

Welcome to BIO-210

Applied software engineering for life sciences

December 2nd 2024 – Lecture 12

Prof. Alexander MATHIS

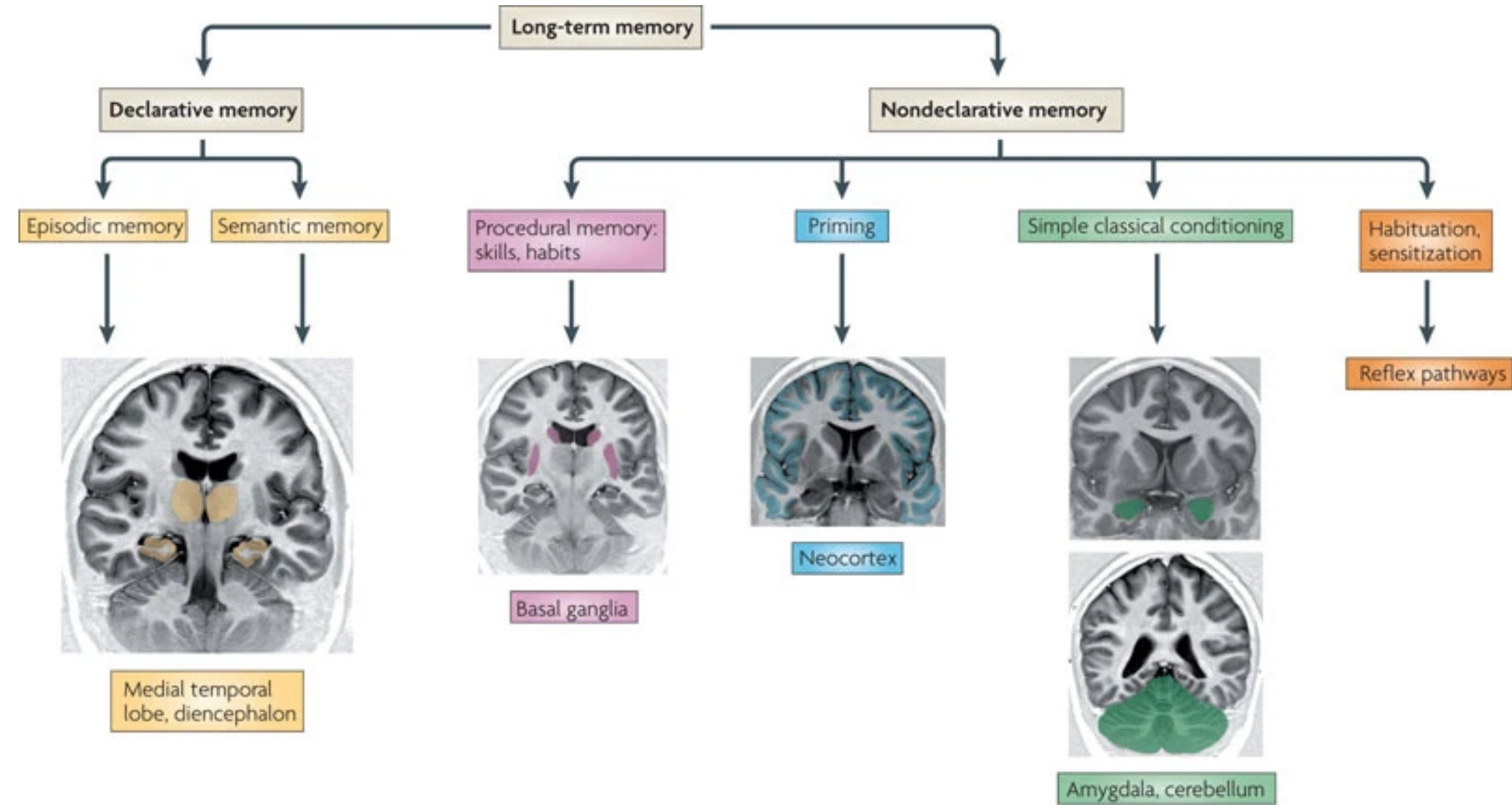
EPFL

	Date	Topic	Software version	Software releases	Grading / Feedback
0	09/09/2024	Python introduction I			
1	16/09/2024	Public holiday			
2	23/09/2024	Python introduction II			
3	30/09/2024	Git and GitHub (+installation VS Code)			
4	07/10/2024	Project introduction	v1		
5	14/10/2024	Functionify	v2	v1	
6	21/10/2024	EPFL fall break			
7	28/10/2024	Visualization and documentation	v3	v2	code review (API)
8	04/11/2024	Unit-tests, functional tests	v4	v3	
9	11/11/2024	Code refactoring	v5	v4	graded (tests)
10	18/11/2024	Profiling and code optimization	v6	v5	code review
11	25/11/2024	Object oriented programming	v7	v6	graded (speed)
12	02/12/2024	Model analysis and project report	v8	v7	code review (OO)
13	09/12/2024	Work on project (no lecture, but exercises)			
14	16/12/2024	Wrap up (incl. prize ceremony)		v8	graded (project)

Model analysis and project reports

- Hopfield network
- Turing pattern formation

Memory



Nature Reviews | Neuroscience

Source: K Henke, Nature Reviews Neuroscience 2010

- memory serves different functions (see diagram)
- different types of memory are supported by different brain areas (how do we know this?)

