

Introduction

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- Course compiled from scratch → inherent incoherency
- Diverse group of students → possibly redundant topics
- Not enough time to rewrite slides → using slides from other sources (in English)
- Trying my best → expecting same from you
- Putting slide credits wherever possible (some sources might be lost)

"Computational and numerical tools" (known as *"Optimization and numerical methods"* in your curriculum)

What this course is about:

- Some of the most relevant computational and numerical tools commonly used in research and engineering
- Tools = algorithms and implementations

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What this course is **not** about:

- Minimal math component: some math for understanding, rare derivations, almost no analysis/proofs
- Not a programming course: you are expected to know basic programming
- Breadth, not depth

This course consists of **lectures and programming seminars**. Usually one lecture and one seminar will be every week with rare exceptions. In addition to that this year I plan to have **research presentation** as part of the class.

Lecture notes and video links will be posted online:

<https://www.mbolonkin.info/teaching/cs170-2022>

Homeworks: basic and advanced version will be posted online

Research presentation: papers will be posted online

Getting your grade:

- Grade “5”
 - + Solve the advanced homework (automatic grade) OR
 - + Solve the basic homework (80%) and attend the oral examination
 - + Do a good research presentation and be able to answer questions
- Grade “4”
 - + Solve the basic homework (80%) and attend the oral examination
 - + Do a decent research presentation
- Grade “3”
 - + Attend the classes and solve the basic homework (50%)
 - + Do a research presentation
- Non-passable grade
 - Attendance below threshold, no solved homeworks, failed oral exam
 - Severe violation of an honor principle

Any work you are submitting must be your own. Collaboration without sharing any code is acceptable.

In case I am **suspicious** of plagiarism in your assignments (in full or partially, based on in-person grading), I reserve the right to not accept your solutions as well as give you a non-passable grade for the course. Plagiarized work will not be counted towards any positive grades.

Burden of proof is entirely on you: I do not have to prove that your work is plagiarized, you have to prove it is not.

Corollary: In case you decided to plagiarize your peer's solution, make sure you understand it thoroughly.

Expected programming tools for this course:

- Matlab/Octave
- Python + Jupyter Notebooks (Recommended)

I have Anaconda packages for Windows downloaded.

Why Python?

Python has well supported scientific libraries

- NumPy - supports wide variety of matrix operations
- SciPy - a lot of computational methods implemented
- Matplotlib - library for plotting and visualizing
- Scikit-Image, Scikit-Learn, etc.
- Very good documentation

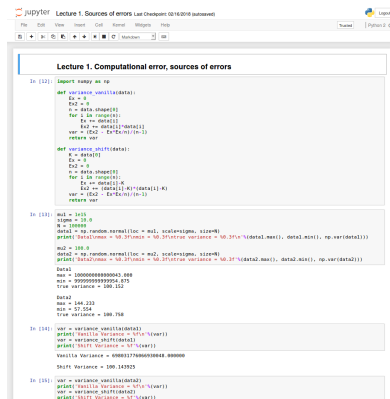
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Jupyter Notebooks:

- Convenient tool for coding and debugging
- Good for reproducible research
- Getting more and more popular



The screenshot shows a Jupyter Notebook window titled "Lecture 1. Sources of errors" with a timestamp of 03/16/2019. The notebook content is titled "Lecture 1. Computational error, sources of errors". It contains three code cells. The first cell defines functions for variance calculation with and without scaling. The second cell generates random data and calculates variances for different scaling factors. The third cell compares the variance of the original data with the variance after shifting.

```
In [32]: import numpy as np

def variance_vanilla(data):
    E = 0
    E2 = 0
    n = data.shape[0]
    for i in range(n):
        E += data[i]
        E2 += data[i]**2
    var = (E2 - E**2/n)/(n-1)
    return var

def variance_shift(data):
    K = data[0]
    E = 0
    E2 = 0
    n = data.shape[0]
    for i in range(n):
        E += data[i]-K
        E2 += (data[i]-K)*(data[i]-K)
    var = (E2 - E**2/n)/(n-1)
    return var

In [33]: mu1 = 1e3
sigma = 1e-6
N = 10000
data1 = np.random.normalloc = mu1, scale=sigma, size=N)
print('Data1: mean = %0.3f, var = %0.3f' % (data1.mean(), data1.min(), np.var(data1)))

mu2 = 1e8
data2 = np.random.normalloc = mu2, scale=sigma, size=N)
print('Data2: mean = %0.3f, var = %0.3f' % (data2.mean(), data2.min(), np.var(data2)))

Data1
min = 100000000000000.0
max = 99999999999999.975
True variance = 1e-12

Data2
min = 1e+23
max = 1e+24
True variance = 1e-12

In [34]: var = variance_vanilla(data1)
print('Vanilla Variance = %f' % var)
var = variance_shift(data1)
print('Shift Variance = %f' % var)

Vanilla Variance = 608817706093868.880000
Shift Variance = 100.142925

In [35]: var = variance_vanilla(data2)
print('Vanilla Variance = %f' % var)
var = variance_shift(data2)
print('Shift Variance = %f' % var)
```

Any questions?

