

# ThesisBook

Mélanie

3/15/23

# Table of contents

<b>Preface</b>	<b>3</b>
<b>1 Introduction</b>	<b>4</b>
<b>2 Motivation</b>	<b>5</b>
<b>3 A test problem - Convection diffusion equation</b>	<b>8</b>
<b>4 Runge Kutta solver applied to the test problem</b>	<b>11</b>
<b>5 Reinforcement learning - Basic</b>	<b>13</b>
5.1 Finite Markov decision process . . . . .	14
<b>6 Summary</b>	<b>15</b>
<b>References</b>	<b>16</b>

# Preface

This is a Quarto book. tests

To learn more about Quarto books visit <https://quarto.org/docs/books>.

# 1 Introduction

## 2 Motivation

Let  $A$  be non singular square matrix of dimension  $n \geq 1$  and let  $b \in \mathbb{R}^n$ . We consider the linear system  $Ay = b$ , where  $y \in \mathbb{R}^n$ . The system has for unique solution  $y^* = A^{-1}b$ . This is a fundamental problem to solve in numerical analysis, and there are numerous numerical methods to solve this, whether they are direct methods or iterative methods. In this thesis, we consider an iterative method. We consider the initial value problem

$$y'(t) = Ay(t) - b, \quad y(0) = y_0$$

where  $y_0 \in \mathbb{R}^n$  and  $t \in \mathbb{R}$ . Multiplying the equation by  $e^{-At}$ , where  $e^{-At}$  is the usual matrix exponential, and rearranging the terms yields

$$e^{-At}y'(t) - Ae^{-At}y(t) = e^{-At}b$$

We recognise on the left hand side the derivative of the product  $e^{-At}y(t)$ , and thus, by the fundamental theorem of calculus,

$$\left[ e^{-Au}y(u) \right]_0^t = \int_0^t -e^{-Au}b \, du.$$

Multiplying by  $A^{-1}A$  inside the integral in the LHS, we get

$$e^{-At}y(t) - y_0 = A^{-1} \left[ e^{-Au} \right]_0^t b = A^{-1}e^{-At}b - A^{-1}b.$$

Multiplying each side by  $e^{At}$  and rearranging the terms we get an expression for  $y(t)$ ,

$$y(t) = e^{At}(y_0 - A^{-1}b) + A^{-1}b.$$

Note that each of those step can be taken backward, which means that the solution we have is unique. We have thus proved

**Theorem 2.1.** Let  $A$  be a non singular, square matrix of dimension  $n \geq 1$ ,  $b \in \mathbb{R}^n$  a vector, and consider the initial value problem

$$y'(t) = Ay(t) - b, \quad y(0) = y_0 \quad (2.1)$$

where  $t \rightarrow y(t)$  is a function from  $\mathbb{R}$  to  $\mathbb{R}^n$ . Then the problem has a unique solution in the form of

$$y(t) = e^{At}(y_0 - y^*) + y^*,$$

where  $y^* = A^{-1}b$ , and  $e^{At}$  is defined using the usual matrix exponential.

Let  $\lambda_1, \lambda_2, \dots, \lambda_n$  be the (not necessarily distinct) eigenvalues of  $A$ , write  $\lambda_i = a_i + iy_i$ , where  $a_i, b_i \in \mathbb{R}$  are respectively the real part and the imaginary parts of the  $i^{\text{th}}$  eigenvalue. The following holds

**Theorem 2.2.**  $y(t) \rightarrow y^*$  as  $t \rightarrow +\infty$  for any initial value  $y_0$  if and only if, for all  $i = 1, \dots, n$ ,  $a_i < 0$ , that is, all the eigenvalues of  $A$  have a strictly negative real part.

*Proof.* (In the diagonalisable case)

We assume that  $A$  is diagonalisable. Write  $A = P\Delta P^{-1}$  where  $\Delta$  is diagonal.

$$\Delta = \begin{pmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_n \end{pmatrix}$$

Then  $e^{At} = Pe^{\Delta t}P^{-1}$ , where

$$e^{\Delta t} = \begin{pmatrix} e^{\lambda_1 t} & & & \\ & e^{\lambda_2 t} & & \\ & & \ddots & \\ & & & e^{\lambda_n t} \end{pmatrix}$$

Let  $z(t) = P^{-1}(y(t) - y^*)$ , where  $y(t)$  is the unique solution to Equation 2.1 for some arbitrary initial value  $y_0$ .

Since  $P$  is non singular,  $y(t) \rightarrow y^*$  if and only if  $z(t) \rightarrow 0$ . We have

$$z(t) = P^{-1}e^{At}(y_0 - y^*)$$

We note that  $P^{-1}e^{At} = e^{\Delta t}P^{-1}$ , thus

$$z(t) = e^{\Delta t}P^{-1}(y_0 - y^*).$$

Looking at the  $i^{\text{th}}$  element  $z(t)_i$ , we have

$$|z(t)_i| = e^{a_i t} (P^{-1}(y_0 - y^*))_i$$

where  $a_i = \Re[\lambda_i]$ . Clearly, if  $a_i < 0$ ,  $z(t)_i \rightarrow 0$  as  $t \rightarrow +\infty$ . If this holds for any  $i = 1, \dots, n$ , then  $z(t) \rightarrow 0$  as  $t \rightarrow +\infty$ . This proves ( $\Leftarrow$ ).

This is also a necessary condition. Indeed, since  $y_0$  is arbitrary, we can chose it so that  $P^{-1}(y_0 - y^*) = (1, \dots, 1)^T$ . Then  $z(t) = (e^{\lambda_1 t}, e^{\lambda_2 t}, \dots, e^{\lambda_n t})^T$  which converges to 0 only if all the eigenvalues have a strictly negative real part.

□

*Remark.* A general proof is available on (Bellman 1953, chap. 1)

We now go back to the original problem of solving the linear system  $Ay = b$ . If all the eigenvalues of  $A$  have a strictly negative real part, then, any numerical solver for the initial value problem  $y'(t) = Ay(t) - b$  with  $y(0) = y_0$  where  $t$  is some pseudo-time variable also becomes an iterative solver for the linear system  $Ay = b$ , as  $y(t) \rightarrow y^*$ .

*Remark.* If all the eigenvalues of  $A$  have a strictly positive real part, then we can simply solve  $y' = (-A)y - (-b) = -Ay + b$  instead.

### 3 A test problem - Convection diffusion equation

As a test case for the solver, we consider the steady state convection-diffusion equation.

$$u_x = bu_{xx} + 1$$

where  $b$  is some physical parameter and  $u(x)$  is defined on the interval  $[0, 1]$ . The boundary condition are given by  $u(0) = u(1) = 0$ . This equation has an analytical solution that is given by

$$u(x) = x - \frac{e^{-(1-x)/b} - e^{-1/b}}{1 - e^{-1/b}}.$$

We are however interested in solving this numerically, with a finite difference approach. We partition the interval  $[0, 1]$  into equidistant points  $x_i, i = 0, \dots, n$ . We note the distance between each points as  $\Delta x$ , and we have  $u(x_0) = u(0) = 0$  and  $u(x_n) = u(1) = 0$ . We use the notation  $u^i = u(x_i)$ . We approximate, for  $i \geq 1$  the derivative

$$u_x^i = \frac{u^i - u^{i-1}}{\Delta x}$$

and the second order derivative is approximated by

$$u_{xx}^i = \frac{u^{i+1} - 2u^i + u^{i-1}}{\Delta x^2}$$

Note that the first derivative is approximated backward in time. For  $i = 1, \dots, n-1$ , we thus have the approximation

$$u_x^i = \frac{u^i - u^{i-1}}{\Delta x} = b \frac{u^{i+1} - 2u^i + u^{i-1}}{\Delta x^2} + 1$$

This can be given in matrix format by letting  $u = (u^1, \dots, u^{n-1})^T$

$$Au = Bu + e$$



where  $e = (1, 1, \dots, 1)^T$ ,

$$A = \frac{1}{\Delta x} \begin{bmatrix} 1 & & & & & \\ -1 & 1 & & & & \\ & -1 & 1 & & & \\ & & \ddots & \ddots & & \\ & & & -1 & 1 & \\ & & & & -1 & 1 \end{bmatrix}$$

and

$$B = \frac{b}{\Delta x^2} \begin{bmatrix} -2 & 1 & & & & \\ 1 & \ddots & \ddots & & & \\ & \ddots & \ddots & \ddots & & \\ & & \ddots & \ddots & 1 & \\ & & & 1 & -2 & \end{bmatrix}.$$

With  $M = A - B$ , we have to solve the linear system

$$Mu = e \tag{3.1}$$

where  $M$  is a square matrix of dimension  $(n-1) \times (n-1)$  and  $e$  is the one vector of dimension  $n-1$ .

*Remark.* (To make better but I think it works) It is apparent that  $M$  is diagonally dominant. Since all elements of the diagonal are positive, then so are the eigenvalues real part. Assuming  $M$  is non singular, we have that  $-M$  is stable.

To solve this linear system, we use the method highlighted before. To make it easier for later, we chose to scale  $M$  so that its diagonal elements are 1. This allows us to have all eigenvalues in the circle centered around 1 with radius 1 independently of the parametrisation. Setting  $\gamma = \frac{1}{\Delta x} + \frac{2b}{\Delta x^2}$ , solving Equation 3.1 is equivalent to solving the system

$$Nu = b$$

where with  $N = M/\gamma$ ,  $b = e/\gamma$ . The eigenvalues of  $M$  are also scaled by  $1/\gamma$  so  $-N$  is stable, assuming it is non singular. We are now ready to solve the system iteratively using ODE solver.

We thus introduce a pseudo time variable  $t$  and we consider the ODE.

$$u'(t) = b - Nu(t)$$

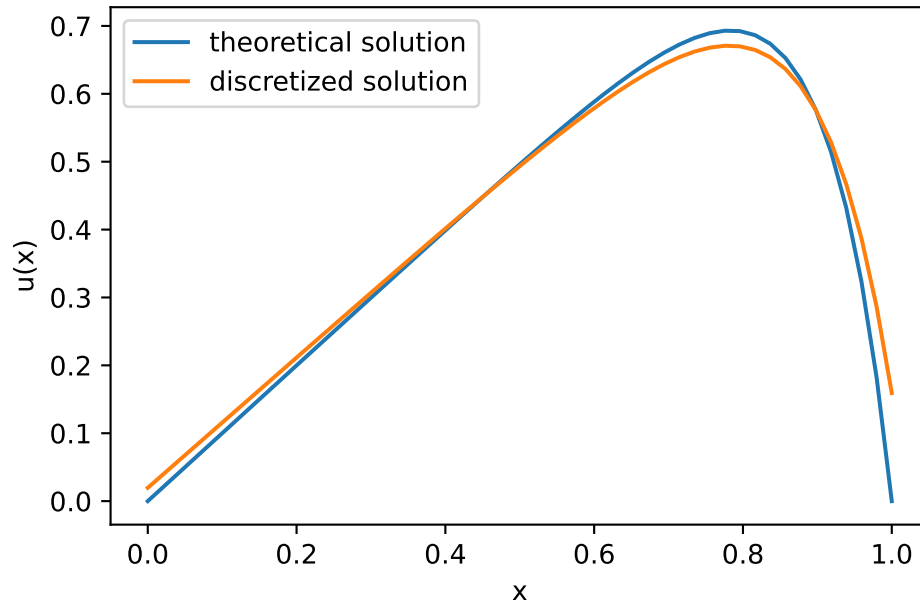


Figure 3.1: Theoretical and discretized solution of the problem with  $b = 0.09$ ,  $n = 50$ .

Assuming  $N$  is non singular, we can use Theorem 2.2 to guarantee that the ODE will converge to a steady state independently of the initial value we chose. In the next chapter, we will apply the Runge-Kutta scheme we saw earlier to the problem and will see how parameters changes results.

## 4 Runge Kutta solver applied to the test problem

We now have to solve the ODE  $u' = b - Nu$  where  $M$  depends on the problem parameters  $b$  and  $\Delta x = 1/(n + 1)$ , where  $n$  is the chosen number of subdivisions of  $[0, 1]$ . Since we are only interested on the asymptotic behavior of  $u$ , we only need to care about the stability of the numerical solver we wish to use. We consider the following RK scheme with two stages.

blablabal

This solver has two parameters  $\Delta t$  and  $\alpha$ . The objective is for the solver to converge to a steady state solution as fast as possible. Set  $u_0 = u(0) = e$  as an initial value. We define the relative residual after  $k$  steps as

$$r_k = \|Nu_k - b\|/\|b\|.$$

where  $\|\cdot\|$  is the 2-norm.

If the solver we chose is stable, then  $\|r_k\| \rightarrow 0$  as  $k \rightarrow \infty$ . We define now the convergence at step  $n$  to be the ratio of residual at step  $k$  and  $k - 1$ . That is

$$c_k = \frac{\|r_k\|}{\|r_{k-1}\|} = \frac{\|Mu_k - e\|}{\|Mu_{k-1} - e\|}$$

where  $\|\cdot\|$  is the 2-norm.

# A small experiment.

We are interested in finding the best parameters  $(\Delta t, \alpha)$  to use for some specific problem parameters  $(b, n)$ . Since the residual ratio vary quite a bit depending on the number of iteration, we decide to investigate the residual ratio after 10 iterations and 100 iterations. So, for the problem parameters  $b = 0.05$ , and  $n = 100$ , we plot  $c_{10} = f(\Delta t, \alpha)$  and  $c_{100} = g(\Delta t, \alpha)$ . We wish to answer the following questions

- Where are the optimal parameters for this specific problem, that is, the ones that minimize  $c_{10}$  and  $c_{100}$ , and do they also depend on the iteration number or not.
- What do these functions look like. In particular, we may be interested in the function convexity.

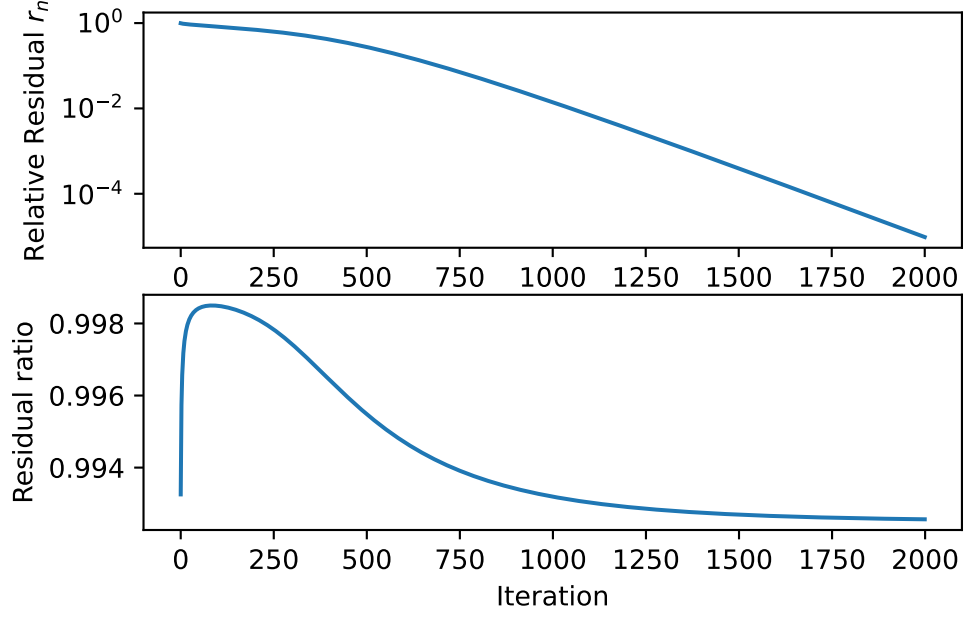


Figure 4.1: Evolution of the residual norm over iteration, with problem parameters  $n = 100$  and  $b = 0.05$ , and RK parameters  $\Delta t = 1.6$  and  $\alpha = 0.3$ .

In both cases, we use a contour plot. In `fig-resRatio10` and `fig-resRatio100`, the residual ratio is clipped when it is  $\geq 1$  so as to maximise contrast.

The stability region after 100 iterations is more narrow, suggesting that convergence may not hold even if it seems to hold for the first few iterations. Nevertheless, we can see how the parameters act on the function.

This is of course an exploration of a particular problem, and it makes no sense in practice to compute the optimal parameters with a grid search. We thus explore a possible solution by using a reinforcement learning algorithm to “learn” these optimal parameters.

## 5 Reinforcement learning - Basic

In this section, we outline the main ideas behind reinforcement learning and how they can be applied in the context of this thesis.

Suppose we want to cook a delicious meal. At any point in time, we are making decisions such as

- which ingredients we use. Do we use tofu or seitan? Do we add spice more chili pepper? When do we incorporate the sauce?
- which cookware we use? Cast iron, or non-stick pan?
- whether to stir or not. It may stick and burn at the bottom of the pan if we don't, but we are lazy and our laziness has to be weighted in.
- Or simply do nothing!

All of these decisions, which we will call *actions* from now on, are taken in reaction to the current *state* of the cooking process, following a certain *policy*, which is shaped by our previous cooking experience.

After each action, the cooking process get to a new *state* and we get a *reward* that depend on how we did. Maybe the food started to burn in which case we get a negative reward, or maybe we made the food better, in which case we get a positive reward. In this example, there is also a terminal state, in which we finished cooking and get to eat the meal.

But how do we learn how to cook, that is, how do we learn the *policy*? We learn it by trying to make the food as good as possible, which is defined by the *reward* we get after each action. Some of those rewards are immediate. For example, if we add some spices to our food and it tastes better, we may be inclined to do it again the next time we cook a meal. We want to have a *policy* that maximize the total *rewards* we get, which also mean that we have to balance our decision between the immediate reward and the future rewards. Adding a spice may make the meal taste better in the short term, but it may clash later when we add other ingredients, leading to a worse meal and bad *rewards*.

Each time we cook, we learn what works and what doesn't, and remember that for the future time we cook. But, if we want to get better at cooking, we must not just repeat the *actions* that worked! We also have to take some risks, and *explore* the potential actions we can take at each state! On the other hand, we still need to rely and *exploit* what we know, so there is a balance between *exploitation* and *exploration* to find so we can learn as fast as possible.

## 5.1 Finite Markov decision process

Before introducing reinforcement learning, we first need to define a Markov decision process (MDP).

**Definition 5.1.** (Markov decision process). A finite Markov decision process is defined as a discrete time process, where we have

- a state set  $\mathcal{S}$ ,
- an action set  $\mathcal{A}$ , containing all possible actions,
- for each state and each action, we have a reward set  $\mathcal{R}(s, a)$ , which contain the potential rewards received after taking action  $a \in \mathcal{A}$  from the state  $s \in \mathcal{S}$ .

A Markov decision process has a model, which consist of

- the probability of getting from state  $s$  to the state  $s'$  by taking action  $a$ , which we call the state transition probability  $p(s'|s, a) = P(s_{t+1} = s' | s_t = s, a_t = a)$ .
- the probability of getting reward  $r$  by taking the action  $a$  at a state  $s$   $p(r|s, a) = P(r_{t+1} = r | s_t = s, a_t = a)$ .

Furthermore, a policy function is also given that governs for a given state  $s \in \mathcal{S}$ , the probability of taking action  $a \in \mathcal{A}$ , that probability is  $\pi(a|s) = Pr(a_{t+1} = a | s_t = s)$ .

*Remark.* We have implicitly defined the random variables designing the state, action, reward at a time  $t$ , those are respectively  $s_t, a_t, r_t$ . A diagram of the process is as follow

**Example 5.1.** (A more mathematical example, adorable)

## 6 Summary

In summary, this book has no content whatsoever.

## References

Bellman, Richard Ernest. 1953. *Stability Theory of Differential Equations* /. New York : McGraw-Hill.