1 - Ordinary Differential Equations 1

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June 12, 2019

1 Introduction

An Ordinary Differential Equation (ODE) is an equation of the form

$$\begin{aligned} \dot{\mathbf{y}}(t) &= \mathbf{f}(t, \mathbf{y}(t)) \\ \mathbf{y}(0) &= \mathbf{y}_0 \end{aligned} \tag{1}$$

where $\mathbf{f} : [-T, T] \times \mathbb{R}^n \to \mathbb{R}^n$ is a continuous function and $\mathbf{y}_0 \in \mathbb{R}^n$ an initial value. We call solution a continuous map $t \mapsto \mathbf{y}(t)$ defined in a neighborhood of $t = 0$ satisfying equations (1). A standard result tells us that if $\mathbf{f}$ is uniformly Lipschitz (i.e. $\|\mathbf{f}(t, \mathbf{y}) - \mathbf{f}(t, \mathbf{y})\| \leq L\|\mathbf{y} - \mathbf{x}\|$) in a neighborhood of $(0, \mathbf{y}_0)$, then a solution exists and it's unique (cfr. (**?**), Theorem 12.1). This results can be proven by constructing a solution in an iterative way. Equation (1) is equivalent to its integral form

$$\mathbf{y}(t) = \mathbf{y}(0) + \int_0^t \mathbf{f}(s, \mathbf{y}(s))\, ds$$

If we define the functions $\mathbf{y}_0 \equiv \mathbf{y}_0$ and

$$\mathbf{y}_{N+1}(t) = \mathbf{y}_0 + \int_0^t \mathbf{f}(s, \mathbf{y}_N(s))\, ds$$

for $N \geq 0$, then one can use the Lipschitz property of $\mathbf{f}$ to show that $\mathbf{y}_{N+1}$ converge uniformly on a neighborhood of $t = 0$ to a continuous function. In particular, calling $\mathbf{y}(t) = \lim_{N\to\infty} \mathbf{y}_N(t)$, we get that

$$\begin{aligned} \mathbf{y}(t) &= \lim_{N\to\infty} \mathbf{y}_N(t) \\ &= \mathbf{y}_0 + \lim_{N\to\infty} \int_0^t \mathbf{f}(s, \mathbf{y}_N(s))\, ds \\ &= \mathbf{y}_0 + \int_0^t \mathbf{f}(s, \lim_{N\to\infty} \mathbf{y}_N(s))\, ds \\ &= \mathbf{y}_0 + \int_0^t \mathbf{f}(s, \mathbf{y}(s))\, ds \end{aligned}$$

This means that $\mathbf{y}(t)$ is thus the solution to our ODE. Unfortunately, this is not a viable method to evaluate the solution numerically.

2 One-step methods

A simple way to approximate the solution to (1) numerically comes from consists in approximation the derivative. By definition

$$\dot{\mathbf{y}}(t) = \lim_{h \to 0} \frac{\mathbf{y}(t+h) - \mathbf{y}(t)}{h}$$

Therefore, if we choose h sufficiently small, we have that

$$\dot{\mathbf{y}}(t) \simeq \frac{\mathbf{y}(t+h) - \mathbf{y}(t)}{h} \tag{2}$$

Plugging this into the equation (1), we get

$$\mathbf{y}(t+h) \simeq \mathbf{y}(t) + h\,\mathbf{f}(t, \mathbf{y}(t))$$

Now, suppose we want to compute an approximation $\hat{\mathbf{y}}(T)$ of $\mathbf{y}(T)$ at time $T > 0$. We can break the interval $[0, T]$ into N intervals, and find approximations $\hat{\mathbf{y}}(0) = \mathbf{y}(0)$ and $\hat{\mathbf{y}}_n = \hat{\mathbf{y}}(t_n) \approx \mathbf{y}(t_n)$, where $t_n = nh$, $h = T/N$. Using the above formula, we can find $\hat{\mathbf{y}}_n$ by the recurrence formula

$$\hat{\mathbf{y}}_{n+1} = \hat{\mathbf{y}}_n + h\,\mathbf{f}(t_n, \hat{\mathbf{y}}_n)$$

Intuitively, we expect this to be a good approximation to the actual solution if h is small enough (or equivalently, N is large enough). This method is known as Explicit Euler. Other methods can be derived in the same way, starting from a formula to approximate the derivative of a function.

