

Math 266A  
Fall 2006

MWF 10-10:50  
Tues recitation  
Th makeup

## I. Intro

ODE's occur throughout analysis and applied math

Examples of ODE's

$$(1) \quad y' = a(t)y + b(t) \quad y(0) = y_0$$

$$y = y_0 \exp\left(\int_0^t a(s) ds\right) + \int_0^t b(s) e^{\int_s^t a(s') ds'} ds$$

existence uniqueness (for all times) - first topic

$$(2) \quad y' = y^2 \quad y(0) = y_0$$

$$\left(\frac{1}{y}\right)' = -\frac{y'}{y^2} = -1 \quad \frac{1}{y} = \frac{1}{y_0} - t$$

$$y = \frac{1}{y_0^{-1} - t} \quad \text{blow up in finite time}$$

$$(3) \quad y' = 2\sqrt{y} \quad y = \begin{cases} 0 & t \leq T \\ (t-T)^2 & T \leq t \end{cases}$$

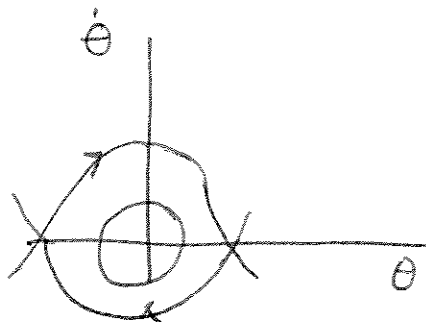
lack of uniqueness

$$(4) \quad \text{IVP for pendulum}$$

$$\ddot{\theta} = -\frac{g}{L} \sin \theta$$

$$\theta(t=0) = \theta_0$$

$$\dot{\theta}(t=0) = \dot{\theta}_0$$



phase plane method

(5) Heat distribution in rod

$$T_{xx} - \lambda T = S(x)$$

$$T(0) = T(1) = 0$$

$\lambda$  = rod length

$S$  = source

Expansion method - Sturm - Liouville Theory

Other topics

- linear systems of ODEs
- bifurcation + ~~chaos~~ chaos
- linear algebra
- Fourier analysis

## II. Initial Value Problems

Thm (local existence) Consider the ODE ~~with~~

$$\begin{aligned}
 y' &= f(y, t) \\
 y(0) &= y_0
 \end{aligned}
 \tag{2.1}$$

Assume that

(i)  $f$  is defined in an open domain  $D = \{ |t| < a, |y - y_0| < b \}$

(ii)  $f$  is uniformly Lipschitz in  $y$  in  $D$ ; i.e.,

$$|f(y, t) - f(z, t)| < L |y - z| \tag{2.2}$$

for all  $(y, t) \in D$  and  $(z, t) \in D$ .

(iii)  $f$  is continuous in  $t$  in  $D$  (uniformly)

Then the ODE (2.1) has a <sup>unique</sup> solution  $y(t)$  for some time interval  $|t| < t_0$ .

### Proof

Rewrite the ODE in the equivalent integral form

$$y(t) = y_0 + \int_0^t f(y(s), s) ds \tag{2.3}$$

Define the iteration

$$\begin{aligned}
 y^0(t) &= 0 \\
 y^{n+1}(t) &= y_0 + \int_0^t f(y^n(s), s) ds
 \end{aligned}
 \tag{2.4}$$

The proof is in several steps

Show that

(i) The iteration is well-defined; i.e.  $\mathbb{R}$

$$(y^n(t), t) \in D \tag{2.5}$$

for all  $n$  and for some time interval.

Let

$$M = \max_{(y, t) \in D} |f(y, t)| \tag{2.6}$$

To show this, we first have  $(y^0(t) = y_0, t) \in D$   
for  $|t| < a$ .

Second take if  $(y^n(t), t) \in D$  for  $|t| < \alpha$ , then

$$\begin{aligned} |y^{n+1} - y_0| &\leq \int_0^t |f(y^n(s), s)| ds \\ &\leq tM \leq \alpha M \\ &< b \end{aligned} \quad (2.7)$$

if  $\alpha < (\frac{b}{M}, a)$ . This shows that  $(y^{n+1}(t), t) \in D$   
for  $|t| < \alpha$ .

