Neural networks cont.

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AARHUS UNIVERSITY

IMC
INTERACTING MINDS CENTRE

CFIN

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Contents

1. Recurrent neural networks
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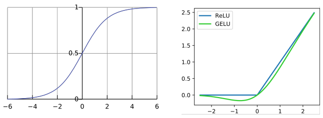
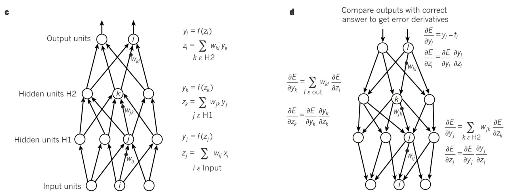
Neural networks recap

	Supervised learning
Data	$\{X, y\}$
Model	$y \approx f_\theta(X)$
Loss/cost	$\mathcal{L}(\theta) = \sum_{i=1}^{N} l(f_\theta(x_i), y_1)$
Optimisation	$\theta^* = \arg\min_\theta \mathcal{L}(\theta)$

- Linear layer
- Activation function
- Loss/cost functions

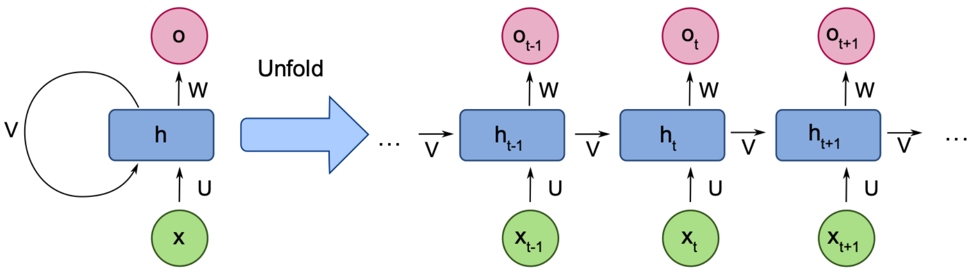


(Figure from https://en.wikipedia.org/wiki/Rectier_(neural_networks))



(Figure from LeCun et al., 2015)

Recurrent neural networks



(Figure from https://en.wikipedia.org/wiki/Recurrent_neural_network)

Recurrent neural networks

	Supervised learning	Sequence modelling
Data	$\{X, y\}$	$\{X\}$
Model	$y \approx f_\theta(X)$	$p(X) \approx f_\theta(X)$
Loss/cost	$\mathcal{L}(\theta) = \sum_{i=1}^{N} l(f_\theta(x_i), y_1)$	$\mathcal{L}(\theta) = \sum_{i=1}^{N} \log p(f_\theta(x_i))$
Optimisation	$\theta^* = \arg\min_\theta \mathcal{L}(\theta)$	$\theta^* = \arg\max_\theta \mathcal{L}(\theta)$

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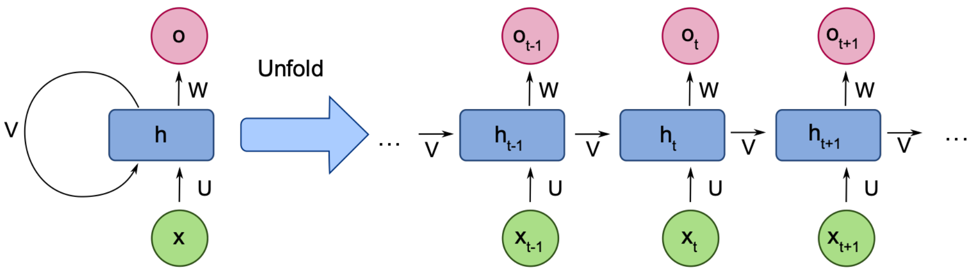
Recurrent neural networks



(Figure from https://en.wikipedia.org/wiki/Recurrent_neural_network)

