The salmon machine

Towards a digital twin of the farmed fish

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> 19/11/2022
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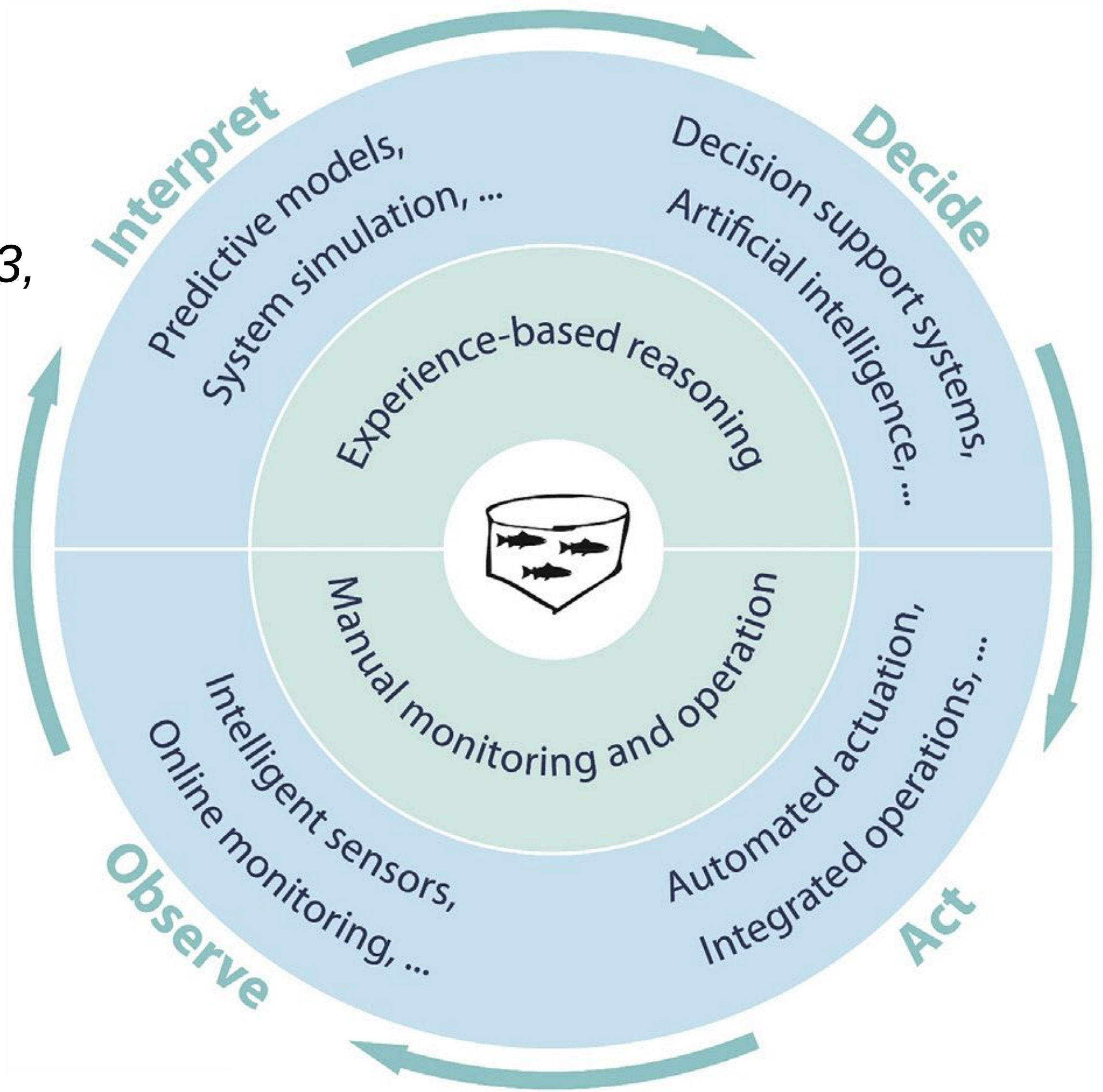
- Precision fish farming
- Digital Twin concept
  - Model-based predictive control
  - AI+ML+ data-oriented
  - Agent-based models
- The digital salmon
  - The predictive brain: Bayesian and AHA approaches
  - Feeding decisions and behaviour
  - Stress, allostasis and uncertainty
  - Subjective feelings, suffering and wellbeing
- What is like to be a salmon?

- **Precision fish farming:**
  - Use of technology to help fish farmers monitor and manage the fish and the farm to optimise operations.
  - Heavy use of digital technology: sensors, big data, AI, ML, model-based control
- **Observe → Interpret → Decide → Act**
  - Smart sensors, computer vision, echo-sounders …
  - Statistical models, appetite indexes, welfare metrics …
  - Decision support, what-if scenario modelling …
  - Integrated operations, automated control, actuators automated feeders, optimised logistics …

- Føre, M. et al. *Precision fish farming: A new framework to improve production in aquaculture. Biosyst. Eng. 173, 176–193 (2018).*

