Computational cognitive neuroscience: 1. Introduction to modeling

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Computational Cognitive Neuroscience

Computational neuroscience
- explain neuronal activity data
- using neurobiologically plausible...
- computational models...
- that perform complex cognitive tasks

Cognitive science
- explain behavioral data

Artificial intelligence
Textbook


Chapters

1. Intro -- Introduction to high-level concepts and issues, and overview of the content of the book.

Part I -- Basic Computational Mechanisms

3. Networks -- Emergent dynamics of networks of neurons -- provides a computational vocabulary for cognition.
4. Learning Mechanisms -- How neurons learn -- creating new functionality from an equipotential substrate -- includes multiple forms of learning.

Part II -- Cognitive Neuroscience

5. Brain Areas -- Large-scale organization of the brain -- functional areas.
6. Perception and Attention -- Feature detection, object recognition, visual attention, etc.
7. Motor Control and Reinforcement Learning -- Motor output systems, sensory-motor coordination and learning, etc. -- includes basal ganglia and reinforcement learning.
8. Learning and Memory -- Semantic and episodic memory, implicit vs. declarative, priming, familiarity, etc.
9. Language -- Reading, semantics, morphology, syntax, etc.
10. Executive Function -- Cognitive control, higher-level cognitive functions.

Simulation Exploration Projects

- Go / Python version of emergent: https://github.com/emer/emergent
- Exercises repository: https://github.com/CompCogNeuro/sims
Computational Cognitive Neuroscience
Master's Program in Cognitive Science, Comenius University in Bratislava

Time/Place: Summer Semester 2020/2021, Room MS Teams, Lectures: Wednesday 14:00 - 15:30, Labs: Thursday 14:00 - 15:30
Credits: 6
Lecturer: Prof. RNDr. Lubica Beňušková, PhD.
Teaching Assistant: RNDr. Kristína Malinská, PhD.

Course aims
Computational cognitive neuroscience relies upon theories of cognitive science coupled with neuroscience and computational modeling. In this course, we will study neurobiological processes that underlie cognition by means of theory of computational models. We will address the questions of how cognitive processes are affected and controlled by neural circuits in the brain. We will be modeling some basic mechanisms of cognitive functions using the Emergent simulator.

Assessment
- Lecture Presentation (guidelines) 20%
- Emergent Presentation (guidelines) 20%
- Project (guidelines) - due TBA 20%
- Final written exam 40%

Marking
- 0-50 % Fx
- 51-60 % E
- 61-70 % D
- 71-80 % C
- 81-90 % B
- 91-100 % A

Course schedule

<table>
<thead>
<tr>
<th>Date</th>
<th>Lecture</th>
<th>Presentation</th>
<th>Exercises in Emergent</th>
<th>Required Reading</th>
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<tbody>
<tr>
<td>17.02</td>
<td>Introduction to computational cognitive neuroscience. Main concepts in modelling. (L1 slides)</td>
<td>Student name / paper</td>
<td>Instructions how to install and use the Emergent simulator.</td>
<td>O'Reilly.ch 1, Farkas (2012)</td>
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<tr>
<td>24.02</td>
<td>Spiking neurons models. Biology of individual neuron and its implementation in Emergent. (L2 slides)</td>
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<td>O'Reilly.ch 2</td>
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<tr>
<td>03.03</td>
<td>Structure of cortical networks, localist and distributed representations, excitation and inhibition of neurons. (L3 slides)</td>
<td>XY / Visual competition</td>
<td>Inhibition Necker Cube</td>
<td>O'Reilly.ch 3</td>
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<tr>
<td>10.03</td>
<td>Biological mechanism of memory and learning, long-term potentiation and depression of synaptic efficacy. (L4 slides)</td>
<td>XY / Synaptic metablility</td>
<td>Pattern Associator Cats and Dogs</td>
<td>O'Reilly.ch 4 (up to XCAL)</td>
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Brain and Mind

- **The Big Question**: Is the mind just a mechanical function of the brain?
- Can **consciousness** be reduced to the firing of nerve cells in the brain?
- Are we really just **machines**?

*The brain operates in three dimensions, but it takes the mind to understand them.*

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Brain is comprised of networks of neurons connected and communicating via synapses

10^{12} neurons

10^4 synapses in & out
How do we study how the brain creates mind?

- **Neuropsychology**—traditionally the study of how brain injury affects mental processes or how healthy brain relates to mental processes.

- **Neuroimaging**—pictures of the brain’s anatomy or function, in relation to mental process.

- **Neuroscience**—invasive recording techniques usually performed on animals or humans during brain surgery.

- **Computational cognitive neuroscience**—the modern area that integrates all of the above.
Example 1: In 1848, Phineas Gage (a foreman) had an iron tamping rod rammed through his left cheek and skull. Could still walk and talk, but became unruly, unsociable, bad-mannered, unable to plan.

Conclusion: Frontal lobe is important for planning, processing of emotion, rational decision-making
Neuropsychology

Example 2: Paul Broca studied patients with damage to left frontal lobe. One patient was called “Tan” because that was the only articulate sound he could make.

Conclusion: Broca’s area on left side is responsible for articulate speech.
Neuroscience and neuroimaging

- individual neural cell recordings
  - invasive

- local field potentials
  - EEG, ERP (event-related potentials), MEG
- high temporal resolution (~ms), weaker spatial resolution (~cm)

- brain imaging
  - CT, PET, MRI, fMRI, TMS(+EEG), ...
- high spatial resolution (~mm),
- weaker temporal resolution (~s)
Example of fMRI neuroimaging

* fMRI recorded while subjects name animals or tools. Left brain more activated by tools, right brain by animals.
The third methodology of (neuro)science

- Computational modelling has become the third methodology of science along with theory and experiment:

- Theory is the way to interpret the results of experiments, the way to analyze experiments and to design new experiments.

- Without experiments there is no point in theorizing--theory becomes speculation. Theory is corroborated or falsified by experiments.

- Computational approach provides a third way, allowing more elaborate tests of theory than would be possible by experiment, thus enabling new ways to refine the theory. It also allows a much more sophisticated analysis of experiment than theory alone could provide.
Karl Popper

- Popper, one of the greatest philosophers of science of the 20th century (empirical falsification).

- Introduced an idea or criterion for theory being a scientific theory. This criterion is called \textit{empirical falsification}.

- Scientific theory is such \textit{theory that can be falsified} by experiment or observation.

- Computational models have the faith of theories, i.e. single real experiment can falsify them, and even countless agreeing experimental data can only \textit{corroborate} them.
Key elements of computational cognitive science

- The subject of study in cognitive science is somewhat ambiguous: it is usually **mind, intelligence, thinking or cognition**.

- The nature of cognitive scientific investigation is **multidisciplinary and interdisciplinary**.

Central hypothesis of cognitive science:

“Thinking can best be understood in terms of

- **representational structures** in the mind and

- **computational procedures** that operate on those structures.”

  *(Thagard, 1996)*

However, there is often **disagreement** about the nature of the representations and computations that constitute thinking.
Marr’s three levels of analysis

- Postulated by neuroscientist David Marr (1982):

1. **Computational** – what does the system do (e.g.: what problems does it solve or overcome) and similarly, why does it do these things;

2. **Algorithmic** – how does the system do what it does, specifically, what representations does it use and what processes does it employ to build and manipulate the representations;

3. **Implementation**al – how is the system physically realised (e.g., in the case of biological vision, what neural structures and neuronal activities implement the visual system).
Example: vision
Reductionism, reconstructionism and emergence

- **Reductionism**: explaining in terms of underlying mechanisms.
  - the complex system is reduced to simpler parts

- **Reconstructionism**: Putting the reduced pieces back together.
  - Critical when there are billions of such pieces (neurons).
  - Computer simulations are essential.

- **Emergent properties**: they emerge only when we put elements into mutual interactions.
Once we develop a mathematical or computational model, we have to compare predictions of the model with data from the system (empirical falsification).

If the model prediction and the data agree, then we can gain confidence the assumptions we have made in creating the model are reasonable, and that we can use the model to make further predictions.

If the model prediction and the data disagree, then we must study and improve our assumptions and re-formulate the model.
Basic steps in creating the model

- **Step 1**: Clearly state the assumptions on which the model will be based. These assumptions should describe the relationship among the quantities to be studied.

- **Step 2**: Completely describe the quantities, i.e. variables and parameters to be studied in the model.

- **Step 3**: Use the assumptions formulated in Step 1 to derive equations relating the quantities in Step 2.

- **Step 4**: use mathematical knowledge and/or computer program to solve the equations and make predictions about the evolution of studied quantities in the future.
Step 1: assumptions

- Assumptions should describe what we think about relationships between variables we want to model.
  - E.g., we assume there are 2 types of inputs to each neuron: excitatory and inhibitory. They add up linearly, i.e. input = excitation – inhibition.

- The quality of assumptions determines the validity of the model and the situations to which the model is relevant.

- We must avoid “hidden assumptions” that make the model seem mysterious or magical.
  - i.e., we include something in the equation that makes the model work but corresponds to nothing in reality.
Step 2: defining the quantities

• **Independent variables**
  - The independent variable is almost always time \( (t) \). Time \( t \) is independent of any other quantity in the model.

• **Dependent variables** are the quantities that are functions of the independent variable.
  - For example, membrane voltage changes over time, \( V = V(t) \), i.e. we say voltage is a function of time.

• **Parameters** are quantities that do not change with time (or any other independent variable), but their value has a profound influence on the behaviour of the dependent variables.
Variables and parameters

- The goal of a model is to describe the behaviour of the dependent variable as the independent variable changes.
  - For example, we may ask whether the dependent variable (e.g. voltage) increases or decreases with time, or whether it oscillates or tends to a limit.

