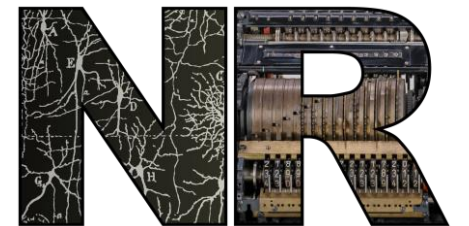
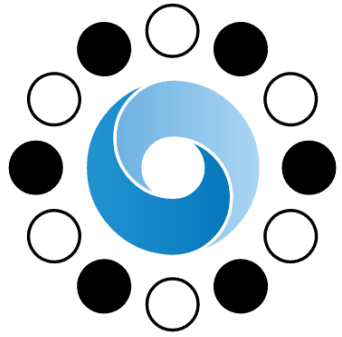


Challenges for ML and neuroscience



Challenges for ML: power efficiency



AlphaGo

AlphaGo

100 kW – 1 MW

5,000 – 50,000 human brains

AlphaGo Zero

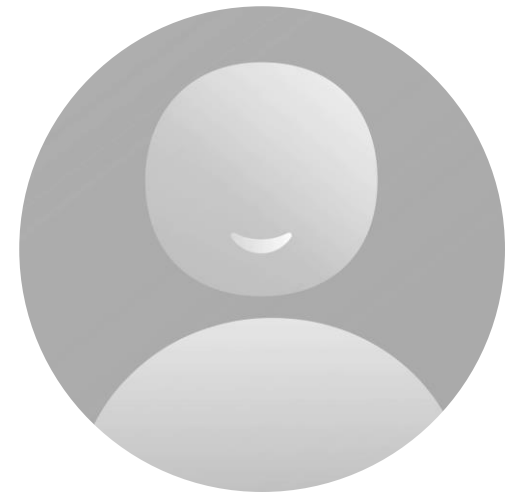
Claimed 1-2 kW

50 – 100 human brains

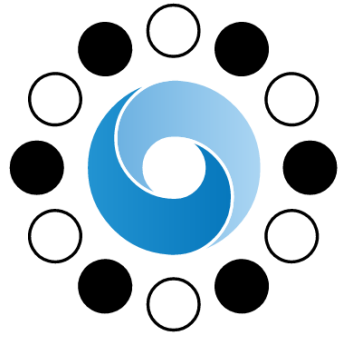


Lee Sedol

20 W



Challenges for ML: sample efficiency



AlphaGo

AlphaGo Zero

>5m games played



Lee Sedol

<50k games played

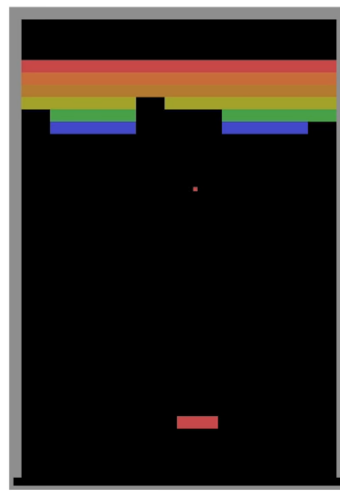


Challenges for ML: generalisation and re-use

Vicarious (2016)