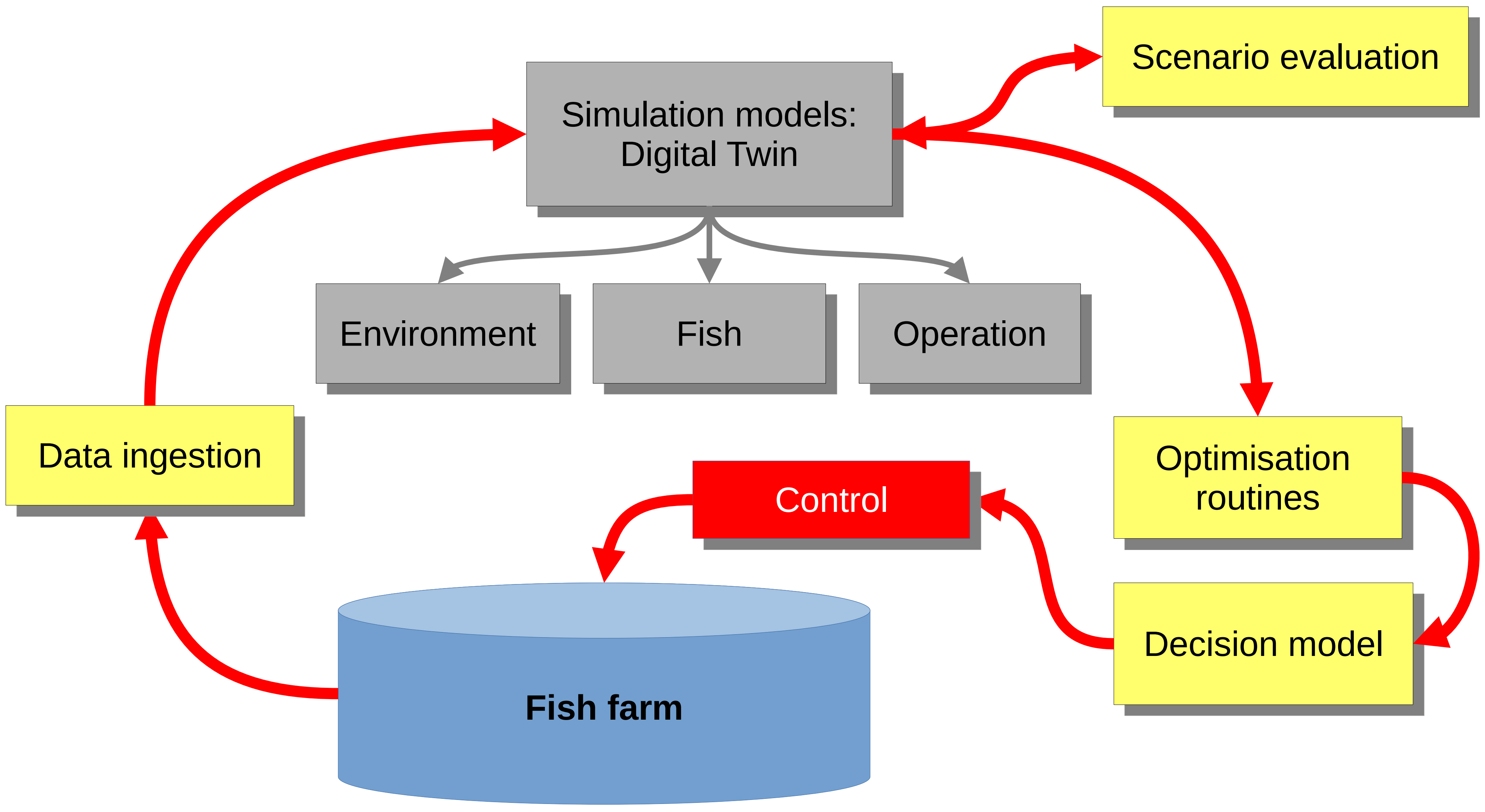


- **Predictive control**
  - A management strategy to forecast possible development of a problem from **early signs** and begin mitigation measures before the problem occurs
- **Fish health and stress**
  - Stress is a major cause of fish mortality, poor growth and quality
  - Fish welfare and stress are of major concern for consumers
  - Stress is part of everyday life of all animals, but how to predict development of acute of chronic stress?
- Observe → **Interpret** → **Decide** → Act
  - Ask the fish:: observe
  - Interpret fish behaviour:: Index, model
  - What-if scenario modelling:: model
  - Act to mitigate developing problem

Predictive digital twin model of the whole farm → **Model of the fish**

- **Digital twin**
  - "*Digital replications of living as well as non-living entities that enable data to be seamlessly transmitted between the physical and virtual worlds*" (El Saddik, 2018).
  - **Holistic** and **dynamic process** model
  - Model **evolves** over time: Constantly updated for current data and knowledge
    - data assimilation
- Computer simulation
- Data assimilation
- Complexity, stochasticity, unplanned effects

- Smart control based on Digital twin



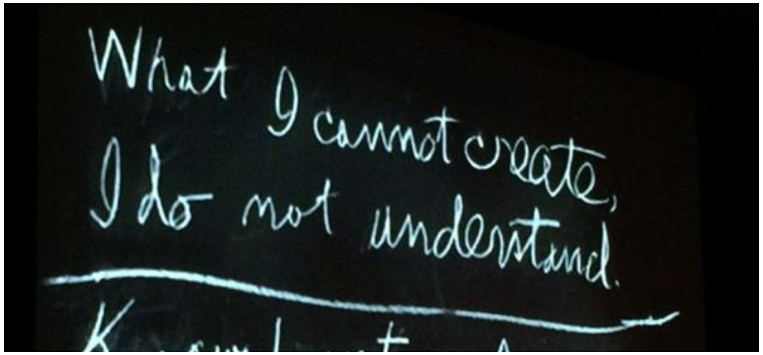
- **The digital fish**
  - Crucial component of the holistic fish farm
    Digital twin
    - Life history
    - Behaviour, cognition, stress response
    - Feeding, appetite, dynamic energy budget
    - Growth, performance

- **Digital twin of the fish:**
  - Dynamic
  - Stochastic
  - Variable
  - Data-driven
  - Decision-making
  - Continuous

- Input
  - Environment parameters (e.g. temperature)
  - Feed parameters (e.g. item size, energy content)
  - Fish parameters (e.g. fish mass)
- Output
  - Feed consumption and loss
  - Feeding decisions and behaviour
  - Appetite level
  - Physiological parameters (SMR, energy budget, stomach and gut fullness, absorption etc.)
  - Fish growth

- “*What I cannot create I do not understand*”
  -- Richard Feynman

- **How to create a (digital) fish?**
  - Represent the fish internal “machinery” or algorithm that can **run** for simulations
  - Start from the **animal’s own** point of view
  - Cognition, decision-making, trade-offs
  - Behaviour



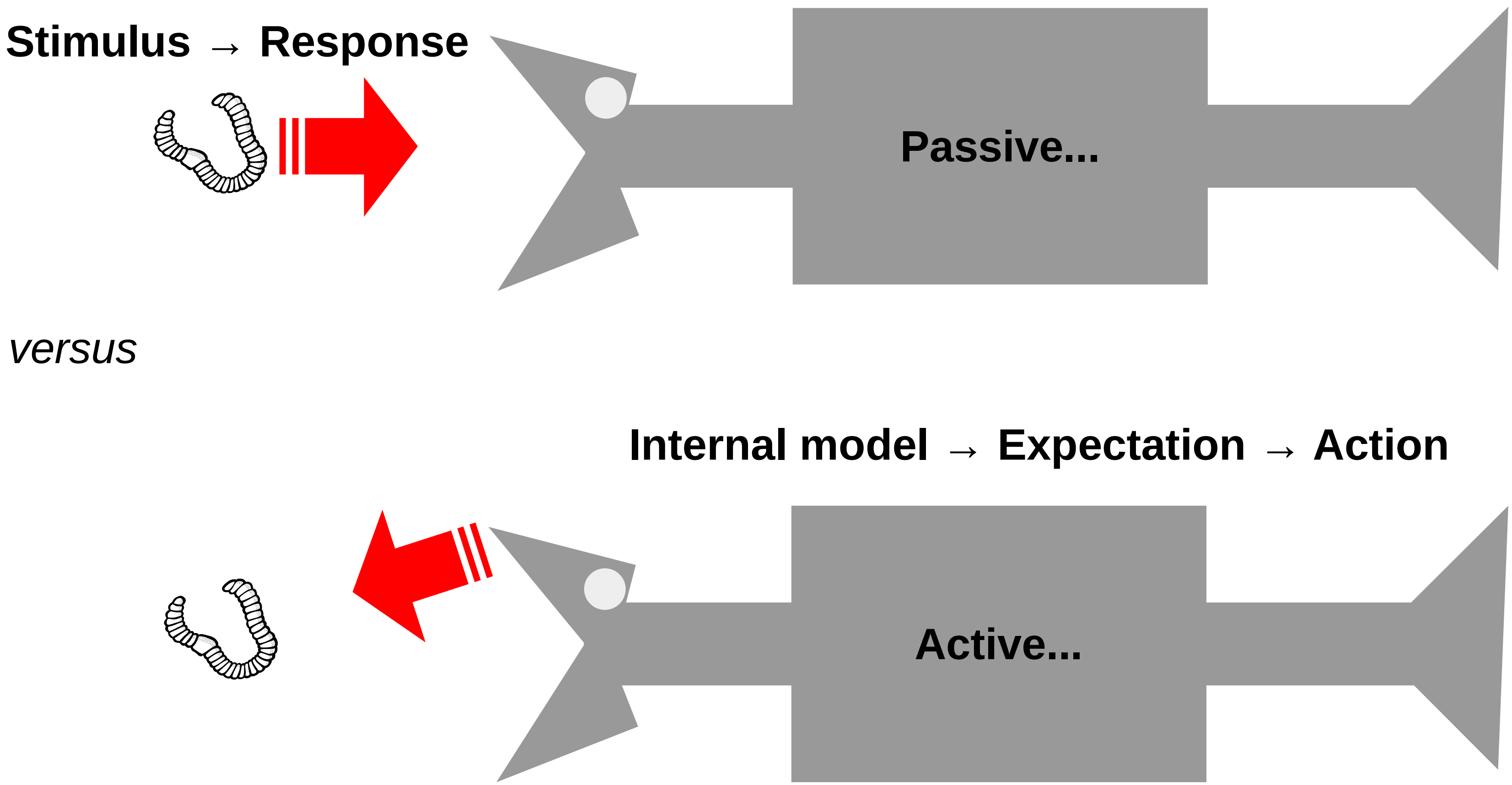
- **Start from metaphysics**
  - Architecture
  - Cognition
  - Decision-making
  - Behaviour

- **The predictive brain**
  - Cognition is based on building **internal model**
  - Top-down **expectation** and **prediction**
  - Prediction **error** analysis

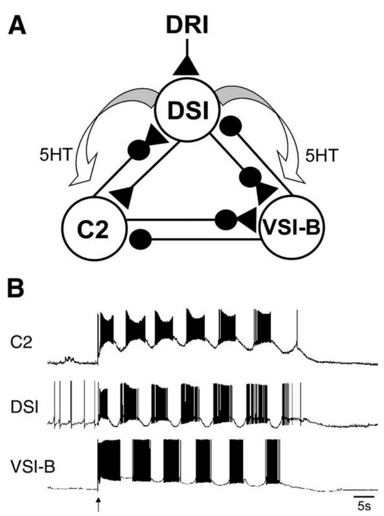
Predictive processing:
“any type of processing which incorporates or generates not just information about the past or the present, but also future states of the body or the environment.”
- Bubic et al 2010

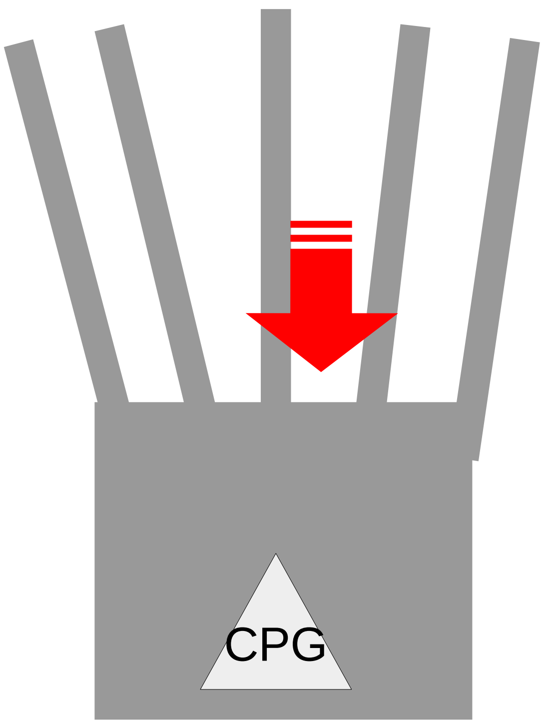
- **Agency**
  - Autonomy (goal-directed, top-down)
  - Spontaneity (default background activity)
- **Modularity**
  - Modules that can be reused
    and rearranged (also through random error)

- Alternative views on consuming food a item…



- What is like to be a polyp? A sessile filtrator? A worm?
  - Source of autonomy (central pattern generator?)
  - Receptors → sensing → pattern matching with model → response





- Cognition and decision-making is a Bayesian decision network:
  - the organism puts forward hypotheses
  - calculates probabilities
  - makes the best probable decision
  - calculates the prediction error (*e*=|*O*-*P*|)
  - update prior *P* for next cycle

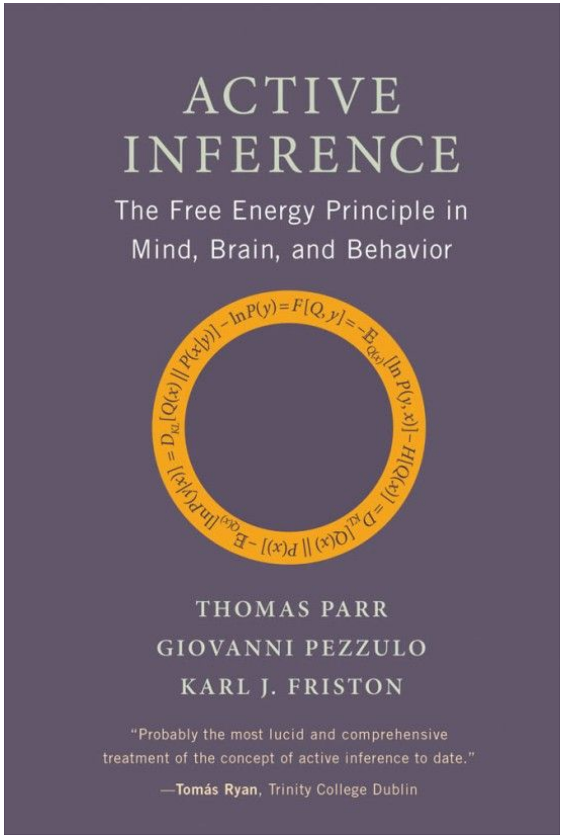
Prior P

$$P(food|stimulus) = \frac{P(stimulus|food)P(food)}{P(stimulus)}$$

$$P(\Delta E > e|food) = \frac{P(food|\Delta E > e)P(\Delta E > e)}{P(food)}$$

- **Active inference** paradigm for cognition: probabilistic inference

- Fundamental principle to **minimizing uncertainty** (quantified as the information-theoretic “free energy”)
  - updating the brain’s internal model (priors) of the environment to fit with the sensory data
  - actions for better sensory information to update the internal model
  - actions to move the organism into an environment that better agrees with its internal model
- Generative model: joint probability distribution *P(x,y)* of inputs (independent var) *x* and outputs (dependent var) *y*



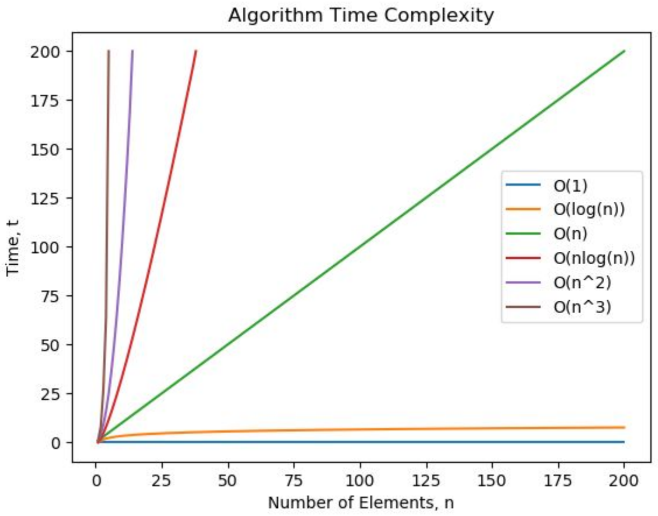
- Assumptions:

  - Animals (brains) should be able to represent, calculate and use probability
  - Use probabilities and accumulate information about the different choice options
  - Animals should ideally possess as much information as possible: update information continuously

- Computational Complexity – Tractability

  - resources (time, memory etc) needed to complete the calculation according to specific algorithm *f(n)*, given *n* is input size

  - polynomial
  - exponential



Opinion

Computational Complexity and Human Decision-Making

Peter Bossaerts[1,2,*] and Carsten Murawski[1]

The rationality principle postulates that decision-makers always choose the best action available to them. It underlies most modern theories of decision-making. The principle does not take into account the difficulty of finding the best option. Here, we propose that computational complexity theory (CCT) provides a framework for defining and quantifying the difficulty of decisions. We review evidence showing that human decision-making is affected by computational complexity. Building on this evidence, we argue that most models of decision-making, and metacognition, are intractable from a computational perspective. To be plausible, future theories of decision-making will need to take into account both the resources required for implementing the computations implied by the theory, and the resource constraints imposed on the decision-maker by biology.

Trends

New research showing that the quality of human decision-making decreases with the computational complexity of decision problems challenges the core assumption of most models of decision-making: that decision-makers always optimise.

CCT can help explain behavioural biases, such as choice overload and negative elasticity of labour supply.

Integrating CCT with decision theory and neurobiology promises to lay the foundations of a more realistic theory of decision-making and metacognition.

The Rationality Principle

Most modern theories of decision-making, including rational choice theory [1–4], game theory

Foundations of Perceptual Theory
S.C. Masin (Editor)

THE ROLE OF COMPUTATIONAL COMPLEXITY IN PERCEPTUAL THEORY

John K. Tsotsos

Department of Computer Science
University of Toronto, Toronto, Canada

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Bayesian Just-So Stories in Psychology and Neuroscience

Jeffrey S. Bowers
University of Bristol

Colin J. Davis
Royal Holloway University of London

According to Bayesian theories in psychology and neuroscience, minds and brains are (near) optimal in solving a wide range of tasks. We challenge this view and argue that more traditional, non-Bayesian approaches are more promising. We make 3 main arguments. First, we show that the empirical evidence for Bayesian theories in psychology is weak. This weakness relates to the many arbitrary ways that priors, likelihoods, and utility functions can be altered in order to account for the data that are obtained, making the models unfalsifiable. It further relates to the fact that Bayesian theories are rarely better at predicting data compared with alternative (and simpler) non-Bayesian theories. Second, we show that the empirical evidence for Bayesian theories in neuroscience is weaker still. There are impressive mathematical analyses showing how populations of neurons could compute in a Bayesian manner but little or no evidence that they do. Third, we challenge the general scientific approach that characterizes Bayesian theorizing in cognitive science. A common premise is that theories in psychology should largely be constrained by a rational analysis of what the mind ought to do. We question this claim and argue that many of the important constraints come from biological, evolutionary, and processing (algorithmic) considerations that have no adaptive relevance to the problem per se. In our view, these factors have contributed to the development of many Bayesian "just so" stories in psychology and neuroscience; that is, mathematical analyses of cognition that can be used to explain almost any behavior as optimal.

JUDEA PEARL

BAYESIANISM AND CAUSALITY, OR, WHY I AM ONLY A HALF-BAYESIAN

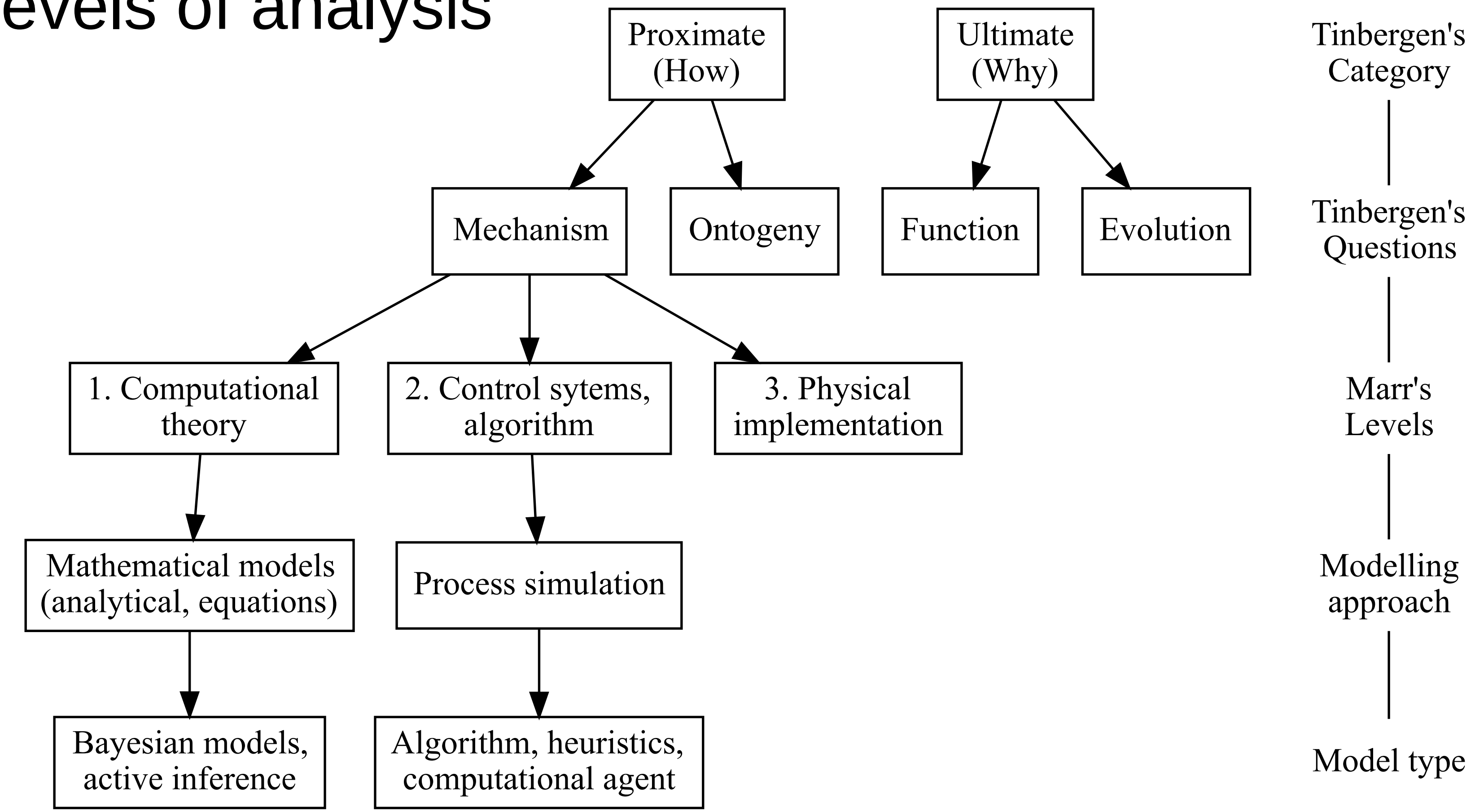
1 INTRODUCTION

I turned Bayesian in 1971, as soon as I began reading Savage's monograph *The Foundations of Statistical Inference* [Savage, 1962]. The arguments were unassailable: (i) It is plain silly to ignore what we know, (ii) It is natural and useful to cast what we know in the language of probabilities, and (iii) If our subjective probabilities are erroneous, their impact will get washed out in due time, as the number of observations increases.

