What is consciousness, and could machines have it?

Psy 3280 – Week 10 Lecture (1 October 2018)

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Learning objective

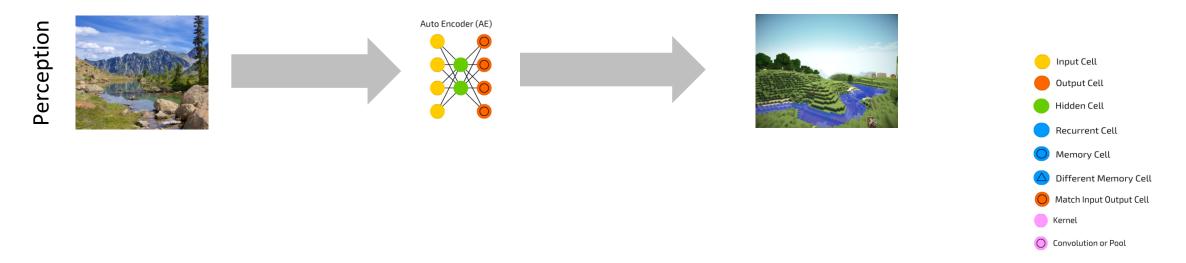
- Can machines have consciousness?
- The multiple meanings of consciousness
 - C0: Unconscious processing
 - C1: Global availability of information
 - C2: Self monitoring
- Relationships between C1 and C2
- Pathways to artificial consciousness
 - Adversarial learning (Dehaene)
 - Maximizing Information Integration (IIT)
 - Minimizing Prediction Error (Predictive coding)

 The natural scene experiment is an example of how perception or report could be artificially replicated

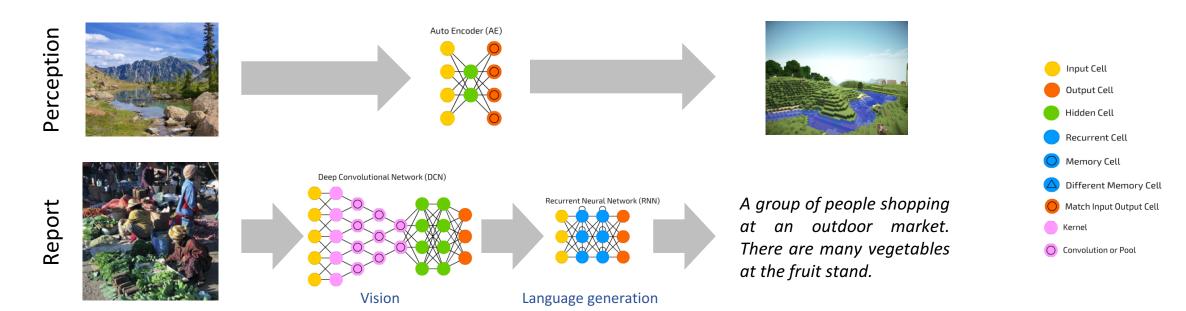




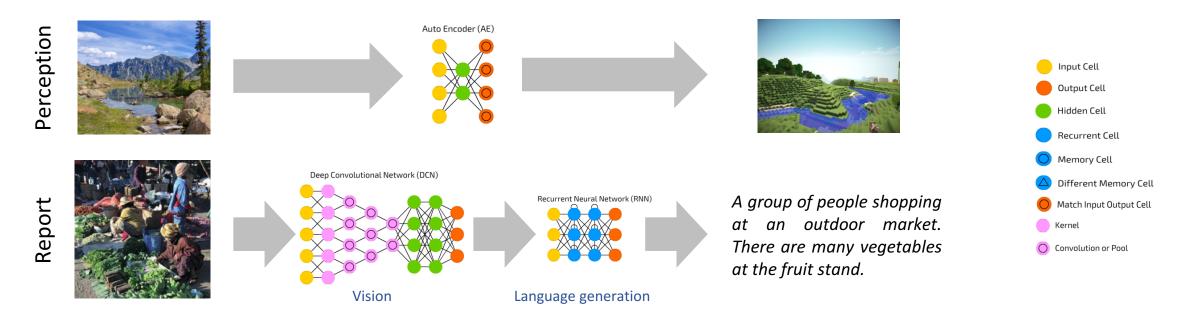
 The natural scene experiment is an example of how perception or report could be artificially replicated using Autoencoders



 The natural scene experiment is an example of how perception or report could be artificially replicated using Autoencoders or Convolutional Nets



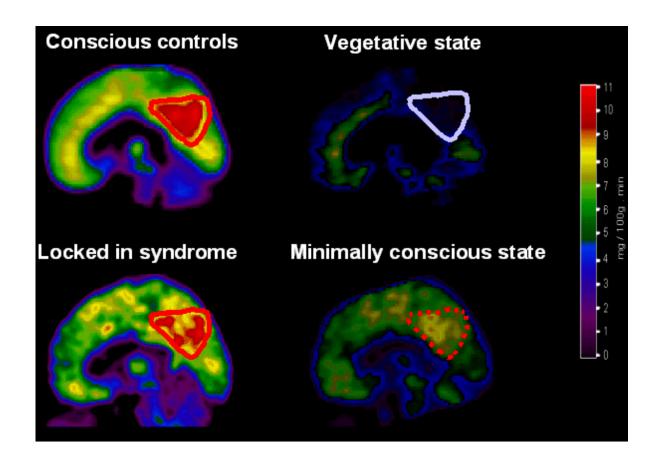
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What about consciousness, can machines have it?

- To answer the question we must carefully consider how consciousness arises in the only physical system that undoubtedly possesses it: the human brain
- Neuroscientists have developed tools and theories to understand consciousness in the human brain:

• Brain imaging



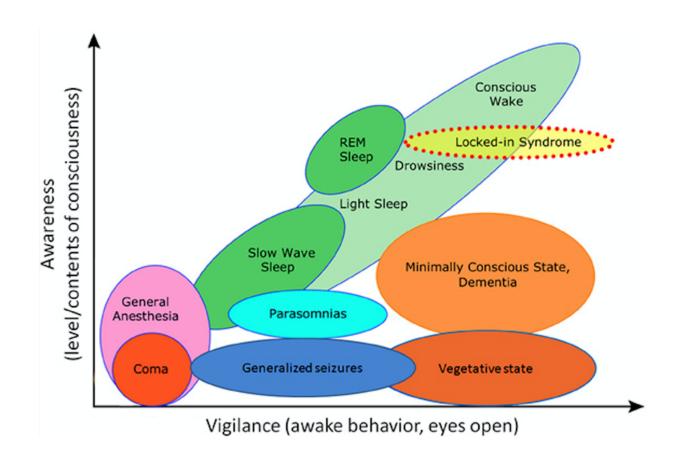
Psychophysical experimentation

Table 1. Relative strengths of various psychophysical techniques for erasing a stimulus from visual awareness

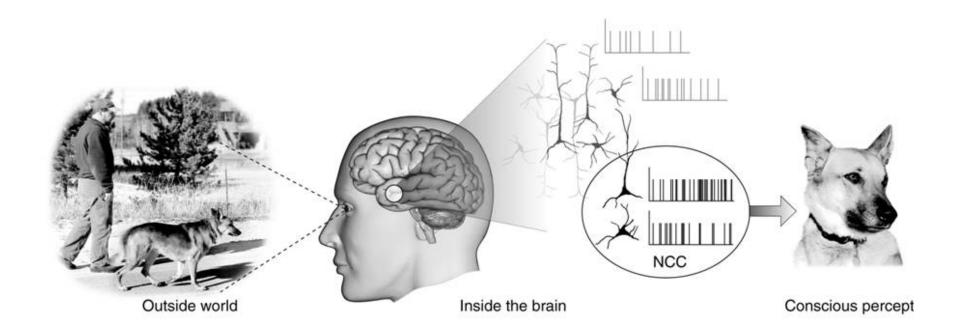
Overarching themes	Stimulus generality				Effectiveness			
Strengths Strategies	Variety of stimuli 4	Stimulus size ^b	Visual field location *	Temporal aspects of stimulation ^d	Unambiguous invisibility *	Invariant stimulation !	Duration 9	Predictability *
Backward masking		<u> </u>			0	<u> </u>		
Crowding	7	?						
Bistable figures								
Binocular rivalry								
Motion-induced blindness								
Inattentional/ Change blindness			(<u> </u>				
Attentional blink					0			
						Relative strength		
						Weat		Street
						wear		Strong in Cognitive Sciences

[&]quot;Variety of stimuli – is the technique effective at rendering a wide variety of stimuli invisible? "Stimulus size – does the technique work over a wide range of stimulus sizes?" Visual field location – does the technique work equally well in central and in peripheral vision? "Temporal aspects of stimulation – are there constraints on the exposure duration or on the timing of the stimulus?" "Unambiguous invisibility – does the state of unawareness involve complete, unambiguous invisibility of the stimulus? "Invariant stimulation – does physical stimulation remain invariant when visual awareness fluctuates? "Duration – do the periods of unawareness last for longer than a few hundred milliseconds?" "Predictability" – is the onset of unawareness controllable, and are the durations of unawareness predictabile?

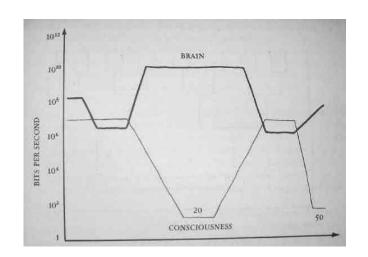
Drawing distinctions between the content and levels of consciousness

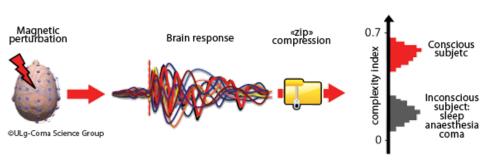


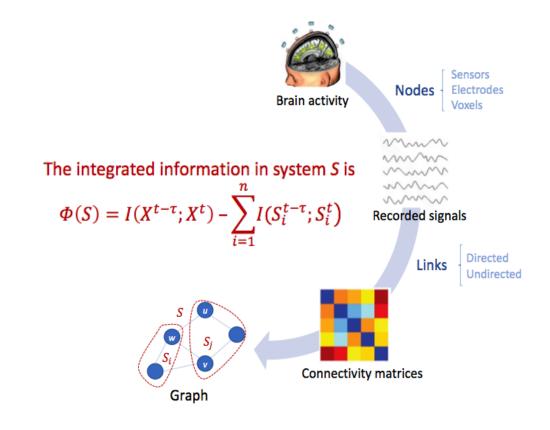
Studying the neural correlates of consciousness (NCC)



 Quantifying consciousness: Bandwidth of Consciousness (BoC), Perturbational Complexity Index (PCI) or Integrated Information (Phi)







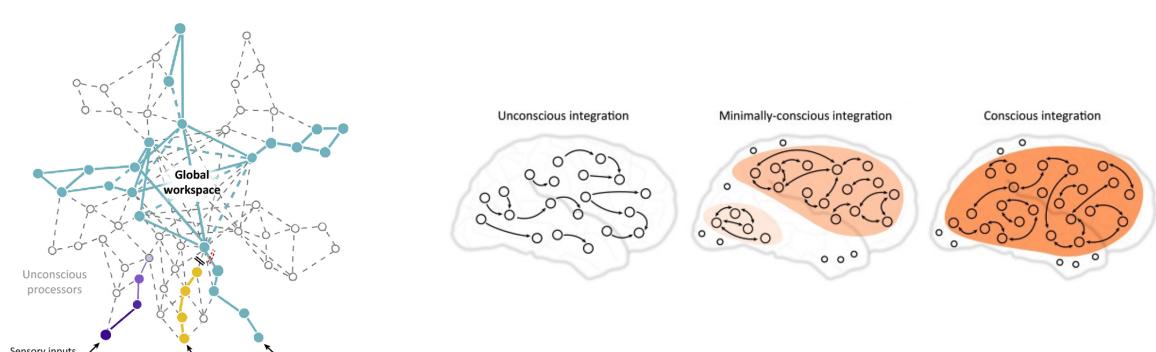
Conscious

high strength and attention

Subliminal

weak strength

 Proposing theories of consciousness: Global workspace Theory, Integrated Information Theory



