PROJECT 2

Carter Rhea

```
In [65]:
```

```
from ODE_IVP_module import *
from ODE_IVP_VECTOR import *
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

```
In [66]:
```

```
a = 0.
b = 2.*np.pi
init = 1.
K=1.
def g(t,y):
    return np.cos(t)-K*(y-np.sin(t))
```

Exact Solution of ODE:

Here I shall solve the ODE exactly so we can compare it to the numerical scheme.

$$\frac{dx}{dt} = \cos(t) - kx + k\sin(t)$$

$$\frac{dx}{dt} + kx = \cos(t) + k\sin(t)$$

Since this is linear we can solve it using the integrating factor... which is $I=e^{kt}$

$$xe^{kt} = \int e^{kt} \cos(t) + ke^{kt} \sin(t) dt$$

For ease I will break the integral into two parts and proceed to do integration by parts...

$$I_1 = e^{kt} \sin(t) - k \int \sin(t)e^{kt} dt$$

$$I_1 = e^{kt} \sin(t) + ke^{kt} \cos(t) - k^2 \int \cos(t)e^{kt}$$

$$I_1 = \frac{e^{kt} \sin(t) + ke^{kt} \cos(t)}{1 + k^2}$$

$$I_2 = -ke^{kt}\cos(t) - k^2 \int \cos(t)e^{kt}dt$$

$$I_2 = -ke^{kt}\cos(t) + k^2e^{kt}\sin(t) - k^3 \int \sin(t)e^{kt}$$

$$I_2 = \frac{-ke^{kt}\cos(t) + k^2e^{kt}\sin(t)}{1 + k^2}$$

Hence our integral is:

$$xe^{kt} = \frac{e^{kt}\sin(t) + ke^{kt}\cos(t)}{1 + k^2} + \frac{-ke^{kt}\cos(t) + k^2e^{kt}\sin(t)}{1 + k^2} + c$$

$$xe^{kt} = \frac{e^{kt}\sin(t) + k^2e^{kt}\sin(t)}{1 + k^2} + c$$

$$xe^{kt} = e^{kt}\sin(t) + c$$

Thus with a bit of division and plugging in our initial condition we obtain,

$$x = \sin(t) + init * e^{-kt}$$

The search for a good step size

Analycially we know that for stability 0 < Kh < 1 where h = (b - a)/n. Therefore,

$$0 < Kh < 1$$

$$0 < K\frac{b-a}{n}$$

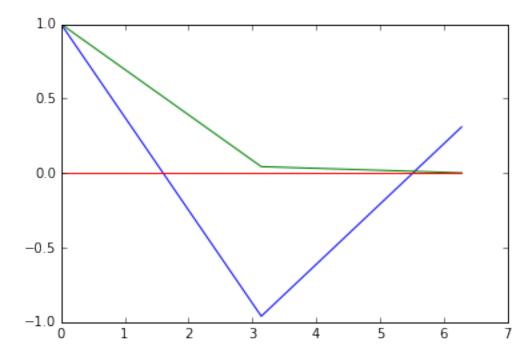
$$n > K(b-a)$$

Hence for K = 1, a = 0, and b = 2 we must have n > 2

```
In [67]:
```

```
n = 3
steps = np.linspace(a,b,n)
def exact(t) : return np.sin(t)+ init*np.exp(-K*t)
plt.plot(steps,Runge_Kutta(g,init,a,b,n),steps,exact(steps),steps,np.sin(steps))
```

Out[67]:



So it works, but it looks really bad!

```
In [73]:
n = 40
steps = np.linspace(a,b,n)
def exact(t) : return np.sin(t)+ init*np.exp(-K*t)
plt.plot(steps,Runge_Kutta(g,init,a,b,n),steps,exact(steps),steps,np.sin(steps))
Out[73]:
[<matplotlib.lines.Line2D at 0x1078d0320>,
 <matplotlib.lines.Line2D at 0x1078d0668>,
 <matplotlib.lines.Line2D at 0x1078d0e80>]
  1.5
  1.0
  0.5
  0.0
 -0.5
-1.0 L
In [74]:
err = Runge_Kutta(g,init,a,b,n).T-exact(steps);
plt.plot(steps,err.T)
Out[74]:
[<matplotlib.lines.Line2D at 0x107ab0908>]
  0.04
  0.02
  0.00
 -0.02
 -0.04
```

Honce we see that the error itself has an exponential sinusoidal form (like the exact solution)

-0.06

-0.08

-0.10

```
richee we see that the error resier has an exponential sindsoldar form (like the exact soldton)
```

```
In [75]:
```

```
print("There is a max error of %s"%(err.max()))
```

There is a max error of 0.0329084269283

So lets go ahead and try a little bit of a better n in order to decreate the error. Here ill go ahead and try a series of n values (20,40,80,160) and plot the graphs and errors....