Thirty years later, I am still a devout Bayesian in the sense of (i), but I now doubt the wisdom of (ii) and I know that, in general, (iii) is false. Like most Bayesians, I believe that the knowledge we carry in our skulls, be its origin experience, schooling or hearsay, is an invaluable resource in all human activity, and that combining this knowledge with empirical data is the key to scientific enquiry and intelligent behavior. Thus, in this broad sense, I am a still Bayesian. However, in order to be combined with data, our knowledge must first be cast in some formal language, and what I have come to realize in the past ten years is that the language of proba-

- **Behavioural ecology**
  - animals have **limited resources** (energy, time, opportunity etc.)
  - omniscient Bayesian machine is not a realistic assumption for an animal
  - obtaining as full as possible information is not reasonable strategy (diminishing returns) given the **costs**
- **Heuristics**
  - cheap and quick (and dirty) approximations that are **good enough** most of the time
  - down-weighting and **limiting** information input
  - live with (some) **uncertainty**, not get rid of it
  - computationally **cheap and tractable** decisions

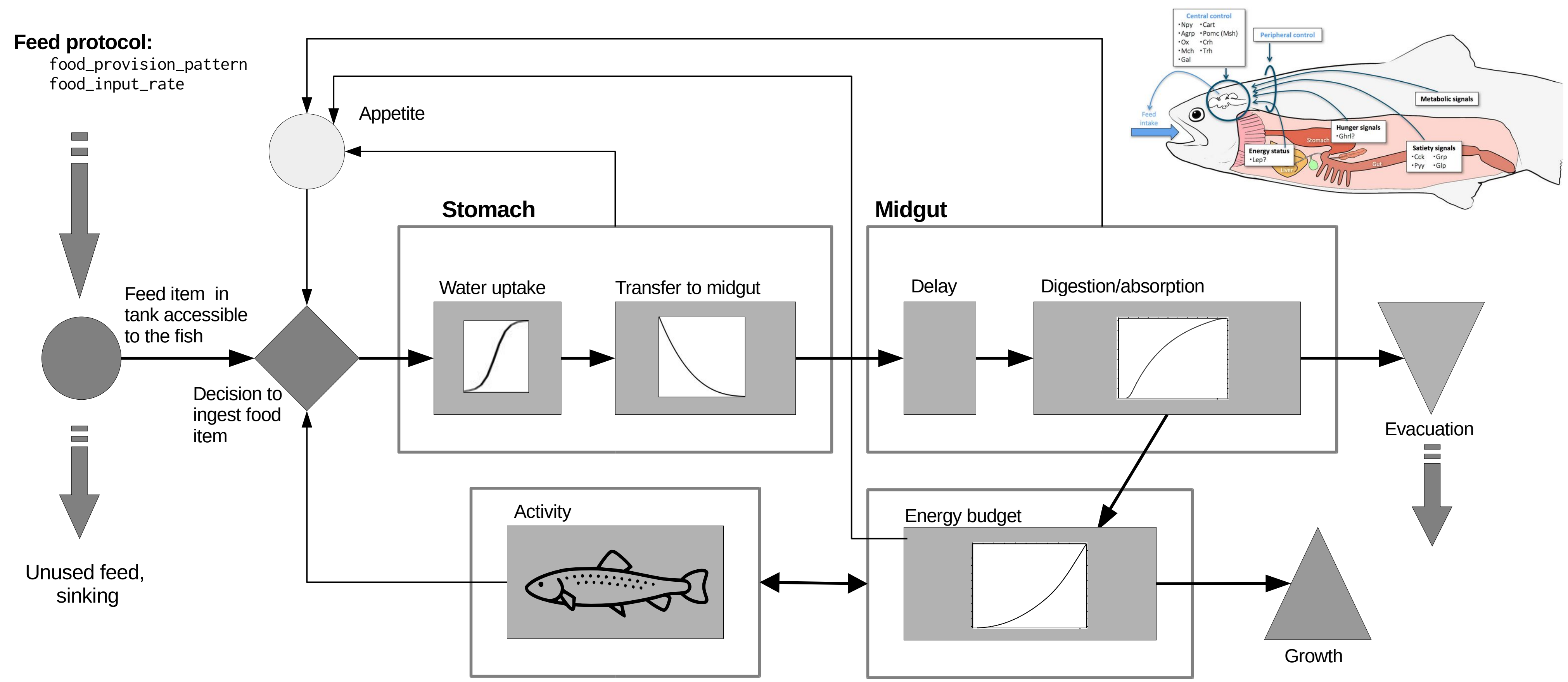
- **Tinbergen and Marr**
  - The levels of analysis



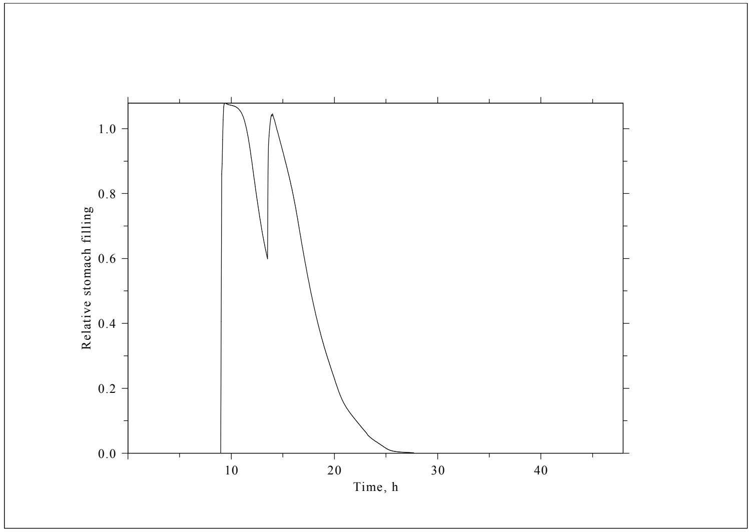
- **Process-based simulation models**
  - Building blocks (modules)
  - Information and energy links
  - Feedback loops
  - Parameters estimation and optimisation

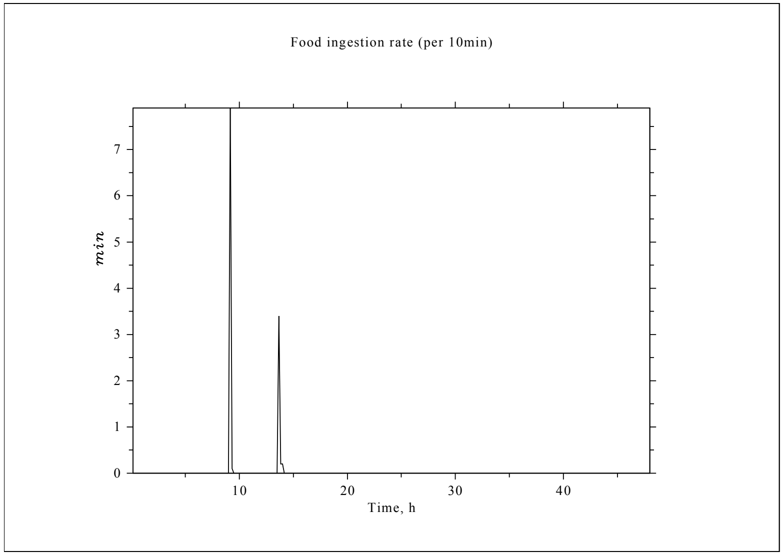
- The FishMet model

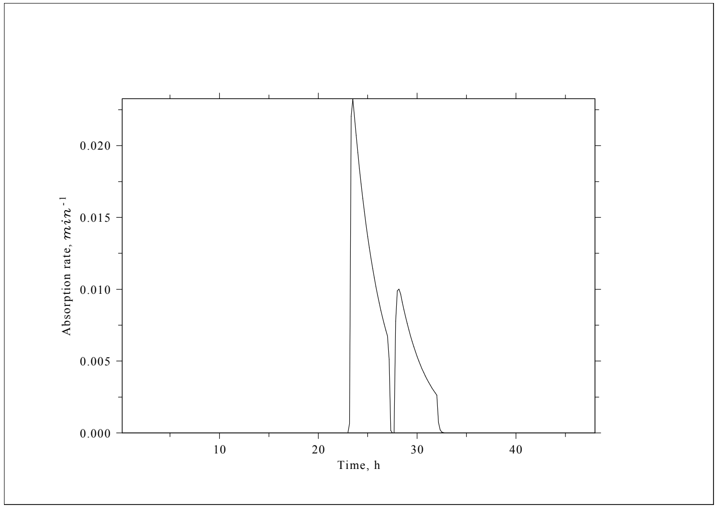
- **The FishMet model**
  - Agent model: feeding, appetite, energy budget, growth