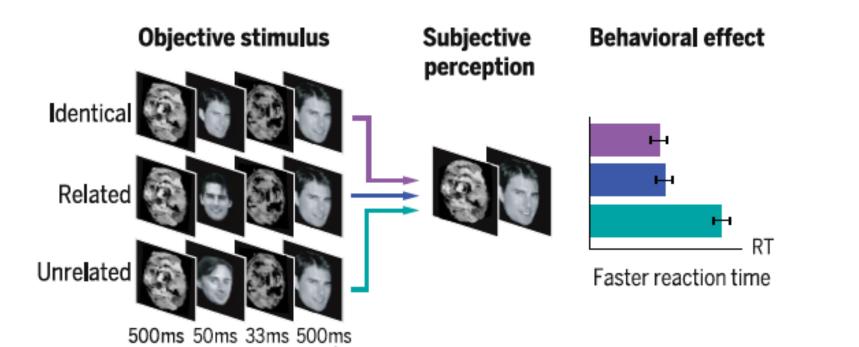
The multiple meanings of Consciousness

- Let us consider the brain as a machine with information-processing capabilities
- And look at different types of information-processing computations
 - Unconscious processing (C0)
 - Global availability of information (C1): The selection of information for global broadcasting, making it flexibly available for computation and report
 - **Self-monitoring (C2)** of those computations, leading to a subjective sense of certainty or error

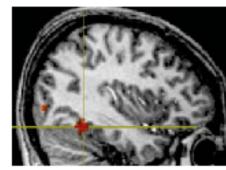
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- Paradigms to probe these types of computations:

Unconscious processing (C0)