```
In [76]:
```

```
for n in [20,40,80,160]:
    steps = np.linspace(a,b,n)
    err = Runge_Kutta(g,init,a,b,n).T-exact(steps);
    print("There is a max error of %s with an n value of %s"%(err.max(),n))
There is a max error of 0.0493553471874 with an n value of 20
There is a max error of 0.0320084360383 with an n value of 40
```

```
There is a max error of 0.0329084269283 with an n value of 40 There is a max error of 0.0180907668919 with an n value of 80 There is a max error of 0.0094625754892 with an n value of 160
```

The n value of 20 is reasonable. We probably wouldnt want it to be any lower since then we would not even have a decent plot

k=10

Now lets try k = 10 and redo all of those plots and n-value errors!

```
In [77]:
```

```
K=10.
for n in [20,40,80,160]:
    steps = np.linspace(a,b,n)
    err = Runge_Kutta(g,init,a,b,n).T-exact(steps);
    print("There is a max error of %s with an n value of %s"%(err.max(),n))
```

```
There is a max error of 13262.183118 with an n value of 20 There is a max error of 0.176995783842 with an n value of 40 There is a max error of 0.0692780684053 with an n value of 80 There is a max error of 0.0345432139179 with an n value of 160
```

In [78]:

```
## Lets check n=30 to find the stability...
steps = np.linspace(a,b,30)
err = Runge_Kutta(g,init,a,b,30).T-exact(steps);
print("There is a max error of %s with an n value of %s"%(err.max(),30))
```

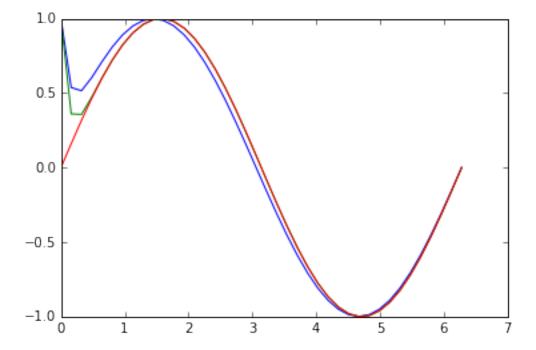
There is a max error of 0.368648424789 with an n value of 30

Hence it seems that an n value of about 30 is reasonable!

```
In [79]:
```

```
steps = np.linspace(a,b,40)
plt.plot(steps,Runge_Kutta(g,init,a,b,n=40),steps,exact(steps),steps,np.sin(steps))
```

Out[79]:



k = 100

Here we are going to use the previously used n-values and try some new ones as well!

In [51]:

```
K=100.
for n in [20,40,80,160,320,640,1280]:
    steps = np.linspace(a,b,n)
    err = Runge_Kutta(g,init,a,b,n).T-exact(steps);
    print("There is a max error of %s with an n value of %s"%(err.max(),n))
```

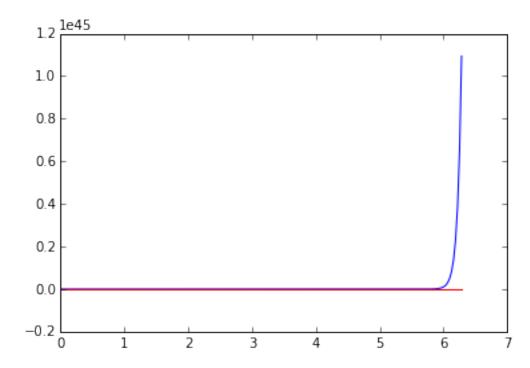
```
There is a max error of 2.41007497898e+86 with an n value of 20 There is a max error of 4.58247762164e+128 with an n value of 40 There is a max error of 3.73260751504e+158 with an n value of 80 There is a max error of 2.25057154478e+105 with an n value of 160 There is a max error of 0.195563003984 with an n value of 320 There is a max error of 0.0137096945988 with an n value of 640 There is a max error of 0.00489374563699 with an n value of 1280
```

```
In [52]:
```

```
steps = np.linspace(a,b,200)
plt.plot(steps,Runge_Kutta(g,init,a,b,n=200),steps,exact(steps),steps,np.sin(steps)
```

Out[52]:

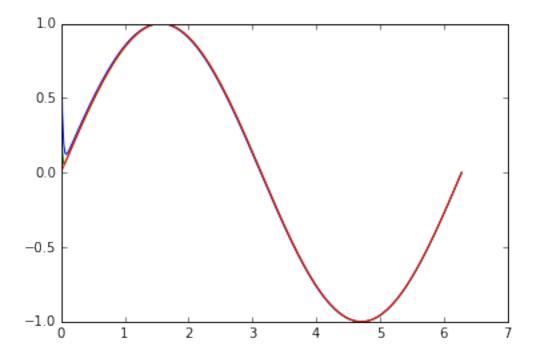
```
[<matplotlib.lines.Line2D at 0x106dd2748>, <matplotlib.lines.Line2D at 0x106a62278>, <matplotlib.lines.Line2D at 0x106dd87f0>]
```



Here we can see with a K value of 100 how horrible 200 steps works! So lets move it to 300!

```
In [53]:
steps = np.linspace(a,b,300)
plt.plot(steps,Runge_Kutta(g,init,a,b,n=300),steps,exact(steps),steps,np.sin(steps)
Out[53]:
```

```
[<matplotlib.lines.Line2D at 0x106ea1470>, <matplotlib.lines.Line2D at 0x106de9630>, <matplotlib.lines.Line2D at 0x106ea1f60>]
```



Here we can see how drastically we must change n when we change the K values...

ADAMS BASHFORTH

I will be employing the Predictor-Corrector AB method using the basic algorithms defined in our book and in class.

```
In [54]:
```

```
def euler_AB(f,y_init,a,b,n):
    y = np.zeros(n)
    y[0] = y_init
    h = (b-a)/n
    t_0=a
    for i in range(1,n):
        t_i = t_0+i*h
        Pred = y[i-1]+(h/24)*(-9*f(t_i-3*h,y[i-3])+37*f(t_i-2*h,y[i-2])-59*f(t_i-h,y)
        y[i] = y[i-1]+(h/24)*(f(t_i-2*h,y[i-2])-5*f(t_i-1*h,y[i-1])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t_i,y[i])+19*f(t
```

```
In [55]:
```

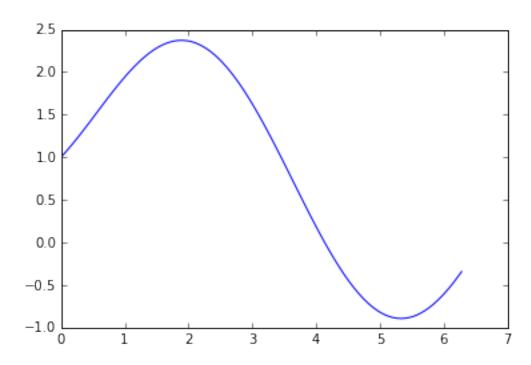
```
K = 1.
n = 100
val = euler_AB(g,init,a,b,n)
steps = np.linspace(a,b,n)
```

In [56]:

```
plt.plot(steps,val)
```

Out[56]:

[<matplotlib.lines.Line2D at 0x106efc0f0>]



Here we can see the asymptotic behavoir of the solutions of the ODE.

Systems of ODEs and the E-B Beam

Take our differential equation:

$$y''''(x) = \frac{f(x)}{IE}$$

We are simply going to turn this into a system of first order differential equations as such by allowing $y = U_0, y' = U_1, y'' = U_2, y''' = U_3$.

$$U_0 = U_1$$

$$U_1 = U_2$$

$$U_2 = U_3$$

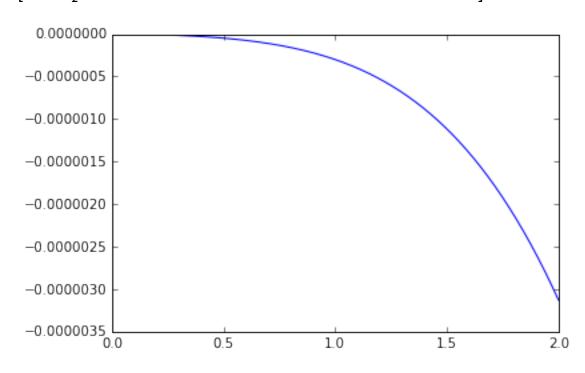
$$U_3 = \frac{f(x)}{IE}$$

```
In [57]:
def I(w,d): return (w*d)/12
w = 0.3
d = 0.03
E = 1.3*(10**(10))
g = 9.81
def f(x): return -480*w*d*g
init_beam_cant = [0,0,f(0)/(12*I(w,d)*E),-f(0)/(12*I(w,d)*E)]
In [58]:
##### Here is our system of functions in python notation to be loaded into the solve
def ydot(t_i,y,i):
    z = np.zeros(4)
    z[0] = y[1]
    z[1] = y[2]
    z[2] = y[3]
    z[3] = f(i)/(I(w,d)*E)
    return z
In [59]:
val,t = Runge_Kutta_vector(ydot,init_beam_cant,0,2,1000,4)
In [60]:
```

```
plt.plot(np.linspace(0,2,1000),val[:,0])
```

Out[60]:

[<matplotlib.lines.Line2D at 0x106f61400>]

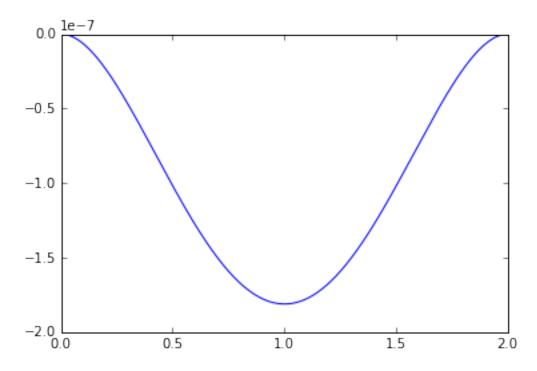


```
In [61]:
```

```
init_beam = [0,0,f(0)/(3*I(w,d)*E),-f(0)/(I(w,d)*E)]
val,t = Runge_Kutta_vector(ydot,init_beam,0,2,1000,4)
plt.plot(np.linspace(0,2,1000),val[:,0])
```

Out[61]:

[<matplotlib.lines.Line2D at 0x106f91278>]



In []:

In []: