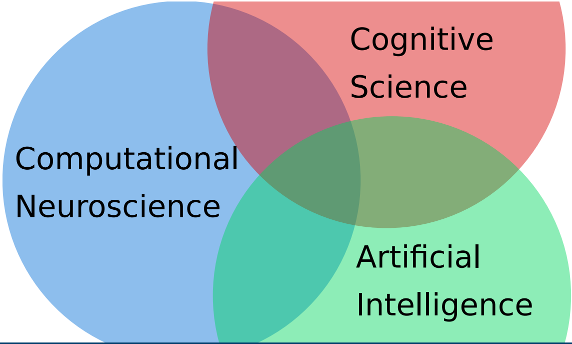

COGNITIVE COMPUTATIONAL NEUROSCIENCE

Kriegeskorte & Douglas (2018) Nature Neuroscience

October 8, 2018 | Journal Club | Julia Sprenger | INM-6

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Historical Background

Cognitive psychology

- study of mental processes such as 'attention, language use, memory, perception, problem solving, creativity, and thinking'[1]

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- 'You can't play 20 questions with nature and win'
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Cognitive Science (1980)
introduction of task-performing computational models (symbolic cognitive architectures, neural networks based on behavioural data)

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Historical Background

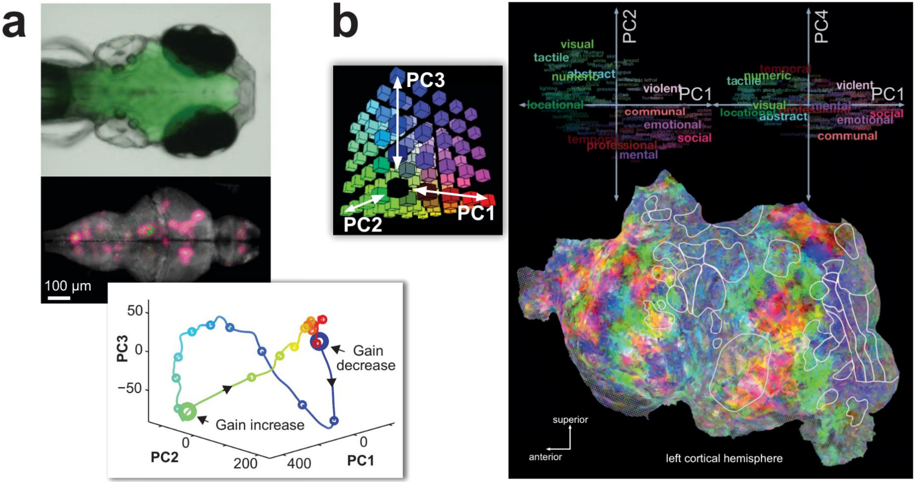
Cognitive Neuroscience

- relate cognitive theories to the (human) brain using functional brain imaging
- mapping of cognitive functions to brain regions using
  - EEG (1875)
  - MEG (1968)
  - PET (1961)
  - fMRI (1990)

Advances in Cognitive Neuroscience

- face-selective regions in human
- spacial clustering of face neurons in non-human primates

Modern Imaging Techniques



- a brain map does not reveal the computational mechanism
- but constrains for theory
- data-driven analysis provides only limited insights

Different Approaches

Cognitive sciences

- interdisciplinary, scientific study of the mind and its processes[2]
- how humans learn & think

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Artificial Intelligence

- how to generate intelligent behaviour

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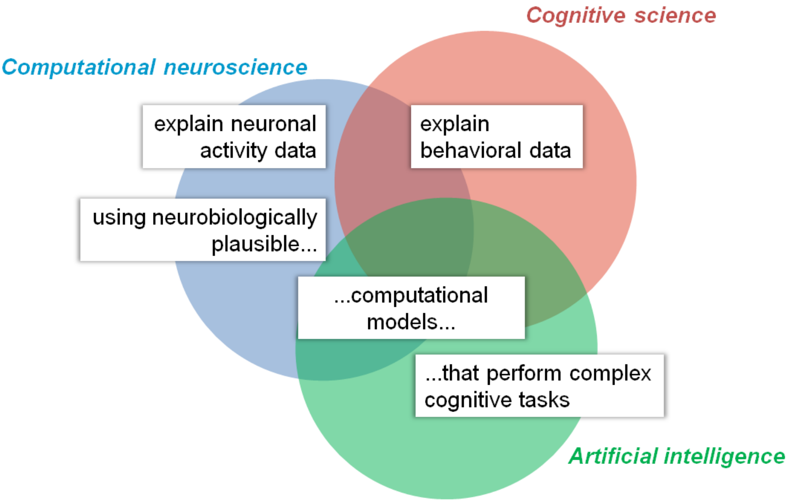
Disciplines



Recent advances

Cognitive Science

- top-down approach
- Bayesian cognitive models (optimal combination of prior knowledge with sensory evidence)
- unified perspective on probabilistic empirical inference

Computational Neuroscience

- bottom-up approach
- mathematical models of elementary computational components and their implementation with biological neurons
  - sensory coding, normalization, working memory, evidence accumulation and decision mechanisms, and motor control

Artificial Intelligence

- demonstrates how component functions can be combined to create intelligent behaviour
- machine learning, deep neural networks

Overarching Challenge build solid bridges between theory and experiment

From Experiment Toward Theory

- Models of connectivity and dynamics
  - correlation among response time series →'functional connectivity'
  - anatomical connectivity
  - graph theoretical analysis of connectivity measures
  - generative modeling of dynamics →effective connectivity
    - Dynamic Causal Modeling
    - Granger Causality
    - Transfer Entropy
  - can be applied within individuals (different states) and across individuals (disorders)