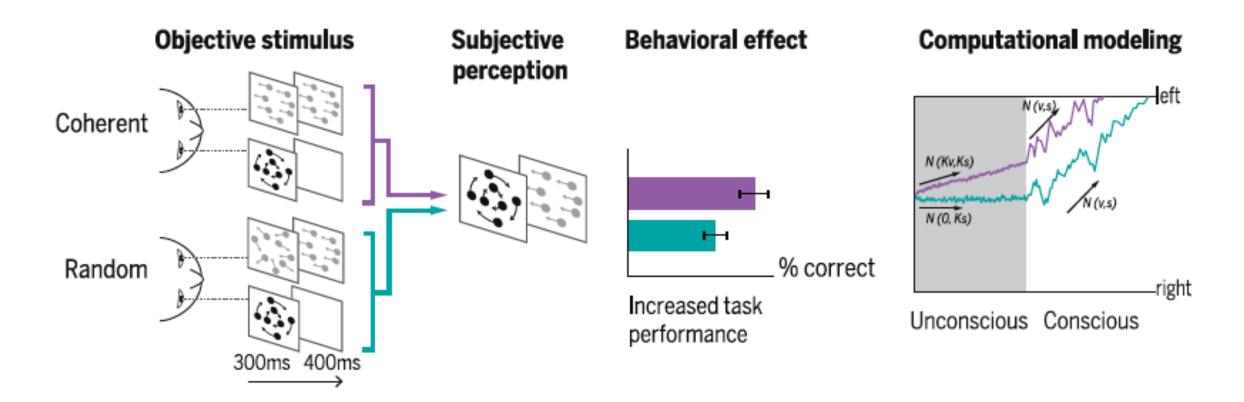


Neural effect

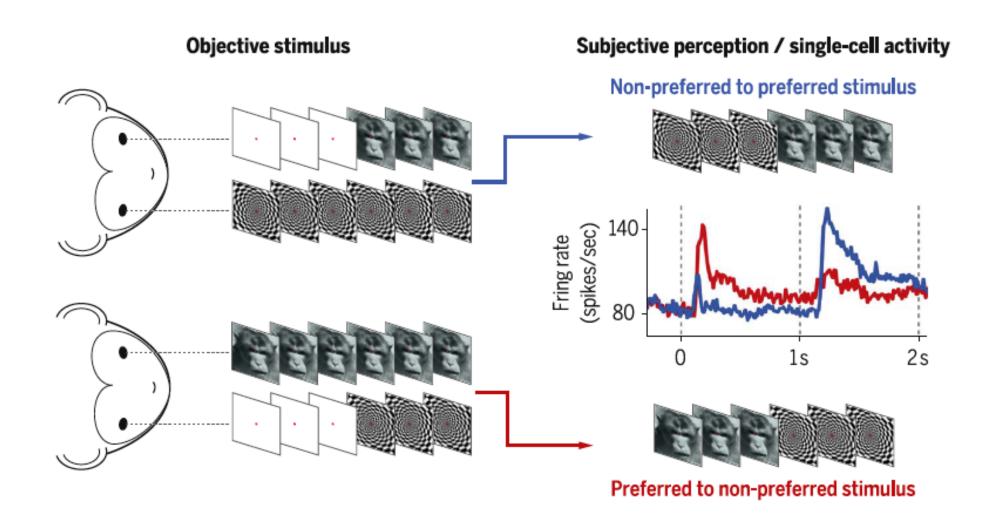


Reduced activity in fusiform face area

Unconscious processing (CO)



Global availability of information (C1)

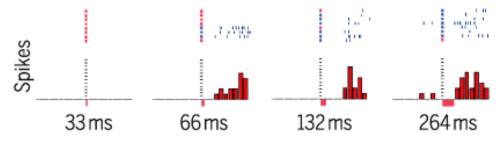


Global availability of information (C1)

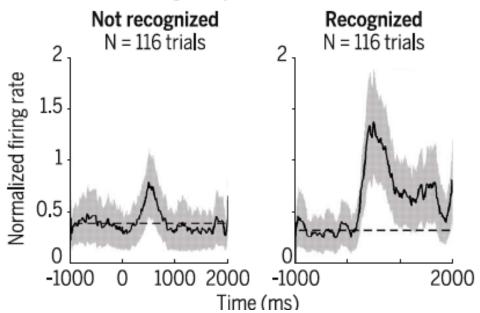


33 ms	467 ms
66 ms	434 ms
132 ms	368 ms
264 ms	236 ms

Response of neuron selective to World Trade Center

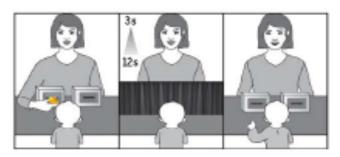


Average response of all neurons



Self-monitoring (C2)

First-order decision Memory recal



Toy location

Delay Task difficulty

Pointing Decision

First-order decision

Perceptual choice



Cue Waiting Reward

visible/ period 3000 ms invisible 2500 ms

Second-order measure

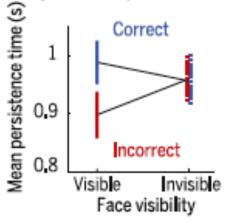
Manual search persistence



Longer searching time when correct

Second-order measure

Eye fixation persistence



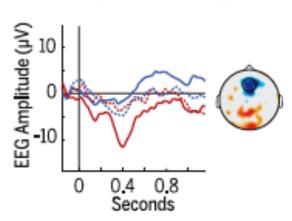
Second-order measure Opt-out



Opt-out by asking for help to avoid errors

Second-order measure

Error-specific neural signal



Dissociation between C1 and C2

 They are largely orthogonal and complementary dimensions of what we call consciousness

Self-monitoring can exist for unreportable stimuli (C2 without C1)

Consciously reportable contents sometimes fail to be accompanied with an adequate sense of confidence (C1 without C2)

