

# Study guide: Analysis of exponential decay models

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Aug 4, 2015

## 1 Analysis of finite difference equations

# Analysis of finite difference equations

Model:

$$u'(t) = -au(t), \quad u(0) = I \quad (1)$$

Method:

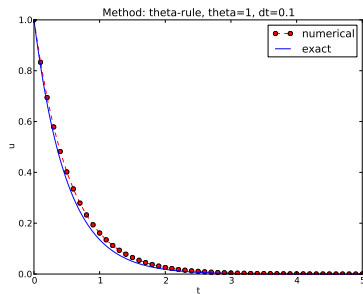
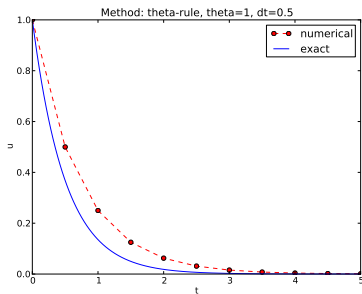
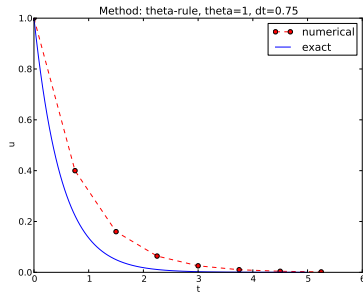
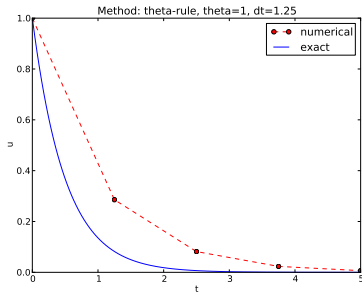
$$u^{n+1} = \frac{1 - (1 - \theta)a\Delta t}{1 + \theta a\Delta t} u^n \quad (2)$$

Problem setting

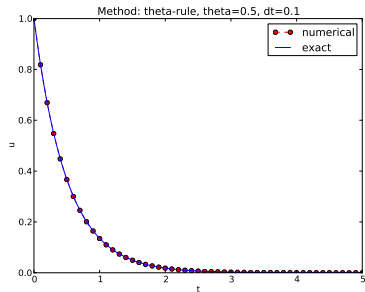
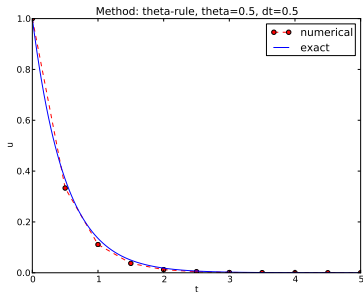
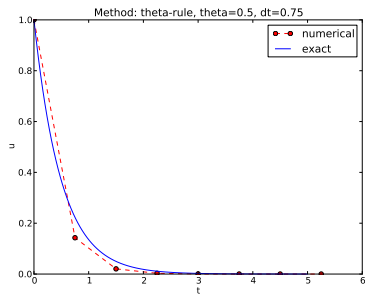
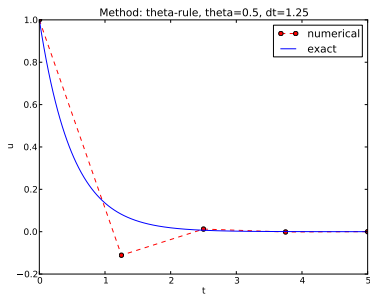
How good is this method? Is it safe to use it?

# Encouraging numerical solutions

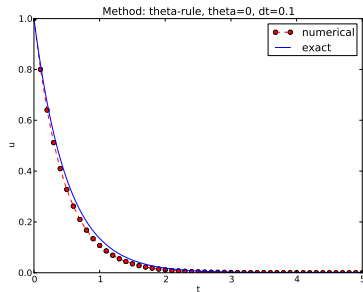
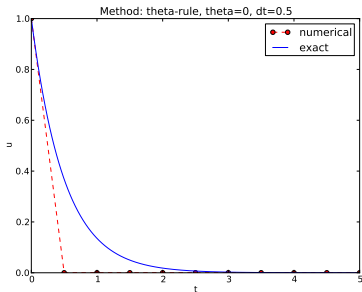
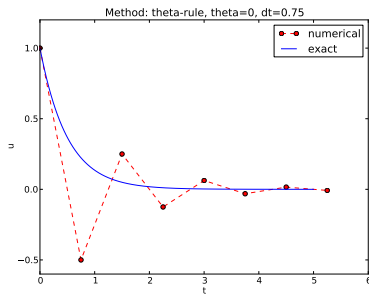
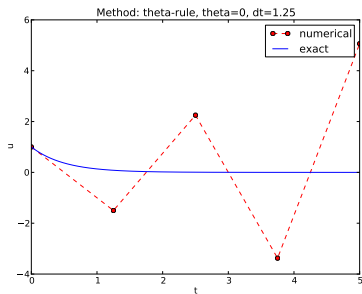
$l = 1, a = 2, \theta = 1, 0.5, 0, \Delta t = 1.25, 0.75, 0.5, 0.1$ .



# Discouraging numerical solutions; Crank-Nicolson



# Discouraging numerical solutions; Forward Euler



# Summary of observations

The characteristics of the displayed curves can be summarized as follows:

- The Backward Euler scheme *always* gives a monotone solution, lying above the exact curve.
- The Crank-Nicolson scheme gives the most accurate results, but for  $\Delta t = 1.25$  the solution oscillates.
- The Forward Euler scheme gives a growing, oscillating solution for  $\Delta t = 1.25$ ; a decaying, oscillating solution for  $\Delta t = 0.75$ ; a strange solution  $u^n = 0$  for  $n \geq 1$  when  $\Delta t = 0.5$ ; and a solution seemingly as accurate as the one by the Backward Euler scheme for  $\Delta t = 0.1$ , but the curve lies *below* the exact solution.

## Goal

We ask the question

- Under what circumstances, i.e., values of the input data  $I$ ,  $a$ , and  $\Delta t$  will the Forward Euler and Crank-Nicolson schemes result in undesired oscillatory solutions?

Techniques of investigation:

- Numerical experiments
- Mathematical analysis

Another question to be raised is

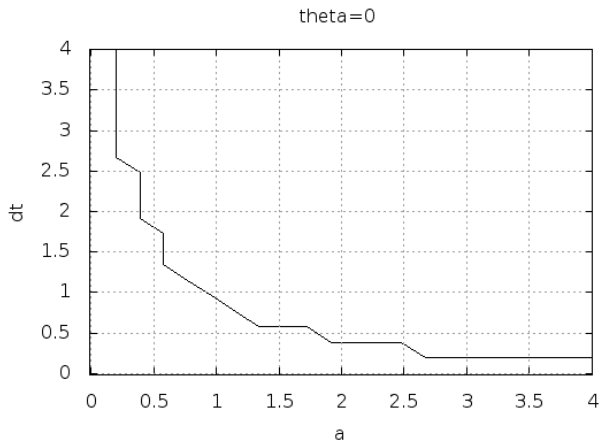
- How does  $\Delta t$  impact the error in the numerical solution?



# Experimental investigation of oscillatory solutions

The solution is oscillatory if

$$u^n > u^{n-1}$$



Starting with  $u^0 = I$ , the simple recursion (2) can be applied repeatedly  $n$  times, with the result that

$$u^n = IA^n, \quad A = \frac{1 - (1 - \theta)a\Delta t}{1 + \theta a\Delta t} \quad (3)$$

Such an exact discrete solution is unusual, but very handy for analysis.

Since  $u^n \sim A^n$ ,

- $A < 0$  gives a factor  $(-1)^n$  and oscillatory solutions
- $|A| > 1$  gives growing solutions
- Recall: the exact solution is *monotone* and *decaying*
- If these qualitative properties are not met, we say that the numerical solution is *unstable*

## Computation of stability in this problem

$A < 0$  if

$$\frac{1 - (1 - \theta)a\Delta t}{1 + \theta a\Delta t} < 0$$

To avoid oscillatory solutions we must have  $A > 0$  and

$$\Delta t < \frac{1}{(1 - \theta)a} \quad (4)$$

- Always fulfilled for Backward Euler
- $\Delta t \leq 1/a$  for Forward Euler
- $\Delta t \leq 2/a$  for Crank-Nicolson

# Computation of stability in this problem

$|A| \leq 1$  means  $-1 \leq A \leq 1$

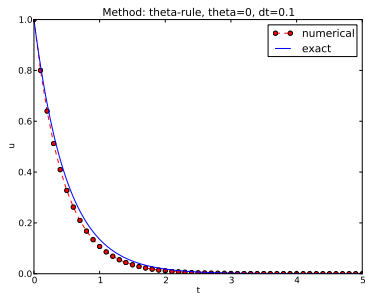
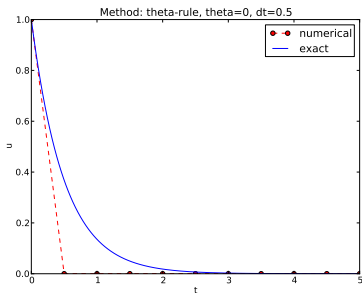
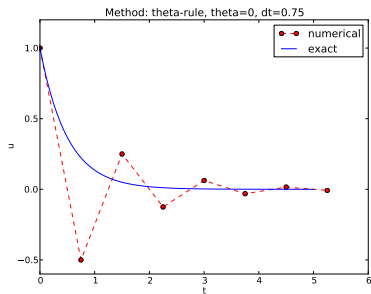
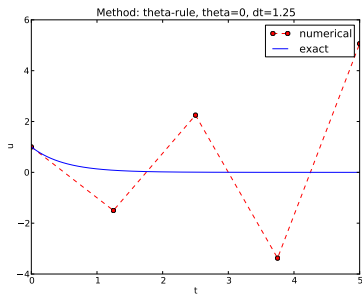
$$-1 \leq \frac{1 - (1 - \theta)a\Delta t}{1 + \theta a\Delta t} \leq 1 \quad (5)$$

$-1$  is the critical limit:

$$\begin{aligned} \Delta t &\leq \frac{2}{(1 - 2\theta)a}, & \theta &< \frac{1}{2} \\ \Delta t &\geq \frac{2}{(1 - 2\theta)a}, & \theta &> \frac{1}{2} \end{aligned}$$

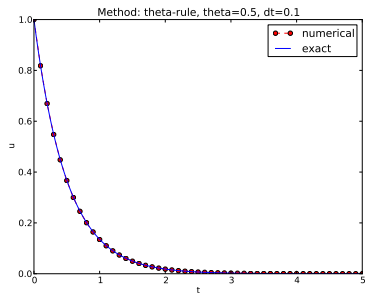
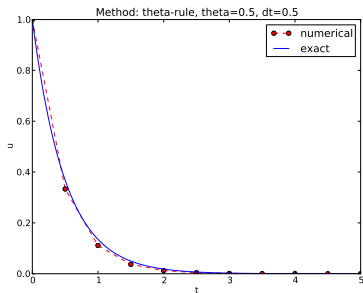
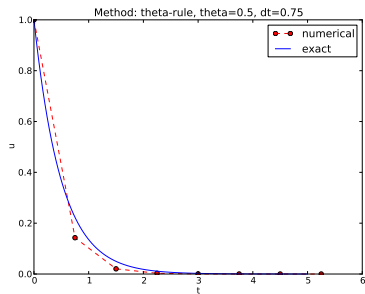
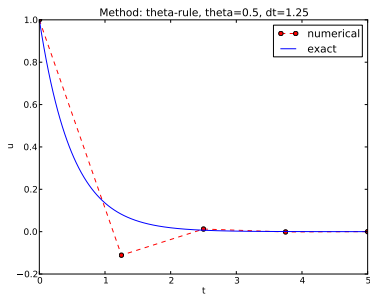
- Always fulfilled for Backward Euler and Crank-Nicolson
- $\Delta t \leq 2/a$  for Forward Euler

# Explanation of problems with Forward Euler



$\Delta t = 2, 1.25, 0.5, 0.1$  illustrating instability

# Explanation of problems with Crank-Nicolson



$$\Delta x = 1.05, \quad \Delta t = 0.25$$

$$\Delta x = 1.05, \quad \Delta t = 0.25$$

# Summary of stability

- 1 Forward Euler is *conditionally stable*
  - $\Delta t < 2/a$  for avoiding growth
  - $\Delta t \leq 1/a$  for avoiding oscillations
- 2 The Crank-Nicolson is *unconditionally stable* wrt growth and conditionally stable wrt oscillations
  - $\Delta t < 2/a$  for avoiding oscillations
- 3 Backward Euler is unconditionally stable



# Comparing amplification factors

$u^{n+1}$  is an amplification  $A$  of  $u^n$ :

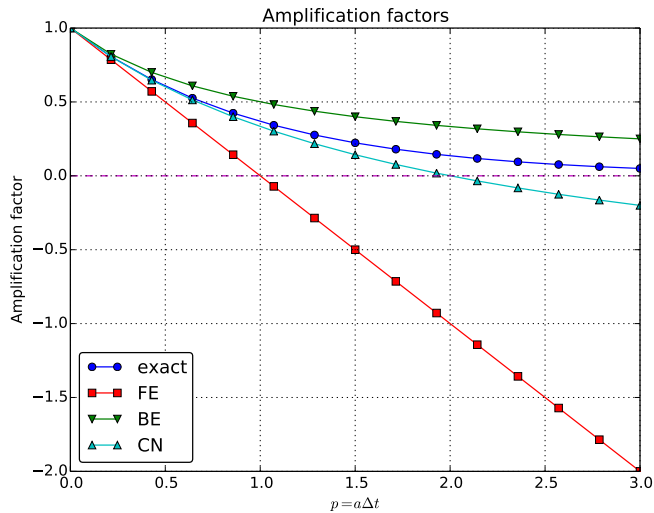
$$u^{n+1} = Au^n, \quad A = \frac{1 - (1 - \theta)a\Delta t}{1 + \theta a\Delta t}$$

The exact solution is also an amplification:

$$u(t_{n+1}) = A_e u(t_n), \quad A_e = e^{-a\Delta t}$$

A possible measure of accuracy:  $A_e - A$

# Plot of amplification factors



$p = a\Delta t$  is the important parameter for numerical performance

- $p = a\Delta t$  is a dimensionless parameter
- all expressions for stability and accuracy involve  $p$
- Note that  $\Delta t$  alone is not so important, it is the combination with  $a$  through  $p = a\Delta t$  that matters

Another “proof” why  $p = a\Delta t$  is key

If we scale the model by  $\bar{t} = at$ ,  $\bar{u} = u/l$ , we get  $d\bar{u}/d\bar{t} = -\bar{u}$ ,  $\bar{u}(0) = 1$  (no physical parameters!). The analysis show that  $\Delta\bar{t}$  is key, corresponding to  $a\Delta t$  in the unscaled model.

# Series expansion of amplification factors

To investigate  $A_e - A$  mathematically, we can Taylor expand the expression, using  $p = a\Delta t$  as variable.

```
>>> from sympy import *
>>> # Create p as a mathematical symbol with name 'p'
>>> p = Symbol('p')
>>> # Create a mathematical expression with p
>>> A_e = exp(-p)
>>>
>>> # Find the first 6 terms of the Taylor series of A_e
>>> A_e.series(p, 0, 6)
1 + (1/2)*p**2 - p - 1/6*p**3 - 1/120*p**5 + (1/24)*p**4 + O(p**6)

>>> theta = Symbol('theta')
>>> A = (1-(1-theta)*p)/(1+theta*p)
>>> FE = A_e.series(p, 0, 4) - A.subs(theta, 0).series(p, 0, 4)
>>> BE = A_e.series(p, 0, 4) - A.subs(theta, 1).series(p, 0, 4)
>>> half = Rational(1,2) # exact fraction 1/2
>>> CN = A_e.series(p, 0, 4) - A.subs(theta, half).series(p, 0, 4)
>>> FE
(1/2)*p**2 - 1/6*p**3 + O(p**4)
>>> BE
-1/2*p**2 + (5/6)*p**3 + O(p**4)
>>> CN
(1/12)*p**3 + O(p**4)
```

## Error in amplification factors

Focus: the error measure  $A - A_e$  as function of  $\Delta t$  (recall that  $p = a\Delta t$ ):

$$A - A_e = \begin{cases} \mathcal{O}(\Delta t^2), & \text{Forward and Backward Euler,} \\ \mathcal{O}(\Delta t^3), & \text{Crank-Nicolson} \end{cases} \quad (6)$$

# The fraction of numerical and exact amplification factors

Focus: the error measure  $1 - A/A_e$  as function of  $p = a\Delta t$ :

```
>>> FE = 1 - (A.subs(theta, 0)/A_e).series(p, 0, 4)
>>> BE = 1 - (A.subs(theta, 1)/A_e).series(p, 0, 4)
>>> CN = 1 - (A.subs(theta, half)/A_e).series(p, 0, 4)
>>> FE
(1/2)*p**2 + (1/3)*p**3 + 0(p**4)
>>> BE
-1/2*p**2 + (1/3)*p**3 + 0(p**4)
>>> CN
(1/12)*p**3 + 0(p**4)
```

Same leading-order terms as for the error measure  $A - A_e$ .

# The true/global error at a point

- The error in  $A$  reflects the *local error* when going from one time step to the next
- What is the *global (true) error* at  $t_n$ ?  
$$e^n = u_e(t_n) - u^n = Ie^{-at_n} - IA^n$$
- Taylor series expansions of  $e^n$  simplify the expression

# Computing the global error at a point

```
>>> n = Symbol('n')
>>> u_e = exp(-p*n)      # I=1
>>> u_n = A**n           # I=1
>>> FE = u_e.series(p, 0, 4) - u_n.subs(theta, 0).series(p, 0, 4)
>>> BE = u_e.series(p, 0, 4) - u_n.subs(theta, 1).series(p, 0, 4)
>>> CN = u_e.series(p, 0, 4) - u_n.subs(theta, half).series(p, 0, 4)
>>> FE
(1/2)*n*p**2 - 1/2*n**2*p**3 + (1/3)*n*p**3 + 0(p**4)
>>> BE
(1/2)*n**2*p**3 - 1/2*n*p**2 + (1/3)*n*p**3 + 0(p**4)
>>> CN
(1/12)*n*p**3 + 0(p**4)
```

Substitute  $n$  by  $t/\Delta t$ :

- Forward and Backward Euler: leading order term  $\frac{1}{2}ta^2\Delta t$
- Crank-Nicolson: leading order term  $\frac{1}{12}ta^3\Delta t^2$



The numerical scheme is convergent if the global error  $e^n \rightarrow 0$  as  $\Delta t \rightarrow 0$ . If the error has a leading order term  $\Delta t^r$ , the convergence rate is of order  $r$ .

# Integrated errors

Focus: norm of the numerical error

$$\|e^n\|_{\ell^2} = \sqrt{\Delta t \sum_{n=0}^{N_t} (u_e(t_n) - u^n)^2}$$

Forward and Backward Euler:

$$\|e^n\|_{\ell^2} = \frac{1}{4} \sqrt{\frac{T^3}{3}} a^2 \Delta t$$

Crank-Nicolson:

$$\|e^n\|_{\ell^2} = \frac{1}{12} \sqrt{\frac{T^3}{3}} a^3 \Delta t^2$$

## Summary of errors

Analysis of both the pointwise and the time-integrated true errors:

- How good is the discrete equation?
- Possible answer: see how well  $u_e$  fits the discrete equation

$$[D_t u = -au]^n$$

i.e.,

$$\frac{u^{n+1} - u^n}{\Delta t} = -au^n$$

Insert  $u_e$  (which does not in general fulfill this equation):

$$\frac{u_e(t_{n+1}) - u_e(t_n)}{\Delta t} + au_e(t_n) = R^n \neq 0 \quad (7)$$

# Computation of the truncation error

- The residual  $R^n$  is the *truncation error*.
- How does  $R^n$  vary with  $\Delta t$ ?

Tool: Taylor expand  $u_e$  around the point where the ODE is sampled (here  $t_n$ )

$$u_e(t_{n+1}) = u_e(t_n) + u'_e(t_n)\Delta t + \frac{1}{2}u''_e(t_n)\Delta t^2 + \dots$$

Inserting this Taylor series in (7) gives

$$R^n = u'_e(t_n) + \frac{1}{2}u''_e(t_n)\Delta t + \dots + au_e(t_n)$$

Now,  $u_e$  solves the ODE  $u'_e = -au_e$ , and then

$$R^n \approx \frac{1}{2}u''_e(t_n)\Delta t$$

This is a mathematical expression for the truncation error.

# The truncation error for other schemes

Backward Euler:

$$R^n \approx -\frac{1}{2}u_e''(t_n)\Delta t$$

Crank-Nicolson:

$$R^{n+\frac{1}{2}} \approx \frac{1}{24}u_e'''(t_{n+\frac{1}{2}})\Delta t^2$$

# Consistency, stability, and convergence

- Truncation error measures the residual in the difference equations. The scheme is *consistent* if the truncation error goes to 0 as  $\Delta t \rightarrow 0$ . Importance: the difference equations approaches the differential equation as  $\Delta t \rightarrow 0$ .
- *Stability* means that the numerical solution exhibits the same qualitative properties as the exact solution. Here: monotone, decaying function.
- *Convergence* implies that the true (global) error  $e^n = u_e(t_n) - u^n \rightarrow 0$  as  $\Delta t \rightarrow 0$ . This is really what we want!

The Lax equivalence theorem for *linear* differential equations: consistency + stability is equivalent with convergence.

(Consistency and stability is in most problems much easier to establish than convergence.)