

Problem 1:

Netbp2.m:

```
1 function cost = netbp2(neurons, data, labels, niter, lr, file)
2 %NETBP Uses backpropagation to train a network
3 [~,num_of_points] = size(data);
4 % Initialize weights and biases
5 rng(5000);
6 W2 = 0.5*randn(neurons(1),2); W3 = 0.5*randn(neurons(2),neurons(1)); W4 = 0.5*randn(2,neurons(2));
7 b2 = 0.5*randn(neurons(1),1); b3 = 0.5*randn(neurons(2),1); b4 = 0.5*randn(2,1);
8
9 % Forward and Back propagate
10 cost = zeros(niter,1); % value of cost function at each iteration
11 for counter = 1:niter
12     k = randi(num_of_points); % choose a training point at random
13     x = data(:,k);
14     % Forward pass
15     a2 = activate(x,W2,b2);
16     a3 = activate(a2,W3,b3);
17     a4 = activate(a3,W4,b4);
18     % Backward pass
19     delta4 = a4.*(1-a4).*(a4-labels(:,k));
20     delta3 = a3.*(1-a3).*(W4'*delta4);
21     delta2 = a2.*(1-a2).*(W3'*delta3);
22     % Gradient step
23     W2 = W2 - lr*delta2*x';
24     W3 = W3 - lr*delta3*a2';
25     W4 = W4 - lr*delta4*a3';
26     b2 = b2 - lr*delta2;
27     b3 = b3 - lr*delta3;
28     b4 = b4 - lr*delta4;
29     % Monitor progress
30     newcost = cost_function(W2,W3,W4,b2,b3,b4); % display cost to screen
31     cost(counter) = newcost;
32     fprintf("i=%d %e\n", counter, newcost);
33 end
34
35 % Show decay of cost function
36 save costvec
37 semilogy([1:le4:niter],cost(1:le4:niter))
38
39 function costval = cost_function(W2,W3,W4,b2,b3,b4)
40     costvec = zeros(num_of_points,1);
41     for i = 1:num_of_points
42         x = data(:,i);
43         a2 = activate(x,W2,b2);
44         a3 = activate(a2,W3,b3);
45         a4 = activate(a3,W4,b4);
46         costvec(i) = norm(labels(:,i) - a4,2);
47     end
48     costval = norm(costvec,2)^2;
49 end % of nested function
50 save(file, 'W2','W3','W4','b2','b3','b4');
51 end
```