Synergy between C1 and C2

- Because C1 and C2 are orthogonal, their joint possession may have synergistic benefits to organisms
 - In one direction, bringing probabilistic metacognitive information (C2) into the global workspace (C1) allows it to be held over time, integrated into explicit long-term reflection, and shared with others
 - In the converse direction, the possession of an explicit repertoire of one's own abilities (C2) improves the efficiency with which C1 information is processed

- What makes the difference to the processing related to C0 into non-conscious?
 What's needed to make it conscious?
- Is C1 sufficient?
- Is C2 sufficient?
- Is there a case of non-conscious processing with C1 AND C2?
- Is there any better alternative to C1 and C2 for AI?

- Current machines are still mostly implementing computations that reflect unconscious processing (C0) in the human brain
- Endowing machines with global information availability (C1) would also allow the different modules to share information and collaborate to address impending problems
- To make optimal use of the information, it would also be useful for the machine to possess a database of its own states. Such self-monitoring (C2) would include an integrated image of itself as well as its internal databases

Combining C1 and C2 in adversarial learning

 Adversarial learning, involves having a secondary network "compete" against a generative network so as to critically evaluate the authenticity of self-generated representations

 When reality monitoring (C2) is coupled with C1 mechanisms, the resulting machine may more closely mimic human consciousness in terms of affording global access to perceptual representations while having an immediate sense that their content is a genuine

How to do it in practice?

• Using a generative adversarial network (GAN): One network generates candidates (generative) and the other evaluates them (discriminative)

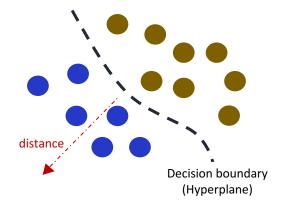
- Using a generative adversarial network (GAN): One network generates candidates (generative) and the other evaluates them (discriminative)
 - What is a discriminative model?
 - What is a generative model?

• Using a generative adversarial network (GAN): One network generates candidates (generative) and the other evaluates them (discriminative)

Discriminative models learn the boundary between classes

Examples:

- Logistic regression
- SVM
- NN

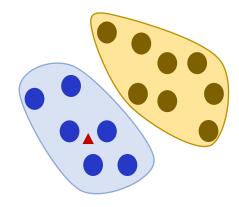


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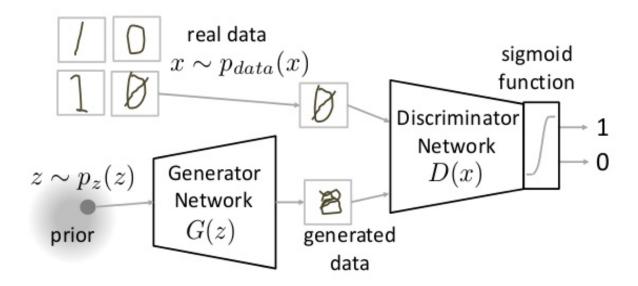
Generative models model the distribution of individual classes

Examples:

- Naïve Bayes
- Gaussian Discriminant Analysis

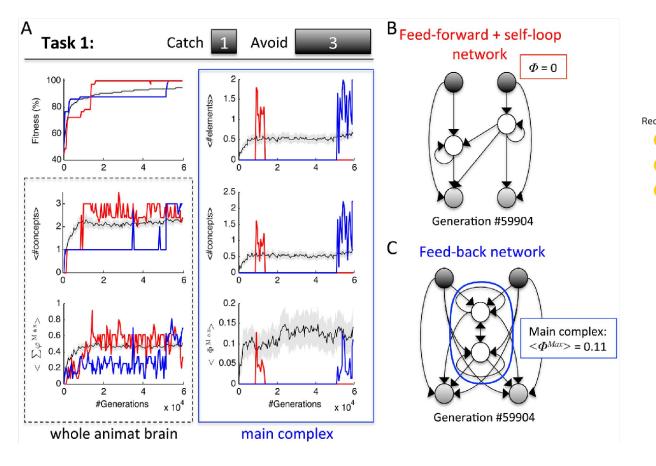


- Using a generative adversarial network (GAN): One network generates candidates (generative) and the other evaluates them (discriminative)
 - Example