- Observing how the behaviour of the dependent variable changes when we change the values of parameters can be the most important aspect of the study of a model.
  - For example, we may ask how the voltage evolves when the strength of excitatory inputs is the same as the strength of inhibitory inputs or how voltage will evolve when these strengths differ, while the values of strengths of excitatory and inhibitory inputs are the parameters of the model.
Step3: the most difficult part

- The hardest part in using the maths or computational algorithms to study phenomena is the translation from real life into mathematical and/or computational formalism.

- It is difficult because it involves
  - knowledge of maths and programming;
  - the conversion of assumptions into mathematical equations and/or computational algorithms.
Equations, i.e. something = something

- We know that the dependent variable changes over time. Thus we are looking for a “rate of change of …” or “rate of increase of …” dependent variable over time.

- Mathematically, the rate of increase of something corresponds to the thing called “derivative”, being written as:

\[
\frac{dV}{dt}
\]

- Where that “something” is for example membrane voltage, \(V\).

- In other words, the rate of change is synonymous with derivative.
We want to express what is the rate of change, i.e. what the derivative amounts to. That is, we want to know what is the “something” in the following equation:

\[
\frac{dV}{dt} = \text{something}
\]

The phrase “\(A\) is proportional to \(B\)” means \(A = k B\), where \(k\) is the so-called proportionality constant. So, to be mathematically correct we have to write the above equation as

\[
\frac{dV}{dt} = k \text{ something}
\]

i.e. the rate of change of voltage is proportional to something. Proportionality constant \(k\) is a parameter of the model.
Derivative = $k$ something

- The equation: $\frac{d(\text{dependent variable})}{dt} = k \text{ something}$

- is at the core of all models in computational neuroscience.

- Dependent variable can be anything from voltage, current, field potential, number of synapses, concentration of neurotransmitter, speed of learning, number of memorized items, etc.

- The biggest challenge is to come up with “something”…
Concrete example: population growth

- We can develop and study mathematical models of systems that change (evolve) over time, for instance the number of rabbits.

- Except time itself, the number of rabbits depend on other variables too.
  - For example, the changes in population of rabbits depend on the amount of food, number of predators (hawks, foxes, etc.), rabbit diseases, etc.

- In order to make a model of evolution of rabbit population simple enough to understand, we have to make simplifying assumptions and neglect the things we know nothing about or not enough.
The simplest model of population growth

- Step 1: The assumption: the rate of growth of population depends only on the size of the population and nothing else. The more rabbits there are the more offspring they have.

- Step 2: definition of quantities:
  - \( t \) = time (independent variable)
  - \( P \) = population size (dependent variable), i.e. \( P = P(t) \)
  - \( k \) = proportionality constant (parameter)

- How about the units of these quantities? They obviously depend on species and environment. If we are talking about population of people then \( t \) would be years and \( P \) would be millions. If talking about rabbits, then \( t \) would be months and \( P \) thousands.
Mathematical equation for the growth

- Step 3: let’s express our assumption as an equation. The rate of growth of the population is the derivative:

\[ \frac{dP}{dt} \]

- Being proportional to the population size is expressed as a product of the proportionality constant \( k \) and the population size \( P \), i.e. \( kP \).
  - Hence our assumption is expressed as the (differential) equation:

\[ \frac{dP}{dt} = kP \]

- Read as: Derivative of \( P \) according to time \( t \) equals \( k \) times \( P \).
Step 4: solution

- In order to be able to predict the change of rabbit population we must know the size of population at time zero $P_0$, the so-called initial condition, i.e.

$$P(t_0) = P_0 > 0$$

- Next we want to predict the value of $P$ at various times in the future, e.g. $P(10)$ or $P(100)$, i.e. we want to know concrete values of quantity $P(t)$ for each value of $t$, that satisfy this equation:

$$\frac{dP}{dt} = k \cdot P$$

- To find a solution to this equation means to find a function $P(t)$ whose derivative is the product $k$ with $P(t)$. 

Analytical solution

- The solution of the differential equation:
  \[ \frac{dP}{dt} = k \, P \]

- is an exponential function
  \[ P(t) = P_0 \, e^{kt} \]

- Where \( P_0 \) is the initial population
  \[ P(t_0) = P_0 > 0 \]

- Now we can make predictions about the size of the population in the future provided we know the value \( P_0 \) and \( k \). The value of \( k \) can be derived by fitting the model to real data. We simply try different values of \( k \) and see which one yields the best fit with the data.
Ockam's razor

– How do we choose from among several consistent models?

- **Ockham’s razor**: prefer the *simplest model* consistent with the data
  - Ockham’s razor or law of parsimony attributed to the 14th century Franciscan logician William of Ockham (Occam)

- In general, there’s a tradeoff between the complexity of function and degree to fit the data
  - Preference to the simpler hypothesis even if it does not fit data perfectly
Summary

- Analytical solutions of models are rarely possible, thus we use computational algorithms to solve the assumed relationships.

- Computational models provide the highest possible rigor in explanations of cognitive phenomena.

- All models are reductionist, they provide mechanistic explanations.

- Mechanistic accounts may not provide satisfactory answers for hard questions in cognitive science (epistemological limitations).
Brain and Mind