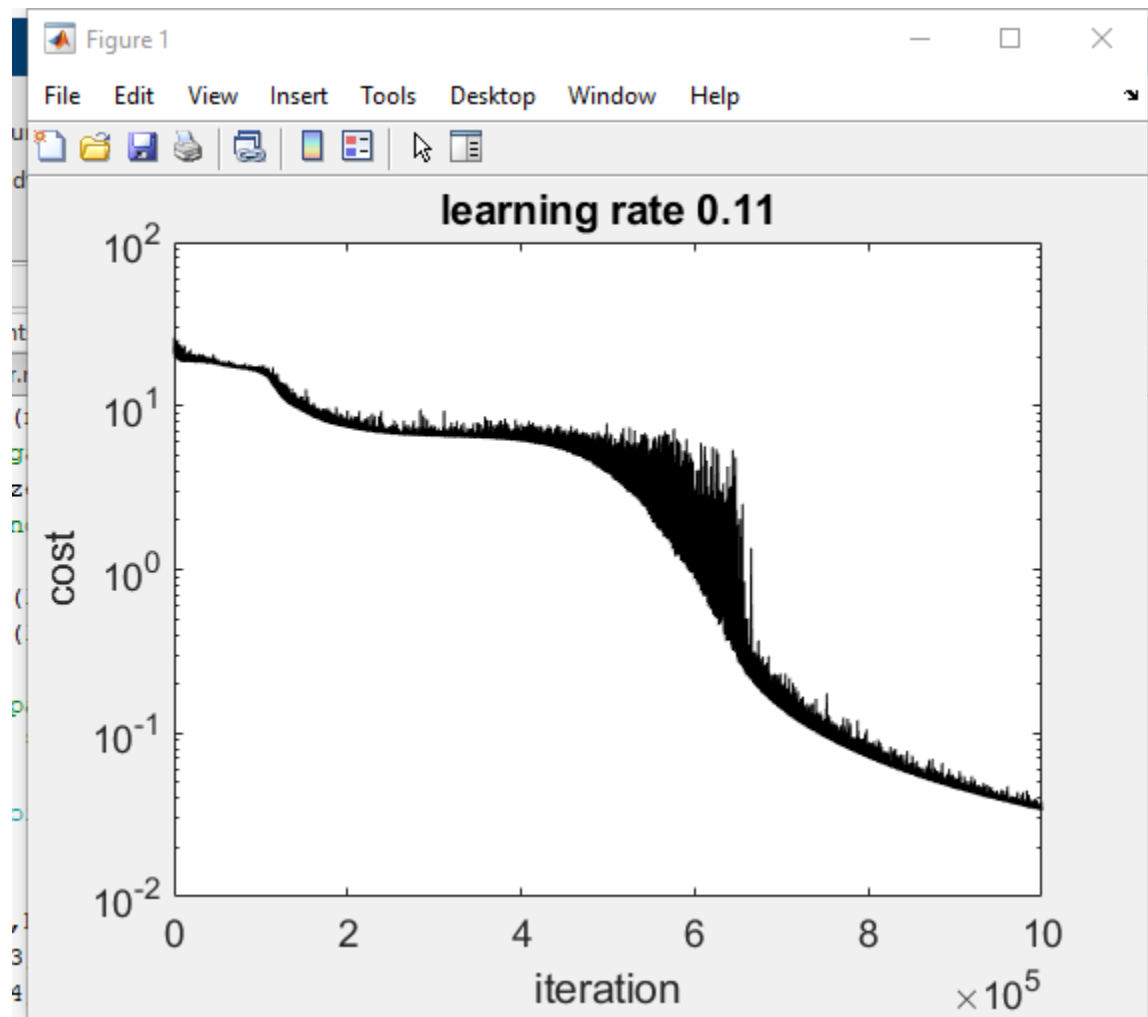
Classifypoints.m:

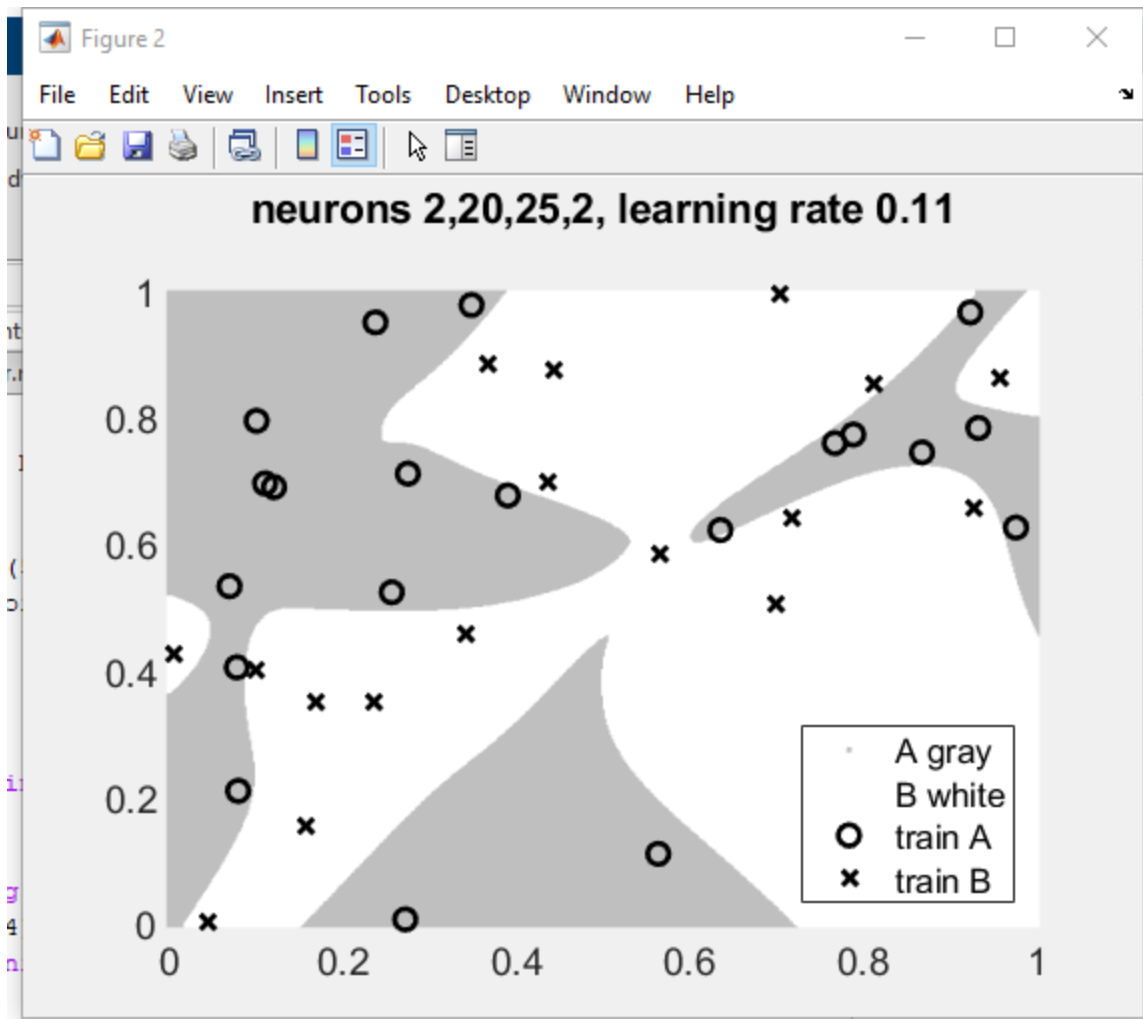
```

function category = classifypoints(file, points)
    load(file);
    [~,num_of_points] = size(points);
    category = zeros(1, num_of_points);
    for i = 1:num_of_points
        x = points(:,i);
        a2 = activate(x,W2,b2);
        a3 = activate(a2,W3,b3);
        a4 = activate(a3,W4,b4);
        if a4(1) >= a4(2)
            category(i) = 1;
        end
    end
end

```

Two plots:





Params:

```
neurons = [20 25];
learning_rate = 0.11;
niter = 1e6;
```

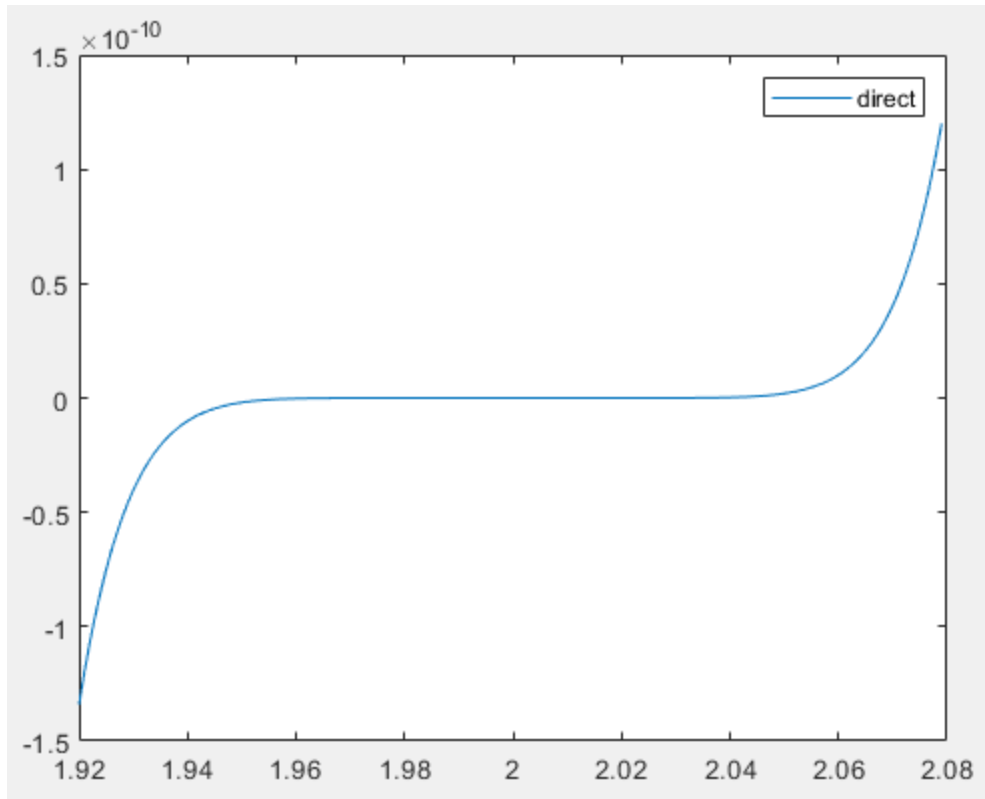
What I found:

1. More neurons will reduce the speed of training.
2. More iterations do not necessarily lead to a better learning and classification outcome.
3. Minimizing the cost will lead to a better learning outcome.
4. We need enough number of iterations to ensure the neural network can minimize the cost function.

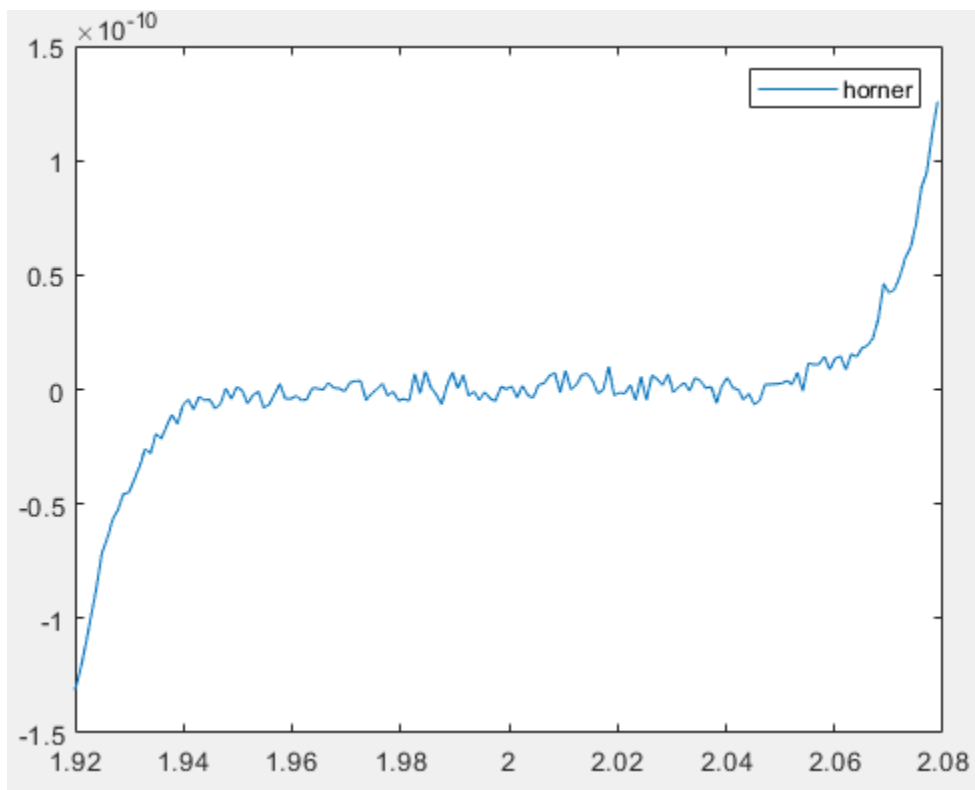
Problem 2:

a)

Direct evaluation:



Horner's method:



We can easily tell that Horner's method appeared to have more visible errors in the plot. This is because we expanded our function and thus introduced more calculations in the evaluation process. Therefore, the errors were larger.

