\theta := \theta - \frac{\alpha}{m} X^T (g(X\theta) - y)$

## 3.3 Multiclass Classification

### 3.3.1 One-vs-all

This approach is when data has more than two categories.We divide our problem into n[1] binary classification problems, in each one, we predict the probability considering one of the category to be +ve and all other to be −ve. Repeating this for all other categories will finally give us all the decesion boundaries.

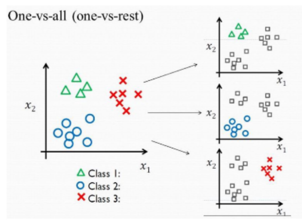
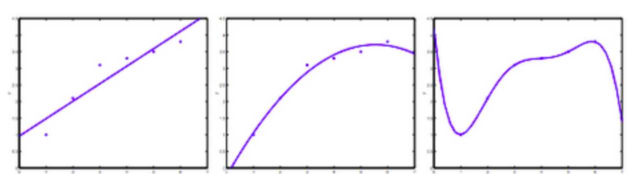



Figure 3.3: One vs all classifiaction method

## 3.4 The Problem of Overfitting

Consider the problem of predicting y from x ∈ R. The leftmost figure below shows the result of fitting a $y = \theta_0 + \theta_1 x$ to a dataset. We see that the data doesn't really lie on straight line, and so the fit is not very good.



Instead, if we had added an extra feature $x^2$ , and fit $t = \theta_0 + \theta_1 x + \theta_2 x^2$ , then we obtain a slightly better fit to the data (See middle figure). Naively, it might seem that the more features we add, the better. However, there is also a danger in adding too many features: The rightmost figure is the result of fitting a $5^{th}$ order polynomial $y = \sum_{j=0}^{5} \theta_j x^j$. We see that even though the fitted curve passes through the data perfectly, we would not expect this to be a very good predictor of, say, housing prices (y) for different living areas (x). Without formally defining what these terms mean, we'll say the figure on the left shows an instance of **underfitting**—in which the data clearly shows structure not captured by the model—and the figure on the right is an example of **overfitting**.

[1] n = no of categories in dataset

**How to address this issue?**

1. Reduce the number of features:
   - Manually select which features to keep.
   - Use a model selection algorithm.[2]
2. Regularisation:
   - Keep all the features, but reduce the magnitude of parameters $\theta_j$.
   - Regularization works well when we have a lot of slightly useful features.

### 3.4.1 Regularized Cost Function

To solve this problem of overfitting, we can eleminate the influence of $\theta_3 x^3$ and $\theta_4 x^4$. Without actually getting rid of these features or changing the form of our hypothesis, we can instead modify our cost function:

$$J_\theta = min\ of\ \left[\frac{1}{2m}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})^2 + \lambda\sum_{j=1}^{2}\theta_j^2\right] \tag{3.6}$$

These extra terms will inflate the cost of extra parameters.

The $\lambda$ is called the **regularisation parameter**/ It determines how much the costs of out theta parameters are inflated.

### 3.4.2 Regularized Linear Regression

Repeat {

$$\theta_0 := \theta_0 - \alpha\ \frac{1}{m}\ \sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})x_0^{(i)}$$

$$\theta_j := \theta_j - \alpha\ \frac{1}{m}\ \sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})x_j^{(i)} + \frac{\lambda}{m}\theta_j \qquad j \in \{1, 2...n\}$$

}

The term $\frac{\lambda}{m}\theta_j$ performs our regularization. With some manipulation our update rule can also be represented as:

[2]we'll cover it later

$\theta_j := \theta_j(1 - \alpha\frac{\lambda}{m}) - \alpha\frac{1}{m}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})x_j^{(i)}$

The first term in the above equation, $\alpha\frac{\lambda}{m}$ will always be less than 1. Intuitively you can see it as reducing the value of $j\theta_j$ by some amount on every update.

**Normal Eequation**

This will be the non-iterative approach for regularazation.

To add in regularization, we'll just add another term:

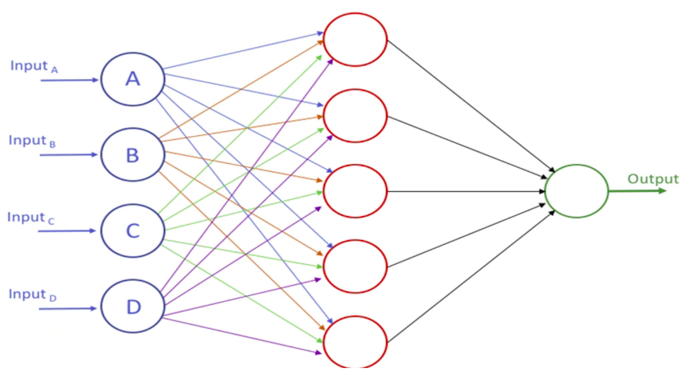
$$\theta = X^T X + \lambda.L^{-1} X^T y \tag{3.7}$$

where, L is $(n+1) \times (n+1)$ matrix with 0 at the top lest, 1's down the diagonal and all other element '0'.