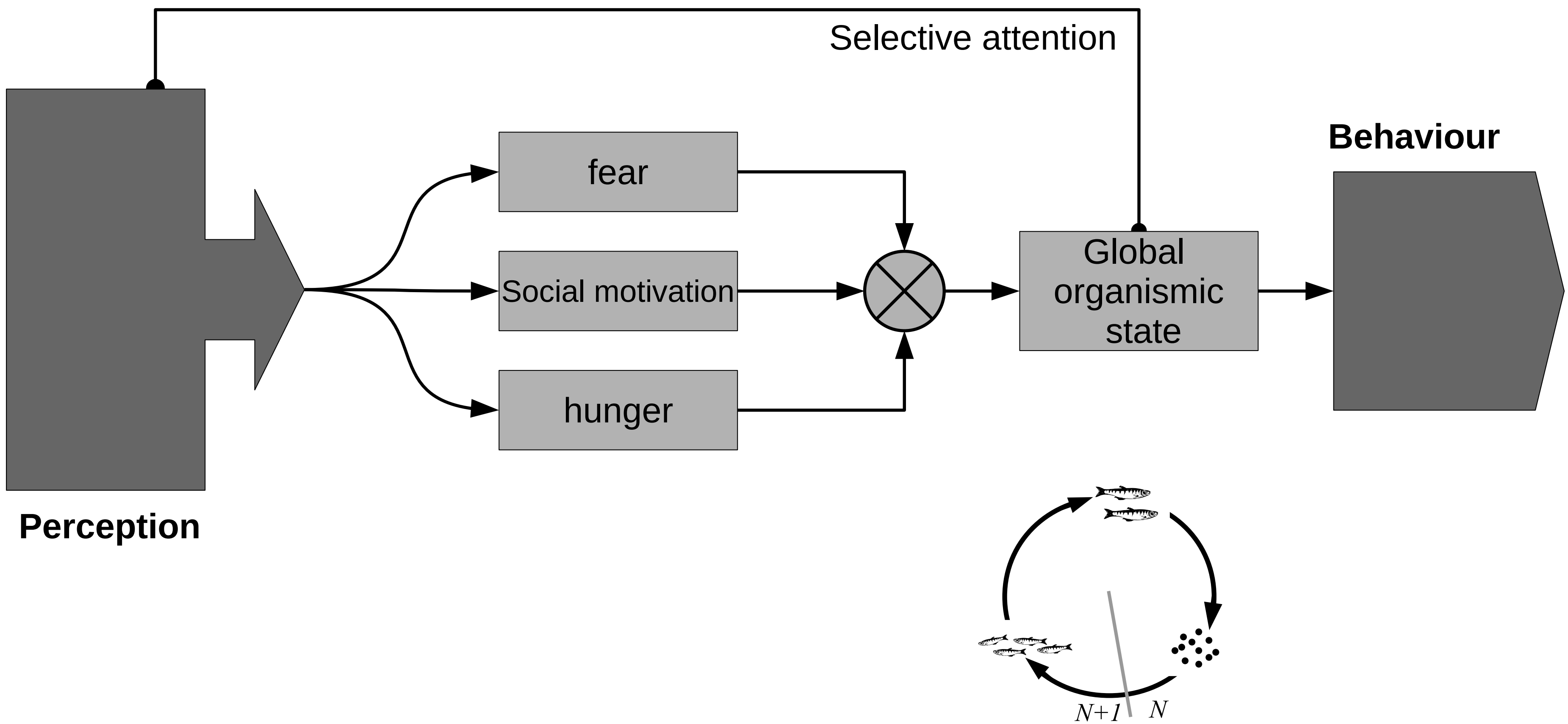
- Feeding decisions
  - appetite → ingestion rate → stomach & gut fullness → absorption → growth





