MA3227 Numerical Analysis II

Topics for Final Exam

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Midterm topics

▶ All topics covered in the midterm can also be tested in the final.

Banach fixed point theorem

Not part of the exam.

Ordinary differential equations

- ➤ You should be familiar with the basic theory for ODEs, but I will not explicitly test this in the exam. Topics in this category include:
 - ▶ Meaning of $\dot{y} = f(y)$.
 - ► Picard-Lindelöf theorem
 - Gronwall's inequality.
 - Stability with respect to initial conditions.
- You should know how to write $\ddot{x} = g(x, \dot{x})$ or $\dot{x} = g(x, t)$ in the form $\dot{y} = f(y)$.

Runge-Kutta methods

Example questions (see lab 5 and assignment 3):

- ► Translate Butcher tableau into one-step equation or vice versa.
- ▶ Perform by hand a few steps of a Runge-Kutta method given in the form of either a Butcher tableau or a one-step equation.
- ▶ Determine the order of consistency of a given scheme.
- ▶ Determine the stability function of a given scheme.

Remarks:

- ➤ You can practice the above questions using the schemes from https://en.wikipedia.org/wiki/List_of_Runge-Kutta_methods. You can test your answers using the convergence() and stability() functions from assignment 3.
- Showing consistency of order p + 1 > 3 is tedious and not required to demonstrate understanding of the theory. I will not ask for this.
- ▶ Unlike in assignment 3, I may also ask you to determine the order of consistency of an implicit method.
- Recall that there are two ways for determining the stability functions, and one may be much easier to execute than the other.

Runge-Kutta methods (continued)

Other things which you should know:

- Lipschitz-continuity of f(y) and (p + 1)th-order consistency imply pth-order convergence.
- ▶ A Runge-Kutta scheme applied to an ODE $\dot{y} = f(y)$ with fixed point y_F may exhibit spurious exponential blow-up if $|R(\lambda \Delta t)| > 1$ for some eigenvalue λ of $\nabla f(y_F)$.
- ▶ The one and only advantage of implicit Runge-Kutta methods is that they allow for R(z) to be bounded for $|z| \to \infty$.

Adaptive time-stepping

Facts you should know:

- Accuracy of Runge-Kutta methods depends on curvature of solution.
- ightharpoonup Errors can be estimated by comparing the numerical results for different step-sizes Δt or Runge-Kutta schemes of different orders.
- There are two algorithms for choosing the "effort parameter" n such that the error e(n) satisfies $e(n) \lesssim \varepsilon$:
 - ▶ Double *n* until converged. This takes at most two times longer than running the algorithm only once with the "correct" *n*.
 - Extrapolate convergence,

$$e(n) pprox C n^{-p} \longrightarrow n_{\mathsf{ideal}} = n_{\mathsf{trial}} \left(\frac{e(n_{\mathsf{trial}})}{\varepsilon} \right)^{1/p}.$$

Pro: close to no overhead compared to using the "correct" n.

Con: n_{ideal} can be wrong if $e(n) \approx C n^{-p}$ is not satisfied.

If this happens, then this is likely because $n_{\rm trial}$ is too small.

Both of these methods can also be used for choosing the step size Δt .

Time-dependent PDEs

Things you should know:

- ► Time-dependent PDEs can be solved by using finite differences in space to convert the PDE to a system of ODEs, and then using a Runge-Kutta scheme to solve the ODE.
- ► The resulting system of ODEs is stiff and should be solved using an implicit Runge-Kutta scheme.

Things I do not expect you to know:

► Convergence theory for finite differences + Runge Kutta.

Trajectory of Cannonball

Things you should know:

▶ Derivatives of y(t) with respect to the initial conditions y_0 can be computed by solving

$$\frac{d}{dt}\frac{\partial y}{\partial y_0} = \nabla f(y)\frac{\partial y}{\partial y_0}, \qquad \frac{dy}{dy_0}(0) = 1.$$

See also the shooting method in lab 7.

Molecular dynamics

Things you should know:

- Newton's equations of motion conserve the total energy.
- Most Runge-Kutta methods lead to a drift in the total energy.
- ▶ This drift can be avoided by using a symplectic integrator.

Things I do not expect you to know:

Anything about molecular dynamics or symplectic integrators not explicitly mentioned above.

Probability theory

You should be familiar with the following definitions and results from probability theory.

- Probability space, random variables (RVs), distributions of RVs.
- ▶ Representations of distributions: PDF / PMF, CDF.

► Expectation:
$$\begin{cases} \mathbb{E}[f(X)] = \int_{\Xi} f(x) \, p(x) \, dx \\ \mathbb{E}[aX + bY] = a \, \mathbb{E}[X] + b \, \mathbb{E}[Y] \end{cases}$$

► Variance:
$$\begin{cases} \operatorname{Var}[X] = \mathbb{E}[(X - \mathbb{E}[X])^2] = \mathbb{E}[X^2] - \mathbb{E}[X]^2 \\ \operatorname{Var}[aX + b] = a^2 \operatorname{Var}[X] \end{cases}$$

▶ Independence: $p(x_1, ..., x_n) = p_1(x_1) ... p_n(x_n)$.

p(x) denotes the PDF / PMF of X in the above formulae.