By iteration  $(y^n(t), t) \in D$  for all  $n$  if  $|t| < \alpha$ .

(ii) Show that the iteration is convergent

Write

$$y^n = y^0 + \sum_{k=0}^{n-1} y^{k+1} - y^k \quad (2.8)$$

Estimate

$$|y^{k+1}(t) - y^k(t)| \leq \left| \int_0^t f(y^k(s), s) - f(y^{k-1}(s), s) ds \right|$$

$$\leq \int_0^t |f(y^k) - f(y^{k-1})| ds$$

$$\leq \int_0^t L \max_{0 \leq s \leq t} |y^k - y^{k-1}|$$

$$\leq tL \max |y^k - y^{k-1}| \quad (2.9)$$

So

$$\max |y^{k+1} - y^k| \leq tL \max |y^k - y^{k-1}| \quad (2.10)$$

It follows

By applying this estimate repeatedly we get

$$\begin{aligned} \max |y^{k+1} - y^k| &\leq tL \max |y^k - y^{k-1}| \\ &\leq (tL)^2 \max |y^{k-1} - y^{k-2}| \\ &\dots \\ &\leq (tL)^k \max |y^1 - y^0| \end{aligned}$$

$$\stackrel{= \delta}{\leq} (tL)^k (tM) \quad (2.11)$$

Choose  $|t| < t_0$  with  $t_0 L < 1$ , then

$$(tL)^k < \delta^k \quad (2.12)$$

This shows that the terms in the series (2.8) are decreasing algebraically. It follows that

$$y^n \rightarrow y = y_0 + \sum_{k=0}^{\infty} y^{k+1} - y^k$$

which is ~~is~~ absolutely and uniformly convergent.

(iii) Show that the limit  $y(t)$  is a solution.

We have  $y^n \rightarrow y$  uniformly. It follows that  $y$  is continuous. Also the integral equation (2.4) has the following limit

$$\begin{aligned} y^{n+1}(t) &= y_0 + \int_0^t f(y^n(s), s) ds \\ \downarrow &\quad \downarrow \quad \downarrow \\ y(t) &= y_0 + \int_0^t f(y(s), s) ds \end{aligned} \quad (2.13)$$

i.e.,  $y$  solves equation (2.3).

(iv) Show uniqueness.

First prove the Gronwall inequality

Gronwall inequality If

$$x(t) \leq a \int_0^t x(s) ds + x_0 \quad (2.14)$$

then

$$x(t) \leq x_0 e^{at} \quad (2.15)$$

Proof Define

$$\underline{X}(t) = a \int_0^t x(s) ds \quad (2.16)$$

Then

$$x(t) \leq \underline{X}(t) + x_0 \quad (2.17)$$

So

$$\underline{X}'(t) = ax(t) \leq a(\underline{X}(t) + x_0) \quad (2.18)$$

and after multiplying by  $e^{-at}$

$$e^{-at} (\underline{X}' - a\underline{X}) \leq e^{-at} ax_0 \quad \text{*****}$$

i.e.

$$\frac{d}{dt} (e^{-at} \underline{X}(t)) \leq e^{-at} ax_0$$

Since  $\underline{X}(0) = 0$

$$e^{-at} \underline{X}(t) \leq \int_0^t e^{-at'} ax_0 dt'$$

$$= (1 - e^{-at}) x_0$$

Multiply by  $e^{at}$  to get

$$\underline{X}(t) \leq (e^{at} - 1) x_0$$

so that

$$x(t) \leq \underline{X}(t) + x_0 \leq x_0 e^{at} \quad (2.19)$$

Now suppose that  $y$  and  $z$  are two solutions of (2.3).  
Subtract to get

$$|y(t) - z(t)| = \left| \int_0^t f(y(s), s) - f(z(s), s) ds \right| \leq L \int_0^t |y(s) - z(s)| ds \quad (2.20)$$

$$x(0) - z(0) = 0 \quad (2.21)$$

Set  $x(t) = y(t) - z(t)$ . Then  $x$  satisfies the assumption of Gronwall's inequality with  $a = L$  and  $x_0 = 0$ . Since  $x_0 = 0$ , then

$$x(t) = 0 \quad (2.22)$$

i.e.

