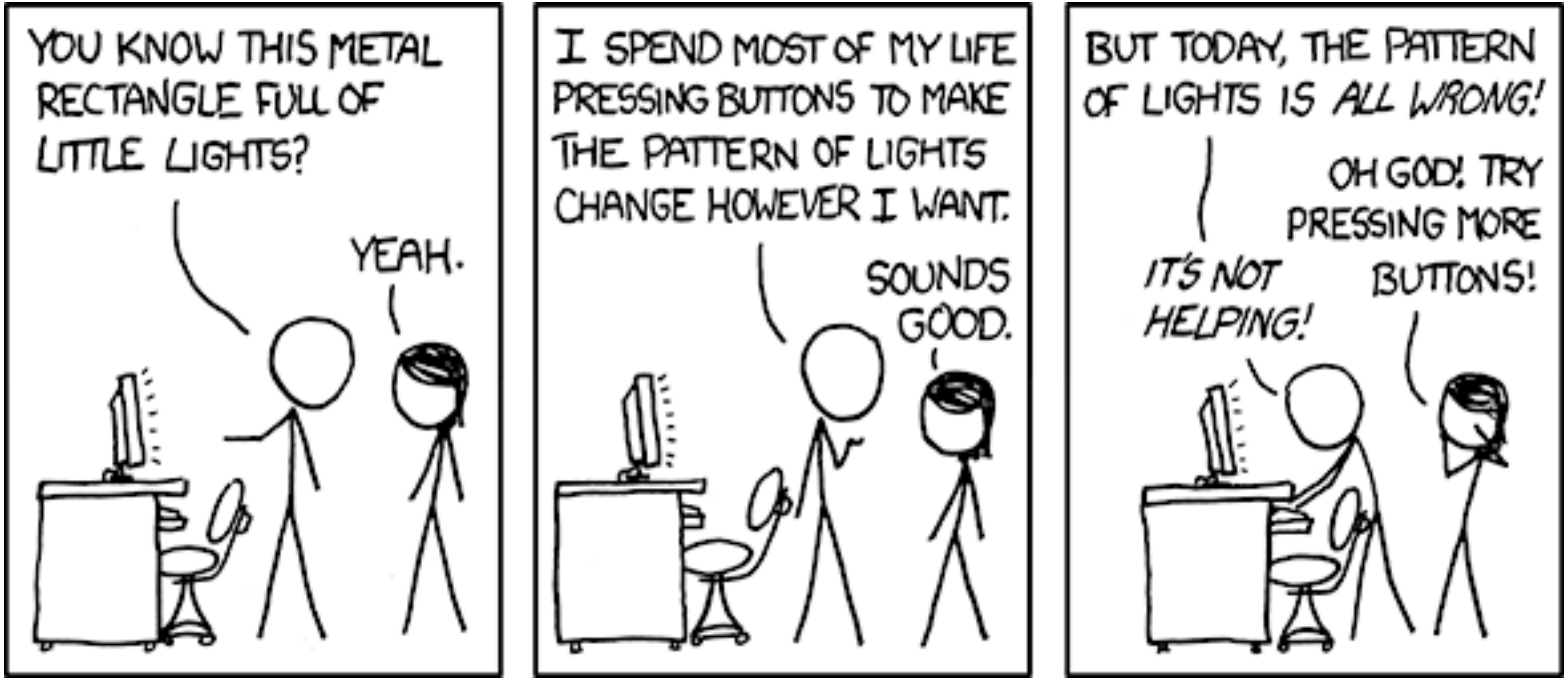

YOU KNOW THIS METAL RECTANGLE FULL OF LITTLE LIGHTS?
YEAH.
I SPEND MOST OF MY LIFE PRESSING BUTTONS TO MAKE THE PATTERN OF LIGHTS CHANGE HOWEVER I WANT.
SOUNDS GOOD.
BUT TODAY, THE PATTERN OF LIGHTS IS *ALL WRONG!*
OH GOD! TRY PRESSING MORE BUTTONS!
IT'S NOT HELPING!

Computational Neuroscience (for cognitive neuroscientists)

BCBL Master's Programme

Cognitive neuroscience of language

James Magnuson & Alejandro Tabas

Lets wake up by doing some computation!

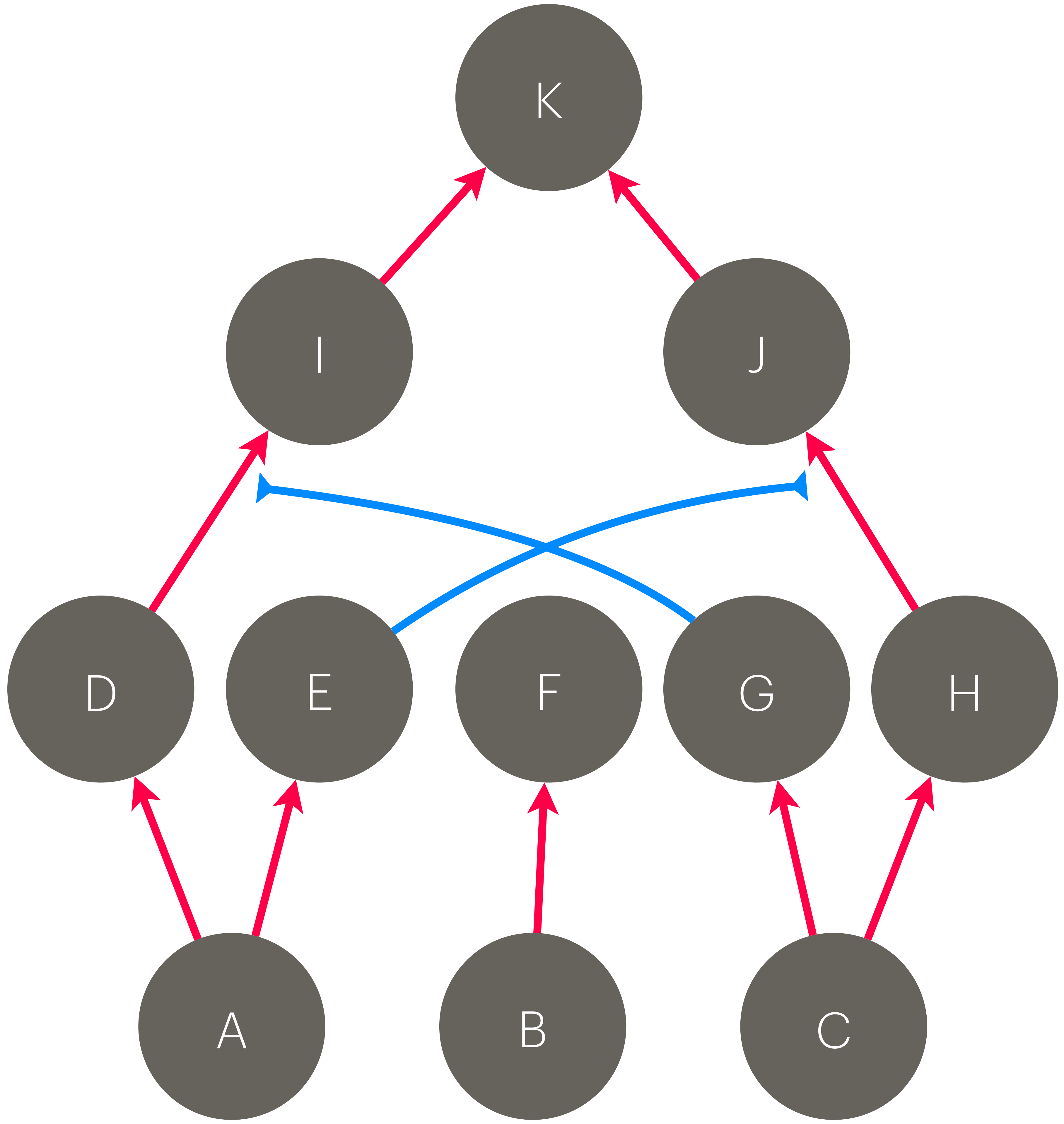
Excitatory neurons:

- Rest your arms on the shoulder of the neighbours you are connected to
- When you spike, gently squeeze the shoulder of all neurons you are connected to
- Spike whenever you feel a spike from your neighbours at the back

Inhibitory neurons (E and G):

- Hold the arm of the neuron connecting to the neuron you are inhibiting
- When you spike, gently lift the arm to block any possible excitatory input

Face this direction



Computational models in Neuroscience research

Computational Neuroscience - Lecture 1

Alejandro Tabas

Computational models in Neuroscience research

Part A

1. What is a model?
2. What is computational neuroscience?
3. Neuroscience needs theory
4. Three levels of description
5. Modelling receptive fields at V1
6. Conclusions

Part B: Overview of the course

Computational models in Neuroscience research

Part A

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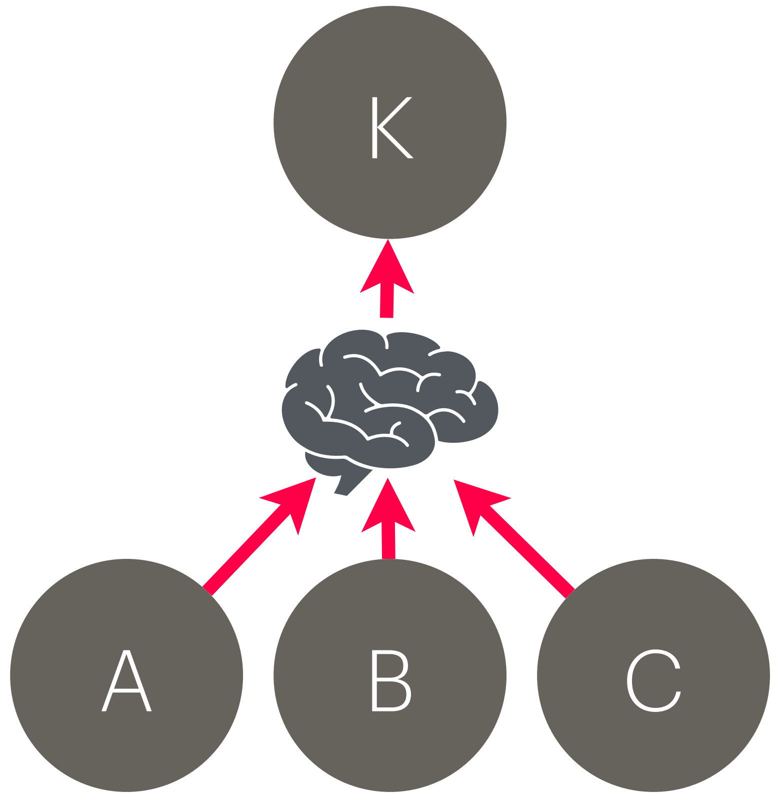
Experimental data 1

- What we learn form this?
- Is there a way to compress the results into a shorter format?

A	B	Q
0	0	0
0	1	1
1	0	1
1	1	0

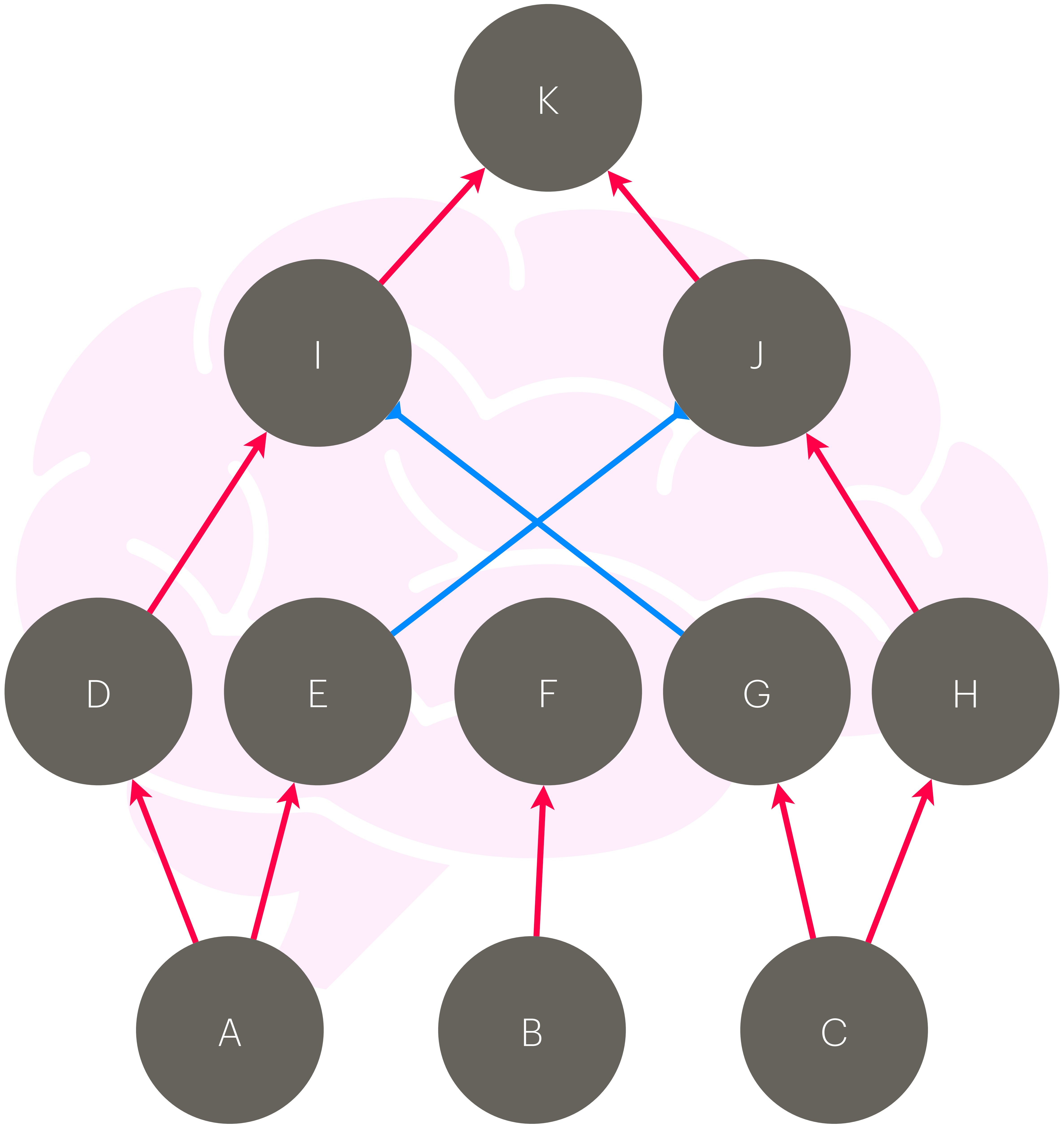
$$K = A \oplus C$$



A	**B**	**C**	**K**
1	0	0	1
0	1	0	0
0	0	1	1
1	1	0	1
0	1	1	1
1	0	1	0
1	1	1	0

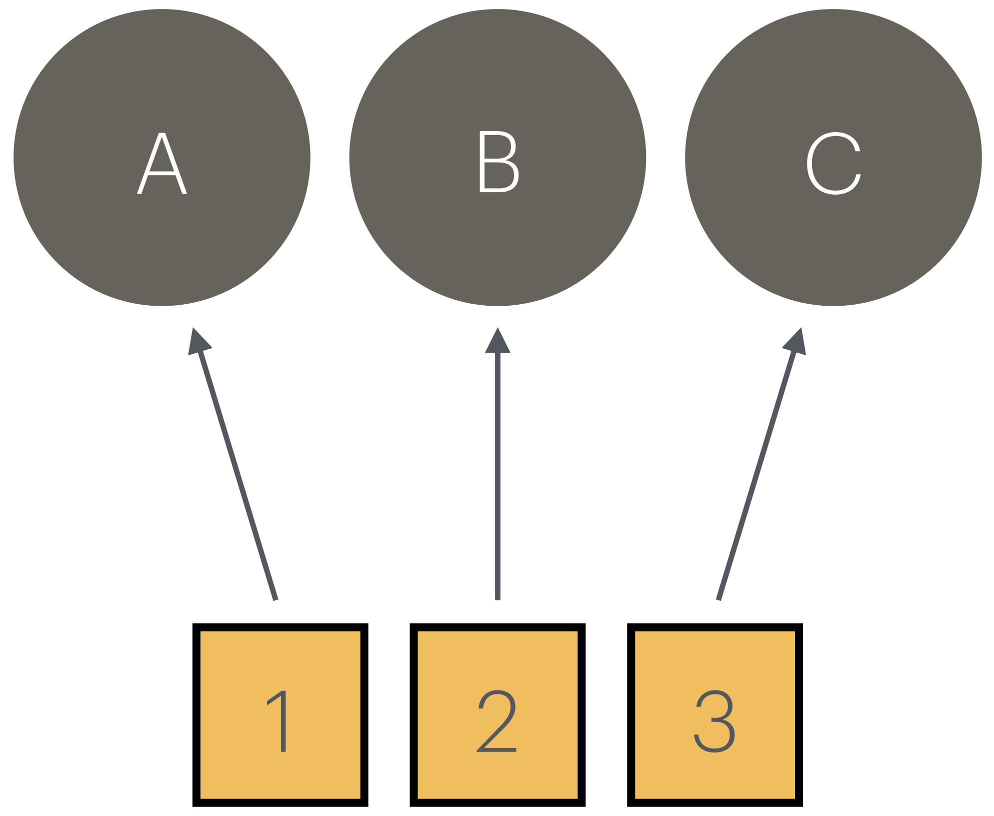
Experimental data 2

- Is it clear how $K = A \oplus C$ stems from this?
- What can we learn from this view?
- Does this view tell us anything we didn't know already after we noticed $K = A \oplus C$?
- Does this describe the entire system?



Experimental data 3

- What are the inputs A, B, C encoding?
- What does the output K encode?
- What can we learn from this view?



Input	A	B	C	K
1	1	0	0	1
2	0	1	0	0
3	0	0	1	1
3	1	1	0	1
5	0	1	1	1
4	1	0	1	0
6	1	1	1	0

What is a model?

Some key features:

- A **simplified** representation of a system
- Designed to capture **specific aspects** of the system
- Defined by its **assumptions and simplifications**
- Not a complete description of reality

All models are wrong, but some are useful

(George) Box's aphorism

Computational models in Neuroscience research

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What is computational neuroscience?

My view:

- A subfield of neuroscience where models (explanations) are the primary target
- Models are specific and perform quantitative predictions that are experimentally testable
- Provides the theoretical backbone for neuroscience

Everything you wanted to know about CompNeuro but were too afraid to ask

Are computers a core aspect of CompNeuro?

- Most models requires simulation, but some don't.
- Most experimentalists need computers to perform their analyses, but they are not computational.
- Computers are a fundamental tool, but not the core of CompNeuro.

Is a strong mathematical background required to do CompNeuro?

- Having a basic background helps.
- Some models are mathematically simple.
- Maths is the language of science.

What's the relationship to Machine Learning?

- CompNeuro uses ML results to inform their models. We will see some examples in the course

Your question here.

Computational models in Neuroscience research

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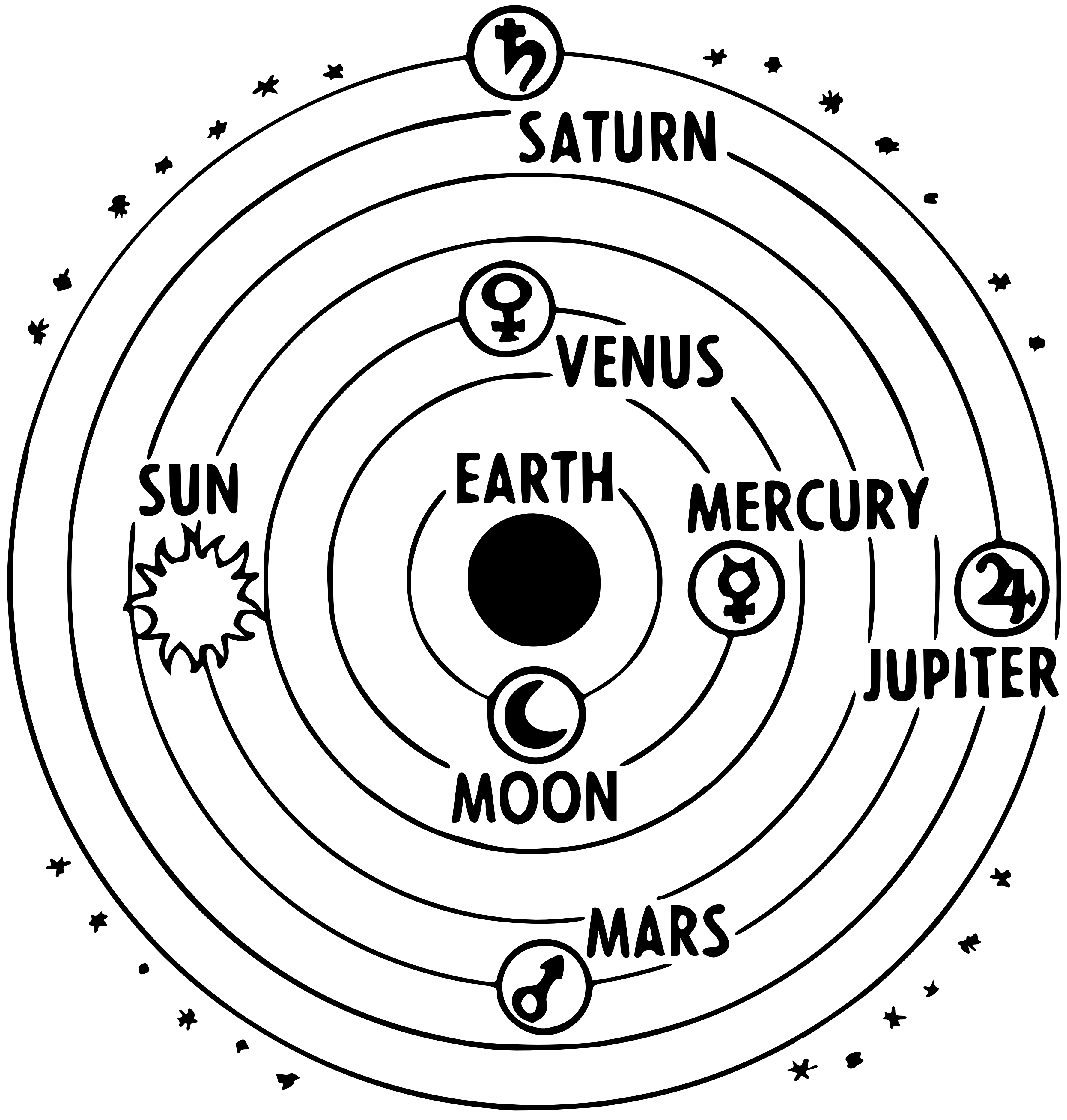
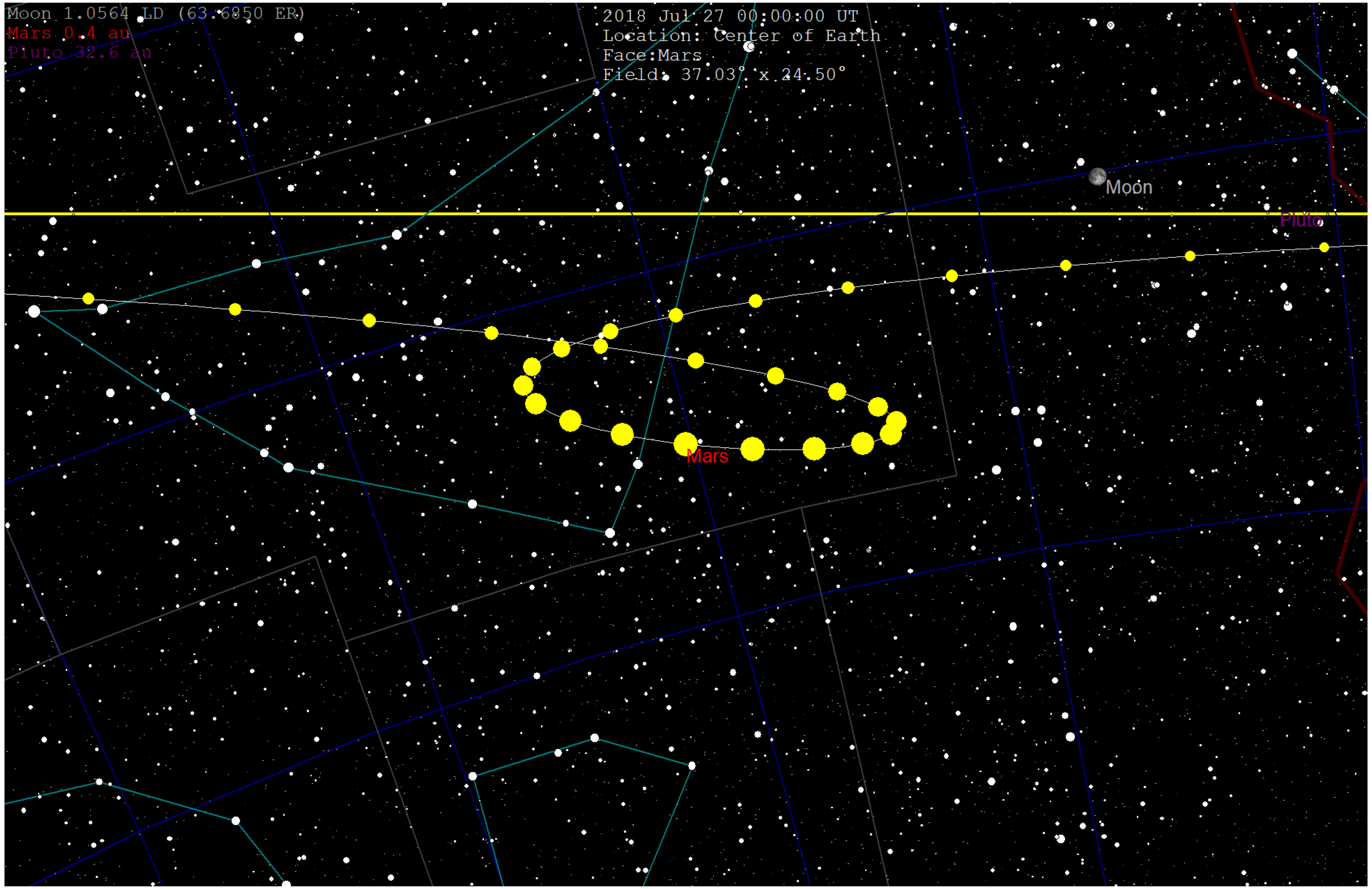
A detour: cosmological models

