Network Analysis -INFOMNWA- 2022

Coordinators

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Context

Data analysis using interlinked network simulations is being applied increasingly broadly in social sciences research. First, machine learning with deep neural networks (deep learning) allows computer systems to perform tasks that have previously been impossible or inaccurate for computers, but typically straightforward for humans. Tasks like visual object identification have traditionally been investigated by cognitive scientists, but recent applications of deep learning to these tasks also position them at the centre of recent artificial intelligence developments. Current deep networks simulate and replicate advanced human brain functions, and in future may be able to simulate full human brains and replicate human behaviour.

Second, analysis of relationships between people using social network models has been greatly advanced thanks to the growing availability of network data and the development of social contagion theory and their numerical simulation. Quantitative evidence and testing of the social contagion processes are accumulating by embracing data science analysis techniques. Theories and social network models have been renewed and proliferated to capture the micro-level assumptions about social influences as well as macro-level predictions.

Therefore, it is important for data science students and researchers to understand the links between the social sciences and data science in these fields.

In this course, you will learn the principles behind deep learning, an approach inspired by the structure of the brain. You will learn how these principles are implemented in the brain, focusing on the aspects of visual processing. You will build your own deep learning systems for the interpretation of natural images, using modern high-level neural network APIs that make implementation of these systems accessible and efficient. You will then study the key features of a social network and how to measure them. You will learn how a network is formed among people and how influences spread through the network. The rich theories in social contagion will be introduced with the corresponding models. You will develop a small social network and simulate the contagion of either diseases or behaviours.

Course goals

At the end of the course, the student will be able to:

- Explain the broad concepts behind deep learning from both computer science and neuroscience perspectives. (Assessed in labs, individual assignments and exams).
- Explain deep learning's advantages and limitations compared to other modelling and machine learning approaches. (Assessed in exams).
- Identify problems that deep learning is suited to addressing in the fields of cognitive (neuro-) science and artificial intelligence. (Assessed in labs, individual assignments and exams).
- Design and implement deep learning approaches to address some problems in the domain of image processing. (Assessed in labs).
- Understand the key concepts and measures of social networks and the models of network formation. (Assessed in labs, individual assignments and exams).
- Explain the factors of social influence and diffusion, their differences and complements. (Assessed in exams).
- Relate the social contagion mechanisms to understand the social drivers of real-world problems. (Assessed in labs, individual assignments and exams).
- Perform social network analysis to investigate social structures. (Assessed in labs).
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Content

Students will attend eight lectures. The first four lectures will focus on image processing and the human visual system, viewing the visual system as a deep network. We will first introduce the basic processing mechanisms of computer deep learning systems. We will then compare this to the mechanisms of neural processing implemented in biological brains. We will then introduce the main applications of deep learning to visual cognitive science, largely as a model of biological neural systems. Finally, we will see how recent advances in artificial deep learning system more closely model biological neural processing, improving simulations of biological neural systems and giving deep networks new abilities and applications. We will explore the logical goal of these developments, simulating full human brains and behaviours.

In the second part of the course, we will introduce important concepts and challenges in social network analysis and modelling, which simulate interactions between humans. We will first go through the basic concepts of social networks and its measures such as centrality, coreness, clustering and path length. We will then study the theories and models to explain the formation of social networks. Next we will study contagion processes within networks. Our focus will be on the simple and complex contagion theories and their explanation in the spread of disease and behaviour. Last we will see how we can either minimise or maximize the diffusion process based upon the advances in diffusion models and influence prediction.

Furthermore, students will work through two lab practical assignments, one on visual processing and one on social network analysis. Students will work in groups of 4 in these assignments, with teachers supervising and grading their progress.

Finally, each student will complete a short individual assignment related to each lab assignment.

All parts of the course will be supported by reading assignments.

Lectures will cover the following topics:

Lecture 1: Principles of deep learning in artificial networks

Lecture 2: Deep learning in biological neurons and networks

Lecture 3: Early and feedforward visual processing

Lecture 4: Higher and recurrent visual processing

Lecture 5: Social networks and their measures

Lecture 6: Network formation

Lecture 7: Simple and complex contagion

Lecture 8: Influence manipulation

Reading assignments (in recommended order):

Part 1:

-Hassabis D, Kumaran D, Summerfield C, Botvinick M (2017) Neuroscience-inspired artificial intelligence. Neuron, 95: 245-258.

-Kay KN, Naselaris T, Prenger RJ, Gallant JL (2008) Identifying natural images from human brain activity. Nature, 452 (7185): 352-355.

