COMP229: Introduction to Data Science Lecture 1: overview and expectations

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Background and contact details

2008 PhD Dynamical Systems, MSU.

till 2008: Lecturer at Higher School of Economics, Moscow.

2009-16 Teaching at Maths dept. in Durham Uni.

2017-19: Teaching in Computer Science.

2020-23: Data Scientist in Population Health, collaborating with Materials Innovation Factory.

2023: Computer Science.

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What is important for COMP229?

The keyword is *Science*, which is "a systematic enterprise that builds and organises knowledge in the form of *testable explanations*" [Wikipedia].

Hence COMP229 will involve many *rigorous* definitions and *logical proofs*.

What is Data Science?

Definition 1.1. Data Science is an interdisciplinary field that uses *scientific methods* and algorithms to extract knowledge from data [Wikipedia].

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Since many companies use their own software (or even languages), COMP229 will focus only on scientific foundations (not specific implementations) to prepare you for any good job on data analysis.





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Accessibility and cost!



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Automated logic example:

- There is nothing better than eternal happiness.
- But a ham sandwich is better than nothing.
- Hence, a ham sandwich is better that eternal happiness.



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- a) with current definitions the total overall happiness is negative, and
- b) 0 is surely an increase from a negative number.

Is it all just stupid machines?



Human pattern recognition

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COMP229 will mainly discuss unsupervised learning.



Yann LeCun's classification

Types of machine learning

Yann Lecun's Black Forest cake



"Pure" Reinforcement Learning (cherry)

- The machine predicts a scalar reward given once in a while.
- A few bits for some samples

Supervised Learning (icing)

- The machine predicts a category or a few numbers for each input
- Predicting human-supplied data
- 10→10,000 bits per sample

Unsupervised/Predictive Learning (cake)

- The machine predicts any part of its input for any observed part.
- Predicts future frames in videos
- Millions of bits per sample



(Yes, I know, this picture is slightly offensive to RL folks. But I'll make it up)

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Linear algebra for dimensionality reduction

Principal Component Analysis and SVD

Do you have skills for COMP229? Probably, if you can compute this without a calculator and in one line: $51 \times 24 - 49 \times 93 + 27 \times 51 + 44 \times 49 = ?$



Lectures, tutorials and rooms

30 lectures in weeks 1-10, 10 tutorials in weeks 2-11.

Lectures + tutorials: 30+10 hours. Expected total: 150 hours. Can you guess where those extra work hours should come from?

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Lectures: Monday at 14.00-15.00 and Friday 9.00 - 11.00 in MATH-029 (Forsyth Lecture Theatre).

Textbooks on Data Science

The textbooks below are in the reading list on CANVAS aren't strictly needed, only for enthusiasts.

- Applied Linear Algebra by Olvert, Shakiban
- Introduction to Statistics by David Lane
- Principles of Data Science by Sinan Ozdemir
- · Learning from Data by Glenberg, Andrzejewski

If you find anything better, please e-mail me.



Collaboration

COMP229 is lectured in parallel to Computer Science and Maths students.

We will be taking a mathematical approach to data science. . .

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CS students - be prepared for abstract definitions and rigorous proofs

... but with practical goals in mind.

Maths students - be prepared for some 'top-level' thinking

Please collaborate and share your knowledge!



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The discussion board is for asking constructive questions and answering them!

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Answer: all content of the lectures & tutorials can be in the exam, and even with different numbers.

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Nonconstructive question: is slide 8 of lecture 4 needed for the exam?

Answer: all content of the lectures & tutorials can be in the exam, and even with different numbers. Positive participation will be noticed and can be later rewarded by references.



Assessment

Your mark for the module = a mid-term test (30%, multiple choice questions) in November + an end-of-term exam (70%) in January.

Assessment

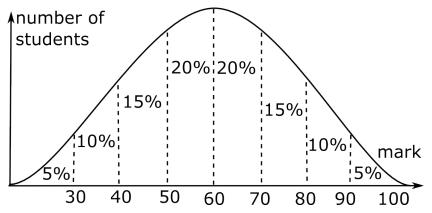
Your mark for the module = a mid-term test (30%, multiple choice questions) in November + an end-of-term exam (70%) in January.

Time: 2.5 hours, all questions will be marked.

Tutorial homework sets are formative (not contributing to the final mark), and will be a great preparation for your hand-written exam.

An example distribution of marks

The pass mark is 40, first class marks are 70+.



An expected average mark should be in [55,65].

Last years exam averages: \approx 63, failure rate \approx 10%.

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Level 4: a student shares his knowledge with his peers. The real test for your understanding is to teach this concept to someone else.



Giving your feedback

For your questions and your feedback:

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The bottom line required by the university: reply to student e-mails within 3 working days.

In the first 12 weeks I'll try to reply faster within few hours, the rest depends on your involvement.

Time to revise and ask questions

Revisions will be at the end of every lecture.

To benefit from the lecture, now you could

- prepare and ask your questions
- write down your summary in 2-3 phrases,
 e.g. list key concepts you have learned.

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Problem 1.2. Have you computed this value?

$$51 \times 24 - 49 \times 93 + 27 \times 51 + 44 \times 49 = ?$$



Final solution and summary

Solution 1.2. No calculator should be needed:

$$51 \times 24 - 49 \times 93 + 27 \times 51 + 44 \times 49 =$$

 $51 \times (24 + 27) - 49 \times (93 - 44) = 51^2 - 49^2 =$
 $(51 - 49) \times (51 + 49) = 2 \times 100 = 200.$

- COMP229 requires deep understanding.
- All the resources of COMP229 are on CANVAS.
- How to learn better: use all resources and share your knowledge with your classmates.