So, when the function is not transformable into a less complicated expression, Horner's method has a better performance because it involves the least amount of calculation possible. However, if the whole expression can be transformed into a simpler one, the simpler expression outperforms Horner's method.

b) Applying bisection to $(x-2)^9$ ended up returning the result 1.999999 which is within $1e-6$ error with the correct result. Applying bisection to horner's ended up returning the result 1.964358 which isn't within the error tolerance.

c) Because the accuracy of horner's method is limited. As you can see from the plot, horner's evaluation's plot was jagged, although the overall shape is very close. Because of this jagged nature of our data, bisection is determining the root based on the signs of two function evaluations, which is obviously very sensitive to the Jagged data that horner's evaluation had.

For example, $f(a)$ and $f(b)$ may actually have the same sign, but in horner's plot because of the inaccuracy of our data, they might even have the same sign and lead the algorithm to proceed with another interval of a and b that doesn't actually contain the correct root.

d)

```
f_fsolve =  
  
    1.9000  
  
Equation solved at initial point.  
  
fsolve completed because the vector of function values at the initial point  
is near zero as measured by the value of the function tolerance, and  
the problem appears regular as measured by the gradient.  
  
<stopping criteria details>  
  
expanded_f_fsolve =  
  
    1.9000
```

Both terminated at 1.9 as solution.

Problem 3:

a)

No solution found.

fsolve stopped because the last step was ineffective. However, the vector of function values is not near zero, as measured by the value of the function tolerance.

<stopping criteria details>

```
system a) fsolve result: [1.141278e+01, -8.968053e-01]
system a) my implementation result: [5.000000e+00, 4.000000e+00]
system a) fsolve num of iterations: 39
system a) my implementation result: 42
```

Because the system is in newton's form and involve more calculations and potential errors.

b)

Equation solved.

fsolve completed because the vector of function values is near zero as measured by the value of the function tolerance, and the problem appears regular as measured by the gradient.

<stopping criteria details>

Warning: Matrix is close to singular or badly scaled. Results may be inaccurate. RCOND = 4.344298e-18.
> In Newtown system solver (line 15)
In main newton (line 19)

```
system b) fsolve result: [1.000000e+00, 1.338358e-09, 2.000000e+00]
system b) my implementation result: [1.666667e+00, -6.666669e-01, 1.333333e+00]
system b) fsolve num of iterations: 6
system b) my implementation result: 56
```

Results are different because the system might have multiple solutions or the fsolve only ends at a root that is close enough to 0 but not actually zero mathematically.

c)

Equation solved.

fsolve completed because the vector of function values is near zero as measured by the value of the function tolerance, and the problem appears regular as measured by the gradient.

<stopping criteria details>

```
system c) fsolve result: [2.036462e-03, -2.036368e-04, 2.036457e-03, 2.036462e-03]
system c) my implementation result: [-8.877841e-04, 8.877841e-05, -8.877841e-04, -8.877841e-04]
system c) fsolve num of iterations: 2
system c) my implementation result: 10
```

Results are different because the system might have multiple solutions or the fsolve only ends at a root that is close enough to 0 but not actually zero mathematically.

d)

[No solution found.](#)

fsolve stopped because the [problem appears regular](#) as measured by the [gradient](#), but the vector of function values is not near zero as measured by the value of the [function tolerance](#).

<[stopping criteria details](#)>

Warning: Matrix is singular to working precision.

> In [Newtown_system_solver](#) (line 15)

In [main_newton](#) (line 41)

Warning: Matrix is singular to working precision.

> In [Newtown_system_solver](#) (line 15)

In [main_newton](#) (line 41)

system d) fsolve result: [1.004816e-02, 1.004816e-02]

system d) my implementation result: [NaN, NaN]