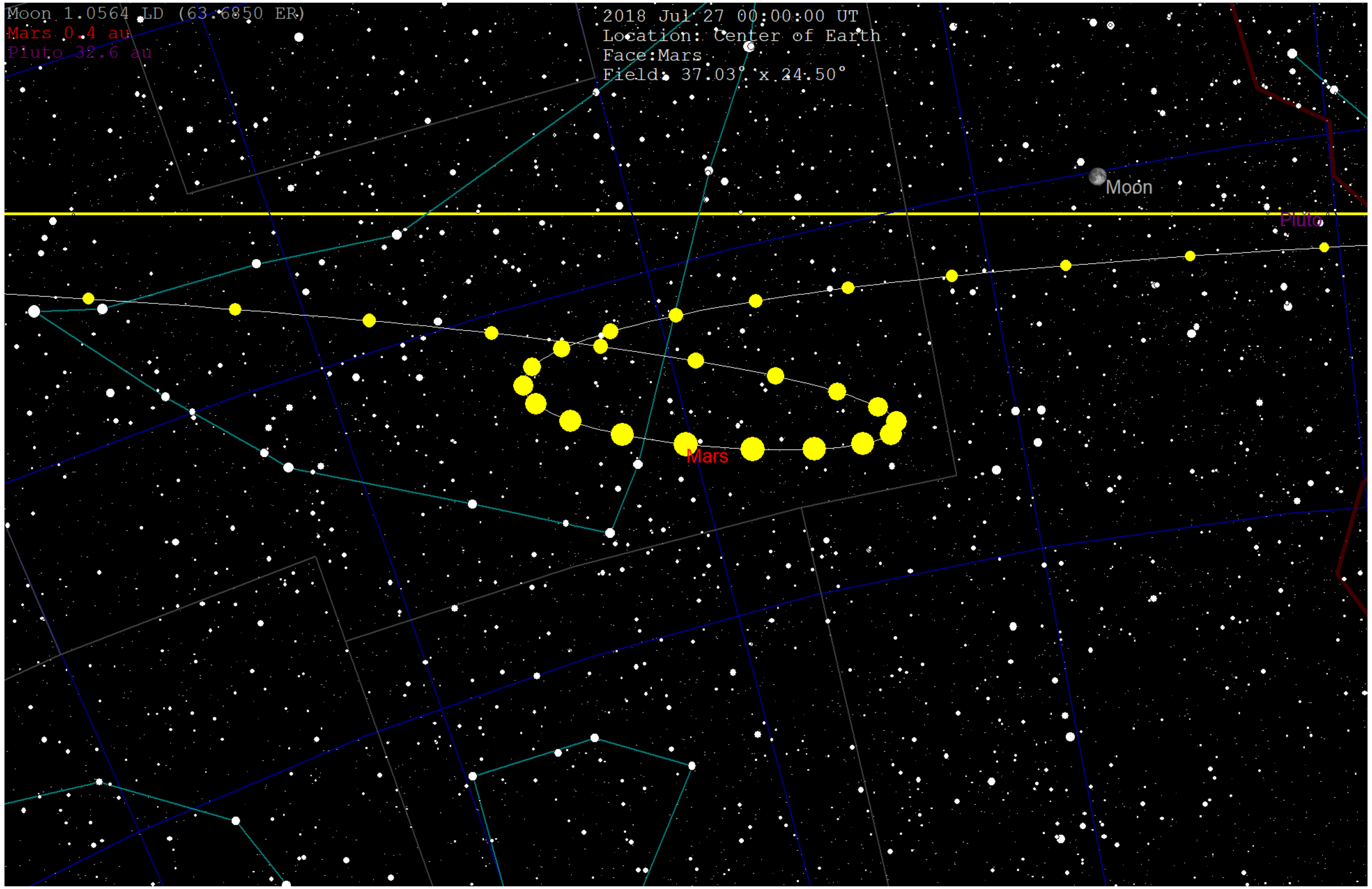
The Aristotelian model

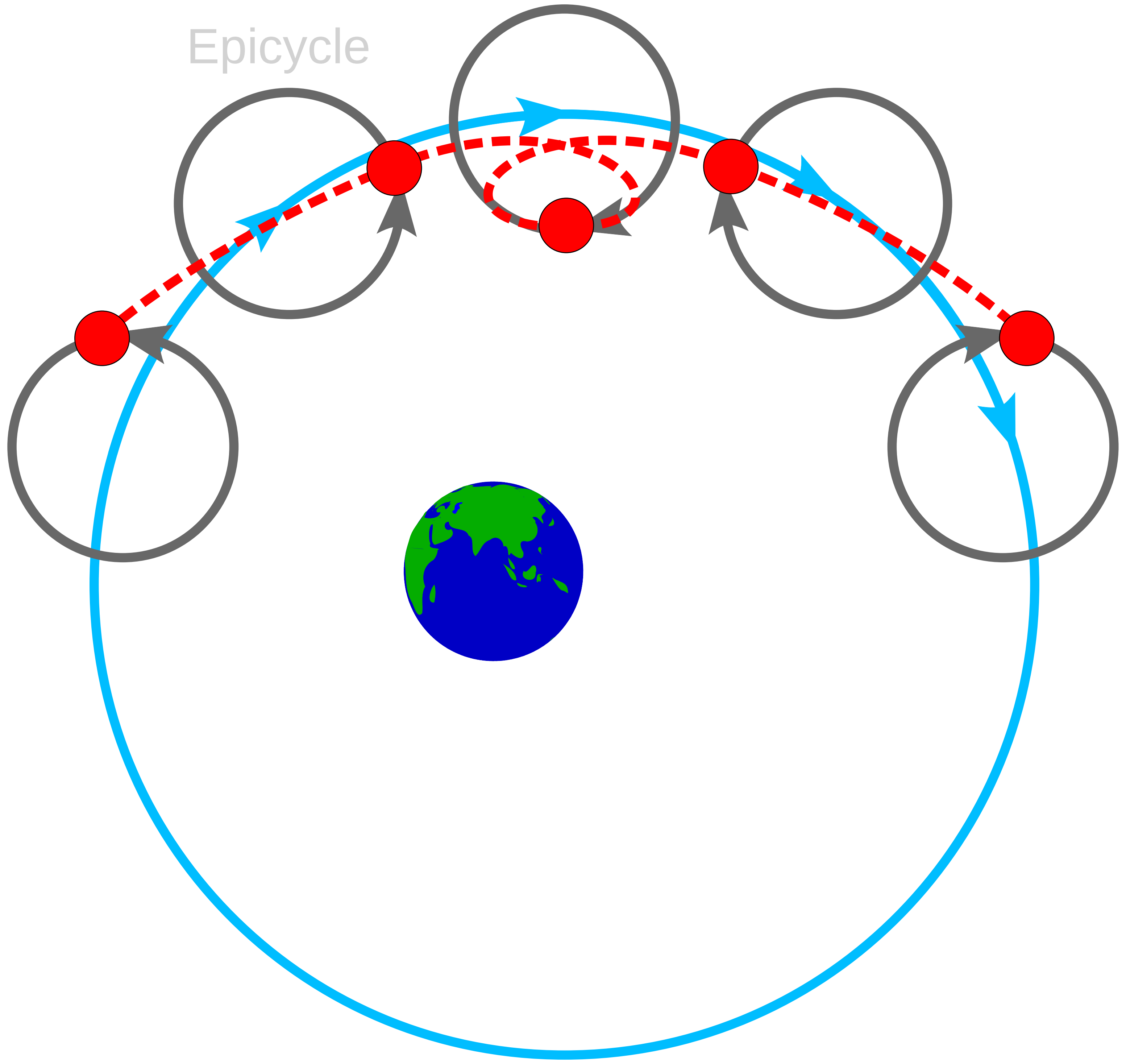


Experimental falsification: retrograde motion

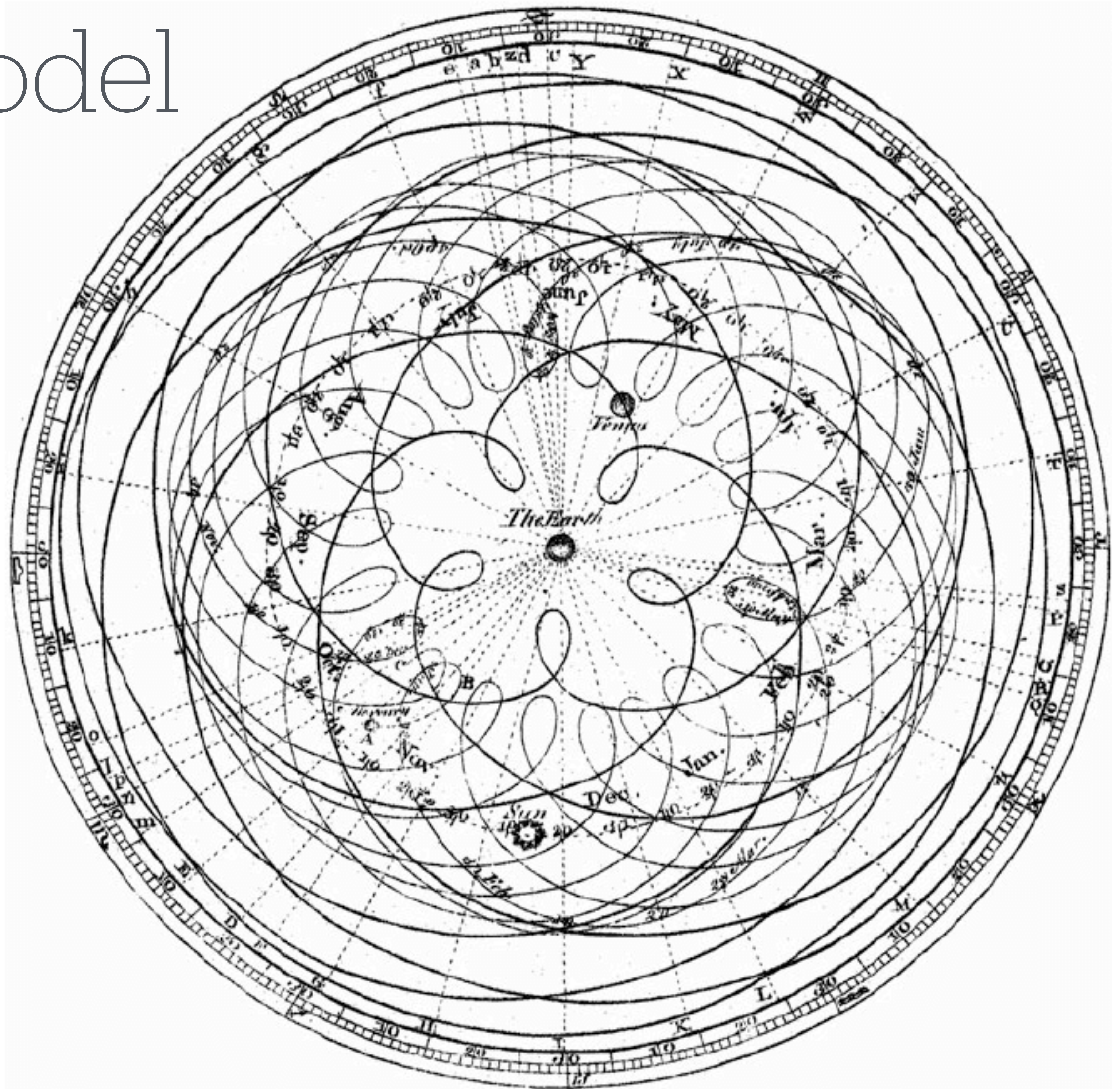


Theoretical refinement: the ptolemaic model

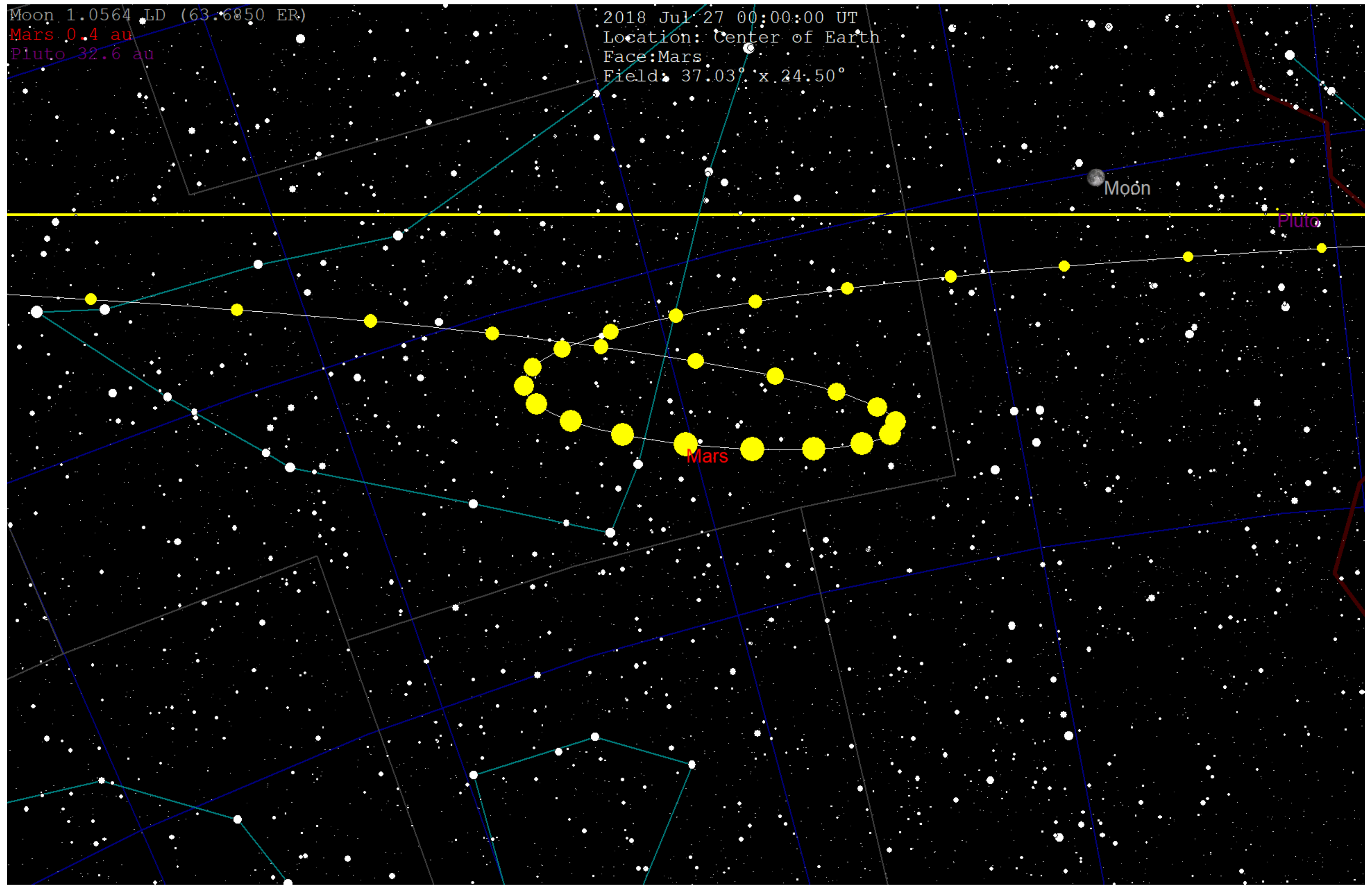


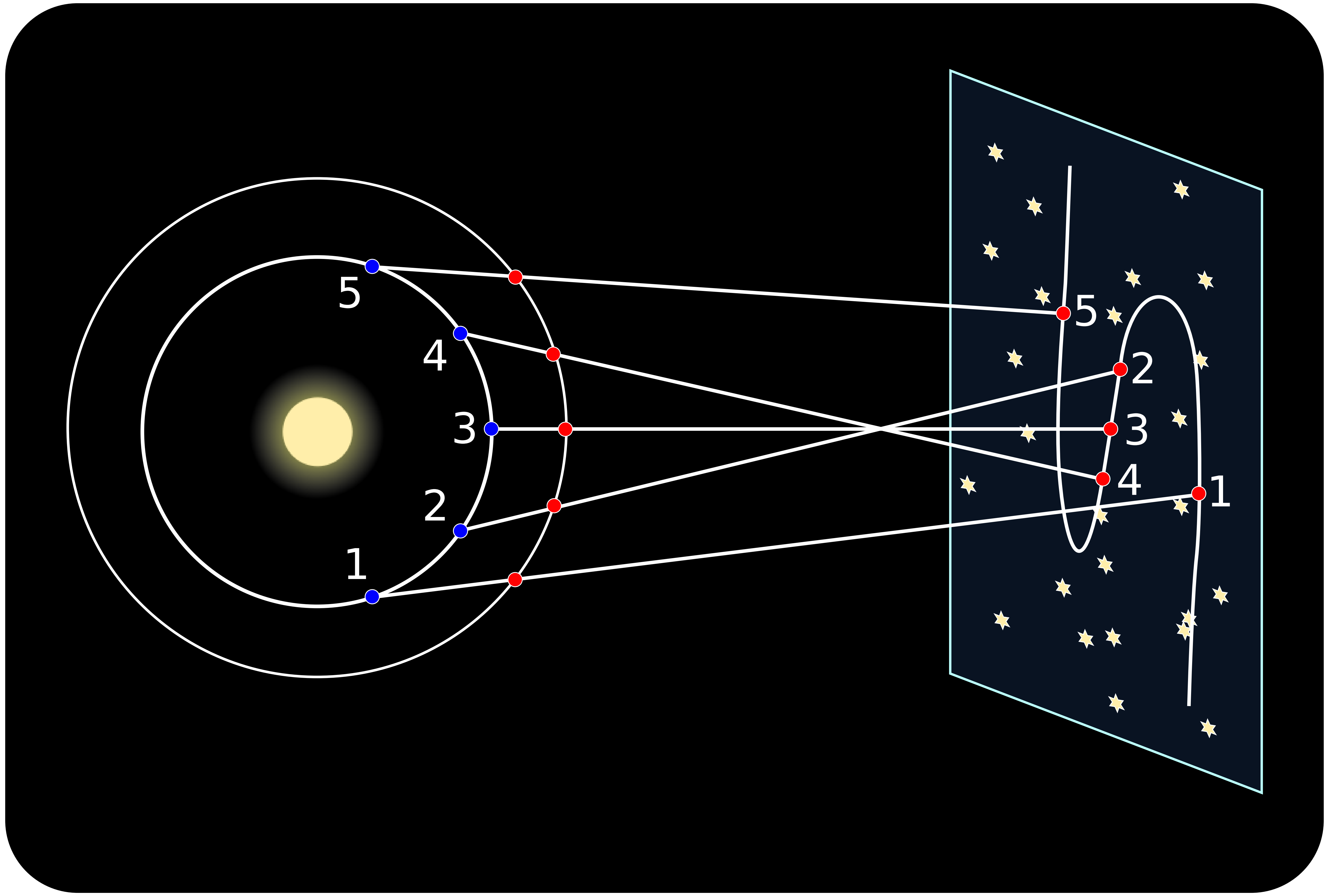


The Ptolemaic model

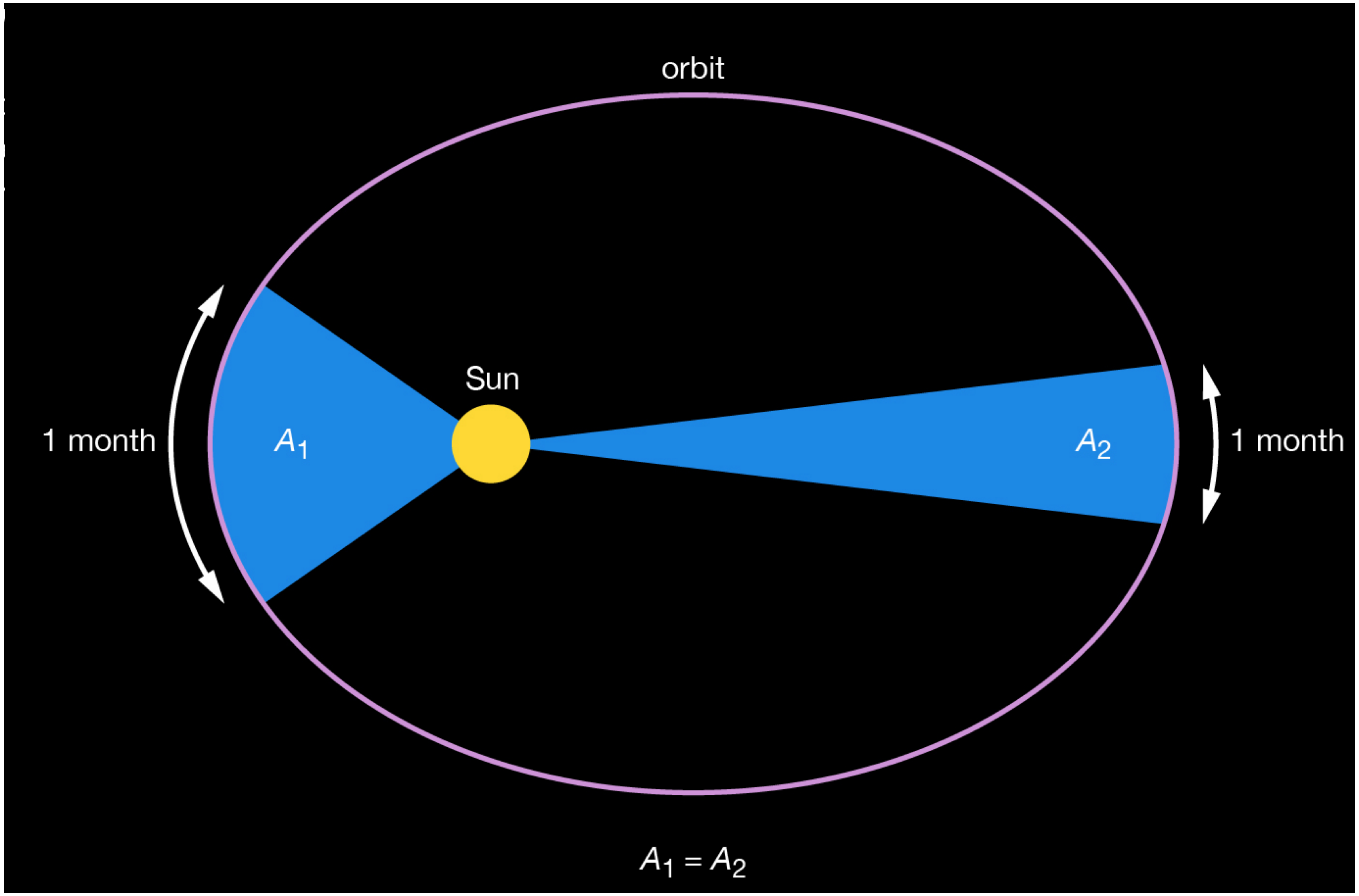


Paradigm shift: Copernican model

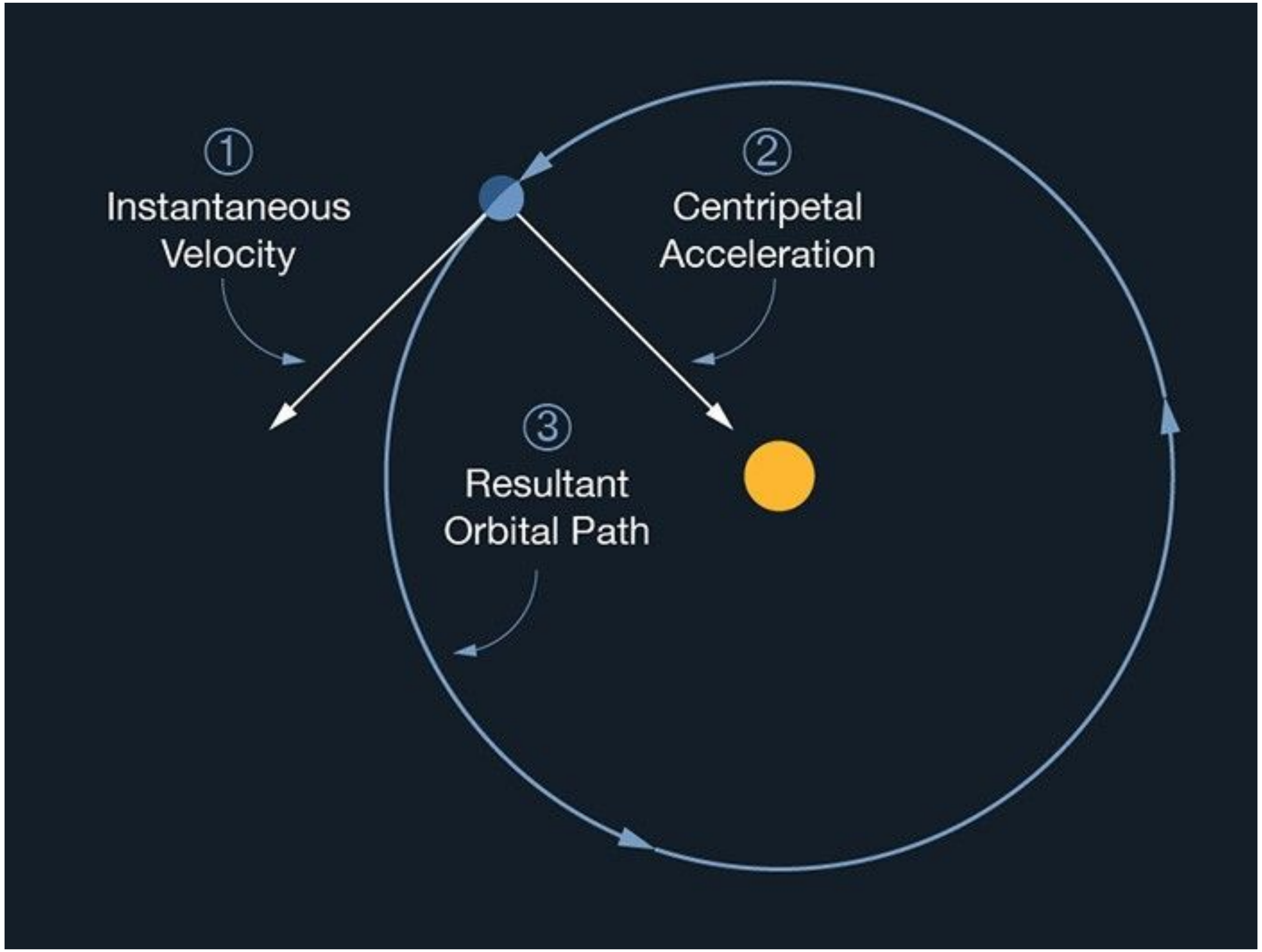




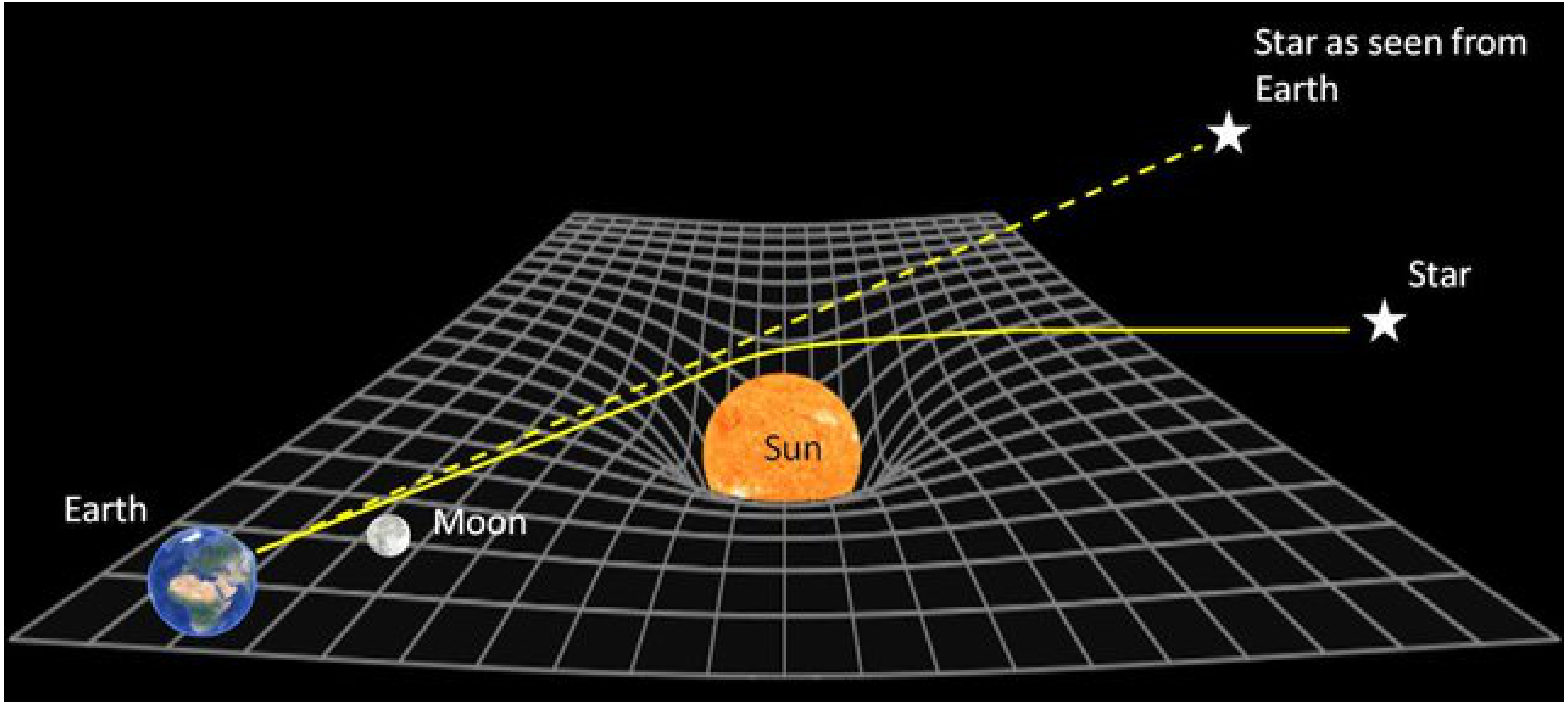
Theoretical expansion: Kepler's laws



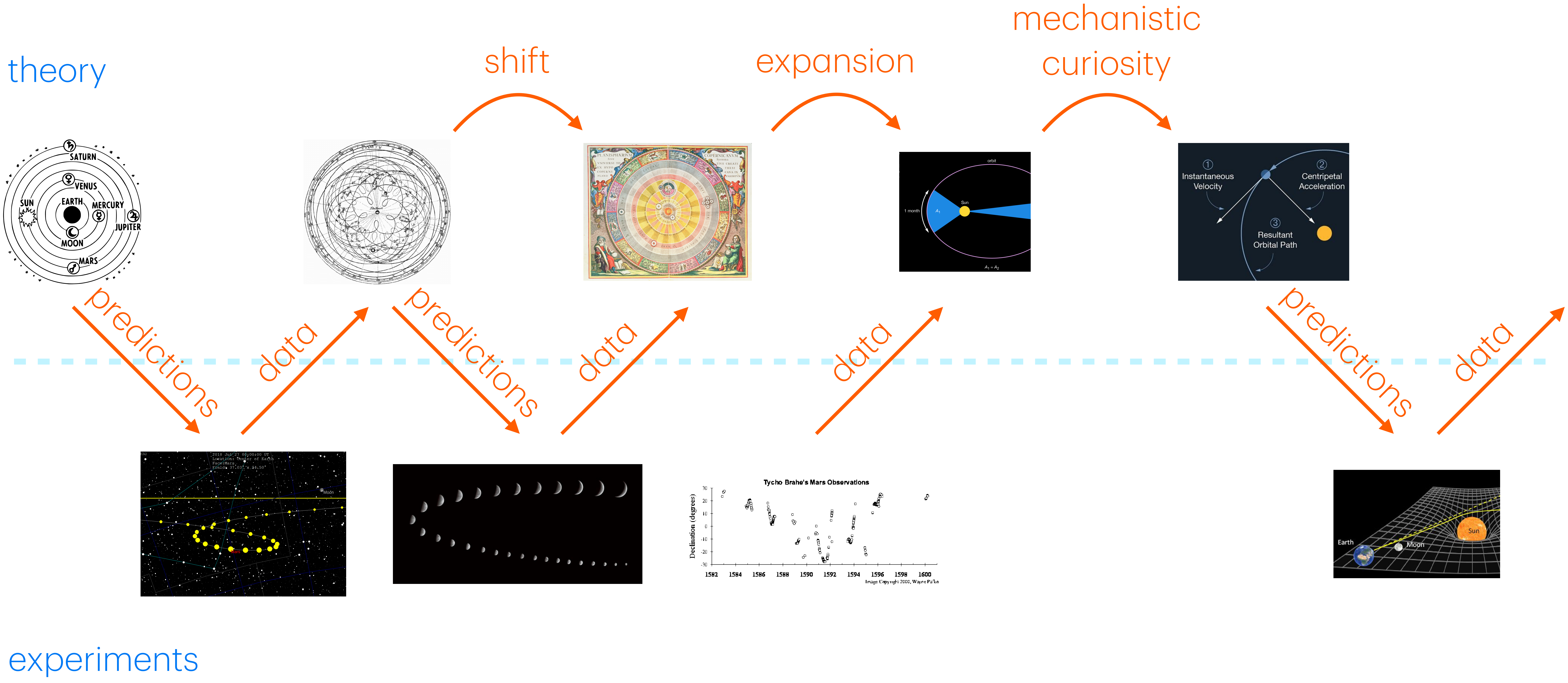
Mechanistic insight: Newton’s law



Theoretical refinement: General relativity



Theory and experiments need each other



What properties should theoretical models have to be useful in neuroscience?

Theory in the natural sciences

Models are as simple as possible, but not more (parsimony)

- compare: Ptolemaic ↔ Copernican; Keplerian ↔ Newtonian

Models make falsable predictions (predictive power)

- Incorrect predictions of the Newtonian model crucial for the Einstenian model

Models generalise to all subsystem (general)

- same model explains dynamics of all solar systems

Explanatory value

- adds understanding of the system (compare with curve fitting)

Models are quantitative and specific (specificity)

- there is only one way to map reality to the model

What properties should theoretical models have to be useful in neuroscience?

- What models do you know that satisfy these properties?
- What models do you know that don't?

Neuroscience needs theory

Cognitive neuroscience is still in Ptolemaic times

- Rich descriptions and mappings with limited explanatory structure
- Conceptual progress lags behind data and methods

Data alone does not produce understanding

- More measurements ≠ more insight
- The same data often support multiple, incompatible interpretations

Theory is needed for

- compression: reduce vast amounts of data to core principles
- constraint: rule out explanations, not just supports narratives
- unification: links tasks, species, and levels of analysis

Who should be in charge of developing theory?

Neuroscience is not yet late-physics:

- Core theoretical objects (representations, codes, networks) remain ill-defined
- Weak integration across levels (behavior, cognition, circuits)
- Experimental sophistication outpaces conceptual clarity

We are not yet ready for an experimentalist–theorist divide

- theory risks becoming unfalsifiable
- experiments risk becoming unconstrained

The field needs

- theory-aware experimentalists
- data- and biology-constrained theorists

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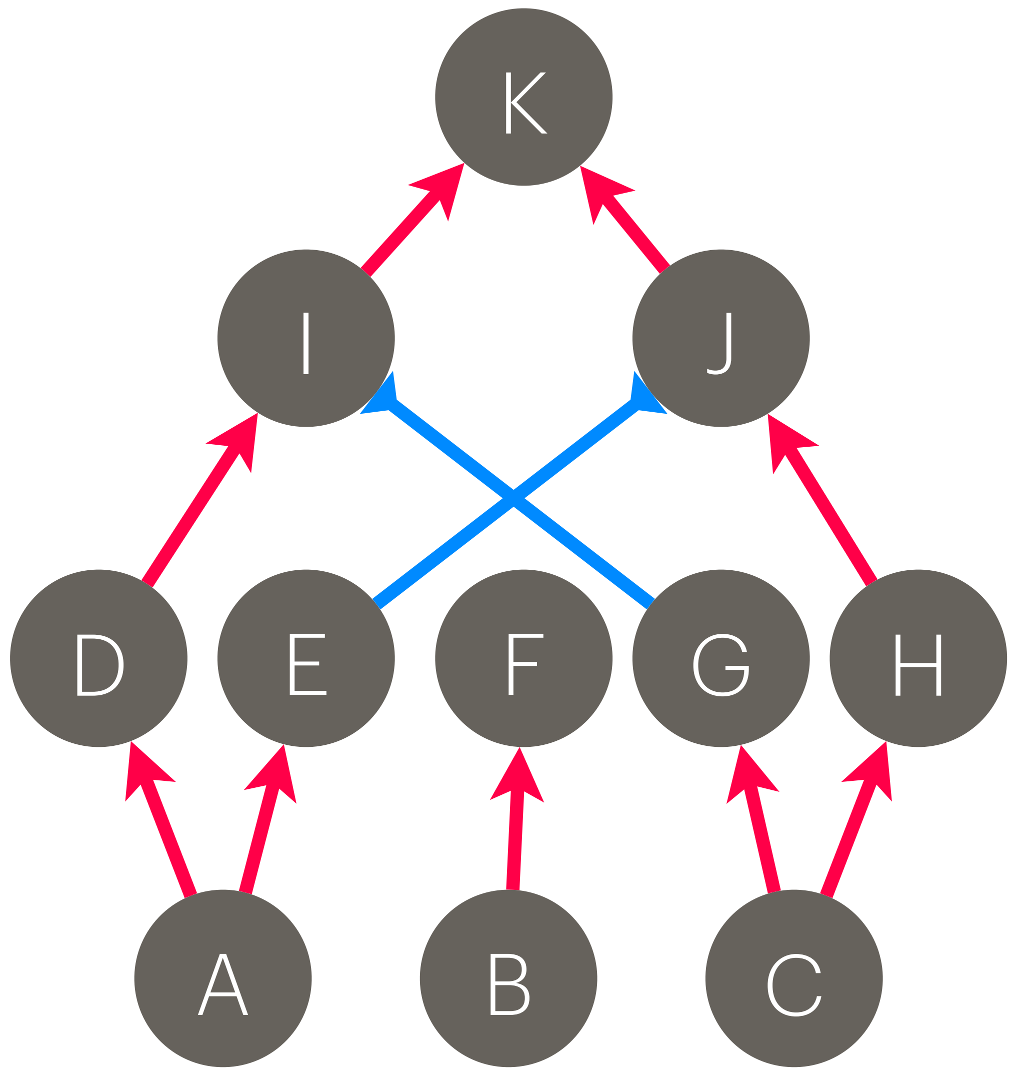
What do we need to know to understand a system?