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  - comprehensive predictions about the representational space
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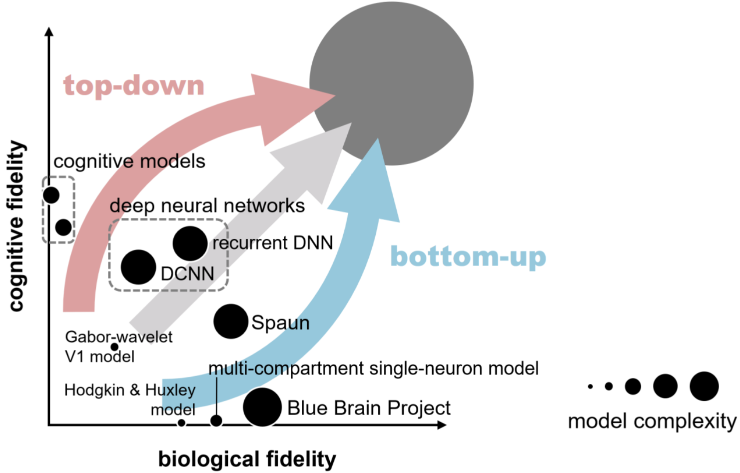
These models do **not** reveal the computational mechanisms of information processing underlying some cognitive function

Interlude: The many meanings of model

- data-analysis models (statistical description of measured variables)
- box-and-arrow models (information processing)
- oracle model (relies on information without describing the extraction from input)
- brain-computational model (mimics brain information processing, eg sensory encoding)
- ...

The Space of Process Models



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From Theory to Experiment

- Neural network models
  - provide a common language for building task-performing models that meet combined criteria from all three disciplines
  - can be constructed as biologically plausible systems (feed forward, recurrent, ...)
  - supervised and unsupervised learning
  - requires large parametric complexity to capture world knowledge for intelligent behaviour
  - over-fitting problem →evaluation in terms of generalization performance
  - example of visual pathways: visual hierarchy is also formed in deep neural networks

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  - example of visual pathways: visual hierarchy is also formed in deep neural networks
- Cognitive models
  - high level description of cognitive processes without biological details
  - production systems
    - sequence of cognitive actions based on 'if ... then ...' rules
  - reinforcement learning
    - learning to maximize long-term cumulative reward through interaction with environment eg. by value functions or policies
    - requires balance between exploitation and exploration
    - model-free control: learning by trial and error
    - model-based control: enables intelligent action in novel situations
    - episodic control: storage of past experiences
  - Bayesian models
    - provides optimal behaviour under given data and priors
    - challenging to learn a generative model from sensory data and computation of posterior

Why do cognitive science, computational neuroscience and AI need each other?

- Cognitive science
  - needs computational neuroscience to discover algorithms of information processing
  - needs brain data to provide constrains for complex models
  - progresses in close interaction with AI
- Computational Neuroscience
  - needs cognitive science to challenge it to engage higher-level cognition
  - needs machine learning / AI to provide theoretical and technological basis for modeling functions with biologically plausible dynamical components
- Artificial Intelligence
  - needs cognitive science to guide the engineering of intelligence (eg. benchmarks for tasks)
  - needs computational neuroscience for algorithmic inspiration
  - main challenge: integration of computational and statistical efficiency

Looking Ahead

The brain seamlessly merges bottom-up discriminative and top-down generative computations in perceptual inference, and model-free and model-based control.

- bottom up and top down
  - most important funding initiatives for bottom-up approach: Human Brain Project (synthesize neuroscience data in biologically detailed dynamic models), US Brain Initiative (measurement and manipulation of brain activity)
  - better understanding in the context of a prior theory
- Marr's levels (1982)
  - computational theory
  - representation and algorithm
  - neurobiological implementation
- →convergence of the three disciplines on algorithms and representations
- example: child seeing escalator
  - neural networks: recognition of visual elements
  - bayesian nonparametric models: concept formation from single experience
- power discrepancy: efficient statistical and computational implementation in the brain based on 20 Watt

→need for collaborations between labs with complementary expertise & open science culture

Interaction Among Sharable Components

Tasks

- provide controlled environment for behaviour
- OpenAI's Gym, Universe, DeepMind's lab
- interactions with virtual stimuli,
  natural environment as games, mass participation

Models

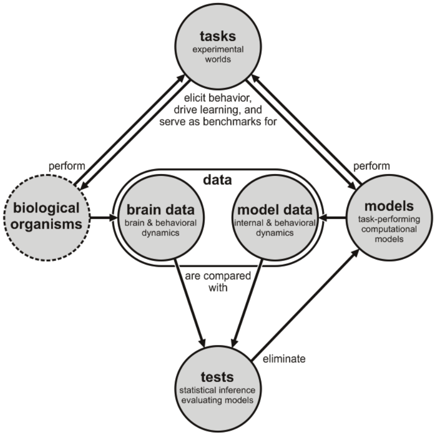
- task-performing computational models
- initially only performing
  specific task, but must ultimately generalize across tasks

Data

- behavioural data during task performance
- structural & functional brain data

Tests

- comparison between computational
  models and brain data (within a specific task)
- conceptual challenge of level of comparison



Challenges

- design shareable tasks and provide human behavioral data set to set bar for AI model performance
- share brain activity data to constrain models and quantitative compare to models