Project: Hopfield networks

Proc. Natl. Acad. Sci. USA
Vol. 79, pp. 2554–2558, April 1982
Biophysics

Neural networks and physical systems with emergent collective computational abilities

(associative memory/parallel processing/categorization/content-addressable memory/fail-soft devices)

J. J. HOPFIELD

Division of Chemistry and Biology, California Institute of Technology, Pasadena, California 91125; and Bell Laboratories, Murray Hill, New Jersey 07974

Contributed by John J. Hopfield, January 15, 1982

ABSTRACT Computational properties of use to biological organisms or to the construction of computers can emerge as collective properties of systems having a large number of simple equivalent components (or neurons). The physical meaning of content-addressable memory is described by an appropriate phase space flow of the state of a system. A model of such a system is given, based on aspects of neurobiology but readily adapted to integrated circuits. The collective properties of this model produce a content-addressable memory which correctly yields an entire memory from any subpart of sufficient size. The algorithm for the time evolution of the state of the system is based on asynchronous parallel processing. Additional emergent collective properties include some capacity for generalization, familiarity recognition, categorization, error correction, and time sequence retention. The collective properties are only weakly sensitive to details of the modeling or the failure of individual devices.

calized content-addressable memory or categorizer using extensive asynchronous parallel processing.

The general content-addressable memory of a physical system

Suppose that an item stored in memory is “H. A. Kramers & G. H. Wannier *Phys. Rev.* **60**, 252 (1941).” A general content-addressable memory would be capable of retrieving this entire memory item on the basis of sufficient partial information. The input “& Wannier, (1941)” might suffice. An ideal memory could deal with errors and retrieve this reference even from the input “Vannier, (1941)”. In computers, only relatively simple forms of content-addressable memory have been made in hardware (10, 11). Sophisticated ideas like error correction in accessing information are usually introduced as software (10).

There are classes of physical systems whose spontaneous behavior can be used as a form of general (and error-correcting)

Link to the original publication

Neurons



Source: neuron drawing by Ramón y Cajal

A simple, computational neuron model

Our computational neuron model is subject to the following simplifications:

- binary neurons, linear integration and thresholding (σ)

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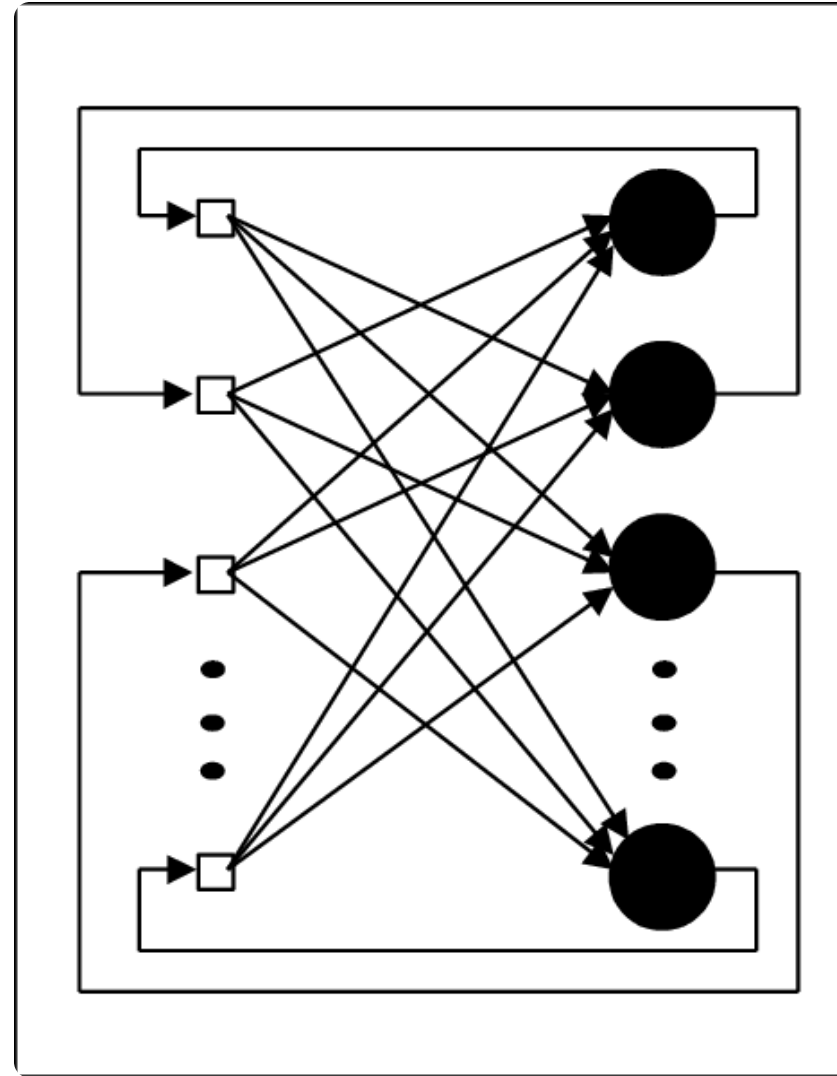
Specifically, the activity of neuron j is given by

$$p_j = \sigma \left(\sum_i \mathbf{W}_{j,i} \cdot \mathbf{p}_i \right)$$

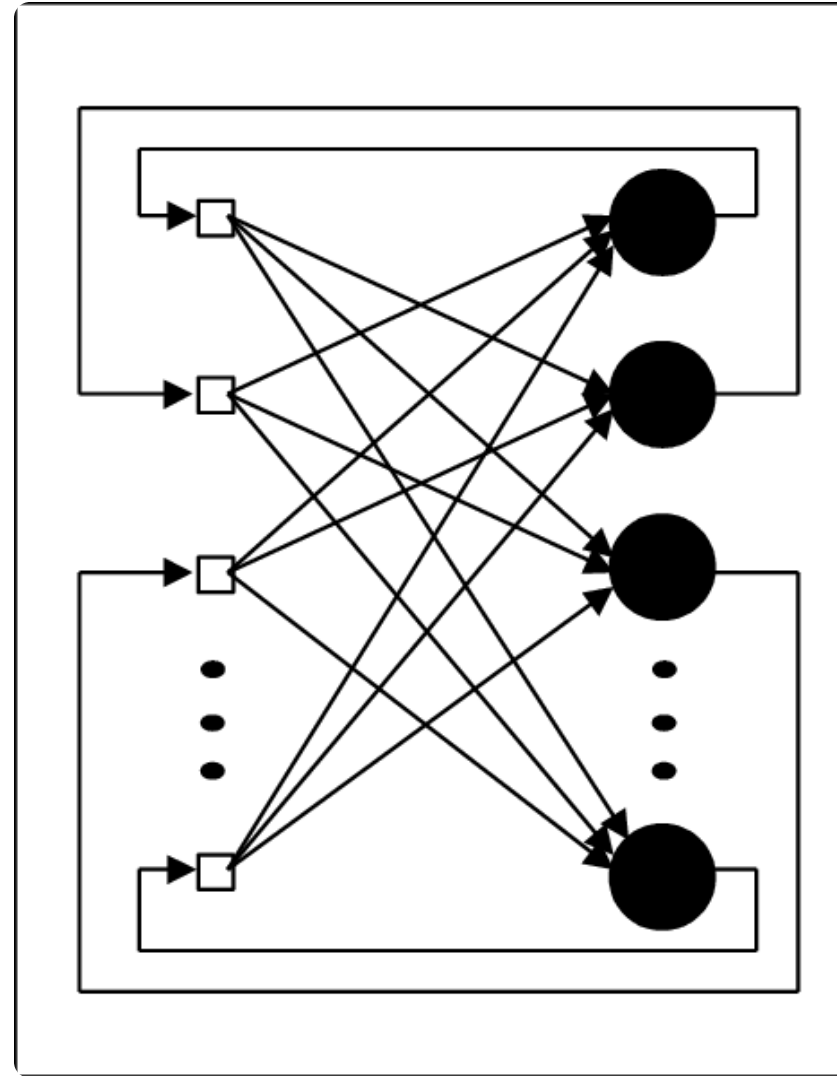
where $\mathbf{W}$ is the weight matrix and the nonlinearity $\sigma(x)$ is defined as

$$\sigma(x) = \begin{cases} -1 & \text{if } x < 0 \\ 1 & \text{if } x \geq 0 \end{cases}$$

The Hopfield network is a recurrent neural network



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At time $t + 1$ the activity is given by the weight matrix and the activity at t .

$$\mathbf{p}^{(t+1)} = \sigma \left(\mathbf{W} \mathbf{p}^{(t)} \right)$$

How are memories stored?

Consider M memory patterns $\mathbf{p}^\mu \in \{-1, 1\}^N, \mu \in \{1, \dots, M\}$.

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The Hebbian learning rule is the simplest one to create a Hopfield network. It is based on the principle "Neurons that fire together, wire together. Neurons that fire out of sync, fail to link". This translates into the following network connectivity:

$$w_{ij} = \frac{1}{M} \sum_{\mu=1}^M p_i^\mu p_j^\mu \quad i \neq j$$

We can observe that the weight is the average of the contribution of each pattern to the synaptic weight.