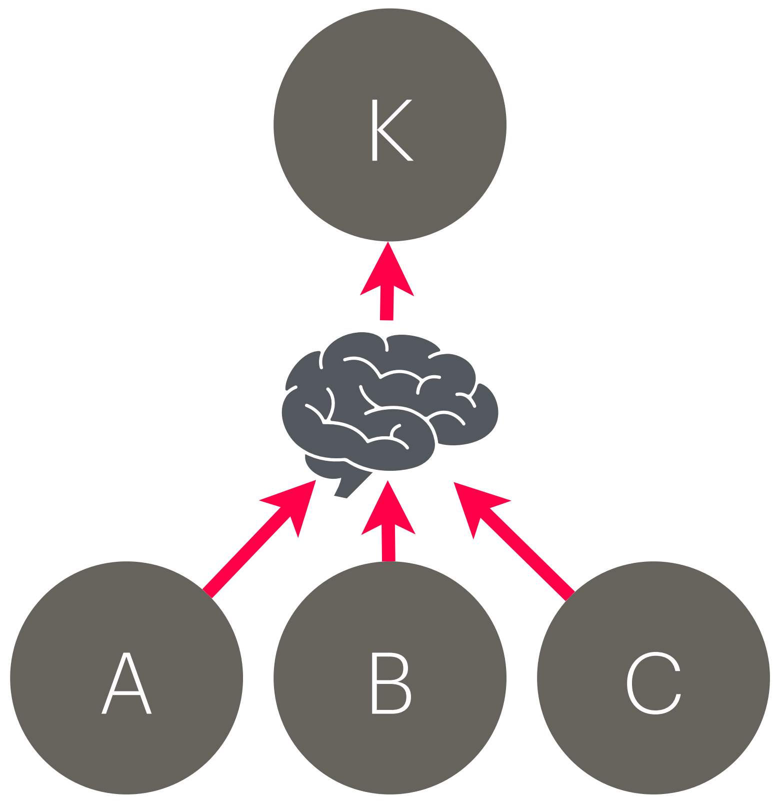


Phenomenology

- **What** does the system do?

A	B	Q
0	0	0
0	1	1
1	0	1
1	1	0

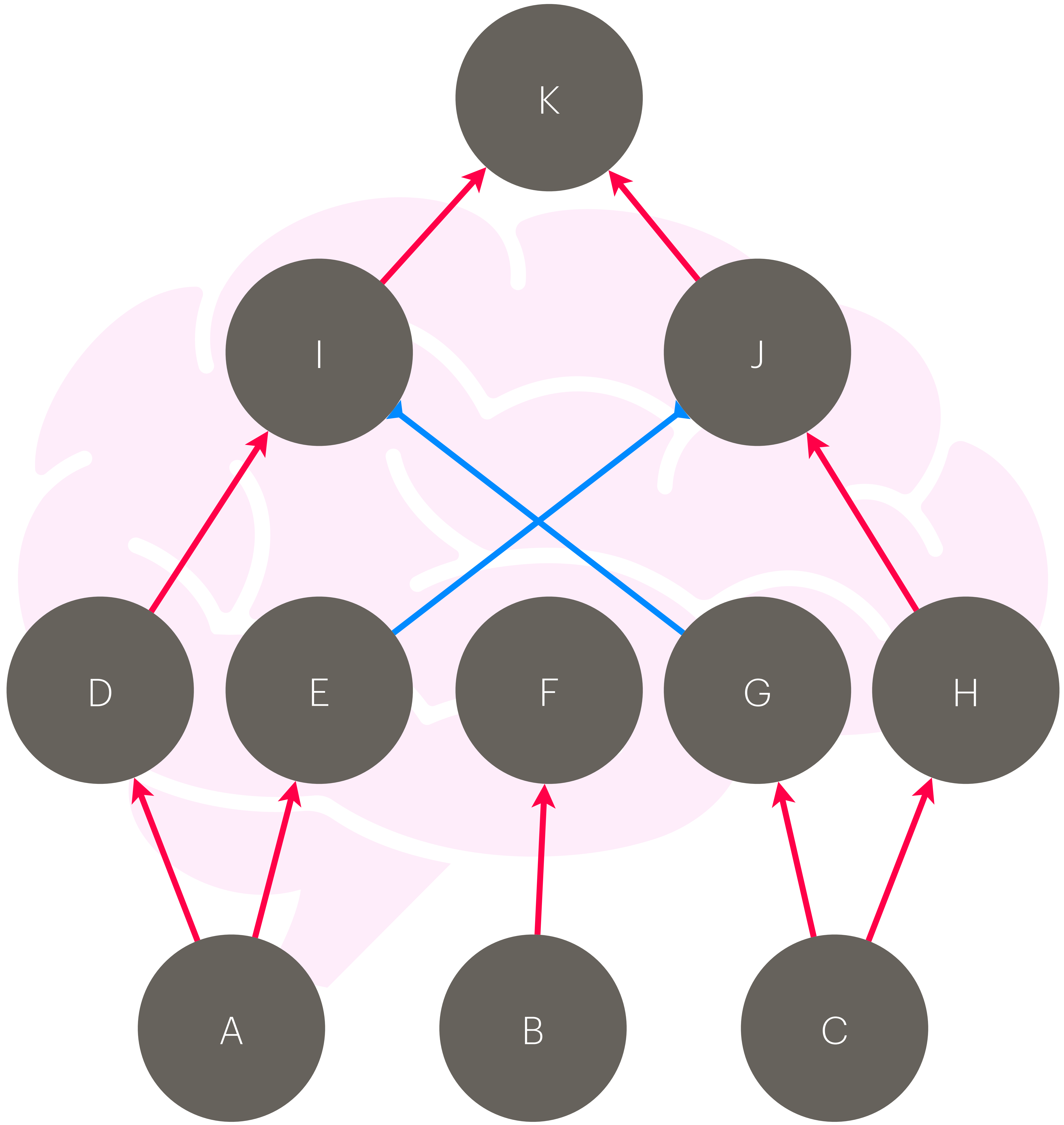
$$K = A \oplus C$$



A	B	C	K
1	0	0	1
0	1	0	0
0	0	1	1
1	1	0	1
0	1	1	1
1	0	1	0
1	1	1	0

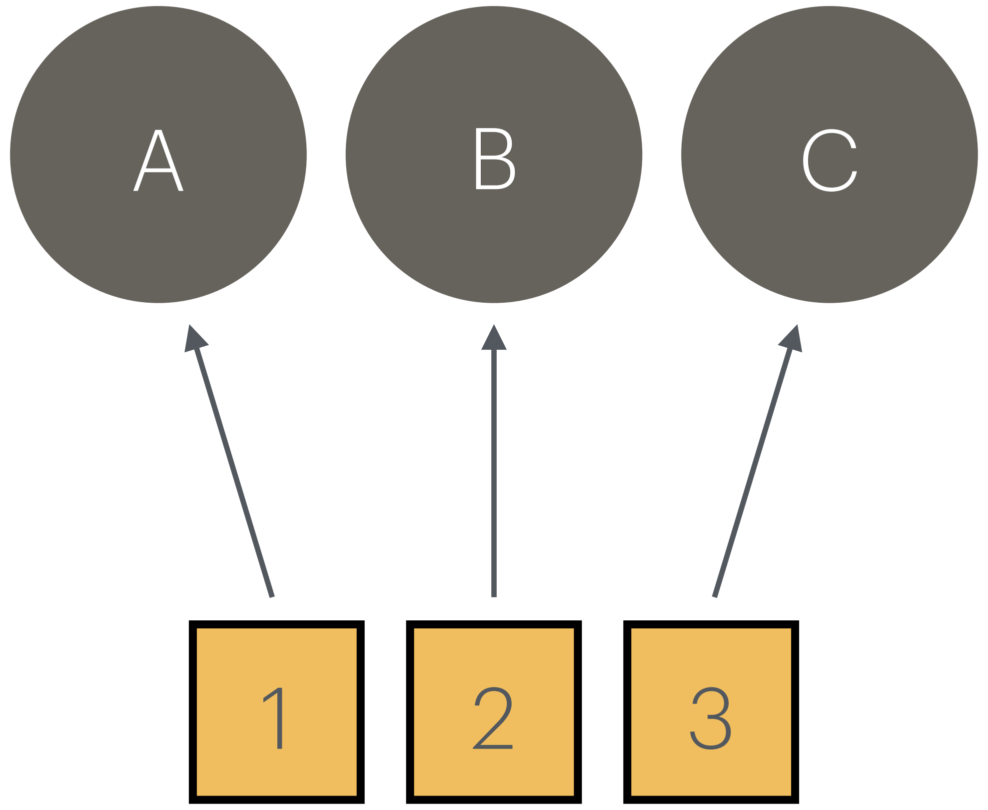
Mechanisms

- **How** does the system do it?



Normative principles

- **Why** does the system do it?



Input	A	B	C	K
1	1	0	0	1
2	0	1	0	0
3	0	0	1	1
3	1	1	0	1
5	0	1	1	1
4	1	0	1	0
6	1	1	1	0

Marr's three levels of description

Phenomenology: What does the system do?

- Compresses data into general principles
- E.g., Kepler's model of planetary motion describes what but not how or why

Mechanisms: How does the system do it?

- Explains how things work, allowing us to design interventions and repair systems
- E.g., Newton's model explains how the orbits are derived from axiomatic principles

Normative principles: Why does the system do it?

- Explain the computational problem that the system solves and its overarching principles
- E.g., Einstein's relativity explains mechanics as a consequence of the Equivalence Principle

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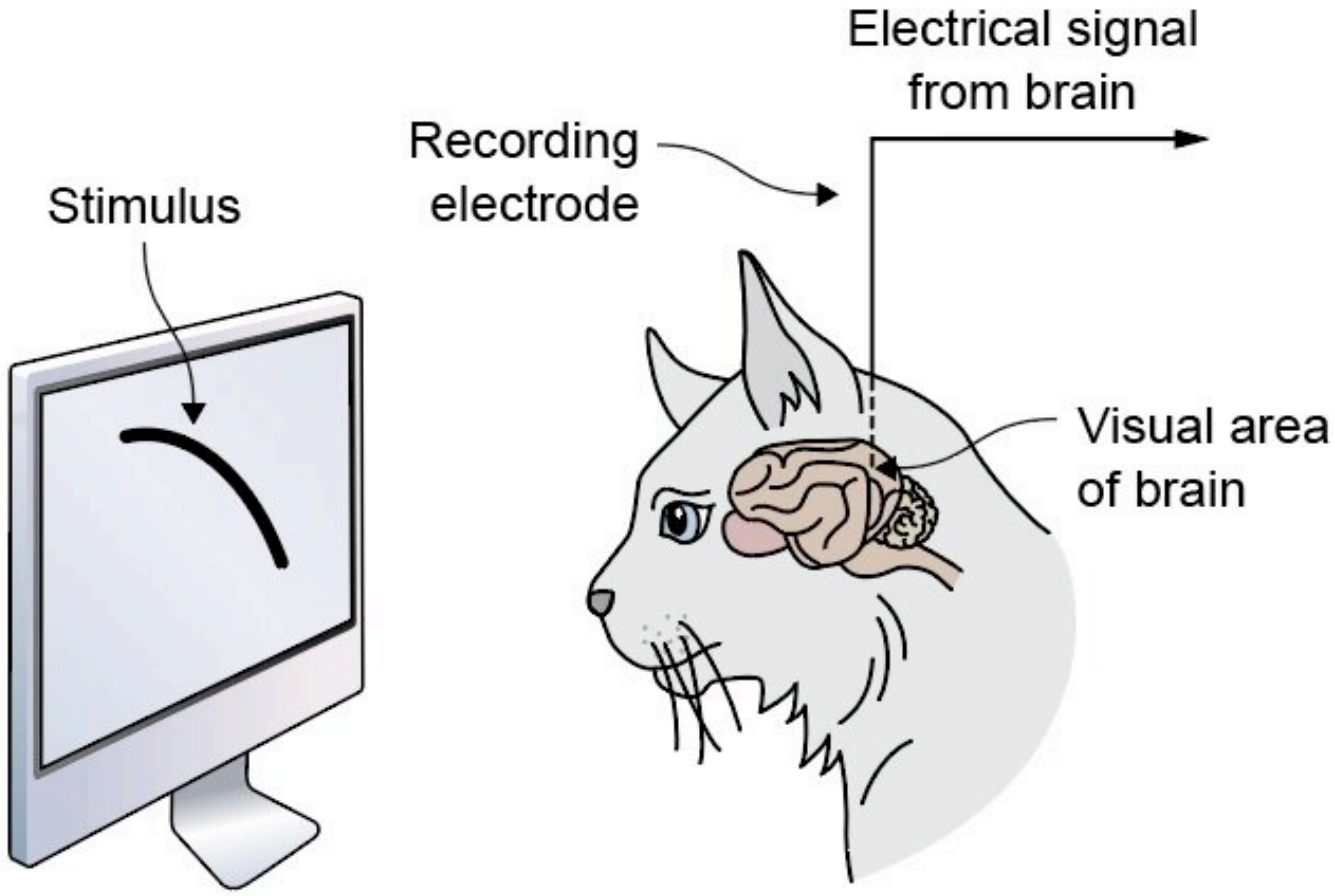
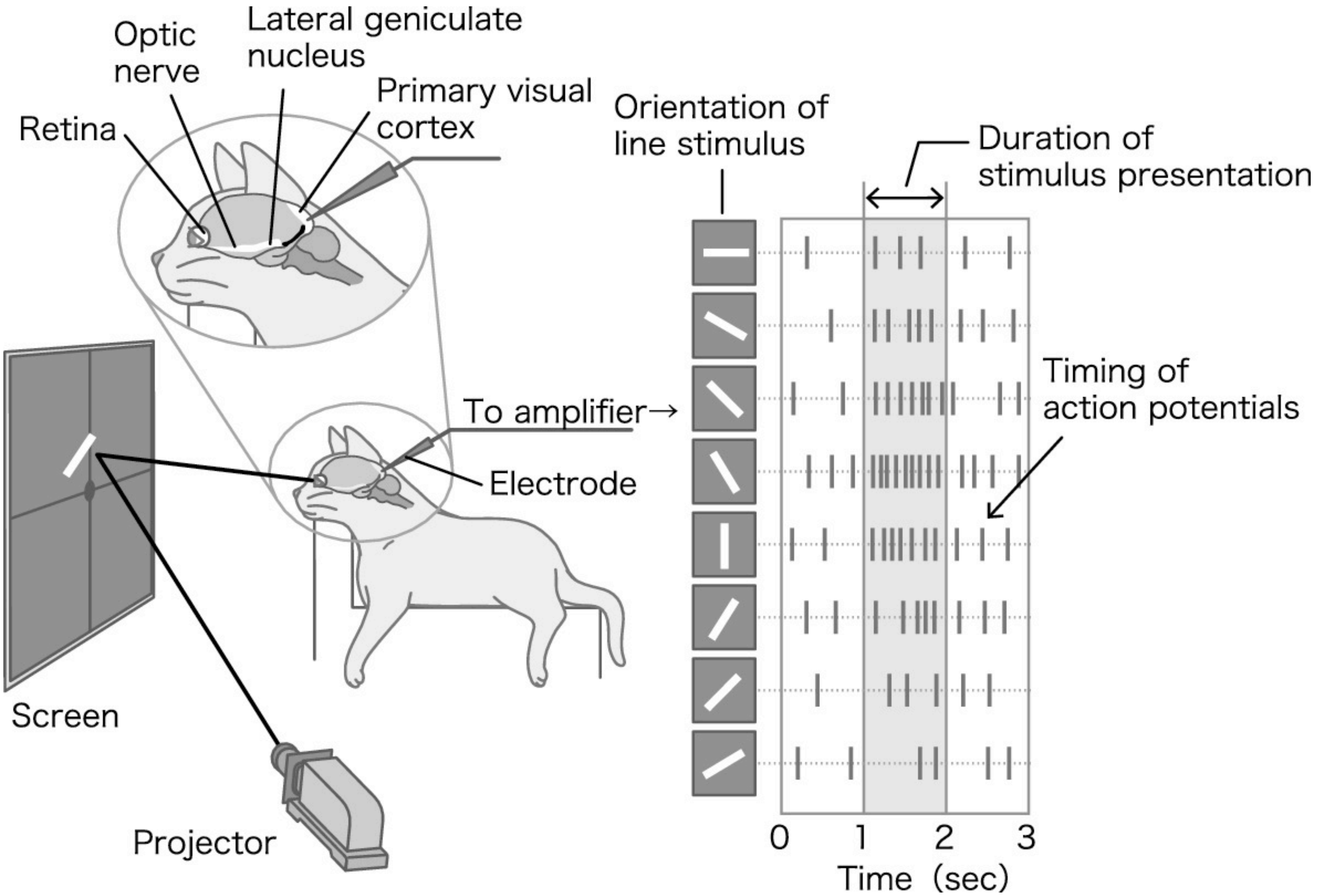
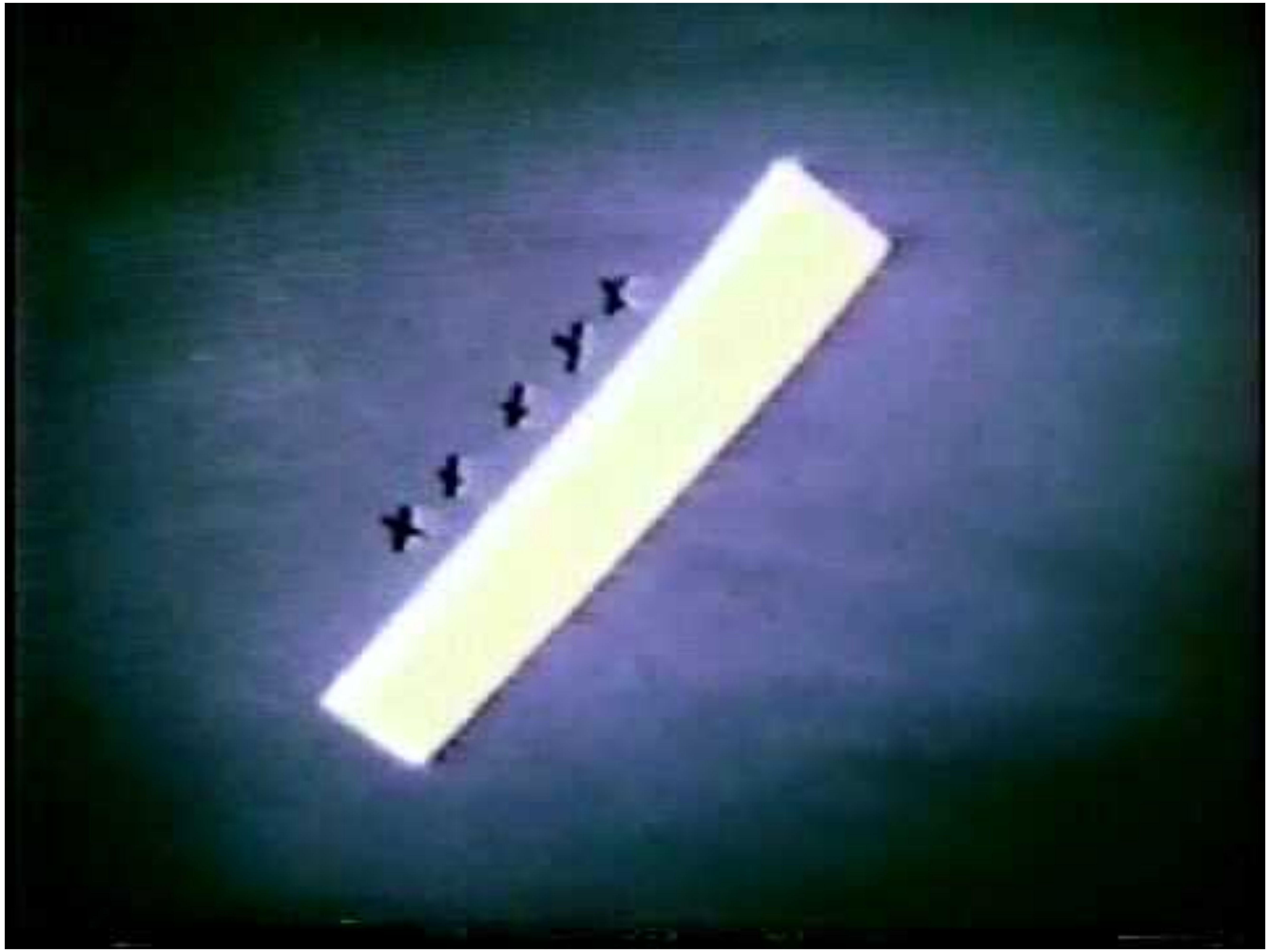
Hubel and Wiesel, 1959