2.1 A simple example

We can start to understand how well different methods work by looking at a simple example (see also the **Colab notebook** to implement and play with a similar example). Consider the ODE

$$\begin{aligned} \dot{y}(t) &= -100\,y(t) \\ y(0) &= 1 \end{aligned}$$

In this case we know the exact solution: $y(t) = e^{-100t}$

2.1.1 Forward Euler's method

Let's look at how the solution given by Explicit Euler looks like. We have that

$$\begin{aligned} \hat{y}_1 &= y_0 - 100h\,y_0 = (1 - 100h)y_0 \\ \hat{y}_1 &= \hat{y}_1 - 100h\,\hat{y}_1 = (1 - 100h)\hat{y}_1 = (1 - 100h)^2 y_0 \end{aligned}$$

Iterating, we see that it holds $\hat{y}_n = (1 - 100h)^n y_0$. How good is this as an approximation to the true solution? Call $K(h) = (1 - 100h)$. If $K(h) < -1$ (or equivalently $h > 0.02$) then it easy to see that the solution diverges as n increases, which is the opposite behavior of $y(t)$! Moreover, if $K(h) < 0$ (or equivalently $h > 0.01$) the solution keeps oscillating around 0, while we know that the actual solution is always positive. Only for $h < 0.01$ our approximation starts to resemble the behaviour of $y(t)$.

2.2 Backward Euler's method

The Implicit Euler's method iteration is given by

$$\hat{y}_{n+1} = \hat{y}_n + hf(t_n, \hat{y}_{n+1})$$

(this formula can be derived from equation (2) by choosing $h < 0$). Re-arranging, for the considered example one finds

$$\hat{y}_n = (1 + 100h)^{-n} y_0$$

We can notice that this method does not have the same issues as the Explicit Euler's method: the approximation *behaves as* the actual solution even for larger h's.

2.3 Trapezoidal method

The trapezoidal method iteration is given by

$$\hat{y}_{n+1} = \hat{y}_n + \frac{h}{2}[f(t_n, \hat{y}_n) + f(t_n, \hat{y}_{n+1})]$$

Re-arranging, for the considered example one finds

$$\hat{y}_n = \left(\frac{1 - 50h}{1 + 50h}\right)^n y_0$$

We see that in this case $\hat{y}_n \to 0$ as $n \to \infty$ for any value for h, but if $\frac{1-50h}{1+50h} < 0$ (i.e. $h > 0.02$) the approximation oscillates around 0.

3 Convergence analysis

Which of the different methods works best? To understand these, one needs to quantify the error due to the approximation of the ODE. We consider a generic one-step method, i.e. which can be written as

$$\hat{y}_{n+1} = \hat{y}_n + h\,\Phi(t_n, \hat{y}_n, h)$$

for some function Φ depending on f.

3.1 Truncation error

The first error we define is the one due to the use of the approximation (2) at one time step. It is called truncation error:

$$T_n = \frac{y_{n+1} - y_n}{h} - \Phi(t_n, y_n, h)$$

where $y_n = y(t_n)$ is the actual solution. Let's try to get an explicit bound for the Euler method. We have

$$hT_n = y_{n+1} - y_n - hf(t_n, y_n)$$

Subsisting y_{n+1} with its first order Taylor approximation, we get

$$y_{n+1} = y_n + h\,\dot{y}_n + O(h^2) = y_n + h\,f(t_n, y_n) + O(h^2)$$

which gives

$$hT_n = O(h^2)$$

Therefore $T_n = O(h)$ goes to 0 as $h \to 0$. In general, a method such that

$$T(h) = \max_{0 \le n \le T/h} |T_n| \to 0$$

as $h \to 0$ is said consistent.

3.2 Convergence

The error at time t_n is given by $e_n = y_n - \hat{y}_n$. The total error is given by $e(h) = \max_{0 \le n \le T/h} |e_n|$. We say that the method converges if $e(h) \to 0$ as $h \to 0$. We can see that if Φ is (uniformly) Lipschitz and the method is consistent, then it is also convergent. Indeed, we have that

$$\begin{aligned}
e_{n+1} &= y_n + h\,\Phi(t_n, y_n, h) + h\,T_n - \hat{y}_n - h\,\Phi(t_n, \hat{y}_n, h) \\
&= e_n + h\,(\Phi(t_n, y_n, h) - \Phi(t_n, \hat{y}_n, h)) + h\,T_n \\
&\le e_n + hL(y_n - \hat{y}_n) + +h\,T_n \\
&\le (1 + hL)e_n + h\,T_n \\
&\le (1 + hL)^2 e_{n-1} + h(1 + hL)T_{n-1} + h\,T_n \\
&\le \cdots \\
&\le (1 + hL)^{n+1} e_0 + h \sum_{i=0}^{n} (1 + hL)^i T_{n-i}
\end{aligned}$$

It follows that

$$\begin{aligned}
e(h) &\le h\,T(h) \sum_{i=0}^{T/h} (1 + hL)^i \\
&= hT(h) \frac{(1 - (1 + hL)^{T/h})}{1 - 1 - hL} \\
&= T(h) \frac{((1 + hL)^{T/h} - 1)}{L} \\
&\le T(h) \frac{e^{TL}}{L}
\end{aligned}$$

Therefore, convergence holds if the method is consistent. Moreover, the order of consistency dictates the speed of convergence.