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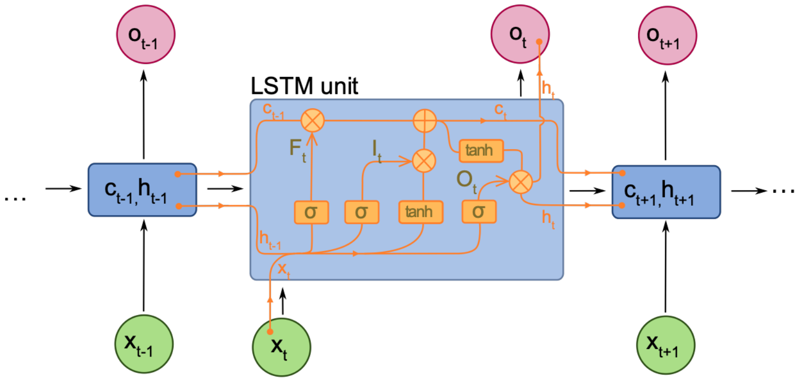
Long short-term memory networks



(Figure from https://en.wikipedia.org/wiki/Recurrent_neural_network)

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Reinforcement learning

https://youtu.be/OjVxXyp7Bxw

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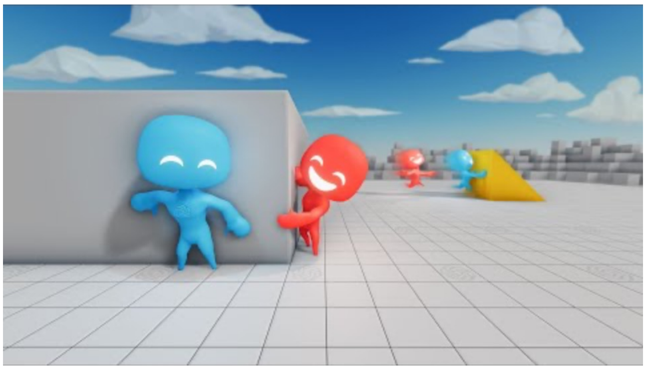
Reinforcement learning



https://youtu.be/kopoLzvh5jY

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Reinforcement learning

Reinforcement learning needs:

- A world, e.g. a game
- Agent(s)
- Self-play, i.e. millions of iterations
- Rewards & penalties

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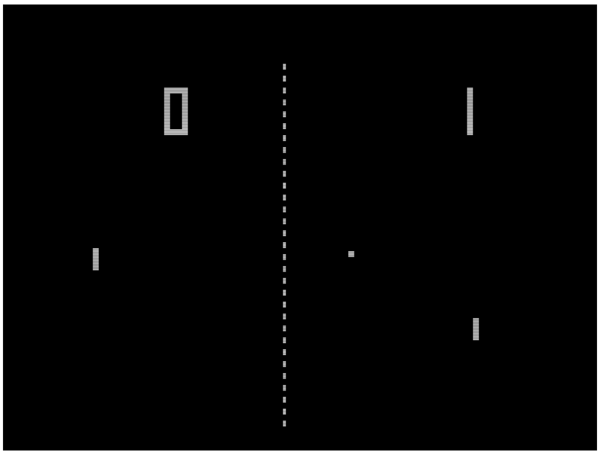
Pong



(Figure from https://en.wikipedia.org/wiki/pong)

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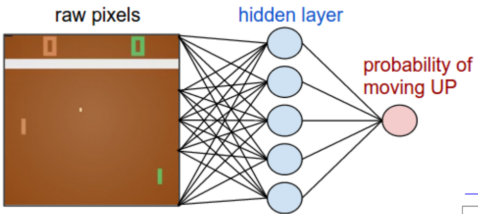
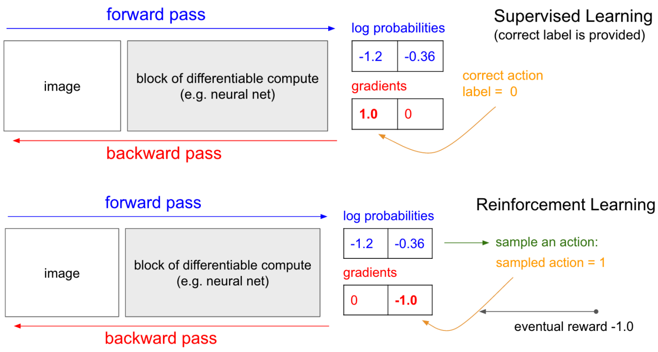
Reinforcement learning



Policy network
This network will take the state of the game and decide what we (i.e. the agent) should do.