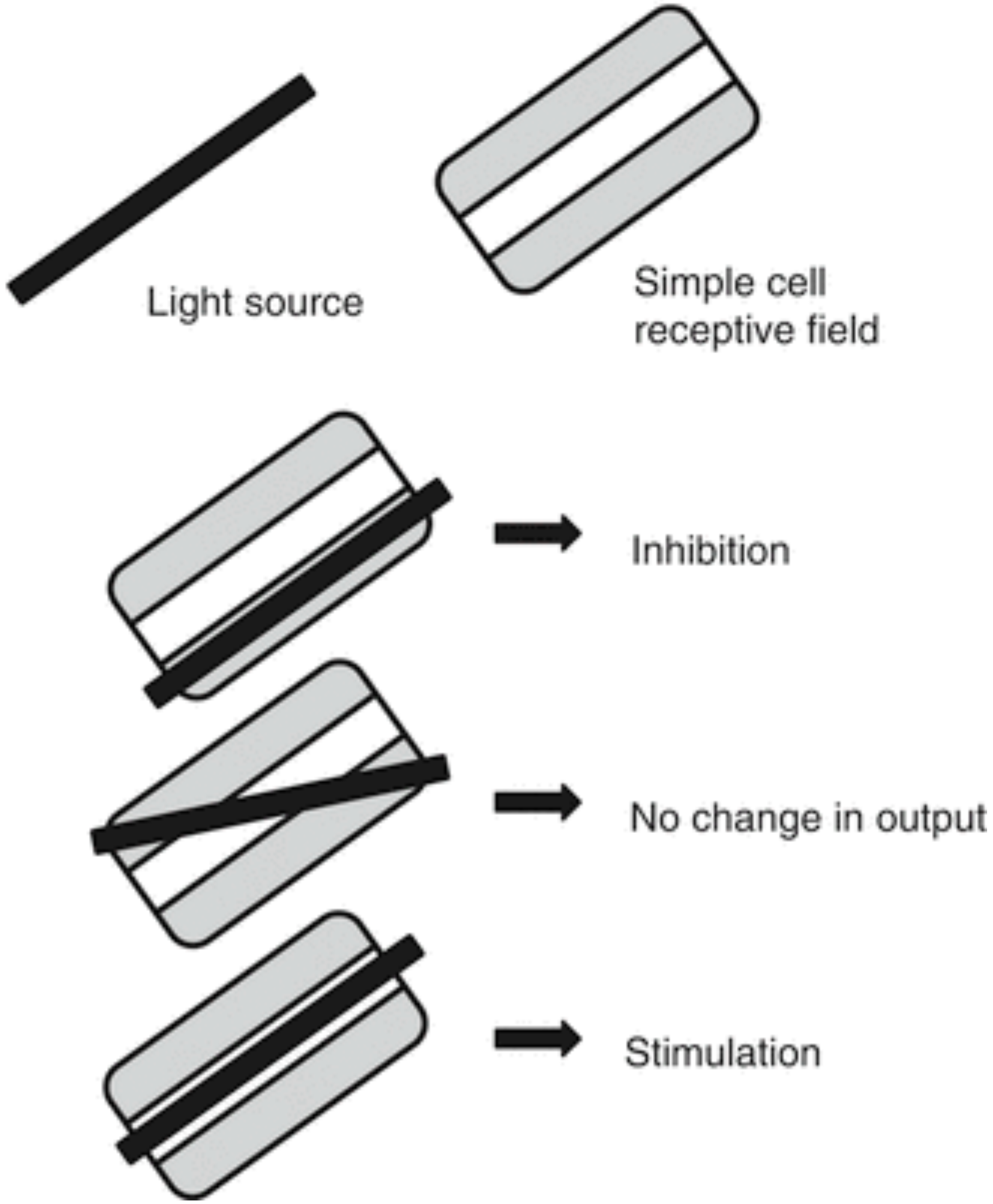


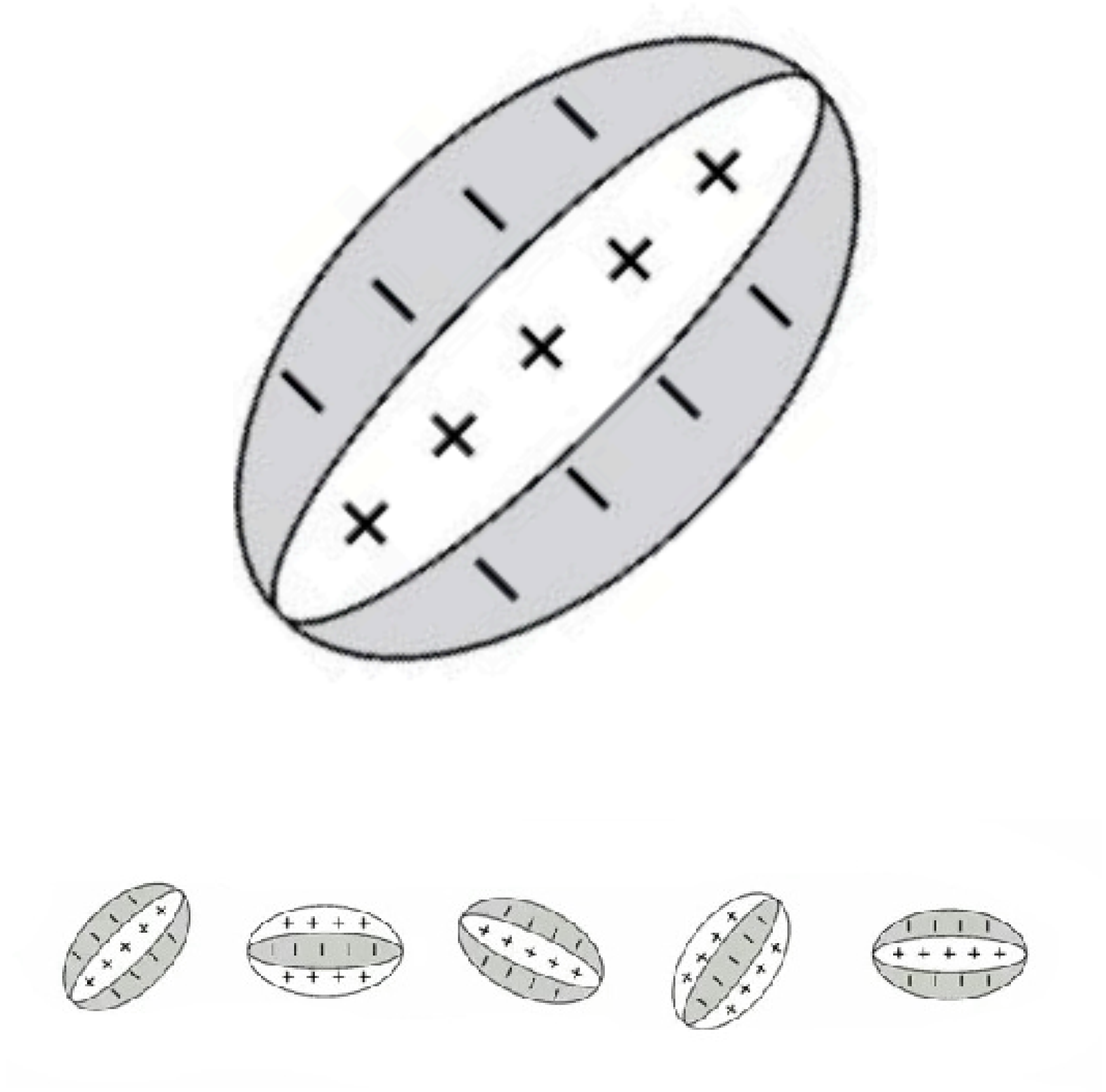
Optic nerve
Lateral geniculate nucleus
Primary visual cortex
Retina
Orientation of line stimulus
Duration of stimulus presentation
To amplifier→
Timing of action potentials
Electrode
Screen
Projector
0
1
2
3
Time (sec)

Hubel and Wiesel, 1959

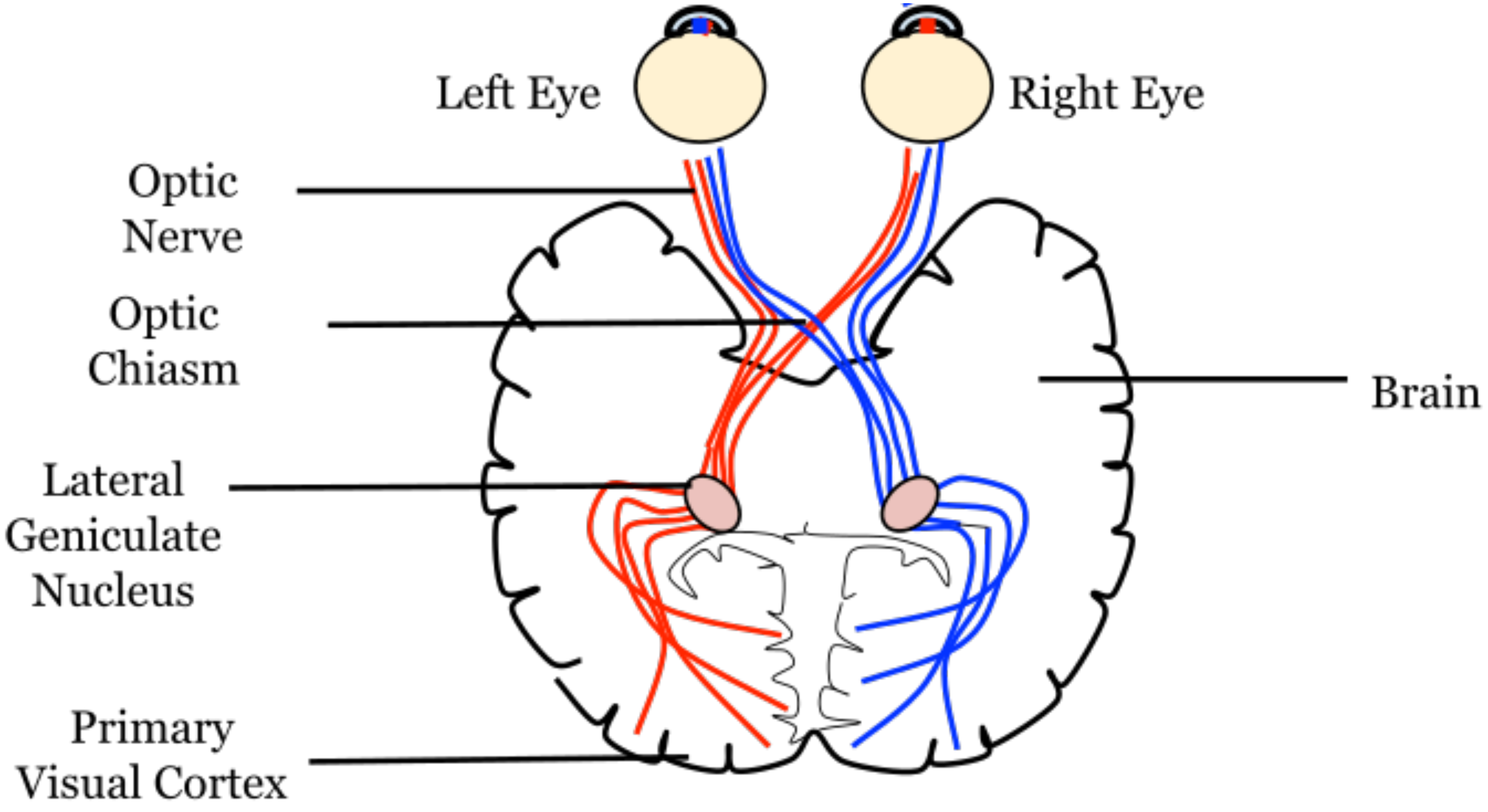


Receptive fields in V1 (phenomenology)

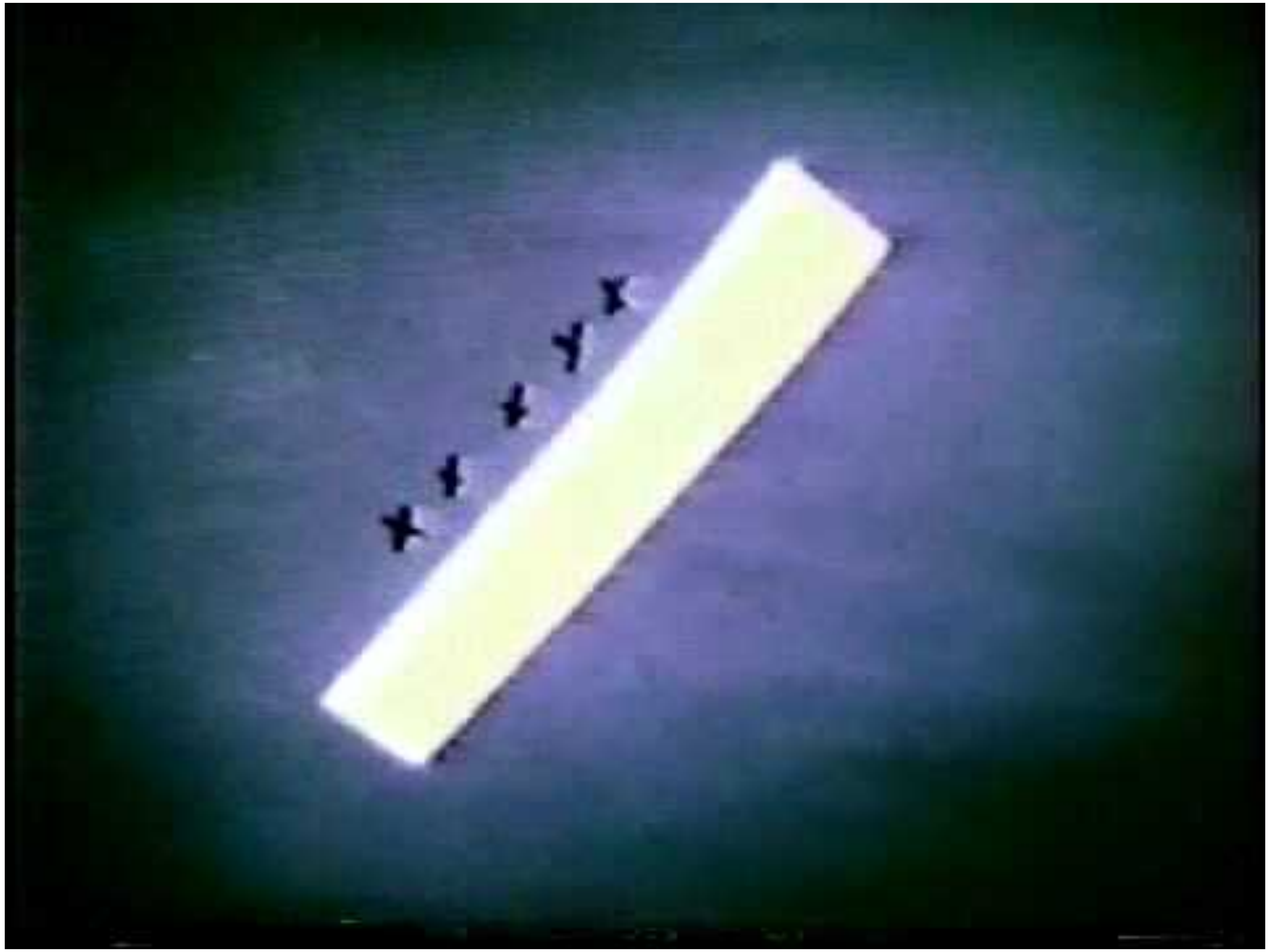




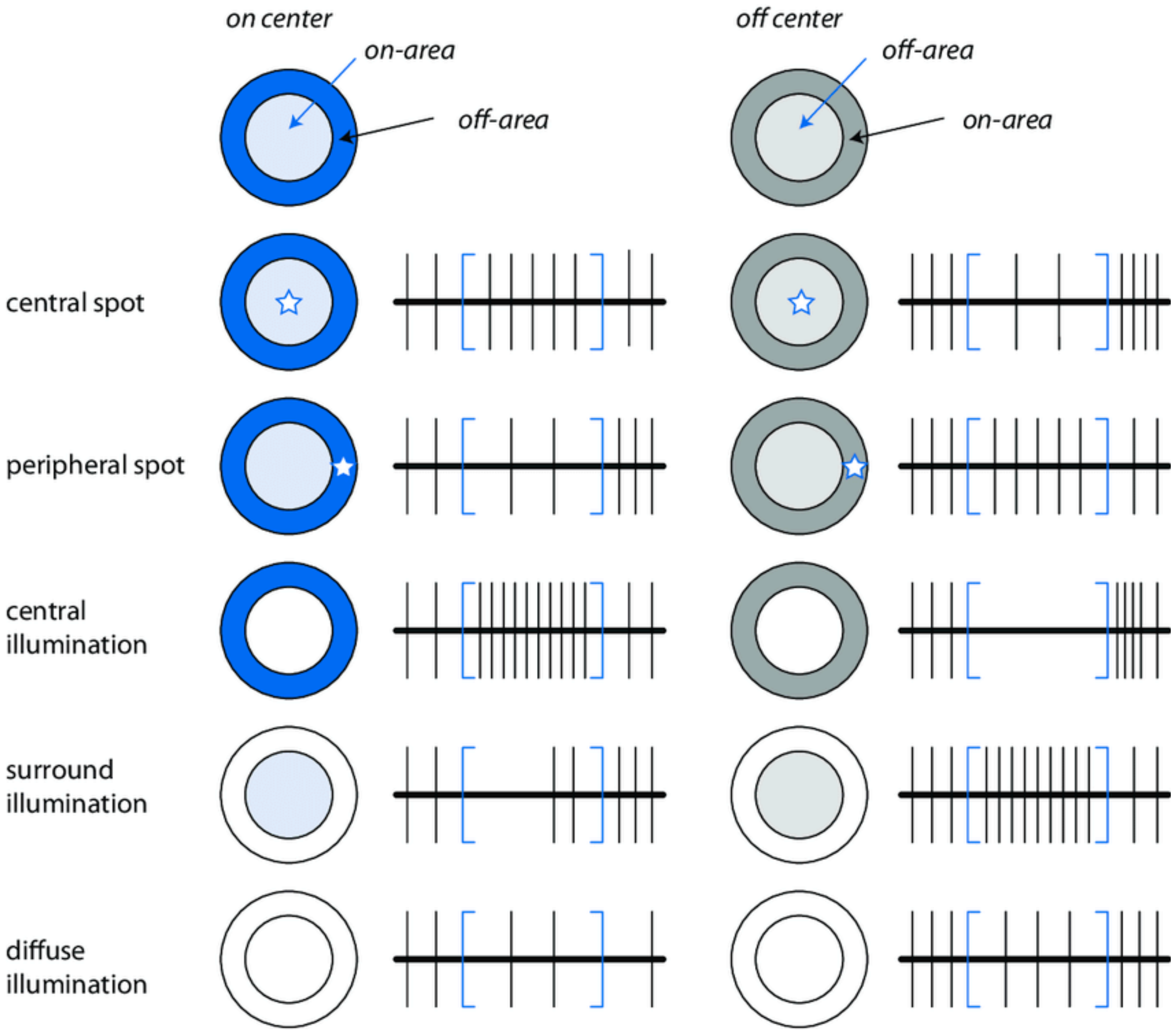
What are the underlying mechanisms?