# Chapter 4

# Neural Networks

At a very simple level, neurons are basically computational units that take inputs (**dendrites**) as electrical inputs (called "spikes") that are channeled to outputs (**axons**). In our model, our dendrites are like the input features $x_1 \dots x_n$, and the output is the result of our hypothesis function. In this model our $x_0$ input node is sometimes called the "bias unit." It is always equal to 1.




Our input nodes (layer 1), also known as the "input layer", go into another node (layer 2), which finally outputs the hypothesis function, known as the "output layer". We can have intermediate layers of nodes between the input and output layers called the "hidden layers."

These "hidden layer" nodes are called as "activation units". The values for each activation nodes are represented as:

$$\begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \end{bmatrix} \rightarrow \begin{bmatrix} a_1^{(2)} \\ a_2^{(2)} \\ a_3^{(2)} \end{bmatrix} \rightarrow h_\theta(x)$$

$$a_1^{(2)} = g(\theta_{10}^{(1)} x_0 + \theta_{11}^{(1)} x_1 + \theta_{12}^{(1)} x_2 + \theta_{13}^{(1)} x_3) \tag{4.1}$$

$$a_2^{(2)} = g(\theta_{20}^{(1)} x_0 + \theta_{21}^{(1)} x_1 + \theta_{22}^{(1)} x_2 + \theta_{23}^{(1)} x_3) \tag{4.2}$$

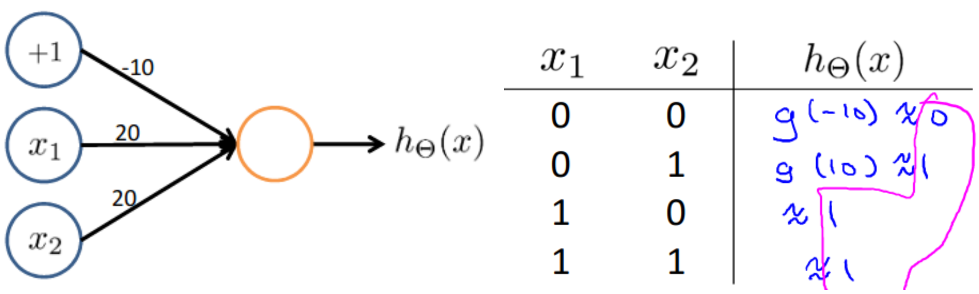
$$a_3^{(2)} = g(\theta_{30}^{(1)} x_0 + \theta_{31}^{(1)} x_1 + \theta_{32}^{(1)} x_2 + \theta_{33}^{(1)} x_3) \tag{4.3}$$

$$h_\theta(x) = a_1^{(3)]} = a_1^{(2)} = g(\theta_{10}^{(2)} x_0 + \theta_{11}^{(2)} x_1 + \theta_{12}^{(2)} x_2 + \theta_{13}^{(2)} x_3)5 \tag{4.4}$$

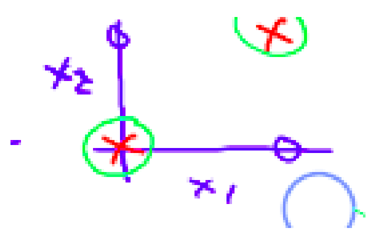
From these equations, we can conclude that we will get a matrix for each layer to calculate the weight for the second layer.

## 4.1 Intutions

### 4.1.1 OR Function




### 4.1.2 Important Note




For any prediction which involve a straight line as decision boundary, we can represent it with a neural network without any hidden layer but otherwise we'll have to include few hidden layers. An important point to note is that we can represent almost any distribution with cenrain arrangement of neural network.

## 4.2 Multiclass Classification

To classify data into multiple classes, we'll have to define out set of resulting classes as y:

$$y^{(i)} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix},$$

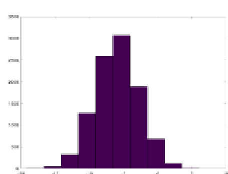
# Chapter 5

# Octave/MATLAB Commands

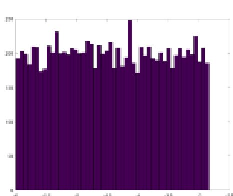
**Basic Operations**

```
octave:1> a = pi
a =  3.1416
octave:2> disp(sprintf('6 decimals: %0.6f', a))
6 decimals: 3.141593
octave:3> a
a =  3.1416
octave:4> format long
octave:5> a
a =  3.141592653589793
octave:6> format short
octave:7> a
a =  3.1416
octave:8> v = 1:0.1:2
v =

    1.0000    1.1000    1.2000    1.3000    1.4000    1.5000
   1.6000    1.7000    1.8000    1.9000    2.0000

octave:9> v = 1:0.1:2
v =

 Columns 1 through 8:

    1.0000    1.1000    1.2000    1.3000    1.4000    1.5000
   1.6000    1.7000

 Columns 9 through 11:

    1.8000    1.9000    2.0000
```

```
octave:10> v = 1:6
v =

   1   2   3   4   5   6

octave:11> zeros(1,3)
ans =

   0   0   0

octave:12> rand(1,3)
ans =

   0.43623   0.76554   0.23635

octave:13> randn(1,3)
ans =

   0.5602642  -0.0043628   0.1344922

octave:14> w = -6 + sqrt(10)*(randn(1,10000))

octave:15> hist(w)
```



```
octave:1> w = -6 + sqrt(10)*(rand(1,10000));

octave:2> hist(w,50)
```



**Moving Data around**

```
octave:1> A = [1,2;3,4;4,5]
A =

   1   2
   3   4
   4   5

octave:2> size(A)
ans =

   3   2

octave:3> sz = size(A)
sz =

   3   2

octave:4> size(sz)
ans =

   1   2

octave:5> size(A,1)
ans =  3
octave:6> size(A,2)
ans =  2
octave:7> length(A)
ans =  3
octave:8> length([1,2,3,4,5])
ans =  5
octave:9>
octave:9>
octave:9> pwd
ans = /home/sahasra
octave:10> cd /home/sahasra/
octave:11> pwd
ans = /home/sahasra
octave:12> ls
Android                 Documents     Music       Public      Videos
AndroidStudioProjects   Downloads     MyPaint     snap
Desktop                 examples.desktop   Pictures   Templates
octave:13> who
Variables in the current scope:
```

```
A      ans   sz

octave:14> whos
Variables in the current scope:

   Attr Name        Size                     Bytes  Class
   ==== ====        ====                     =====  =====
        A           3x2                         48  double
        ans         1x13                        13  char
        sz          1x2                         16  double

Total is 21 elements using 77 bytes

octave:15> clear
octave:16> whos
octave:17> A = [1,2;3,4;5,6]
A =

   1   2
   3   4
   5   6

octave:18> A(3,2)
ans =  6
octave:19> A(2,:)
ans =

   3   4

octave:20> A(:,2)
ans =

   2
   4
   6

octave:21> A([1,3], :)
ans =

   1   2
   5   6

octave:22> A([2,3], :)
ans =
```

```
    3    4
    5    6

octave:23> A(:,2) = [10;11;12]
A =

     1    10
     3    11
     5    12

octave:24> A = [A, [5;6;7]]
A =

     1    10     5
     3    11     6
     5    12     7

octave:25> A(:)
ans =

     1
     3
     5
    10
    11
    12
     5
     6
     7

octave:26> A
A =

     1    10     5
     3    11     6
     5    12     7

octave:27> B = [45;46;47]
B =

    45
    46
    47
```

```
octave:28> C = [A,B]
C =

    1    10     5    45
    3    11     6    46
    5    12     7    47
```

**Computing on Data**

```
octave:1> A = [1 2;3 4;5 6]
A =

   1   2
   3   4
   5   6

octave:2> B = [11 12; 13 14; 15 16]
B =

   11   12
   13   14
   15   16

octave:3> C = [1  1; 2 2]
C =

   1   1
   2   2

octave:4> A*C
ans =

    5    5
   11   11
   17   17

octave:5> A .* B % A .* B gives element wise operation
ans =

   11   24
   39   56
   75   96

octave:6> 1 ./ A
ans =
```

```
   1.00000   0.50000
   0.33333   0.25000
   0.20000   0.16667

octave:7> v = [1;2;3]
v =

   1
   2
   3

octave:8> log(v)
ans =

   0.00000
   0.69315
   1.09861

octave:9> exp(v)
ans =

    2.7183
    7.3891
   20.0855

octave:10> abs([-1; 2; -3])
ans =

   1
   2
   3

octave:11> A
A =

   1   2
   3   4
   5   6

octave:12> A' % A' = A transpose
ans =

   1   3   5
   2   4   6
```