(Figure from http://karpathy.github.io/2016/05/31/rl/)

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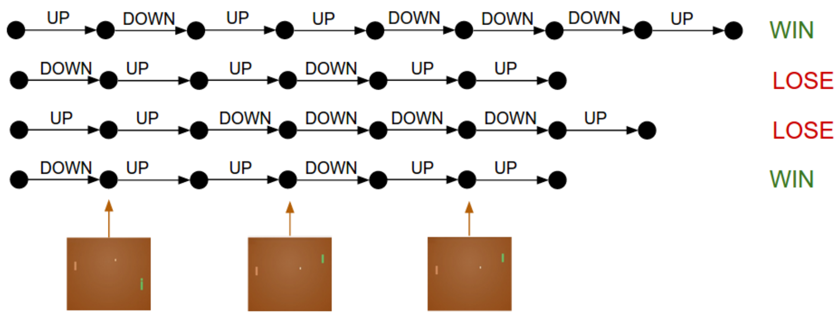
Reinforcement learning



Credit assignment problem
Which actions are the actions
that make a difference

(Figure from http://karpathy.github.io/2016/05/31/rl/)

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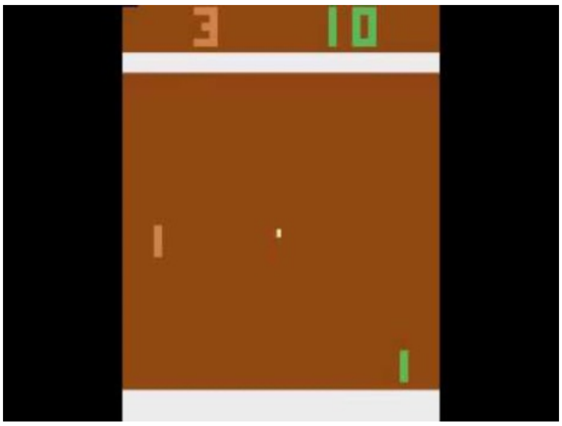
Reinforcement learning



https://youtu.be/YOW8m2YGtRg

(Film from http://karpathy.github.io/2016/05/31/rl/)

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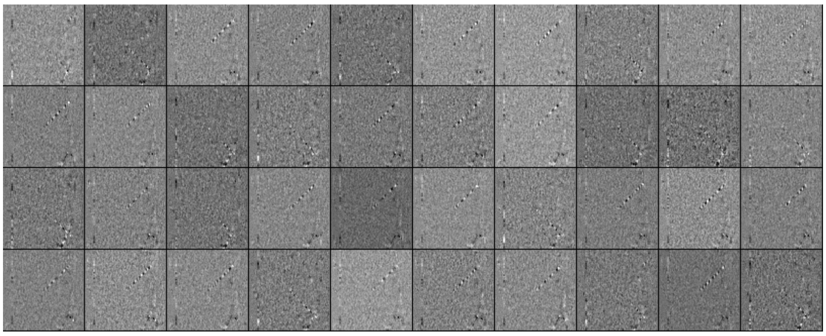
Reinforcement learning



(Figure from http://karpathy.github.io/2016/05/31/rl/)

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Reinforcement learning

- World to act in
- Agent(s) that act in the world
- Policy network, what to do
- Self-play
- Rewards & penalties

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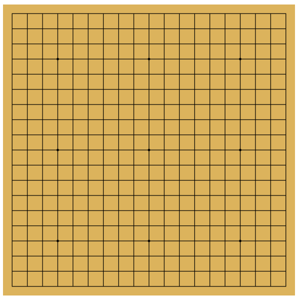
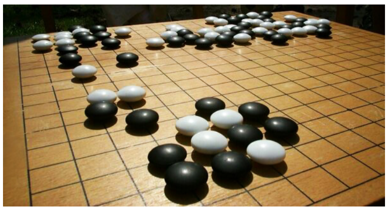
Go

- $2.08168199382 \times 10^{170}$ possible moves
- No AI/software has beating a professional

"The Game of Go is the holy grail of artificial intelligence. Everything we've ever tried in AI, it just falls over when you try the game of Go."
David Silver