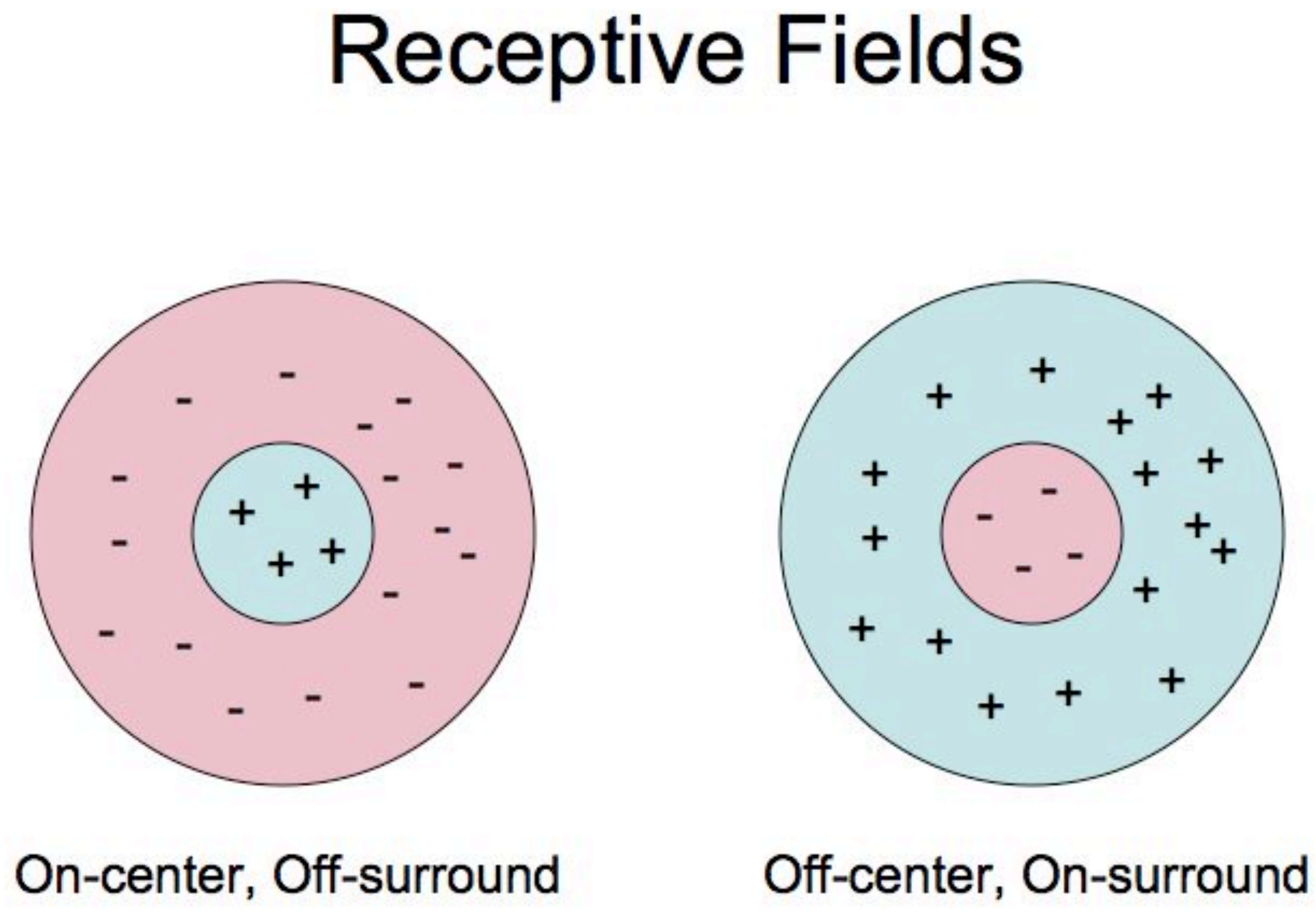


Hubel and Wiesel, 1959

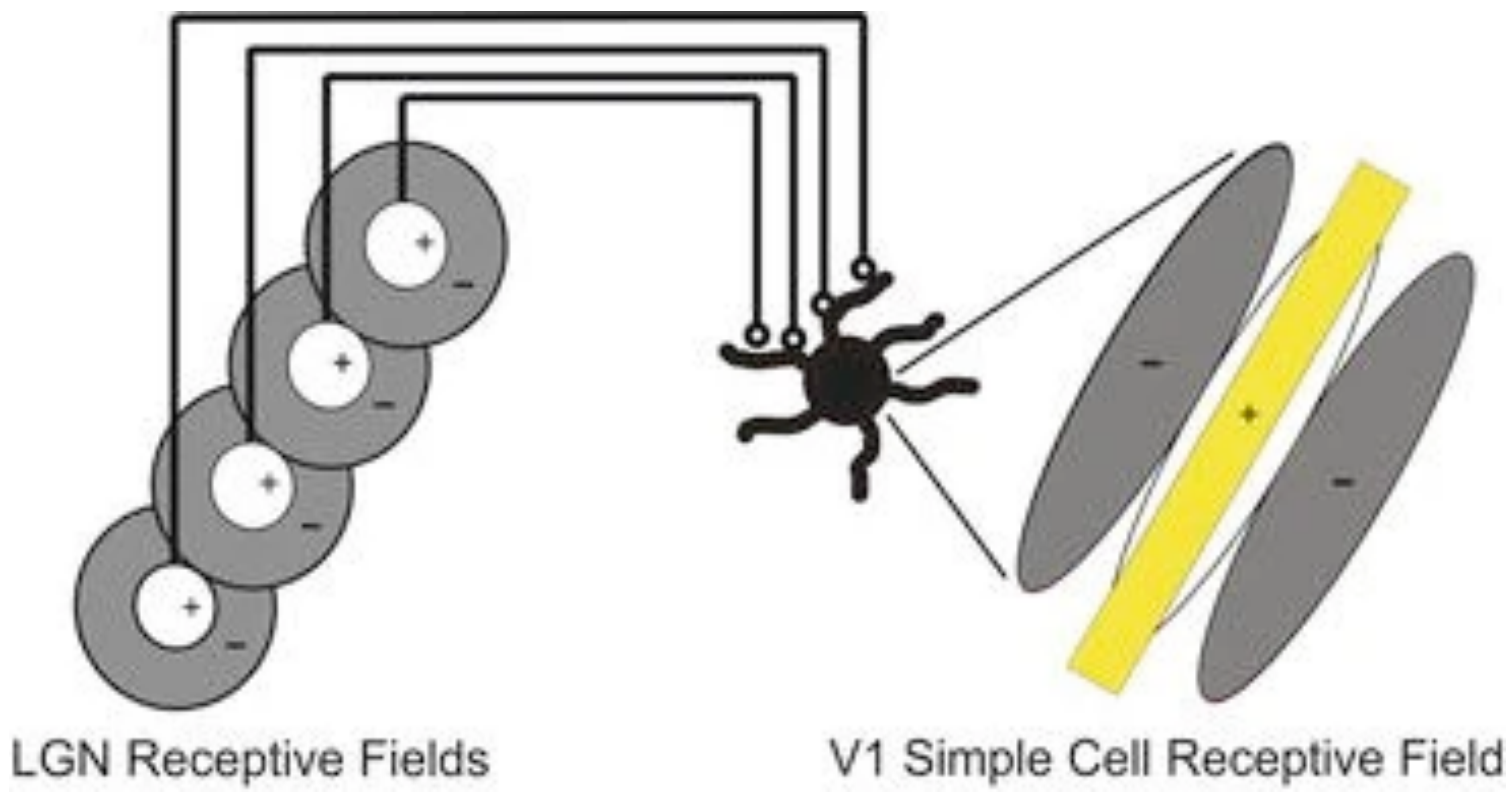


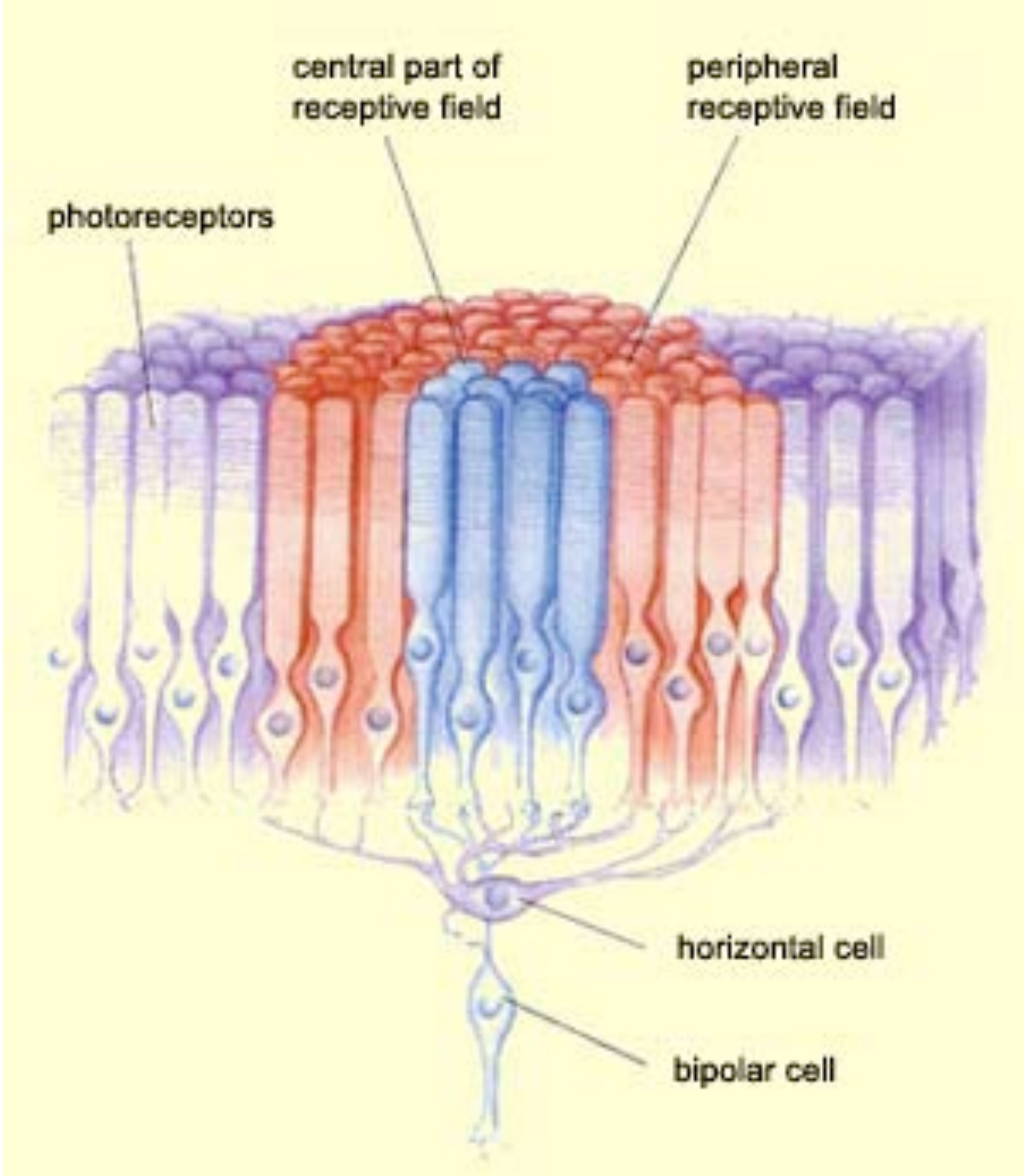
Receptive fields in the retina (phenomenology)

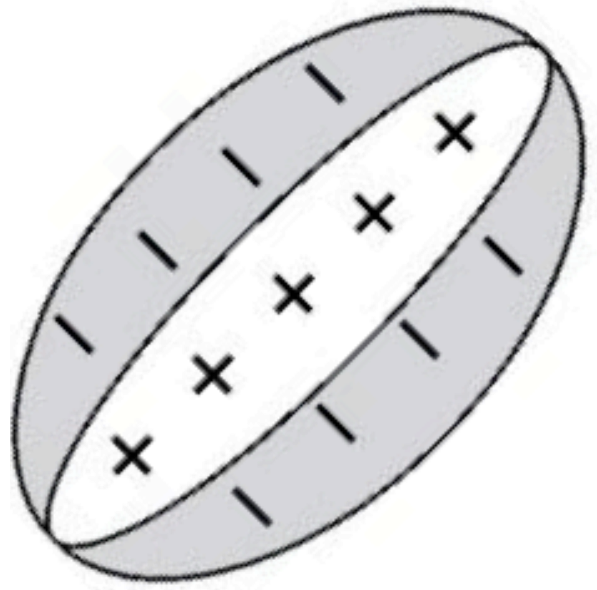


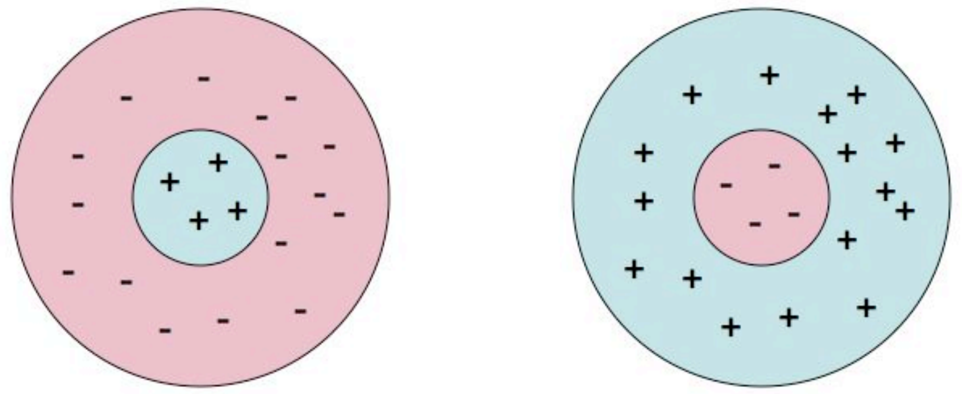


Visual receptive fields (mechanisms)





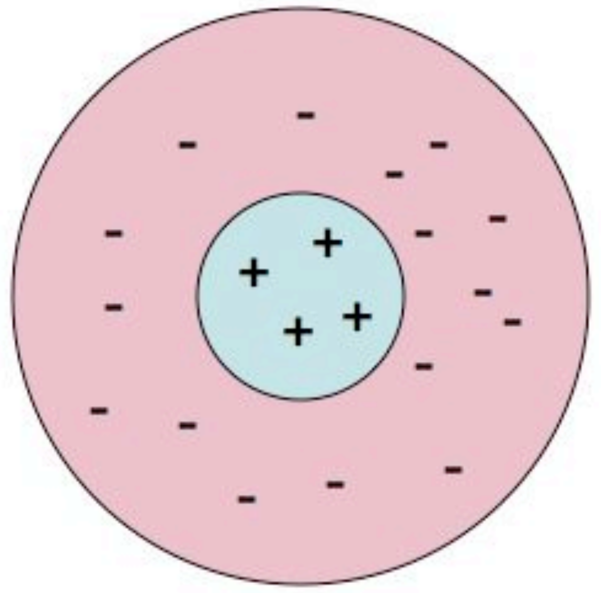




Receptive fields in retina (normative principles)

On-off receptive fields:

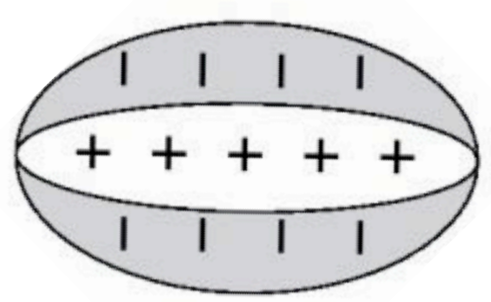
- Respond selectively to edges

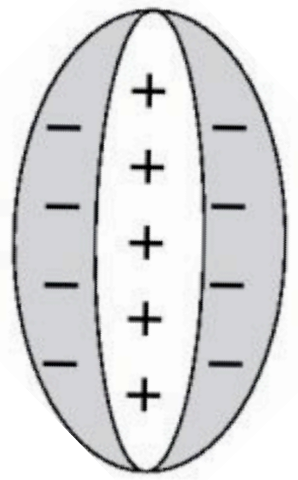


Receptive fields in V1 (normative principles)

V1 receptive fields:

- Respond selectively to oriented lines





Three levels of description on V1 receptive fields

Phenomenology: What does the system do?

- Single cells respond selectively to oriented bars of light
- Each cell selectively responds to one position and orientation

Mechanisms: How does the system do it?

- Each cells receives inputs from a series of on-off cells that respond selectively to points of light
- Each input cell responds selectively to specific positions that are arranged in a straight line

Normative principles: Why does the system do it?

- Each cell orientation detects edges spanning in that orientation
- V1 receptive fields decompose the input image into sets of oriented edges

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Part B: Overview of the course

Conclusions

Computational neuroscience provides neuroscience with theory

- Subfield of neuroscience mainly concerned with models
- Models is crucial to the development of neuroscience
- Is too early for a clean experimentalist/theoretician cut in cognitive neuroscience

Models will be the main target of our study

- Simplified abstractions that give us a deeper understanding of a system of phenomenon
- All models are false, but some are useful

(Most) models can be classified within three levels of description

- Phenomenological (what), mechanistic (how), and normative (why)

Computational models in Neuroscience research

Part A

Part B: Overview of the course

1. Syllabus
2. Projects
3. Session structure
4. Introductions

Computational models in Neuroscience research

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Part B: Overview of the course

1. **Syllabus**
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Computational Neuroscience: Syllabus

1. Intro to computational neuroscience and modelling
2. Information Processing and Representation
3. The Bayesian Brain Hypothesis
4. Representational Learning and Predictive Coding
5. Reinforcement Learning
6. Additional approaches to modelling in cognitive neuroscience
7. Basics of neural networks
8. Learning in neural networks
9. Recurrent neural networks

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Computational models in Neuroscience research

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The Projects

Computational neuroscience best learnt hands-on

The projects are a fundamental part of the course:

- You will implement a neuroscientific computational model
- You will present your results and conclusions to the class
- 80% of your grade will be determined by the project and presentations

Project rules:

- Projects are to be developed independently
- You are expected to spend around 16h of independent work in your project
- Each project will be developed by only one person
- Choose your project as soon as possible! (First come first serve)

P01. Circuit model of V1 Receptive Fields

Target

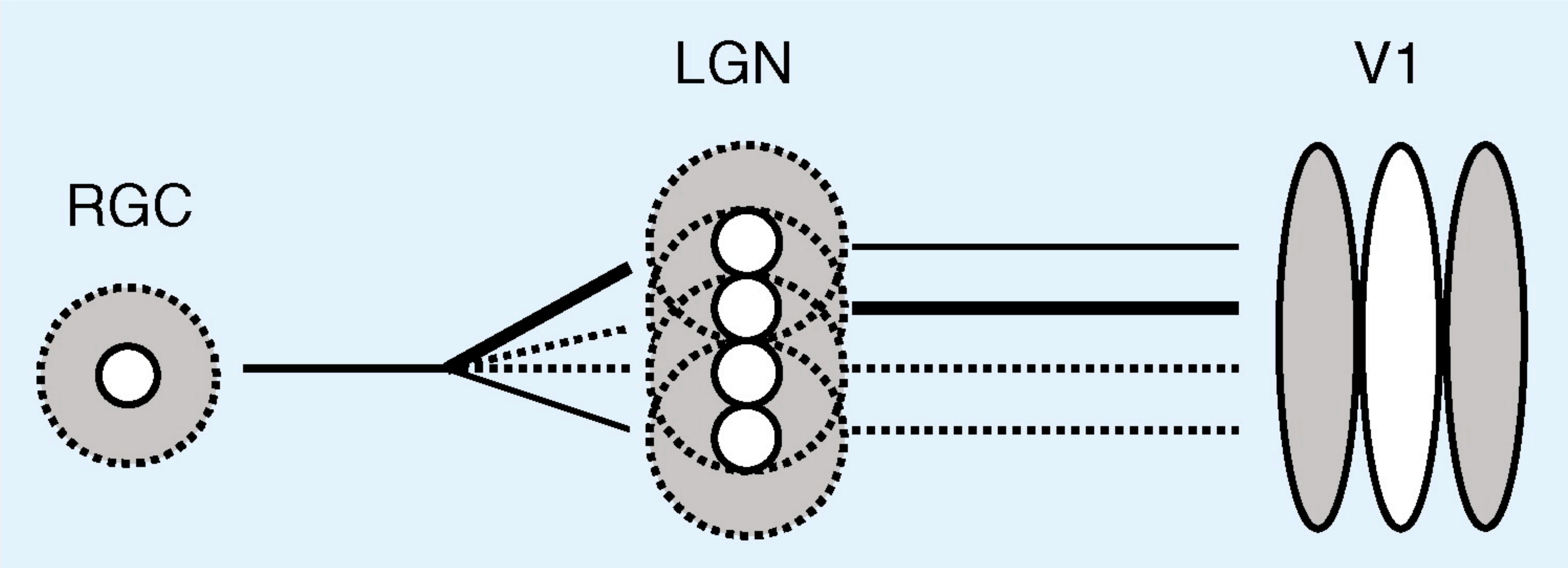
- Code a circuit model of the visual pathway
- From pixels to V1 receptive fields