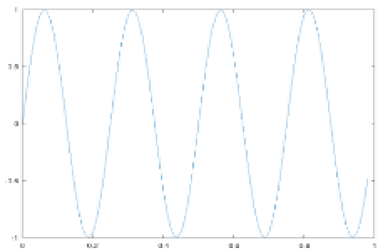
```
octave:13> val = max([1;2;3;6;7])
val =  7
octave:14> max(A)
ans =

   5   6

octave:15> A
A =

   1   2
   3   4
   5   6

octave:16> a = [1;4;6;7;9]
a =

   1
   4
   6
   7
   9

octave:17> a < 3
ans =

  1
  0
  0
  0
  0

octave:18> find(a<3)
ans =  1
octave:19> A = magic(3) % Magic Square
A =

   8   1   6
   3   5   7
   4   9   2

octave:20> [r,c] = find(a >= 7)
r =

   4
```

```
    5

c =

    1
    1

octave:21> a
a =

    1
    4
    6
    7
    9

octave:22> a = a'
a =

    1    4    6    7    9

octave:23> sum(a)
ans =  27
octave:24> rand(3)
ans =

    0.272471    0.059338    0.757392
    0.414497    0.174242    0.354694
    0.811891    0.935437    0.956667

octave:25> A
A =

    8    1    6
    3    5    7
    4    9    2

octave:26> max(A,[],1)
ans =

    8    9    7

octave:27> max(A,[],2)
ans =
```

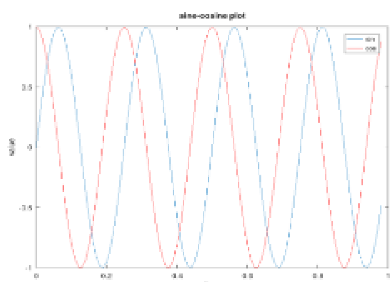
```
   8
   7
   9

octave:28> max(max(A))
ans =  9
octave:29> A
A =

   8   1   6
   3   5   7
   4   9   2

octave:30> pinv(A)
ans =

   0.147222  -0.144444   0.063889
  -0.061111   0.022222   0.105556
  -0.019444   0.188889  -0.102778

octave:31> temp = pinv(A)
temp =

   0.147222  -0.144444   0.063889
  -0.061111   0.022222   0.105556
  -0.019444   0.188889  -0.102778


octave:32> temp * A
ans =

   1.0000e+00   2.0817e-16  -3.1641e-15
  -6.1062e-15   1.0000e+00   6.2450e-15
   3.0531e-15   4.1633e-17   1.0000e+00

octave:33> % this is the 3x3 Identity matrix,
           % not having exact values beacuse of variable overflow
```

```
octave:1> t = [0:0.01:0.98];
octave:2> y1 = sin(2*pi*4*t);
octave:3> plot(t,y1)
```

```

octave:4> y2 = cos(2*pi*4*t);
octave:5> plot(t,y1);
octave:6> hold on;
```



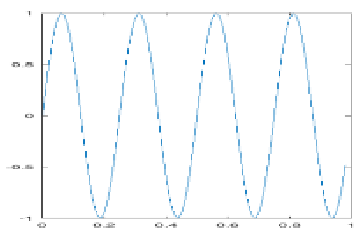
```
octave:7> plot(t, y2, 'r');
octave:8> xlabel('time')
octave:9> ylabel('value')
octave:10> legend('sin', 'cos')
octave:11> title('sine-cosine plot')
octave:12> print -dpng 'myPlot.png'
```

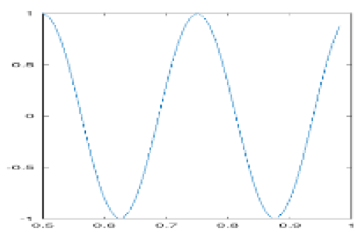


```
octave:13> close
octave:14> figure(1); plot(t, y1);
octave:15> figure(2); plot(t, y2);
octave:16> subplot(1,2,1);   % Divides plot a 1x2 grid
octave:17> plot(t,y1);
octave:18> subplot(1,2,2)
octave:19> plot(t,y2);
octave:20> axis([0.5 1 -1 1])
```

**Control Statements: for, while, if, else-if ...**

```
octave:1> v = zeros(10,1)
v =

   0
   0
```





```
   0
   0
   0
   0
   0
   0
   0
   0

octave:2> for i=1:10,
> v(i) = 2^i;
> end;

octave:3> v
v =

      2
      4
      8
     16
     32
     64
    128
    256
    512
   1024

octave:4> i=1;
octave:5> while i <= 5,
> v(i) = 100;
> i = i+1;
> end;
octave:6> v
v =
```

```
     100
     100
     100
     100
     100
      64
     128
     256
     512
    1024

octave:7> i = 1;
octave:8> while true,
> v(i) = 999;
> i = i+1;
> if i == 6,
>   break;
> end;
> end;

octave:9> v
v =

     999
     999
     999
     999
     999
      64
     128
     256
     512
    1024
```