Figures from https://da.wikipedia.org/wiki/Go

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Deep blue

Garry Kasparov (1963–)

https://en.wikipedia.org/wiki/chess

https://en.wikipedia.org/wiki/Deep_Blue_(chess_computer)

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AlphaGo

AlphaGo

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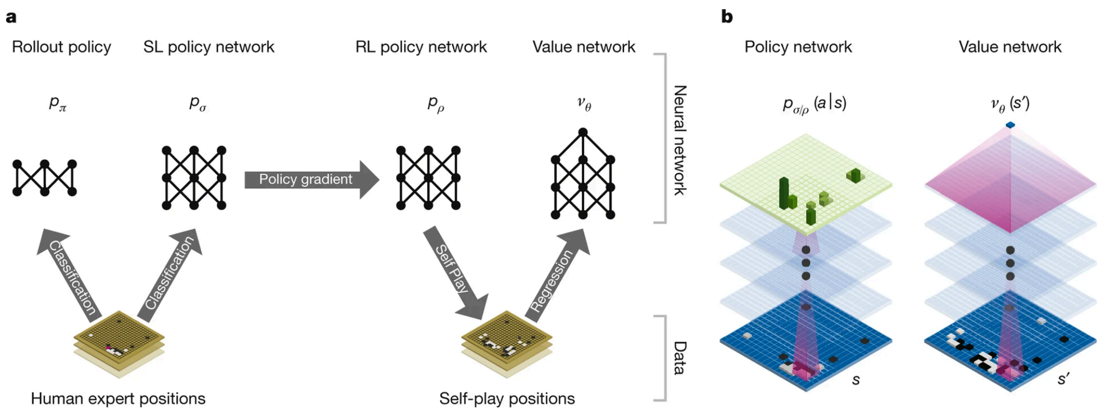
AlphaGo



(Figure from Silver et al. 2016)

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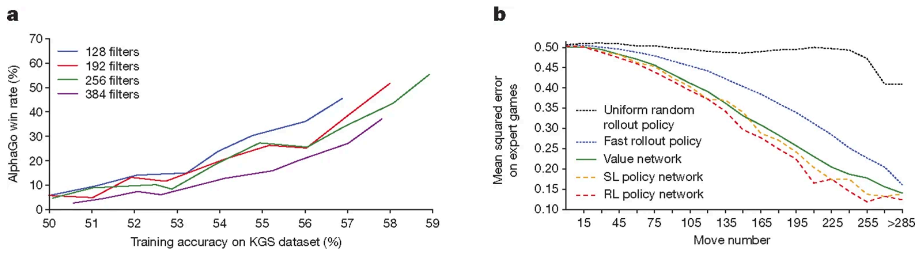
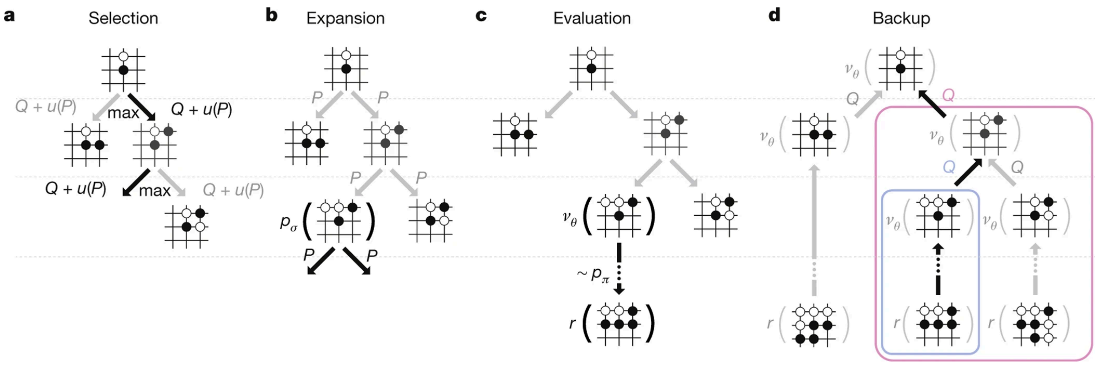
AlphaGo