$$y = z \quad (2.23)$$

This shows uniqueness

Well-posedness. A differential equation, such as (2.1) is said to be well-posed if the following hold

(i) existence

(ii) uniqueness

(iii) smooth dependence on parameters.

The system is well-posed for a time interval  $|t| < t_0$  if (i), (ii) and (iii) hold in this time interval.

The ~~third~~ condition (iii) is often omitted from the definition of well-posedness. To explain the meaning of (iii) consider an ODE with a parameter

$$x_t(t, \lambda) = f(x(t, \lambda), t, \lambda)$$

$$x(0, \lambda) = x_0(\lambda)$$

(2.24)

We wish to show that  $x$  depends smoothly on  $\lambda$ .

As an example, set  $f = f(x, t)$  and  $x_0(\lambda) = \lambda$ . Then the result is that the solution depends smoothly on the initial data.

Then Suppose that  $f \in C^1(x, \lambda) \cap C^0(t)$  and that  $x_0 \in C^1(\lambda)$ . Then  $x \in C^1(\lambda, t)$ .

Proof For each  $\lambda$ , the solution exists by the previous existence theorem. Take the derivative w.r.t.  $\lambda$  of (2.1) to get

$$\frac{d}{dt} x_\lambda = f_x x_\lambda + f_\lambda$$

(2.25)

$$x_\lambda(0) = x_{0\lambda}$$

For each  $\lambda$ , this is a linear equation for  $y = x_\lambda$

$$\frac{d}{dt} y = \cancel{f(x)} g_1(t) y + g_2(t)$$

(2.26)

with

$$y(0) = y_0$$

$$g_1(t) = f_x(x(t, \lambda), t, \lambda)$$

$$g_2(t) = f_\lambda(x(t, \lambda), t, \lambda)$$

(2.27)

$$y_0 = x_{0\lambda}(0, \lambda)$$

Existence follows from the existence theorem. To see that  $y = \frac{\partial}{\partial \lambda} x(t, \lambda)$ , repeat the Picard proof (i.e. iteration)

taking the  $\lambda$ -derivative at each step.

## Systems of ODE's

The Picard Theorem is formulated for a first-order ODE

$$x' = f(x, t)$$

"First order" means that only the first derivative  $x'$  appears in the equation, along with  $x$  itself. The function  $x$  can be a vector

$$x(t) = (x_1(t), \dots, x_n(t)) \quad (2.28)$$

and then the function  $f$  is a vector-valued function of the vector  $x$  and the scalar  $t$

$$f = (f_1, \dots, f_n).$$

The only change in the Picard Theorem is that  $|x|$  refers to the vector length, i.e.

$$|x| = \sqrt{x_1^2 + \dots + x_n^2} \quad (2.29)$$

Actually any other norm would work just as well.

Most ODE's can be written as first-order systems, so that this restriction feature of the Picard system is not much of a restriction. As an example consider a particle of mass  $m$  and position  $x(t)$  moving in a force field  $F(x, t)$ . Newton's equation is force = mass  $\times$  acceleration, which can be written as a second-order ODE

$$m x'' = F(x, t)$$

This is put in first order form by defining the ~~new~~ velocity  $v = x'$  and the vector

$$\underline{X} = \begin{pmatrix} x \\ v \end{pmatrix} \quad (2.30)$$

The equations for  $x$  and  $v$  are

$$\begin{aligned}x' &= v \\v' &= x'' = \frac{1}{m} F(x, t)\end{aligned}\tag{2.31}$$

so that

$$\underline{X}' = \begin{pmatrix} x' \\ v' \end{pmatrix} = \begin{pmatrix} v \\ \frac{1}{m} F(x, t) \end{pmatrix}$$

$$= f(\underline{X}, t)\tag{2.32}$$

in which

$$f(x, v, t) = \begin{pmatrix} v \\ \frac{1}{m} F(x, t) \end{pmatrix}\tag{2.33}$$

## Linear Systems of First Order ODE's

Let  $x(t)$  be an  $n$ -vector function of  $t$  and let  $A(t)$  be an  $n \times n$  matrix function of  $t$ . Consider the linear, homogeneous first order system

$$\begin{aligned} x' &= Ax \\ x(0) &= x_0 \end{aligned} \quad (2.34)$$

In order to describe the solution of (2.34), we need some definitions and results from linear algebra. ~~We always assume~~ Unless stated otherwise the vectors here are column vectors.

1. Eigenvalues and eigenvectors.  $\lambda$  is an eigenvalue and  $v$  is an eigenvector for a matrix  $A$  if

$$Av = \lambda v \quad (2.35)$$

in which  $A$  is an  $n \times n$  matrix,  $v$  is an  $n$ -vector and  $\lambda$  is a scalar

2. Inverse matrix.  $A^{-1}$  is the inverse matrix for  $A$  if

$$A^{-1}A = AA^{-1} = I \quad (2.36)$$

in which  $I$  is the identity matrix

3. Similarity transformation. If

$$B = C^{-1}AC \quad (2.37)$$

then  $B$  is similar to  $A$

4. Orthogonal matrix. A matrix  $U$  is orthogonal if

$$U^+ = U^{-1} \quad (2.38)$$

in which  $(U^+)_{ij} = U_{ji}$ .

5. Self-adjoint matrix A ~~matrix~~ matrix  $A$  with real components is self adjoint if  $A^T = A$ , i.e.

$$A_{ij} = A_{ji} \quad (2.39)$$

6. Diagonalization of a self-adjoint matrix, If  $A$  is self-adjoint then

$$A = U \Lambda U^T \quad (2.40)$$

in which  $U$  is orthogonal and  $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_n)$  is the  $n \times n$  matrix with the eigenvalues  $\lambda_k$  of  $A$  on its diagonal, i.e.

$$\Lambda_{kk} = \lambda_k \quad (2.41)$$

$$\Lambda_{kl} = 0 \quad \text{if } k \neq l$$

Moreover, the columns of  $U$  are the corresponding eigenvectors, i.e.

$$U = (v_1 \dots v_n) \quad (2.42)$$

7. Dot product. For two (real) vectors  $x$  and  $y$  both of length  $n$ , the dot product is

$$x \cdot y = \sum_{k=1}^n x_k y_k \quad (2.43)$$

This is an example of an inner product

$$(x, y) = x \cdot y = x^T y \quad (2.44)$$

Two vectors  $x$  and  $y$  are said to be orthogonal if  $x \cdot y = 0$ .

More generally, the angle  $\theta$  between two vectors satisfies

$$\cos \theta = \frac{x \cdot y}{|x| |y|} \quad (2.45)$$

8. Orthogonality of eigenvectors. Let  $A$  be a self adjoint matrix with eigenvectors  $v$  and  $w$  and corresponding eigenvalues  $\lambda$  and  $\mu$ ; i. e.

$$Av = \lambda v$$

$$Aw = \mu w$$

with  $\lambda \neq \mu$ . Then  $v$  and  $w$  are orthogonal

Proof

$$\begin{aligned} v \cdot w &= v \cdot \left( \frac{1}{\mu} Aw \right) \\ &= \mu^{-1} v^T (Aw) \\ &= \mu^{-1} (v^T A) w \\ &= \mu^{-1} (A^T v)^T w \\ &= \mu^{-1} (Av)^T w \\ &= \mu^{-1} (\lambda v)^T w \\ &= \mu^{-1} \lambda v \cdot w \end{aligned}$$

Since  $\frac{\lambda}{\mu} \neq 1$ , then  $v \cdot w = 0$ .