### MAT 228B Notes

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### 1 Review

• Trapezoidal Rule

$$\frac{y^{n+1} - y^n}{\Delta t} = \frac{1}{2} (f(y^n) + f(y^{n+1}))$$

This is actually a centered difference around the half-time level.

$$\frac{y^{n+1} - y^n}{\Delta t} = \frac{1}{2} \left( f(y^n) + f(y^{n+1}) \right) = f(y^{n+1/2}) + \mathcal{O}\left( (\Delta t)^2 \right)$$

using Taylor Series.

• BDF-2

$$\frac{3y^{n+1} - 4y^n + y^{n-1}}{2\Delta t} = f(y^{n+1})$$

• Both of these are A-Stable (both of their regions of absolute stability contain the left half of the complex plane, i.e. if the solution *should* decay, it does, independent of timestep).

## 2 Region of Absolute Stability for the Trapezoidal Rule

$$\frac{y^{n+1} - y^n}{\Delta t} = \frac{\lambda}{2} \left( y^n + y^{n+1} \right)$$
$$\left( 1 - \frac{z}{2} \right) y^{n+1} = \left( 1 + \frac{z}{2} \right) y^n$$
$$y^{n+1} = \left( \frac{2+z}{2-z} \right) y^n$$

So the region of absolute stability is defined by

$$\left| \frac{2+z}{2-z} \right| < 1$$
$$|2+z| < |2-z|$$

This is the left half of the complex plane because the above says the distance to -2 must be less than the distance to 2. This is the minimal amount you need to be A-Stable.

• Trapezoidal Rule for Diffusion with standard 3-point second order (1D) spacial discretization is called "Crank-Nicolson." The scheme is 2nd order in space and time and is unconditionally stable (pick any timestep you want).

# 3 Runga-Kutta Methods vs. Linear Multistep Methods

Runga-Kutta are single-step multi-stage methods, whereas Linear Multistep Methods use information from past time.

#### 3.1 Runga-Kutta Methods

• 2nd Order "Improved Euler" Runga-Kutta Method

$$y^* = y^n + \Delta t f(y^n)$$
$$y^{n+1} = y^n + \frac{Dt}{2} (f(y^n) + y(y^*))$$

Note we are only using  $y^n$ , not any other past timesteps. We are using stages to get  $y^{n+1}$ .

• General form of an r-stage RK Method:

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

$$y_i^* = y^n + \Delta t \sum_{j=1}^r A_{ij} f(t_n + c_j \Delta t, y_j^*) \qquad i = 1, \dots, r$$

$$y^{n+1} = y^n + \Delta t \sum_{j=1}^r b_j f(t_n + c_j \Delta t, y_j^*)$$

This is an implicit Runga-Kutta scheme. Explicit RK schemes sum from j = 1 to i - 1 rather than r.

ullet A is called the Runga-Kutta Matrix, b are called the RK weights, and c are called the RK nodes. These are expressed it Butcher Tables in the form

$$y_{1}^{*} = y^{n}$$

$$y_{2}^{*} = y^{n} + \Delta t f(t_{n}, y_{1}^{*})$$

$$y^{n+1} = y^{n} + \frac{\Delta t}{2} (f(t_{n}, y^{*}) + f(t_{n} + \Delta t, y_{2}^{*}))$$

gives the Butcher Table

$$\begin{array}{c|cccc}
0 & 0 & 0 \\
1 & 1 & 0 \\
\hline
& \frac{1}{2} & \frac{1}{2}
\end{array}$$

• Classical RK4 Scheme

If A is strictly lower-triangular, it is an explicit time method. It doesn't have to be, though, and is very high-order accurate in time, but it is very expensive.

- DIRK are "diagonally implicit" RK methods, which include nonzero elements on the diagonals:
  - TR-DBF2 Method

$$y^* = y^n + \frac{\Delta t}{4} (f(y^n) + f(y^*))$$
$$y^{n+1} = \frac{1}{3} (4y^* - y^n + \Delta t f(y^{n+1}))$$

This is a combination of the Trapezoidal Rule and BDF2. This tries to blend the best of both worlds. The Butcher Table is

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### 3.2 Linear Multistep Methods

• "Adams Bashforth 2" or "AB2"

$$\frac{y^{n+1} - y^n}{\Delta t} = \frac{1}{2} (3f(y^n) - f(y^{n-1}))$$

This uses data at  $y^n$  and  $y^{n-1}$  to get  $y^{n+1}$ . This is an extrapolation in time.

- BDF-2 is an implicit time method.
- $\bullet$  General form of an r-step Method

$$\sum_{j=0}^{r} \alpha_j y^{n+j} = \Delta t \sum_{j=0}^{r} \beta_j f(y^{n+j})$$

• The Adams Methods

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$$y^{n+r} - y^{n+r-1} = \Delta t \sum_{j=0}^{r} \beta_j f(y^{n+j})$$

- If  $\beta_r = 0$ , this is called Adams-Bashforth (eg. Forward Euler is an AB method)

$$y^{n+1} - y^n = \Delta t f(y^n)$$

and AB2 is

$$y^{n+1} - y^n = \Delta t \frac{1}{2} (3f(y^n) - f(y^{n-1}))$$

– If  $\beta_r \neq 0$ , Adams Moulton Method implicit time (e.g. trapezoidal rule)

$$y^{n+1} - y^n = \Delta t \frac{1}{2} (f(y^n) + f(y^{n+1}))$$

• BDF-Backward (difference formulas)

$$\sum_{j=0}^{r} \alpha_j y^{n+j} = \Delta t \beta_r f(y^{n+r})$$

These are good for stiff equations. Backward Euler is BDF1. High order BDFs are great if you have lots of eigenvalues clustered along the negative real axis.