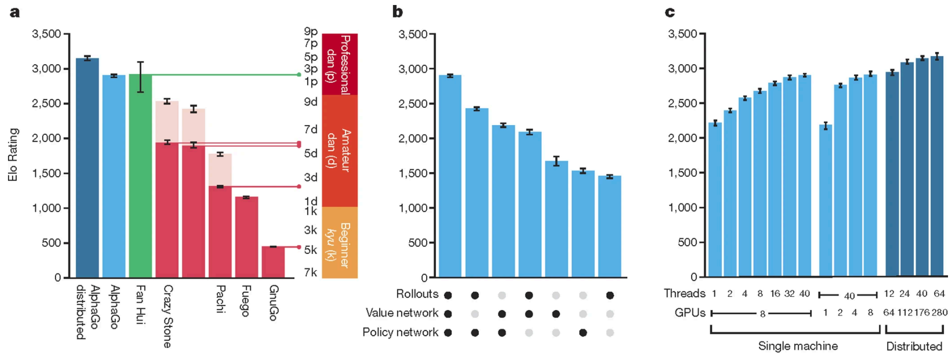
(Figure from Silver et al. 2016)

AlphaGo



(Figure from Silver et al. 2016)

AlphaGo



(Figure from Silver et al. 2016)

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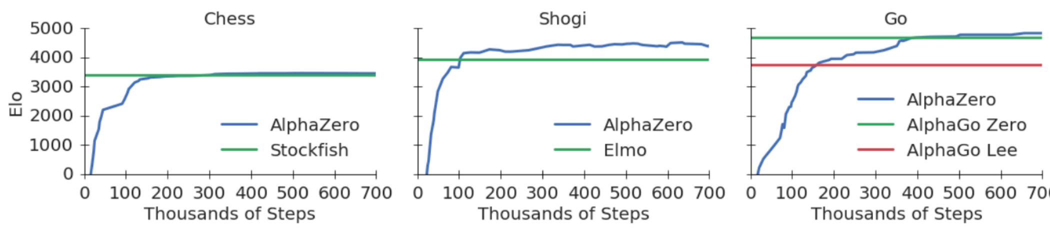
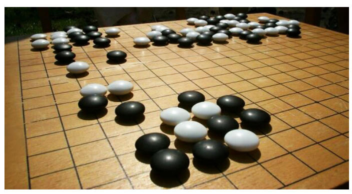
AlphaZero



https://en.wikipedia.org/wiki/chess

https://en.wikipedia.org/wiki/shogi



Figures from https://da.wikipedia.org/wiki/Go

(Figure from Silver et al. 2017)

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Cognitive computational neuroscience

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Neural networks as models

"Understanding the brain requires that we develop theory and experiment in tandem and complement the bottom-up, data-driven approach by a top-down, theory-driven approach that starts with behavioral functions to be explained"

(Kriegeskorte & Douglas, 2018, p. 1157)

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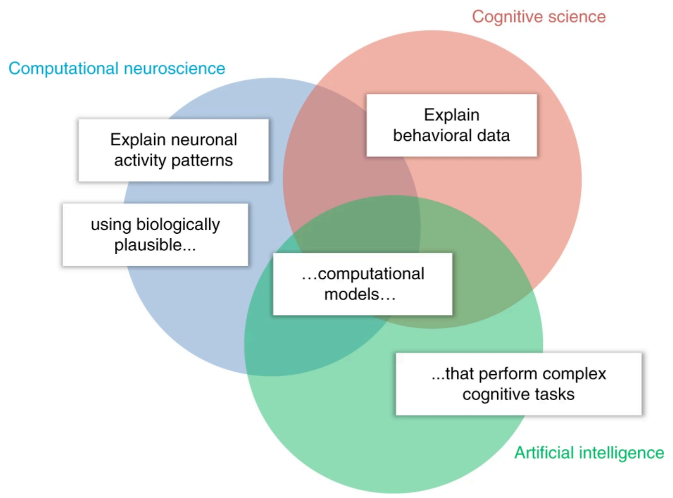
Cognitive computational neuroscience



(Figures from Kriegeskorte & Douglas 2018)