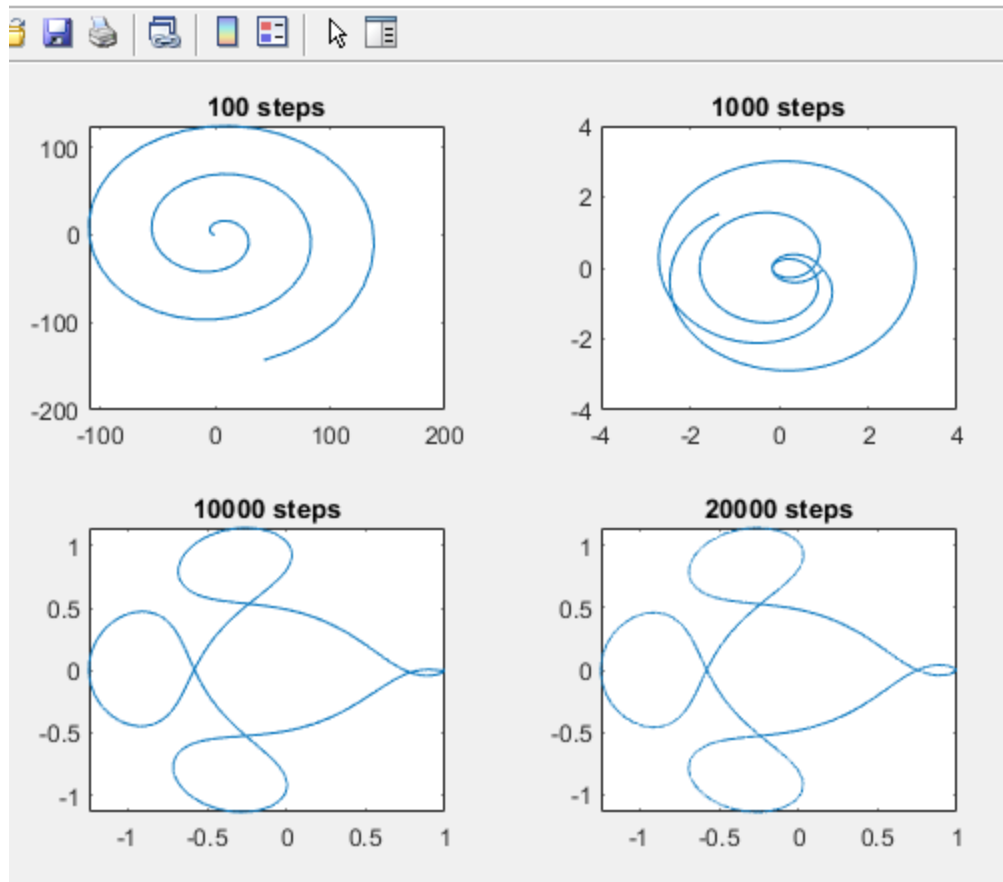
system d) fsolve num of iterations: 11

system d) my implementation result: 2

Reason that it is not working is the matrix itself is singular to working precision.

Problem 4:

About 10000 steps and more are needed.