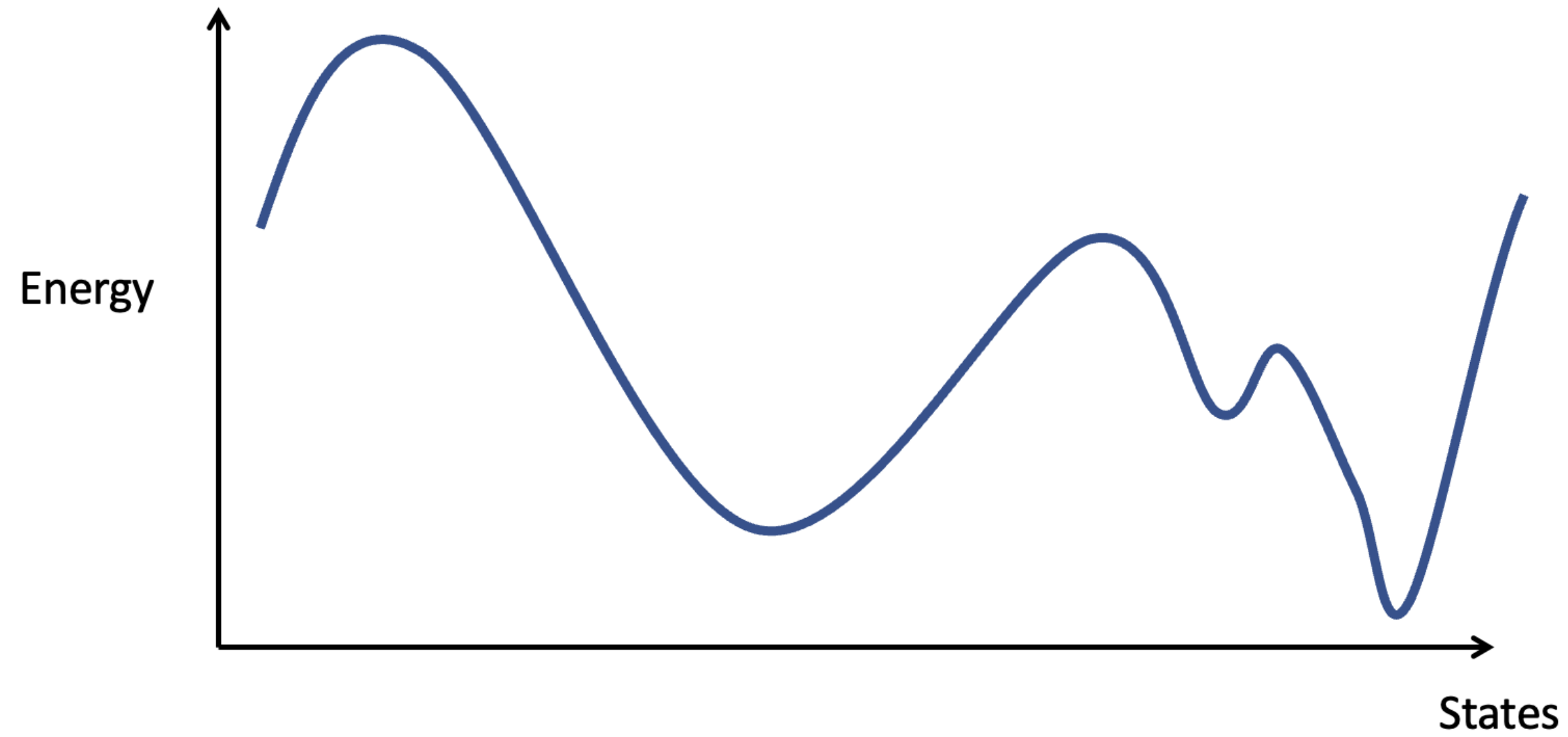
Each pattern contributes positively to a certain weight, if the state of the two connected neurons is the same, and negatively otherwise.

You also implemented a different learning rule, the Storkey learning rule. It is also a local, and incremental learning rule (with higher capacity, as you will show).