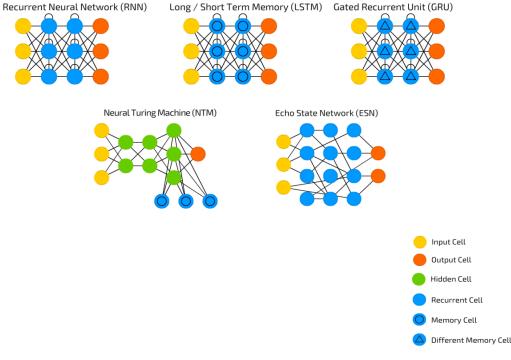


- Other ways?
 - 2. Optimizing integration in animats through evolution (IIT)
 - 3. Minimizing error (Predictive coding)

Optimizing integration in animats through evolution (IIT)



Feedback networks are the key?

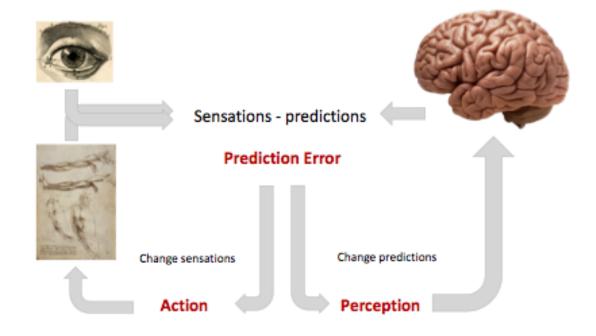


- Minimizing error between two generative models
 - Error detection provides a particularly clear example of self-monitoring; just after responding, we sometimes realize that we made an error and change our mind

Minimizing error between two generative models



Sensory observations generated by P are observed by the agent while the agent is acting on the world to change P



Summary

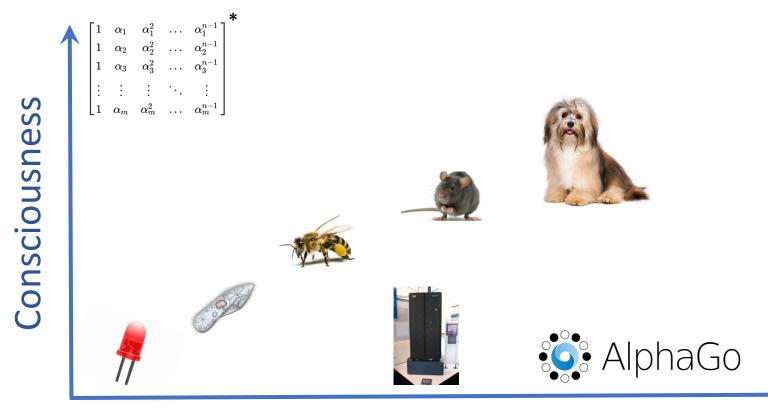
- The human brain as blueprint for artificial consciousness
- The multiple meanings of consciousness: C0, C1, C2
- Generative models and the ability to reflexively represent oneself

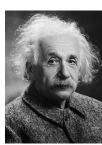
Discussion

• Intelligence = consciousness?

Discussion

• Intelligence vs. Consciousness





Discussion

- Does one give rise to the other?
- Measuring intelligence and consciousness
 - IQ (humans), fitness (animat example), utility (artificial agents), etc.
 - Phi, BoC, etc.
- Access/Phenomenal consciousness and C1/C2

References

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- 2. Kim, Chai-Youn, and Randolph Blake. "Psychophysical magic: rendering the visible 'invisible'." Trends in cognitive sciences 9.8 (2005): 381-388.
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- 4. Albantakis, L., Hintze, A., Koch, C., Adami, C., & Tononi, G. (2014). Evolution of Integrated Causal Structures in Animats Exposed to Environments of Increasing Complexity. *PLoS Computational Biology*, 10(12).
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