

1. Heat equation:  $\frac{\partial u}{\partial t} = k \frac{\partial^2 u}{\partial x^2}$

a) backward Euler difference scheme

We derive:

$$u_t = (t_{n+1}, x_j) = \frac{u_j^{n+1} - u_j^n}{\Delta t}$$

$$u_{xx} = (t_{n+1}, x_j) = \frac{u_{j+1}^{n+1} - 2u_j^{n+1} + u_{j-1}^{n+1}}{\Delta x^2}$$

Let  $r = \Delta x$  and  $h = \Delta t$ . Now we will use Taylor expansion to derive our method

$$u(t_n, x_j) = u(t_{n+1}, x_j) - h u_t(t_{n+1}, x_j) + \frac{h^2}{2} u_{tt}(t_{n+1}, x_j) + O(h^3)$$

$$u(t_{n+1}, x_{j+1}) = u(t_{n+1}, x_j) + r u_x(t_{n+1}, x_j) + \frac{r^2}{2!} u_{xx}(t_{n+1}, x_j) + \frac{r^3}{3!} u_{xxx}(t_{n+1}, x_j) + \frac{r^4}{4!} u_{xxxx}(t_{n+1}, x_j) + O(r^5)$$

$u(t_{n+1}, x_j)$  = the centered part of our expansion

$$u(t_{n+1}, x_{j-1}) = u(t_{n+1}, x_j) - r u_x(t_{n+1}, x_j) + \frac{r^2}{2!} u_{xx}(t_{n+1}, x_j) - \frac{r^3}{3!} u_{xxx}(t_{n+1}, x_j) + O(r^4)$$

Local Truncation error is denoted by:

$$\tau_j^{n+1} = \frac{u(t_{n+1}, x_j) - u(t_n, x_j)}{h} - k \frac{u(t_{n+1}, x_{j+1}) - 2u(t_{n+1}, x_j) + u(t_{n+1}, x_{j-1}))}{r^2}$$

$$\frac{u(t_{n+1}, x_j) - u(t_n, x_j)}{h} = \frac{u(t_{n+1}, x_j) - (u(t_{n+1}, x_j) - h u_t(t_{n+1}, x_j) + \frac{h^2}{2} u_{tt}(t_{n+1}, x_j) + O(h^3))}{h}$$

$$= \frac{u(t_{n+1}, x_j) - u(t_{n+1}, x_j) + h u_t(t_{n+1}, x_j) - \frac{h^2}{2} u_{tt}(t_{n+1}, x_j) + O(h^3)}{h}$$

$$= \frac{h [u_t(t_{n+1}, x_j) - \frac{h}{2} u_{tt}(t_{n+1}, x_j) + O(h^2)]}{h}$$

$$= u_t(t_{n+1}, x_j) - \frac{h^2}{2} u_{tt}(t_{n+1}, x_j) + O(h^2)$$

Next, we need to solve for the local truncation error

$$\begin{aligned} & -K \frac{u(t_{n+1}, x_{j-1}) - 2u(t_{n+1}, x_j) + u(t_{n+1}, x_{j+1}))}{r^2} \\ &= -K \frac{u(t_{n+1}, x_j) + r u_x(t_{n+1}, x_j) + \frac{r^2}{2} u_{xx}(t_{n+1}, x_j) + \frac{r^3}{6} u_{xxx}(t_{n+1}, x_j) + \frac{r^4}{24} u_{xxxx}(t_{n+1}, x_j) + O(r^5) - 2u(t_{n+1}, x_j) \\ &+ u(t_{n+1}, x_j) - r u_x(t_{n+1}, x_j) + \frac{r^2}{2} u_{xx}(t_{n+1}, x_j) - \frac{r^3}{6} u_{xxx}(t_{n+1}, x_j) + \frac{r^4}{24} u_{xxxx}(t_{n+1}, x_j) + O(r^5)}{r^2} \\ &= \frac{-K r^2 [u_{xx}(t_{n+1}, x_j) + \frac{r^4}{12} u_{xxxx}(t_{n+1}, x_j) + O(r^5)]}{r^2} \end{aligned}$$

$$= -K u_{xx}(t_{n+1}, x_j) + \frac{r^4}{12} u_{xxxx}(t_{n+1}, x_j) + O(r^5)$$

$$\text{From LTE: } \frac{u(t_{n+1}, x_j) - u(t_n, x_j)}{h} = K \frac{u(t_{n+1}, x_{j+1}) - 2u(t_{n+1}, x_j) + u(t_{n+1}, x_{j-1}))}{r^2}$$

$$= u_t(t_{n+1}, x_j) - K u_{xx}(t_{n+1}, x_j) - \frac{h}{2} u_{tt}(t_{n+1}, x_j) + O(h^2) - K \frac{r^2}{12} u_{xxxx}(t_{n+1}, x_j) + O(r^3)$$

$$= 0 - \frac{h}{2} u_{tt}(t_{n+1}, x_j) + O(h^2) - K \frac{r^2}{12} u_{xxxx}(t_{n+1}, x_j) + O(r^3)$$

When we subtract our Taylor approx, we get

$$= \frac{h}{2} u_{tt}(t_{n+1}, x_j) + O(h^2) - K \frac{r^2}{12} u_{xxxx}(t_{n+1}, x_j) + O(r^3)$$

So, our local truncation error is

$$\mathcal{T}_j^{n+1}(h, r) = \frac{h}{2!} u_{tt}(t_{n+1}, x_j) + O(h^2) + \frac{r^2}{4!} u_{xxxx}(t_{n+1}, x_j) + O(r^3)$$

where  $h = \Delta t$ ,  $r = \Delta x$

The time  $h$  is order 2 and space  $r$  is order 3

From definition 14.2, we know that a PDE is consistent

if  $\mathcal{T}_j^{n+1}(\Delta t, \Delta x) \rightarrow 0$  as  $\Delta t, \Delta x \rightarrow 0$ . We can clearly see

$$\mathcal{T}_j^{n+1}(\Delta t, \Delta x) = O(\Delta t)^2 + O(\Delta x)^3$$

$$\lim_{\Delta t, \Delta x \rightarrow 0} \mathcal{T}_j^{n+1}(\Delta t, \Delta x) = 0$$

Therefore, this is consistent

Now, we need to check for stability, let  $u_m^n = \xi^n e^{ikr}$

where  $m = 1, 2, \dots, M-1$  and  $\lambda = \frac{h k}{r^2}$

For our scheme:

$$\frac{u_m^{n+1} - u_m^n}{h} = k \frac{u_{m+1}^{n+1} - 2u_m^{n+1} + u_{m-1}^{n+1}}{r^2}$$

We have:  $\xi^{n+1} e^{ikmr} - \xi^n e^{ikmr} = \lambda \xi^{n+1} e^{ik(m+1)r}$

$$e^{ikmr} (\xi^{n+1} - \xi^n) = \lambda \xi^{n+1} (e^{ik(m+1)r} - 2e^{ikmr} + e^{ik(m-1)r})$$

$$= \lambda \xi^{n+1} (e^{ikmr} e^{kir} - 2e^{ikmr} + e^{ikmr} e^{-kir})$$

$$\cancel{e^{ikmr}} (\xi^{n+1} - \xi^n) = \lambda \xi^{n+1} \cancel{e^{ikmr}} (e^{kir} - 2 + e^{-kir})$$

$$\xi^{n+1} - \xi^n = \lambda \xi^{n+1} (e^{kir} - 2 + e^{-kir})$$

$$\xi - 1 = \lambda \xi (e^{kir} - 2 + e^{-kir})$$

$$\Rightarrow 1 = \xi - \lambda \xi (e^{kir} - 2 + e^{-kir})$$

$$= \xi (1 - \lambda (e^{kir} - 2 + e^{-kir}))$$

$$= \xi (1 + 2\lambda (1 - \cos(kr)))$$

$$= \xi (1 + 2\lambda \sin^2(\frac{kr}{2}))$$

$$\Rightarrow \xi = \frac{1}{1 + 2\lambda \sin^2(\frac{kr}{2})}$$

Since  $\lambda > 0$  and  $\sin(x) \in [0, 1]$  when  $x \in \mathbb{R}$  we can say that  $\sin^2(x) \in [0, 1]$

$$\Rightarrow 1 + 2\lambda \sin^2(\frac{kr}{2}) \geq 1$$

Since our denominator is always positive and the numerator is one, we can say  $\xi = \frac{1}{1 + 2\lambda \sin^2(\frac{kr}{2})} \leq 1$  and  $0 < \xi \leq 1$

Therefore, this is stable for any value  $h = \Delta t$ ,  $r = \Delta x$   
 $\Rightarrow$  Unconditionally Stable with time order 2 and space order 3.

```
In [192]: 1 import numpy as np
          2 import matplotlib.pyplot as plt
          3 from copy import deepcopy
```

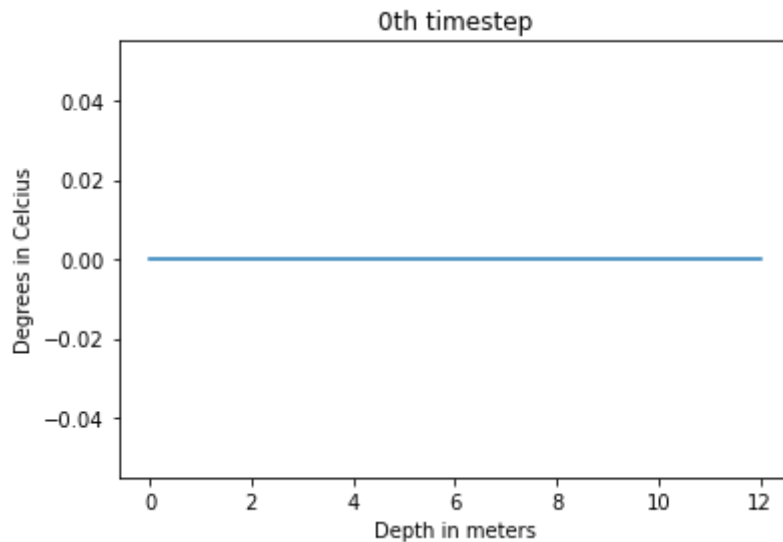
```
In [223]: 1 #1b
          2
          3 def tridiag(n, alpha): #define our tri diagonal matrix, we implemented
          4     result = 2 * np.eye(n)
          5
          6     for i in range(n - 1):
          7         result[i + 1][i] = -1
          8         result[i][i + 1] = -1
          9
         10     return np.eye(n) + alpha * result
```

```
In [224]: 1 def backward_findiff(t0, uinit, alpha, delta_t, N, timesteps): #define
          2     t_curr = t0
          3     u_curr = uinit[1 : -1]
          4     M = len(uinit)
          5     A = tridiag(M - 2, alpha) #initialize our matrix to be used in equa
          6     results = []
          7     if 0 in timesteps:
          8         results.append(deepcopy(uinit))
          9     for i in range(1, N + 1): #this implements each time step, current
         10         t_curr += delta_t #adds delta t to create the next sep
         11         b = u_curr
         12         b[0] += alpha * u_t(t_curr)
         13         u_curr = np.linalg.solve(A, b) #uses a matrix solver to define
         14         if i in timesteps:
         15             result = np.concatenate(([u_t(t_curr)], u_curr, [0.0]))
         16             results.append(result)
         17     return results
```

```
In [225]: 1 q1 = 0.71 #0.71 m is the initial condition
          2 t0 = 0.0 #our initial time
          3 K = 2e-3 * 1e-4 #convert from cm^2/s to m^2/s^2, our initial condition
          4 Y = 3.15e7 #convert one year into seconds so our time steps match
          5 A = 20.0 #define A as described in the problem
          6
          7 u_t = lambda t: A * np.sin(2 * np.pi * t / Y) #solve for the sinusoidal
          8 uinit_calc = lambda t, xval: u_t(t) * np.exp(-q1 * xval) #this is used
          9
         10 xval = np.linspace(0, 12, 51) #define the x values
         11 uinit = uinit_calc(t0, xval) #define our initial u value
         12 delta_x = xval[1] - xval[0] #delta x is distance between our consecuti
         13 delta_t = Y / 250 #define the number of timesteps we want to observe
         14 alpha = K * delta_t / (delta_x ** 2) #define our alpha value
         15
         16
         17 timesteps = [i * 5 for i in range(101)] #20 time steps displayed with 5
         18 u_approxs = backward_findiff(t0, uinit, alpha, delta_t, 1000, timesteps)
```

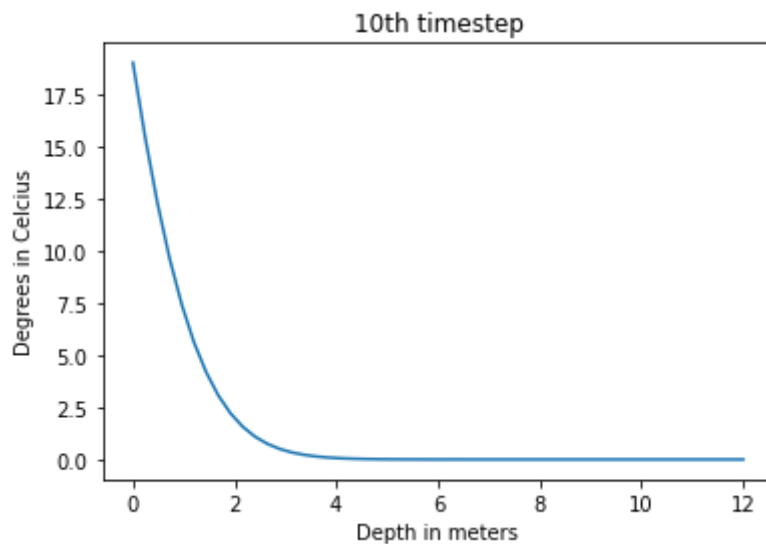
```
In [226]: 1 # Plotting 0 timestep
          2 plt.plot(xval, u_approx[0])
          3 plt.xlabel("Depth in meters")
          4 plt.ylabel("Degrees in Celcius")
          5 plt.title("0th timestep")
          6
```

Out[226]: Text(0.5, 1.0, '0th timestep')



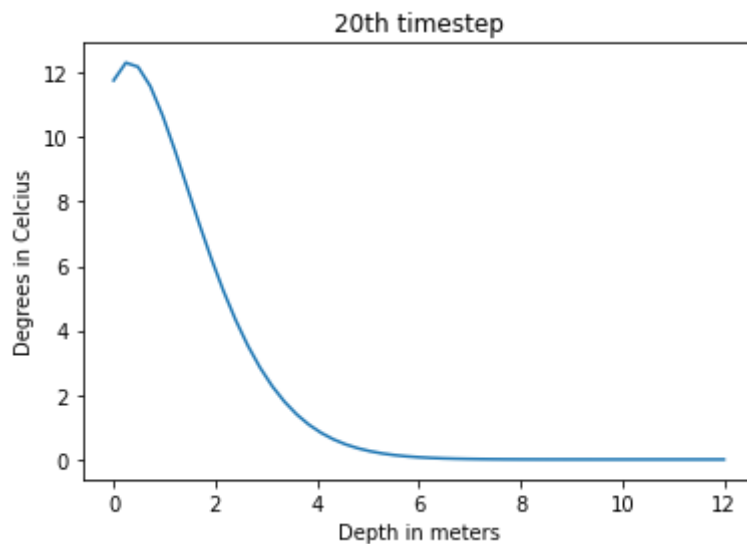
```
In [227]: 1 # Plotting 10 timestep
          2 plt.plot(xval, u_approxs[10])
          3 plt.xlabel("Depth in meters")
          4 plt.ylabel("Degrees in Celcius")
          5 plt.title("10th timestep")
```

Out[227]: Text(0.5, 1.0, '10th timestep')



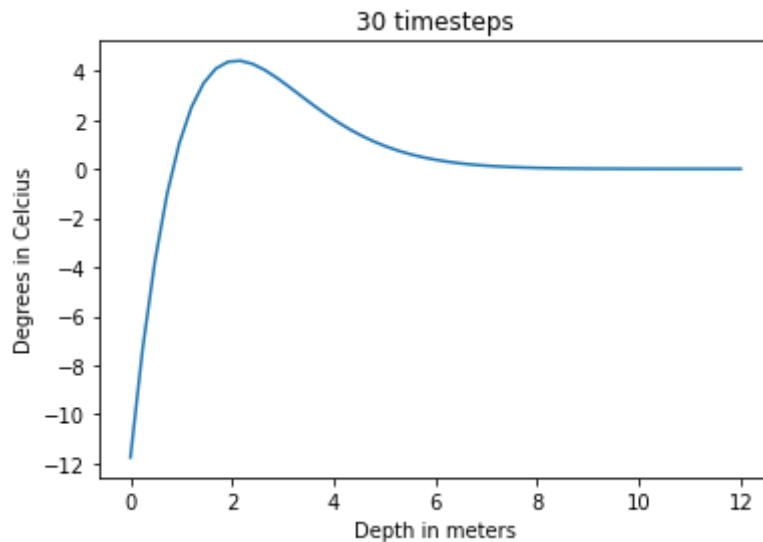
```
In [228]: 1 # Plotting 20 timestep
          2 plt.plot(xval, u_approxs[20])
          3 plt.xlabel("Depth in meters")
          4 plt.ylabel("Degrees in Celcius")
          5 plt.title("20th timestep")
```

