CSci 5304 Fall 2024
Computational Aspects of Matrix Theory

General Information

Please note: 1) additional information provided online (canvas and instructor's class pages); 2) This syllabus may still undergo small changes in the coming couple of weeks. This course introduces the basic numerical techniques of linear algebra. It covers basic tools (e.g., norms), design of matrix algorithms, their analysis, and related applications. Students taking this class should have a good background in linear algebra (prerequisite is csci 2033 or equivalent) and be familiar with Matlab or Python+numpy/scipy.

- **Class Schedule:** TTh 08:15 AM - 09:30 AM — Ack 209
- **Lectures:** *This course is scheduled as an in-person course. I intend to hold all class sessions in-person except if situational factors arise, such as personal illness of the instructor, when the class may be held synchronously via Zoom or recorded for later viewing.*
- **Instructor:** Yousef Saad ≪ saad@umn.edu ≫ `http://www.cs.umn.edu/~saad`
- **Teaching Assistant:** Zechen Zhang ≪ zhan5260@umn.edu ≫
- **Office hours:** The office hours are posted online.

  The Instructor's office hours will be will be held in person in the instructor office. Zoom meetings can be set up with appointments for the 2nd half of the Office hour or at other times if needed.

  See class web-site for details on the TA's office hours

- **Class Website:** Basic information and lecture notes will be posted here:

  `www-users.cse.umn.edu/~saad/csci5304/`

  Detailed schedule, Homeworks, grades, will be posted on canvas. Homeworks and some exams (see section on tests) will be submitted via canvas.

  It is your responsability to check both Canvas (especially for homeworks) and the instructor's class website (for lecture notes) on a regular basis.

Textbook

With so much available online, there is no *required* textbook for this class. However, you may need a good reference for an in-depth coverage of the material that will be taught. Here are three listed in order of preference.

- Main reference: *Matrix Computations* 4th edition, G. Golub and C. Van Loan. John Hopkins, 2015. This is a rather comprehensive book and it is especially recommended as a reference for those of you who will do research involving numerical linear algebra. A PDF version of the older edition of the book can be obtained online – and it is sufficient.
- *Numerical linear algebra*, Lloyd N. Trefethen and David Bau, III. SIAM, 1997 (pbk). Very well written, easy to understand and insightful presentation of most topic to be covered. Not as detailed (or complete) as the ones above.
- *New* *Linear Algebra for Data Science, Machine Learning, and Signal Processing* by Jeffrey A. Fessler and Raj Rao Nadakuditi. Cambridge University Press, 2024. DOI: 10.1017/9781009418164. Good coverage of new topics of Linear Algebra.

Matlab and Python : Matlab and/or Python will often be used in class for illustrating algorithms. You will also use either of these options for writing small programs when needed in assignments. Both Matlab and Python have extensive online documentation and other resources posted on the web.

Lecture Notes

Lecture notes will be posted regularly on the class web-site (see above – not on canvas). (Icon "Lect. Notes" in menu). These notes will be posted by topic rather than lecture by lecture, and they are usually posted prior to the lectures.

Evaluation

Your evaluation for this class will be based on *7 homeworks (HW), and 4 tests. There will be no final exam* The final score will consist of the following:

- Homework total: 35 % for a total of 7 homeworks (5 % each).
- Tests: 4 tests at 16.25% each for a total of 65%

There will actually be a total of 5 tests but the lowest grade among the 5 tests will be dropped and so the calculated score for exams will be based on your best 4 grades. There will be no make-up tests. If you miss more than one test and have a good justification (e.g. note from doctor in case of sickness) it may be possible, in some exceptional situations, to assign a 'neutral' grade by replacing the missing grade entry by the mean of the other three (this is equivalent to taking the average of the remaining 3 tests as the total for the 'tests' category).
All tests will be written exams returned on paper and will take place in class. Their duration will be 40mn or less. All tests will be taken at the end of the class when they are scheduled. Each will count 16.25% toward the final score.
Your final letter grade for this class will be decided based on the following scale, where T is the total score (out of 100) you achieved in the class.

A : $100 \geq T \geq 93$	**A-** : $93 > T \geq 87$	**B+** : $87 > T \geq 82$
B : $82 > T \geq 77$	**B-** : $77 > T \geq 72$	**C+** : $72 > T \geq 65$
C : $65 > T \geq 60$	**C-** : $60 > T \geq 55$	**D+** : $55 > T \geq 50$
D : $50 > T \geq 40$	**F** : $40 > T$	

If you are taking the class on an S-N basis your total score must be at least 60% in order to get an S grade.

Grading

Grades will be posted immediatly after each homework or test is graded. This will usually take up to one week. It is important that you check your grades regularly. If you see a discrepancy between your grades and the grades posted, you need to alert the TA immediatly. You have one week after the homework/ test is returned for requesting a change. Details on this can be found in the general **policy on homeworks and tests** – posted in the schedule of the instructor's class web-site.

Cheating

All homeworks and tests must represent your own individual effort. Please read the course policy on homeworks and tests.
Cheating cases will be dealt with in a very strict manner. At a minimum, violators of this policy will fail the course and will have their names recorded. For additional information please consult the student code of conduct which can be found here: `https://regents.umn.edu/policies/index`

Overview of topics to be covered

[Tentative and the order of coverage may be different]

- Subspaces, Bases, Matrices, Special matrices, Vector and matrix norms.
- Solving systems of linear equations. LU factorization.
- Floating point arithmetic. Error analysis. Forward and Backward errors.
- Condition numbers. Estimating accuracy.
- Orthogonality, the Gram-Schmidt process. Classical and modified Gram-Schmidt. Householder QR factorization. Givens rotations. Least-squares systems. Rank deficient LS problem. Regularization.
- Eigenvalues, singular values. The Singular Value Decomposition. Applications of the SVD.
- Eigenvalue problems: Background, Schur decomposition, perturbation analysis, power and inverse power methods, subspace iteration; the QR algorithm.
- The Symmetric Eigenvalue Problem: special properties and perturbation theory, Law of inertia, Min-Max theorem, symmetric QR algorithm.
- If time permits: Sparse matrix techniques. The Lanczos algorithm. Lanczos bidiagonalization. Krylov subspace methods.