

Numerical-solver  
Assignment Report

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# Contents

<b>1</b>	<b>Numerical methods</b>	<b>2</b>
1.1	One-step methods . . . . .	3
1.2	Predictor-corrector methods . . . . .	5
1.3	Adaptive method . . . . .	6
<b>2</b>	<b>Implementation</b>	<b>8</b>
2.1	Software details . . . . .	8
2.2	Unit testing . . . . .	9
2.3	Testing initialisation of problem . . . . .	9
2.4	Testing function . . . . .	10
<b>3</b>	<b>Fitzhugh-Nagumo Model Example</b>	<b>12</b>
3.1	Background . . . . .	12
3.2	Fitzhugh-Nagumo model . . . . .	12
3.3	Convergence of Fitzhugh-Nagumo model . . . . .	14

# Chapter 1

## Numerical methods

In real world problems, ODE systems are frequently used. A general form of an initial value problem is as follows:

$$y' = f(x, y) \quad (1.1)$$

$$y(x_0) = y_0 \quad (1.2)$$

for  $x \in [x_0, X_M]$ .

Throughout the report, the following notation will be used.

$y_n$  - numerical approximation of  $y(x_n)$

$y(x_n)$  - analytical solution at mesh point  $x_n$

$x_n$  - mesh points of defined range, where

$$x_n = x_0 + nh \quad (1.3)$$

$$h = \frac{(X_M - x_0)}{N} \quad (1.4)$$

for  $n = 0, \dots, N$ .

However, in general, these models cannot be solved analytically. Therefore, the solution has to be estimated by numerical methods. The most popular and simple method is the Euler's method.

Intuitively, the Euler's explicit method tries to estimate the value at the next step following the gradient of the solution at current point.

## 1.1 One-step methods

The Euler's explicit method has the following definition,

$$y_{n+1} = y_n + hf(x_n, y_n) \quad (1.5)$$

Starting from the initial value, the solution at the subsequent mesh point is estimated to follow a straight line with gradient as given.

The implementation is as follows:

```
1 y_n = [self.initial_value]
2 x_n = [self.x_min]
3
4 # Calculate approximated solution for each mesh point.
5 for n in range(1, self.mesh_points + 1):
6     step = [self.mesh_size * f for f in self.func(x_n[-1], y_n
7     [-1])]
8     y_n.append([a + b for a, b in zip(y_n[-1], step)])
9     x_n.append(self.x_min + n * self.mesh_size)
10 return x_n, y_n
```

A vector of numerical solution and a vector of mesh points are initialised with their respective initial values. At each iteration, the mesh point and the numerical solution at the mesh point are calculated. The series of mesh points and its solution are returned.

The truncation error of the Euler's explicit method is defined to be the difference of exact solution with the numerical solution given the exact solution of previous mesh point is known. Therefore, we have that the truncation error for Euler's explicit method to be

$$T_n := \frac{y(x_{n+1}) - y(x_n)}{h} - f(x_n, y(x_n)) \quad (1.6)$$

According to Taylor's series expansion, we have

$$y(x_n + h) = y(x_n) + hy'(x_n) + \frac{1}{2}hy''(\xi_n) \quad (1.7)$$

for  $\xi_n \in (x_n, x_{n+1})$ . Substitute this to the truncation error, noting that  $f(x_n, y(x_n)) = y'(x_n)$ , we get

$$T_n = \frac{1}{2}hy''(\xi_n) \quad (1.8)$$

Therefore, the truncation error for Euler's explicit method varies linearly with the step size.

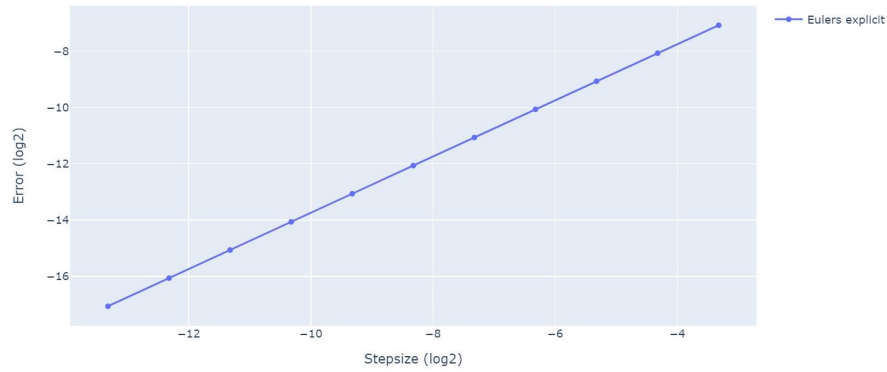
An example model

$$f(x, y) = -y \quad (1.9)$$

$$y(0) = 1 \quad (1.10)$$

for  $x \in [0, 5]$  is used throughout the report to check that the implementation follows the theory. The analytical solution to this problem is  $y = e^{-x}$ . Some examples of the solution to the given model can be found here: Example model notebook

According to the computation of the software, the truncation error graph is shown below. It is observed that  $\log |T_n|$  increases linearly with  $\log h$ , same as the theoretical prediction.



Other than the Euler's explicit method, the other one-step methods implemented are the Euler's implicit method, trapezium rule method and four-stage explicit Runge-Kutta method. The Euler's implicit method is defined to be

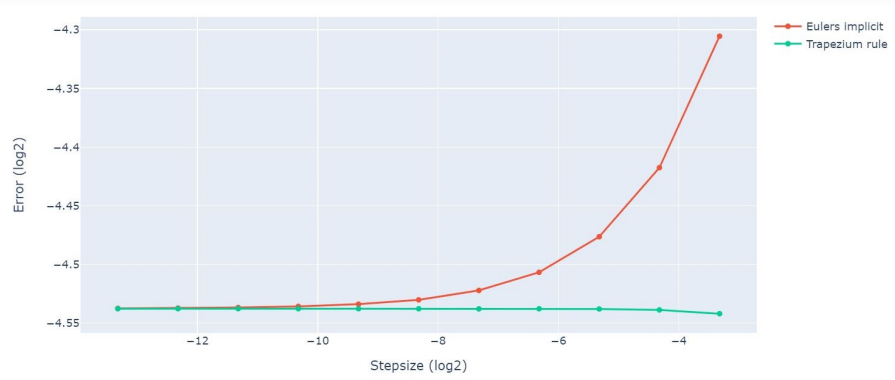
$$y_{n+1} = y_n + hf(x_{n+1}, y_{n+1}), \quad (1.11)$$

while the trapezium rule method is

$$y_{n+1} = y_n + \frac{1}{2}h[f(x_n, y_n) + f(x_{n+1}, y_{n+1})]. \quad (1.12)$$

Using the same definition for truncation error in 1.6, we have that the truncation error of Euler's implicit method and trapezium rule method are  $T_n = -\frac{1}{2}hy''(\xi_n)$  for  $\xi_n \in (x_n, x_{n+1})$  and  $T_n = -\frac{1}{12}h^2y^{(3)}(\xi_n)$  for  $\xi_n \in (x_n, x_{n+1})$  respectively.

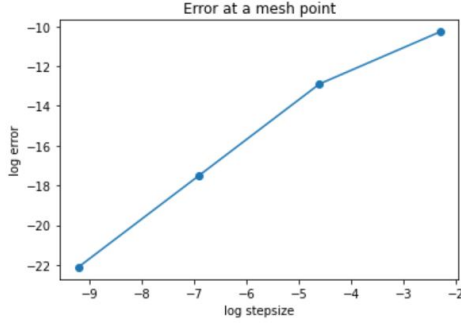
When these methods are tested on the example model 1.9, the truncation error does not behave as expected, as shown in the graph below. This is probably due to the use of fixed point iteration algorithm to estimate the solution of implicit functions. The error of the fixed point iteration algorithm might be added to the error of the numerical method. Therefore, the difference of the numerical solution with the exact solution is larger for implicit methods as compared to Euler's explicit methods.



## 1.2 Predictor-corrector methods

For the implicit one-step methods, numerical value at previous mesh point is chosen as the initial guess for the fixed point iteration algorithm. The predictor-corrector method suggests a more carefully chosen initial guess for the implicit methods. An explicit numerical method is used as a predictor for the initial guess of an implicit method. The initial value is then used for the iterations in the algorithm to solve an implicit function. The implicit method that refines the solution is known as the corrector method.

The Euler-Trapezoidal method is a predictor-corrector that uses an Euler's explicit method as the predictor and trapezium rule method as the corrector. In this implementation, the trapezium rule method corrector is iterated until a set of conditions are satisfied. The conditions are set to be the difference between current iteration and previous iteration is lesser than a given threshold value or the number of iterations exceeds a certain amount. The figure below shows the graph of  $\log |T_n|$  against  $\log h$ .



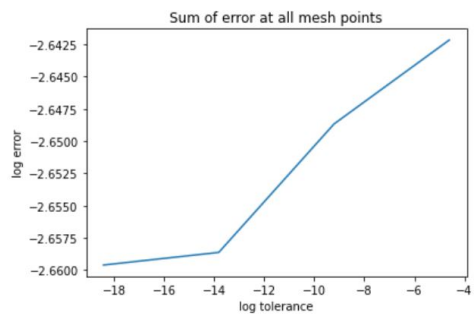
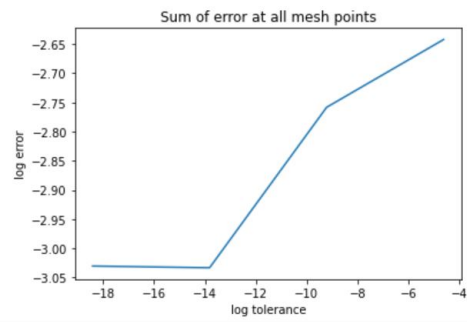
### 1.3 Adaptive method

In some types of problem, the solution to the problem exhibits a behaviour where step sizes have to be sufficiently small for a stable solution. In other words, the solution have small changes with mesh points. Such problems are called stiff problems. In order to obtain a stable solution, the computational cost is high. Moreover, such stable solution would have resolutions higher than required for practical purposes.

The adaptive method focus on the achieving desired accuracy with low computational cost. The main idea of an adaptive method is to control the precision at each mesh point. The error at each mesh point is estimated. If the error is larger than a threshold value, a smaller step size is chosen. These steps are repeated until the error is smaller than the given threshold value.

The adaptive method implemented in this software is based on the BS23 (Bogacki and Shampine) and RK45 (Runge-Kutta-Fehlberg) method. A lower order method is used to estimate the solution, while a higher order method is used to estimate the error.

Absolute tolerance and relative tolerance were used in the implementation of the adaptive methods. Similarly, the implemented adaptive method is used to solve the example model 1.9. The adaptive methods were tested for convergence. Two comparisons were made, one based on absolute tolerance and the other on relative tolerance. As shown in the graph below, the error of the method is smaller for smaller tolerance, regardless of absolute tolerance or relative tolerance.





## Chapter 2

# Implementation

### 2.1 Software details

The numerical methods implemented in this software are classified into three classes: one-step methods, predictor-corrector methods and adaptive methods. The methods included are:

1. One-step method
  - Euler's explicit method
  - Euler's implicit method
  - Trapezium rule method
  - Four-stage Runge-Kutta method
2. Predictor-corrector method
  - Euler-Trapezoidal method
3. Adaptive method
  - BS23 algorithm
  - RKF45 algorithm

The code is available on Github via [this link](#). There are badges displayed on the main page of the Github repository to indicate that the code are tested to work on several python versions and operating systems. One of the badges shows the code coverage of the software, which will be described in details

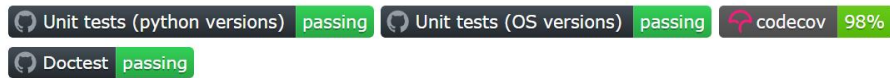


Figure 2.1: Badges on Github repository

in the next section 2.2. Finally, there is a status badge to verify that the documentation of the software is built successfully. The documentation of the software can be found [here](#).

## 2.2 Unit testing

In the progress of constructing the software, a unit testing infrastructure was put in place. The purpose of the unit testing is to create a robust and sustainable software. Written codes are tested to make sure it runs as intended and reproduces expected results. If code is tested while writing, it would be easier to fix bugs in the future.

Code coverage is used to define the percentage of codes covered in the unit testing process. It is usually aim to achieve a 100% code coverage. However, a 100% code coverage does not necessarily mean that the code is correct or free of errors. Nevertheless, it provides some confidence that the code is implemented correctly.

Every method in this numerical-solver software is tested, including the initialisation of the problem. The numerical solution produced by each method is tested to give the same solution as a manually calculated solution. The methods are mostly tested against the example model 1.9.

## 2.3 Testing initialisation of problem

The initialisations of each class are tested to ensure that variables are initialised correctly and input type satisfies the requirements. For example,

```
1 def test__init__(self):
2
3     def func(x, y):
4         return [-y[0]]
5     x_min = 0
6     x_max = 1
7     initial_value = [1]
```

```

8     mesh_points = 10
9
10    problem = solver.OneStepMethods(
11        func, x_min, x_max, initial_value, mesh_points)
12
13    # Test initialisation
14    self.assertEqual(problem.x_min, 0)
15    self.assertEqual(problem.mesh_points, 10)
16
17    # Test raised error for callable function
18    with self.assertRaises(TypeError):
19        solver.OneStepMethods(
20            x_min, x_min, x_max, initial_value, mesh_points)
21
22    # Test raised error if initial_value not list
23    with self.assertRaises(TypeError):
24        solver.OneStepMethods(
25            func, x_min, x_max, 1, mesh_points)

```

. A simple model with known solution is first initialised. Required inputs were check to make sure the problem is set up properly, in line 14 and 15 of the code snippet above. To ensure that the inputs to the function are of the desired data type, errors are raised whenever the user inputs a wrong data type. The unit testing also tests that these errors are raised appropriately (line 17 to 25) whenever the data type does not satisfy the requirements.

## 2.4 Testing function

After making sure the problem is properly initialised, we then test that the numerical methods are working correctly. Take the adaptive method, BS23 algorithm, as an example,

```

1  def test_ode23(self):
2
3  def func(x, y):
4      return [-y[0]]
5  x_min = 0
6  x_max = 1
7  initial_value = [1]
8
9  problem = solver.AdaptiveMethod(
10      func, x_min, x_max, initial_value, initial_mesh=0.5)
11  mesh, soln = problem.ode23()
12
13  # Test end point of mesh
14  self.assertGreaterEqual(mesh[-1], 1.0)
15
16  # Test mesh point

```

```
17 self.assertAlmostEqual(mesh[1], 0.3483788976565)
18
19 # Test solution at first stepsize
20 self.assertAlmostEqual(soln[1][0], 0.7052580305097)
```

The method is first tested to execute computations up to the maximum mesh point indicated. Then, it is checked that the first adaptive mesh point and its solution, obtained from the software, matches the value computed manually.

## Chapter 3

# Fitzhugh-Nagumo Model Example

### 3.1 Background

We will look into the Fitzhugh-Nagumo model in this assignment. The Fitzhugh-Nagumo model is a model that describes an excitable system, such as the action potential of cardiac cells. The action potential is first described by Hodgkin & Huxley. Their model were then simplified to the Fitzhugh-Nagumo model, retaining the fast-slow phase and excitability of the Hodgkin & Huxley model.

### 3.2 Fitzhugh-Nagumo model

The definition of the Fitzhugh-Nagumo model is

$$\epsilon \frac{dv}{dt} = f(v) - w + \mathbf{I}_{app} \quad (3.1)$$

$$\frac{dw}{dt} = v - \gamma w \quad (3.2)$$

where  $f(v) = v(1-v)(v-\alpha)$ ,  $0 < \alpha < 1$ ,  $\epsilon \ll 1$  and  $\mathbf{I}_{app}$  is the applied current. The fast  $v$  is the excitation variable, while the slow  $w$  is the recovery variable.