Monte Carlo sampling

Things you should know:

- ▶ Monte Carlo estimator $\tilde{\mathbb{E}}_N[X] = \frac{1}{N} \sum_{k=1}^N X_k$.
- ▶ Error estimation using central limit theorem. In particular:
 - The two interpretations of the central limit theorem regarding expected error and likelihood of outliers.
 - ▶ How to estimate Var[X] using the X_k computed for the Monte Carlo estimator $\tilde{\mathbb{E}}_N[X]$ (see Lecture 24).

Simulation of random variables

Things you should know:

- pRNGs: what they are and why we use them.
- ► Transformation sampling theorem.
- ► Rejection sampling theorem.
- ► Importance sampling theorem.

The above is a complete list of all exam-relevant topics for this module. If you have any questions about it, please do not hesitate to ask.

The remaining slides contain:

- A one-page list of topics of particular importance for the exam. The idea of this list is to help you focus your study efforts on topics which guarantee a decent passing grade. Obviously, if you want an outstanding grade then you should master all of the above topics.
- ► An overview of the module which is intended to help you organise the various topics in this module in a unified framework.

Key exam topics

Some key techniques to master for the exam:

- ▶ Application of fill path theorem (practise using Q1 in lab 2).
- ▶ Root-finding algorithms by hand (practise using codes in Lect. 12 & 13).
- Runge-Kutta methods by hand (see slide 3 for practice material).
- ▶ Determining the order of consistency and stability function of Runge-Kutta methods (see slide 3 for practice material).
- ► Application of transformation, rejection and importance sampling. (see assignment 4 and lab 9 for practice material).

Furthermore, make sure you are aware of the following facts:

- Krylov methods:
 - Cost of k Krylov iterations:

$$k \text{ matvecs} + \begin{cases} \mathcal{O}(nk^2) \text{ other operations for GMRES} \\ \mathcal{O}(nk) \text{ other operations for CG and MinRes} \end{cases}$$

- \triangleright k distinct eigenvalues \implies convergence in at most k iterations.
- Eigenvalues in $[a,b] \Rightarrow \mathcal{O}(|\log(\varepsilon)|\sqrt{b/a})$ required for error ε .
- ► Jacobi-type methods:
 - ► Error analysis amounts to determining the error recurrence $x_{k+1} x = R(x_k x)$ and determining the eigenvalues $\hat{\lambda}$ of R.

Module overview

Numerical algorithms discussed in this module, grouped by the type of problem that they solve.

- ▶ Poisson equation (or more generally, PDEs)
 - ► Finite difference discretisation
- ► Linear systems of equations
 - ► Sparse LU factorisation
 - Krylov subspace methods
 - Jacobi and multigrid iteration
- ► Nonlinear equations and systems of equations
 - ► Bisection and false position
 - Newton's method
 - Secant and Broyden's method
 - ► Steepest descent / gradient descent
- Ordinary differential equations
 - Explicit and implicit Runge-Kutta methods
- ► High-dimensional problems
 - Monte Carlo methods

Module overview (continued)

For each problem type listed above, make sure you can comment on the following:

- Precise problem formulation
- Existence and uniqueness
 - Poisson equation: not discussed in this module.
 - Linear equations: A nonsingular.
 - Nonlinear equations: convexity, fixed-point theorems. (Only briefly mentioned in this module.)
 - ODEs: Picard-Lindelöf theorem.
 - ► High-dim : usually not an issue since we have explicit formulae.
- ► Conditioning / stability / sensitivity
 - Poisson equation: not discussed in this module.
 - Linear equations: condition number $\kappa(A) = ||A|| ||A^{-1}||$.
 - Nonlinear equations: not discussed in this module
 - ODEs: Gronwall inequality and the stability corollary.
 - ► High-dim: not discussed in this module.

Module overview (continued)

For each algorithm, make sure you can comment on the following:

- ► Runtime & algorithmic details.
- Is the algorithm exact up to rounding errors? Answer is no for all algorithms except LU factorisation.
- If no, which result guarantees convergence?
 - ► Finite differences: stability & consistency ⇒ convergence theorem.
 - ► Krylov methods: equivalence to polynomial minimisation problems.
 - ▶ Jacobi, multigrid, Newton, secant: error recursion $e_{k+1} = f(e_k)$.
 - Bisection & false position: shrinking bracketing intervals.
 - Runge-Kutta methods: consistency and Lipschitz continuity theorem.
 - ▶ Monte Carlo: central limit theorem.
- ► How do we estimate the error?
 - PDEs: not discussed in this module.
 - ▶ Linear equations: residual $||A\tilde{x} b||$.
 - Nonlinear equations: either residual ||f(x)|| or progress $||x_{k+1} x_k||$.
 - ▶ ODEs: compare results for different orders or step sizes.
 - Monte Carlo: estimate Var[X].