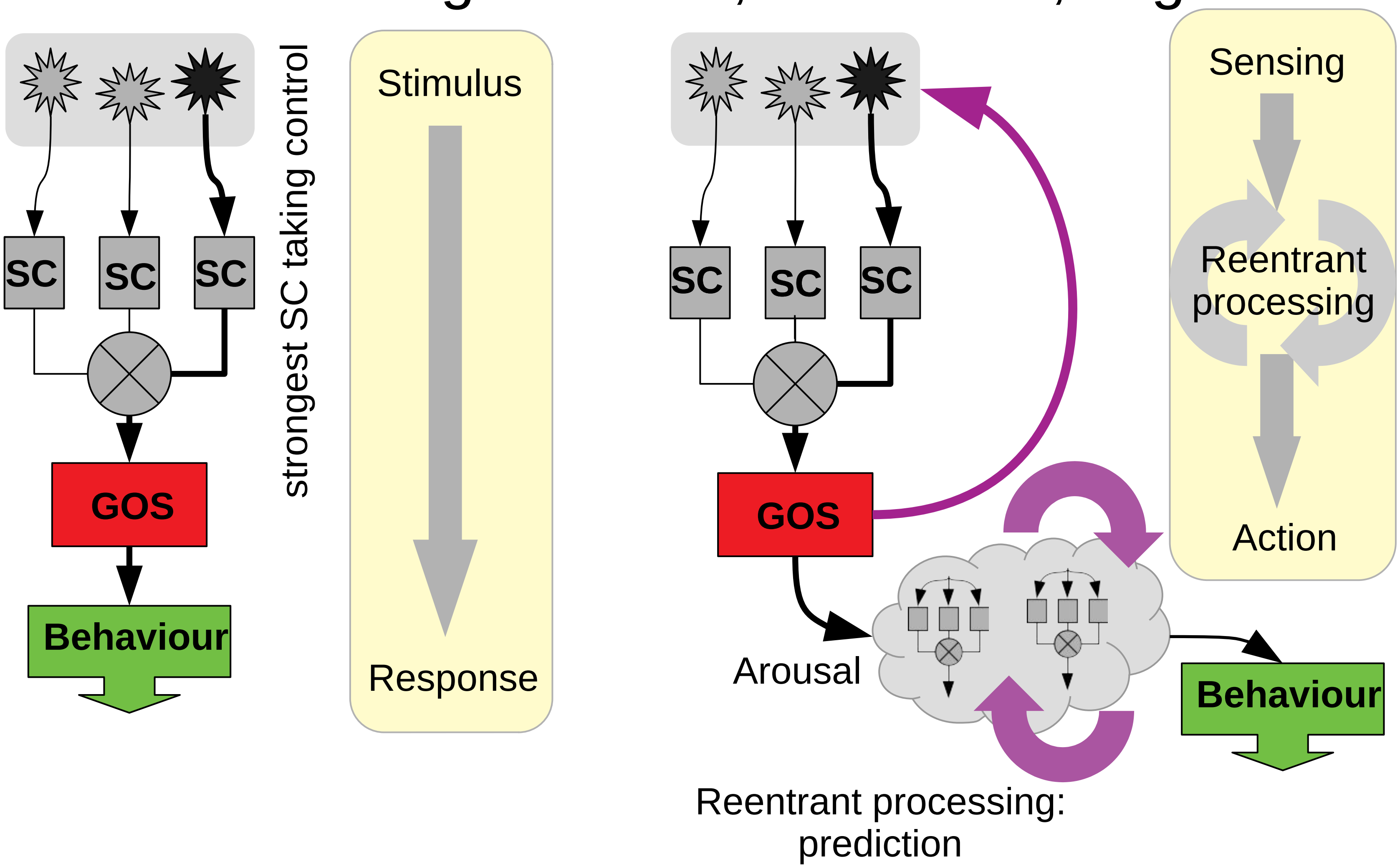


- The AHA model

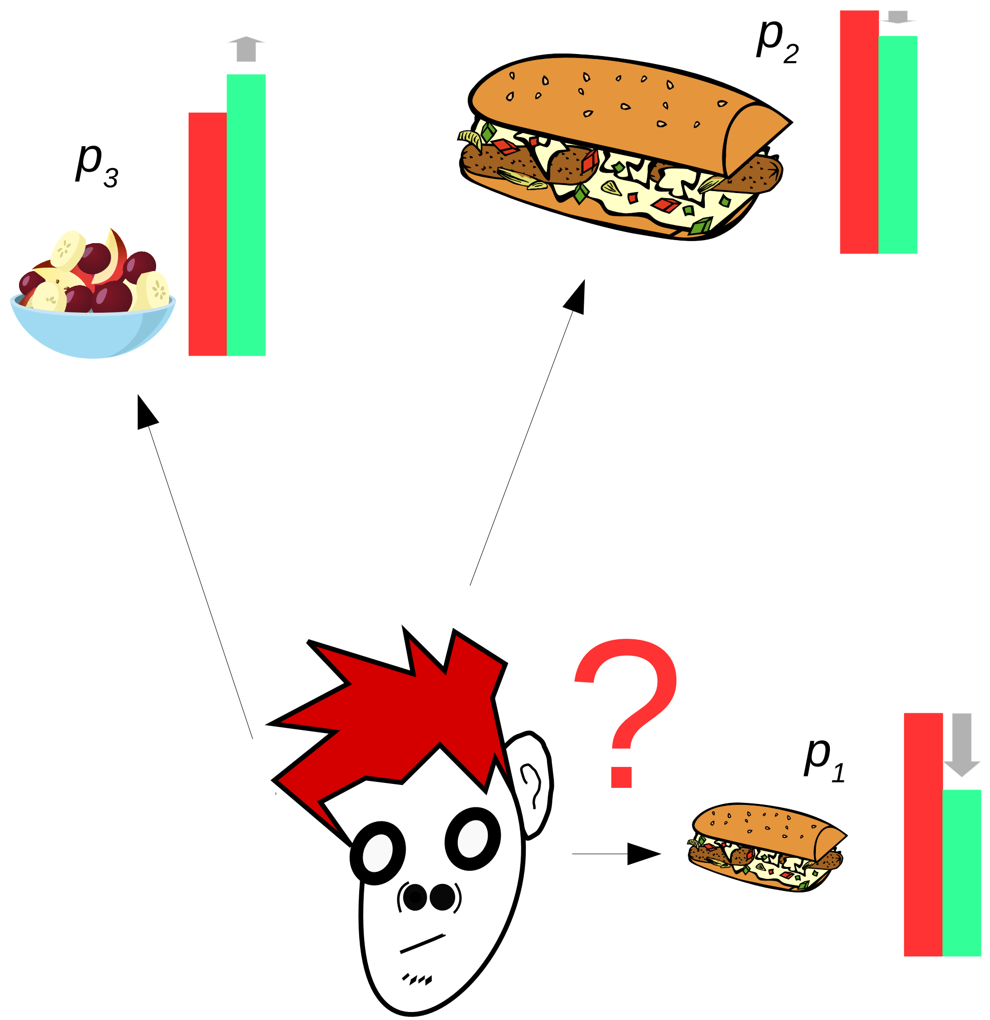


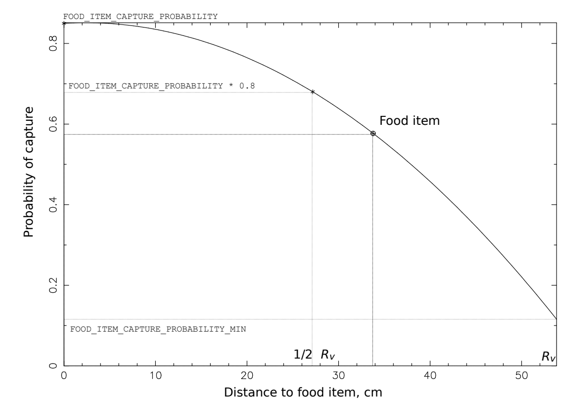
Selective attention
Behaviour
fear
Social motivation
hunger
Global organismic state
Perception
N+1
N

- **The AHA model**
  - Decision-making: emotion, motivation, cognition



- Decisions through self-simulation





Predict oneself: The minimum expected arousal principle

- Simulation theory of cognition

Review

The current status of the simulation theory of cognition

*Germund Hesslow**

Department of Experimental Medical Science, University of Lund, Sweden

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frontiers in Psychology

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Check for updates

An Embodied Approach to Understanding: Making Sense of the World Through Simulated Bodily Activity

*Firat Soylu**

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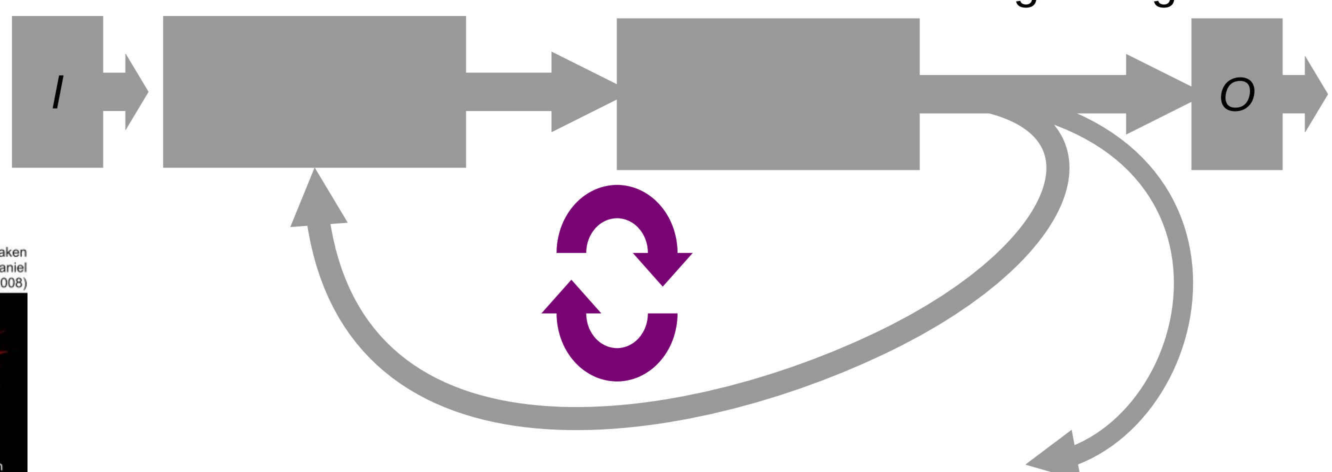
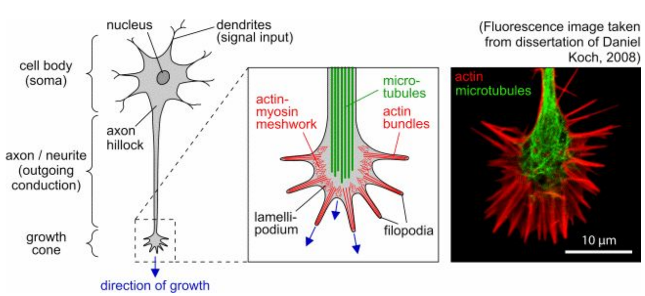
- Scenario: evolution of reentrant architecture