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Models

- Data-analysis models
- Effective connectivity; Causal-interaction models
- Box-and-arrow model
- Word model
- Oracle mode
- Brain-computational model (BCM)
- Reinforcement learning models
- Sensory encoding model
- Internal-transformation model
- Behavioral decoding model
- Psychophysical models
- Cognitive models
- Model is used to refer to models of the world employed by the brain

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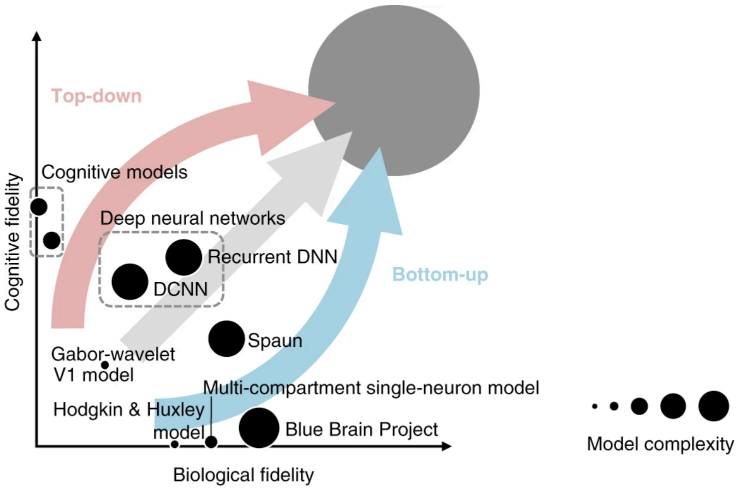
Models



(Figures from Kriegeskorte & Douglas, 2018)

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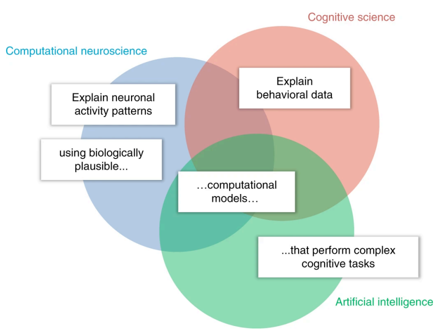
Marr's levels of analysis

1) Computational theory
2) Representation and algorithm; and
3) Neurobiological implementation



- "**Cognitive science** starts from computational theory, decomposing cognition into components and developing representations and algorithms from the top down."
- "**Computational neuroscience** proceeds from the bottom up, composing neuronal building blocks into representations and algorithms thought to be useful components in the context of the brain's overall function."
- "**AI** builds representations and algorithms that combine simple components to implement complex feats of intelligence."

(Kriegeskorte & Douglas 2018, p. 1157)

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Yamins & DiCarlo 2016

PERSPECTIVE FOCUS ON NEURAL COMPUTATION AND THEORY

nature neuroscience

Using goal-driven deep learning models to understand sensory cortex

Daniel L K Yamins[1,2] & James J DiCarlo[1,2]

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Using goal-driven deep learning models…

"The goal–driven approach is inspired by the idea that, whatever parameters are used, a neural network will have to be effective at solving the behavioral tasks the sensory system supports to be a correct model of a given sensory system."

(Yamins & DiCarlo, 2016, p. 359)

Figure from Yamins & DiCarlo (2016)

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Using goal-driven deep learning models…

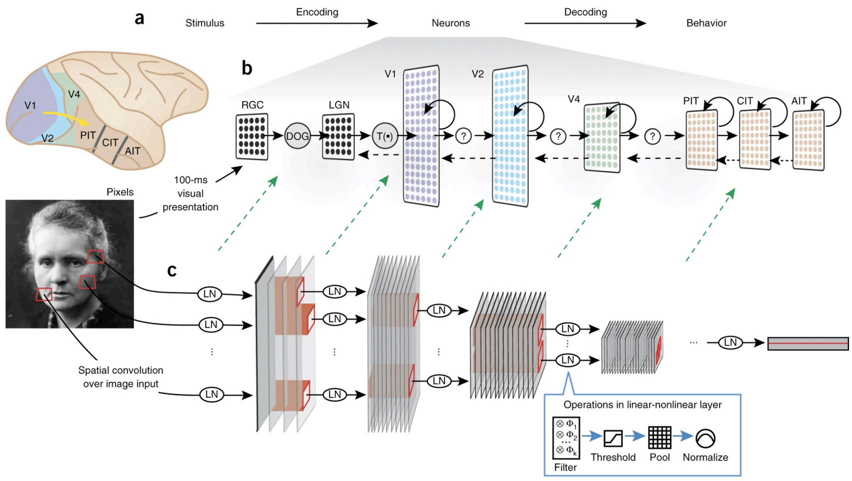

Figure from Yamins & DiCarlo (2016)

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Using goal-driven deep learning models…

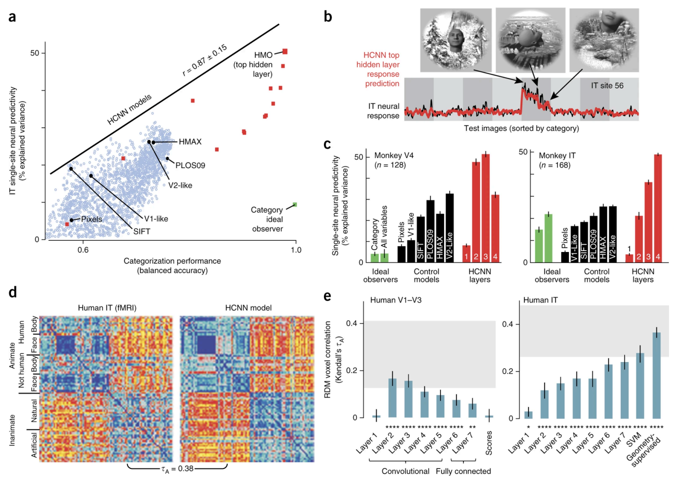

Figure from Yamins & DiCarlo (2016)

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Using goal-driven deep learning models…

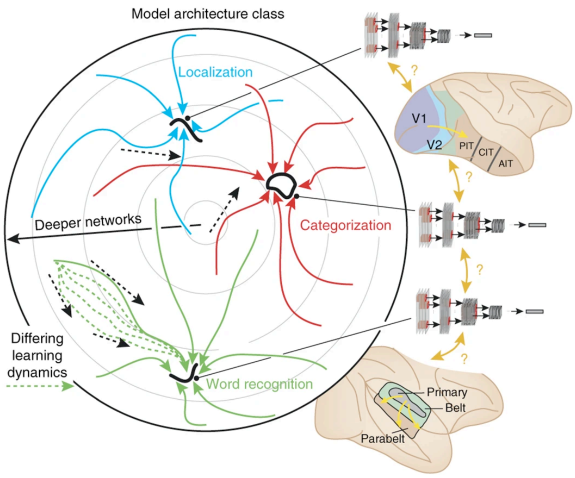

Figure from Yamins & DiCarlo (2016)

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Generative Adversarial Networks

"The main focus for GAN (Generative Adversarial Networks) is to generate data from scratch"

(From *GAN — What Is Generative Adversarial Networks GAN?*, 2018)

https://jonathan-hui.medium.com/gan-whats-generative-adversarial-networks-and-its-application-f39ed278ef09

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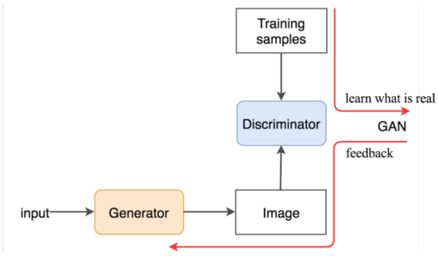
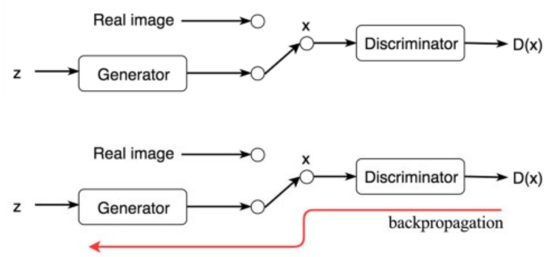
Generative Adversarial Networks





(Figures from *GAN — What Is Generative Adversarial Networks GAN?*, 2018)