Requisites

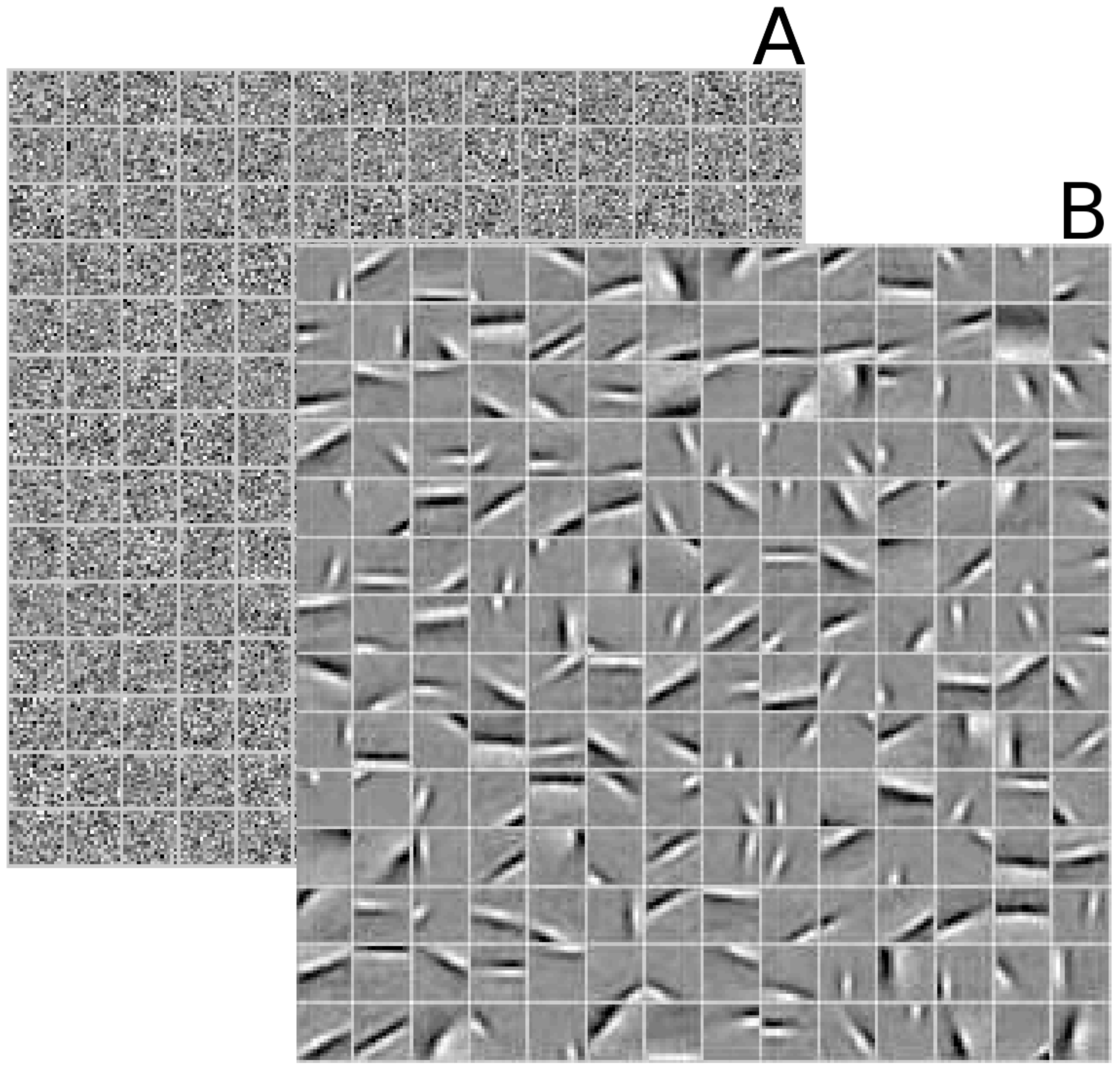
- Basic python

You'll learn

- Circuit modelling



PO2. Sparse coding: normative model of V1 RFs



Target

- Derive the RFs of V1 using sparse coding
- Develop a normative model of the early visual system

Requisites

- Basic python
- Basic matrix calculus is useful but not necessary
- Notions of information theory useful but not necessary

You'll learn

- Normative modelling, optimisation,

P03. Representational Similarity Analysis in LLMs

Target

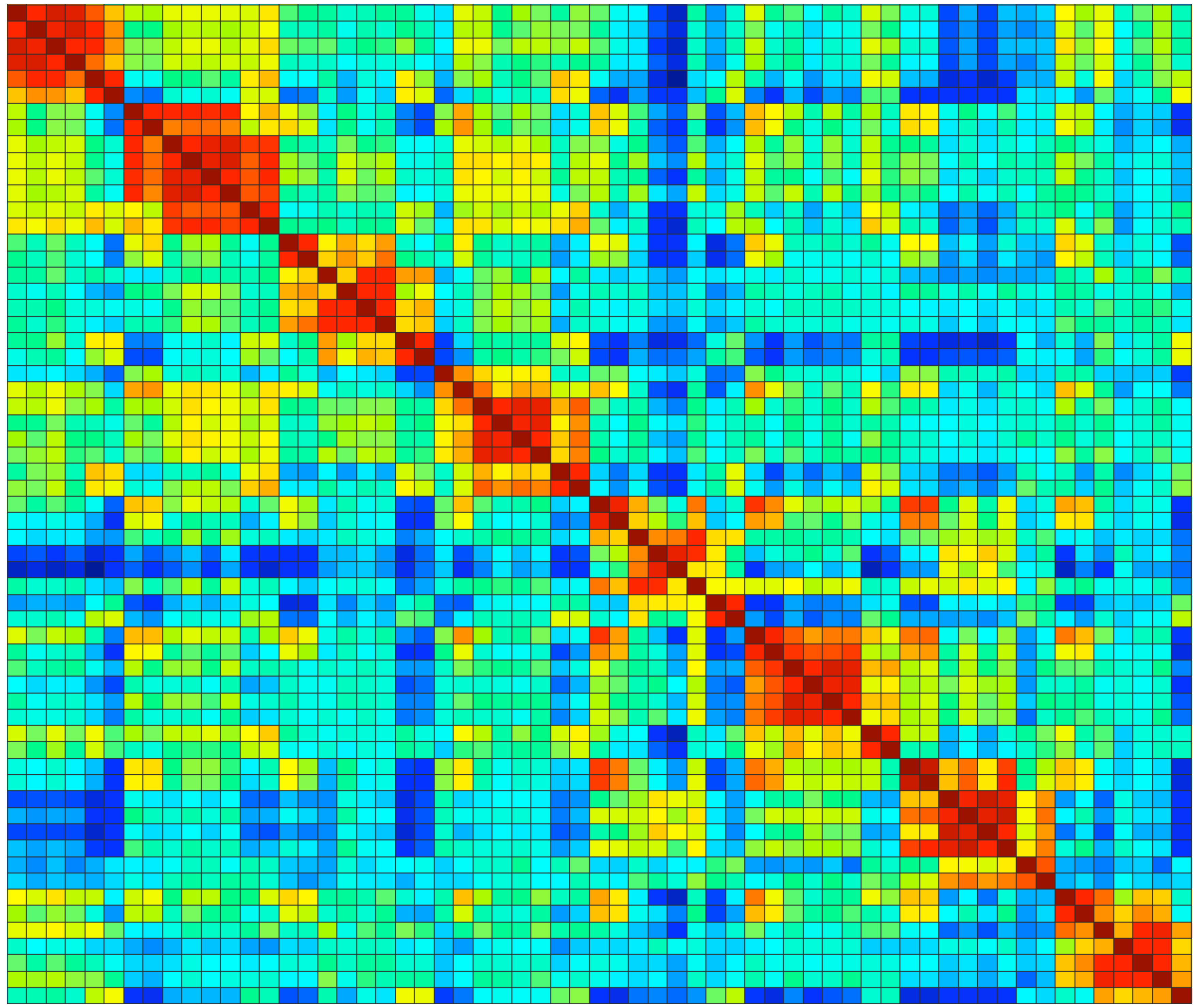
- Analyse coding of linguistic information across layers of an LLM
- Develop model-specific research questions

Requisites

- Intermediate user python

You'll learn

- RSA, running LLMs in your computer



P04. Dynamics of bi-stable perception

Target

- Model the statistics of perception switching in bistable stimuli
- Implement neural models of evidence accumulation

Requisites

- Beginner user python / Matlab
- Notions of dynamic systems would be helpful

You'll learn

- Neural population modelling

P05. Optimal Bayesian perception of moving objects

Target

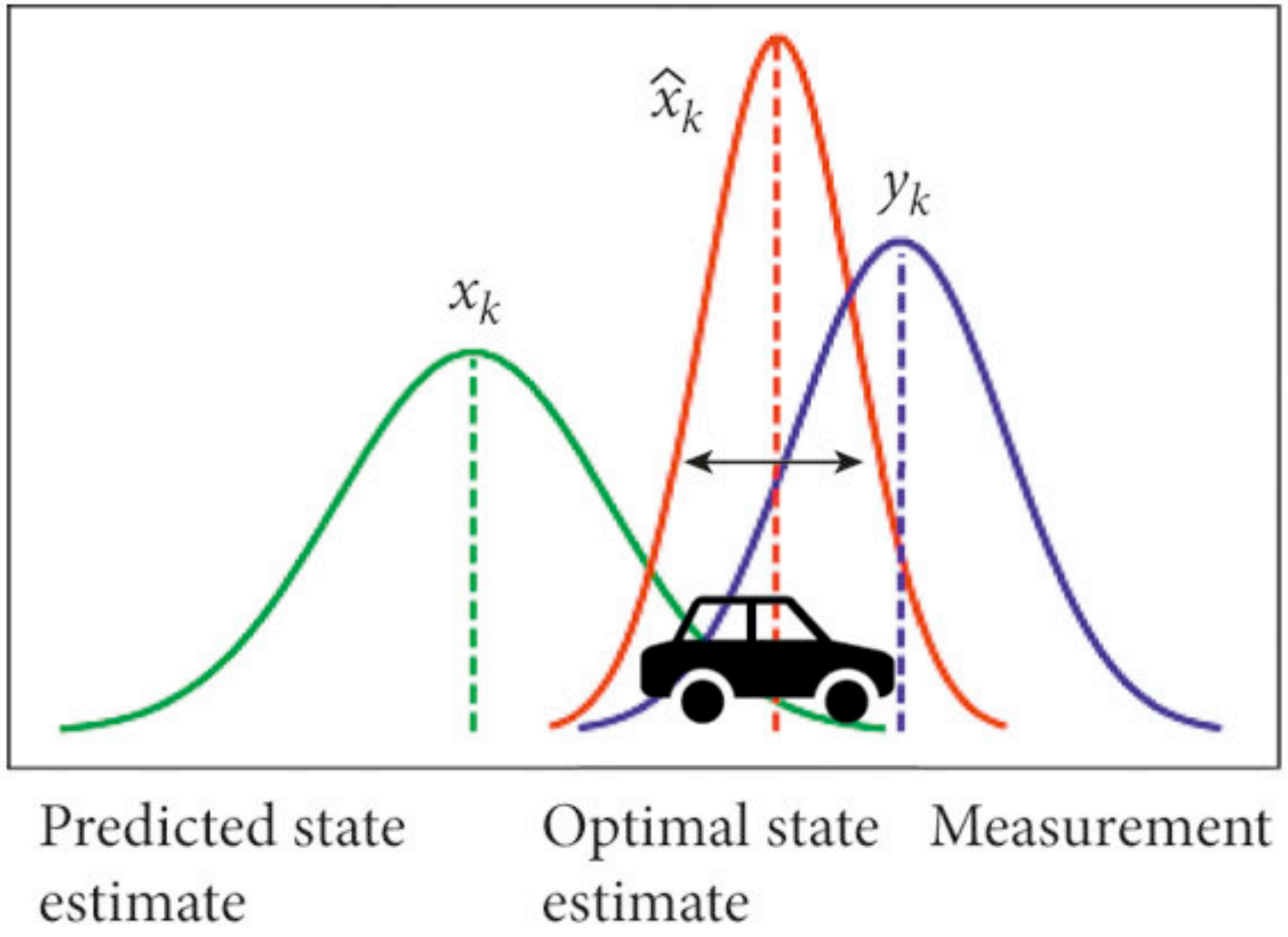
- Derive and implement optimal Bayesian movement tracking

Requisites

- Beginner user python
- Linear algebra
- Basic probability theory useful but not necessary

You'll learn

- Bayesian modelling of perception



P06. Drift-diffusion modelling of perceptual decisions

Target

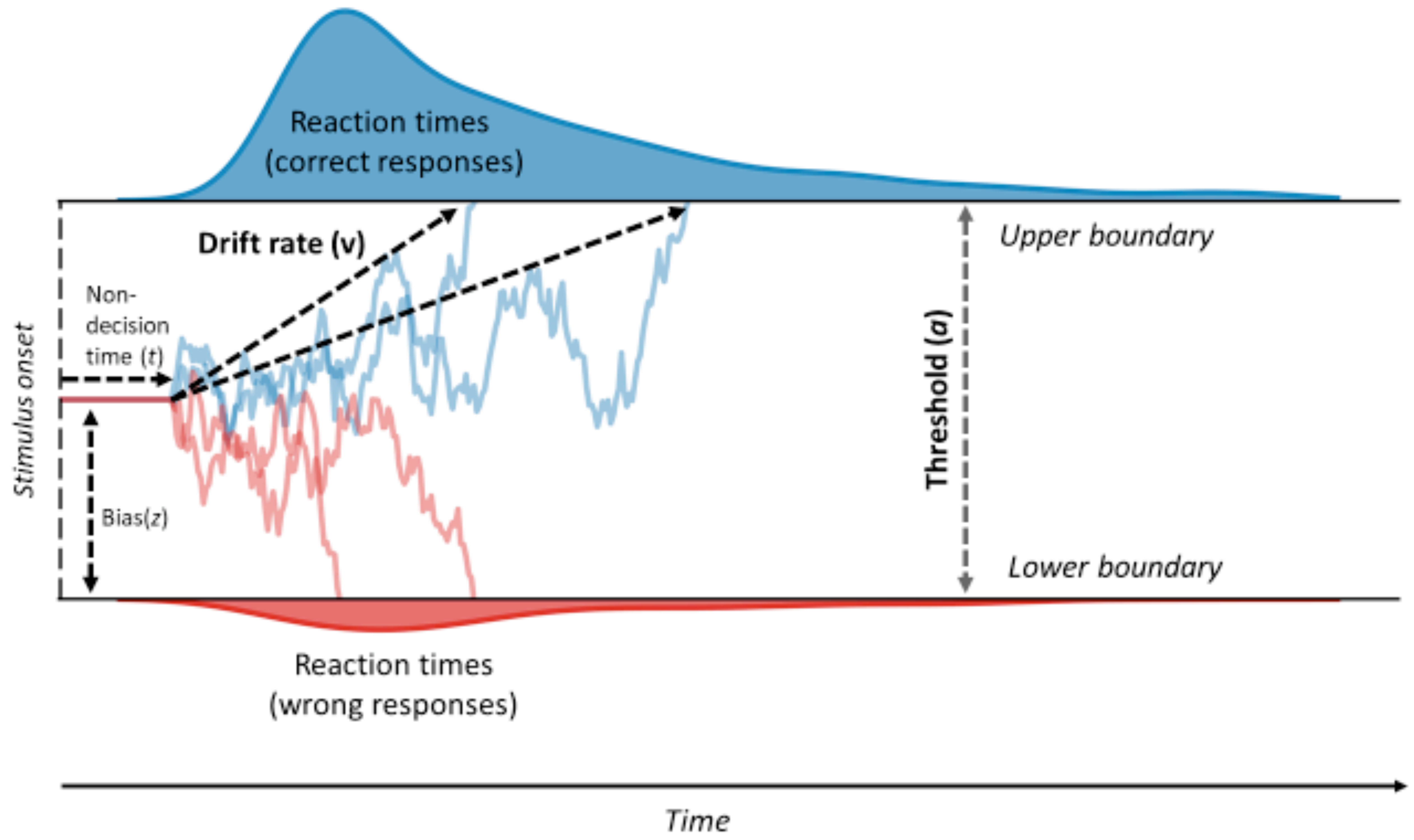
- Implement drift-diffusion models of evidence accumulation

Requisites

- Beginner user python / Matlab

You'll learn

- Drift-diffusion models for 2FC
- Classical decision making



P07. Sampling implementation of perceptual inference

Target

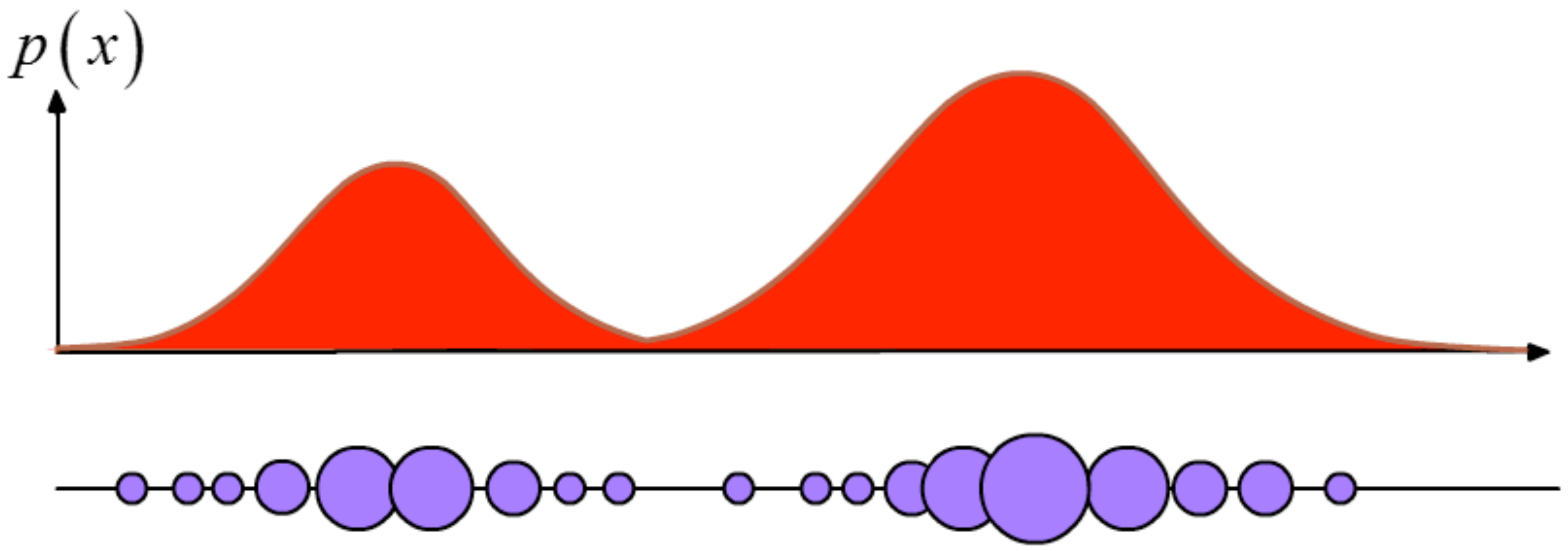
- Implement a model of the sampling hypothesis of perceptual inference
- Compare sampling and variational estimators

Requisites

- Beginner user python
- Intermediate-level calculus

You'll learn

- Monte Carlo and particle filtering
- Implementing Bayesian models of cognition



P08. Reinforcement learning modelling of choices

Target

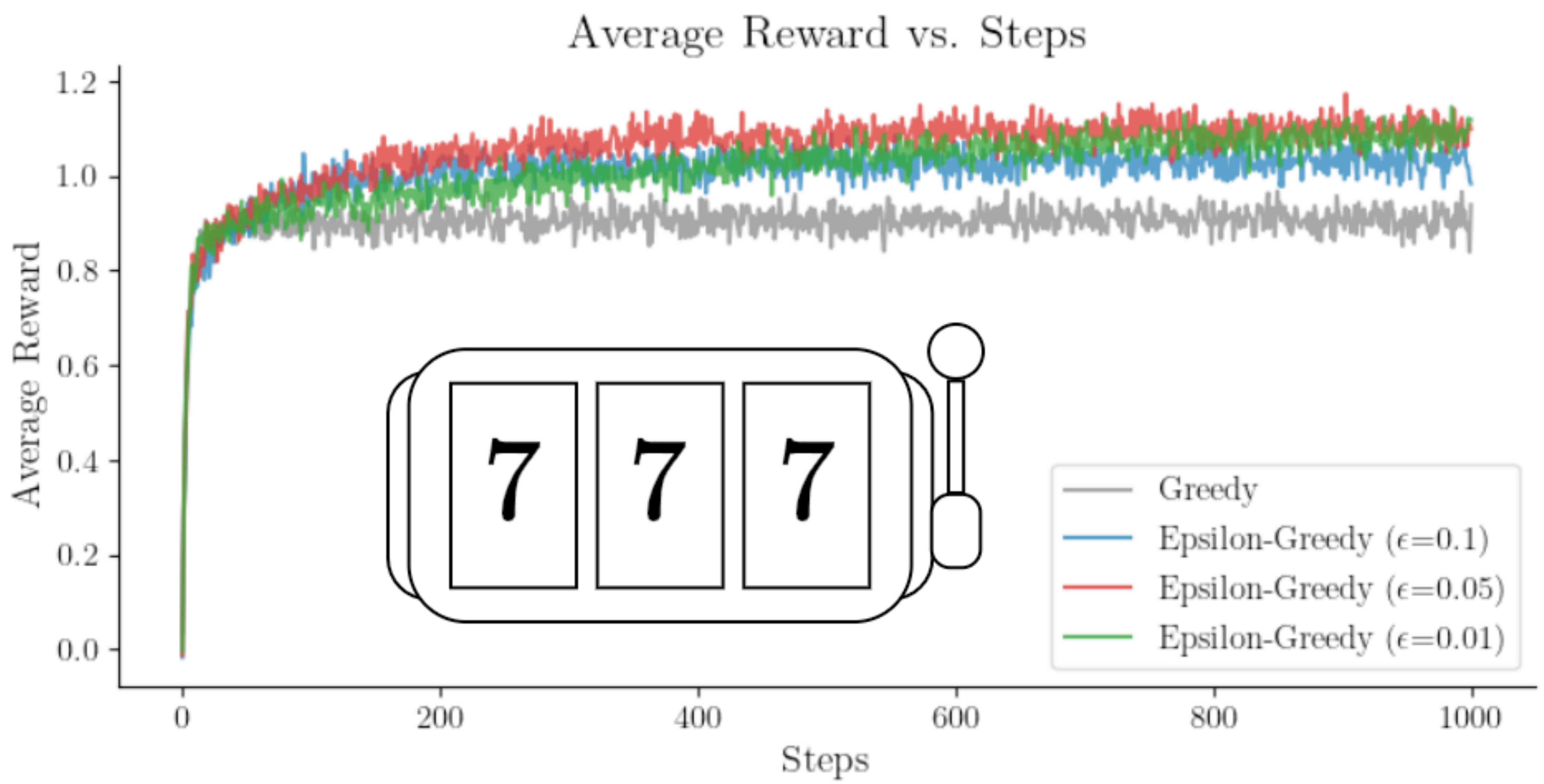
- Model behavioural results from a k-armed bandit
- Implement an compare reinforcement learning algorithm s