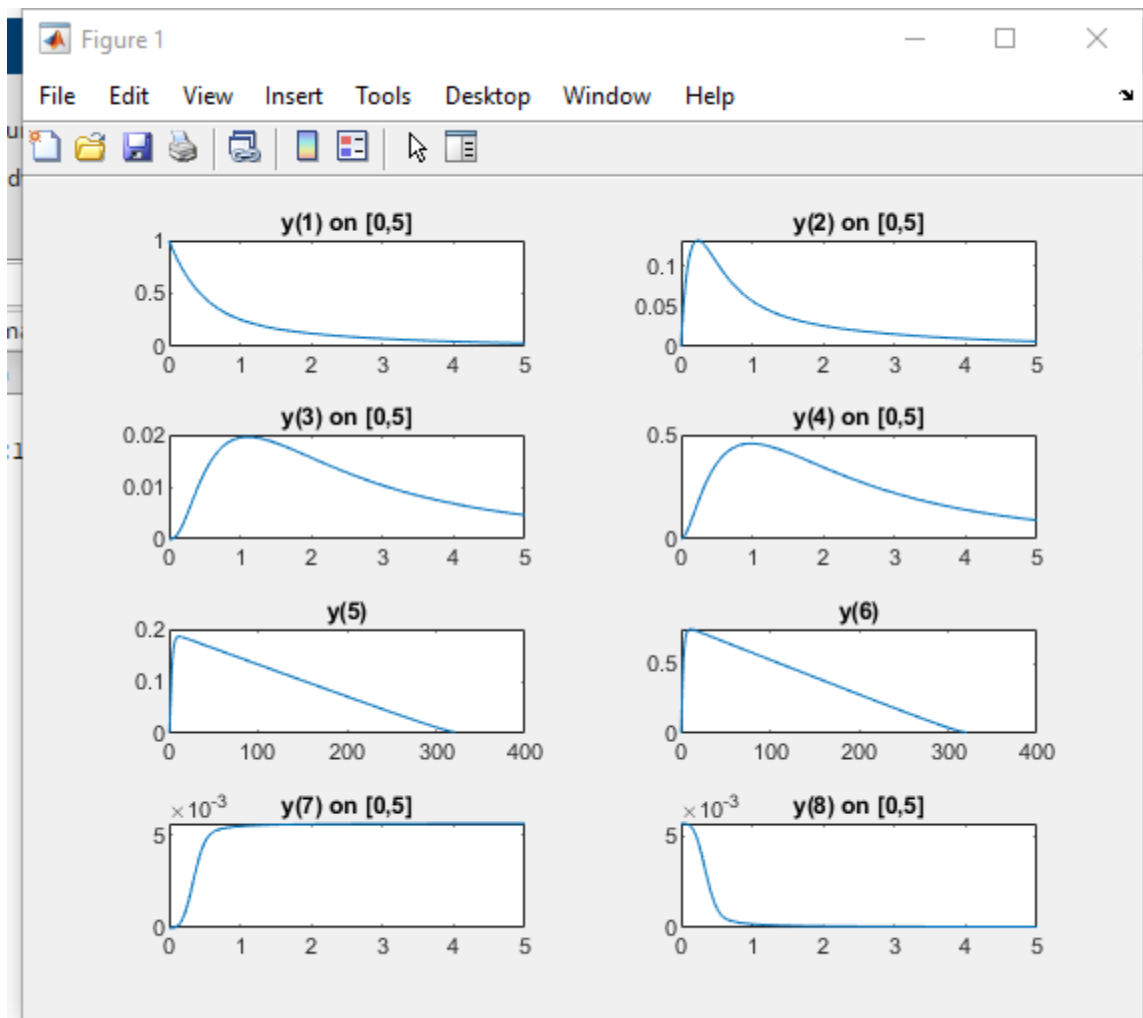
Problem 5:

Table

		number of		
		steps	failed steps	function evaluations
solver	CPU time			
ode23	1.6330e+01	1198181	0	3594544
ode45	6.0485e-01	43825	2	262963
ode23s	1.4540e+01	153152	708	1073488
ode15s	1.0300e+00	50169	843	66811
ode113	8.9711e-01	25628	378	51635

Ode45 most efficient.

Problem 6:



```
>> main_bonus
```

solver	CPU time	number of				
		steps	failed steps	function evaluations	LU decompositions	nonlinear solves
ode23s	8.1774e-02	303	0	3336	303	909
ode15s	2.0482e-01	200	22	435	55	370
ode45	2.6702e-01	10381	641	66133		

Conclusion: When solving stiff problems, stiff solvers like ode23s and ode15s are much faster than solvers like ode45. We should always choose the most suitable ode solvers depending on the problem that we are dealing with.

Problem 7:

- a) Words: Check along the dataset, starting from some point away from the first xyz. See if at any point of $t(i)$ the norm of the difference between $[x(i) \ y(i) \ z(i)]$ and $[x(1) \ y(1) \ z(1)]$ is smaller than tolerance. I used 0.028 as tolerance.

Pseudocode:

```
function T = findPeriod(t, x, y, z)
    vector0 = [x(1) y(1) z(1)];
```

```

x_size = size(x);
n = x_size(1);
tol = 0.028;

for i=100:n
    if abs(norm([x(i) y(i) z(i)]-vector0))<tol && sign(x(i))==sign(x(1))
    && sign(y(i))==sign(y(1)) && sign(z(i))==sign(z(1))
        T = t(i)*100/365;
        return;
    end
end
T = -1;
End

```

b)

```

>> main_nbody
Jupiter    11.859730
Saturn      29.478098
Uranus      84.057336
Neptune     164.880286
Pluto       247.993944

```

Problem 8:

