Exercise class 9

(week 16)

Introduction to Programming and Numerical Analysis

Class 4 and 8
Rosa Haslund Meyer
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KØBENHAVNS UNIVERSITET





Solving equations – linear and non-linear

Symbolic math / Python

Problem set 6



Linear equations

Linear equations refer to anything that can be written in matrix form, i.e.:

$$Ax = b \iff \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix}$$

If A in invertible (a square matrix such that the product of the matrix and its inverse generates the identity matrix), the solution is $x = A^{-1}b$. There are standard routines for inverting matrices, however, these can sometimes be computationally expensive, which is where the following algos come in:

- Gauss-Jordan elimination (not that much more efficient)
- Gauss-Seidel iterations are faster (but may not always converge)
- **LU-factorization** has no matrix inversion, i.e. very fast



Non-linear equations

With non-linear equations, it's often necessary for us to be more *general* in our approach. As such, we often use a root finder/solver:

$$f(x) = b \iff \hat{f}(x) = 0, \quad \hat{f}(x) = f(x) - b$$

Root-finding algos include (among others):

- Bisection (as you worked with in ps5), no gradient, but may sometimes be slow
- **Newton** or **Halley**, use gradient (and Hessian) to update guesses effectively
- **Brent** finds an efficient combination

Different algos work well under different conditions – feel free to experiment!

Symbolic math / Python

Symbolic Python (sympy-package) can do complicated math and solve equations analytically! Everything is much like what we know from micro and macro courses, which is nice as:

- More familiar, recognisable and intuitive
- Can find solutions to problems with more than one solution
- Can solve the problems exactly, not just down to a numerical approximation
- The code is nice to look at and easy to read

Not so nice as:

- Doesn't provide a deeper understanding of numerical methods... :(
- Many models have no analytical solution

Problem set 6 – task 1-4

Task 1-4: linear algebra, solving matrix equations – general tips:

- Go through the tasks slowly and think logically.
- If you forgot some of the math, look that up instead of looking at solutions
- Look at the scipy package linalg, it has almost everything you would need
- For task A4, remember to import the given module numecon_linalg
- Hint for A4: you need to stack the two arrays F and e to get X: F:

Problem set 6 – task 5-6

Task 5-6: symbolic math / Python – general tips:

- Go through the tasks slowly
- Think logically, these tasks should be quite straight forward
- Look up the most useful methods/documentation of sympy, it has the main functions you will use: sm.limit() and sm.diff()
- To use sympy, you need to "define" your variables: x = sm.symbols('x')

Problem set 6 – Problem: the Solow model

Task 5-6: symbolic math / Python – general tips:

Make sure to understand the setting and if needed refresh the Solow model:

"A standard Solow model predicts that in the long run, economies converge to their balanced growth equilibrium and that permanent growth of per capita income is achievable only through technological progress."

- Dived expressions into multiple entities to make the code more readable
- Symbolic equations in SymPy are represented as sm.Eq(x, y)
- For task A8 you should use sm.lambdify, google the documentation
- Define each function one at a time



Next time...

Video lectures:

- Unconstrained optimization
- Constrained optimization
- Dynamic optimization

Exercises – Problem set 7. Solving the consumer problem with income risk

Note: ps7 is quite long and covers some difficult concepts, so I suggest you have a quick look before class. Ps7 is also the last problem set!

Remember to give peer feedback on data projects by April 21st.