

# Time-dependent PDEs & PETSc TS

yes, we can do time-stepping

Ed Bueler

Dept. of Mathematics and Statistics, UAF

26 April 2016

# outline for today

## Chapter 6 of book:

- ▶ ODE initial value problem examples and methods
- ▶ PETSc TS object can do time-stepping
  - explicit Runge-Kutta methods
  - implicit methods (backward Euler,  $\theta$ , IMEX)
    - ▶ require solving equations at each time step: SNES
- ▶ `c/ch6/heat.c` solves classical heat equation

$$u_t = D\nabla^2 u + f(x, y)$$

- diffusions are stiff, so implicit appropriate
- ▶ `c/ch6/pattern.c` solves system of coupled nonlinear diffusions for pattern formation:

$$u_t = D_u \nabla^2 u - uv^2 + F(1 - u)$$

$$v_t = D_v \nabla^2 v + uv^2 - (F + k)v$$

# systems of ODEs

- ▶ we can solve ODE systems of form

$$\mathbf{y}' = \mathbf{g}(t, \mathbf{y})$$

- $\mathbf{y}(t) \in \mathbb{R}^N$
  - ODE describes motion of point in  $N$  dimensions
  - $\mathbf{g}$  can be linear or nonlinear in  $t$  or  $\mathbf{y}$
- ▶ *initial value problem* specifies solution at one time:

$$\mathbf{y}(t_0) = \mathbf{y}_0$$

- exists unique solution if  $\mathbf{g}(t, \mathbf{y})$  is continuous in both inputs and Lipschitz in  $\mathbf{y}$  ... that is, you can *predict*
- for  $N < \infty$  cases (i.e. *not* PDEs), one can generally go forward or backward from  $t = t_0$

## example with fixed size $N = 2$

- ▶ example with initial time  $t_0 = 0$

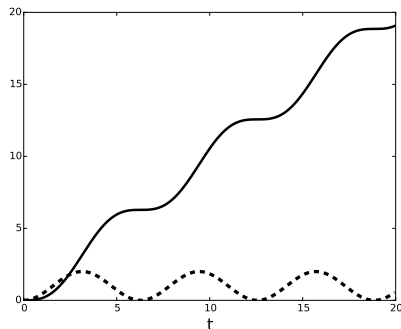
$$\mathbf{y}' = \begin{bmatrix} y_1 \\ -y_0 + t \end{bmatrix}, \quad \mathbf{y}(0) = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

- ▶ exact solution is

$$\mathbf{y}(t) = \begin{bmatrix} t - \sin t \\ 1 - \cos t \end{bmatrix}$$

- ▶ it is a linear system  
 $\mathbf{g}(t, \mathbf{y}) = A\mathbf{y} + \mathbf{f}(t)$  where

$$A = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}, \quad \mathbf{f}(t) = \begin{bmatrix} 0 \\ t \end{bmatrix}$$



# Euler numerical methods: forward and backward

- ▶  $t_0 < t_1 < t_2 < \dots < t_L$  a sequence of times
- ▶ steps  $h = t_\ell - t_{\ell-1}$ ; assume equal only for convenience
- ▶  $\mathbf{Y}_\ell \approx \mathbf{y}(t_\ell)$ , and  $\mathbf{Y}_0 = \mathbf{y}_0$
- ▶ explicit forward Euler method

$$\frac{\mathbf{Y}_\ell - \mathbf{Y}_{\ell-1}}{h} = \mathbf{g}(t_{\ell-1}, \mathbf{Y}_{\ell-1})$$

- one can also write as update formula

$$\mathbf{Y}_\ell = \mathbf{Y}_{\ell-1} + h\mathbf{g}(t_{\ell-1}, \mathbf{Y}_{\ell-1})$$

- ▶ implicit backward Euler method is just as easy to state

$$\frac{\mathbf{Y}_\ell - \mathbf{Y}_{\ell-1}}{h} = \mathbf{g}(t_\ell, \mathbf{Y}_\ell)$$

- *but* requires solving system of eqns at each time step

# Runge-Kutta methods

- ▶ Runge-Kutta methods with  $s$  stages have form

$$\hat{\mathbf{Y}}_i = \mathbf{Y}_{\ell-1} + h \sum_{j=1}^s a_{ij} \mathbf{g}(t_{\ell-1} + c_j h, \hat{\mathbf{Y}}_j), \quad 1 \leq i \leq s$$

$$\mathbf{Y}_{\ell} = \mathbf{Y}_{\ell-1} + h \sum_{i=1}^s b_i \mathbf{g}(t_{\ell-1} + c_i h, \hat{\mathbf{Y}}_i)$$

- ▶ some “tableau” for explicit instances:

0		
1	1	
	$\frac{1}{2}$	$\frac{1}{2}$

0				
$\frac{1}{2}$	$\frac{1}{2}$			
$\frac{1}{2}$	0	$\frac{1}{2}$		
1	0	0	1	
	$\frac{1}{6}$	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{6}$

0				
$\frac{1}{2}$	$\frac{1}{2}$			
$\frac{3}{4}$	0	$\frac{3}{4}$		
1	$\frac{2}{9}$	$\frac{1}{3}$	$\frac{4}{9}$	
	$\frac{2}{9}$	$\frac{1}{3}$	$\frac{4}{9}$	0
	$\frac{7}{24}$	$\frac{1}{4}$	$\frac{1}{3}$	$\frac{1}{8}$

Table 6.1: Tableau for the explicit trapezoidal rule (RK2a; left), the classical fourth-order Runge-Kutta method (RK4; middle), and an embedded four-stage, third-order scheme (RK3bs, the PETSc default; right).

# PETSc TS basic setup

---

```
TSCreate(COMM,&ts);
TSSetProblemType(ts,TS_NONLINEAR);
TSSetRHSFunction(ts,NULL,FormRHSFunction,NULL);
TSSetType(ts,TSRK);
TSSetInitialTimeStep(ts,t0,dt);
TSSetDuration(ts,maxsteps,tf-t0);
TSSetFromOptions(ts);
TSSolve(ts,y);
```

---

- ▶ setup similar to SNES, KSP, etc.
- ▶ setting `TS_NONLINEAR` says ODE is in form  $\mathbf{y}' = \mathbf{g}(t, \mathbf{y})$
- ▶ calling `TSSetRHSFunction()` sets a call-back to our code `FormRHSFunction()`, which evaluates  $\mathbf{g}(t, \mathbf{y})$
- ▶ `TSSetFromOptions()` allows overrides:
  - the `TSSetType()` choice by `-ts_type`
  - values of `t0, dt, maxsteps, tf` by ...
- ▶ `y` must be an allocated `Vec` of size  $N$  containing initial value  $\mathbf{Y}_0$

# first PETSc TS example

- recall our example:

$$\mathbf{g}(t, \mathbf{y}) = \begin{bmatrix} y_1 \\ -y_0 + t \end{bmatrix}$$

- thus implementation of  $\mathbf{g}(t, \mathbf{y})$ :

---

```
PetscErrorCode FormRHSFunction(TS ts, double t, Vec y,
                               Vec g, void *ptr) {
    const double *ay;
    double      *ag;
    VecGetArrayRead(y, &ay);
    VecGetArray(g, &ag);
    ag[0] = ay[1];
    ag[1] = - ay[0] + t;
    VecRestoreArrayRead(y, &ay);
    VecRestoreArray(g, &ag);
    return 0;
}
```

---



## running ode.c

- ▶ `c/ch6/ode.c` is essentially just the stuff on the last two slides ... simple!
- ▶ basic run with adaptive, explicit RK  $O(h^3)$  method (default):

```
$ make
$ ./ode -ts_monitor
0 TS dt 0.1 time 0.
1 TS dt 0.170141 time 0.1
...
87 TS dt 0.11548 time 19.8845
88 TS dt 0.205616 time 20.
error at tf = 20.000 : |y-y_exact|_inf = 0.00930352
```

variations:

- ▶ changing solver and time axis:  
| \$ ./ode -ts\_type euler -ts\_final\_time 1.0 -ts\_dt 0.5
- ▶ generating run-time movie of trajectory:  
| \$ ./ode -ts\_monitor\_lg\_solution -draw\_pause 0.1

# implicit solvers need SNES and Jacobian

- ▶ backward Euler:

```
| $ ./ode -ts_type beuler          # error  
| $ ./ode -ts_type beuler -snes_fd # works
```

- ▶ odejac.c adds Jacobian function to ode.c:

```
| $ make odejac  
| $ ./odejac -ts_type beuler          # works
```

- ▶ larger class of implicit methods are “ $\theta$ ”-methods with  $0 < \theta \leq 1$ :

$$\frac{\mathbf{Y}_\ell - \mathbf{Y}_{\ell-1}}{h} = (1 - \theta) \mathbf{g}(t_{\ell-1}, \mathbf{Y}_{\ell-1}) + \theta \mathbf{g}(t_\ell, \mathbf{Y}_\ell)$$

- $\theta = 1/2$  is  $O(h^2)$  accurate: “trapezoid” or “Crank-Nicolson”

```
| $ ./odejac -ts_type theta -ts_theta_theta 0.4  
| $ ./odejac -ts_type cn
```

## “stiff” ODE systems

- ▶ consider ODE systems of the form  $\mathbf{y}' = \mathbf{g}(\mathbf{y})$ ,  
i.e. “autonomous” without  $t$ -dependence
- ▶ system is *asymptotically stable* if eigenvalues  $\lambda$  of Jacobian  $J = \frac{\partial g_i}{\partial y_j}$  have negative real part
- ▶ such a system is *stiff* if

$$\min(\operatorname{Re} \lambda) \ll \max(\operatorname{Re} \lambda) < 0$$

◦ or:  $\kappa(J) \gg 1$  in symmetric case

- ▶ idea:

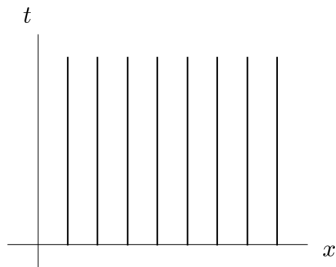
*stiff implies the “ $\min(\operatorname{Re} \lambda)$ ” eigenvalues will control time steps of explicit ODE method, causing very short time steps, even though the “ $\max(\operatorname{Re} \lambda)$ ” eigenvalues control the macroscopic behavior of solution*

## “method of lines” (MOL) for PDEs

- ▶ one might recognize time-dependent PDEs as “ODEs in  $\infty$  dimensions”; you can discretize with this in mind
  - this is how to solve time-dependent PDEs using PETSc
- ▶ consider time-dependent PDEs of form

$$u_t = G(t, u, \nabla u, \nabla^2 u)$$

- ▶ *idea*: spatial discretization only gives system of ODEs



# MOL for heat equation

- ▶ *example*: if  $\{x_i\}$  is an  $N$ -point spatial grid then

$$u_t = u_{xx} \quad \rightarrow \quad U_j'(t) = \frac{U_{j-1}(t) - 2U_j(t) + U_{j+1}(t)}{\Delta x^2}$$

gives system in form “ $\mathbf{y}' = \mathbf{g}(t, \mathbf{y})$ ” in  $\mathbb{R}^N$ , where  $U_j(t) \approx u(t, x_j)$  and  $\mathbf{U}(t) = \{U_j(t)\} \in \mathbb{R}^N$

- ▶ symmetric matrix for RHS is

$$A = \frac{1}{\Delta x^2} \begin{pmatrix} -2 & 1 & 0 & & 0 \\ 1 & -2 & 1 & & 0 \\ 0 & 1 & -2 & & 0 \\ & & & \ddots & \\ 0 & 0 & 0 & & -2 \end{pmatrix}$$

has negative real eigenvalues, some  $\approx 0$  and some  $\lambda \rightarrow -\infty$

- ▶ this is generic:

*MOL on diffusion equations gives stiff ODE systems*

## TS example codes in `c/ch6/`

- ▶ using form  $\mathbf{y}' = \mathbf{g}(t, \mathbf{y})$ :

`ode.c` solves above example

`odejac.c` adds Jacobian so that implicit methods can be used

`heat.c` MOL for classical heat equation

$$u_t = D\nabla^2 u + f$$

- ▶ using “implicit-explicit” form  $\mathbf{f}(t, \mathbf{y}, \mathbf{y}') = \mathbf{g}(t, \mathbf{y})$ :

`pattern.c` MOL for system of two coupled nonlinear heat-like PDEs

$$\begin{aligned}u_t - D_u \nabla^2 u &= -uv^2 + F(1 - u) \\v_t - D_v \nabla^2 v &= +uv^2 - (F + k)v\end{aligned}$$

- ▶ a model for two chemical species with reaction, diffusion, and feed (Pearson, 1993)
- ▶ “adaptive Runge-Kutta implicit-explicit” appropriate  
(`-ts_type arkimex`)

## running `heat.c`

- ▶ `c/ch6/heat.c` solves  $u_t = D\nabla^2 u + f(x, y)$ 
  - on unit square  $\Omega = (0, 1) \times (0, 1)$
  - non-homogeneous Neumann boundary conditions in  $x$
  - periodic boundary conditions in  $y$
  - energy is conserved
- ▶ high-res Crank-Nicolson run on 4 processes with saving of time axis and solution:

```
mpirun -n 4 ./heat -ts_type cn -da_refine 7 \  
-ts_dt 0.0001 -ts_final_time 0.05 \  
-ts_monitor binary:theat.dat \  
-ts_monitor_solution binary:uheat.dat
```

- ▶ output can be transformed into an off-line movie:

```
./plotTS.py -mx 385 -my 384 theat.dat uheat.dat \  
-oroot heat  
ffmpeg -r 8 -i heat%03d.png heat.m4v
```

## running pattern.c

- ▶ `c/ch6/pattern.c` solves

$$\begin{aligned}u_t - D_u \nabla^2 u &= -uv^2 + F(1 - u) \\v_t - D_v \nabla^2 v &= +uv^2 - (F + k)v\end{aligned}$$

- periodic boundary conditions in both directions
- creates 2D DMDA with `dof=2`
- ▶ problem in form  $\mathbf{f}(t, \mathbf{y}, \mathbf{y}') = \mathbf{g}(t, \mathbf{y})$ :
  - `-ts_type arkimex` is default
  - `FormIFunctionLocal()` for  $\mathbf{f}$ ; with Jacobian
  - `FormRHSFunctionLocal()` for  $\mathbf{g}$ ; no Jacobian
- ▶ high-res run on 4 procs, and off-line movie of  $u$  component:

```
mpiexec -n 4 ./pattern -ts_adapt_type none \  
  -ts_final_time 5000 -ts_dt 10 -da_refine 8 \  
  -ts_monitor binary:t8.dat \  
  -ts_monitor_solution binary:uv8.dat \  
./plotTS.py -mx 768 -my 768 -dof 2 -c 0 \  
  t8.dat uv8.dat -oroot uhigh8 \  
ffmpeg -r 8 -i uhigh8%03d.png uhigh8.m4v
```