Out[228]: Text(0.5, 1.0, '20th timestep')



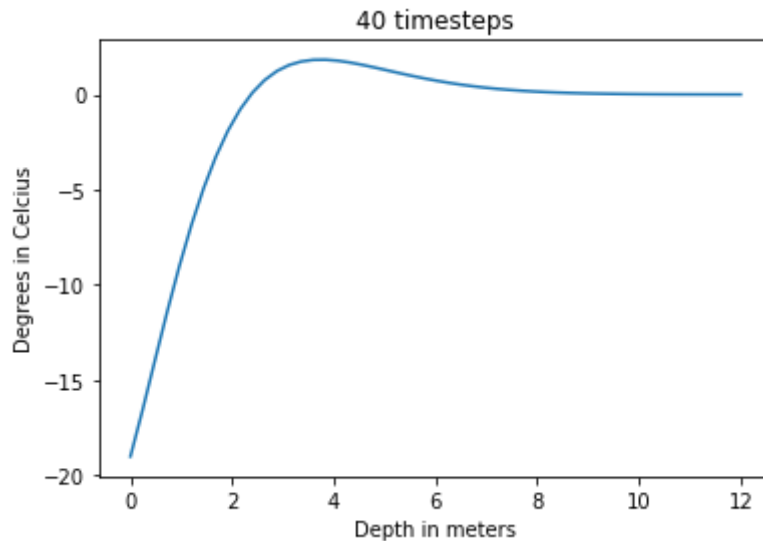
```
In [229]: 1 # Plotting 30 timestep
          2 plt.plot(xval, u_approxs[30])
          3 plt.xlabel("Depth in meters")
          4 plt.ylabel("Degrees in Celcius")
          5 plt.title("30 timesteps")
```

Out[229]: Text(0.5, 1.0, '30 timesteps')



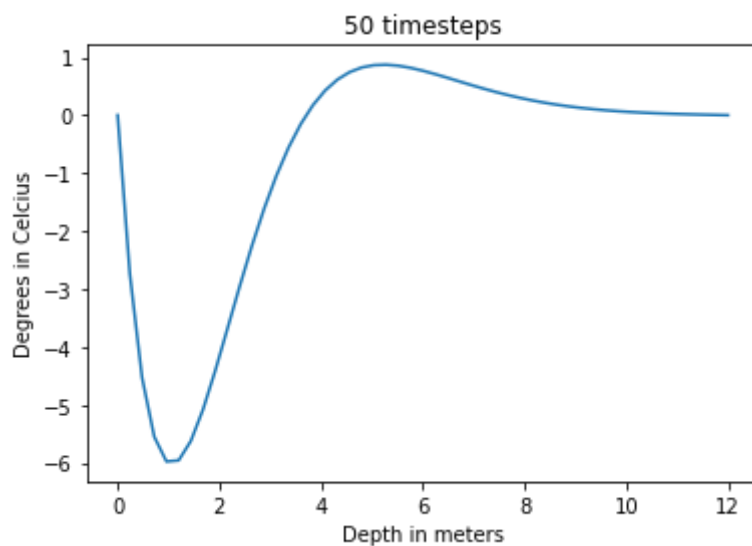
```
In [230]: 1 # Plotting 40 timestep
          2 plt.plot(xval, u_approxs[40])
          3 plt.xlabel("Depth in meters")
          4 plt.ylabel("Degrees in Celcius")
          5 plt.title("40 timesteps")
```

Out[230]: Text(0.5, 1.0, '40 timesteps')