In this implementation, the parameters are chosen to be  $\alpha = 0.1$ ,  $\gamma = 0.5$ ,  $\epsilon = 0.01$  and  $\mathbf{I}_{app} = 0.026$ , taking reference from The initial values are taken to be near the origin, that are  $(v_0, w_0) = (0.01, 0.01)$ .

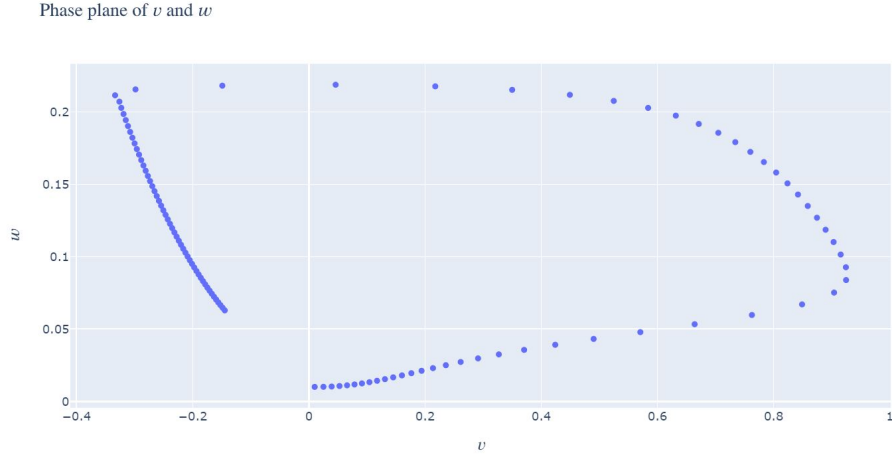


Figure 3.1: Phase plane of  $v$  and  $w$

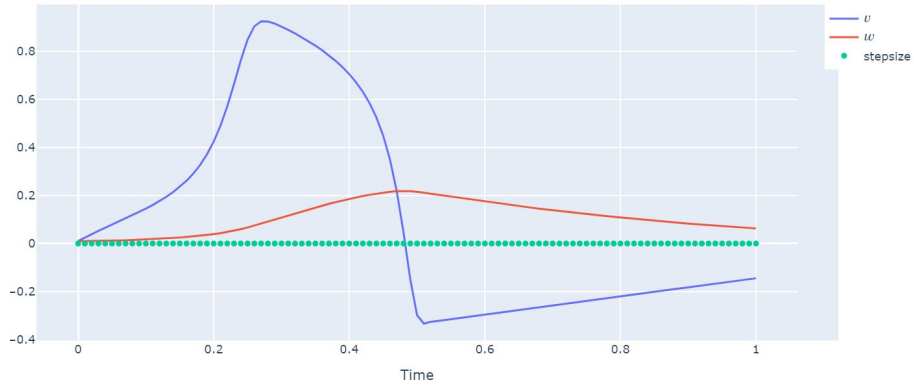


Figure 3.2: Graph of  $v$  and  $w$  against time

The Fitzhugh-Nagumo is solved with various numerical methods in this Fitzhugh-Nagumo solution notebook.

From the figure 3.2, we can see that  $v$ , the excitation variable is excited in the early stage. While  $v$  increases significantly, the change in  $w$  is small. After  $v$  reaches its peak and starts to reduce,  $w$  increases slowly. This can be observed in both phase plane (Fig. 3.1) and variable graph (Fig. 3.2). When the variable  $v$  starts to recover to its original value,  $w$  is at its maximum. The scattering of points in the phase plane captures the feature of the model, where the change in  $v$  is rapid while the change in  $w$  is slow. When the change in  $v$  is significantly larger than the change in  $w$ ,