-Yamins, D. L., H. Hong, C. F. Cadieu, E. A. Solomon, D. Seibert and J. J. DiCarlo (2014). "Performance-optimized hierarchical models predict neural responses in higher visual cortex." Proc Natl Acad Sci U S A 111(23): 8619-8624.

The above paper is very important, but some students may find it very difficult. If so, read this paper first: Yamins DL, DiCarlo JJ (2016) Using goal-driven deep learning models to understand sensory cortex. Nature Neuroscience,19(3): 356-65.

- Çukur T, Nishimoto S, Huth AG, Gallant JL (2013) Attention during natural vision warps semantic representation across the human brain. Nature Neuroscience, 16: 763-770

-Huth AG, de Heer WA, Griffiths TL, Theunissen FE, Gallant JL (2016) Natural speech reveals the semantic maps that tile human cerebral cortex. Nature. 532(7600):453-8.

Part 2:

- Watts, D. J. (2004). The “New” Science of Networks. *Annual Review of Sociology, 30*, 243-270.

- Newman, M. (2018). *Networks*. Oxford: Oxford University Press. (Ch. 6 & 7)

- Albert, R., & Barabási, A.-L. (2002). Statistical mechanics of complex networks. *Review of Modern Physics, 74*(1), 47-97.

- Granovetter, M (1978). Threshold Models of Collective Behaviour. American Journal of Sociolology 83, 1420–1443.

- Centola, D. & Macy, M (2007). Complex contagions and the weakness of long ties. Am. J. Sociol. 113, 702–734.

- Per Block, Marion Hoffman, Isabel J. Raabe, et al. (2020). Social network-based distancing strategies to flatten the COVID-19 curve in a post-lockdown world. Nature Human Behaviour, vol. 4, 588–596.

Assessment

The course goals will be examined in the following ways:

1) Students' understanding of lectures and reading assignments will be assessed in a final exam that determines 40% of the final grade.
2) Individual assignments will be graded for depth and completion, with each of the two assignments determining 10% of the final grade.
3) Group lab assignments will be graded for depth and completion, with each of the two assignments determining 20% of the final grade.
4) **You are required to achieve a passing grade (5.5) as a weighted average across the exam and individual assignments to pass the course**. Students scoring above 4.0 as a weighted average over all course assessments qualify for a repair exam.

Schedule: SEE NEXT PAGE

Date	Time	Format	Teacher	On Campus Room
09/02	13:15-15:00	Lecture 1	Harvey	BBG 223
09/02	15:15-17:00	Lab 1	Strauch	BBG 223, Ruppert 005 or 116
11/02	09:00-10:45	Lecture 2	Harvey	Ruppert Paars
16/02	13:15-17:00	Lab 1	Strauch	BBG 223 or 115, Ruppert 005 or 116
18/02	09:00-10:45	Lecture 3	Harvey	Ruppert Paars
23/02	13:15-17:00	Lab 1	Strauch	BBG 223 or 115, Ruppert 005 or 116
25/02	09:00-10:45	Lecture 4	Harvey	Ruppert Paars
02/03	13:15-17:00	Lab 1	Strauch	BBG 223 or 115, Ruppert 005 or 116
04/03	09:00-10:45	Lab 1	Strauch	Ruppert Paars
06/03	23:59	Deadline: Lab 1 Group Assignment		Blackboard
09/03	13:15-17:00	NO CLASS		
10/03	23:59	Deadline: Individual Assignment 1		Blackboard
11/03	09:00-10:45	Lecture 5	Przepiorka	Ruppert Paars
16/03	13:15-17:00	Lab 2	Ou	BBG 223 or 115, Bolognalaan 1.152 or 1.202
18/03	09:00-10:45	Lecture 6	Przepiorka	Ruppert Paars
23/03	13:15-17:00	Lab 2	Ou	BBG 223 or 115, Bolognalaan 1.152 or 1.202
25/03	09:00-10:45	Lecture 7	Ou	Ruppert Paars
30/03	13:15-17:00	Lab 2	Ou	BBG 223 or 115, Bolognalaan 3.108 or 3.112
01/04	09:00-10:45	Lecture 8	Ou	Ruppert Paars
06/04	13:15-17:00	Lab 2	Ou	BBG 223 or 115, Ruppert 002
06/04	23:59	Deadline: Lab 2 Group Assignment		Blackboard
08/04	09:00-10:45	Exam question time	Harvey,Ou	Ruppert Paars
13/04	17:00-19:00	EXAM		Educatorium Gamma
18/04	23:59	Deadline: Individual Assignment 2		Blackboard
06/07	17:00-19:00	Repair exam		Ruppert 040