Modularity in evolution: reuse

Developmental mutation:
wrong wiring by disturbed
molecular signalling





- **Internal state** as source of information for **adaptive decisions**:

  - Decision policy based on self-assessment of ones' own energy reserves is approximates omniscient Bayesian policy

Similar principles could well apply in other (non-foraging) contexts: any physiological or psychological state variable that is altered by experience might function as an efficient integrator (a 'memory') of past experiences. An obvious candidate is emotions and moods, which have been modelled mechanistically [47] and may help an

Trust your gut: using physiological states as a source of information is almost as effective as optimal Bayesian learning

Andrew D. Higginson[1], Tim W. Fawcett[1], Alasdair I. Houston[2] and John M. McNamara[3]

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Approaches to understanding adaptive behaviour often assume that animals

Effects of the Emotion System on Adaptive Behavior

Jarl Giske,[1,*] Sigrunn Eliassen,[1] Øyvind Fiksen,[1,2] Per J. Jakobsen,[1] Dag L. Aksnes,[1] Christian Jørgensen,[2] and Marc Mangel[1,3]

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Online enhancement: appendix.

ABSTRACT: A central simplifying assumption in evolutionary be-

Mooij 2003; McNamara and Houston 2009; Fawcett et al.

- Stress and wellbeing

- Homeostatic response: **predictive** versus reactive
- Stress and wellbeing: allostasic regulation
  - **Allostasts**: *predictive regulation* of body functions and budget that enables organism to maintain stability of its homeostasis through change
  - **Costs** of allostatic preparation:
    (a) the challenge is wrongly estimated (prediction error is excessive)
    (b) the challenge exceeds the capacity (or reserves) of the organism
    (c) the challenge is chronic and will continue for a long time.
  - **Allostatic load**: adverse effects on the health and wellbeing

- Stress and well-being: active inference
  - Organism minimises uncertainty (“free energy”)
  - Minimising this free energy is costly.
    An organism unable to reduce the informational free energy, finds itself persistently in a high uncertainty state irrespective of its own actions.
  - This increasingly depletes the brain energy
    => allostatic load and systemic pathology.
  - *habituate* to the adverse environment by altering the internal model and goal state of the system

- Both allostasis and Bayesian active inference models align with the AHA model
  - The **need state** → GOS arousal = signal of poor internal model (big **prediction error**) → **uncertainty**
  - Fish response depends on its Global Organismic State
  - Simultaneous pressures lead to stress
  - Uncertainty increase behavioural **heterogeneity/complexity**, but not at high arousal/stress
    - Stress is linked with low behavioural heterogeneity/complexity
  - High need state and stress may cause **ambiguity bias**
  - Subjective **suffering** → self-simulation of negative emotion

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Review

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Computational animal welfare: towards cognitive architecture models of animal sentience, emotion and wellbeing

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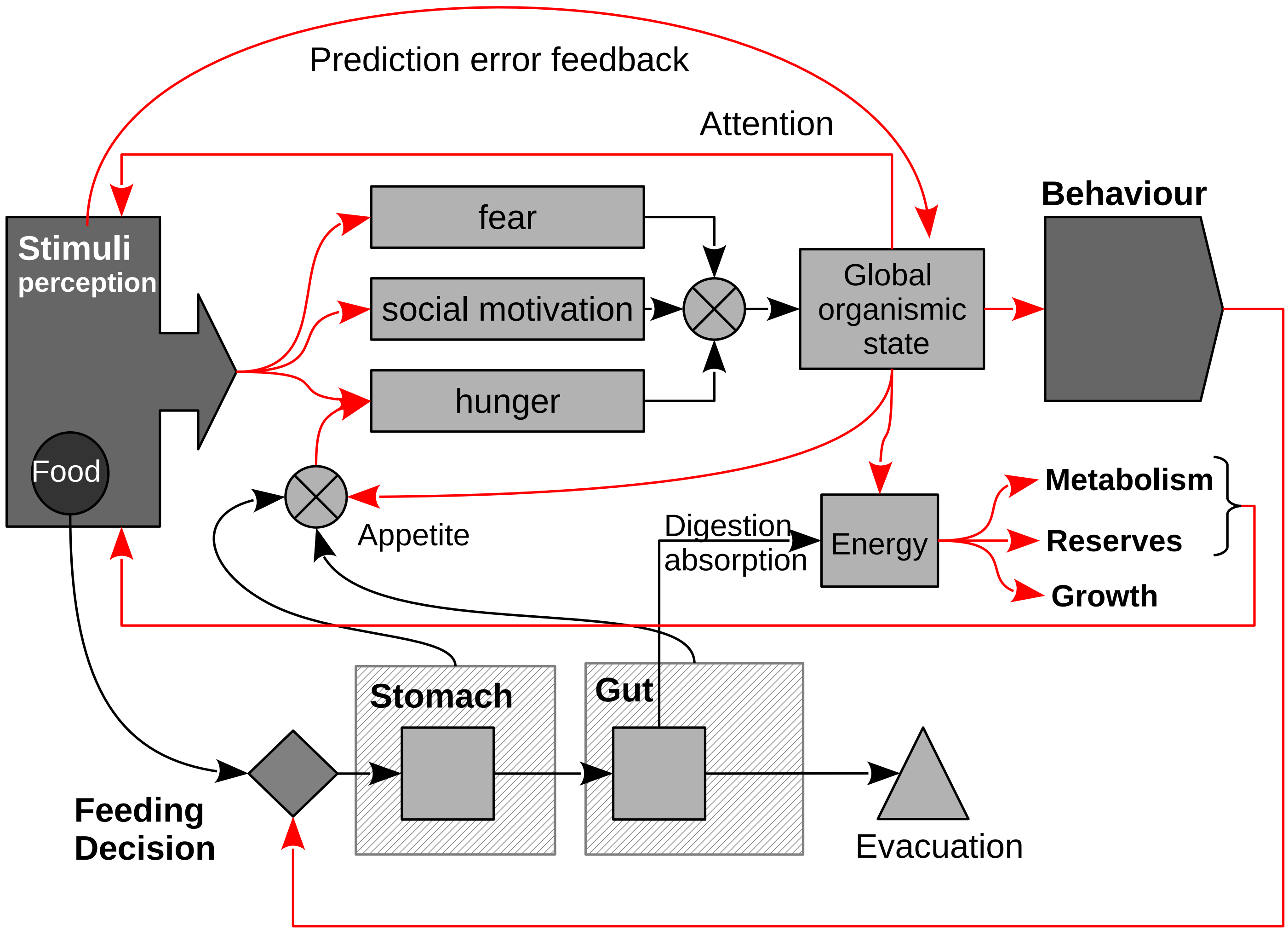
To understand animal wellbeing, we need to consider subjective phenomena and sentience. This is challenging, since these properties are private and cannot be observed directly. Certain motivations, emotions and related internal states can be inferred in animals through experiments that involve choice, learning, generalization and decision-making. Yet, even though there is significant progress in elucidating the neurobiology of human consciousness, animal consciousness is still a mystery. We propose that computational animal welfare

- Predictive Digital Twin of the salmon

- Combining the AHA and FishMet models



- **What is like to be a salmon?**
- Digital twin autonomous agent model:
  - Motivation, emotion, appetite, global state, stress
  - Decision-making and behavioural action selection
  - Sentience (by reentrant self-simulation)
  - Feeding, food intake, dynamic energy budget
  - Growth, health status
- Virtual fish growing in a virtual farm
  - Decision support for physical farm

- Thank you!