

MA30287: Mathematics of Planet Earth

Philippe H. Trinh

2024-02-28

Table of contents

Preface	3
Lectures and office hours	3
Coursework and examinations	3
Resources	3
Prerequisites	5
Resources	5
Lecture plan	6
I Introduction	7
1 Conservation laws and constitutive laws	10
1.1 Derivation of the 1D heat equation	10
1.1.1 Steady states and long-time behaviours	12
1.2 Deriving the 1D transport (continuity) equation	13
2 Dimensional scaling analysis	16
2.1 Dimensional quantities	16
2.1.1 SI units	16
2.2 Dimensional homogeneity and non-dimensionalisation	17
2.3 Returning to the heat equation	17
2.4 Choice of units	18
2.4.1 Interpretation	19
3 Basic energy models	21
3.1 The basic energy model	21
3.2 The history of global warming	24
3.3 Next in the study of energy balance models?	25
4 Problem class 1	26
4.1 Projectile motion	26
4.2 Terminal velocity	27

II Practical applied mathematics	28
5 Asymptotic approximations I	30
5.1 A simple quadratic	30
5.1.1 The singular root	31
5.2 Order notation and the tilde sign for asymptotic	33
6 Asymptotic approximations II	35
6.1 Returning to the projectile problem	35
6.2 Numerical solutions of IVPs	37
7 Numerical solutions of IVPs	39
8 Asymptotic approximations III	42
8.1 Boundary layer theory	44
8.1.1 The inner scaling	44
8.1.2 The inner equation	45
8.1.3 Summary	47
9 Problem class 2	48
10 Nonlinear root finding	49
10.1 Demo of Newton's method for scalar equations	49
10.2 Newton's method for systems of nonlinear equations	51
10.3 Secant method	52
11 Numerical solutions of PDEs	53
12 Problem class 3	54
III Energy balance models	55
13 The basic EBM (steady-state)	56
13.1 Steady-state analysis	56
13.2 Dynamics and phase line solutions	58
13.3 Numerical continuation of the steady states	59
13.4 Bifurcation diagram	61
13.5 Re-scaling and Budyko's model	62
14 EBM with latitude I	63
14.1 Incoming energy	63
14.2 Outgoing energy	66
14.3 Transport energy	66
14.4 Steady-state temperature	66

15 EBM with latitude II	68
15.1 Numerical quadrature	69
15.2 Latitude vs. temperature-dependent albedo	69
15.3 Numerical implementation via Newton's method	70
16 Problem class 4	71
17 EBM with latitude III	72
17.1 Placement of the ice line	72
17.2 Development of an equation for the ice line	72
17.3 A word about the parameter space	74
17.4 A bifurcation diagram for Q vs y_s	74
17.5 Ice-free state	76
17.6 Ice-covered state	77
17.7 Partially ice-covered states	78
18 EBM with latitude IV	80
18.1 Studying the mean temperature	80
18.2 Stability	81
IV Box models of the ocean	85
19 Basic models of the ocean	86
19.1 Terminology and context	86
19.2 Temperature	86
19.3 Salinity and density	89
19.4 Two-box model of the ocean	89
19.5 A one-dimensional model (constant temperature)	90
19.6 Reducing the equations via symmetry	92
19.7 Analysis of a reduced 1D model for the salinity	93
20 Stommel's box model	94
20.1 Non-dimensionalisation	94
20.2 Equilibrium states	95
20.3 Stability	98
20.4 Bifurcation diagrams	100
20.5 Stommel's conclusion	100
V Exercises	102
21 Problem set 1	104
Q1. Bump lemma	104

Q2. A source in the heat equation	104
Q3. Choice of scalings	105
Q4. The unique timescale in the heat equation	105
Q5. Timescale in the surface energy	106
22 Problem set 2	107
22.1 Getting started with Noteable	107
22.2 Testing the solutions of a cubic	108
22.3 Analysis of singular cubic equation	108
22.4 A damped projectile problem	109
22.5 ODE solvers and Euler's method	109
23 Problem set 3	111
Q1. Conversion to first-order system	111
Q2. Numerical solutions	112
Q3. Investigation of the boundary layer	112
Q4. Outer asymptotic solutions	113
Q5. Inner asymptotic solutions	113
Q6. Matching and comparison	113
24 Problem set 1 solutions	114
Q1 The bump lemma	114
Q2. A source in the heat equation	114
Q3. Choice of scalings	116
Q4. The unique timescale in the heat equation	119
Q5. Timescale in the surface energy	120
25 Problem set 2 solutions	122
25.1 Getting started with Jupyter	122
25.2 Testing the solutions of a cubic	122
25.3 Analysis of singular cubic equation	122
25.4 A damped projectile problem	126
25.5 ODE solvers and Euler's method	128
VI Appendices	130
26 Differential equations	131
26.1 First-order linear differential equations	131
26.2 Second-order constant coefficient ODEs	131
27 Dynamical systems	133
27.1 Stability analysis for 2x2 systems	133

28 Vector calculus	135
28.1 Surface integrals	135
29 Modelling	136
30 Finite difference approximations	137
30.1 Forwards, backwards, and centred differences	137
30.2 Jacobian matrices	138
31 Coding	141
31.1 Variable scope	141
References	144

Preface

Welcome to the 2023-24 delivery of [MA30287 Maths of Planet Earth](#) at the University of Bath.

Here is a picture that represents the course.

Lectures and office hours

Lectures take place at the following times and locations:

- Tuesdays 9:15 in 6W 1.2
- Wednesdays 11:15 in 6W 1.2
- Thursdays 15:15 in 8W 3.22

Office hours: You will be able to find me for an office hour in 4W 2.18 on Thursdays (following the lecture). Typically it is best to set this up, beforehand, by email appointment.

Coursework and examinations

Your final mark will be 25% coursework and 75% final exam.

Details of the coursework will be released in Week 7 and it will be due in Week 10¹.

Resources

In general, you will have access to a few kinds of resources:

1. The [Moodle portal](#) will be the main organisation portal.
2. Lecture notes, coursework, and other resources will be found in an online format and will be linked on Moodle.
3. Coding will be done via Noteable, accessed via the Moodle website.

¹Subject to confirmation.

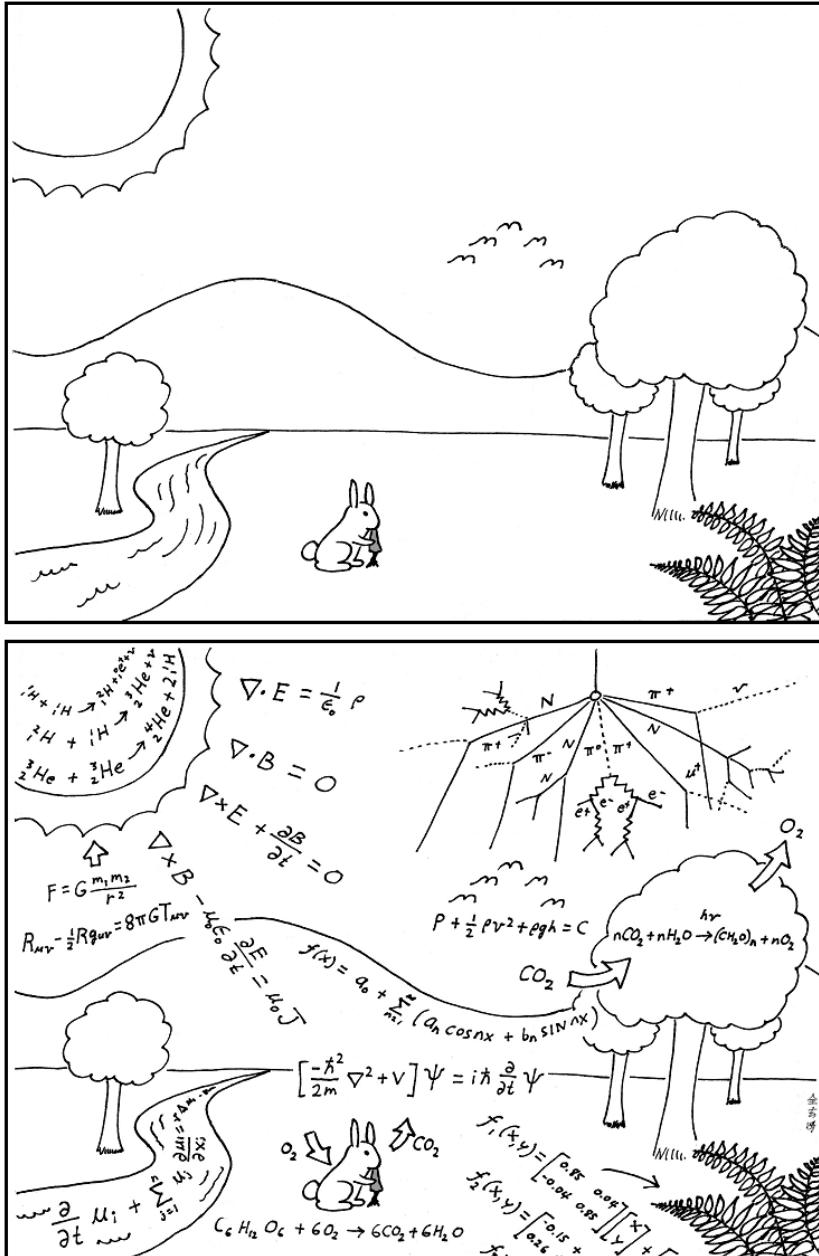


Figure 1: This picture was produced by [Abstruse Goose](#) and has the title “This is how scientists see the world”.

Naturally, because this is a relatively new module at Bath, there will be a fair amount of activity as we settle the material over the semester. Whenever we complete a lecture note (i.e. a ‘chapter’), we will use a box like this to indicate when the material was covered and in which lecture:

2023-24 note

The material in this note was covered in Lecture XX.

Hopefully by the time the module ends, every relevant chapter will have such a note. This allows you to judge what material has been ‘finalised’.

Prerequisites

This course officially requires MA20221 (modeling and dynamical systems) or XX20231 (mathematical and statistical methods for the life sciences).

It is designed to be somewhat stand-alone in the sense that applied mathematical techniques learned in other courses will be introduced in some capacity. Such techniques will involve:

- Solutions of ordinary differential equations (MA10230 and MA20220).
- Multivariable calculus, partial differentiation, and multiple integrals (MA10230 and MA10236); some review/introduction of concepts from MA20223.
- Dynamical systems, stability, phase planes (MA20221, MA30060).
- Numerical methods in Python (MA10276).

Whenever possible, I have isolated such reviews/introductions and these can be found in the *Mathematical methods* section of these notes.

Resources

This course is designed around the following sources:

- Sustainable energy – without the hot air by (MacKay 2009)
- Mathematics & Climate by (Kaper and Engler 2013)
- Mathematical Geoscience by (Fowler 2011)
- [A gentle introduction to numerical simulations with Python](#)

Lecture plan

A lecture plan can be found at [this link](#).

Part I

Introduction

Mathematics of Planet Earth seems like an incredibly broad description for a course, but perhaps in order to give a rough idea of what such a course might include, we can consider the following diagram, which illustrates different categories and subject areas that are involved in the modelling of a full Earth system.

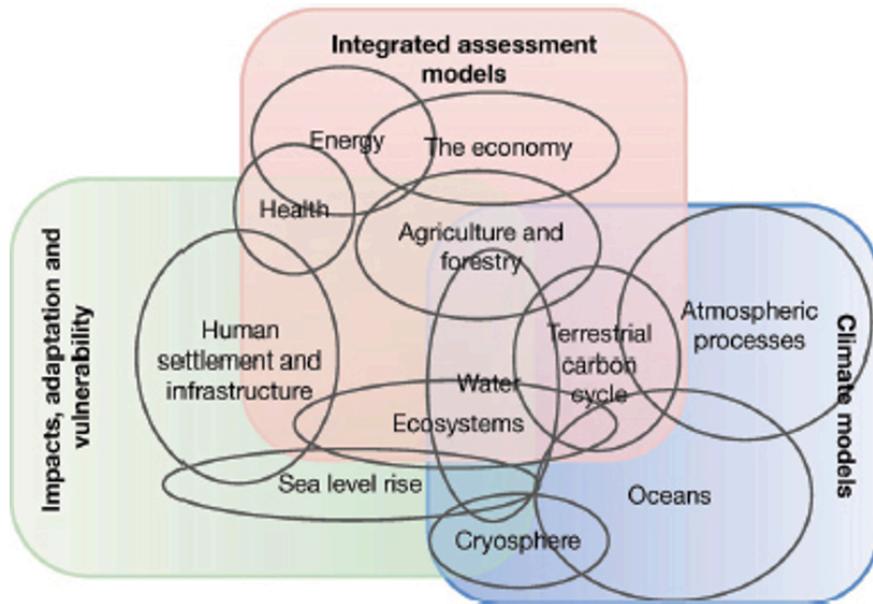


Figure 2: The many components of a full Earth System Model

It would be possible to spend a lifetime studying any one aspects of the above categories, and they span many different areas of study, including: (i) engineering (civil, fluids, mechanical, etc.); (ii) physics (geosciences, mechanics); (iii) Earth sciences; (iv) policy and health; and so forth and so on. As mathematicians, we also have a unique perspective, and applied mathematics plays important roles in many of the above categories.

In essence, this course will include topics and themes are united by aspects of **mathematical modelling** and **mathematical analysis** and this is what distinguishes our style of study from adjacent areas of science and social science.

We will study so-called conceptual or box models of the climate. This involves some of the blue elements of the above figure, and thus we use coarse-grained models of describing the climate. This will involve applying some of the dynamical systems (phase-plane analysis of ODEs) you have learned previously, along with new methods of computation and analysis. The source for this part of the course will be (Kaper and Engler 2013).

A secondary part of this course will involve more in-depth analysis of the physical models that govern the blue elements of the above figure. This moves us from the toy box models studied

above to digging into the underlying physics—this also falls into the category of Mathematical Geoscience. For example, we will use partial differential equations to study the atmosphere and develop a deeper understanding of greenhouse gases. The source for this part of the course will be (Fowler 2011).

1 Conservation laws and constitutive laws

In the first chapter of (Fowler 2011), there is a concise introduction to the different categories of techniques and approaches that you might use when doing mathematical modelling in the real world. Some of these ideas will be introduced to you in this course.

Here, we provide a brief intro to the highlights, involving the use of conservation laws (and PDEs) and also the concept of non-dimensionalisation (which you would have encountered previously), studied in Chapter 2.

Vectors and PDEs

Vectors and PDEs is not a prerequisite for this course, but naturally in studying anything related to the physical real world, we must discuss partial differential equations. The hope is that the necessary theory for PDEs will be presented to you as this course evolves, so that it can appreciated by both newcomers and experienced readers.

Conservation laws can be expressed as mathematical equations that represent the idea that some quantity is conserved. In processes governing the planet, these might correspond to conservation of heat, of water, of air, of momentum, etc.

In Chapter 3, we will develop the simplest possible model governing the temperature on the surface of the Earth. It is a conservation equation for energy and is zero-dimensional (does not involve time and does not involve spatial variation).

1.1 Derivation of the 1D heat equation

In order to demonstrate some of the basic principles of this course, let us demonstrate the derivation of the heat equation. We are interested in modelling the heat in a volume, V , which, for the sake of concreteness is given by a long cylinder with its axis along $x \in [0, L]$. We assume that the side walls of the cylinder are insulated and the temperature only varies along the x direction.

At any point along this rod, the internal heat is given by $\rho c T(x, t)$, where ρ is the density of the material (kg/m^3), c is the specific heat capacity ($\text{J}/(\text{kg K})$), and T is the temperature (K). Therefore, the heat energy along any segment in the rod is calculated from

Internal heat energy

$$\text{heat energy in } [a, b] = \int_a^b \rho c T \, dx.$$

If the heat changes, then the rate of change of heat energy is given the time derivative of the above quantity. By conservation of energy, any change of the internal energy must be equal to the inflow or outflow of heat at the ends, $x = a$ or $x = b$. We therefore write q for the flux (or flow) of heat.

We need a **constitutive law** that dictates how energy is exchanged at the boundaries. Based on intuition, it is sensible to assume that the flow of heat proceeds from hot to cold. For example, hot air rises towards cool air; or heat from a hot mug of tea flows and diffuses outwards into a cold room. Therefore, we write this as

Fourier's law

Fourier's law in 1D specifies that the heat flux is given by

$$q(x, t) = -k \frac{\partial T}{\partial x}.$$

This is known as Fourier's law. The quantity k is the thermal conductivity, and its units are $\text{W}/(\text{m K})$. Because a Watt is a Joule/s, you can also see that the units of k are $\text{J}/(\text{m K s})$. The quantity q is the flux, and you can verify that it is given in units of $\text{J}/(\text{m}^2 \text{s})$.

Therefore by energy conservation, we have

$$\frac{d}{dt} \int_a^b \rho c T \, dx = q(x = a, t) - q(x = b, t),$$

i.e. the change in internal heat is equal to the flow through the ends. Note that we have added-in the heat flux due to $x = a$ assuming positive q refers to heat moving from left-to-right. Conversely, we subtract it away from $x = b$. We can alternatively write this as

$$\frac{d}{dt} \int_a^b \rho c T \, dx = - \int_a^b \frac{\partial q}{\partial x} \, dx.$$

Substitution Fourier's law, we can then write

$$\int_a^b \rho c \frac{\partial T}{\partial t} \, dx = \int_a^b k \frac{\partial^2 T}{\partial x^2} \, dx.$$

Because the above integral identity needs to be true for all possible values of a and b , then it must be true everywhere (this is sometimes referred to as the *du Bois-Reymond lemma* or the *bump lemma*). Therefore we are left with the classic heat equation.

Heat equation

$$\rho c \frac{\partial T}{\partial t} = k \frac{\partial^2 T}{\partial x^2}. \quad (1.1)$$

In order to produce a sensible physical solution, partial differential equations are typically supplemented by initial conditions and boundary conditions. The **initial condition** prescribes the state of the function at some initial time, typically $t = 0$. **Boundary conditions** prescribe how the function behaves on the boundary of its domain, which in this case is $x = 0$ and $x = L$. An example might be

Initial conditions (IC) and boundary conditions (BC)

$$\begin{aligned} T(x, 0) &= T_0 \\ T(0, 0) &= T_a \\ T(L, 0) &= T_b \end{aligned}$$

which expresses, respectively, that the temperature starts from a constant temperature, T_0 , and where the ends of the rod are kept at temperature T_a and T_b .

1.1.1 Steady states and long-time behaviours

2024 note

This was a new addition in 2024.

When we refer to a **steady-state** solution, we are typically referring to a time-independent solution.

Definition 1.1 (Steady-state solutions). Given an evolving system described by a function, say $f(x, t)$, defined on some spatial domain and with $t > 0$, the steady-state solution refers to time-independent solutions with

$$\frac{\partial f}{\partial t} = 0.$$

One can envisage that as the system evolves with $t \rightarrow \infty$, it reaches a state that is independent of time. However, not all systems will approach a steady state. Moreover, not all steady states are stable or attractive (and might never be reachable in a real-life experiment).

For the case of heat flow, such a steady-state solution would be $T(x, t) = T(x)$. In this case,

$$\frac{\partial T}{\partial t} = 0 \implies k \frac{\partial^2 T}{\partial x^2} = 0.$$

Therefore, for the heatflow along a segment of length L with left boundary held at T_a and right boundary held at T_b we have

$$T_{\text{steady}}(x) = \left(\frac{T_b - T_a}{L} \right) x + T_a.$$

1.2 Deriving the 1D transport (continuity) equation

2024 note

This was a new addition in 2024.

Consider the mass transport of some substance with density $\rho(x, t)$, immersed in a fluid, along a one-dimensional line in x . If desired, you may consider the substance as existing in three-dimensional space, and propagating along the x -direction, with its behaviour independent of y and z . Initially, when considered at time t , the mass of the substance between two points, a , and b , is:

$$m_{\text{blob}}(t) = \int_{a(t)}^{b(t)} \rho(x, t) dx.$$

As time increases the particles of the substance will move due to the fluid moving; at the same time, the fluid volume which is initially contained in $x \in [a(0), b(0)]$ will also move. We want to find how the mass of the blob changes in time, and hence consider the quantity

$$\frac{dm_{\text{blob}}}{dt} = \int_a^b \frac{\partial \rho}{\partial t} dx + \rho(b, t) \frac{db}{dt} - \rho(a, t) \frac{da}{dt}.$$

The above considers the intrinsic rate of change of the function within the integrand, but then adds the extra mass due to the right boundary shifting rightwards (b) and subtracts the mass due to the left boundary shifting rightwards (a). It is known as the [Leibniz integral rule](#). We can thus write this within the integral as

$$\frac{dm_{\text{blob}}}{dt} = \int_a^b \left[\frac{\partial \rho}{\partial t} + \frac{\partial}{\partial x} \left(\rho(x, t) \frac{dx}{dt} \right) \right] dx.$$

However, the quantity

$$\frac{dx}{dt} \equiv u(x, t)$$

represents the velocity of the fluid (which for the moment we assume to be a known and provided quantity). Therefore we can write the mass change as

$$\frac{dm_{\text{blob}}}{dt} = \int_a^b \left[\frac{\partial \rho}{\partial t} + \frac{\partial}{\partial x} (\rho u) \right] dx.$$

This result, which explains how to pass a derivative through an integral express mass of a substance within a flow is known as the *Reynolds Transport Theorem*. We have just derived it in 1D.

Reynolds Transport Theorem

Let $\rho = \rho(x, t)$ be some quantity (such as density) that is advected along a one-dimensional line in x due to a fluid with velocity $u(x, t)$. Then

$$\frac{d}{dt} \int_{a(t)}^{b(t)} \rho dx = \int_{a(t)}^{b(t)} \left[\frac{\partial \rho}{\partial t} + \frac{\partial}{\partial x} (\rho u) \right] dx.$$

We may now consider the substance being transported along the x -direction. If there is no interior creation or destruction of the source, then by conservation of mass, it must be the case that

$$\frac{dm_{\text{blob}}}{dt} = 0.$$

Thus, again since the above integral identity applies to all possible values of a and b , it must be the case that the integrand is zero. Thus we conclude with the so-called transport equation.

One-dimensional transport equation

The transport of a substance described by $\rho(x, t)$ advected along a one-dimensional line in x due to a fluid with velocity $u(x, t)$ is given by

$$\frac{\partial \rho}{\partial t} + \frac{\partial}{\partial x} (\rho u) = 0.$$

Again, we must consider the above problem in combination with potential initial conditions and boundary conditions. For instance, we might specify that the substance begins from some initial state, say

$$\rho(x, 0) = \rho_0(x).$$

The boundary conditions are more subtle. It is not always obvious what the boundary conditions should be on a problem.

Here is an example of a solution of such a problem.

Linear advection equation with constant speed

Solve the problem given by

$$\frac{\partial \rho}{\partial t} + c \frac{\partial \rho}{\partial x} = 0,$$

where the velocity $u = c$ is constant. You may assume the initial condition is given by

$$\rho(x, 0) = \rho_0(x) = e^{-x^2}.$$

Solution

The general solution is given by

$$\rho(x, t) = F(x - ct),$$

where F is an arbitrary (differentiable) function. You can verify this via the chain rule, noting that

$$\frac{\partial F}{\partial t} = -cF'(x - ct) \quad \text{and} \quad \frac{\partial F}{\partial x} = F'(x - ct).$$

Applying the initial condition at $t = 0$ gives $F(x) = \rho_0(x)$ and thus

$$\rho(x, t) = e^{-(x-ct)^2}.$$

You may plot this to discover that it is, as perhaps expected, a Gaussian profile moving to the right at constant speed (for $c > 0$).

2 Dimensional scaling analysis

Putting a mathematical model into non-dimensional form is fundamental (Fowler 2011). When we refer to a “back-of-the-envelope calculation”, we often mean simple algebraic calculations that still nevertheless provide enormous insight on problems. Such analyses are often based on dimensional analysis, which identifies the relationships between the different quantities involved in the problem.

2.1 Dimensional quantities

Every physical quantity, say Q , can be expressed as a product of a dimensional unit, denoted $[Q]$, and a magnitude, say Q' . Thus we write

$$Q = Q'[Q]$$

For example, if x corresponds to the physical length in a problem, we might select $[x] = \text{km}$ or $[x] = \text{yards}$ or $[x] = \text{m}$. It is important to choose the dimensionalisation to suit the problem under consideration.

2.1.1 SI units

The International System (SI) of Base Units sets out a distinct selection of choices for dimensions in certain physical quantities. The seven fundamental dimensional units are

- [Length] = metre
- [Time] = seconds
- [Mass] = kilogram
- Temperature = Kelvin
- [Electric current] = ampere
- [Light intensity] = candela
- [Material quantity] = mole

Dimensional units that can be expressed in terms of other fundamental units are known as *derived units*. For example:

- [Speed] = metre/second

- [Acceleration] = metre/second²
- [Force] = kilogram . metre/second²

2.2 Dimensional homogeneity and non-dimensionalisation

All terms in any equation must have the same dimensions. This is the principle of dimensional homogeneity. For example, Newton's second law expresses the fact that

$$F = m \frac{d^2x}{dt^2}$$

We can check, then, that the units do indeed match up on either side. Here, the RHS has units of [m] [x]/[t]² or in SI units, kg . metres / seconds². This indeed matches our previous given SI unit decomposition for force.

Notice in addition that the input to functions like $\cos \theta$ and e^z must be non-dimensional (or dimensionless).

The process of nondimensionalisation is then as follows. Given an equation, we know that each term must have the same dimension. Therefore, we can scale all the dependent and independent variables by dimensional constants in order to yield a non-dimensional equation.

Why this is an important tool is demonstrated by the below.

2.3 Returning to the heat equation

2023-24 note

The below has been cleaned up to match the notation on the 13 Feb 2023 delivery.

Exact units are not relevant for dynamics, and it is instead the ratio of units that we care about. To apply this principle, let us non-dimensionalise the equation Equation 1.1. Let us consider the heat equation as given by the system

$$\begin{aligned} \frac{\partial T}{\partial t} &= \kappa \frac{\partial^2 T}{\partial x^2} \\ T(x, 0) &= T_{\text{init}} \\ T(0, t) &= T_a \\ T(L, t) &= T_b. \end{aligned}$$

Note that the constant κ is known as the thermal diffusivity, and is given by

$$\kappa = \frac{k}{\rho c},$$

which were the units previously introduced.

We introduce typical scales for each of the variables. For example, we non-dimensionalise the temperature, distance, and time by setting

$$T = [T]T', \quad x = [x]x', \quad t = [t]t'.$$

Remember that via the chain rule, we have that

$$\frac{d}{dx} = \frac{dx'}{dx} \frac{d}{dx'} = \frac{1}{[x]} \frac{d}{dx'}.$$

Substitution into the equation now yields

$$\begin{aligned} \frac{\partial T'}{\partial t'} &= \frac{\kappa[t]}{[x]^2} \frac{\partial^2 T}{\partial x^2} \\ T'(x', 0) &= T_{\text{init}} \\ T'(0, t') &= \frac{T_a}{[T]} \\ T'(L/[x], t') &= \frac{T_b}{[T]}. \end{aligned}$$

Be sure to work out the above for yourself. For example, notice that the previous boundary at $x = L$ is now sent to $x' = L/[x]$. Now we see that the final equation is beautifully simple: At this point, we can identify a crucial non-dimensional parameter given by

$$\Pi = \frac{\kappa[t]}{[x]^2} = \frac{k[t]}{\rho c[x]^2}.$$

Although this looks quite complicated, you can test that this parameter is indeed non-dimensional by looking up the units for thermal conductivity, k , density ρ , and specific heat c , and verifying that indeed Π is non-dimensional.

2.4 Choice of units

It is important to remember that there are technically no wrong choices for the scales $[x]$, $[T]$, and $[t]$, as long as they yield consistent balances. However, some choices are better than others for the context of the problem. Let us select:

$$[x] = L \quad [T] = T_{\text{init}}.$$

This means our unit of length is “one pipe” (if this is indeed a pipe), and our unit of temperature is whatever the initial temperature was set to be. The choice of time is free at the moment, and therefore we can select time as

$$\Pi = \frac{\kappa[t]}{[x]^2} = 1 \implies [t] = \frac{L^2}{k}.$$

Now we see that the final equation is beautifully simple:

$$\begin{aligned} \frac{\partial T'}{\partial t'} &= \frac{\partial^2 T}{\partial x^2} \\ T'(x', 0) &= 1 \\ T'(0, t') &= \frac{T_a}{T_{\text{init}}} \equiv A, \\ T'(1, t') &= \frac{T_b}{T_{\text{init}}} \equiv B. \end{aligned} \tag{2.1}$$

2.4.1 Interpretation

What is the whole point of the above exercise?

In the original problem, there were five parameters:

$$\kappa, \quad T_{\text{init}}, \quad T_a, \quad T_b, \quad L.$$

Imagine a situation where you are performing an analysis of heat spread in different pipes of different materials (characterised by κ) and lengths (L), with different initial and boundary temperatures. That is potentially a highly complicated parameter space to search (five-dimensional).

Rather than solving the problem again and again for each change in parameters, what the analysis yielding (Equation 2.1) reveals is that the parameter space only needs to be two-dimensional, for parameters A and B . Therefore, by solving the problem at many different values of A and B , the solution space can be completely mapped.

Here is an example. Consider heat diffusion through common [brick](#), which possesses a thermal diffusivity of

$$\kappa = 5.2 \times 10^{-7} \text{m}^2/\text{s}.$$

Therefore a brick that is about $L = 10\text{cm} = 0.1\text{m}$ in size has a typical timescale of

$$[t] = \frac{L^2}{\kappa} \approx 1.9 \times 10^4 \text{s} \approx 5 \text{hrs.}$$

The above choice of $[t]$ is representative of the typical timescale you can expect for heat to diffuse through the brick. As you can see it's very long.

In summary, we have gone from a system where we needed to consider five parameters to a system where we only need to specify two (essentially, the ratio of the initial heat to the boundary values). This is an enormous simplification.

Moreover, your analysis has further identified the key non-dimensional parameters that appear, including:

$$\Pi = \frac{\kappa[t]}{[x]^2}, \quad A = \frac{T_a}{T_{\text{init}}}, \quad B = \frac{T_b}{T_{\text{init}}}, \quad \frac{L}{[x]}$$

In this particular problem, you had the freedom to choose L to remove one parameter (the ratio of lengths), and time could be chosen to set $\Pi = 1$.

3 Basic energy models

In this chapter, we introduce the simplest climate model to describe the temperature of the Earth. Despite its apparent simplicity, this basic climate model is the foundation of all further discussion. We will find that, according to the most basic model, the surface temperature of the Earth is expected to be much colder than it is actually; we conclude that the likely culprit is greenhouse gases.

Consider the Earth as a single averaged body. Our goal is to obtain an equation for the surface temperature, T , by considering the energy received from the sun versus the energy the Earth must emit into space. This kind of balance-equation procedure is used everywhere in mathematical modelling. In essence, we are looking to write down a precise statement of the following:

Basic energy balance

$$\text{Change in internal energy of Earth} = E_{\text{in}} - E_{\text{out}}, \quad (3.1)$$

where E_{in} is the incoming energy from the sun and E_{out} is the energy leaving the Earth. Note that the left hand-side (the internal energy) will depend on the temperature, T .

3.1 The basic energy model

The basic model is derived as follows.

1. By considering the incoming radiation from the sun, obtain an estimate for the incoming energy, E_{in} .
2. Use a constitutive law that indicates how much outgoing energy is produced by an object heated to some temperature.
3. Equate the change in internal energy to be equal to the difference between the above two items.

Note that the primary components of the global energy balance are radiative fluxes: we receive short-wave radiation (UV and visible light) from the Sun, and emit longwave radiation (infra-red) to space.

First we consider incoming energy.

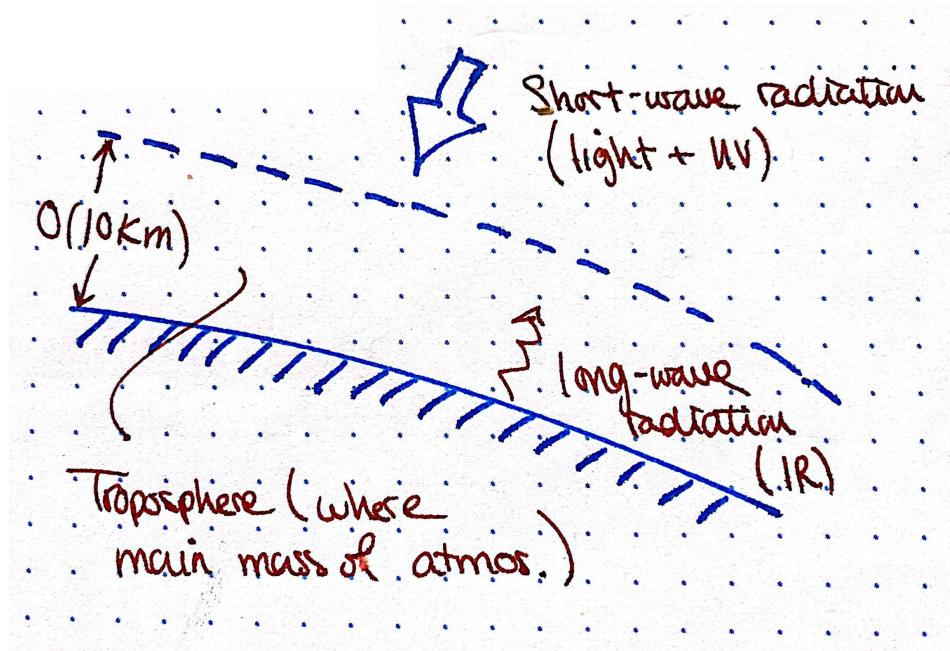


Figure 3.1: Radiation in the atmosphere

Energy from the Sun

First, note that the shortwave radiation (UV and radiation) received from the sun is $Q \approx 1370 \text{ W}\cdot\text{m}^{-2}$ (which we consider measured at a point near the planet). If we consider only that radiation that is absorbed into the Earth, we have

$$E_{\text{in}} = \pi R^2 Q (1 - a), \quad (3.2)$$

where R is the Earth's radius.

In the above formula, we have multiplied the flux, Q , with the visible surface area, πR^2 . There is an additional multiplication by $(1 - a)$ where a is the *planetary albedo*, which characterises amount of energy reflected due to the surface properties. Light surfaces like snow will have high albedo, $a \approx 0.9$, while darker surfaces like the ocean have smaller albedo, $a \approx 0.3$. The global average albedo is $a \approx 0.3$.

Next we consider outgoing energy.

Energy from the Earth

We now wish to characterise the energy, E_{out} , and in the case of Earth, this will correspond to longwave radiation (infra-red) emitted into space. All bodies characterised by

a temperature, say T_e , will emit radiation, Q_e . As a model, we can consider Q_e to be given by the [Stefan-Boltzmann law](#), which states that

$$Q_e = \sigma T_e^4, \quad (3.3)$$

where $\sigma \approx 5.67 \times 10^{-8} W m^{-2} K^{-4}$ is the Stefan-Boltzmann constant.

Now although the Earth's surface may emit radiation according to (Equation 3.3), some of this radiation will be absorbed by the atmosphere and reflected back. This is the **greenhouse effect**. As a consequence of the greenhouse gas, the surface temperature of the Earth, T , will be larger than the effective emitting temperature, T_e . For the moment, we model this as

$$T_e = \gamma^{1/4} T, \quad (3.4)$$

where $\gamma < 1$ is a greenhouse gas factor, which depends on the properties of the atmosphere.

Now combining the above equations, we have

$$E_{\text{in}} - E_{\text{out}} = \pi R^2 Q(1 - a) - 4\pi R^2 \sigma \gamma T^4, \quad (3.5)$$

which gives the incoming energy per unit time.

Internal heat energy

Due to this incoming energy, the Earth will cool or heat in response. We need to know how the internal temperature of an object responds to an input in energy. The general formula is

$$\text{Internal heat energy} = \text{volume} \times (\rho c_p) \times T.$$

The key quantity is the experimentally determined, c_p , which corresponds to the [specific heat capacity](#). It is given in the SI units of $J \cdot kg^{-1} \cdot K^{-1}$, i.e. energy per unit mass per unit temperature. Note that this applied to a shell around the planet of thickness d in the atmosphere, and so the mass is given by

$$\text{mass} = (4\pi R^2)d\rho \quad (3.6)$$

where ρ is the average density of the atmosphere. Let us imagine the increase in temperature, ΔT , during an interval of time, Δt . You can now verify that

$$[(4\pi R^2)d\rho]c_p(\Delta T)$$

returns the units of Joules—i.e. this is the internal energy produced during the time Δt . We then have

$$[(4\pi R^2)d\rho]c_p\Delta T = \Delta t(E_{\text{in}} - E_{\text{out}}).$$

Putting in (Equation 3.5) and taking the limit of $\Delta t \rightarrow 0$, we finally have a heat equation for the Earth's temperature.

Zero-dimensional model for the surface temperature of the Earth

The Earth's temperature, as measured on a layer of thickness d at the troposphere is given by the following ordinary differential equation (ODE) for $T = T(t)$:

$$C \frac{dT}{dt} = \frac{1}{4} Q(1 - a) - \sigma\gamma T^4, \quad (3.7)$$

where we have defined

$$C = \rho c_p d$$

as the heat capacity of the atmosphere. Above, the solar flux, Q is often taken to be $Q = 1370 \text{ W/m}^2$, $\sigma = 5.67 \times 10^{-8} \text{ W/(m}^2\text{K}^4)$, and $\gamma \leq 1$ is the greenhouse gas factor.

The above equation Equation 3.7 is time-dependent, but we may consider that the surface temperature, either over long-time or in an averaged sense, is dictated by the steady-state (time-independent) solution. Setting dT/dt to zero, we see that there is a unique steady-state given by

$$T = \left(\frac{Q(1 - a)}{4\sigma\gamma} \right)^{1/4}.$$

If we take $Q \approx 1370 \text{ W m}^{-2}$, $a \approx 0.3$, $\sigma \approx 5.67 \times 10^{-8} \text{ W m}^{-2} \text{ K}^{-4}$, we then get

$$T \approx 255 \text{ K} = -18^\circ \text{C}.$$

under the assumption that $\gamma = 1$. That's pretty cold! The actual average temperature is around $288 \text{ K} \approx 15^\circ \text{C}$.

The above back-of-the-envelope calculation seems to suggest that the parameter $\gamma < 1$ plays an important role in keeping the Earth warm enough for us to live on, and indeed the value of γ inferred by the above is roughly $\gamma \approx 0.61$. Later on in the course, we will develop a more rigorous model to predict such a γ by studying the properties of the atmosphere.

3.2 The history of global warming

The history of global warming (and hence the estimation of γ) is convoluted, but the origins can be considered as far back as the work of (Fourier 1827) and (Pouillet 1838), and is discussed in the work by (Van der Veen 2000).

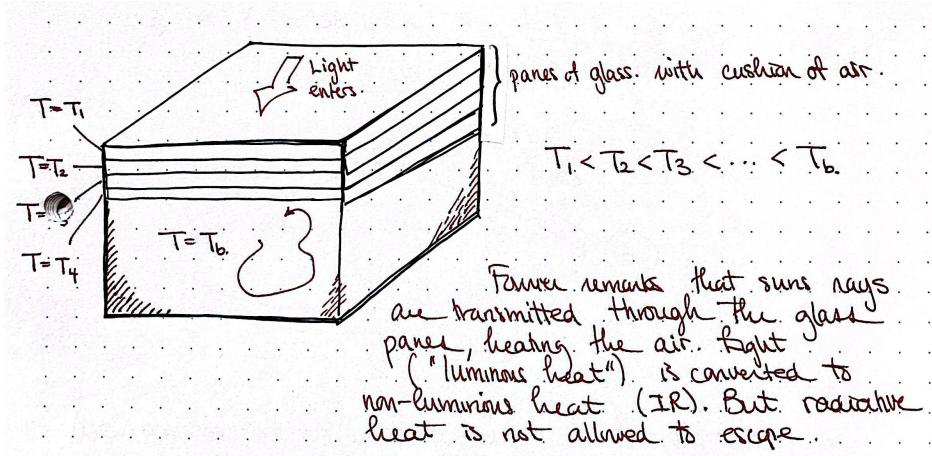


Figure 3.2: An illustration of Fourier's glass box

3.3 Next in the study of energy balance models?

At this stage, the basic energy balance model studied in this chapter can be made more complex and realistic through many different extensions. For instance:

- Consider the effects of a non-constant and nonlinear albedo. Since the albedo depends on the material property (water vs. ice vs. land), we can incorporate a toy model for spatial variability by allowing the albedo to depend on temperature, $a = a(T)$.
- Consider the time-dependence. What happens if the system starts out of the steady state? Does it tend to relax to its equilibrium profile? Can we analyse the temporal properties of the solutions?
- Can we incorporate latitude (or longitudinal) dependence into the model. For instance, should the albedo and solar radiation be considered as functions of the latitude?
- Should we incorporate the effects of diffusion (heat spreading out) or convection (heat transported with flows)?
- To what extent should we consider the effects of the atmosphere on the absorption and reflection properties of the incoming (and outgoing) energy?

Many of these questions are much more involve, as they require differential or partial differential equations. Therefore in the next few chapters, we will discuss, in a very general way, the collection of applied and numerical mathematics techniques that can be used when studying problems in the physical sciences.

4 Problem class 1

Abstraction

It may seem strange to study examples from elementary physics in a course that is supposed to be about Planet Earth. But simple examples are the best ways to learn these important techniques. The full climate equations are often very involved. These toy models still nevertheless capture the spirit of what you must do when attacking any scientific problem.

In this problem class, we will practice some concepts about non-dimensionalising in preparation for the Problem Set 1 in Chapter 21. We will cover these two strategies in choosing scalings.

Scaling principle 1

Select the characteristic scales so that as many of the possible non-dimensional numbers, Π_i , $i = 1, 2, 3, \dots$ are normalised.

Scaling principle 2

Select characteristic scales so that no terms in the model diverge in the physical limit of interest.

Here are the problems we shall do in the problem class.

4.1 Projectile motion

A projectile of mass M (in kg) is launched vertically with initial velocity V_0 (in m/s) from a position Y_0 (in m) above the surface. Thus the mass's position, $Y(t)$ is governed by Newton's second law (applied to the mass and the mass of the Earth) and the set of equations

$$MY_{tt} = -\frac{gR_E^2 M}{(R_E + Y)^2},$$
$$Y(0) = Y_0,$$

where $g = 9.81 \text{ m/s}^2$ and $R_E = 6.4 \times 10^6 \text{ m}$ is the radius of the Earth.

1. Non-dimensionalise the equation using arbitrary length and time scales.
2. Identify the non-dimensional constants, Π_i .
3. Choose a length scale of $L = Y_0$ and time scale of $T = (L/g)^{1/2}$. Discuss the resultant equation and the interpretation of choosing these scales.
4. Does your above choice allow you to easily study the limit of $R_E \rightarrow \infty$? If the limit can be taken, reduce the governing system to a simpler equation.
5. Does your choice in 3. allow you to easily study the limit of $Y_0 \rightarrow 0$? If not, choose an alternative choice of length and time scales and in that case, reduce the set of equations.

4.2 Terminal velocity

A ball of radius R (in m) and uniform density ρ (in kg/m³) falls in a viscous fluid. The fluid has density ρ_f (in kg/m³) and viscosity (a measure of friction or resistance) μ (in kg/(m s)). The equation that governs the velocity is

$$\frac{4}{3}\pi R^3 \rho \frac{dV}{dt} = \frac{4}{3}\pi R^3 (\rho - \rho_f)g - 6\pi\mu RV,$$

$$V(0) = V_0.$$

1. Choose appropriate velocity and time scales to non-dimensionalise the equation so as to leave only a single non-dimensional number on the drag term (the last term on the right hand-side).
2. Define the non-dimensional parameter expressing a ratio between drag force and gravity force by the Stokes number (St) and confirm that it is

$$St = \frac{9\mu V_0}{2(\rho - \rho_f)gR^3}.$$

3. Comment on the two limits of $St \rightarrow 0$ and $St \rightarrow \infty$. Can the problem be reduced in these two limits? If so, reduce and solve.

Part II

Practical applied mathematics

As we go deeper into formulating the equations that model or govern aspects of Planet Earth, we will quickly come to the realisation that many such equations, even for the simplest minimal models, are not exactly solvable.

For example, in the analysis of the Ocean models later in the course, we develop the following “simple” model for the temperature in the ocean:

$$\frac{dx}{dt} = \delta(1 - x) - |f(x, y)|x, \quad (4.1)$$

$$\frac{dy}{dt} = 1 - y - |f(x, y)|y, \quad (4.2)$$

where we have introduced the function,

$$f(x, y; R, \lambda) = \frac{1}{\lambda}(Rx - y),$$

This is quite a difficult problem! This is essentially a set of two nonlinear differential equations for two unknowns and three parameters. What kind of practical applied mathematics can we apply to study such problems?

The intention of this part is to introduce (and in some cases, review) three key concepts:

1. Asymptotic approximations.
2. Numerical solutions of differential equations.
3. Numerical solutions of nonlinear equations (Newton’s method).

as well as any additional tools you may need to study the kinds of differential equations involved in Maths of Planet Earth!

5 Asymptotic approximations I

One powerful set of techniques for approximating solutions to equations is called *asymptotic analysis* or *perturbation theory*. To begin with, in this chapter, we introduce you to these techniques as a means to approximating the solutions to equations like:

$$\epsilon x^2 + x - 1 = 0,$$

when ϵ is a small parameter.

Soon, we apply the techniques to approximating solutions of differential equations.

5.1 A simple quadratic

A singular quadratic

Consider the solution of

$$\epsilon x^2 + x - 1 = 0, \quad (5.1)$$

where ϵ is a fixed and very small positive number, say 0.000001. Forget that we know how to solve a quadratic equation: is it possible to develop a systematic approximation method?

If $\epsilon = 0$, then $x = 1$. Moreover, if we substitute $x = 1$ into the equation, then we see that the error is small and proportional to ϵ . It is natural to seek an approximation in powers of ϵ . We call this an *asymptotic expansion*. We write

$$x = x_0 + \epsilon x_1 + \epsilon^2 x_2 + \dots$$

Substitution into the equation yields

$$\epsilon \left(x_0 + \epsilon x_1 + \epsilon^2 x_2 + \dots \right)^2 + \left(x_0 + \epsilon x_1 + \epsilon^2 x_2 + \dots \right) - 1 = 0.$$

Expand and collect terms in powers of ϵ :

$$\left(x_0 - 1 \right) + \epsilon \left(x_1 + x_0^2 \right) + \epsilon^2 \left(x_2 + 2x_0 x_1 \right) + \dots = 0.$$

Now we equate coefficients at each order in ϵ . This gives

$$\begin{aligned}x_0 - 1 &= 0 \implies x_0 = 1 \\x_1 + x_0^2 &= 0 \implies x_1 = -1 \\x_2 + 2x_0x_1 &= 0 \implies x_2 = 2\end{aligned}$$

We therefore have obtained the three-term approximation,

$$x = 1 - \epsilon + 2\epsilon^2 + \dots$$

Clearly we could continue this process *ad infinitum* obtaining increasingly accurate approximations to one of the roots.

5.1.1 The singular root

But where has the other quadratic root gone?

The problem is that in considering ϵ to be small, we began by ignoring the leading term, ϵx^2 . We effectively assumed that the equation was primarily *balanced* by setting the x term with the -1 term, and the sum of the two terms approximately equalling zero.

But if $|x|$ is large, then clearly our assumption that ϵx^2 being small may not be necessarily true for it depends on how large $|x|$ is compared to ϵ . Note that if $|x|$ is large, then necessarily the last term, -1 , is negligible in comparison. Therefore, in order for ϵx^2 to balance x , we see that $|x|$ must be of size $1/\epsilon$.

Therefore this suggests that we should re-scale our solution as follows

$$x = \frac{X}{\epsilon}.$$

Substitution into the original quadratic now yields

$$X^2 + X - \epsilon = 0.$$

Now notice that $\epsilon = 0$ expresses the correct balance in order to detect that missing root. Again we write

$$X = X_0 + \epsilon X_1 + \epsilon^2 X_2 + \dots$$

and attempt to solve order by order. Substitution into the equation yields

$$(X_0 + \epsilon X_1 + \epsilon^2 X_2 + \dots)^2 + (X_0 + \epsilon X_1 + \epsilon^2 X_2 + \dots) - \epsilon = 0.$$

Expand and collect orders of ϵ :

$$\begin{aligned}X_0^2 + X_0 = 0 &\implies X_0 = -1 \\2X_0 X_1 + X_1 - 1 = 0 &\implies X_1 = -1,\end{aligned}$$

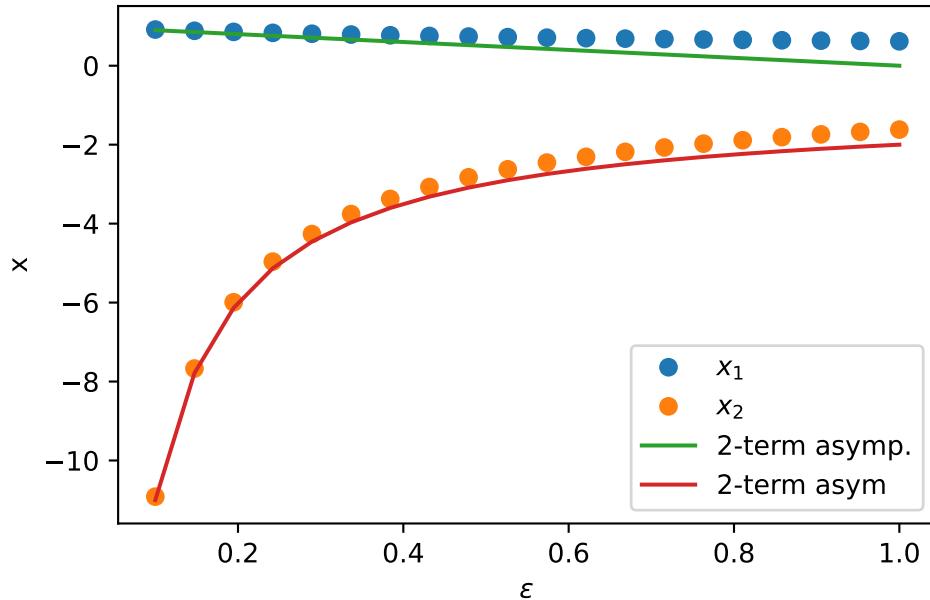
and thus to two orders, we have

$$X = -1 - \epsilon + \dots \implies x = -\frac{1}{\epsilon} - 1 + \dots$$

Of course, we have used a very simple example (a solvable quadratic) to illustrate the idea of asymptotic approximations, but you should hopefully see that this method is extensible to much more complicated equations.

```
import numpy as np
import matplotlib.pyplot as plt

ep = np.linspace(1,0.1, 20)
root1 = (-1 + np.sqrt(1-4*ep*(-1)))/(2*ep)
root2 = (-1 - np.sqrt(1-4*ep*(-1)))/(2*ep)
asym1 = 1 - ep
asym2 = -1/ep - 1
plt.plot(ep, root1, 'o')
plt.plot(ep, root2, 'o')
plt.plot(ep, asym1, '-')
plt.plot(ep, asym2, '-')
plt.legend(['$x_1$', '$x_2$', '2-term asymp.', '2-term asym'])
plt.xlabel('$\epsilon$')
plt.ylabel('x');
```



5.2 Order notation and the tilde sign for asymptotic

We define precisely what we mean when we say that two functions, say f and g , exhibit the same behaviour in some limit, say $\epsilon \rightarrow 0$ or $x \rightarrow x_0$ or $x \rightarrow \infty$ and so forth. For instance, we claim that the graphs of $\sin(x)$ and x look very similar as $x \rightarrow 0$. Thus we might write

$$\sin(x) \sim x \quad \text{as } x \rightarrow 0. \quad (5.2)$$

This notation of similarity allows us to specify functional behaviours at a deeper level than just limits. As you can see, it is not as useful to specify that

$$\lim_{x \rightarrow 0} \sin x = \lim_{x \rightarrow 0} x.$$

In contrast, the asymptotic relation is much more prescriptive about the way that the functions are approaching the limit.

Definition of \sim , \gg , and \ll

First, the notation

$$f(x) \ll g(x), \quad x \rightarrow x_0,$$

is read as “ $f(x)$ is much smaller than $g(x)$ as $x \rightarrow x_0$ ” and means

$$\lim_{x \rightarrow x_0} \frac{f(x)}{g(x)} = 0.$$

We may analogously use $g(x) \gg f(x)$ for “much greater than...”.

Second, the notation

$$f(x) \sim g(x), \quad x \rightarrow x_0,$$

is read as “ $f(x)$ is asymptotic to $g(x)$ as $x \rightarrow x_0$ ”, and means that the error between f and g tends to zero as $x \rightarrow x_0$, or

$$\lim_{x \rightarrow x_0} \frac{f(x)}{g(x)} = 1.$$

We will often say “ f is like g ” or “ f behaves like g ”,

Here are some examples.

Examples

- $\sin x \sim x \sim \tan x$ as $x \rightarrow 0$
- $x^2 + x + 1 \sim \frac{x^3 + \sin x}{1 + x}$ as $x \rightarrow \infty$
- $\sin x \ll \cos x$ as $x \rightarrow 0$

In the examination of limiting processes, often the main issue of consideration is the relative sizes of quantities defined according to their powers. For example, if x is a very small number, with $x = 10^{-5}$, then x^5 is much smaller than x (in terms of our notation, $x^5 \ll x$ as $x \rightarrow 0$). On the other hand, we might not care so much about the difference between

$$x^5 \quad \text{vs.} \quad 5x^5$$

The point is that the *order* of x^5 and $5x^5$ is the same as $x \rightarrow 0$. The “Big-Oh” notation formalises this distinction.

Definition of Big-Oh

We write $f = O(g)$ as $x \rightarrow x_0$ to mean that there exists constants $K > 0$ and $x^* > 0$ such that

$$|f| < K|g| \quad \text{for all } |x - x_0| < x^*.$$

In practice, the use of the order symbol is very natural and you will not need to work with the technical definition. For example, when you derive the terms of the Maclaurin/Taylor series, you are naturally clustering all the terms of the same order (power) together. For us, the O symbol provides a very convenient way of separating terms of different sizes.

Examples

- $2 \sin x = O(\tan x)$ as $x \rightarrow 0$
- $x^2 + x + 1 = O\left(\frac{5x^3 + \sin x}{1 + x}\right)$ as $x \rightarrow \infty$

Let us return to the case of the quadratic example (Equation 5.1). Using the O notation, we can write

$$x = \begin{cases} 1 - \epsilon + 2\epsilon^2 + O(\epsilon^3) \\ -\frac{1}{\epsilon} - 1 + O(\epsilon^2) \end{cases}$$

for the two roots. Alternatively, we can truncate the expansions and simply using the \sim symbol:

$$x \sim \begin{cases} 1 - \epsilon \\ -\frac{1}{\epsilon} - 1 \end{cases}$$

6 Asymptotic approximations II

In the previous chapter, we learned about the technique of asymptotic expansions, whereby the solution of an equation is expressed in terms of a series in powers of a small parameter:

$$x = x_0 + \epsilon x_1 + \epsilon^2 x_2 + \dots$$

The precise choice of power progression (here integer powers of ϵ will depend on the particular problem. The same idea can be extended to approximating solutions of differential equations. The upshot of this procedure is that at each order of the scheme, a simpler problem can be studied.

Again it is best to demonstrate through examples.

6.1 Returning to the projectile problem

In Chapter 4 and Chapter 21 you studied the non-dimensionalisation of the projectile problem. Once re-scaled, it takes the following form:

$$\begin{aligned} \frac{d^2y}{dt^2} &= -\frac{1}{(1 + \epsilon y)^2}, & t > 0 \\ y(0) &= 0, \\ y'(0) &= 1. \end{aligned} \tag{6.1}$$

This is a difficult problem without, in fact, any explicit solutions. However, we can estimate the solution in the limit $\epsilon \rightarrow 0$. We expand the solution as

$$y(t) = y_0(t) + \epsilon y_1(t) + \epsilon^2 y_2(t) + \dots$$

In order to expand the denominator, you can use Taylor's theorem to expand the function

$$f(x) = (1 + x)^\alpha = f(0) + f'(0)x + \dots = 1 + \alpha x + \dots$$

around $x = 0$.

The differential equation now yields

$$y_0'' + \epsilon y_1'' + \epsilon^2 y_2'' + \dots = -[1 - 2\epsilon(y_0 + \epsilon y_1 + \dots) + \dots]$$

so grouping terms together order-by-order yields

$$[y_0'' + 1] + \epsilon [y_1'' - 2y_0] + \dots = 0.$$

We can similarly substitute the expansion into the initial conditions. Altogether, at leading order, we obtain the following system to solve:

$$\begin{aligned} y_0'' + 1 &= 0, \\ y_0(0) &= 0, \\ y_0'(0) &= 1. \end{aligned}$$

Integrating twice and applying the boundary conditions gives us

$$y_0(t) = -\frac{1}{2}t^2 + t.$$

In fact, this is simply the parabolic motion you would expect from school Physics. The $\epsilon = 0$ solution corresponds to assuming that the mass at the centre of the planet is dominant and then acceleration is constant.

However, we can now proceed to higher order and examine the nonlinear effects. Proceeding to $O(\epsilon)$, we have the following system to solve:

$$\begin{aligned} y_1'' &= 2y_0, \\ y_1(0) &= 0, \\ y_1'(0) &= 0. \end{aligned}$$

Notice the boundary conditions come from the fact there are no ϵ corrections in the original boundary conditions, so $y_n(0) = y_n'(0) = 0$ for all $n > 0$. Again this system is simple to integrate. Integrating the solution for y_0 twice and substitution of the initial conditions yields

$$y_1(t) = -\frac{1}{12}t^4 + \frac{1}{3}t^3.$$

We have thus solved for the asymptotic approximation to two orders. We have

$$y(t) \sim \left[-\frac{1}{2}t^2 + t \right] + \epsilon \left[-\frac{1}{12}t^4 + \frac{1}{3}t^3 \right].$$

This was quite an accomplishment! We have taken a problem that was not easily solvable in explicit form and through fairly simple integrations, obtained an approximation to two orders in ϵ . How good is it? Let us solve the problem numerically and compare with the asymptotic approximation.

6.2 Numerical solutions of IVPs

We first demonstrate how to solve ODEs (initial-value-problems, IVPs) using black-box functions in Python. For starters, most numerical formulations for ODEs will require that the problem be posed in terms of a first-order system of equations. To convert (Equation 6.1) into such a form, create a set of unknowns for the derivatives. Set

$$\mathbf{Y}(t) = \begin{pmatrix} y_1(t) \\ y_2(t) \end{pmatrix} = \begin{pmatrix} y(t) \\ y'(t) \end{pmatrix}$$

Then we have the following first-order system:

$$\begin{aligned} \mathbf{Y}'(t) &= \mathbf{F}(t, \mathbf{Y}(t)) = \begin{pmatrix} y'_1 \\ -\frac{y'_1}{(1+\epsilon y_1)^2} \end{pmatrix} \\ \mathbf{Y}(0) &= \begin{pmatrix} 0 \\ 1 \end{pmatrix} \end{aligned} \tag{6.2}$$

You can find a little guide on using `solve_ivp` in Python [here](#). Here is the Python code to solve the differential equation.

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.integrate import solve_ivp

ep = 0.2 # epsilon value
tmax = 2 # max time
t = np.linspace(0, tmax, 100) # mesh used for plotting

# Define function for the ODE
def f(t, Y):
    ep = 0.2
    y, yp = Y
    ypp = -1/(1 + ep*y)**2
    return [yp, ypp]

# define the initial condition
Y0 = [0, 1]

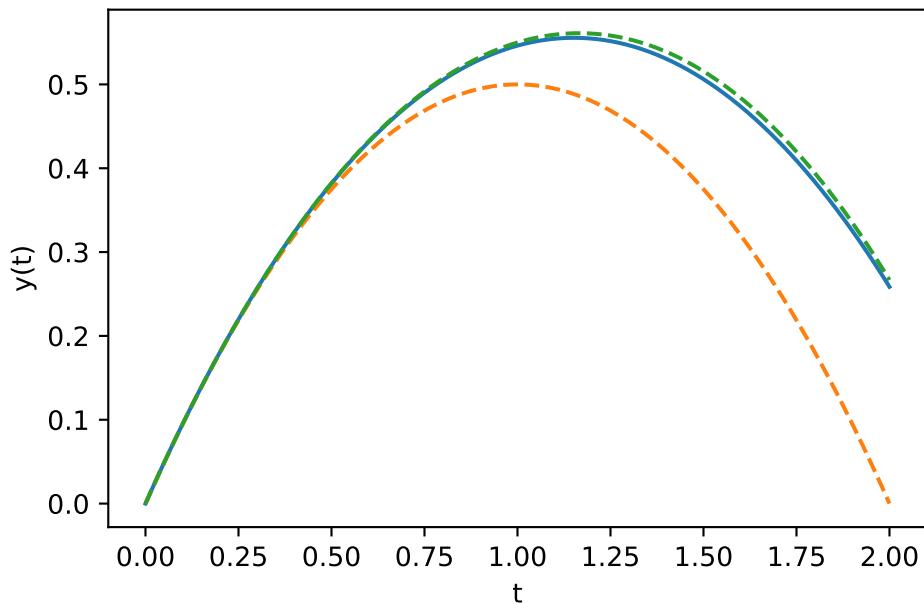
sol = solve_ivp(f, [0, tmax], Y0, dense_output=True)

# Prior to plotting, re-interpolate solution on a fine grid
yy = sol.sol(t)
```

```
# Asymptotic solutions
y0 = -1/2*t**2 + t
y1 = -1/12*t**4 + 1/3*t**3
```

```
# Plot it all
plt.plot(t, yy[0,:])
plt.plot(t, y0, '--')
plt.plot(t, y0 + ep*y1, '--')
plt.xlabel('t')
plt.ylabel('y(t)')
```

Text(0, 0.5, 'y(t)')



The two-term approximation does beautifully well, even at this moderate value of $\epsilon = 0.2$.

7 Numerical solutions of IVPs

In the previous section, we used built-in ODE solvers to develop numerical solutions. It is important to gain an understanding how a simple ODE solver works. The simplest scheme is called [Euler's method](#), and this we now explain.

Begin from the system (Equation 6.2). We assume that the solution is represented by a discrete set of points, $\mathbf{Y}_n = \mathbf{Y}(t_n)$ at the times $t_0 = 0$, $t_1 = \Delta t$, $t_2 = 2\Delta t$, and so on. The time derivative is written as a discrete derivative while we approximate the right hand side by its value at the nth time step:

$$\frac{\mathbf{Y}_{n+1} - \mathbf{Y}_n}{\Delta t} = \mathbf{F}(t_n, \mathbf{Y}_n)$$

Rearranging yields a very simple algorithm for solving the ODE:

$$\mathbf{Y}_n = \mathbf{Y}_{n-1} + \mathbf{F}(t_{n-1}, \mathbf{Y}_{n-1})\Delta t$$

for $n = 1, 2, 3, \dots$

This would be implemented via the following pseudocode:

Euler's method

1. Input: function $f(t, Y)$
time step, dt
initial condition, Y_0
2. Set initial condition $Y = Y_0$
2. Take one Euler step and overwrite previous value
$$Y = Y + f(t, Y)$$
3. Increment t by dt and goto 2

Euler's method is conceptually simple but quite inaccurate. But in this case, we see that it works fairly well in comparison to the built-in solvers.

```

import numpy as np
import matplotlib.pyplot as plt
from scipy.integrate import solve_ivp

ep = 0.2          # epsilon value
tmax = 2          # max time
N = 20            # number of steps
t = np.linspace(0, tmax, N) # mesh used for plotting
dt = t[1] - t[0]

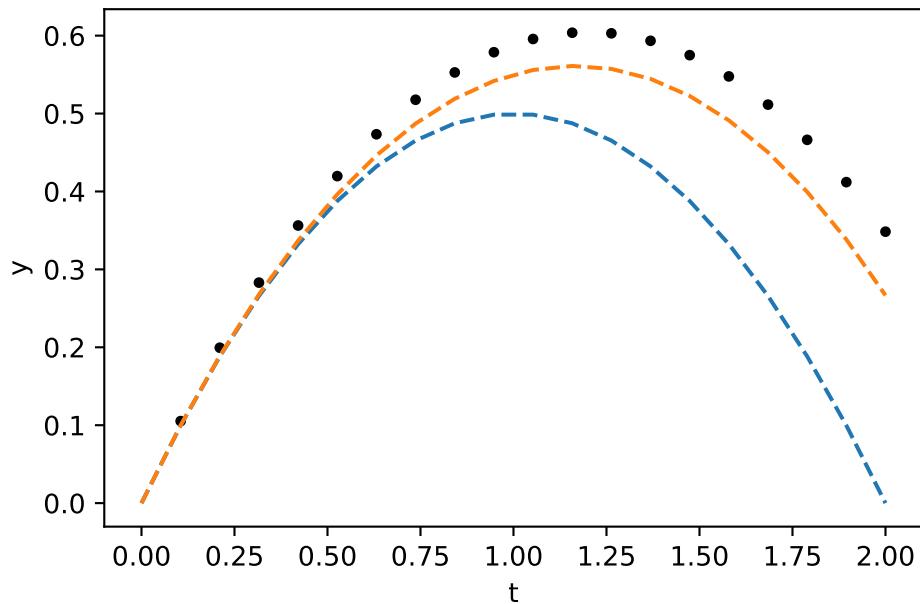
# Define function for the ODE
def f(t, Y, ep):
    y, yp = Y
    ypp = -1/(1 + ep*y)**2
    return np.array([yp, ypp])

# define the initial condition
Y = [0.0, 1.0]
ti = 0

# define the solution vector
for i in range(1, N):
    ti = ti + dt # Increment time
    Y = Y + f(ti, Y, ep)*dt # Euler step
    plt.plot(ti, Y[0], 'k.')

# Asymptotic solutions
y0 = -1/2*t**2 + t
y1 = -1/12*t**4 + 1/3*t**3
plt.plot(t, y0, '--')
plt.plot(t, y0 + ep*y1, '--')
plt.xlabel('t');
plt.ylabel('y');

```



8 Asymptotic approximations III

In Chapter 6, we studied how asymptotic expansions can be used to approximate equations like

$$\frac{d^2y}{dt^2} = -\frac{1}{(1+\epsilon y)^2}$$

by expanding the solution as $y(t) = y_0(t) + \epsilon y_1(t) + \dots$. These are known as *regular* problems because a small perturbation, ϵ , does not seem to fundamentally change the $\epsilon = 0$ solution beyond a small perturbation. This is not always the case. In *singular* problems, the situation of $\epsilon \neq 0$ is fundamentally different than the situation from $\epsilon = 0$. You have already seen such an example in Chapter 5. The equation

$$\epsilon x^2 + x - 1 = 0$$

has one root for $\epsilon = 0$ and two roots for non-zero small ϵ —even infinitesimally small values! This is quite interesting. From a wider scientific perspective, you may wonder what other problems in nature possess such singular effects.

The point of this lecture is study a technique known as *matched asymptotics*. These matched asymptotics are often necessary for singularly perturbed differential equations.

Previously in Chapter 3, we derived a basic equation that governs the temperature on the surface of the planet. This equation had the following form:

$$(\rho c_p V) \frac{dT}{dt} = E_{\text{in}}(t, T) - E_{\text{out}}(t, T).$$

For the purpose of this section, let us make up a toy model. We suggest, in non-dimensional form,

$$\begin{aligned} \epsilon \frac{dT}{dt} &= R(t) - T, \quad t \geq 0 \\ T(0) &= T^*, \end{aligned} \tag{8.1}$$

where we consider $\epsilon > 0$ and $\epsilon \ll 1$. You can think of the above model as modelling the temperature on a substance that radiates heat in a fashion proportional to itself ($-T$) and is being subjected to an (incoming) heat source, R . Let us take as an example,

$$R(t) = 1 + A \cos(t).$$

Our choice for R is not so important. This equation is, in fact, solvable in closed form (how?) but let us get additional practice solving numerically.

```

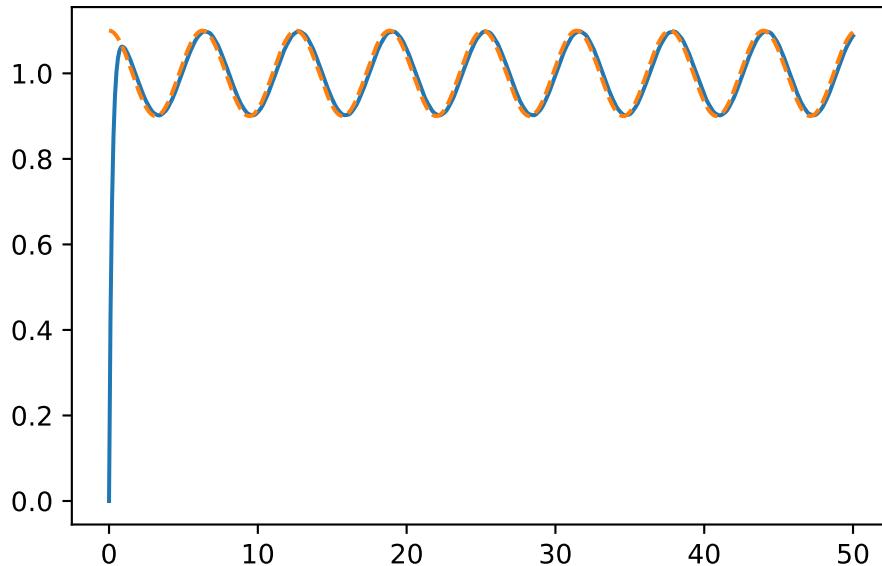
import numpy as np
import matplotlib.pyplot as plt
from scipy.integrate import solve_ivp

Ts = 0
ep = 0.2
A = 0.1
f = lambda t, T: 1/ep*(1 + A*np.cos(t) - T)

tmax = 50
sol = solve_ivp(f, [0, tmax], [Ts], dense_output=True)

t = np.linspace(0, tmax, 1000)
y = sol.sol(t)
plt.plot(t, y[0])
plt.plot(t, 1 + A*np.cos(t), '--')

```



What do we observe? If $\epsilon = 0$, then we expect the solution $T \sim R(t)$. This is shown with the dashed line. However, this solution does not satisfy the necessary initial condition. We observe that near $t = 0$, the exact solution seems to very rapidly diverge from the approximation in order to satisfy the proper boundary condition. The region in t where this rapid change occurs is called a *boundary layer*.

If we repeat the experiment with an even smaller value of ϵ , we would observe that the size of this boundary layer seems to tends to zero as $\epsilon \rightarrow 0$. This numerical experiment thus inspires

the following method.

8.1 Boundary layer theory

We seek a method that will allow us to develop a uniformly valid approximation, i.e. an approximation that is good everywhere in the relevant domain, $t \geq 0$. Begin by performing the usual asymptotic approximation:

$$T(t) = T_0(t) + \epsilon T_1(t) + \epsilon^2 T_2(t) + \dots$$

Substitution into the ODE (Equation 8.1) yields at leading order,

$$0 = R(t) - T_0(t) \implies T_0(t) = R(t) = 1 + A \cos(t).$$

As we have noted, this approximation fails to satisfy the initial condition, $T(0) = T^*$ in general. It is possible to go to higher order but this is not so important at the moment. So for now, we have obtained:

$$T_{\text{outer}} \sim [1 + A \cos t].$$

We have chosen to refer to this as the **outer** solution for reasons that will be abundantly clear. But rather than satisfying $T(0) = T^*$, this approximation has the limiting behaviour of

$$\lim_{t \rightarrow 0} T_{\text{outer}} \sim [1 + A]$$

Above, we have only included the leading term in the limit expression.

8.1.1 The inner scaling

Our intuition follows a very similar logic to the examination of the singular root in Section 5.1.1. Above, our naive assumption was that $\epsilon T'(t)$ could be ignored since ϵ is a small number. However, this may not be the case if the gradient is very large.

Our intuition further suggests that the boundary layer occurs near $t = 0$ and that it scales in size with ϵ . Therefore, let us set

$$t = \epsilon^\alpha s,$$

as a change of coordinates. We expect $\alpha > 0$ (otherwise t is not small), and within this region, we expect the new coordinate, s , to be $O(1)$ (of moderate size). We then transform the unknown function:

$$T(t) = T(\epsilon s) = U(s),$$

and seek a new differential equation for U . By the chain rule,

$$\frac{dT}{dt} = \epsilon^{-\alpha} \frac{dU}{ds}.$$

Before substituting into the equation, we are prudent to examine the behaviour of $R(t)$ near $t = 0$. We know by Taylor's theorem that

$$R(t) = 1 + A \left(1 - \frac{t^2}{2} + \dots \right).$$

Therefore, under the substitution, we may approximate R by its leading terms:

$$R(\epsilon^\alpha s) \sim 1 + A.$$

For now, we will not need more terms than this. Substituting into the ODE now gives

$$\epsilon^{1-\alpha} \frac{dU}{ds} \sim [1 + A] - U.$$

Now in order to involve the first term, it is sensible to select

$$1 - \alpha = 0 \implies \alpha = 1.$$

8.1.2 The inner equation

Therefore, the correct coordinate re-scaling was the ‘obvious’ one:

$$t = \epsilon s.$$

Substituting this again in (Equation 8.1):

$$\begin{aligned} \frac{dU}{ds} &= 1 + A \cos(\epsilon s) - U, \\ U(0) &= T^*. \end{aligned}$$

The procedure is now exactly the same. We expand

$$U(s) = U_0(s) + \epsilon U_1(s) + \epsilon^2 U_2(s) + \dots$$

At leading order, we get

$$\begin{aligned} U'_0 &= 1 + A - U_0 \\ U_0(0) &= T^*. \end{aligned}$$

The above ODE can be solved by integrating factors. Multiplying both sides by e^s , we have

$$(U_0 e^s)' = (1 + A) e^s.$$

Integrate and use the initial condition:

$$U_0(s) = (1 + A) + (T^* - (1 + A)) e^{-s}.$$

This is exactly what we expect. Notice that

$$\lim_{s \rightarrow \infty} U_0(s) = \lim_{t \rightarrow 0} T_{\text{outer}} \quad (8.2)$$

therefore the outer limit of our inner solution matches the inner limit of our outer solution. In terms of outer coordinates, our inner solution is approximated as follows:

$$T_{\text{inner}} \sim (1 + A) + (T^* - (1 + A))e^{-t/\epsilon}.$$

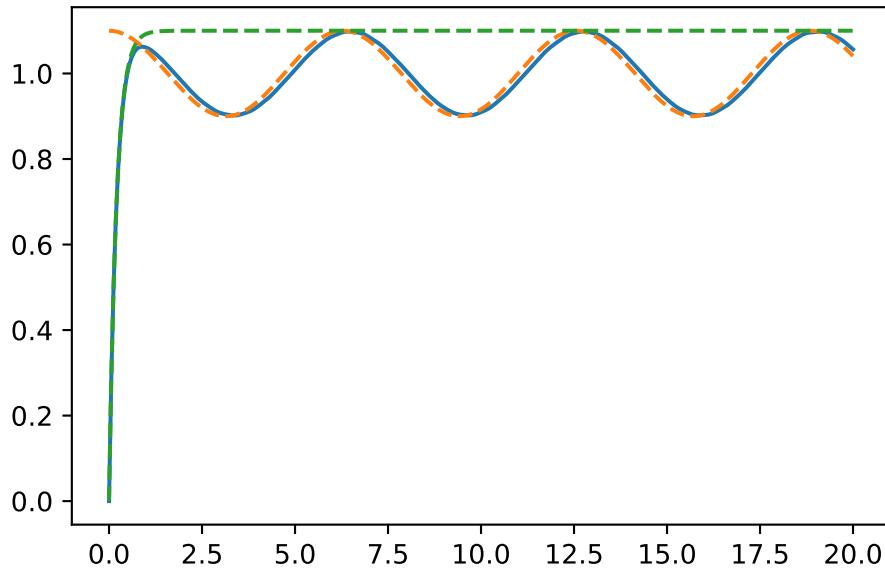
Let's finally plot this with our previous curves:

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.integrate import solve_ivp

Ts = 0
ep = 0.2
A = 0.1
f = lambda t, T: 1/ep*(1 + A*np.cos(t) - T)

tmax = 20
sol = solve_ivp(f, [0, tmax], [Ts], dense_output=True)

t = np.linspace(0, tmax, 1000)
y = sol.sol(t)
plt.plot(t, y[0])
plt.plot(t, 1 + A*np.cos(t), '--')
plt.plot(t, (1 + A) + (Ts - (1 + A))*np.exp(-t/ep), '--')
```



It works beautifully!

8.1.3 Summary

Let us summarise the procedure of matched asymptotics.

1. Expand the solution of the differential equation naively in the typical asymptotic expansion (e.g. in powers of ϵ).
2. Notice that the approximation does not satisfy certain boundary conditions.
3. Re-scale the coordinates in the ‘inner’ regions.
4. Develop an inner solution that satisfies the boundary condition. Ensure it matches the outer solution.

You will get more practice of this procedure in the problem sets.

9 Problem class 2

10 Nonlinear root finding

Before we move on back to the subject of applications, it is worth providing an introduction to methods for solving nonlinear equations. Many problems you will encounter in applications, including for ordinary or partial differential equations, can be re-formulated as the solution of a nonlinear system of equations.

Newton's method is the most well-known scheme for solving nonlinear equations. Suppose we wish to solve the scalar equation,

$$f(x) = 0,$$

given some initial guess, $x = x_0$, of the root. Suppose the root lies at $x = x^*$. Then by Taylor's theorem,

$$f(x^*) = f(x_0) + f'(x_0)(x^* - x_0) + O(f''(x_0)(x - x_0)^2).$$

If we assume the quadratic terms are negligible then solve for x^* this gives

$$x^* \approx x_0 - \frac{f(x_0)}{f'(x_0)}.$$

There is a geometrical interpretation of the above. Essentially, in order to estimate the root of $f(x) = 0$, we have used the tangent line at the point $x = x_0$, and used the intersection of this tangent line with the axis as the approximation. This procedure can then be iterated.

Thus, provided that the desired root, x^* , is such that $f'(x^*) \neq 0$, and x_0 is sufficiently close to x^* , then the following iterates converge to the root:

$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}.$$

10.1 Demo of Newton's method for scalar equations

Here is a simple demonstration of Newton's method in order to solve for one of the roots of the following:

$$f(x) = x^3 + x - 1.$$

We will start with the initial guess of $x_0 = 0$. We can do this by hand in lectures using a pocket calculator. The solution is $x^* \approx 0.6823278..$

i	xi	f(xi)	f'(xi)	-f(xi)/f'(xi)	error
0					
1					
2					

```

import numpy as np

x0 = 0
N = 10

def Newton(f, df, x, maxiter=10):
    i = 0
    while (i < maxiter):
        err = f(x)
        x = x - err / df(x)
        print("f(x) = ", np.abs(err), ", x = ", x)
        i = i + 1
    return x, err

f = lambda x: x**3 + x - 1
df = lambda x: 3*x**2 + 1

x, err = Newton(f, df, x0, N)
print("Final approximation = ", x)

```

```

f(x) = 1 , x = 1.0
f(x) = 1.0 , x = 0.75
f(x) = 0.171875 , x = 0.686046511627907
f(x) = 0.008941036638283384 , x = 0.6823395825973142
f(x) = 2.823062168566537e-05 , x = 0.6823278039465127
f(x) = 2.839946056099052e-10 , x = 0.6823278038280194
f(x) = 2.220446049250313e-16 , x = 0.6823278038280193
f(x) = 1.1102230246251565e-16 , x = 0.6823278038280193
f(x) = 1.1102230246251565e-16 , x = 0.6823278038280193
f(x) = 1.1102230246251565e-16 , x = 0.6823278038280193
Final approximation = 0.6823278038280193

```

It is a good idea to also learn how to do this using built-in packages. The ‘fsolve’ function provides a Newton-like nonlinear solver. In fact, it can estimate the Jacobian (derivative), so only the function values need to be provided.

```

import numpy as np
from scipy.optimize import fsolve

f = lambda x: x**3 + x - 1

x0 = 1
x, info, ier, msg = fsolve(f, x0, full_output=True)

print(msg)
print(x)

```

The solution converged.
[0.6823278]

10.2 Newton's method for systems of nonlinear equations

Newton's method generalises naturally to the case of a system of equations. Suppose we wish to solve for the n unknowns $\mathbf{x} = (x_1, \dots, x_n)$ via

$$\mathbf{F}(\mathbf{x}) = \begin{pmatrix} F_1(\mathbf{x}) \\ F_2(\mathbf{x}) \\ \vdots \\ F_n(\mathbf{x}) \end{pmatrix} = 0.$$

We have, via Taylor's formula,

$$\mathbf{F}(\mathbf{x}_{i+1}) \sim \mathbf{F}(\mathbf{x}_i) + J(\mathbf{x}_i)(\mathbf{x}_{i+1} - \mathbf{x}_i) + \mathcal{O}(\|\mathbf{x}_{i+1} - \mathbf{x}_i\|^2),$$

where J is the Jacobian matrix

$$J(\mathbf{x}) = \nabla \mathbf{F}(\mathbf{x}) = \begin{pmatrix} \frac{F_1}{x_1} & \cdots & \frac{F_1}{x_n} \\ \vdots & \ddots & \vdots \\ \frac{F_n}{x_1} & \cdots & \frac{F_n}{x_n} \end{pmatrix}.$$

Therefore, Newton's method forms the iterates of

$$\mathbf{x}_{i+1} = \mathbf{x}_i - J^{-1}(\mathbf{x}_i)\mathbf{F}(\mathbf{x}_i),$$

which takes a very similar form to the scalar case.

However, solution of the inverse of J is typically inefficient, and it is better to instead solve for $\delta_{i+1} = \mathbf{x}_{i+1} - \mathbf{x}_i$ via

$$J(\mathbf{x}_i)\delta_{i+1} = -\mathbf{F}(\mathbf{x}_i),$$

and then calculate $\mathbf{x}_{i+1} = \mathbf{x}_i + \delta_{i+1}$. There are many ways of solving the above matrix problem efficiently using built-in routines that perform, e.g. Gaussian elimination.

10.3 Secant method

In many situations, evaluation of the Jacobian (or derivative) is the most time-consuming or difficult part of a nonlinear solver. Built-in solvers like ‘fsolve’, in fact, have the ability to approximate the derivative numerically.

The Secant Method is similar to Newton’s Method but replaces the derivative by a finite difference. Geometrically, the tangent line is replaced with a line through the two last known guesses. The algorithm goes as follows.

Secant method

1. Develop two initial guesses to the solution, x_0 and x_1
2. Compute

$$x_{n+1} = x_n - \frac{f(x_n)}{\frac{f(x_n) - f(x_{n-1})}{x_n - x_{n-1}}} = x_n - \frac{f(x_n)(x_n - x_{n-1})}{f(x_n) - f(x_{n-1})}.$$

11 Numerical solutions of PDEs

New material on solving PDEs in Python.

12 Problem class 3

Part III

Energy balance models

13 The basic EBM (steady-state)

Recall that we previously introduced the basic energy balance model in Chapter 3. There, we derived the basic heat equation model (Equation 3.7) for the Earth's temperature given by the following ordinary differential equation (ODE) for $T = T(t)$,

$$C \frac{dT}{dt} = Q(1 - a) - \sigma\gamma T^4, \quad (13.1)$$

where we have defined $C = \rho c_p d$ as the heat capacity of the atmosphere. Above, the solar flux, Q is often taken to be $Q = 1370/4 = 342 \text{ W/m}^2$, $\sigma = 5.67 \times 10^{-8} \text{ W/(m}^2\text{K}^4)$, and $\gamma \leq 1$ is the greenhouse gas factor.

In this chapter, we discuss some of the numerical and analytical tools at our disposal for studying the above equation.

13.1 Steady-state analysis

Previously, we have assumed that the planetary albedo, a , is constant and independent of temperature. In actuality, water can turn to snow and ice and vice versa; since snow and ice have much higher albedo than open water, then we should consider $a = a(T)$.

Let us assume that there are two relevant ranges to consider: $T < 150\text{K}$ (cold) and $T > 280\text{K}$ (hot). Let us assume that the albedo is, in these two regions:

$$a(T) \approx \begin{cases} 0.7 & \text{if } T < 150\text{K}, \\ 0.3 & \text{if } T > 280\text{K}. \end{cases}$$

The above guarantees that more energy is reflected if temperatures are low. To model this process, we can use a ramp function to specify the albedo over all temperatures:

$$a(T) = A - B \tanh(k(T - 265)). \quad (13.2)$$

where $A = 0.5$, $B = 0.2$, $k = 0.1$, and $T_0 = 265\text{K}$. Recall that the tanh function is given by

$$\tanh(x) = \frac{\sinh(x)}{\cosh(x)} = \frac{e^x - e^{-x}}{e^x + e^{-x}}.$$

Let us further assume that the system is in steady state, so that the temperature is determined by solving the equation

$$f(T) = Q[1 - a(T)] - \sigma\gamma T^4 = 0. \quad (13.3)$$

In the following code, we plot the two terms that make up f , and their intersections indicate roots of $f = 0$. We then use the Python ‘fsolve’ function to approximate the roots given initial guesses.

```
import numpy as np
import matplotlib.pyplot as plt
import scipy.optimize as sciopt

Q = 342
sigma = 5.67e-8
gamma = 0.62

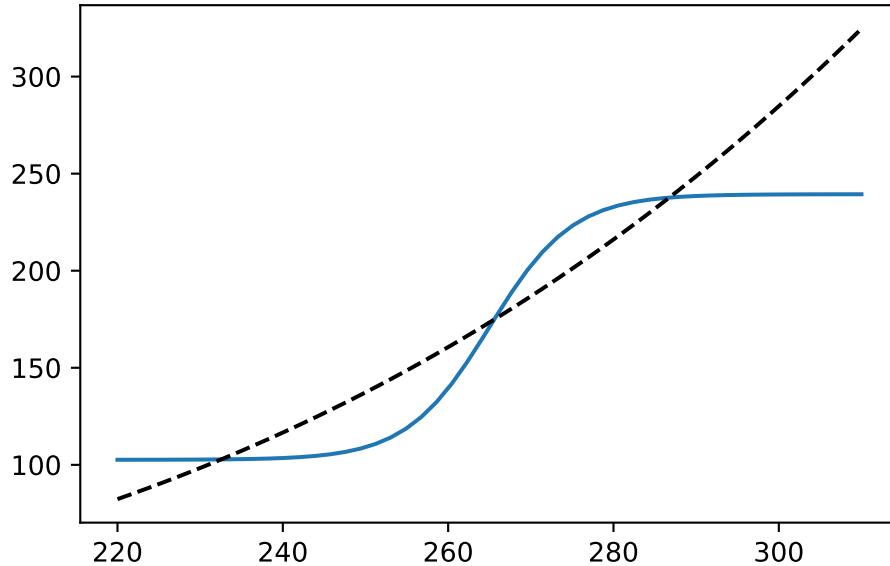
TT = np.linspace(220,310,50)

def fun(T):
    a = 0.5 - 0.2*np.tanh((T - 265)/10)
    x = (1-a)*Q
    return x
LHS = fun(TT)

plt.plot(TT, LHS)
plt.plot(TT, gamma*sigma*TT**4, 'k--')

def eq(T):
    x = fun(T) - gamma*sigma*T**4
    return x
T1 = sciopt.fsolve(eq, 230)
T2 = sciopt.fsolve(eq, 265)
T3 = sciopt.fsolve(eq, 290)
print("T1 = {:.2f}".format(T1[0]))
print("T2 = {:.2f}".format(T2[0]))
print("T3 = {:.2f}".format(T3[0]))
```

```
T1 = 232.55
T2 = 265.56
T3 = 286.74
```



Therefore multiple equilibria are observed.

13.2 Dynamics and phase line solutions

The full time-dependent model is given by

$$C \frac{dT}{dt} = f(T),$$

so we may use the positivity or negativity of f in order to sketch the time-dependent behaviour of the system.

To see this, we can perform an asymptotic analysis near the fixed points. Let the initial condition be considered near the fixed point:

$$T(t=0) = T^* + \delta,$$

where $\delta \ll 1$. Then we expand the solution into an asymptotic expansion,

$$T(t) = T^* + \delta T_1(t) + \delta T^2(t) + \dots$$

Substitution into the above ODE gives, at $O(\delta)$,

$$C \frac{dT_1}{dt} = f'(T_0)T_1,$$

and hence, with $T_1(0) = 1$, we have

$$T_1(t) = e^{f'(T_0)t/C}.$$

Therefore, depending on the positivity or negativity of the gradient function, the perturbation will either decay or grow as $t \rightarrow \infty$.

It can then be verified that the centre equilibria is unstable while the other two are stable. The higher temperature corresponds to the one that the Earth is currently in, but according to this model, there seems to be the possibility of a colder climate (50 degrees colder) where the Earth is entirely covered with snow and ice.

Interestingly, there is some evidence that the Earth's climate may have been in this so-called *Snowball Earth* state up to four times between 750 million and 580 million years ago (Neoproterozoic age). Observations of geological deposits suggest that the Earth has undergone periods of complete global glaciation where there have been very minimal biological activity. During this period, there is a massive build-up of CO₂ in the atmosphere, leading to huge greenhouse effect. As γ decreases in our model, the equilibrium can then shift, suddenly transitioning the Planet into the warm state.

13.3 Numerical continuation of the steady states

We have done a preliminary steady-state analysis of

$$Q(1 - a(T)) - \sigma\gamma T^4,$$

but we would like to better understand how these steady-states may change depending on the parameters. For example, we would like to understand how the solutions vary of the solar constant related to Q varies; or we would like to understand how solutions vary as γ varies.

More specifically, we would like to design some numerical routines that would allow us to (smartly!) solve for the roots of the above equation as the parameters are varied. Although the above problem (roots of a single equation) is simple enough to do this in a manual way, the methods of *numerical continuation* we learn in this chapter is applicable to much more general set of problems.

Suppose that we are interested in studying how the steady-states (up to three) change as Q changes. Then we are interested in producing a diagram of Q vs. T . The basic idea is to start with an initial solution at some value of Q , increment Q , then solve for the next value using the previous value as a guess. This involves the following pseudocode:

Numerical continuation

1. Input guess T_0 , f , df , parameter Q_1
 - a. Call Newton's method via $\text{Newton}(f, df, T_0, Q_1)$
 - b. Obtain a preliminary solution (T_1, Q_1)

2. Increment $Q_1 = Q_1 + dQ$
 - a. Call Newton's method via $\text{Newton}(f, df, T_1, Q_1)$
 - b. Obtain a new solution (T_1, Q_1)
3. Repeat 2 until we reach a desired Q value

The following code provides continuation for one of the roots.

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.optimize import fsolve
from scipy.optimize import root

sigma = 5.67e-8
gamma = 0.62
a = lambda T: 0.5 - 0.2*np.tanh((T - 265)/10)

Q0 = 342
Qmat = np.linspace(250, 450, 30)
Tmat = 0*Qmat

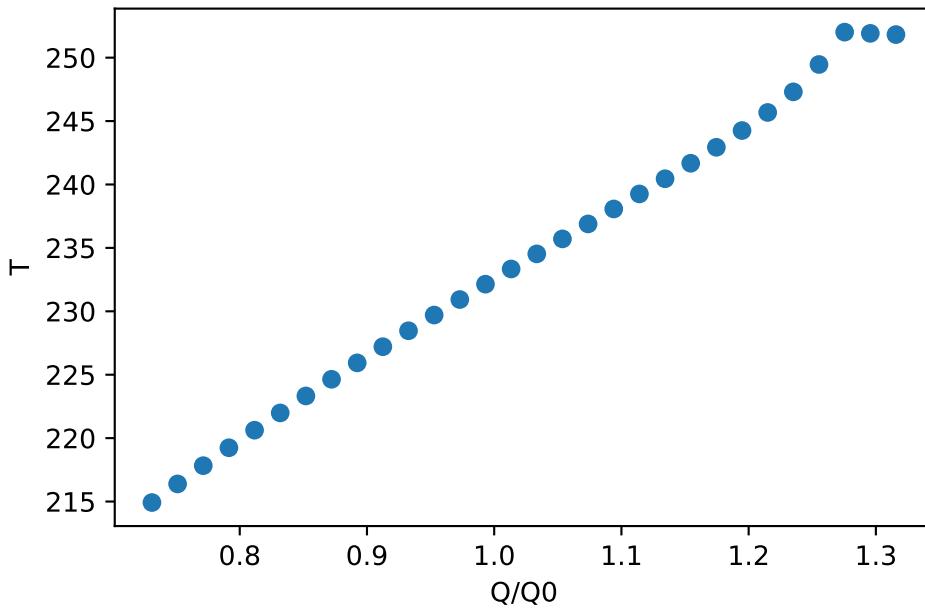
# Initial guess
x = 220
for i, Q in enumerate(Qmat):
    f = lambda T: Q*(1-a(T)) - sigma*gamma*T**4
    sol = root(f, x)
    # If solution not found, output error
    if sol.success != 1:
        print("Q/Q0 = ", Q/Q0, ":", sol.message)
    Tmat[i] = sol.x

plt.plot(Qmat/Q0, Tmat, 'o');

plt.xlabel('Q/Q0');
plt.ylabel('T');
```

```
Q/Q0 = 1.2754587618471467 : The iteration is not making good progress, as measured by the
improvement from the last ten iterations.
Q/Q0 = 1.2956241177656787 : The iteration is not making good progress, as measured by the
improvement from the last ten iterations.
```

$Q/Q_0 = 1.3157894736842106$: The iteration is not making good progress, as measured by the improvement from the last five Jacobian evaluations.



Above, we have scaled Q with the reference value of $Q_0 = 342$.

In your lecture, problem class, or exercises, you will design continuation on the other branches of solutions, and then study the result and its implications. During the lecture, we studied MA30287/notebooks/lecture13_EBM.ipynb which can be found [at this link](#).

13.4 Bifurcation diagram

In reference to the above note, the following diagram was drawn and discussed in Lecture 15.

We noted the following:

- The system has three steady states, given by the green, red, and blue curves.
- The middle state is unstable (shown dashed).
- The system exhibits hysteresis. Note that if we decrease Q/Q_0 past the tipping point, marked Q_{T1} in the image, then we would evolve to the lower stable steady state (which is the ice state). However, while we are in the ice state, if we were to attempt to increase the solar radiation to return to the green branch, we would need to arrive at Q_{T2} to do so; this irreversibility is known as hysteresis.

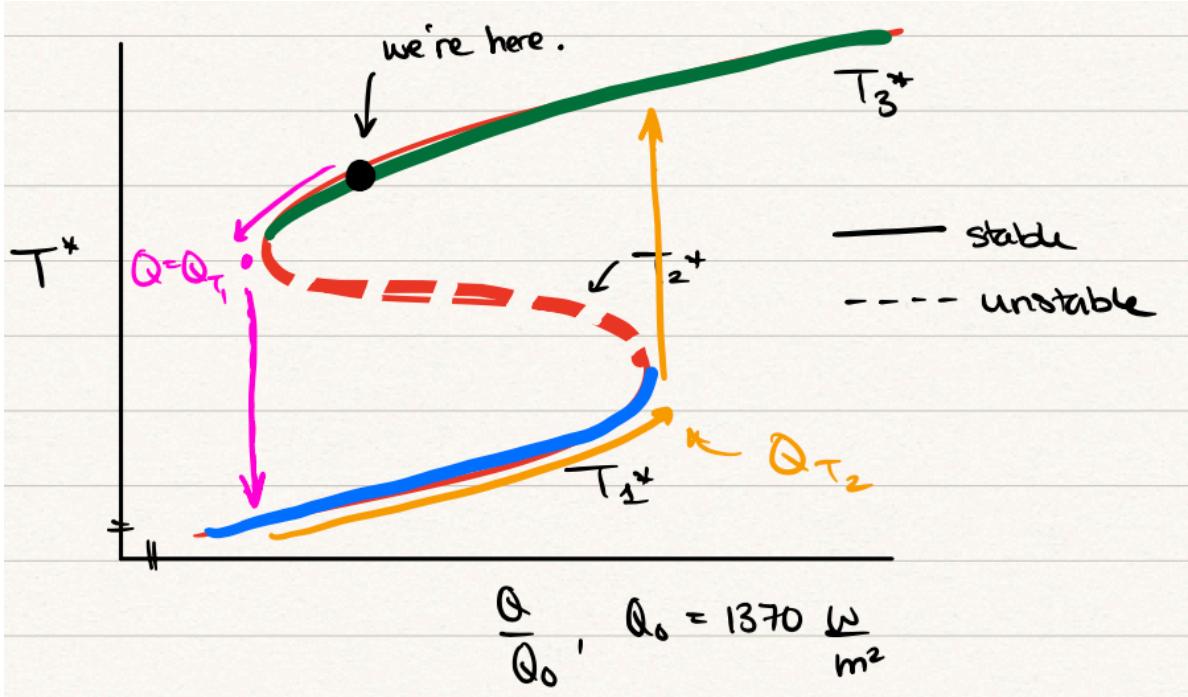


Figure 13.1: Bifurcation diagram of Q/Q_0 vs T^*

13.5 Re-scaling and Budyko's model

To model the outgoing radiation, we use the quartic Stefan-Boltzmann law. However, over the range of temperatures we are interested-in, it seems that a simpler approximation is sufficient. In your homework, you will investigate the re-scaling and shifting of temperature, such that

$$T = T_0 + [T]\tilde{T},$$

where $T_0 = 265\text{K}$. Then under the assumption that temperatures are not-so-far from T_0 , we expand

$$(T_0 + [T]\tilde{T})^4 \sim T_0^4 + 4T_0^3[T]\tilde{T} = C_1 + C_2\tilde{T}.$$

This simplifies the model considerably.

14 EBM with latitude I

We now introduce a model that allows for two additional effects: an albedo that models ice dynamics and latitude variation; and a transport term, which allows for heat movement (primarily convection).

To begin, let us use a spherical coordinate system where φ is the latitude angle, with $\varphi = 0$ at the equator and $\varphi = \pi/2$ at the North Pole. Note that this differs from the [traditional spherical coordinate system](#) where ϕ is the polar angle. It is moreover convenient to use

$$y = \sin \varphi, \quad y \in [-1, 1], \varphi \in [-\pi/2, \pi/2].$$

Our conservation equation takes the general form for the temperature, $T(y, t)$:

$$C \frac{\partial T}{\partial t} = E_{\text{in}} - E_{\text{out}} + E_{\text{transport}}, \quad t > 0 \quad (14.1)$$

where we shall use the following:

$$E_{\text{in}}(y, t) = Qs(y)(1 - \alpha(y)), \quad (14.2)$$

$$E_{\text{out}}(y, t) = A + BT, \quad (14.3)$$

$$E_{\text{transport}}(y, t) = k(\bar{T} - T), \quad (14.4)$$

{#eq-EBMlatcomp} Each of these terms we explain below in turn.

The above equation will be supplemented with initial conditions:

$$T(y, 0) = T_i(y).$$

14.1 Incoming energy

We make the following remarks about E_{in} .

- Notice that now, compared to the previous model, we have weighted the incoming solar constant Q with a term $s(y)$ and also our albedo no longer directly depends on temperature but instead depends on the latitude.
- Points on Earth that are closer to the equator receive more direct sunlight and experience more hours of daylight on average. We thus define a function $s(x)$ to account for this and consider the incoming radiation as weighted by $Qs(y)$.

- Note that the total solar input is calculated by a surface integral:

$$\int_{\theta=0}^{\theta=2\pi} \int_{\varphi=-\pi/2}^{\pi/2} Q s(y = \sin \varphi) (a^2 \cos \varphi) d\varphi d\theta = 4\pi a^2 Q \int_0^1 s(y) dy = 4\pi a^2 Q,$$

if the function $s(y)$ has been normalised appropriately so that its integral is equal to one, and furthermore the radiation is assumed symmetric about the equator.

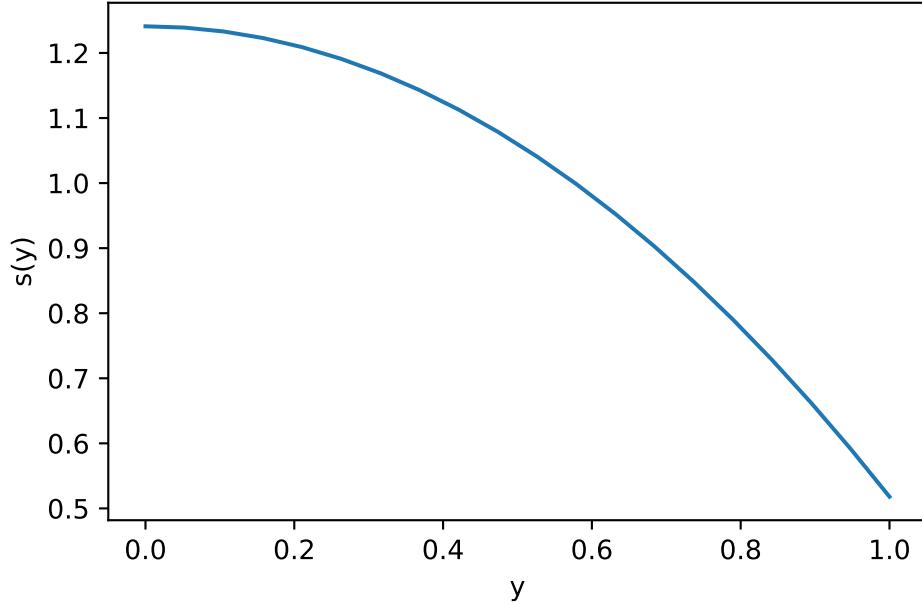
- The above is equal to the solar flux intercepted by an area of the circular disk of the earth seen by the sun, which is $\pi a^2 S$ for $S = 1370 \text{W/m}^2$. Therefore $Q = S/4 \approx 342 \text{W/m}^2$.

Finally the function $s(y)$ is fitted to data. We can assume it to be given by

$$s(y) = 1 - S_2 P_2(y), \quad S_2 = 0.482, \quad P_2(y) = (3y^2 - 1)/2. \quad (14.5)$$

```
import numpy as np
import matplotlib.pyplot as plt

y = np.linspace(0, 1, 20)
plt.plot(y, 1 - 0.482*(3*y**2 - 1)/2)
plt.xlabel('y'); plt.ylabel('s(y)');
```



We assume that an ice sheet forms if the temperature is sufficiently low, and $T < T_c = 10^\circ\text{C}$.

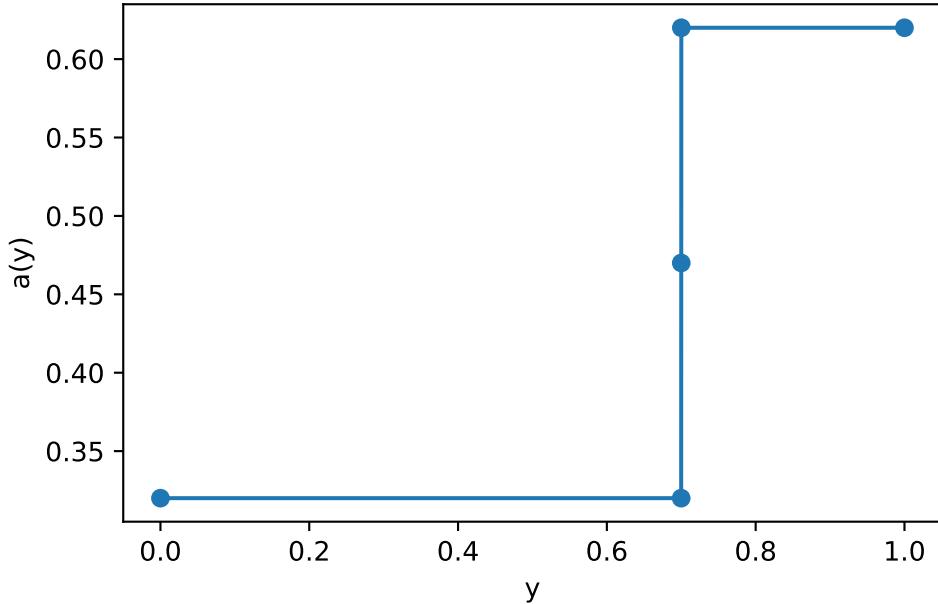
The ice forms at an ice line, where $y = y_s$. We then have the following form from the albedo:

$$a(y) = \begin{cases} a_i = 0.62 & y > y_s, \\ a_w = 0.32 & y < y_s, \\ \frac{1}{2}(a_i + a_w) & y = y_s. \end{cases}$$

Therefore we are using a discontinuous model for the albedo. Note that the ice boundary y_s is an unknown to be determined by the model.

```
import numpy as np
import matplotlib.pyplot as plt

ys = 0.7
y = np.array([0, ys-0.0001, ys, ys+0.0001, 1])
ai = 0.62; aw = 0.32;
a = np.piecewise(y, [y < ys, y == ys, y > ys], [aw, 0.5*(aw+ai), ai])
plt.plot(y, a, '-o')
plt.xlabel('y'); plt.ylabel('a(y)');
```



The above forms what is referred to as a free-boundary problem, as the boundary $y = y_s$ is solved as part of the model. Because y_s is essentially determined by where the temperature reaches the critical value, i.e. $T(y_s, t) = T_c$, then the above albedo not only depends on latitude, but also on the current temperature distribution as well.

14.2 Outgoing energy

The outgoing energy is approximated via the linear Budyko approximation discussed in Section 13.5.

$$E_{\text{out}} = A + BT,$$

where $A = 202 \text{W/m}^2$ and $B = 1.9 \text{W}/(\text{m}^2\text{C})$. These figures are taken from a 1993 paper by Graves, Lee, and North.

14.3 Transport energy

The next term we should consider is the transport. In the case of this simple model, transport is taken to be modelled via a “Newton law of cooling” type expression. We assume that

$$\text{rate of change of heat energy} = k(\bar{T} - T),$$

where it can be verified (exercise) that the global mean temperature is the same as the hemispherically averaged temperature, i.e.

$$\bar{T} = \frac{1}{\text{surface area}} \iint T S = \int_0^1 T(y) dy.$$

Above, we shall use a value of $k = 1.6B$, again estimated based on data and studies.

This completes our review of all the components ([?@eq-EBMlatcomp](#)) that make up the EBM model (Equation 14.1).

14.4 Steady-state temperature

Let $T^*(y)$ be the steady-state temperature and \bar{T}^* be the corresponding global mean temperature. Then from setting the LHS of (Equation 14.1) to zero, we have the fact that T^* is given by solving the implicit equation:

$$T^*(y) = \Phi(T^*) = \frac{k\bar{T}^* + Qs(y)(1-\alpha(y)) - A}{B + C}.$$

It is important to remember that the albedo, $\alpha(y)$, implicitly depends on T^* because at each location y , we must decide if the temperature is less or greater than the threshold T_c , which is the temperature of the ice line.

The above equation is somewhat tricky because of its implicit nature; it is made even trickier by virtue that multiple equilibria exist at the same parameter values. We will begin studying this problem, but before doing so, let us make a few remarks:

- It is possible to solve for the steady-state global mean, \bar{T}^* as a function of the ice line location, y_s .
- It is possible to solve for the ice line location, y_s , although not entirely explicitly. Up to four solutions are possible.
- Once the ice line is known it is possible to solve for the steady-state.

However:

- A numerical solution can be developed without the need to go through the above procedures.

15 EBM with latitude II

This lecture, we continue our investigation of the latitude-dependent EBM.

Latitude-dependent EBM

Our conservation equation takes the general form for the temperature, $T(y, t)$:

$$C \frac{\partial T}{\partial t} = E_{\text{in}} - E_{\text{out}} + E_{\text{transport}}, \quad t > 0 \quad (15.1)$$

where we shall use the following:

$$E_{\text{in}}(y, t) = Qs(y)(1 - a(y)), \quad (15.2)$$

$$E_{\text{out}}(y, t) = A + BT, \quad (15.3)$$

$$E_{\text{transport}}(y, t) = k(\bar{T} - T), \quad (15.4)$$

{#eq-EBMlatcomp2}

Our goal is to study the steady-state solutions, $T = T^*(y)$, given by solving the implicit equation:

$$T^*(y) = \Phi(T^*) = \frac{k\bar{T}^* + Qs(y)(1 - a(y)) - A}{B + k}. \quad (15.5)$$

Rather than doing analysis on this problem (which is quite prudent), we will take the sledgehammer approach first: we use the previous techniques of nonlinear root finding to solve the above problem.

Our algorithm is as follows. (Below, we use T to represent the steady states.)

1. First, we distribute a set of N equally spaced mesh points at the points $y = y_i$, $i = 0, 1, 2, \dots, N - 1$ with $y_0 = 0$ and $y_{N-1} = 1$.
2. We provide some initial guess of the solution, $T = T_i$, evaluated at those mesh points.
3. We compute the albedo function, $a(y_i)$.
4. We compute the mean temperature, \bar{T} .

5. We then evaluate

$$F(T_i) = F_i = T_i - \Phi(T_i), \quad i = 0, 1, 2, \dots, N-1.$$

6. Finally, Newton's method or a similar root finder is applied to solve $F = 0$. This yields a system of N nonlinear equations for the N unknowns, T_i .

15.1 Numerical quadrature

Above, one step that requires a comment is the integration for \bar{T} . There is a name for the long list of techniques of numerically calculating integrals: *numerical quadrature*. For our purposes, it is sufficient to go with a very simple approximation. In order to estimate the integral

$$\bar{T} = \int_0^1 T(y) dy.$$

we estimate its value by a Riemann sum, i.e. a sum of rectangles approximating the area:

$$\bar{T} \approx \sum_{i=0}^{N-2} T(y_i)(y_{i+1} - y_i).$$

15.2 Latitude vs. temperature-dependent albedo

During the lecture, we will also discuss the two different albedos that have been introduced, namely, the latitude-dependent version,

$$a(y) = \begin{cases} a_i & y > y_s, \\ a_w & y < y_s, \\ \frac{1}{2}(a_i + a_w) & y = y_s. \end{cases}$$

which depends on the specification of a *single* ice sheet location, $y = y_s$, where $T = T_C$. This is to be compared with the alternative definition:

$$a(T) = \begin{cases} a_i & T < T_C, \\ a_w & T > T_C, \\ \frac{1}{2}(a_i + a_w) & T = T_C. \end{cases}$$

It seems that the first definition is inferior since the second allows for multiple transitions.

15.3 Numerical implementation via Newton's method

The remainder of the lecture is devoted to following the code written in MA30287/notebooks/lecture17-latitude which you can find [here](#).

The result is a graph of $T(y)$ vs y for a set of parameters.

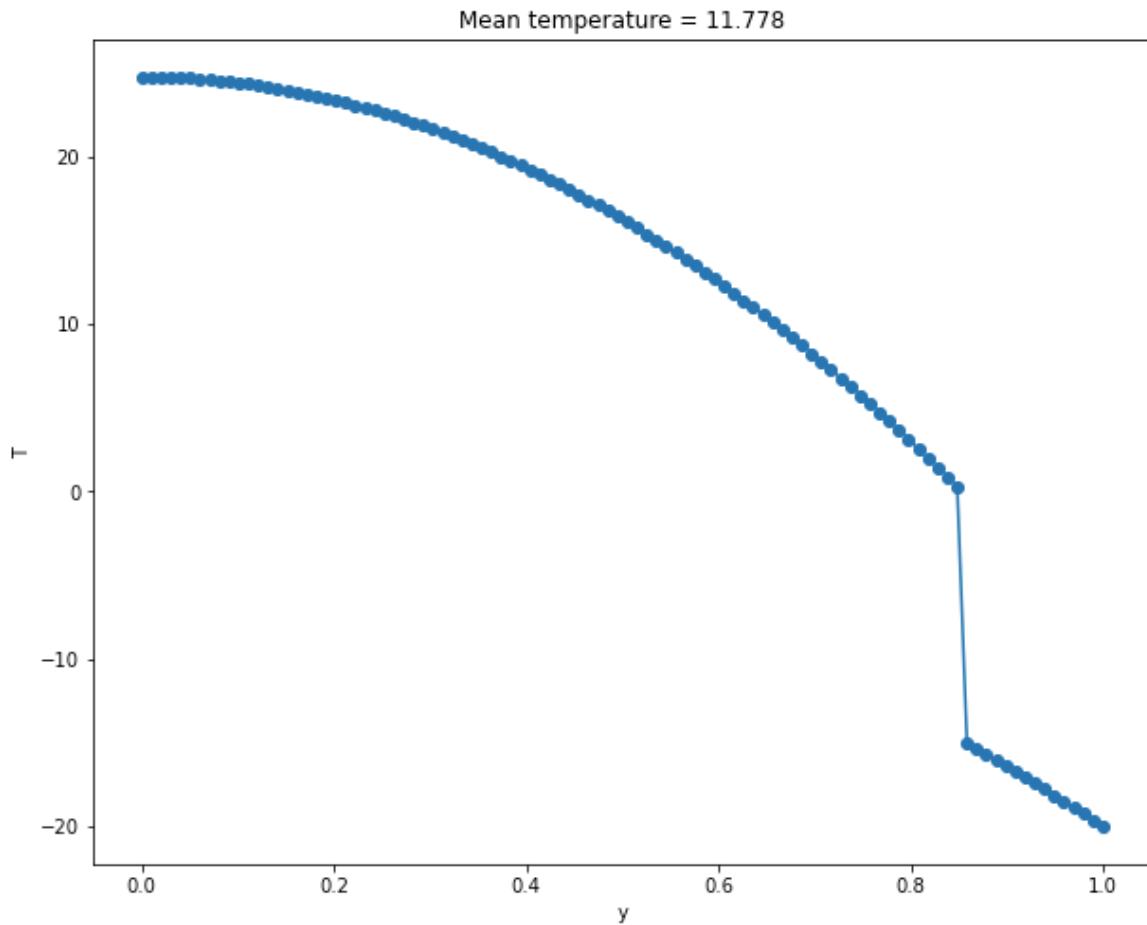


Figure 15.1: Temperature distribution

16 Problem class 4

This problem class will be devoted to getting started on problems from Problem Set 4 ?@sec-ps4.

17 EBM with latitude III

We continue our investigation of the latitude-dependent model of Chapter 15.

17.1 Placement of the ice line

Using Newton's method, we previously solved for a complete solution by starting off with a ‘lucky’ initial guess. For example, starting with a linear temperature distribution set to $T(0) = 20$ and $T(1) = -20$ we were able to converge to the profile shown below.

It is seen in the image that the ice line lies roughly at $y_s = 0.85$. Actually, this turns out to be *wrong* because the numerical method we applied previously in Chapter 15 was flawed in a very subtle way. We will eventually come to this realisation after the material from this chapter.

Interactive matplotlib plots

Note that it is now possible to gain interactivity with your `matplotlib` plots by inserting the magic command `matplotlib ipympl` at the top of your notebook files. The kernel will need to be restarted for this to take effect.

We want to know whether other solutions exist with ice lines at $y_s \in [0, 1]$.

17.2 Development of an equation for the ice line

It turns out to be possible to develop an equation for the ice line.

First, note from your problem set ?@sec-ps4 you find that it is possible to solve for the steady-state mean temperature, which we write as \bar{T}^* . In your problem set, you will develop the following equation (given by (?@eq-ps4-Tbar)):

$$\bar{T}^* = \frac{Q(1 - \bar{a}) - A}{B}. \quad (17.1)$$

The quantity \bar{a} is given by integrating the albedo as follows:

$$\bar{a} = \int_0^1 s(y)a(y) dy = a_i + (a_w - a_i)y_s[1 - 0.241(y_s^2 - 1)], \quad (17.2)$$

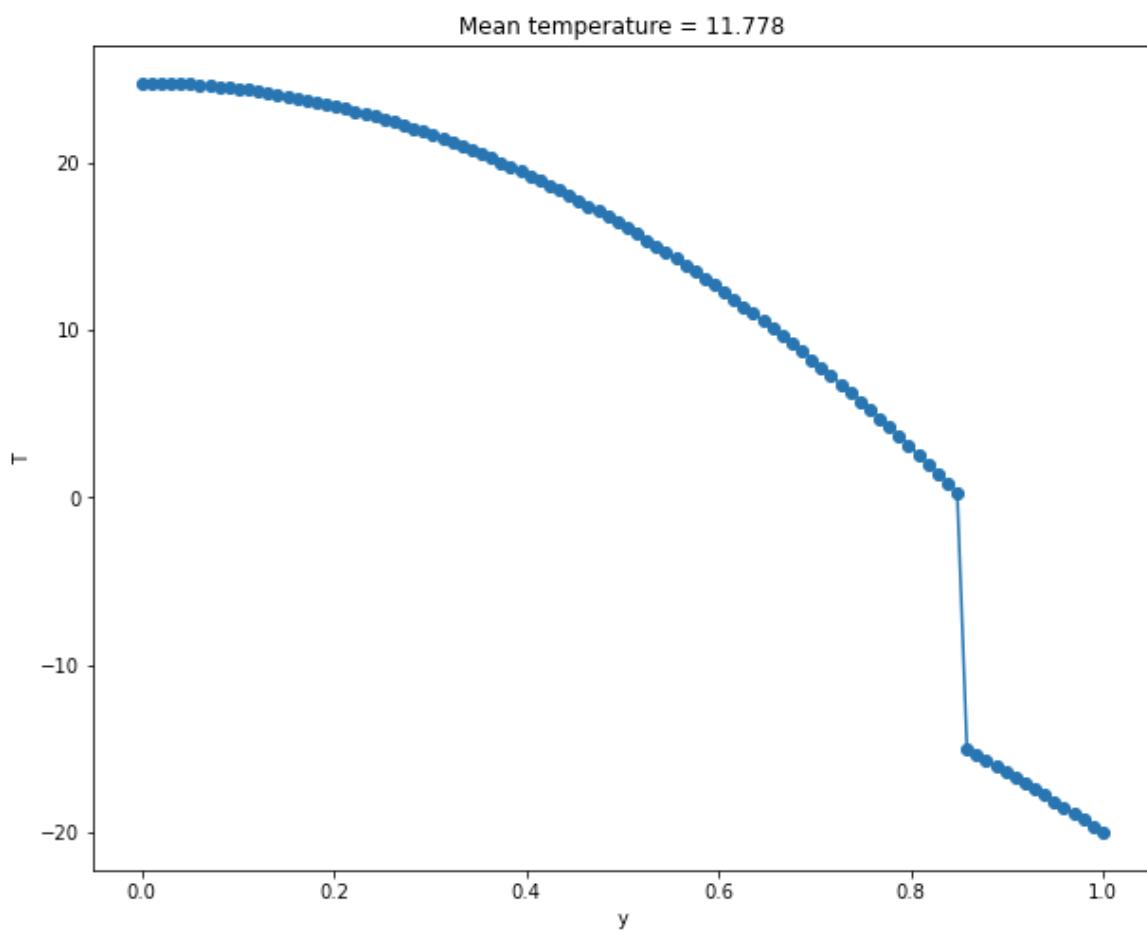


Figure 17.1: Temperature distribution

which is given by (?@eq-ps4-abar). You may check that the above formula has the right signs by considering either the complete ice case (ice line at the equator $y_s = 0$) or the complete water/land case (ice line at $y_s = 1$).

Now we return to the implicit equation for the temperature, which is given by (Equation 15.5) and repeated here:

$$T^*(y) = \Phi(T^*) = \frac{k\bar{T}^* + Qs(y)(1-a(y)) - A}{B + k}.$$

Substitute the mean temperature in, and this now yields

$$T^*(y) = \frac{Q}{B + k} \left[s(y)[1 - a(y)] + \frac{k}{B}(1 - \bar{a}) \right] - \frac{A}{B}. \quad (17.3)$$

This ice line is then found by setting $T = T_C$ at $y = y_s$ in the above formula. Notice, though, that since $s(y)$ is a cubic function, then we would need to solve a cubic equation in general.

17.3 A word about the parameter space

Solutions to our latitude-dependent EBM can be symbolically written as follows:

$$T = T(t, y) = G(y; A, b, k, C, Q, a_i, a_w).$$

As you can see, even though it is a relatively simple equation in the sense it is only an ODE in time (and does not involve any spatial derivatives in y), is still complicated because the behaviour of the system can depend in a non-trivial way on all the parameters.

You can schematically think of the solution space as being plotted in 8-dimensional space (or even higher, since the albedo a can be specified more generally). So for instance, bifurcation diagrams can then be plotted for some norm of the solution, say \bar{T} versus the seven other parameters.

There are other representations of the bifurcation diagram(s). For example, you might plot y_s vs Q or \bar{T} vs A , and so forth.

17.4 A bifurcation diagram for Q vs y_s

Returning to the ice line, we are interested in keeping all other parameters fixed, and then attempting to understand how the ice line evolves as the solar constant Q is changed. For example, we might believe that as Q increases (and hence temperatures rise), the ice line will move towards the North Pole. And as Q decreases, the ice line moves towards the equator.

We return to (Equation 17.3) and consider inverting the formulation. For each given ice line location, $y_s \in (0, 1)$, we solve for the Q value. This gives

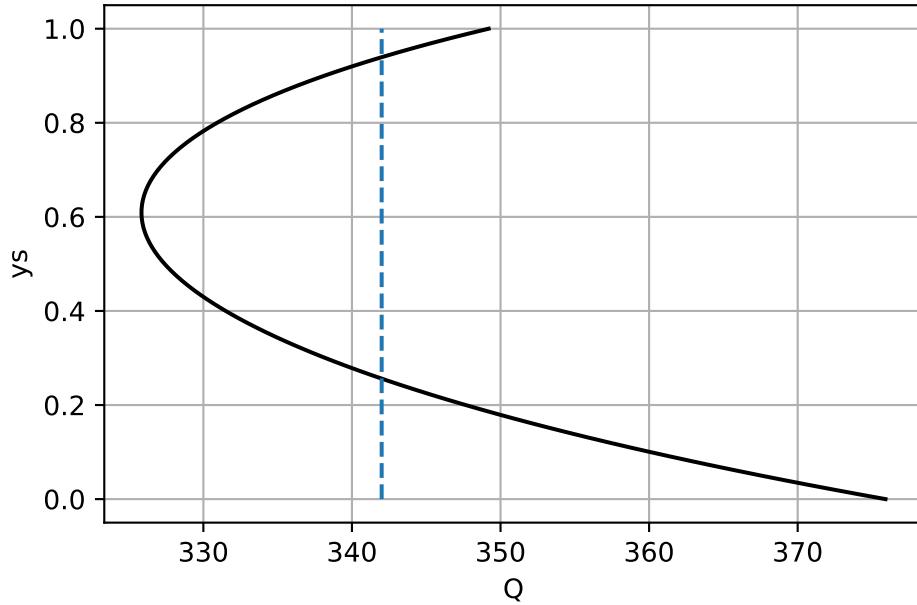
$$Q = \frac{\left(T_C + \frac{A}{B}\right)(B + k)}{s(y_s)[1 - \frac{1}{2}(a_i + a_w)] + \frac{k}{B}(1 - \bar{a})}.$$

Above, we have used the fact that $a(y_s) = \frac{1}{2}(a_i + a_w)$. This can now be plotted in Python, either in the notebook written during lectures, or via the code below.

```
import numpy as np
import matplotlib.pyplot as plt
A = 202 # outgoing radiation
B = 1.9 # outgoing radiation
k = 1.6*B # transport parameter
s = lambda y: 1 - 0.482*(3*y**2 - 1)/2 # solar weighting
aw = 0.32 # water albedo
ai = 0.62 # ice albedo
Tc = -10.0 # critical temperature for ice formation
Q0 = 342.0 # solar constant (1370 W/m^2 divided by 4)

# Note version in lectures was a 1/2 factor off on the second grouping of terms;
# now corrected to match Q6 of PS4
abar = lambda ys: ai + (aw - ai)*ys*(1 - 0.241*(ys**2 - 1))
Qfunc = lambda ys: (Tc + A/B)*(B+k)/(s(ys)*(1 - (ai+aw)/2) + k/B*(1 - abar(ys)))

# Solve for the ice line
ys = np.linspace(0, 1, 100);
Qs = Qfunc(ys);
plt.plot(Qs, ys, 'k')
plt.plot([Q0, Q0], [0, 1], '--')
plt.xlabel('Q');
plt.ylabel('ys');
plt.grid(1)
```



On the above graph, we have plotted the reference line, which is at $Q = 342$ W-m-sq. So amazingly, there are two intersections with the black curve, which in fact indicates that two ice lines seem to be possible. One ice line as y_s near 0.95 and the other has y_s much lower down and near the equator.

Moreover, the above graph is not complete! When we computed it, we specified that $a(y_s) = \frac{1}{2}(a_i + a_w)$ but this would not be true if there were no ice line, or equivalently if the ice line is located directly at $y = 1$ or $y = 0$. These yield the so-called ice-free states and ice-covered states, respectively.

17.5 Ice-free state

The ice-free state is the state for which $a = a_w = \bar{a}$ for all $y \in [0, 1]$. In this case, the solution can be directly calculated from Equation 17.3. It would then be given by

$$T^*(y) = \frac{Q(1 - a_w)}{B + k} \left[s(y) + \frac{k}{B} \right] - \frac{A}{B}.$$

This solution has a requirement, which is that when considering the solar constant Q , the solar constant cannot be so weak so that an ice line appears for $y < 1$. The minimum value of Q is therefore determined by pinning the ice line right at the North Pole. Thus

$$Q > \frac{(B + k)(T_C + A/B)}{(1 - a_w)[s(1) + k/B]} \approx 330 \text{W m}^{-2}.$$

It is of interest to verify that the global mean temperature for a system in this state is a warm 16 degrees Celsius. According to this model, then, if the mean temperature is above this value, it is possible to have a state where there is no ice anywhere!

17.6 Ice-covered state

A similar argument applies setting $a = a_i = \bar{a}$ for all $y \in (0, 1]$. In this case,

$$T^*(y) = \frac{Q(1 - a_i)}{B + k} \left[s(y) + \frac{k}{B} \right] - \frac{A}{B}.$$

This time, there is a maximal condition on Q such that any higher value would require an ice line somewhere within the domain, i.e. $y > 0$. Thus

$$Q < \frac{(B + k)(T_C + A/B)}{(1 - a_i)[s(0) + k/B]} \approx 441 \text{ W m}^{-2}.$$

Again we may verify that this corresponds to a mean temperature of -38 degrees Celsius.

```
import numpy as np
import matplotlib.pyplot as plt
A = 202 # outgoing radiation
B = 1.9 # outgoing radiation
k = 1.6*B # transport parameter
s = lambda y: 1 - 0.482*(3*y**2 - 1)/2 # solar weighting
aw = 0.32 # water albedo
ai = 0.62 # ice albedo
Tc = -10.0 # critical temperature for ice formation
Q0 = 342.0 # solar constant (1370 W/m^2 divided by 4)

Qmin = ((B+k)*(Tc + A/B))/((1-aw)*(s(1)+k/B))
Qmax = ((B+k)*(Tc + A/B))/((1-ai)*(s(0)+k/B))
print("Minimal Q for ice-free state = ", Qmin)
print("Max Q for ice-covered state = ", Qmax)

# Note version in lectures was a 1/2 factor off on the second grouping of terms;
# now corrected to match Q6 of PS4
abar = lambda ys: ai + (aw - ai)*ys*(1 - 0.241*(ys**2 - 1))
Qfunc = lambda ys: (Tc + A/B)*(B+k)/(s(ys)*(1 - (ai+aw)/2) + k/B*(1 - abar(ys)))

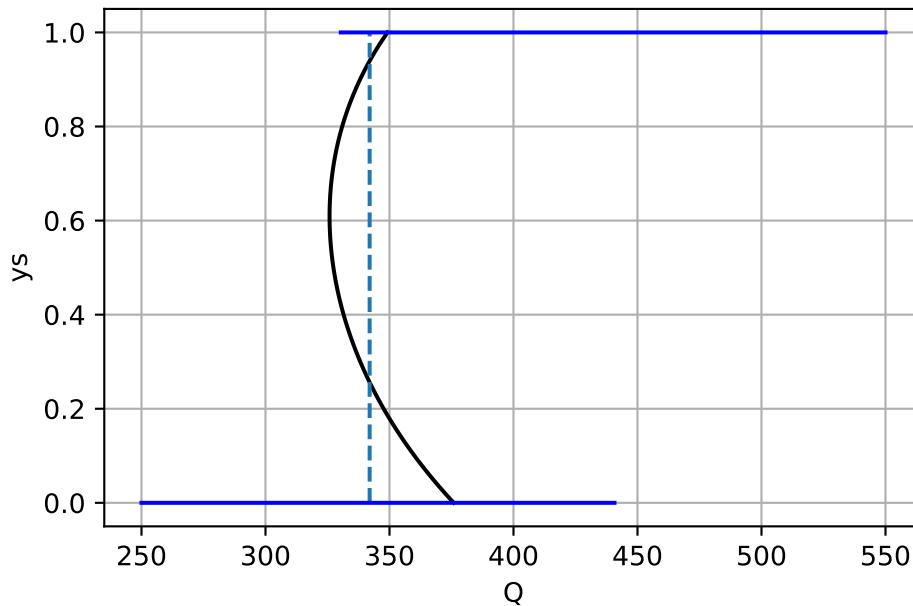
# Solve for the ice line
ys = np.linspace(0, 1, 100);
Qs = Qfunc(ys);
```

```

plt.plot(Qs, ys, 'k')
plt.plot([Q0, Q0], [0, 1], '--')
plt.plot([250, Qmax], [0, 0], 'b')
plt.plot([Qmin, 550], [1, 1], 'b')
plt.xlabel('Q');
plt.ylabel('ys');
plt.grid(1)

```

Minimal Q for ice-free state = 330.3616063989335
 Max Q for ice-covered state = 440.72694936919913



17.7 Partially ice-covered states

In lectures, we demonstrated, via the code [here](#) the four possible solutions of the latitude EBM. Two of the solutions, developed above, correspond to completely covered ice-state and ice-free states. The other two solutions are partially-iced states.

In the next chapter, we will examine the stability of these four states.

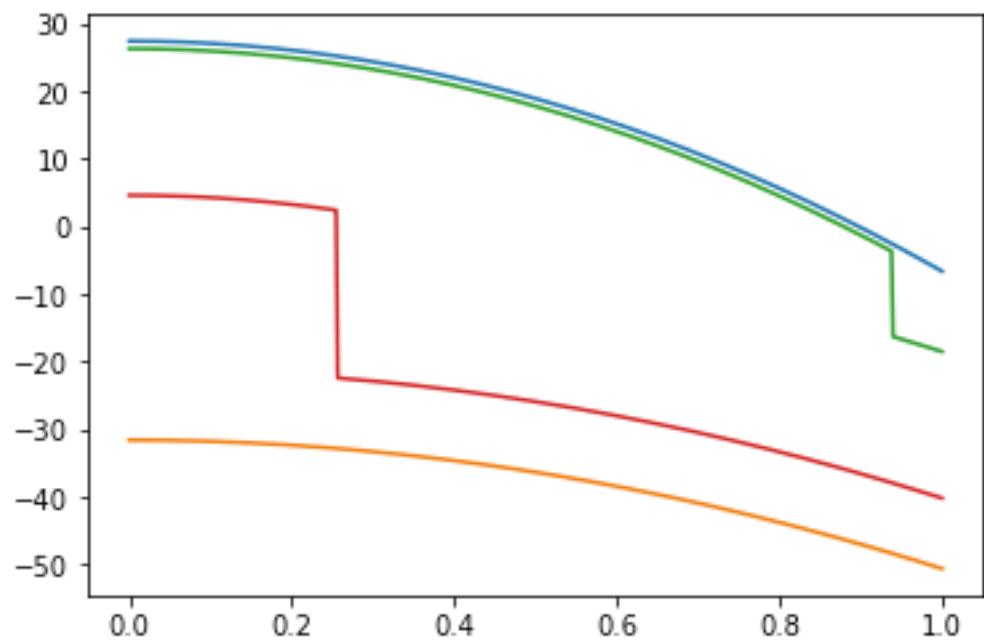


Figure 17.2: The four possible solutions; orange and blue show the completely-ice and ice-free states; red and green show the partial ice-covered state. These are shown for $A = 202$, $B = 1.9$, $k = 1.6B$, and $Q = 342\$$

18 EBM with latitude IV

18.1 Studying the mean temperature

Following the previous chapter, we now have a better understanding of the relationship between the ice line, y_s , and the solar forcing, Q . We demonstrated that for the baseline case of $Q = 342$, (at least) four solutions are possible.

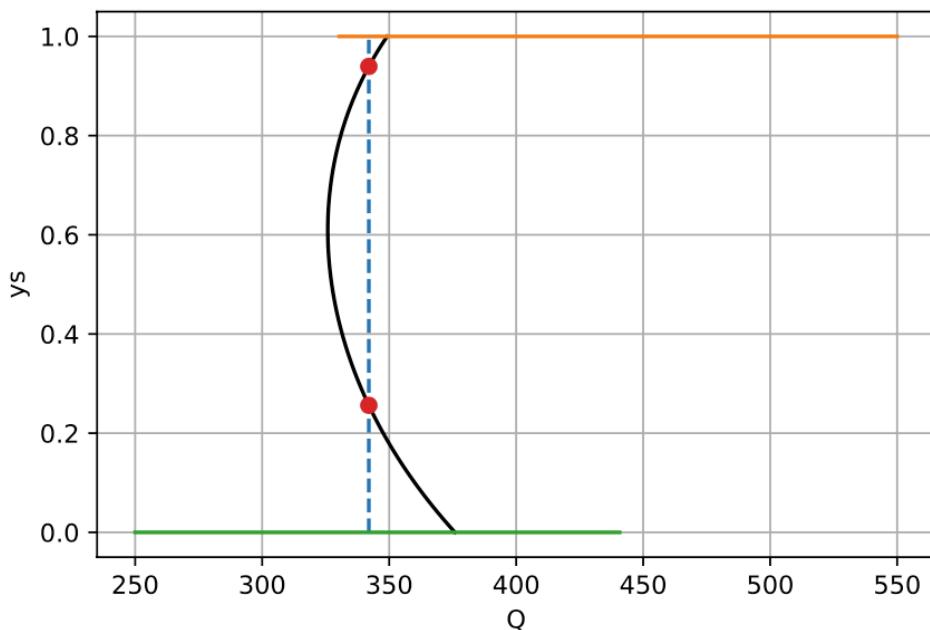


Figure 18.1: The iceline

Examination of the root shows that the two non-trivial ice lines are approximately at $y_s = 0.256$ and $y_s = 0.939$ for $Q = 342$. Using the script developed in lectures, we can study a similar graph of the mean temperature versus the solar forcing. [Jupyter hub link](#).

This yields the following picture:

During the lecture, we discussed the so-called *Snowball Earth* scenario where decreasing the solar constant may cause the stable state of the planet to jump down to the green branch

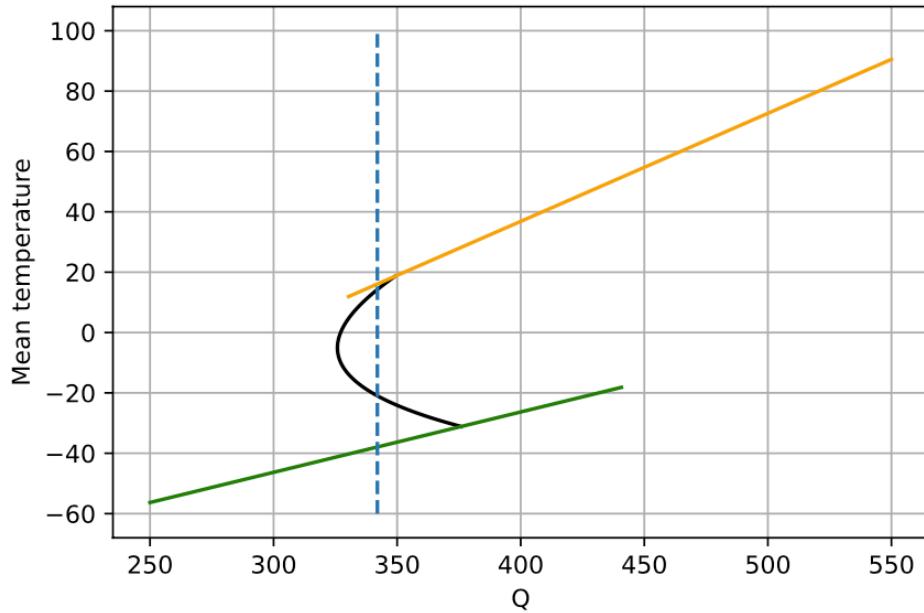


Figure 18.2: Mean temperature

shown above (completely frozen Earth). The solution exhibits *hysteresis* which describes the non-reversibility shown in the bifurcation diagram. This will be further expounded in the following discussion on stability.

18.2 Stability

So far, we have only discussed the steady-state solutions of the latitude-dependent EBM, repeated below:

$$C \frac{T}{t} = Q s(y)[1 - a(y)] - (A + BT) + k(\bar{T} - T).$$

In this section, we investigate the stability analysis for the mean temperature, \bar{T} . This was given in `?@eq-meanT-evo-ps` and repeated below:

$$C \frac{d\bar{T}}{dt} = G(\bar{T}) \equiv Q(1 - \bar{a}) - (A + B\bar{T}), \quad (18.1)$$

The following linearisation argument was presented by [Cahalan and North \(1979\)](#), with some additional details to avoid confusion. Let us linearise this about a steady-state solution, writing

$$\bar{T} = \bar{T}^* + u(t),$$

where $u \ll 1$. By Taylor series,

$$G(\bar{T}) = G(\bar{T}^*) + G'(\bar{T}^*)u + O(u^2),$$

so substitution into the ODE yields the linear equation

$$C \frac{du}{dt} = G'(\bar{T}^*)u. \quad (18.2)$$

We need to calculate the derivative term on the RHS. First, using the equation for G in Equation 18.1, we have

$$G'(T^*) = -B - Q \frac{d\bar{a}}{dT} \Big|_{\bar{T}=\bar{T}^*}. \quad (18.3)$$

The above calculation assumes that Q is a fixed number, as it should, since Q is regarded as a parameter (we choose a value of Q , then this allows us to evolve the ODE).

Calahan & North's "trick"

The following presentation took about 3 lines of text in the presentation of Cahalan & North (1979), between eqns (1.2) and (1.3) in the image below. Students have inquired about the manipulations.

In order to examine the linear stability, let $T_0 = T_0^0 + \delta(t)$, where T_0^0 is a solution to the steady-state problem. Then to the first order in $\delta(t)$,

$$C\dot{\delta}(t) + (I' - Q\bar{a}')\delta(t) = 0, \quad (1.2)$$

where a prime denotes the derivative, evaluated at $T_0 = T_0^0$. The stability is determined by the sign of the expression in parentheses. This sign can be expressed in terms of the slope of the solution curve $Q(T_0)$, as follows. Differentiating the steady-state equation $I = Q\bar{a}$ and substituting, Eq. (1.2) becomes

$$C\dot{\delta}(t) + \frac{dQ}{dT_0} \bar{a}\delta(t) = 0. \quad (1.3)$$

This last equation embodies the "slope-stability" theorem

$$\left. \begin{array}{l} \frac{dQ}{dT_0} > 0 \leftrightarrow \text{stability} \\ \frac{dQ}{dT_0} < 0 \leftrightarrow \text{instability} \end{array} \right\}. \quad (1.4)$$

Figure 18.3: From Cahalan & North, p.1179

The problem is what to do with the derivative of \bar{a} that appears in (Equation 18.3). This is a strange quantity, since \bar{a} does not explicitly depend on \bar{T} , and is given in (Equation 17.2). The issue is that there is a hidden dependence: \bar{a} depends on the ice line, y_s , which depends on not only Q , but is multivalued as well!

Cahalan & North, whether knowingly or unknowingly, applied a trick, which is to consider that Q is not a parameter, but that it can be viewed as depending on \bar{T}^* , the steady state (this dependence is shown in Figure 18.2). Therefore, Cahalan & North returned to the equation (Equation 17.1) that gives the steady-state:

$$T^* = \frac{Q(1 - \bar{a}) - A}{B}.$$

We differentiate this equation with respect to \bar{T}^* , but now assume both Q and \bar{a} depend on \bar{T}^* . This yields

$$1 = \frac{1}{B} \frac{dQ}{d\bar{T}^*}(1 - \bar{a}) - \frac{Q}{B} \frac{d\bar{a}}{d\bar{T}^*} \implies B = \frac{dQ}{d\bar{T}^*}(1 - \bar{a}) - Q \frac{d\bar{a}}{d\bar{T}^*} \quad (18.4)$$

We substitute the above value of B into (Equation 18.3), and then finally into the equation for the linearisation (Equation 18.2). Then we have

$$C \frac{du}{dt} = - \left[(1 - \bar{a}) \frac{dQ}{d\bar{T}^*} \right] u(t) = -\gamma u(t),$$

where the constant γ has been defined by the above. Thus, the solution is given by

$$u(t) = u(0)e^{-\gamma t/C}.$$

Note then that the crucial quantity is

$$\gamma \equiv (1 - \bar{a}) \frac{dQ}{d\bar{T}^*}.$$

If γ is positive, the equilibrium point is stable, while if γ is negative, the equilibrium is unstable. Because $(1 - \bar{a}) > 0$, then this yields the so-called slope-stability theorem coined by [Cahalan and North \(1979\)](#):

$$\frac{dQ}{d\bar{T}^*} > 0 \implies \text{stable}, \quad (18.5)$$

$$\frac{dQ}{d\bar{T}^*} < 0 \implies \text{unstable}. \quad (18.6)$$

We may now plot the bifurcation diagram, shown in (Q, \bar{T}) -space. First, return to Figure 18.2. In lecture 21, we drew the following picture:

Note the following characteristics.

1. There are up to four steady states (green, orange, two blacks).
2. Those branches with positive gradient are stable; there is only one branch with a negative gradient and it is thus unstable. In the image, these are shown solid for stable and dashed for unstable.

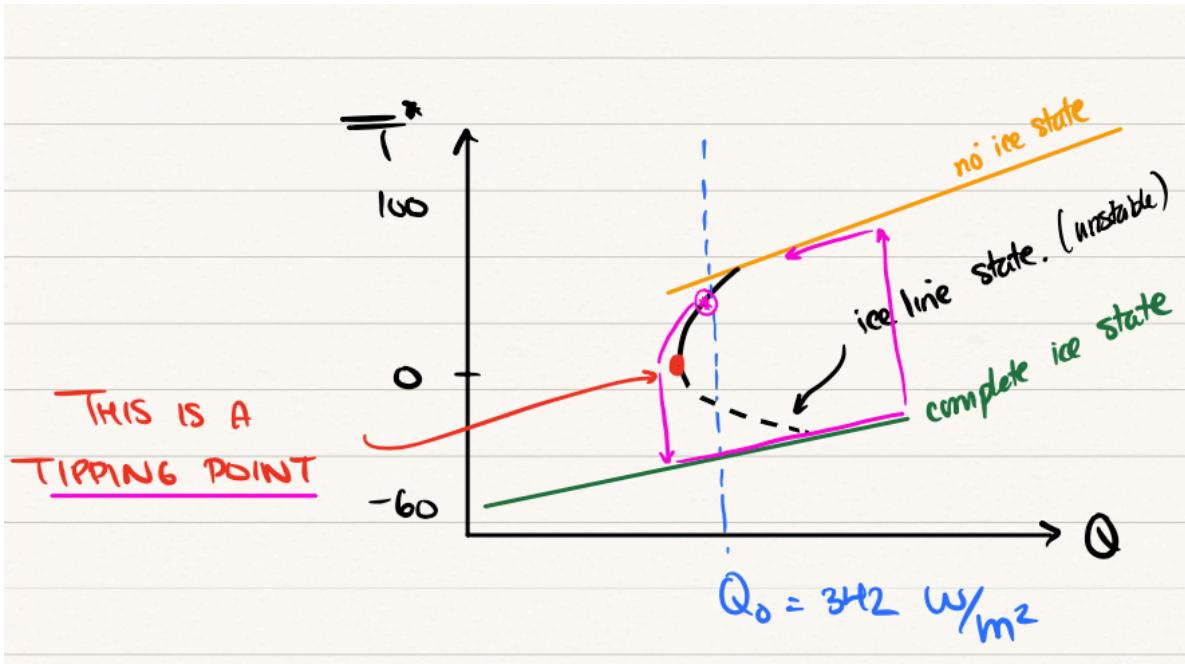


Figure 18.4: Bifurcation diagram for (Q, \bar{T})

3. The diagram indicates tipping points and hysteresis. As explained in the lectures, one can encounter a situation where, beginning from the upper orange branches, the solar radiation is decreased past the tipping point. The solution must then evolve to the lowermost stable state (green). However, increasing Q does not return us to the original non-frozen state—unless Q is increased by a massive amount. This ‘hysteresis’ loop is shown with the maroon colours in the image above.

Part IV

Box models of the ocean

19 Basic models of the ocean

19.1 Terminology and context

The ocean plays a significant role in regulating the Earth's climate, as it acts as a massive heat sink and helps to distribute heat and moisture around the planet. In addition, carbon dioxide is water soluble, and through precipitation and wave motion, is transferred into the oceans. Thus the ocean acts as a sink, absorbing large amounts of this greenhouse gas from the atmosphere.

The thermohaline circulation (THC), also known as the global ocean conveyor belt, is a complex ocean circulation pattern that is driven by differences in water temperature and salinity. It is an important component of the Earth's climate system, as it helps to distribute heat and other properties throughout the planet's oceans.

The thermohaline circulation is driven by the sinking of cold, dense water in the polar regions, which then spreads out and flows towards the equator. As the water warms and becomes less dense, it rises to the surface and returns to the poles, creating a continuous loop of ocean currents. The role of salinity in driving the thermohaline circulation is due to the fact that the dissolved salts in seawater increase its density.

This circulation pattern has a significant impact on global climate, as it helps to regulate the exchange of heat and other properties between the oceans and the atmosphere. Changes in the thermohaline circulation, such as those caused by global warming, can have far-reaching effects on the planet's climate and weather patterns.

19.2 Temperature

Extra content

The material in this subsection is not examinable in 2022-23 and is given here for further context.

In regards to the temperature, the ocean can be divided into three layers.

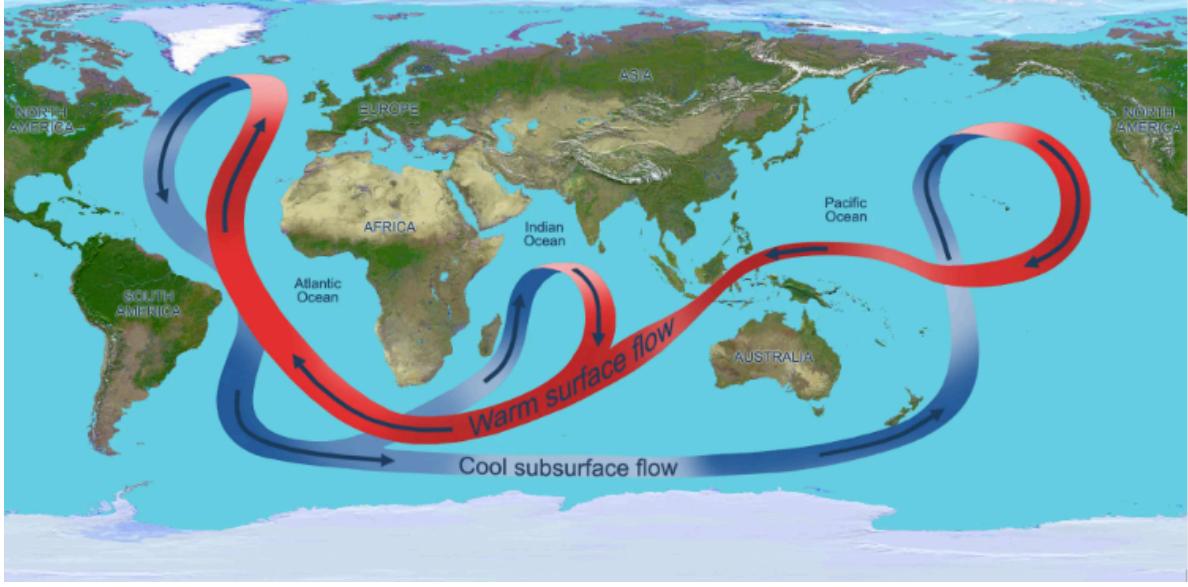


Figure 19.1: The thermohaline circulation. In the Atlantic, the circulation carries warm water (red) north near the surface and cold deep water (blue) south. Image from NASA/JPL.

1. The top layer is thin (on the order of metres) and is heated from the Sun. Mixing is a dominant effect due to wind and waves, and so the temperature in this region is mostly constant.
2. The *thermocline region* is the intermediate layer. Here, the temperature decreases approximately linearly.
3. The deep *abyssal zone* comprises 98% of the total volume of the oceans. The temperature in this region is mostly constant, and a few degrees above freezing.

Within the intermediate region, the temperature can be modelled by an **advection diffusion** equation,

$$\frac{T}{t} + w \frac{T}{z} = \kappa \frac{2T}{z^2}, \quad (19.1)$$

where w is the upswelling velocity and κ is the diffusion coefficient of the fluid.

Let us assume that the temperature in this region is near steady state and that the upwards velocity is constant. Then we integrate the ODE to find

$$T(z) = T_0 + T_1 e^{-z/z^*},$$

where T_0 and T_1 are constants. From (Kaper and Engler 2013), the typical orders for the parameters are $\kappa \sim 10^{-2} \text{ m}^2 \text{s}^{-1}$ and $z^* \sim 10^2 \text{ m}$, so $w \sim 10^{-4} \text{ m s}^{-1}$, which is quite slow.

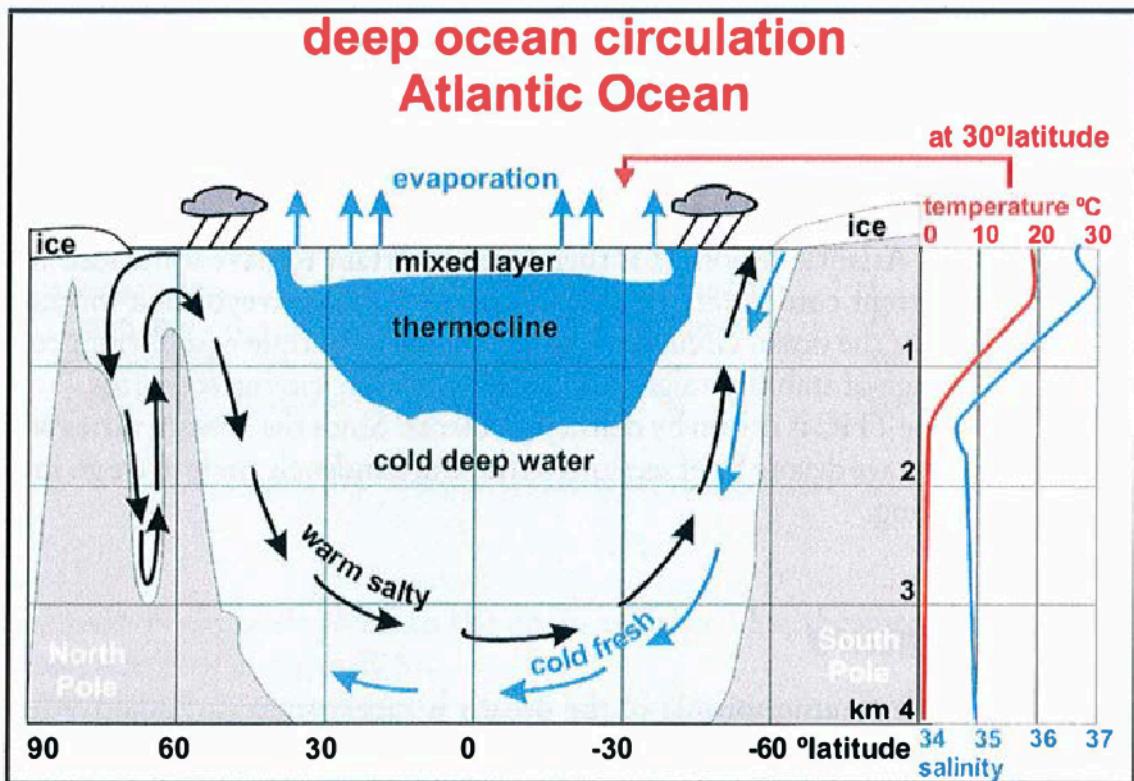


Figure 3.4. Cross-section of the Atlantic Ocean. Reprinted with permission from Seafriends.

Figure 19.2: Cross section of the Atlantic Ocean, showing the temperature and salinity profiles on the right. Image from (Kaper and Engler 2013).

19.3 Salinity and density

Salinity is a key component in the oceans since the salts have a large effect on the water density (which consequently drives motion). Salinity is measured in psu or *practical salinity units*, which is a non-dimensional ratio of conductivities. In the mixed layer, the salinity ranges from 31-39 psu, and is about 35 in the abyssal zone. You can inspect the profile in Figure 19.2.

Below in the study of the ocean, we will need a so-called *equation of state*, which connects the density, ρ , with the salinity, say S , and temperature, say T . Here is a typical graph of the relationship.

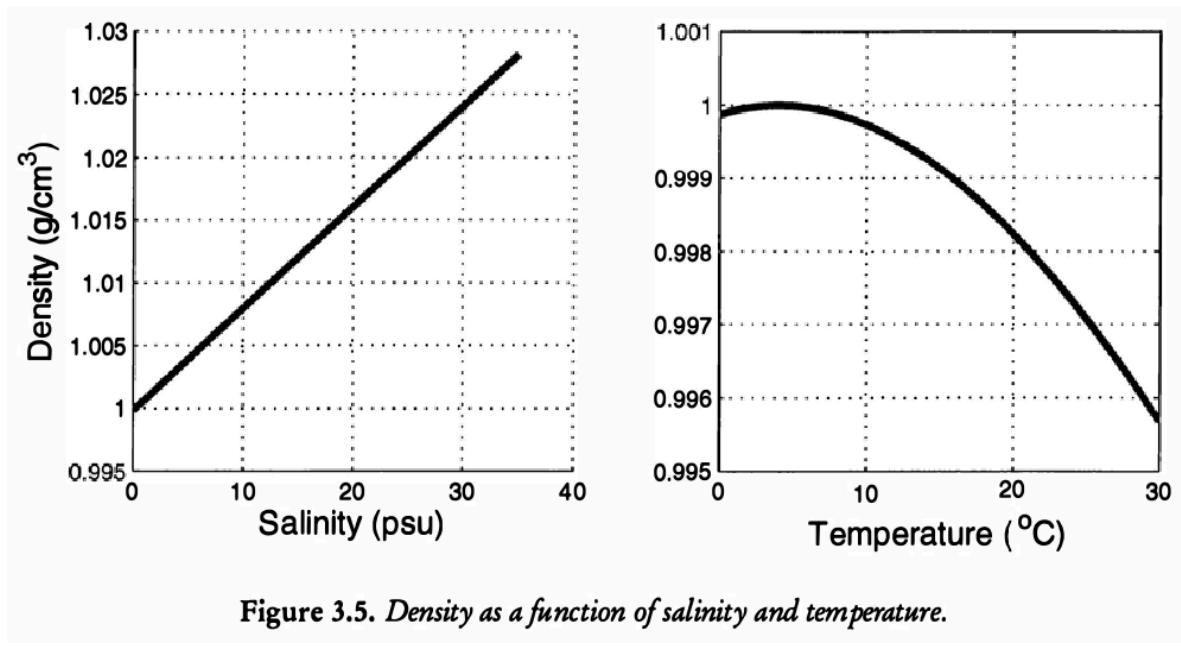


Figure 3.5. Density as a function of salinity and temperature.

Figure 19.3: Image from (Kaper and Engler 2013)

19.4 Two-box model of the ocean

Modelling the THC is a challenging task! In principal, this might involve the solution of multiple coupled PDEs for the flows and temperatures, which would then need to be solved on a very complicated domain. In addition, such models require a number of empirical equations of state (connecting density to temperature and salinity).

Toy models can be developed much more easily at the ‘systems level’ via box models.

19.5 A one-dimensional model (constant temperature)

Construction and assumptions of the box model.

- We consider two boxes, labeled ‘1’ and ‘2’, respectively via subscripts. Box 1 corresponds to high latitudes (near poles) and Box 2 to low latitudes (near equator). Each box has a corresponding temperature, T_i , and salinity, S_i . In each box, the temperature and salinities are well mixed, so they take different values in either box, in general.

Differences between the two boxes will drive a flow through the capillary pipe that connects the boxes at the bottom. A compensating flow at the surface ensures that the volume of water in each box does not change. Together, these two exchanges (top and bottom) represent the overturning circulation of the THC.

- We assume (see above) that the strength of the exchange flow between the boxes is linearly proportional to their differences of temperature and salinity. In particular, let ρ_1 and ρ_2 be the two densities in the corresponding boxes. The flow q in the capillary pipe is driven by the difference

$$q = k \frac{\rho_1 - \rho_2}{\rho_0}, \quad (19.2)$$

where k is the hydraulic constant and takes the typical value of $k = 1.5 \cdot 10^{-6} \text{ s}^{-1}$. The reference density ρ_0 is defined in conjunction with the equation of state.

In the normal state of the planet, $q > 0$ when the flow through the capillary goes in the direction of the equator as a result of higher densities at high latitudes.

- We need an equation of state that connects the densities, ρ , with the temperature and salinities. This concerns the figure Figure 19.3. We assume that

$$\rho = \rho_0(1 - \alpha(T - T_0) + \beta(S - S_0)), \quad (19.3)$$

where T_0 and S_0 are average values of temperature and salinity; ρ_0 is the density if $T = T_0$ and $S = S_0$; α and β are constants with typical values $\alpha = 1.5 \times 10^{-4} \text{ deg}^{-1}$ and $\beta = 8 \times 10^{-4} \text{ psu}^{-1}$. Combining (Equation 19.2) with (Equation 19.3) gives

$$q = k[\alpha(T_2 - T_1) - \beta(S_2 - S_1)]. \quad (19.4)$$

- External wind forces and Coriolis effects are ignored.
- We assume that in each box, there is an exchange of heat and salinity to the surrounding environment. For instance, salinity will exchange due to evaporation, precipitation, and runoff. These will have constant of proportionality of c and d in the equations below.

6. Precipitation, evaporation, and runoff from the continents and atmosphere will also cause the salinity in either box to change. We therefore assume that this is modeled by a flux H .

Remember that in general, $T_2 > T_1$ (the temperatures at the equator are higher). Consequently, evaporation dominates Box 2; there is a net loss of salt-free moisture in the atmosphere and this causes a compensating virtual flux of salt, $H > 0$, into Box 2. At the same time, there is higher precipitation and runoff into Box 1 (due to lower temperatures), causing a net gain of salt-free moisture and therefore a loss of virtual salt, say $-H < 0$. We assume these two virtual salt fluxes sum to zero.

Note that in the normal state of affairs, $S_2 > S_1$, and the lower latitude water is saltier than that of high latitudes.

An image of the box model is shown below.

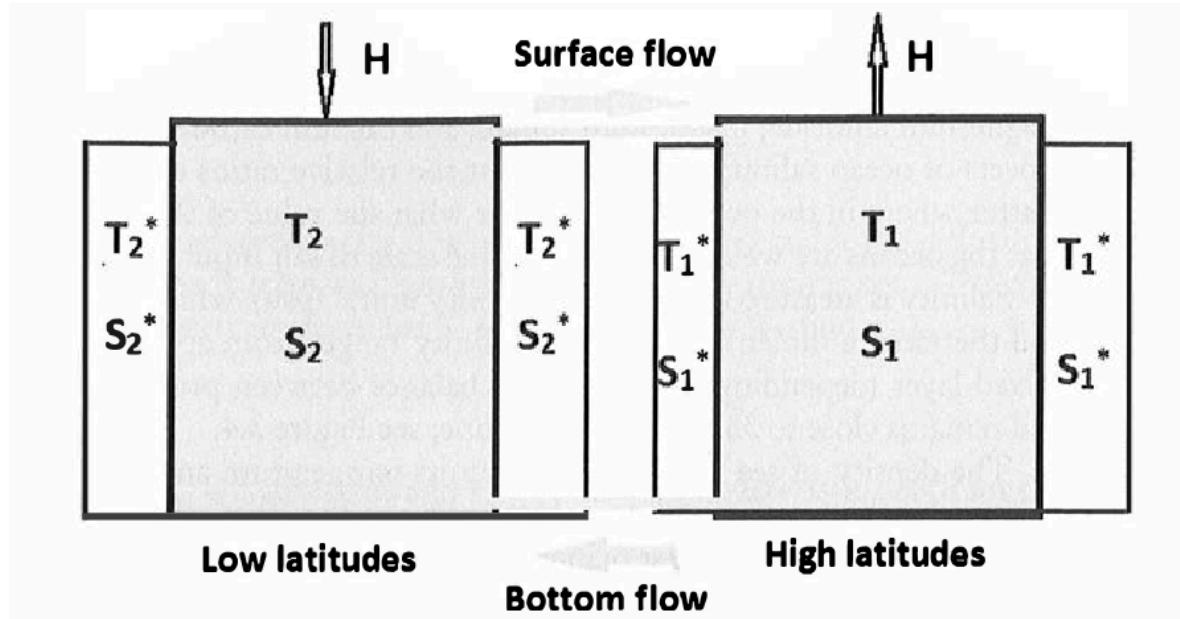


Figure 19.4: Two-box model of the North Atlantic with evaporation and precipitation. Image from (Kaper and Engler 2013)

The equations are given as follows.

$$\begin{aligned}\frac{dT_1}{dt} &= c(T_1^* - T_1) + |q|(T_2 - T_1) \\ \frac{dT_2}{dt} &= c(T_2^* - T_2) + |q|(T_1 - T_2) \\ \frac{dS_1}{dt} &= -H + d(S_1^* - S_1) + |q|(S_2 - S_1) \\ \frac{dS_2}{dt} &= H + d(S_2^* - S_2) + |q|(S_1 - S_2)\end{aligned}\tag{19.5}$$

Note that in the exchange terms corresponding to the flow q in the capillary pipes, we use an absolute value since it does not matter (flows are exchanged in both lower and upper pipes).

Note also that $q = q(T_1, T_2, S_1, S_2)$ as given in (Equation 19.4).

19.6 Reducing the equations via symmetry

By adding the equations (Equation 19.5), it can be verified that in the limit $t \rightarrow \infty$, the average temperature in the system, $1/2(T_1 + T_2)$ tends to the average temperature in the surrounding basins $1/2(T_1^* + T_2^*)$. The same conclusion can be drawn for the corresponding salinities.

It is then sensible to write all temperature and salinity in terms of this baseline scenario. So let us write

$$\begin{aligned}T_1 &= \frac{1}{2}m + U_1, \\ T_2 &= \frac{1}{2}m + U_2,\end{aligned}$$

where $m = T_1^* + T_2^*$. Then the first equation becomes

$$\begin{aligned}\frac{dU_1}{dt} &= c\left(T_1^* - U_1 - \frac{1}{2}m\right) + |q|(U_2 - U_1) \\ &= c(-T^* - U_1) + |q|(U_2 - U_1).\end{aligned}$$

where $T^* = \frac{1}{2}(T_2^* - T_1^*)$.

The analogous manipulations are done to the quantities for the salinity. In the end, if we (confusingly) re-write T for U , then we obtain

$$\begin{aligned}\frac{dT_1}{dt} &= c(-T^* - T_1) + |q|(T_2 - T_1) \\ \frac{dT_2}{dt} &= c(T^* - T_2) + |q|(T_1 - T_2) \\ \frac{dS_1}{dt} &= -H + d(-S^* - S_1) + |q|(S_2 - S_1) \\ \frac{dS_2}{dt} &= H + d(S^* - S_2) + |q|(S_1 - S_2)\end{aligned}\tag{19.6}$$

Comparing the above to Equation 19.5, the main difference is that, in expressing the temperature and salinities with respect to the average values in the basin, we have eliminated two of the constants from the set $(T_1^*, T_1^*, S_1^*, S_2^*)$ now only into two constants (T^*, S^*) .

In the situation of zero salt flux. $H = 0$, the above model reduces to Stommel's box model studied later in this course.

19.7 Analysis of a reduced 1D model for the salinity

It is possible to do some analysis on the system (Equation 19.6), though we may prefer to simply move on to study the more historically well-known reduction called *Stommel's box model*.

We make the following assumptions:

- We assume that on the timescale of interest in the THC, the temperature of each box equilibrates quickly with the surrounding basin. Therefore the system can be regarded as being in steady state.
- The difference in temperatures between the two boxes is small; together with the top assumption, this implies that $T_1(t) = -T^*$ and $T_2(t) = T^*$.
- Salinity exchanges by negligible amounts with its surrounding basin, i.e. $d = 0$

This leaves us with

$$\begin{aligned}\frac{dS_1}{dt} &= -H + |q|(S_2 - S_1) \\ \frac{dS_2}{dt} &= H + |q|(S_1 - S_2),\end{aligned}$$

where $q = k(2\alpha T^* - \beta(S_2 - S_1))$.

Now, the formulation for the salinities can be placed into a single equation for $\Delta S = S_2 - S_1$, which satisfies

$$\frac{d\Delta S}{dt} = 2H - 2k|\alpha\Delta T - \beta\Delta S|\Delta S. \quad (19.7)$$

This is now a much simpler and elegant formulation for study. Under a suitable non-dimensionalisation and scaling, we can even place the above equation in the final simplified form of

$$\dot{x} = \lambda - |1-x|x,$$

where $\lambda > 0$ (for temperatures in the usual configuration, with $T_2 - T_1 > 0$, and a suitably defined function $x = x(t)$).

20 Stommel's box model

In addition to the model studied in Section 19.7, there is another kind of reduced model that is examined in this chapter.

In his work (Stommel 1961) did not account for evaporation or precipitation, so there is no virtual salt flux, $H = 0$, but each box does exchange salinity with its surrounding environment, so $d > 0$. The set of four differential equations presented in Chapter 19 (Equation 19.6) can be reduced two coupled differential equations for the mean temperature and salinity. We notice that if we subtract the pairs of equations, then we can write

$$\begin{aligned}\frac{d\Delta T}{dt} &= c(\Delta T^* - \Delta T) - 2|q|\Delta T, \\ \frac{d\Delta S}{dt} &= d(\Delta S^* - \Delta S) - 2|q|\Delta S,\end{aligned}\tag{20.1}$$

where $\Delta T^* = 2T^*$, $\Delta S^* = 2S^*$, and we have defined the two new unknowns,

$$\Delta T = T_2 - T_1,\tag{20.2}$$

$$\Delta S = S_2 - S_1,\tag{20.3}$$

and now, the flow q is given by

$$q = k(\alpha\Delta T - \beta\Delta S).$$

20.1 Non-dimensionalisation

We can then nondimensionalise the system by setting

$$x = \frac{\Delta S}{\Delta S^*}, \quad y = \frac{\Delta T}{\Delta T^*}, \quad t' = ct,$$

where t' is nondimensional time. Dropping the primes henceforth, we have the following set of non-dimensional equations to study for the unknowns, $x = x(t)$, and $y = y(t)$:

$$\frac{dx}{dt} = \delta(1 - x) - |f(x, y)|x, \quad (20.4)$$

$$\frac{dy}{dt} = 1 - y - |f(x, y)|y, \quad (20.5)$$

{#eq-stommelsys} where we have introduced the function,

$$f(x, y; R, \lambda) = \frac{1}{\lambda}(Rx - y), \quad (20.6)$$

where there are now three non-dimensional parameters given by

$$\delta = d/c, \quad (20.7)$$

$$\lambda = c/(2\alpha k \Delta T^*), \quad (20.8)$$

$$R = \beta \Delta S^*/(\alpha \Delta T^*). \quad (20.9)$$

Together ?@eq-stommelsys and Equation 20.6 form a system of equations for $(x(t), y(t))$, with parameters δ , λ , and R .

Although there are many parameters, it is important to note that the quantity f is crucial since it corresponds to the direction of flow in the bottom pipe of the Ocean model. By convention, the system was set up so that $f > 0$ corresponds to flow through the bottom pipe goes in the direction of the equator (Box 1) as a result of higher densities at the high latitudes. We are subsequently interested in whether it is possible for f to switch sign, which would correspond to a bottom flow going from equator to poles, and the entire system switching direction.

20.2 Equilibrium states

Let the equilibrium states be given by (x^*, y^*) with $f(x^*, y^*) = f^*$. Then setting the right hand sides of (?@eq-stommelsys) to zero and solving, we find

$$x^* = \frac{\delta}{\delta + |f^*|} \quad \text{and} \quad y^* = \frac{1}{1 + |f^*|}. \quad (20.10)$$

We can solve for f^* in both equations and equate the result to one another. This gives

$$\delta \frac{1 - x^*}{x^*} = \frac{1 - y^*}{y^*} = |f^*|.$$

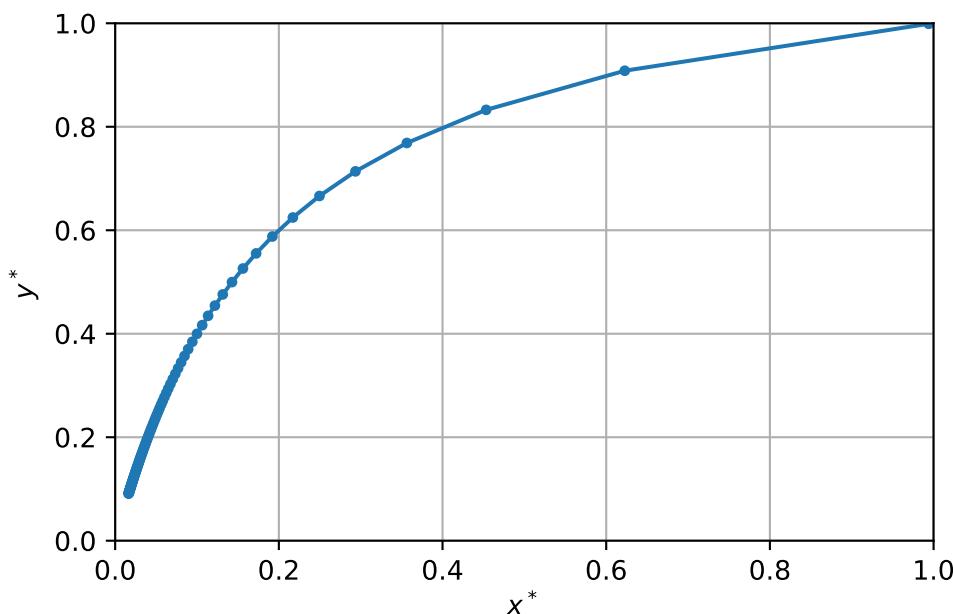
Therefore the equilibrium points lie along the above curve. Let us generate different values of f^* and plot the combination.

```

import numpy as np
import matplotlib.pyplot as plt

delt = 1/6
fmat = np.linspace(1e-3, 10, 101)
xs = delt/(delt + np.abs(fmat))
ys = 1/(1 + np.abs(fmat))
plt.plot(xs, ys, '.-')
plt.xlim((0,1))
plt.ylim((0,1))
plt.xlabel("$x^*$"); plt.ylabel("$y^*$");
plt.grid(1)

```



The above shows the steady-state values at $\delta = 1/6$. Each point refers to a different value of $|f^*|$. Note that as $|f^*| \rightarrow \infty$, then $(x^*, y^*) \rightarrow (0, 0)$ while as $|f^*| \rightarrow 0$, then $(x^*, y^*) \rightarrow (1, 1)$.

Now the above does not tell us what equilibrium states will exist at a specific value of δ since it requires information about f^* . We take (Equation 20.6) and combine with (Equation 20.10). We conclude that the equilibrium points must satisfy

$$\lambda f^* = \phi(f^*),$$

where we have defined the function ϕ according to

$$\phi(f^*) = \frac{\delta R}{\delta + |f^*|} - \frac{1}{1 + |f^*|}. \quad (20.11)$$

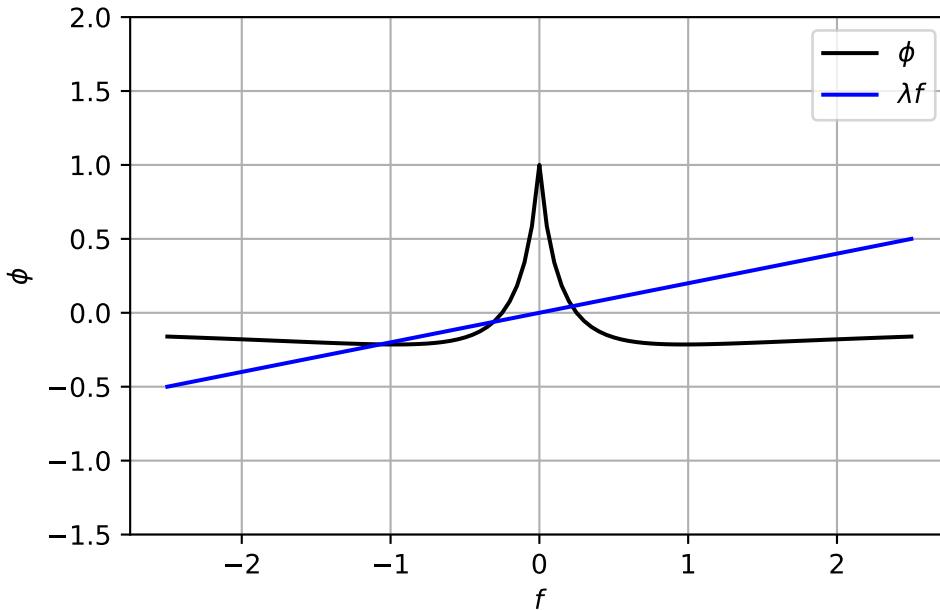
Therefore, for each combination of the parameters (λ, δ, R) , we must solve $\delta f^* = \phi(f^*)$ to determine f^* . Once the values of f^* are known, then the steady-states (x^*, y^*) are also known. Here is a typical graph showing the potential intersections at the values of $\lambda = 1/5$, $\delta = 1/6$ and $R = 2$.

```
import numpy as np
import matplotlib.pyplot as plt
import scipy.optimize as sciopt

lam = 1/5;
delt = 1/6;
R = 2;

f = np.linspace(-2.5, 2.5, 101)
phi = delt*R/(delt + np.abs(f)) - 1/(1 + np.abs(f))

plt.plot(f, phi, 'k', label='$\phi$')
plt.plot(f, lam*f, 'b', label='$\lambda f$' )
plt.ylim((-1.5,2))
plt.xlabel("$f$")
plt.ylabel("$\phi$")
plt.legend()
plt.grid(1)
```



Although there are many parameters that can alter the shape of the overall graphs, note that if λ is increased from its current value of $\lambda = 1/6$, then two of the left roots will disappear, leaving only a single root.

20.3 Stability

We let $x = x^* + \xi$ and $y = y^* + \eta$ and linearise the system about the fixed points. This gives

$$\begin{pmatrix} \dot{\xi} \\ \dot{\eta} \end{pmatrix} = A \begin{pmatrix} \xi \\ \eta \end{pmatrix},$$

where the matrix A is given by

$$A = \begin{pmatrix} -(\delta + |f^*|) \mp \frac{Rx^*}{\lambda} & \pm \frac{x^*}{\lambda} \\ \mp \frac{Ry^*}{\lambda} & -(1 + |f^*|) \pm \frac{y^*}{\lambda} \end{pmatrix}$$

if $f^* \gtrless 0$.

There are two ways of proceeding. We can numerically substitute the fixed points into the above matrix for A and then calculate the eigenvalues (numerically or otherwise). Or we can directly proceed analytically.

If proceeding analytically, we can then calculate the trace and determinant, giving

$$T = -(1 + \delta + 3|f^*|), \tag{20.12}$$

$$D = (\delta + 2|f^*|)(1 + |f^*|) \pm (1 - \delta) \frac{y^*}{\lambda}. \tag{20.13}$$

Using the above, we can analytically calculate the key discriminant expression of $T^2 - 4D$ (or numerically) in order to verify stability. The details of the classification scheme is given in the appendix Chapter 27.

For our purposes, we will mainly proceed using numerics, and bypass the need to study the above results analytically.

In the accompanying lecture script, we will obtain the eigenvalues numerically, and generate the phase plane. At the test point $R = 2$, $\delta = 1/6$, and $\lambda = 1/5$, we generate the following phase plane picture.

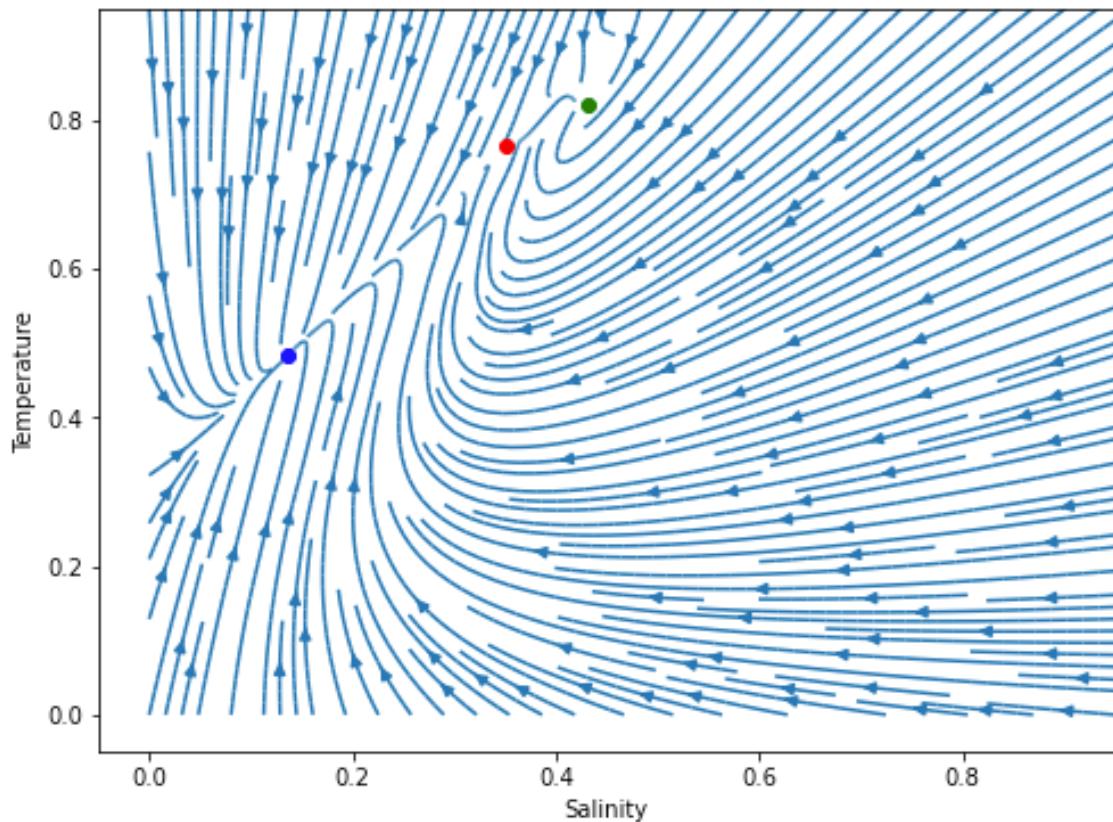


Figure 20.1: Phase plane for $R = 2$, $\lambda = 1/5$ and $\delta = 1/6$. The blue, red, and green fixed points correspond to f_1 , f_2 , and f_3 in order. The blue point is a stable node, the red point is an unstable saddle, and the green point is a stable spiral.

20.4 Bifurcation diagrams

Once the above stability analysis, it is possible to sketch the final bifurcation diagram.

First, we can note that as λ increases, the graph in Section 20.2 indicates that there may either be three intersections (as shown) or if λ increases then two of the intersections may disappear. We can note that:

f_i^*	$\lambda \rightarrow 0^+$	$\lambda \rightarrow \infty$
f_1^*	$-\infty$	none
f_2^*	fixed point < 0	none
f_3^*	fixed point > 0	0

We can also ascertain that there should be a point, say $\lambda = \lambda^*$ where the two roots coalesce, $f_1^* = f_2^*$, and thereafter disappear. This allows us to now plot the bifurcation (λ, f^*) -plane:

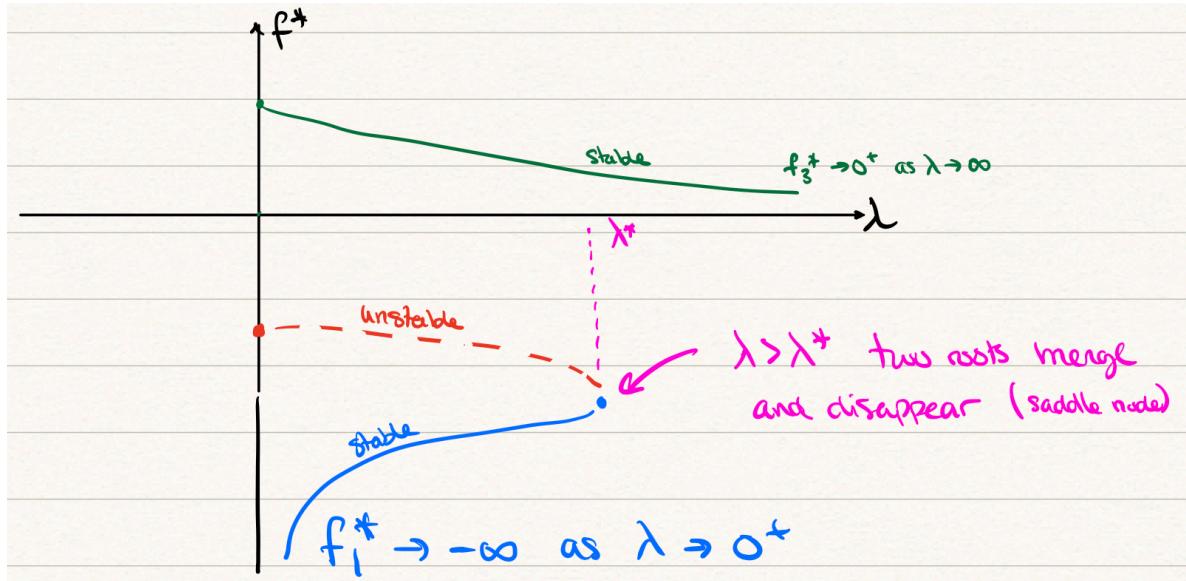


Figure 20.2

20.5 Stommel's conclusion

What is the final takeaway message(s)?

1. It is possible to pose a conceptual model of the ocean and the thermohaline circulation, which governs the exchange of hot-and-cold waters and salty waters from equatorial-to-pole zones.
2. This conceptual model suggests that tipping points and hysteresis are possible in such systems. In particular, it is possible, according to these models, for the flow directions to entirely change!

As noted by [@kaper_book]:

“Clearly, two-box models are only a caricature of the THC. At best, they account for the pole-to-equator circulation in single ocean basin (the North Atlantic). They certainly do not account for the fact that all the Earth’s oceans are connected, nor for the fact that the oceans are coupled to the atmosphere and other components of the climate system. Nevertheless, the finding that such simple models predict the possibility of two distinct stable modes of circulation, and that transitions from one more to another can be induced by changing the forcing parameters [–] has had a significant impact in oceanography and climate science.”

Part V

Exercises

Exercises and problem sets to be released as the term progresses.

21 Problem set 1

For feedback, hand in by Friday Week 3.

The intention of this problem set is to practice concepts from material related to conservation laws and non-dimensionalisation. Although these concepts seem quite separate from “Maths of Planet Earth”, actually, they form important pillars of mathematical modelling.

Q1. Bump lemma

Prove the following one-dimensional lemma, which was used in the derivation of the heat equation.

If $\int_a^b g(x) dx = 0$ for all a and $b \in [0, 1]$, then $g(x) \equiv 0$ for all $x \in [0, 1]$.

Hint: think of a proof by contradiction.

Q2. A source in the heat equation

Consider the same heat experiment discussed in Chapter 1 but now consider a bar that has an internal source or sink generating or removing heat, such as the case of a boiler with an internal heating element. By adapting a similar derivation to the one presented, explain why the modified conservation of heat equation is

$$-\frac{1}{t} \int_a^b \rho c T dx = q(x=a, t) - q(x=b, t) + \int_a^b R(x, t) dx.$$

In addition:

- a. By studying the dimensions of the other terms in the above equation, find what the dimensions of R are. What does $R > 0$ mean and $R < 0$?
- b. Hence derive the partial differential equation that governs the temperature T .
- c. By introducing the appropriate scalings on each of the variables, x , t , and T , non-dimensionalise the PDE and discuss the non-dimensional parameters (there will be two).

Q3. Choice of scalings

Consider the dimensional problem for the motion of a projectile launched from close to the surface of the Earth. The dimensional height of the projectile, $y(t)$, is given by

$$\frac{d^2y}{dt^2} = -\frac{GM}{(R+y)^2}, \quad (21.1)$$

$$y(0) = 2 \text{ m}, \quad (21.2)$$

$$y'(0) = -V_0 \text{ m/s}. \quad (21.3)$$

Assume that the Earth is spherical and of uniform density, with its mass given by $M = (4/3)\pi R^3 \rho$. Non-dimensionalise the height using $y = L\tilde{y}$ and time using $t = T\tilde{t}$. Consider the following cases:

- (i) R fixed, $V_0 \rightarrow \infty$, ρ fixed;
- (ii) R fixed, V_0 fixed, $\rho \rightarrow \infty$;
- (iii) R fixed, V_0 fixed, $\rho \rightarrow 0$;
- (iv) $R \rightarrow 0$, V_0 fixed, M fixed.

For each case:

- a. Explain the physical interpretation of the limits.
- b. Choose the scalings L and T to normalise as many terms as possible.
- c. Choose the scalings so that the time it takes for the projectile to fall should be finite for the given limit, and for the speed, acceleration, and initial height to be well behaved (finite).
- d. Write out the scaled problem and identify all remaining nondimensional parameters.
- e. Identify the limiting small parameter for each case. Write out the problem (leading-order problem) when the parameter is set to zero.

Q4. The unique timescale in the heat equation

During our investigation of the heat equation, we found that it was possible to scale time so as to scale out the only non-dimensional parameter that appears in the PDE (II). This produced (Equation 2.1). The disappearance of all non-dimensional parameters is due to the fact that only a single sensible timescale exists.

By adjusting the boundary conditions, we may create a new problem involving heat flow where a unique ‘special’ timescale can no longer be chosen.

Consider a system where one side of the rod is heated in some periodic fashion, e.g. set the initial and boundary conditions to be

$$T(x, 0) = T_0 \quad (21.4)$$

$$T(0, t) = T_a \cos(\omega t), \quad (21.5)$$

$$T(L, t) = T_b. \quad (21.6)$$

- a. What must the units of ω be?
- b. Non-dimensionalise as usual and, without selecting the timescale, $[t]$, identify the key non-dimensional parameters that remain. Write a brief sentence to describe their physical interpretation.
- c. There are two sensible choices for setting the timescale, $[t]$. Identify the two choices and present the reduced set of equations in each case.

Q5. Timescale in the surface energy

Take the basic zero-dimensional energy model studied in (Equation 3.7) for the temperature of the troposphere:

$$C \frac{dT}{dt} = \frac{1}{4} Q(1 - a) - \sigma \gamma T^4.$$

- a. Non-dimensionalise the model by choosing $T = [T]T'$, $t = [t]t'$, and $Q = [Q]Q'$. Show that it is possible to select the scalings on the temperature and time so as to completely remove all constants from the problem when Q is assumed to be constant.
- b. Thus, show that the analysis of the above equation is equivalent to studying

$$\frac{dT}{dt} = 1 - T^4,$$

where we have dropped the primes and assumed that the albedo is such that $1 - a \neq 0$.

- c. From your choice of $[t]$, estimate the typical dimensional value using $d \approx 10\text{km}$, $\rho \approx 1\text{kg m}^{-3}$, $c_p \approx 10^3 \text{J kg}^{-1} \text{K}^{-1}$.

Use a pocket calculator to verify your calculations and conclude that this time-scale is on the order of a month. What is the relevance of this approximation as it concerns the steady-state solution?

22 Problem set 2

For feedback, hand in by Friday Week 4.

The intention of this problem set is to practice concepts from Chapter 5 (asymptotic approximations of algebraic equations) to Chapter 7 (Euler's method and numerical solutions of differential equations). These techniques form some of the most powerful techniques at your disposal in applied maths.

22.1 Getting started with Noteable

Use your [Moodle course page](#) to access the Noteable Python interface by clicking on the appropriate link in the course materials. Follow the instructions on the Moodle page to add the Git repository to your directory.

1. Navigate to the welcome screen for MA30287 and follow the instructions in `Welcome.ipynb` and `FirstTimeSetup.ipynb` in order to create your own local directory at `/MA30287_workspace/`
2. Navigate to the workspace folder. Click `New -> Notebook`. If asked, select the kernel `Python 3 (ipykernel)`.
3. In the first line of input, select, in toolbar `Code -> Markdown`. This allows you to annotate your notebook with Markdown-style text input.

In the first line of input, type `# Problem set 2`. Then either type `Shift + Enter` or press the play button which will execute the line(s) of input. Your markdown text should render as a nicely formatted entry.

4. Rename the file to something appropriate, like `ps02_scripts`. You can do this by right-clicking the filename in the file manager and selecting `Rename`.

Proceed to the next question.

22.2 Testing the solutions of a cubic

In this question, you will develop the numerical solutions for the roots of the cubic equation:

$$\epsilon x^3 - x + 1 = 0, \quad \epsilon > 0$$

Type the following code into your Jupyter notebook. This code uses a command, which you will learn in a later week, called `fsolve`, in order to solve nonlinear equations. When writing the below code, you may want to separate the import commands into their own input field in the notebook.

```
import numpy as np
from scipy.optimize import fsolve

ep = 0.1          # epsilon value
xguess = 1.1      # Initial guess of root

f = lambda x: ep*x**3 - x + 1
xsol = fsolve(f, xguess)
print("Solved root at x = ", xsol)
```

Solved root at x = [1.15346731]

22.3 Analysis of singular cubic equation

Consider the cubic equation

$$\epsilon x^3 - x + 1 = 0,$$

with $\epsilon \ll 1$ and $\epsilon > 0$.

1. Develop the first three terms of an asymptotic expansion about the root by setting

$$x = x_0 + \epsilon x_1 + \epsilon^2 x_2 + \dots$$

2. Fill out the following table.

ϵ	x_{exact}	$x_{\text{exact}} - x_0$
0.1	—	—
0.08	—	—
0.06	—	—

ϵ	x_{exact}	$x_{\text{exact}} - x_0$
0.04	—	—
0.02	—	—

Use your code in Section 22.2 to input numerical approximations to the above entries.

Create a graph **by hand** of the data (it does not have to be extremely accurate), as plotted in the $(\epsilon, x_{\text{exact}} - x_0)$ -plane. Fit a line to this graph and estimate the gradient. Is this consistent with what you derived above?

3. By rescaling x appropriately in terms of ϵ , derive the first three terms of the asymptotic approximations of the remaining roots.

22.4 A damped projectile problem

In Chapter 6 you performed the asymptotic analysis for a projectile. The small parameter was ϵ and represented $v_0^2/(gR_E)$ (a parameter that includes the initial velocity, v_0 , gravity g , and the radius of the Earth, R_E).

If air resistance is included, then the non-dimensional toy model is instead

$$\begin{aligned} \frac{d^2y}{dt^2} &= -\frac{1}{(1+\epsilon y)^2} - \frac{\alpha}{(1+\epsilon y)} \frac{dy}{dt}, \\ y(0) &= 0, \\ y'(0) &= 1. \end{aligned} \tag{22.1}$$

where $\alpha \geq 0$ is the parameter that controls air resistance.

1. Begin by assuming that α is a fixed number and consider the limit where $\epsilon \ll 1$. Find a **one-term** asymptotic expansion of the solution for small ϵ .
2. (**Challenging**) Is the effect of the air resistance to increase or decrease the flight time? Justify based on your analytical solution.

22.5 ODE solvers and Euler's method

Return to the setup of the above question.

1. Modify the script shown in Section 6.2 in order to solve the initial-value problem from the previous question at a prescribed value of ϵ and α .

2. Using **a pocket calculator** (or your phone calculator) apply Euler's method with $\Delta t = 0.2$, $\epsilon = 0.2$, and $\alpha = 1$ to determine the position of the projectile at $t = 0.6$.
3. Compare your hand calculation with the result from the Python output, as well as with your asymptotic approximations.

23 Problem set 3

For feedback, hand in by Friday Week 5.

In Chapter 8 we discussed how the zero-dimensional energy equation occurs in the form of

$$(\rho c_p V) \frac{dT}{dt} = E_{\text{in}}(t, T) - E_{\text{out}}(t, T).$$

This is oversimplistic since in actuality, your temperature function, T , should also depend on space. For instance, if you are interested in modelling T with a depth coordinate, then it would be $T(z, t)$. In this case, we know that temperature would be governed by a second-order differential equation (in space) such as the kind that appears in (Equation 1.1).

In this problem set, we will make up a toy example of a differential equation that might be encountered in heat flow. Consider now (in non-dimensional coordinates):

$$\frac{T}{t} = \epsilon \frac{2T}{z^2} + 2 \frac{T}{z} + T = 0,$$

which is determined for some function $T(z, t)$. Here, the small parameter $\epsilon > 0$, $\epsilon \ll 1$, is linked to the heat diffusion.

We will study the steady-state version of the problem. So consider only $T = T(z)$. We will make up some boundary conditions as well.

$$\begin{aligned} \epsilon T'' + 2T' + T &= 0, \\ T(0) &= 0, \\ T(1) &= 1. \end{aligned} \tag{23.1}$$

The challenge is to study the above problem for small values of ϵ .

Q1. Conversion to first-order system

By using the procedure reviewed in Section 6.2, convert (Equation 23.1) to a first-order system of equations.

Q2. Numerical solutions

The problem Equation 23.1 is a different kind of problem than you may have encountered previously. Previously, you have encountered initial-value problems (IVPs), where the solution is entirely specified by initial conditions at a single point. This is a boundary-value problem (BVP), where the solution is required to satisfy values at multiple points.

During lecture 12/problem class 3, we will describe how the BVP can be solved using the **Shooting Method**. The Shooting Method uses the following algorithm.

Pseudocode for the Shooting Method

1. Input an initial guess, a , of $T'(0) = a$.
2. Solve the ODE as an initial-value problem using the two boundary conditions of $T(0) = 0$ and $T'(0) = a$. Solve on the domain z in $[0, 1]$.
3. Set $F = T(1) - 1$
4. Apply a Newton solver to solve $F = 0$.

Write a numerical code to solve (Equation 23.1) using a Shooting Method. Use your code to investigate the solution profiles for different values of ϵ .

Q3. Investigation of the boundary layer

Using your code, use the following command in order to investigate the maxima (x_m, T_m) as ϵ varies:

```
ind = np.argmax(Y[0])
print(ep, z[ind], Y[0, ind])
```

You may want to consider, as an example, the values $\epsilon = \{0.05, 0.1, 0.15, 0.2\}$ and fill the following table.

ϵ	x_m	T_m
0.05		
0.1		
0.15		
0.2		

Create a plot of (ϵ, x_m) and discuss the observed trend and its implications.

Q4. Outer asymptotic solutions

Begin by setting

$$T = T_{\text{outer}} = T_0(z) + \epsilon T_1(z) + \epsilon^2 T_2(z) + \dots$$

Substitute the above expansion into the system and solve for the first two orders.

You may verify that the solution is given by

$$T_0 = e^{1/2} e^{-z/2}, \quad (23.2)$$

$$T_1 = -\frac{1}{8} e^{1/2} e^{-z/2} (z - 1). \quad (23.3)$$

Q5. Inner asymptotic solutions

There will be a boundary layer near $z = 0$. Set $z = \epsilon^\alpha s$ and $T(z) = U(s)$. Follow the same procedure, as in Chapter 8 in order to determine the correct choice of α for the inner region. This choice should balance the two terms $\epsilon T''$ and $2T'$.

Q6. Matching and comparison

Expanding the inner solution as $U = U_0(s) + \epsilon U_1(s) + \dots$, write down the equation and boundary conditions that U_0 must satisfy. You will notice that U_0 is governed by a second-order differential equation and therefore needs two boundary conditions. One boundary condition comes from $z = 0$, i.e.

$$U_0(0) = 0.$$

The other boundary condition is a matching condition:

$$\lim_{s \rightarrow \infty} U_0(s) = \lim_{z \rightarrow 0} T_0(z),$$

which imposes that the inner solution, as it leaves the boundary layer, matches the outer solution, it tends into the inner region.

Solve for U_0 .

24 Problem set 1 solutions

Q1 The bump lemma

Prove the following one-dimensional lemma, which was used in the derivation of the heat equation.

If $\int_a^b g(x) dx = 0$ for all a and $b \in [0, 1]$, then $g(x) \equiv 0$ for all $x \in [0, 1]$.

Hint: think of a proof by contradiction.

Solution

Assume by contradiction that $f(x) \neq 0$ between two arbitrary points, say x_0 and x_1 , both in the interval $[a, b]$. Then $\int_{x_0}^{x_1} f(x) dx \neq 0$. This assumes some degree of smoothness and integrability (as long as f is not too pathological).

Q2. A source in the heat equation

Consider the same heat experiment discussed in Chapter 1 but now consider a bar that has an internal source or sink generating or removing heat, such as the case of a boiler with an internal heating element. By adapting a similar derivation to the one presented, explain why the modified conservation of heat equation is

$$-\frac{1}{t} \int_a^b \rho c T dx = q(x = a, t) - q(x = b, t) + \int_a^b R(x, t) dx.$$

In addition:

- By studying the dimensions of the other terms in the above equation, find what the dimensions of R are. What does $R > 0$ mean and $R < 0$?

Solution

On the left, density has units kg/m^3 , specific heat $\text{J}/(\text{kg K})$, and temperature K . But then dx has units of m . And d/dt has units of $1/\text{s}$. So altogether, we have the following

SI units on the left:

$$\frac{J}{m^2 \cdot s}$$

So its energy per unit area per unit time. The reason why it's per unit area is because you have not integrated over the sides of the cylinder/bar.

So therefore this needs to match the units on the right, which are $[R] [dx]$. So you conclude that

$$[R] = \frac{J}{m^3 \cdot s}$$

i.e. energy per unit time per unit volume. This is energy density.

$R > 0$ means heat is added into the system (source). $R < 0$ means heat is removed from the system (sink).

- b. Hence derive the partial differential equation that governs the temperature T .

Solution

The derivation follows exactly as in the notes, except you have an additional term on the RHS. Use Fourier's law to convert $q = -k\partial T/\partial x$. Write everything under the integral and this yields:

$$\rho c \frac{T}{t} = k \frac{\partial^2 T}{\partial x^2} + R.$$

- c. By introducing the appropriate scalings on each of the variables, x , t , and T , non-dimensionalise the PDE and discuss the non-dimensional parameters (there will be two).

Solution

Same derivation as in the notes. Let

$$x = Lx', T = [T]T' \quad \text{and} \quad t = [t]t'.$$

This time you will remember to scale out the typical source strength, so

$$R = [R]R'.$$

This leads to

$$\frac{T'}{t'} = \left(\frac{k[t]}{L^2 \rho c} \right) \frac{\partial^2 T'}{\partial x'^2} + \left(\frac{[R][t]}{\rho c[T]} \right) R'.$$

So this gives the two sets of non-dimensional numbers

$$\Pi_1 = \frac{k[t]}{L^2 \rho c} \quad (24.1)$$

$$\Pi_2 = \frac{[R][t]}{\rho c[T]}. \quad (24.2)$$

If you want, you can write it in the alternative form by taking the time scaling to be $[t] = L/U$, where U is some unspecified velocity scale.

For the interpretation, you can simply take Π_1 to be a measure of diffusive effects (heat spreading out) and Π_2 to be a measure of source strength. Note that this problem can be simplified even further by choosing the time scale so as to set $\Pi_1 = 1$. If you do this, you will be left with a single non-dimensional parameter that balances diffusion with the strength of the source.

Q3. Choice of scalings

Consider the dimensional problem for the motion of a projectile launched from close to the surface of the Earth. The dimensional height of the projectile, $y(t)$, is given by

$$\frac{d^2y}{dt^2} = -\frac{GM}{(R + y)^2}, \quad (24.3)$$

$$y(0) = 2 \text{ m}, \quad (24.4)$$

$$y'(0) = -V_0 \text{ m/s}. \quad (24.5)$$

Assume that the Earth is spherical and of uniform density, with its mass given by $M = (4/3)\pi R^3 \rho$. Non-dimensionalise the height using $y = L\tilde{y}$ and time using $t = T\tilde{t}$. Consider the following cases:

- (i) R fixed, $V_0 \rightarrow \infty$, ρ fixed;
- (ii) R fixed, V_0 fixed, $\rho \rightarrow \infty$;
- (iii) R fixed, V_0 fixed, $\rho \rightarrow 0$;
- (iv) $R \rightarrow 0$, V_0 fixed, M fixed.

NB!

This problem ended up a lot longer than expected. Nevertheless do at least of the few cases to get a feel.

For each case:

- a. Explain the physical interpretation of the limits.

Solution

- i. Very fast initial velocity
 - ii. Very heavy object
 - iii. Very light object
 - iv. Very small Earth radius
- b. Choose the scalings L and T to normalise as many terms as possible.
- c. Choose the scalings so that the time it takes for the projectile to fall should be finite for the given limit, and for the speed, acceleration, and initial height to be well behaved (finite).
- d. Write out the scaled problem and identify all remaining nondimensional parameters.
- e. Identify the limiting small parameter for each case. Write out the problem (leading-order problem) when the parameter is set to zero.

Solution

The solution for parts (b) to (d) is given below. The solution for part (e) is simply setting $\epsilon = 0$ in each case.

4.1 For cases (i, ii, iii) the scaled problem is

$$\frac{d^2y}{dt^2} = -\frac{\Pi_1}{(1 + \Pi_2 y)^2} \quad y(0) = \Pi_3 \quad y'(0) = -\Pi_4$$

$$\Pi_1 = \frac{4\pi G \rho_E R_E T^2}{3L} \quad \Pi_2 = \frac{L}{R_E} \quad \Pi_3 = \frac{2}{L} \quad \Pi_4 = \frac{V_0 T}{L}$$

(i) Starting with $\Pi_4 = 1$ we get $L = V_0 T$ then $\Pi_3 = 1$ sets $L = 2$, $T = 2/V_0$, $\Pi_1 = 8\pi G \rho_E R_E / (3V_0^2) = \varepsilon \rightarrow 0$

$$\frac{d^2y}{dt^2} = -\frac{\varepsilon}{(1 + \Pi_2 y)^2} \quad y(0) = 1 \quad y'(0) = -1$$

(ii) Starting with $\Pi_1 = 1$ we get $L = 4\pi G \rho_E R_E T^2 / 3$ then $\Pi_3 = 1$ sets $T = \sqrt{3/(2\pi G \rho_E R_E)}$ and $L = 2$ and $\Pi_4 = V_0 \sqrt{3/(8\pi G \rho_E R_E)} = \varepsilon \rightarrow 0$

$$\frac{d^2y}{dt^2} = -\frac{1}{(1 + \Pi_2 y)^2} \quad y(0) = 1 \quad y'(0) = -\varepsilon$$

(iii) Starting with $\Pi_3 = 1$, we get $L = 2$, then $\Pi_4 = 1$ sets $T = 2/V_0$ and $\Pi_1 = 8\pi G \rho_E R_E / (3V_0^2) = \varepsilon \rightarrow 0$

$$\frac{d^2y}{dt^2} = -\frac{\varepsilon}{(1 + \Pi_2 y)^2} \quad y(0) = 1 \quad y'(0) = -1$$

For (iv) the scaled problem is

$$\frac{d^2y}{dt^2} = -\frac{\Pi_1}{(y + \Pi_2)^2} \quad y(0) = \Pi_3 \quad y'(0) = -\Pi_4$$

$$\Pi_1 = \frac{GM_E T^2}{L^3} \quad \Pi_2 = \frac{R_E}{L} \quad \Pi_3 = \frac{2}{L} \quad \Pi_4 = \frac{V_0 T}{L}$$

Setting $\Pi_3 = \Pi_4 = 1$ yields $L = 2$ and $T = 2/V_0$ and $\Pi_2 = R_E/2 = \varepsilon \rightarrow 0$

$$\frac{d^2y}{dt^2} = -\frac{\Pi_1}{(y + \varepsilon)^2} \quad y(0) = 1 \quad y'(0) = -1$$

Q4. The unique timescale in the heat equation

During our investigation of the heat equation, we found that it was possible to scale time so as to scale out the only non-dimensional parameter that appears in the PDE. As explained in lectures, the disappearance of all non-dimensional parameters is due to the fact that only a single sensible timescale exists.

By adjusting the boundary conditions, we may create a new problem involving heat flow where a unique ‘special’ timescale can no longer be chosen.

Consider a system where one side of the rod is heated in some periodic fashion, e.g. set the initial and boundary conditions to be

$$T(x, 0) = T_0 \quad (24.6)$$

$$T(0, t) = T_a \cos(\omega t), \quad (24.7)$$

$$T(L, t) = T_b. \quad (24.8)$$

- a. What must the units of ω be?

Solution

Note ωt must be unitless. Therefore $[\omega] = 1/s$.

- b. Non-dimensionalise as usual and, without selecting the timescale, $[t]$, identify the key non-dimensional parameters that remain. Write a brief sentence to describe their physical interpretation.

Solution

This is exactly the same as in the above heat question. You will still obtain

$$\frac{T'}{t'} = \Pi_1 \frac{x'^2}{T'^2}$$

where the non-dimensional parameters is the Peclet number introduced in lectures:

$$\Pi_1 = \left(\frac{k[t]}{L^2 \rho c} \right).$$

The main difference is that now, your boundary conditions are

$$T'(0, t') = \Pi_3 \cos(\Pi_2 t') \quad \text{and} \quad T'(1, t') = \Pi_4$$

where

$$\Pi_2 = \omega[t], \quad \Pi_3 = \frac{T_a}{T_0}, \quad Pi_4 = T_b/T_0.$$

The scaling on the temperature was taken to be such that the final initial condition is set to unity:

$$T'(x', 0) = 1.$$

- c. There are two sensible choices for setting the timescale, $[t]$. Identify the two choices and present the reduced set of equations in each case.

Solution

So there are now two ways of choosing the time scale. Either choose it to set $\Pi_1 = 1$ or choose it to set $\Pi_2 = 1$. In the former choice, you are choosing to set time according to the diffusive rate. In the latter, you are setting time according to how the boundary is heated.

Q5. Timescale in the surface energy

Take the basic zero-dimensional energy model studied in (Equation 3.7) for the temperature of the troposphere:

$$c \frac{dT}{dt} = \frac{1}{4} Q(1-a) - \sigma\gamma T^4.$$

- a. Non-dimensionalise the model by choosing $T = [T]T'$, $t = [t]t'$, and $Q = [Q]Q'$. Show that it is possible to select the scalings on the temperature and time so as to completely remove all constants from the problem when Q is assumed to be constant.

Solution

The question's suggestion of setting $Q = [Q]Q'$ was excessive since Q is just a constant in this case. So proceeding as usual:

Set in the scalings. This time it is easier to balance the right hand-side first.

$$\frac{c[T]}{[t']} \frac{T'}{t'} = \left(\frac{Q(1-a)}{4} \right) - (\sigma\gamma[T]^4) T'^4.$$

So select the temperature scaling so that both coefficients on the RHS are equal.

$$[T] = \left(\frac{Q(1-a)}{4\sigma\gamma} \right)^{1/4}.$$

Now choose the time scaling also to match the LHS coefficient to the RHS coefficient.

$$c \frac{[T]}{[t]} = \sigma\gamma[T]^4 \implies [t] = \frac{c}{\sigma\gamma[T]^4}$$

Once you have done this, the equation transforms to the one given in part b.

b. Thus, show that the analysis of the above equation is equivalent to studying

$$\frac{dT}{dt} = 1 - T^4,$$

where we have dropped the primes and assumed that the albedo is such that $1 - a \neq 0$.

Solution

Done above.

- c. From your choice of $[t]$, estimate the typical dimensional value using $d \approx 10\text{km}$, $\rho \approx 1\text{kg m}^{-3}$, $c_p \approx 10^3\text{J kg}^{-1}\text{K}^{-1}$.

Use a pocket calculator to verify your calculations and conclude that this time-scale is on the order of a month. What is the relevance of this approximation as it concerns the steady-state solution?

Solution

Below (Equation 3.7), we defined $C = \rho c_p d$. So the scaling on time is (put in the scaling for $[T]$):

$$[t] = \left(\frac{4}{(1-a)} \right)^{3/4} \left(\frac{C}{(\sigma\gamma)^{1/4} Q^{3/4}} \right).$$

So we know that $\sigma = 5.67 \times 10^{-8} \text{ J}/(\text{m}^2 \text{ s K}^4)$, $Q = 1.38 \times 10^3 \text{ J}/(\text{m}^2 \text{ s})$. We can also calculate

$$C = \rho c_p d = 10^7 \text{ J}/(\text{K} \cdot \text{m}^2).$$

We can use $\gamma = 1$ for an estimate. The right-most factor is

$$\frac{10^7}{(5.67 \times 10^{-8})^{1/4} (1.378 \times 10^3)^{3/4}} \text{ s} = 2.88 \times 10^6 \text{ s}$$

If we use $a = 0.3$ then this gives a total of

$$[t] = 3.7 \times 2.88 \times 10^6 \text{ s}.$$

To convert to days, note 1 day = 24 hours = 2460 minutes = 2460*60 seconds. This is then

$$[t] = \frac{1.65 \times 10^7}{8.64 \times 10^4} \text{ days} = 0.19 \times 10^3 \text{ days} = 190 \text{ days}.$$

So on the order of 6 months. Any answer you get that's roughly on the order of months sounds about right. This is the rough approximation of how long time-scale effects take to appear.

25 Problem set 2 solutions

25.1 Getting started with Jupyter

Note

N/A

25.2 Testing the solutions of a cubic

Note

See `notebook/ps2_sol.ipynb` notebook for the code.

25.3 Analysis of singular cubic equation

Consider the cubic equation

$$\epsilon x^3 - x + 1 = 0,$$

with $\epsilon \ll 1$ and $\epsilon > 0$.

1. Develop the first three terms of an asymptotic expansion about the root by setting

$$x = x_0 + \epsilon x_1 + \epsilon^2 x_2 + \dots$$

Solution

Substitution into the cubic gives

$$\epsilon(x_0^3 + 3x_0x_1 + \dots) - (x_0 + \epsilon x_1 + \epsilon^2 x_2) + 1 = 0.$$

Equating at each order and solving gives

$$-x_0 + 1 = 0 \implies x_0 = 1 \quad (25.1)$$

$$x_0^3 - x_1 = 0 \implies x_1 = 1 \quad (25.2)$$

$$3x_0x_1 - x_2 = 0 \implies x_2 = 3 \quad (25.3)$$

So the three-term approximation is

$$x \sim 1 + \epsilon + 3\epsilon^2.$$

2. Fill out the following table.

Solution

ϵ	x_{exact}	x_0
0.1	1.1535	0.1535
0.08	1.1092	0.1092
0.06	1.0744	0.0744
0.04	1.0457	0.0457
0.02	1.0213	0.0213

This is a really excellent demonstration of an ‘organic’ discovery process. Below we plot the errors we found in the above table. I rounded the values to only the first two decimals. It is not so important to be extremely accurate (in fact, this is the point of requiring you to do so by hand!)

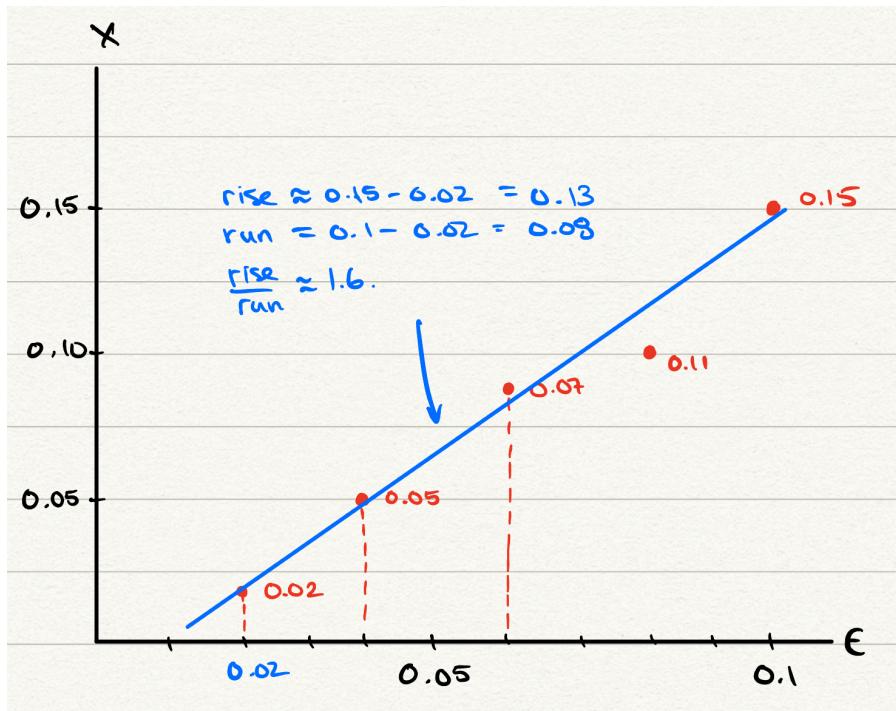


Figure 25.1: Hand drawn image

When doing this, I tried to fit to a line because I knew the error was supposed to be

$$x - x_0 \sim \epsilon$$

so was expecting a line of unit gradient. But the gradient estimated above was a bit higher, at 1.6. Returning to Python, we see the problem.

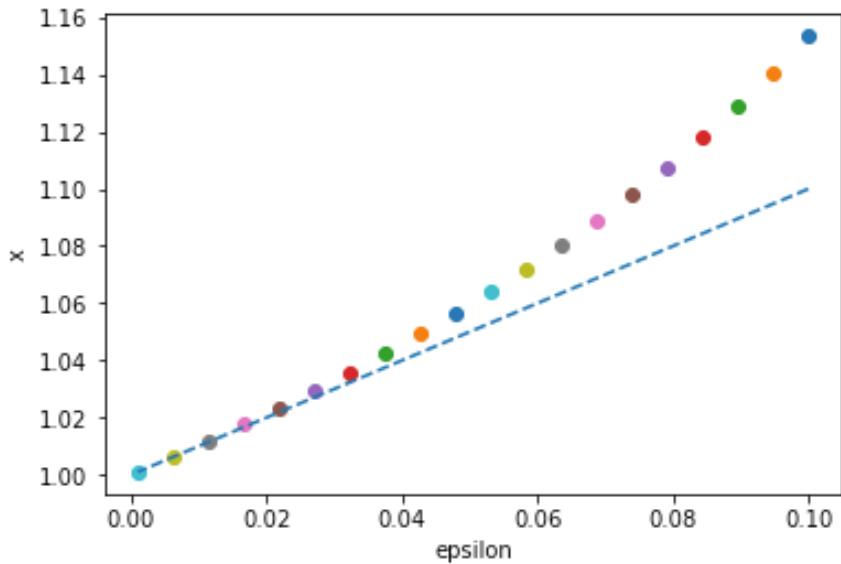


Figure 25.2: Python image

So over the range investigated of $0.02 < \epsilon < 0.1$, the behaviour is quadratic. This is a nice lesson on how to discover new results based on computation and analysis.

3. By rescaling x appropriately in terms of ϵ , derive the first three terms of the asymptotic approximations of the remaining roots.

Solution

We expect the critical scaling to balance ϵx^3 with x since these two will be dominant when x is large. So we set

$$x = \frac{X}{\sqrt{\epsilon}}$$

Now we have

$$X^3 - X + \sqrt{\epsilon} = 0.$$

You will notice that the progression here should go in powers of $\epsilon^{1/2}$. Alternatively set $\delta = \epsilon^{1/2}$ and now the problem is standard in δ :

$$X^3 - X + \delta = 0.$$

And we expand

$$X = X_0 + \delta X_1 + \delta^2 X_2 + \dots$$

We get

$$X_0^3 - X_0 = 0 \implies X_0^2 = 1 \implies X_0 = \pm 1 \quad (25.4)$$

$$3X_0^2 X_1 - X_1 + 1 = 0 \implies X_1 = -\frac{1}{2} \quad (25.5)$$

$$3X_0^2 X_2 + 3X_0 X_1^2 - X_2 = 0 \implies X_2 = \mp \frac{3}{8}. \quad (25.6)$$

So it seems that the three-term approximation for the other two roots is

$$x \sim \frac{1}{\sqrt{\epsilon}} \left(\pm 1 - \sqrt{\epsilon} \frac{1}{2} \mp \epsilon \frac{3}{8} \right).$$

25.4 A damped projectile problem

If air resistance is included, then the non-dimensional toy model is instead

$$\frac{d^2y}{dt^2} = -\frac{1}{(1+\epsilon y)^2} - \frac{\alpha}{(1+\epsilon y)} \frac{dy}{dt}, \quad (25.7)$$

$$y(0) = 0, \quad (25.8)$$

$$y'(0) = 1. \quad (25.9)$$

where $\alpha \geq 0$ is the parameter that controls air resistance.

1. Begin by assuming that α is a fixed number and consider the limit where $\epsilon \ll 1$. Find a one-term asymptotic expansion of the solution for small ϵ .

Solution

First, note that

$$(1+\epsilon y)^\alpha = 1 + \alpha(\epsilon y) + O(\epsilon y)^2.$$

You will not need more terms than that. Substitute $y = y_0(t) + \epsilon y_1(t) + \dots$ into the equation. This gives, for the leading terms

$$y_0'' = -1 - \alpha y_0' \quad (25.10)$$

$$y_0(0) = 0 \quad (25.11)$$

$$y_0'(0) = 1 \quad (25.12)$$

To solve this, you will need to refresh your memory on second-order differential equations learned in 2nd year. You can see Chapter 26 for references. To solve this set $y_0 = e^{rt}$ and solve for r for the homogeneous equation. You will get

$$y_{\text{homogeneous}} = (c_1 + c_2 e^{-\alpha t}).$$

From here, we need a particular solution. This can be obtained by guessing (also see [this reference](#)). If we guess

$$y_p = Ct,$$

we see that

$$y_p'' + \alpha y_p' = \alpha C = -1$$

implies $C = -1/\alpha$. Therefore the general solution is

$$y_0 = (c_1 + c_2 e^{-\alpha t}) - \frac{t}{\alpha}.$$

We now select the constants to satisfy the initial conditions. This yields

$$c_1 + c_2 = 0 \quad \text{and} \quad -\alpha c_2 - 1/\alpha = 1,$$

from which the solution can be easily derived. It is

$$y(t) \sim \left(\frac{1}{\alpha^2} + \frac{1}{\alpha} \right) - \left(\frac{1}{\alpha^2} + \frac{1}{\alpha} \right) e^{-\alpha t} - \frac{t}{\alpha}.$$

The solution of y_1 proceeds in the same way, but since we did not anticipate that this question would be so algebraically involved, we will not require solving for y_1 . This can be left as an exercise if you so wish.

2. (**Challenging**) Is the effect of the air resistance to increase or decrease the flight time?
Justify based on your analytical solution.

Solution

The above solution seems quite strange. After all, when $\alpha = 0$, we know that parabolic motion is expected. We found previously that

$$y_{\alpha=0}(t) \sim -\frac{1}{2}t^2 + t.$$

which matches our intuition about the expected flight being parabolic. However, notice that if α is small, we can expand the exponential, $e^{-\alpha t} = 1 - \alpha t + \dots$ to show

$$y_0 \sim \left(-\frac{1}{2}t^2 + t \right) + \alpha \frac{1}{6} (-3t^2 + t^3) + O(\alpha^2).$$

This is a fairly sophisticated argument. Instead, you can simply plot the curves and show the difference.

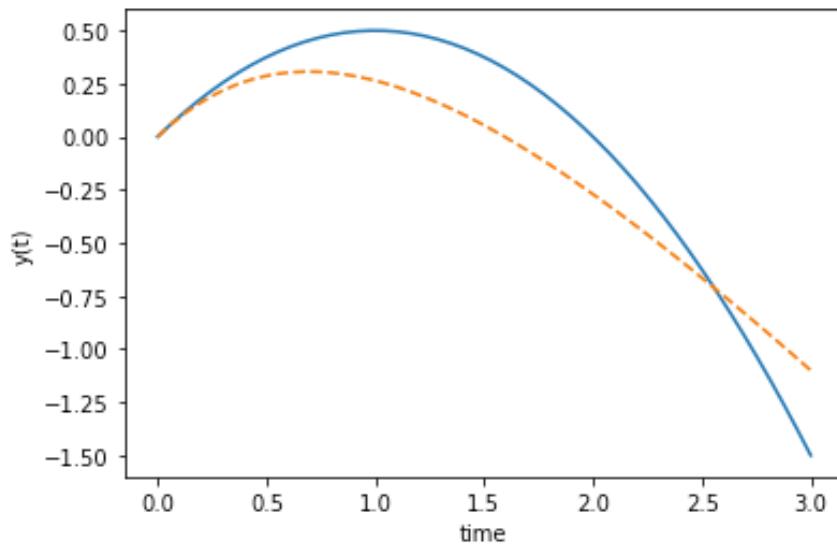


Figure 25.3: With (solid) and without damping (dashed)

25.5 ODE solvers and Euler's method

Return to the setup of the above question.

1. Modify the script developed in lecture 8 or alternatively copy-and-paste the script shown in Section 6.2 in order to solve ([?@eq-ps2-air](#)) at a prescribed value of ϵ and α .

Solution

This is found in `notebooks/sol02_solutions.ipynb`.

2. Using a pocket calculator (or your phone calculator) apply Euler's method with $\Delta t = 0.2$, $\epsilon = 0.2$, and $\alpha = 1$ to determine the position of the projectile at $t = 0.6$.

Solution

Euler's method is simply

$$Y_{n+1} = Y_n + F(t_n, y_n)\Delta t.$$

Here

$$F = \begin{pmatrix} y' \\ -\frac{1}{(1+\epsilon y)^2} - \frac{\alpha}{(1+\epsilon y)} \end{pmatrix}.$$

We split the time steps into $\{0, 0.2, 0.4, 0.6\}$. We also round to two figures.

t	Y	$1 + \epsilon y$	F	$F\Delta t$
0	(0, 1)	1	(1, -2)	(0.2, -0.4)
0.2	(0.2, 0.6)	1.04	(0.6, -1.5)	(0.12, -0.3)
0.4	(0.32, 0.3)	1.06	(0.3, -1.16)	(0.06, -0.23)
0.6	(0.38, 0.07)			

After three iterations, we get a value of $y(0.6) \approx 0.38$.

3. Compare your hand calculation with the result from the Python output, as well as with your asymptotic approximations.

Solution

We have (rounded to two digits)

$$y_{\text{exact numerical}} \approx 0.31$$

$$y_{\text{euler}} \approx 0.38$$

$$y_{\text{asym}} \approx 0.30$$

Part VI

Appendices

26 Differential equations

Appendices

These appendices may contain material that is added during the term, dependent on student enquiries and need.

26.1 First-order linear differential equations

First-order linear differential equations are of the form

$$y' + q(x)y = r(x).$$

These are solved by integrating factors. Multiply both sides by

$$e^{\int^x q(x') dx'}$$

so that the equation can be placed in the form

$$\frac{d}{dx} \left(y e^{\int^x q(x') dx'} \right) = r(x) e^{\int^x q(x') dx'}$$

Then integrate and solve for y .

References

- [Paul's online notes](#)

26.2 Second-order constant coefficient ODEs

Second-order linear constant-coefficient ODEs are of the form

$$y'' + ay' + by = f(x).$$

With both forced ($f \neq 0$) and unforced ($f = 0$) varieties studied. For the unforced variant (homogeneous), you will remember that the equation is solved by attempting the ansatz $y = e^{rx}$ and solving for r .

There are many references on this topic since it is the standard second-order theory learned in most initial differential equations courses.

References:

- [Paul's online notes](#)

27 Dynamical systems

Appendices

These appendices may contain material that is added during the term, dependent on student enquiries and need.

We will need some of the theory from your prior ODEs and Modelling and Dynamics courses as related to the solution of 2x2 linear systems of the form

$$\mathbf{Y}'(t) = \mathbf{A}(t)\mathbf{Y},$$

where

$$\mathbf{Y}(t) = \begin{pmatrix} x(t) \\ y(t) \end{pmatrix}, \quad \text{and} \quad \mathbf{A} = \begin{pmatrix} a & b \\ c & d \end{pmatrix}.$$

If you need a refresher, refer to your old notes; there is also a good review on [these notes](#) and also [these notes](#).

27.1 Stability analysis for 2x2 systems

In the case of 2x2 systems, there is a useful classification and shortcut. The eigenvalues, λ_1 and λ_2 are given by

$$\lambda_{1,2} = \frac{1}{2}(T \pm \sqrt{T^2 - 4D}),$$

where $T = \text{tr}(A) = a + d$ and $D = \det(A) = ad - bc$. Once T and D are known, then the fixed points can be classified based on the following diagram.

Above, the critical parabola is where $T^2 - 4D = 0$.

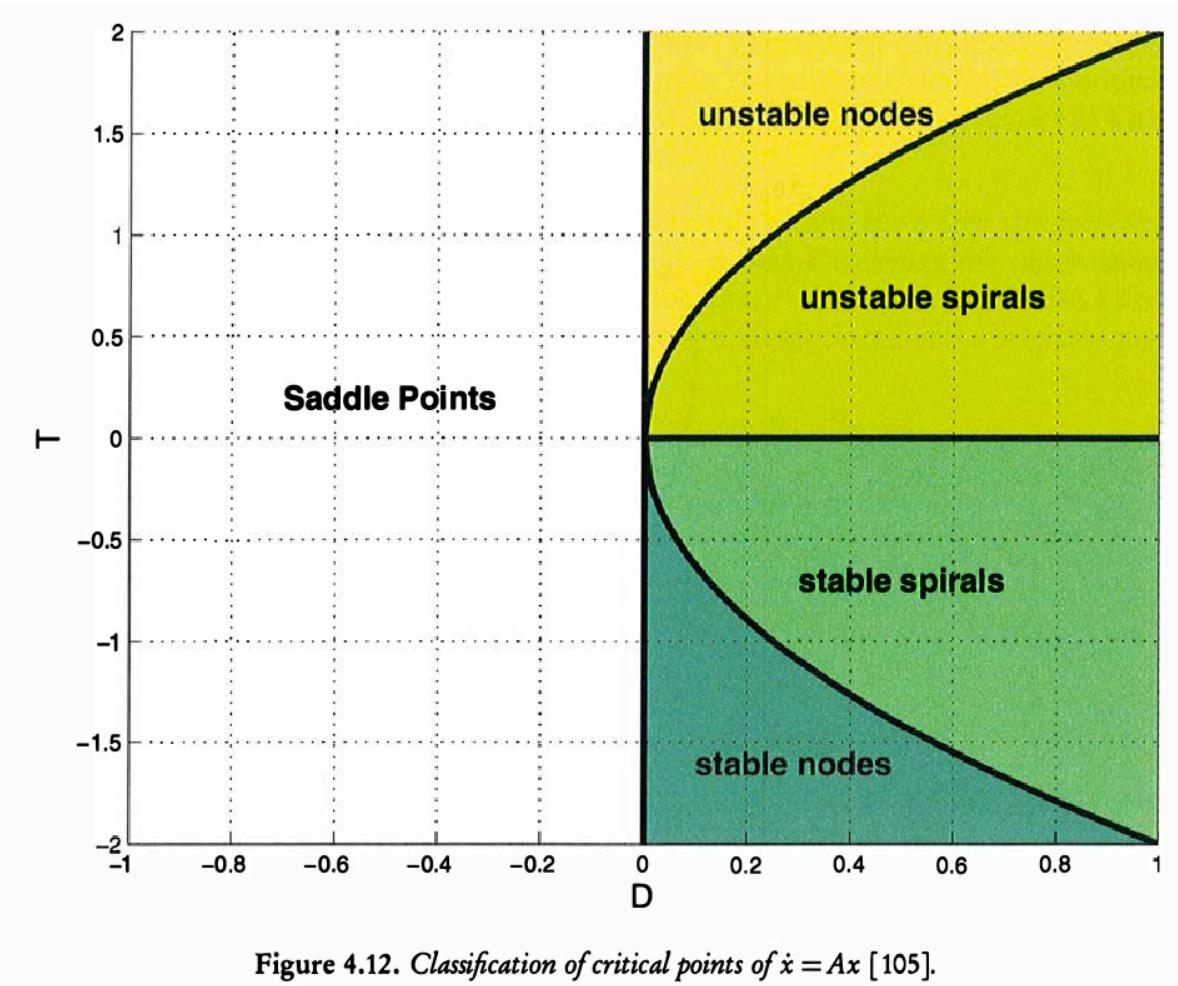


Figure 4.12. Classification of critical points of $\dot{x} = Ax$ [105].

Figure 27.1: Classification diagram from (Kaper and Engler 2013)

28 Vector calculus

Appendices

These appendices may contain material that is added during the term, dependent on student enquiries and need.

28.1 Surface integrals

Surface integrals are generalisations of the concept of a multiple integrals to integrals over surfaces. For example, consider a flat plate of area A heated to a certain temperature, and thus emits a certain amount of energy, E , per unit area (per unit time). The total energy emitted per unit time would then be EA .

If we want to consider the same problem, but now posed on a general surface, say the planet S , and where E varies along the surface, then we must consider adding together $E(\mathbf{x})dS$. We thus chop our surface into smaller pieces, each with area dS , multiply each piece with its corresponding energy, and then sum the result.

The result is the surface integral

$$\iint_S E(\mathbf{x}) dS.$$

A tutorial for computing surface integrals can be found [here](#).

You will not need to know how to calculate surface integrals in general in the course.

29 Modelling

Appendices

These appendices may contain material that is added during the term, dependent on student enquiries and need.

30 Finite difference approximations

Appendices

These appendices may contain material that is added during the term, dependent on student enquiries and need.

Many of the numerical methods we need will require using numerical approximations for the derivatives of functions. For instance, using Newton's method to solve for the zeros of a system of equations requires calculating the Jacobian matrix.

30.1 Forwards, backwards, and centred differences

We want to learn how to use finite differences in order to approximate derivatives numerically. We know that

$$f'(x) = \lim_{h \rightarrow 0} \frac{f(x + h) - f(x)}{h},$$

provided the limit exists. Therefore, a simple idea to approximating the value of $f'(x)$ is to use a small numerical value for h , and calculate (the gradient of the secant line),

$$f'(x) \approx \frac{f(x + h) - f(x)}{h},$$

where h is a specified small number. The above is known as the **two-point forward-difference formula**. In fact, we can determine exactly the error of such an approximation via Taylor's theorem. If f is twice continuously differentiable, then

$$f(x + h) = f(x) + hf'(x) + \frac{h^2}{2}f''(c),$$

for some point $c \in [x, x + h]$. Therefore by re-arrangement, we see the following.

Two-point forward-difference formula

$$f'(x) = \frac{f(x + h) - f(x)}{h} - \frac{h}{2}f''(c),$$

where $c \in (x, x + h)$.

Notice that the error in using the two-point forward difference approximation is then $\mathcal{O}(h)$, and this error tends to zero as $h \rightarrow 0$ (as long as f'' is continuous). We thus call the above formula a first-order finite-difference approximation. If the error is $\mathcal{O}(h^n)$, we call the corresponding formula an n th-order approximation.

Example

Use the two-point forward difference formula with different values of h in order to approximate the derivative of $f(x) = 1/x$ at $x = 2$.

$f(x)$	$f(x + h)$	h	$f'(x)$	Error
...
...
...

Similar formulae can be developed for the backwards difference (send $h \rightarrow -h$).

A more accurate formula can be developed via subtracting the Taylor series for $f(x - h)$ from that for $f(x + h)$. This results in:

Three-point centered-difference formula

$$f'(x) = \frac{f(x + h) - f(x - h)}{2h} - \frac{h^2}{6} f'''(c),$$

where $c \in (x - h, x + h)$.

Thus we see that the centered difference formula is accurate to $O(h^2)$.

30.2 Jacobian matrices

Reference

You will have encountered the Jacobian, firstly in your first-year Methods courses when performing change-of-coordinates in integration formulae, and secondly in your second-year Modelling and Dynamics courses when studying differential equations. It also comes up in the second-year Vectors and PDEs course.

The Jacobian matrix, \mathbf{J} , of a vector function, $\mathbf{F} : \mathbb{R}^n \rightarrow \mathbb{R}^m$,

$$\mathbf{F}(\mathbf{x}) = \begin{pmatrix} f_1(\mathbf{x}) \\ f_2(\mathbf{x}) \\ \vdots \\ f_m(\mathbf{x}) \end{pmatrix},$$

is the matrix of all its first-order partial derivatives,

$$\mathbf{J}(\mathbf{x}) = \begin{pmatrix} \frac{f_1}{x_2} & \dots & \frac{f_1}{x_n} \\ \vdots & \ddots & \vdots \\ \frac{f_m}{x_1} & \dots & \frac{f_m}{x_n} \end{pmatrix} = \begin{pmatrix} \nabla f_1(\mathbf{x})^T \\ \vdots \\ \nabla f_n(\mathbf{x})^T \end{pmatrix}.$$

We can essentially think of the Jacobian as the multi-dimensional extension of the basic derivative. It encodes all of the (first-order) information about the rate-of-change of the function.

It is interesting and important to consider the numerical evaluation of the Jacobian, in the event that the function \mathbf{F} cannot be easily differentiated exactly. The simplest algorithm is based on approximating each entry of the matrix by a finite difference.

For example, let us consider approximating

$$\frac{f_i}{x_j}(\mathbf{x}_0).$$

We define the j th unit vector by $\mathbf{e}_j = [0 \ 0 \ \dots \ 1 \ \dots \ 0]$, which the j th entry being one and all entries being zero. Then we can approximate the derivative by a central difference,

$$\frac{f_i}{x_j}(\mathbf{x}_0) \approx \frac{f_i(\mathbf{x}_0 + \mathbf{e}_j h) - f_i(\mathbf{x}_0 - \mathbf{e}_j h)}{2h},$$

where h is a small step size.

Let us test this by calculating the Jacobian for

$$\mathbf{F}(\mathbf{x}) = \begin{pmatrix} x_1^2 \\ x_2^2 \\ x_1 x_2 \end{pmatrix}.$$

The pseudocode for this looks like this

Pseudocode for numerical Jacobian

Input: function F (size m), point x (size n), step size h

1. Create an ($m \times n$) matrix, J
2. a. Loop through all the rows indexed by i

b. Loop through all the columns indexed by j
 Create the ej unit vector
 Calculate the difference of $F_i(x + h e_j) - F_i(x - h e_j)$
 Divide by $2h$
 Assign this value to the (i,j) th value of the Jacobian

Output: the $(m \times n)$ Jacobian matrix J

Here is a code that puts it into practice.

```
import numpy as np

def jacobian(func,initial,delta=1e-3):
    f = func
    nrow = len(f(initial))
    ncol = len(initial)
    output = np.zeros(nrow*ncol)
    output = output.reshape(nrow,ncol)
    for i in range(nrow):
        for j in range(ncol):
            ej = np.zeros(ncol)
            ej[j] = 1
            dij = (f(initial+ delta * ej)[i] - f(initial- delta * ej)[i])/(2*delta)
            output[i,j] = dij
    return output

def myf(x):
    x1 = x[0]
    x2 = x[1]
    output = np.zeros(3)
    output[0] = x[0]**2
    output[1] = x[1]**2
    output[2] = x[0]*x[1]
    return output

jacobian(myf,[1,2])

array([[2., 0.],
       [0., 4.],
       [2., 1.]])
```

31 Coding

31.1 Variable scope

During the 27 Feb 2024 lecture, the question of variable scope came up. Firstly, here is what ChatGPT says:

The screenshot shows a conversation between a user (PH) and ChatGPT. The user asks why Python knows the value of 'a' within a function definition if it has local scope. ChatGPT explains that Python uses lexical scoping (closure), so it looks for the variable 'a' in the enclosing scope where it was defined, resulting in a value of 1.

You

In the following code, why does Python know the value of 'a' within the function definition? Doesn't 'a' have local scope?

```
a = 1
def myfunc():
    print(a)
```

ChatGPT

In Python, when you reference a variable within a function, if that variable is not defined locally within the function, Python will look for it in the enclosing scopes. This behavior is known as "lexical scoping" or "closure".

In your example, since the variable 'a' is not defined locally within the function `myfunc()`, Python looks for it in the enclosing scope, where it finds the variable 'a' defined with a value of 1. Therefore, when you call `myfunc()`, it prints the value of 'a' from the enclosing scope, which is 1.

So, yes, 'a' has global scope in this context, and Python is able to access its value within the function `myfunc()`.

Figure 31.1: What ChatGPT says on scope

So indeed it looks like Python uses a scheme where if a variable is not locally declared, it will use values of the variable outside of the function. This can allow us to produce this kind of thing:

```
def myfunc():
    print(a)

a = 1
myfunc()
a = 2
myfunc()
a = 3
myfunc()
```

```
1
2
3
```

So I was wrong! Python variables are global when defined outside the function! [Here is a reference.](#)

This is certainly easier to use! However it can lead to confusion because for very complex codes, you may not be sure what value of a variable is being used within a function. Because most of the programming you will do in this course is very simple, this is unlikely to lead to trouble.

It's generally good to avoid this whenever it is possible, though. For instance in this particular case, it makes much more sense to pass in the variable.

```
def myfunc(a):
    print(a)

a = 99
myfunc(1)
myfunc(2)
myfunc(3)
```

```
1
2
3
```

In the above case, the `a` that appears in the function is different from the `a` that is declared outside the function. This makes it very easy to understand what your function is doing without knowing what is happening outside of it.

For example, there is no danger of values being reset:

```
def myfunc(a):
    a = a + 1000
    print(a)

a = 99
myfunc(1)
myfunc(2)
myfunc(3)
print(a)
```

1001
1002
1003
99

References

- Fourier, Joseph. 1827. “Mémoire Sur Les Températures Du Globe Terrestre Et Des Espaces Planétaires.” *Mémoires de l'Académie Royale Des Sciences de l'Institut de France* 7: 570–604.
- Fowler, Andrew. 2011. *Mathematical Geoscience*. Vol. 36. Springer.
- Kaper, Hans, and Hans Engler. 2013. *Mathematics and Climate*. SIAM.
- MacKay, D. J. C. 2009. *Sustainable Energy – Without the Hot Air*. UIT Cambridge Ltd.
- Pouillet, Claude Servais Mathias. 1838. “Memoire Sur Le Chaleur Solaire.” *Paris*.
- Stommel, Henry. 1961. “Thermohaline Convection with Two Stable Regimes of Flow.” *Tellus* 13 (2): 224–30.
- Van der Veen, CJ. 2000. “Fourier and the ‘Greenhouse Effect’.” *Polar Geography* 24 (2): 132–52.