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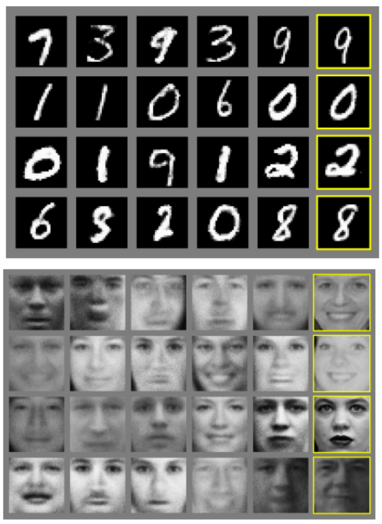
Generative Adversarial Networks



(Figures from Goodfellow et al., 2014)

(Figures from Karras et al., 2018)

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Lawhern et al. 2016

IOP Publishing — Journal of Neural Engineering
J. Neural Eng. 15 (2018) 056013 (17pp) — https://doi.org/10.1088/1741-2552/aace8c

EEGNet: a compact convolutional neural network for EEG-based brain–computer interfaces

Vernon J Lawhern[1,5], Amelia J Solon[1,2], Nicholas R Waytowich[1,3], Stephen M Gordon[1,2], Chou P Hung[1,4] and Brent J Lance[1]

[1] Human Research and Engineering Directorate, U.S. Army Research Laboratory, Aberdeen Proving Ground, MD, United States of America
[2] DCS Corporation, Alexandria, VA, United States of America
[3] Department of Biomedical Engineering, Columbia University, New York, NY, United States of America
[4] Department of Neuroscience, Georgetown University, Washington, DC, United States of America

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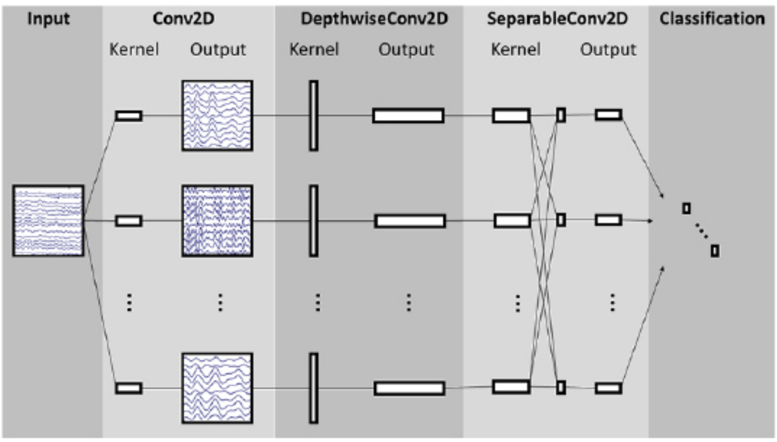
Neural network for EEG



(Figure from Lawhern et al., 2016)

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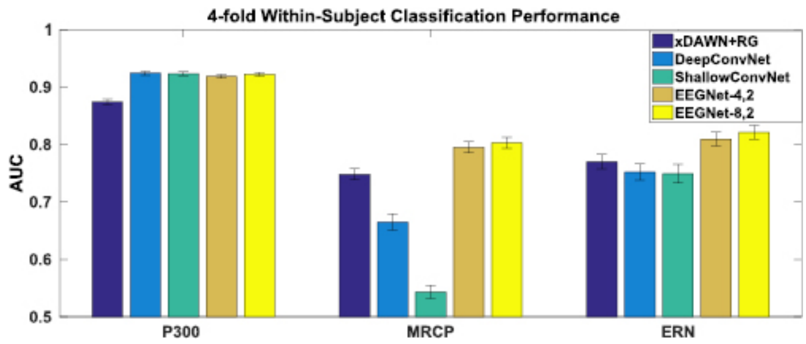
Neural network for EEG



(Figure from Lawhern et al., 2016)

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Topic(s) for last lecture?

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Questions?

1. Recurrent neural networks
2. Reinforcement learning
   1. Pong
   2. AlphaGo
3. Networks as models
4. Generative Adversarial Networks (GANs)
5. Neural network for EEG
6. Last lecturez

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