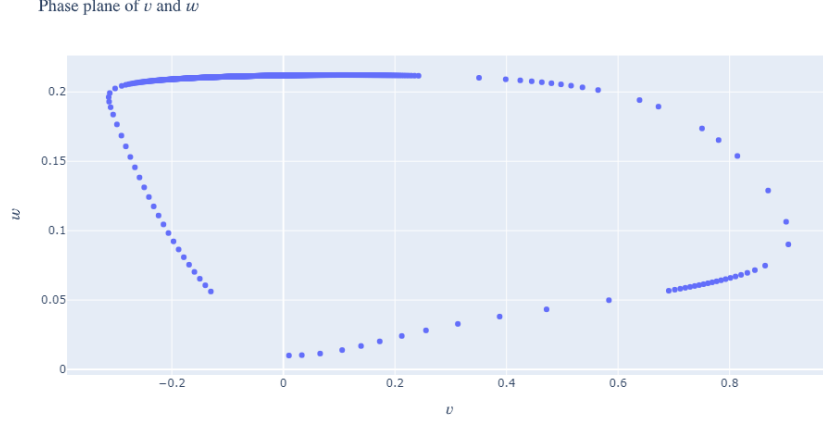


Figure 3.3: Phase plane of  $v$  and  $w$  for adaptive method

the points are sparse. On the other hand, the points are packed when  $w$  increases or decreases more than  $v$ . However, in the adaptive methods, such insights cannot be interpreted directly from the phase plane. Therefore, green triangles were plotted in Fig. 3.4 to indicate the adapted mesh points. The mesh points are adapted towards large difference in  $v$  or  $w$  over a short period of time.

### 3.3 Convergence of Fitzhugh-Nagumo model

A notebook is created to test the convergence of the solution to the Fitzhugh-Nagumo model. Since the model has no analytical solution, it is tested against a reference solution. The reference solutions are assumed to be sufficiently accurate. For methods with fixed step size, which are the one-step methods and predictor-corrector method, the reference solutions are constructed by using smaller step size. For methods with adaptive step size, reference solutions are obtained by using smaller tolerance value. This notebook shows the numerical solution computed for different methods at different step sizes or tolerance values. The numerical solutions are then compared with their respective reference solutions. In both methods, the error decreases as step size or tolerance decreases.

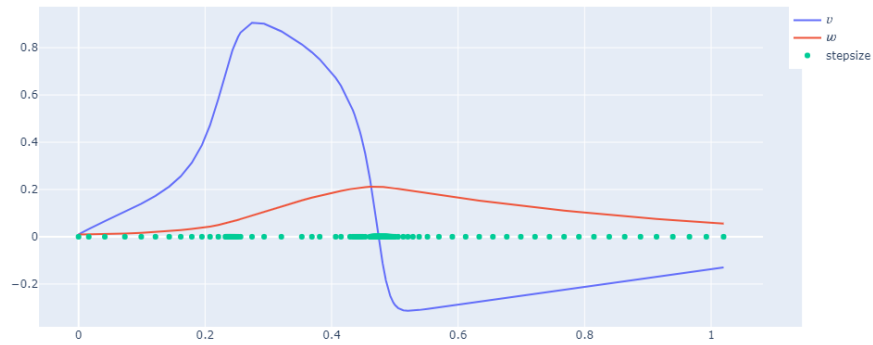


Figure 3.4: Graph of  $v$  and  $w$  against time for adaptive method

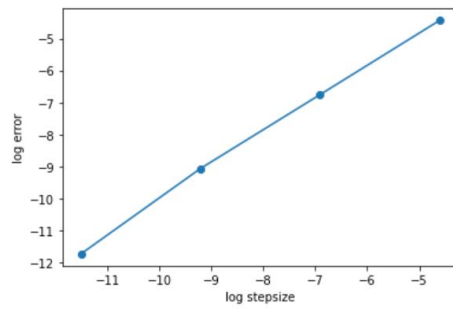


Figure 3.5: Error at a mesh point for Euler's explicit method

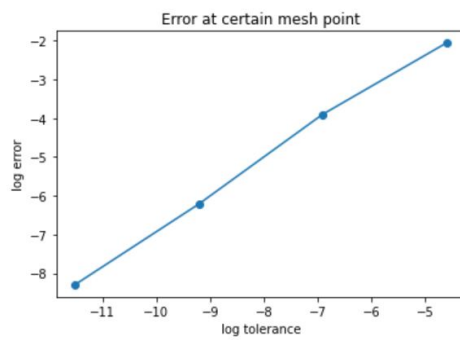


Figure 3.6: Sum of error for adaptive method