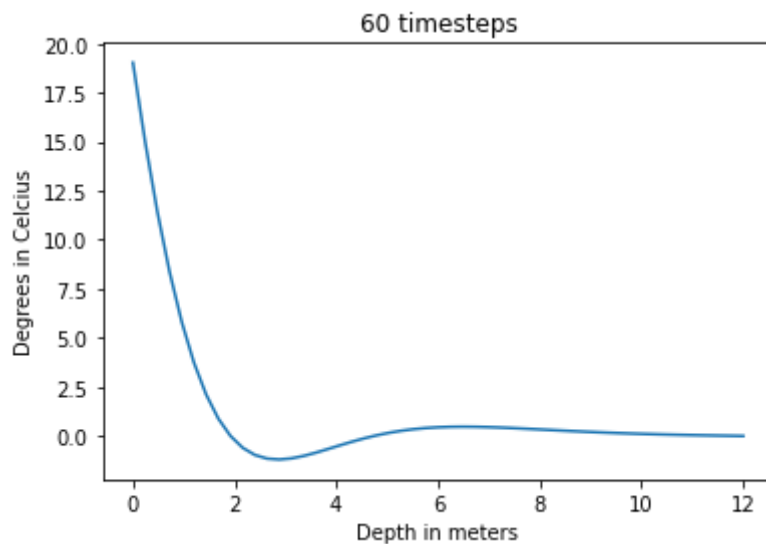
```
In [231]: 1 # Plotting 50 timestep
          2 plt.plot(xval, u_approxs[50])
          3 plt.xlabel("Depth in meters")
          4 plt.ylabel("Degrees in Celcius")
          5 plt.title("50 timesteps")
```

Out[231]: Text(0.5, 1.0, '50 timesteps')



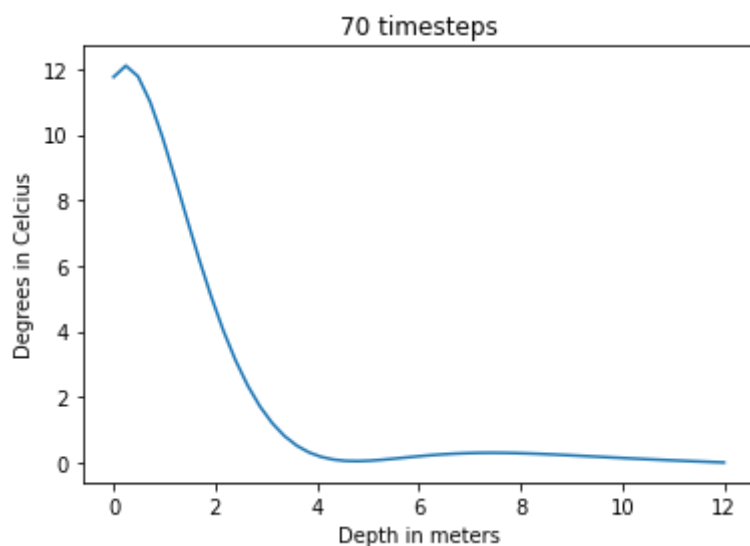
```
In [232]: 1 # Plotting 60 timestep
          2 plt.plot(xval, u_approxs[60])
          3 plt.xlabel("Depth in meters")
          4 plt.ylabel("Degrees in Celcius")
          5 plt.title("60 timesteps")
```

Out[232]: Text(0.5, 1.0, '60 timesteps')



```
In [233]: 1 # Plotting 70 timestep
          2 plt.plot(xval, u_approxs[70])
          3 plt.xlabel("Depth in meters")
          4 plt.ylabel("Degrees in Celcius")
          5 plt.title("70 timesteps")
```

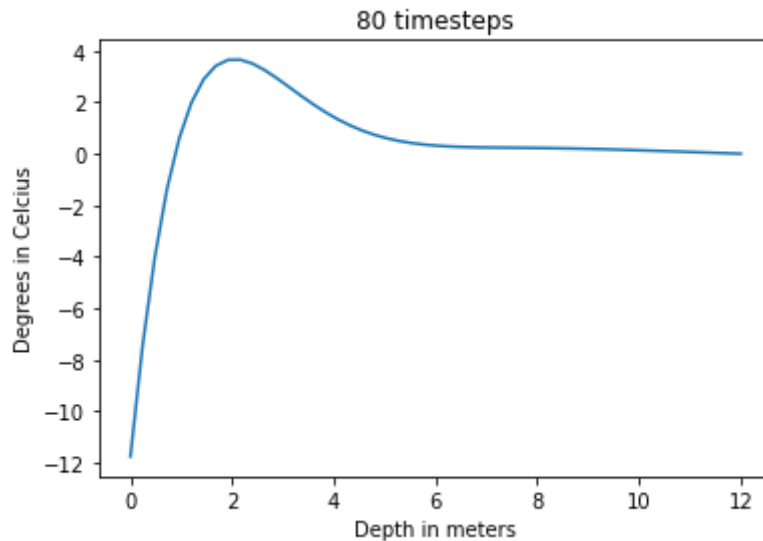
Out[233]: Text(0.5, 1.0, '70 timesteps')