- Computation allows exploring models without analytical solution
- This is usually the case for real-world problems
- Advances in hardware and software make it easier to use computational models

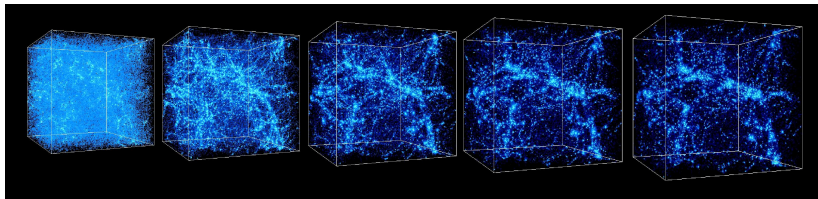


Figure: Galaxy formation (cosmicweb.uchicago.edu)

Why bother?

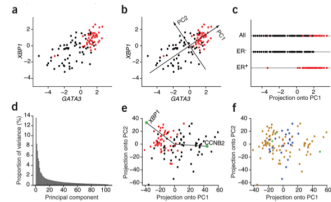
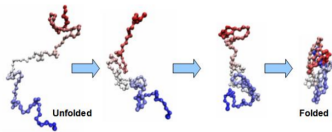


Figure: Protein unfolding simulation and analysis of gene expression

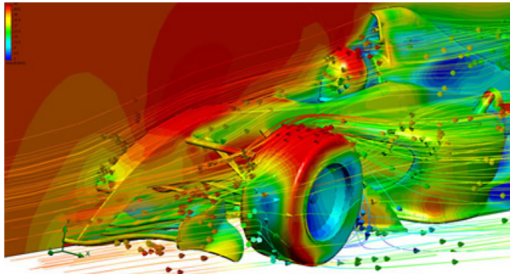


Figure: Fluid dynamics simulation

In 2000 January-February issue of *Computing in Science and Engineering* editors selected 10 algorithms that influenced science and engineering in 20th century.

- 1 Metropolis algorithm for Monte Carlo**

1946: John von Neumann, Stan Ulam, and Nick Metropolis

- 2 Simplex method for linear programming**

1947: George Dantzig, at the RAND Corporation

- 3 Krylov subspace iteration methods**

1950: Magnus Hestenes, Eduard Stiefel, and Cornelius Lanczos

- 4 The decompositional approach to matrix computations**

1951: Alston Householder of Oak Ridge National Laboratory

5 The Fortran optimizing compiler

1957: John Backus, IBM

6 QR algorithm for computing eigenvalues

1959–61: J.G.F. Francis

7 Quicksort algorithm for sorting

1962: Tony Hoare

8 Fast Fourier transform

1965: James Cooley of the IBM T.J. Watson Research Center and John Tukey of Princeton University and AT&T Bell Laboratories

9 Integer relation detection

1977: Helaman Ferguson and Rodney Forcade of Brigham Young University

10 Fast multipole method

1987: Leslie Greengard and Vladimir Rokhlin of Yale University

In 2016 editors of the CiSE updated the list of top 10 algorithms, adding the following:

- 1 **Newton and quasi-Newton methods**
- 2 **Jpeg**
- 3 **PageRank**
- 4 **Kalman filter**

What we are going to cover in this course:

- **Data fitting**

Some topics: linear least squares, non-linear least squares, maximum likelihood, maximum a posteriori, expectation maximization

- **Optimization**

Some topics: gradient-free optimization, gradient descent, non-linear optimization, heuristics

- **Dimensionality reduction and component analysis**

Some topics: PCA, ICA, t-SNE, LDA

- **Signal Processing**

Some topics: signals, filters, DFT

- **Randomized methods**

Some topics: random number sampling, Monte-Carlo methods, RANSAC

- **Differential equations**

Some topics: numerical solutions for Ordinary Differential Equations (ODE), Partial Differential Equations (PDE)

- Replacing difficult problem by simplified problem with the same or close enough solution
 - Infinite \rightarrow Finite
 - Differential \rightarrow Algebraic
 - Continuous \rightarrow Discrete
 - Non-linear \rightarrow Linear
 - ...
- Solution obtained only **approximates** the exact solution of the original problem
 - Approximation before computation (empirical measurements, previous computation)
 - Approximation during computation (covered in next part)
 - Final result accuracy reflects all those errors, possibly amplified by an algorithm/problem