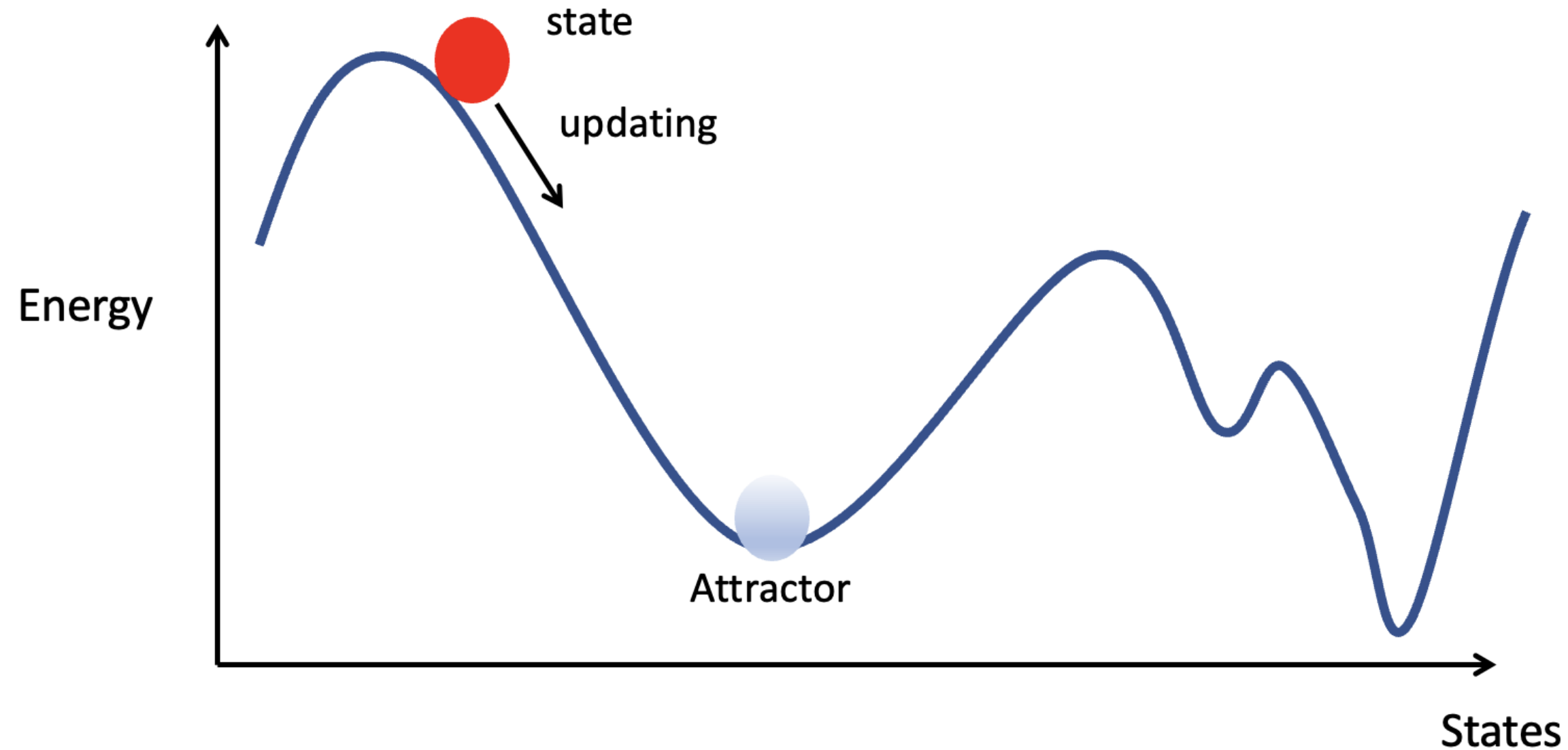
Project goals

- implement Hopfield nets for a given set of memories (dynamics and learning)
- *understand the Hopfield network*
- *study dynamics, memory capacity (incl. visualization)*
- integrate tests, provide specified API
- refactor (functions, oop, speed-up)
- developed on GitHub with git

Hopfield network



Hopfield network



- stored patterns are local minima of the energy surface
- spurious minima also exist (e.g., $-\mu$ for pattern μ)
- the type and *number* of patterns shape the energy landscape!

Hopfield networks project

You will analyze the model and answer two key questions:

- How robust are stored memories?
- How many memories can be stored?

Associative memory (for binary images of 130x180)

Left: initial state, middle: intermediate and right: final state for 3 examples.



Try it out for your model!

From Introduction To The Theory Of Neural Computation by J. Hertz

Project: Morphogenesis

[37]

THE CHEMICAL BASIS OF MORPHOGENESIS

By A. M. TURING, F.R.S. *University of Manchester*

(*Received 9 November 1951—Revised 15 March 1952*)

It is suggested that a system of chemical substances, called morphogens, reacting together and diffusing through a tissue, is adequate to account for the main phenomena of morphogenesis. Such a system, although it may originally be quite homogeneous, may later develop a pattern or structure due to an instability of the homogeneous equilibrium, which is triggered off by random disturbances. Such reaction-diffusion systems are considered in some detail in the case of an isolated ring of cells, a mathematically convenient, though biologically unusual system. The investigation is chiefly concerned with the onset of instability. It is found that there are six essentially different forms which this may take. In the most interesting form stationary waves appear on the ring. It is suggested that this might account, for instance, for the tentacle patterns on *Hydra* and for whorled leaves. A system of reactions and diffusion on a sphere is also considered. Such a system appears to account for gastrulation. Another reaction system in two dimensions gives rise to patterns reminiscent of dappling. It is also suggested that stationary waves in two dimensions could account for the phenomena of phyllotaxis.

The purpose of this paper is to discuss a possible mechanism by which the genes of a zygote may determine the anatomical structure of the resulting organism. The theory does not make any new hypotheses; it merely suggests that certain well-known physical laws are sufficient to account for many of the facts. The full understanding of the paper requires a good knowledge of mathematics, some biology, and some elementary chemistry. Since readers cannot be expected to be experts in all of these subjects, a number of elementary facts are explained, which can be found in text-books, but whose omission would make the paper difficult reading.