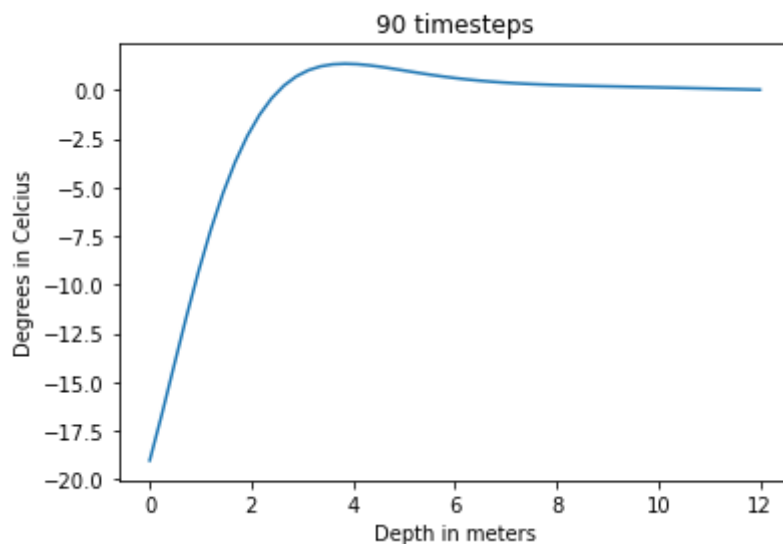
```
In [234]: 1 # Plotting 80 timestep
          2 plt.plot(xval, u_approxs[80])
          3 plt.xlabel("Depth in meters")
          4 plt.ylabel("Degrees in Celcius")
          5 plt.title("80 timesteps")
```

Out[234]: Text(0.5, 1.0, '80 timesteps')



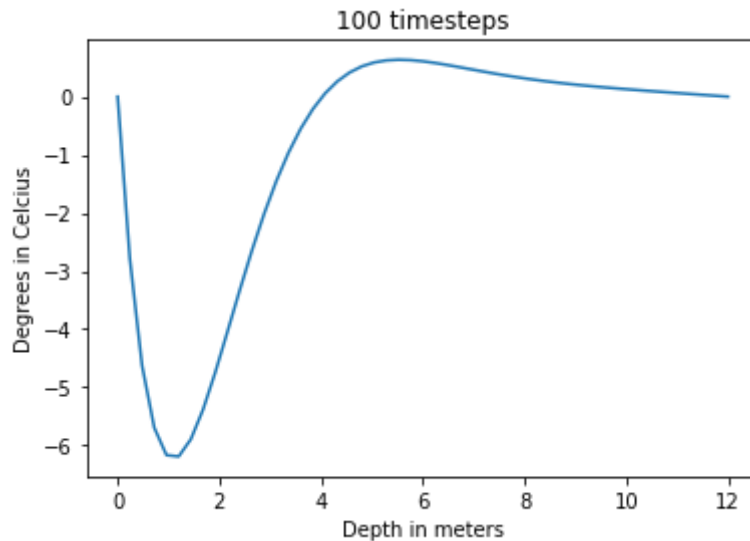
```
In [235]: 1 # Plotting 90 timestep
          2 plt.plot(xval, u_approxs[90])
          3 plt.xlabel("Depth in meters")
          4 plt.ylabel("Degrees in Celcius")
          5 plt.title("90 timesteps")
```

Out[235]: Text(0.5, 1.0, '90 timesteps')



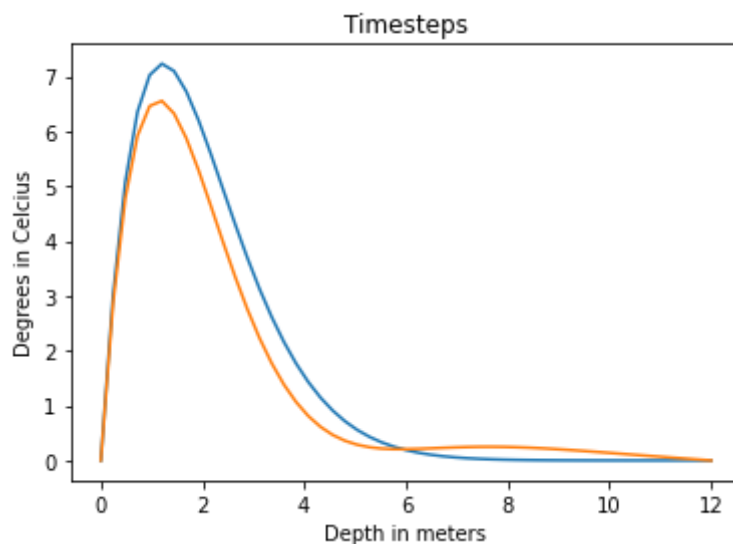
```
In [236]: 1 # Plotting 100 timestep
          2 plt.plot(xval, u_approxs[100])
          3 plt.xlabel("Depth in meters")
          4 plt.ylabel("Degrees in Celcius")
          5 plt.title("100 timesteps")
```

Out[236]: Text(0.5, 1.0, '100 timesteps')

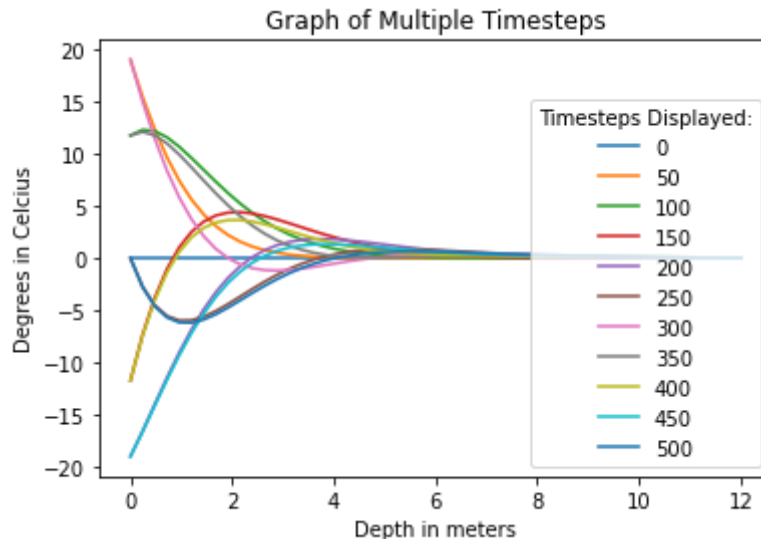


```
In [237]: 1 # Plotting 100 timestep
          2 plt.plot(xval, u_approxs[25])
          3 plt.plot(xval, u_approxs[75])
          4 plt.xlabel("Depth in meters")
          5 plt.ylabel("Degrees in Celcius")
          6 plt.title("Timesteps")
```

Out[237]: Text(0.5, 1.0, 'Timesteps')



```
In [212]: 1 timestep_graphs = [0,10,20,30,40,50,60,70,80,90,100] #define our timest
2 timesteps_guide = [0, 50, 100, 150, 200, 250, 300, 350, 400, 450, 500]
3 for i in range(0, len(timestep_graphs)):
4     plt.plot(xval, u_approx[timestep_graphs[i]])
5     plt.legend((timesteps_guide), title = "Timesteps Displayed:", loc =
6     plt.xlabel("Depth in meters")
7     plt.ylabel("Degrees in Celcius")
8     plt.title("Graph of Multiple Timesteps")
```



```
In [238]: 1 #c
2 print("The optimal for x* is when the temperature is the opposite of th
3 print("In our plot of multiple timesteps, we observe that temperature i
4 print("After our depth of 4m, we see our temperature begin to fluctuate
5 print("We see that the optimal x* value is approximately 3.7m for the m
6 print("This is optimal as you can cool wine during the hot summer and c
```

The optimal for  $x^*$  is when the temperature is the opposite of the surface temperature.

In our plot of multiple timesteps, we observe that temperature is opposite of the surface between 3 and 5.

After our depth of 4m, we see our temperature begin to fluctuate much less, this tends to zero.

We see that the optimal  $x^*$  value is approximately 3.7m for the majority of time steps that we have plotted

This is optimal as you can cool wine during the hot summer and cultivate vegetables during the cold winter

```
In [ ]: 1
```