Requisites

- Beginner user python

You'll learn

- Reinforcement learning



P09. Rescorla-Wagner model of classical conditioning

Target

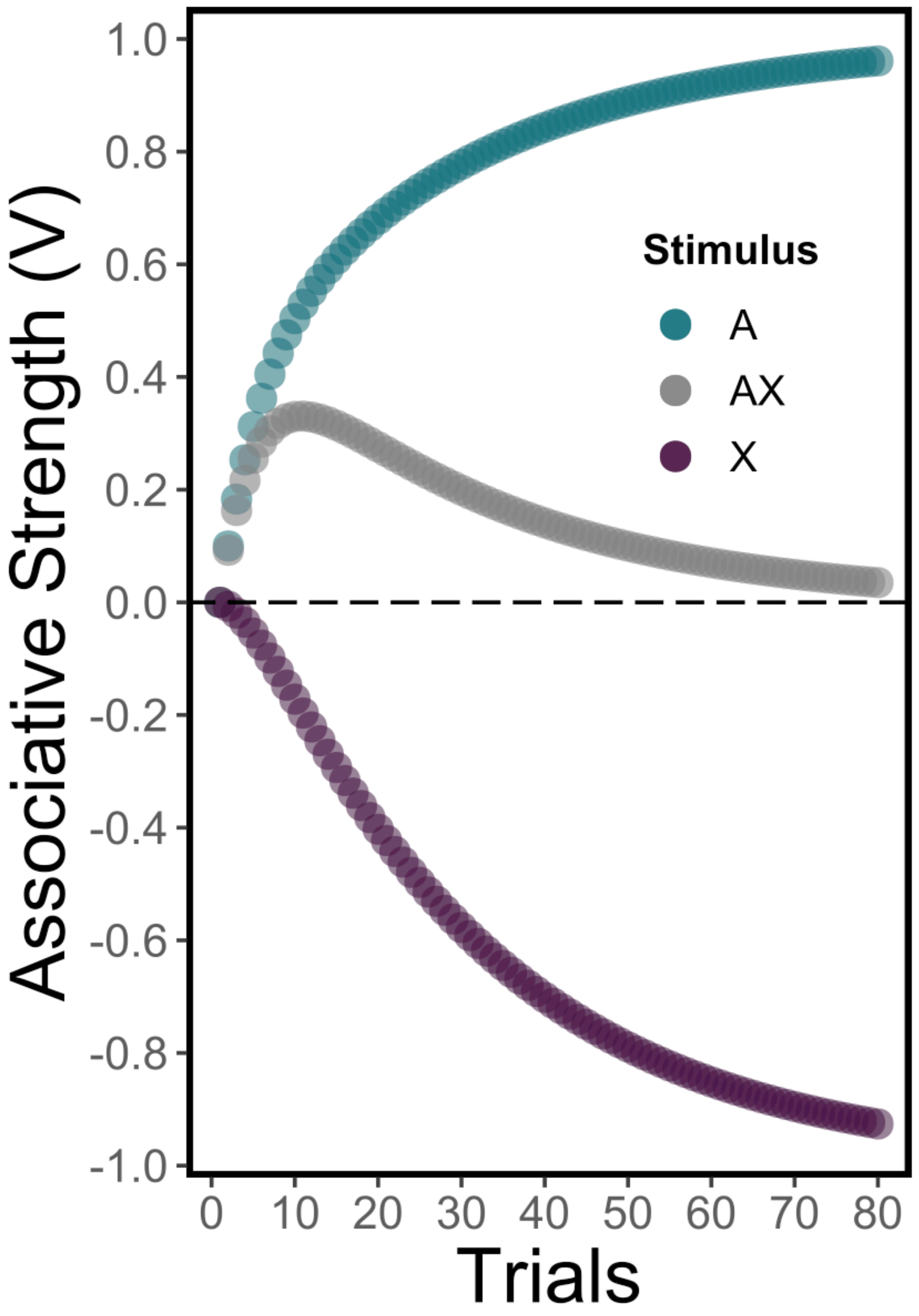
- Understand classical conditioning as reinforcement learning
- Implement the Rescorla-Wagner model

Requisites

- Beginner user python
- Basic maths helpful

You'll learn

- Classic reinforcement learning
- Rescorla-Wagner



P10. Neuronal and population dynamic models

Target

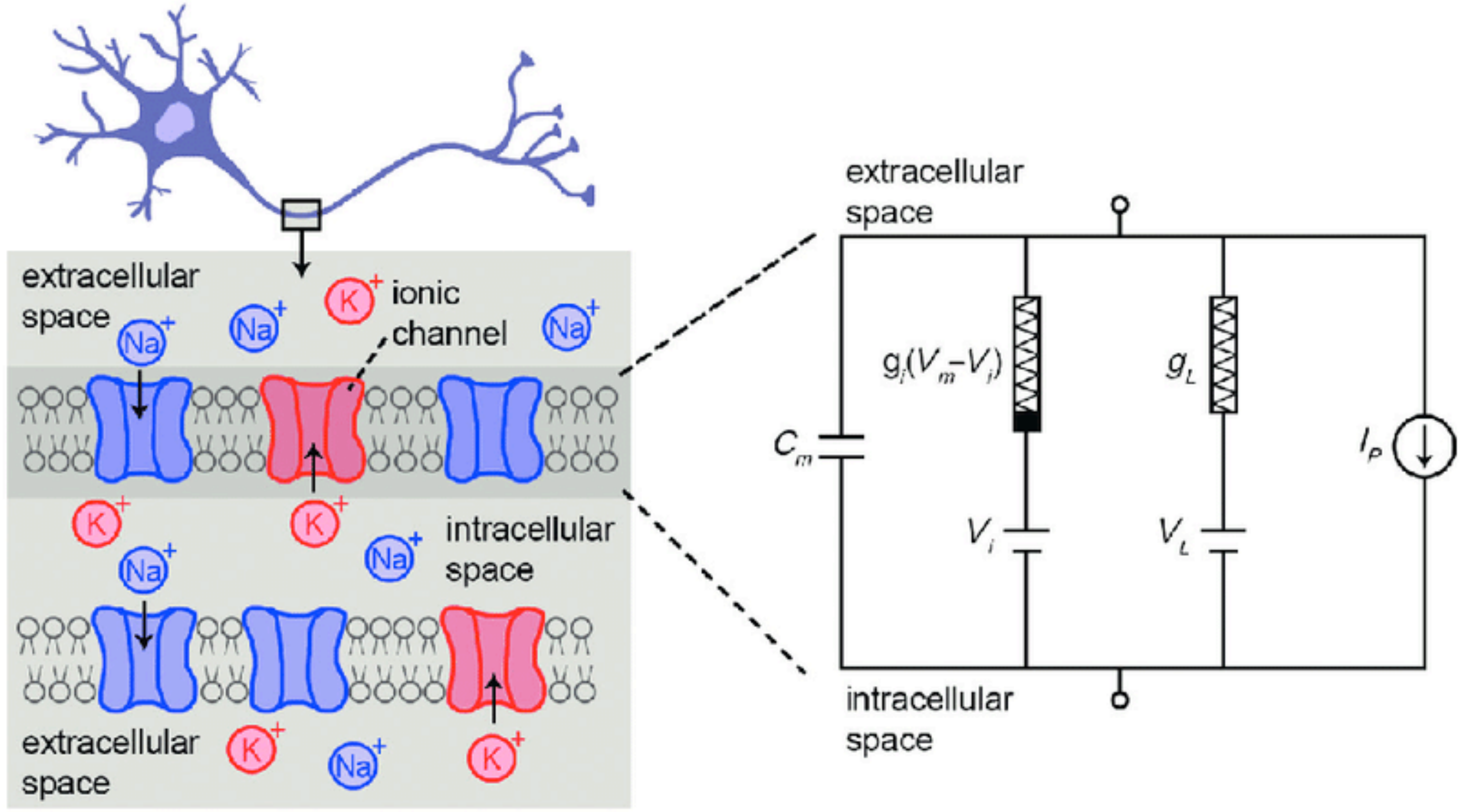
- Implement a physiological model of neuronal dynamics
- Study the effect of model simplifications in network dynamics

Requisites

- Beginner user python
- Basic dynamic systems theory
- Basic electrostatics helpful but not necessary

You'll learn

- Modelling of neuronal dynamics
- Simulation of dynamic systems



P11. Network learning rules

Target

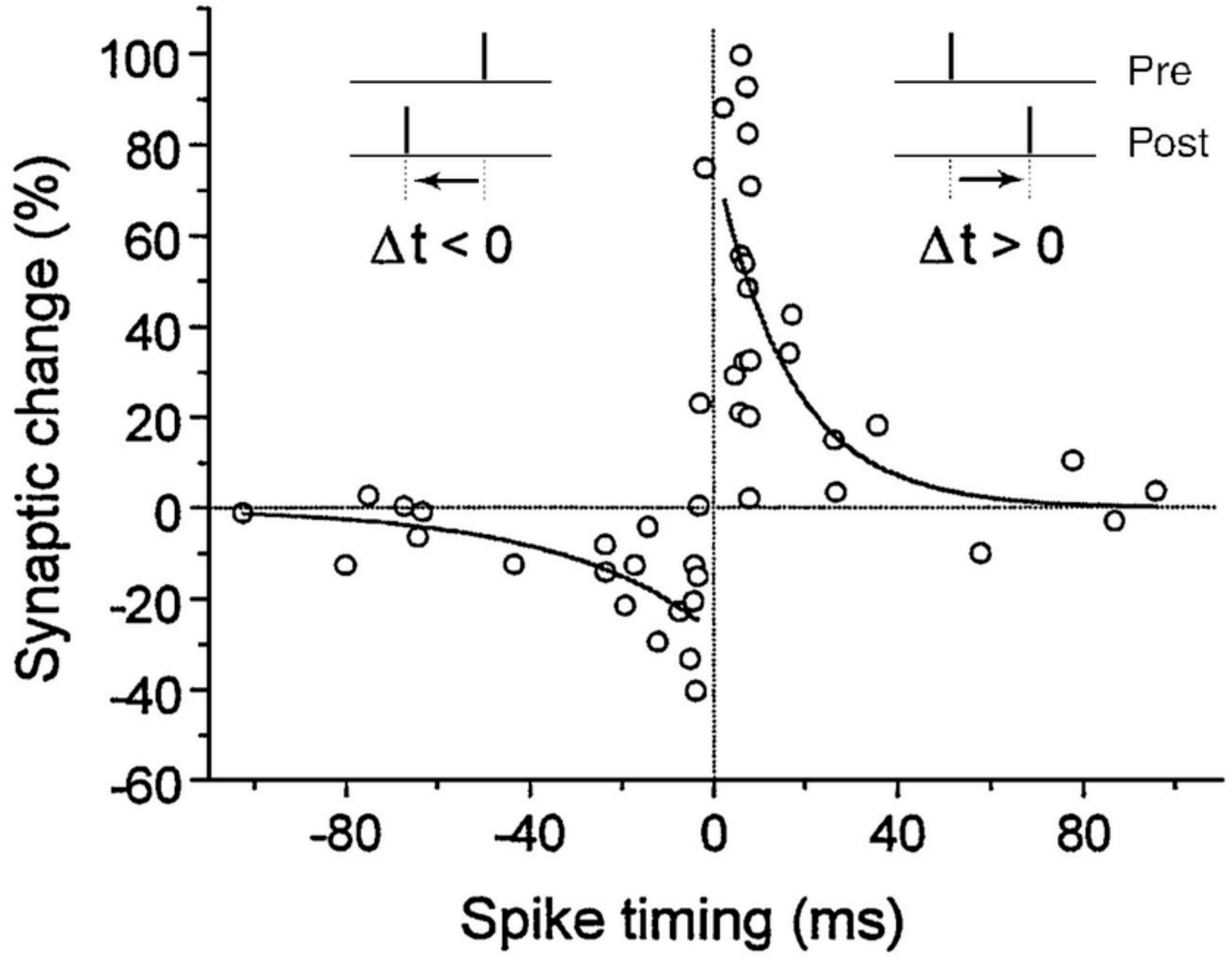
- Implement spike-timing dependent plasticity (STDP) in neuronal networks
- Compare Hebbian and STDP learning

Requisites

- Beginner user python
- Basic dynamic systems theory

You'll learn

- Modelling of neuronal dynamics
- Modelling of neuronal plasticity



P12. Linear vs feedforward vs recurrent networks

Target

- Compare how linear, feedforward (MLP), and recurrent architectures (SRN) learn (or not) the same sequential task (e.g., the Saffran et al. statistical learning 'language')
- Determine when nonlinearities or recurrence provide genuine computational advantages
- Design a sequence-learning task that requires memory/recurrence rather than local input statistics

Requisites

- Basic python
- Ability to modify existing neural network code

You’ll learn

- How architectural constraints shape learning
- How to challenge and extend current theories of human statistical learning
- Principled model comparison and model-behaviour comparison

P13. Network representations

Target

- Investigate what internal representations an SRN develops while learning a structured sequence
- Relate hidden-layer activity to syllable identity, word position, or word identity
- Link representational structure to predictive performance

Requisites

- Basic python
- Comfort with plotting and data analysis

You'll learn

- Analysing model internals
- Dimensionality reduction for neural data (PCA, t-SNE)
- Connecting representations to cognitive theory

P14. Simulating brain damage in neural networks

Target

- Simulate neural damage at different stages of learning
- Compare immediate impairment and recovery following early versus late lesions
- Explore compensatory mechanisms such as increased network capacity

Requisites

- Basic python
- Ability to run and checkpoint training

You'll learn

- Computational neuropsychology logic
- Plasticity and recovery dynamics
- Quantitative analysis of impairment and recovery, links to neuropsychology

P15. Competing predictions over time

Target

- Investigate how an SRN represents uncertainty and competition between multiple predictions (e.g., local vs. long-distance dependencies)
- Track how predictions evolve as additional input is received
- Relate model dynamics to theories of competition and evidence accumulation

Requisites

- Intermediate python
- Working with time-resolved model outputs

You'll learn

- Dynamic analysis of predictions
- Competition metrics such as entropy
- Links between model dynamics and neural data

P16. Catastrophic Interference and L2 learning

Target

- Model interference when a network is trained sequentially on two toy languages
- Examine how training order and spacing affect forgetting
- Test mitigation strategies such as interleaving or added capacity

Requisites

- Intermediate python
- Managing multi-phase training regimes

You'll learn

- Continual learning limitations
- Interference and recovery mechanisms
- Computational perspectives on multilingual learning

P17. Beyond the Simple Recurrent Network

Target

- Implement a fully recurrent or gated recurrent neural network
- Compare SRNs with plain RNNs, GRUs, or LSTMs on sequence learning tasks
- Identify sequence structures that require richer forms of recurrence

Requisites

- Intermediate python
- Acquire basic familiarity with neural network libraries

You'll learn

- Differences among recurrent architectures, comparing competing computational frameworks
- Role of gating and memory mechanisms
- Task design for probing computational limits
- Evaluating implications for studies with humans

P18. Predictive Coding and Statistical Learning

Target

- Implement a predictive coding model extended to sequential input
- Apply the model to the Saffran statistical learning task
- Compare predictive coding with recurrent neural network approaches

Requisites

- Intermediate python
- Conceptual understanding of predictive coding (PC)
- Willingness to grapple with extending PC to sequences (solution is known, implementation will be challenging)

You'll learn

- Formal predictive processing models
- Prediction-error dynamics in learning
- Comparing competing computational frameworks

Computational Neuroscience: Calendar

January 7th: 1. Intro to computational neuroscience and modelling

January 14th: 2. Information Processing and Representation

January 21st: 3. The Bayesian Brain Hypothesis

January 28th: 4. Representational Learning and Predictive Coding

February 4th: 5. Reinforcement Learning

February 11th: 6. Additional approaches to modelling in cognitive neuroscience

February 16th: 7. Basics of neural networks

February 18th: 8. Learning in neural networks

February 23th: 9. Recurrent neural networks

February 25th: Project presentations

March 2nd: Project presentations

March 4th: Project presentations

Computational models in Neuroscience research

Part A

Part B: Overview of the course

1. Syllabus
2. Projects
3. **Session structure**
4. Introductions

The Questions

Computational neuroscience best learnt by deep thinking

The questions are small pieces of critical thinking homework

- After each session we will present a few take-home questions
- Up to five students will take one question each as homework
- It should take around 1h to prepare the answer
- Each student will have 4 minutes each to discuss their conclusions, followed by up to 3 minutes discussion
- 20% of your grade will be determined by the questions (take at least 3 questions for max grade)

Question rules:

- Do a small research if you need to inform yourself. Then think about it. Deeply.
- Feel free to discuss your question with your peers and friends: that's the best sort of thinking!
- Be succinct and organised in the presentation of your results (you'll be timed!)
- Try to be provocative and deep. It's all about the thinking, not about ticking the box.

Structure of a session

Answers to the questions	→	Main lecture	→	Break	→	Project time!
25-40 minutes		50-75 minutes		5-15 minutes		30-45 minutes

Computational models in Neuroscience research

Part A

Part B: Overview of the course

1. Syllabus
2. Projects
3. Session structure
4. **Introductions**

Know your lecturer: Alejandro Tabas

BSc: **Theoretical Physics** → MSc: **Machine Learning** → PhD: **Computational Neuroscience** → Postdoc: **Human fMRI** → Postdoc: **Neuro Machine Learning** → PI: **Cognitive Computational Neuroscience**

Know your peers!

1. What is your name?
2. What have you studied?
3. Why are you studying this master programme?
4. Are you planning on continuing a career in academia?
5. Why have you enrolled in this course?
6. How strong are your maths and coding skills?
7. What do you want to get out of
8. (optional) Tell us something about yourself!

Questions for next session

Questions for next session: Q1.1

The replication crisis in psychology raised questions about whether many "established" findings are real. What mechanistic role, if any, could computational modelling play in addressing this crisis?

Questions for next session: Q1.2

We have presented models as tools for understanding. However, models are increasingly also tools for prediction and control, specially in AI. When does a model's usefulness for control become ethically problematic, even if it aids understanding? Should neuroscientists consider how their models might be used?

Questions for next session: Q1.3

Foucault argued that scientific categories do not merely describe reality but actively shape it through institutional power. If this is true, what responsibility do scientists bear for the categories they create and propagate? Can a model be simultaneously useful, socially constructed, and in some sense true?

Questions for next session: Q1.4

For Judith Butler, gender is not discovered but performed into existence: a model that consolidates itself through use. Do you agree with Butler? Consider Box's aphorism. In what sense is gender a “wrong" model? In what sense is it a “useful" model? And useful for whom? Apply the same reasoning to sexuality.

Questions for next session: Q1.5

We have argued that cognitive neuroscience is still in Ptolemaic times. Do you agree? Find a specific example from recent neuroscience literature (last 20 years) that you think exemplifies this Ptolemaic approach. What would a Copernican revolution look like for this example? What evidence would falsify the current approach?

Questions for next session: Q1.6

The same data often support multiple, incompatible interpretations. This is the underdetermination problem in philosophy of science. If data can't uniquely determine theory, what does? Aesthetics? Social consensus? Pragmatic success? What implications does this have for neuroscience?

Questions for next session: Q1.7

We have mapped Marr's levels onto cosmology (Kepler = phenomenology, Newton = mechanism, Einstein = normative). But is this mapping accurate? Could you argue for a different assignment? What does the difficulty of this mapping reveal about Marr's framework?

Questions for next session: Q1.8

Pick three findings from cognitive neuroscience that you're familiar with. Try to articulate it at each of Marr's three levels. Where are the gaps? Which level is most developed, and why do you think that is?

Questions for next session: Q1.9

Consider Chomsky's generative grammar. Where does it fit within Marr's three levels? Where does it not? Has the separation of levels been productive for linguistics? What are the costs and benefits of developing theory largely independently of neural data?

Questions for next session: Q1.10

Consider a deep neural network trained to predict V1 responses with very high accuracy, but whose internal computations are opaque. Does this constitute a good model of V1?

Questions for next session: Q1.11

V1 neurons respond to oriented edges. How do we get from this to recognising your grandmother's face? Sketch out what you think the computational problem is at each subsequent stage. Where do you think the biggest gaps in our understanding are?

All course materials:

github.com/qtabs/compneuro4cogneuros