1. A MODEL OF THE EMBRYO. MORPHOGENS

[Link to the original publication](#)

Reaction-diffusion equations

The Turing pattern formation mechanism can be modeled with two time-dependent reaction-diffusion equations, describing the evolution and the interaction between an activator $u(x, y)$ and an inhibitor $v(x, y)$ morphogen.

$$\frac{\partial u}{\partial t} = \gamma f(u, v) + \nabla^2 u$$

$$\frac{\partial v}{\partial t} = \gamma g(u, v) + d \nabla^2 v$$

with diffusion terms $\nabla^2 u$ and $\nabla^2 v$ as well as reaction terms $\gamma f(u, v)$ and $\gamma g(u, v)$.

See [problem set](#) for more details.

You'll implement discretized equations

Reaction-diffusion equations:

$$u_{ij}^{(t+1)} = u_{ij}^{(t)} + \Delta t \left[\gamma f(u_{ij}^{(t)}, v_{ij}^{(t)}) + \frac{u_{i-1,j}^{(t)} + u_{i+1,j}^{(t)} + u_{i,j-1}^{(t)} + u_{i,j+1}^{(t)} - 4u_{ij}^{(t)}}{\Delta x^2} \right]$$

and

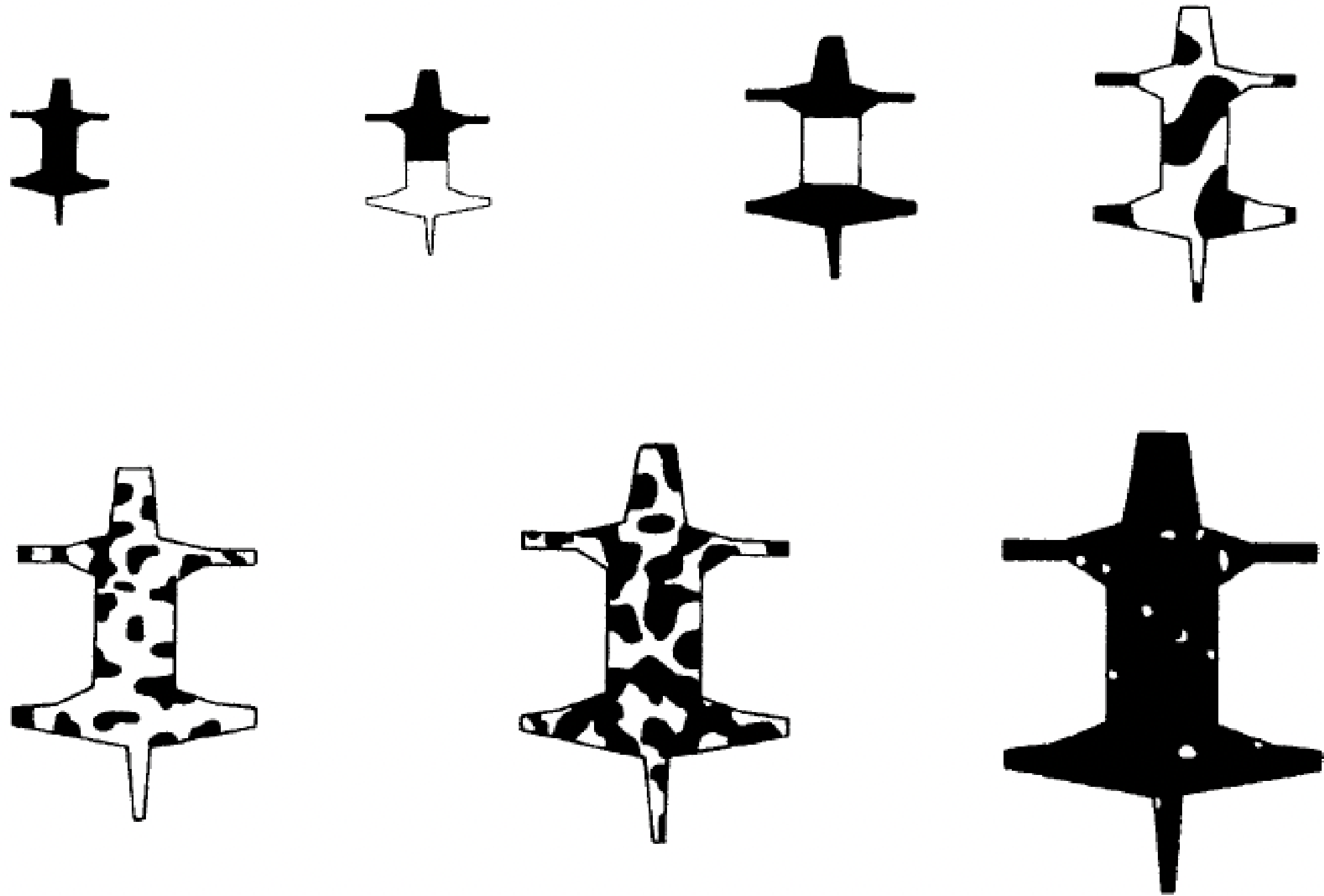
$$v_{ij}^{(t+1)} = v_{ij}^{(t)} + \Delta t \left[\gamma g(u_{ij}^{(t)}, v_{ij}^{(t)}) + d \frac{v_{i-1,j}^{(t)} + v_{i+1,j}^{(t)} + v_{i,j-1}^{(t)} + v_{i,j+1}^{(t)} - 4v_{ij}^{(t)}}{\Delta x^2} \right]$$

with parameters defined on the problem set.

Morphogenesis project

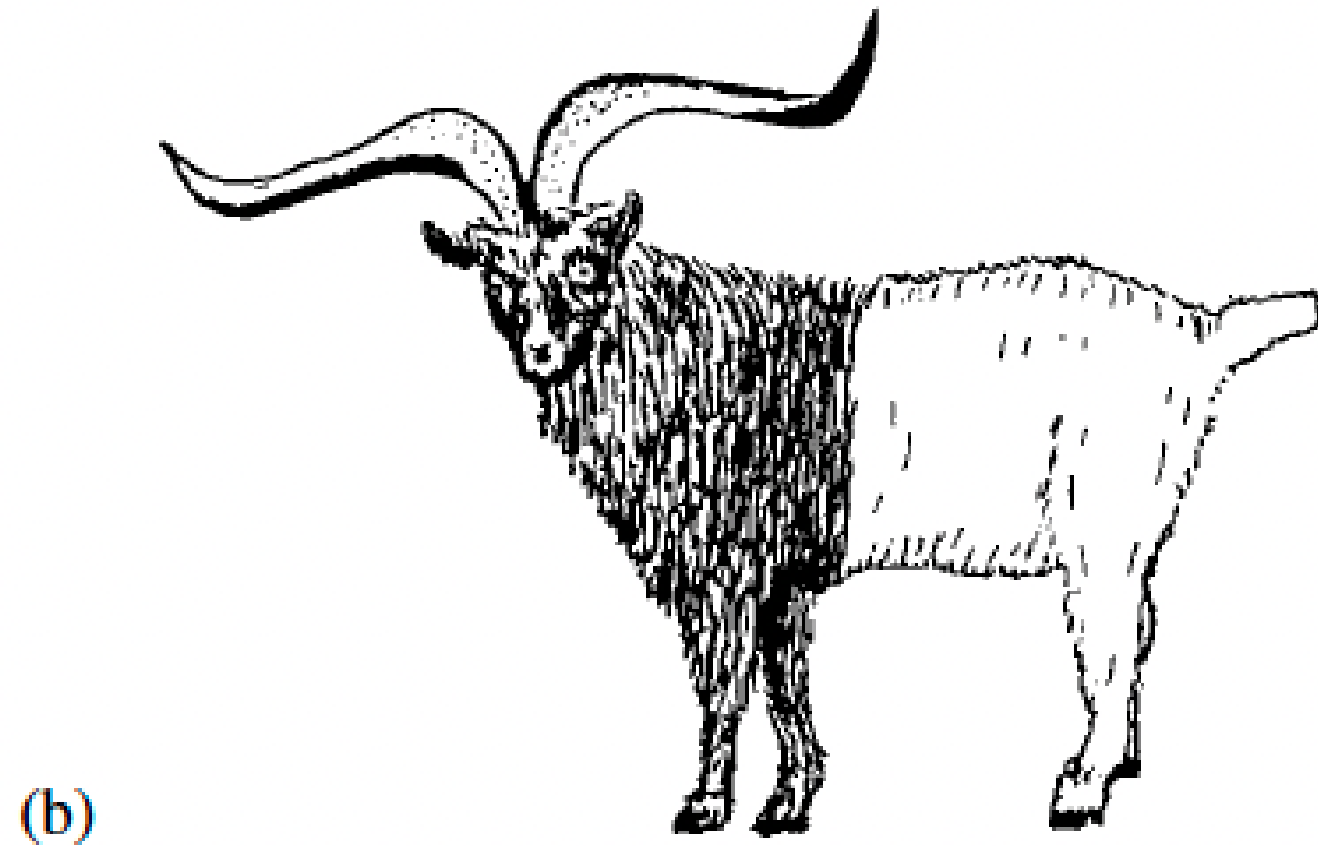
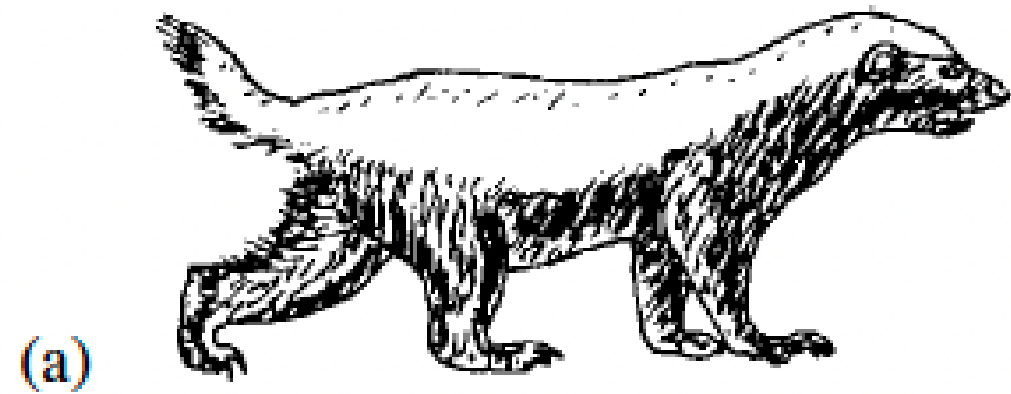
- implement a model of morphogenesis (discretized partial differential equation)
- integrate tests, provide specified API
- refactor (functions, oop, speed-up)
- developed on GitHub with git
- *understand why patterns can emerge with this mechanism*
- *study what patterns can emerge (incl. visualization)*

Reaction-diffusion model



Adapted from Mathematical Biology II by Murray

The simplest, non-trivial coat patterns



Honey badger & valais goat; adapted from Mathematical Biology II by Murray

The next bifurcation ...



(d)



Anteater and galloway cows; adapted from Mathematical Biology II by Murray

Reaction-diffusion model

You will analyze the model and answer two key questions:

- When is the solution numerically stable?
- What type of coat patterns can emerge?

How to document your work?

- write the report in markdown (on GitHub)
- store results as pandas files
- embed visualizations and results
- make your final release before Dec 23 at 10am

The final problem set gives all details.

Note: we will not grade speed/coverage in this release. This was already done. Of course, put forward your best code version with all features working. Use the fastest code, so that all simulations are achieved quicker. All the best!

Questions?

Upcoming schedule:

Today:

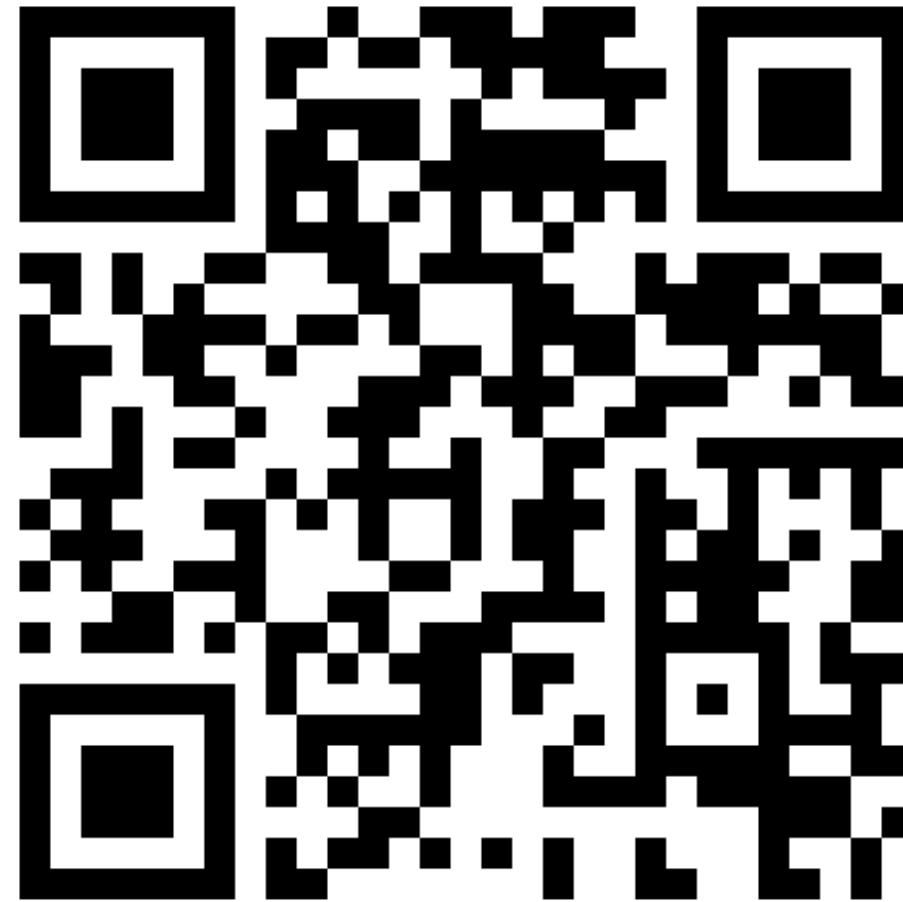
- Monday 13 - 15: exercises working on your project (final version)

Next weeks:

- Monday, Dec 9: *NO* class (so you can work on your project)
- Monday, Dec 9, 13 - 15: exercises working on your project
- Monday, Dec 16: final class (incl. award ceremony)
- Monday, Dec 16, 13 - 15: exercises working on your project

Release your final version on 23.12. at 10am!

Let's fill out the class feedback form



[Link to questionnaire](#)

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