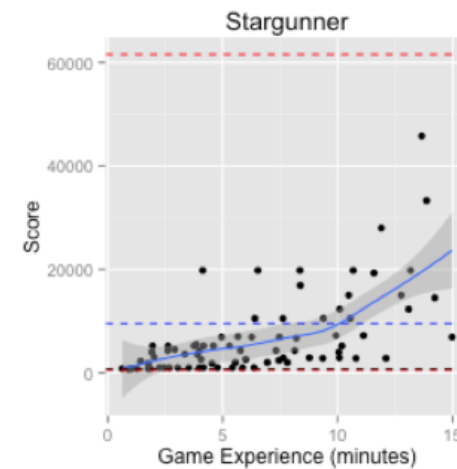
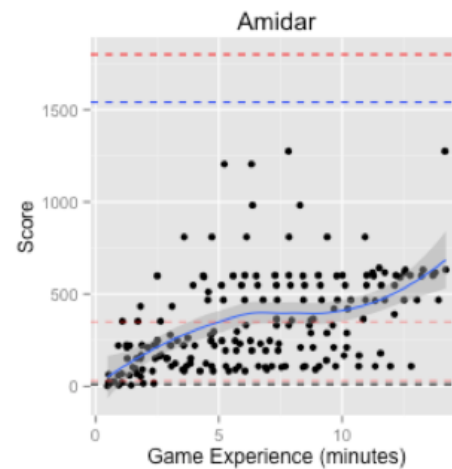
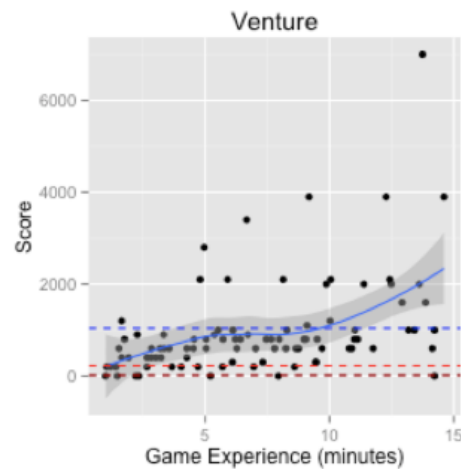
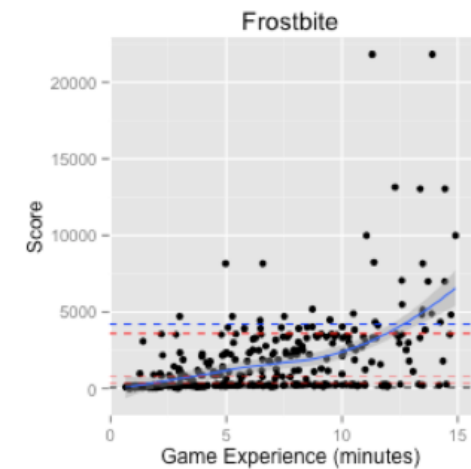
Normal



Higher paddle



Center wall



Tsividis et al. (2017)

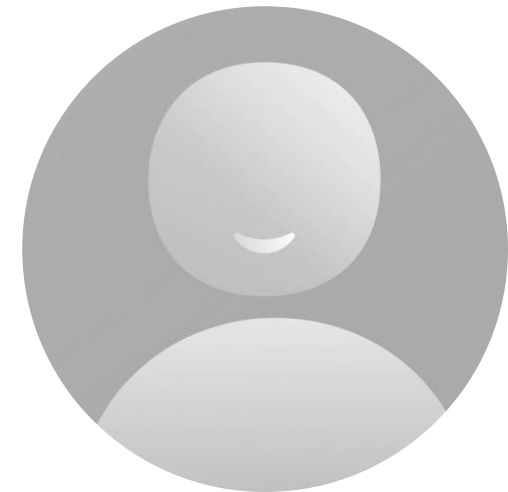


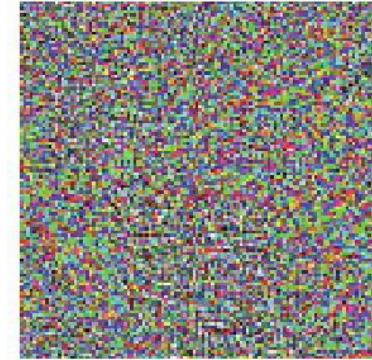
Figure 1: Human learning curves for four Atari games. Black horizontal line: random play. Blue horizontal line: ‘expert’ play. Red horizontal lines: DDQN after 10, 25, and 200 million frames of game-play experience (46, 115, and 920 hours, respectively).

Challenges for ML: robustness

[Goodfellow et al. \(2014\)](#)



+ 0.007 ×



=



$x + \epsilon \cdot \text{sign}[\nabla_x J(\theta, x, y)]$
 “Gibbon”
 99.3% confidence

$\text{sign}[\nabla_x J(\theta, x, y)]$
 “Nematode”
 8.2% confidence

x
 “Panda”
 57.7% confidence

(b) Content image
 71.1% **tabby cat**
 17.3% grey fox
 3.3% Siamese cat

(a) Texture image
 81.4% **Indian elephant**
 10.3% indri
 8.2% black swan



[Geirhos et al. \(2019\)](#)

(c) Texture-shape cue conflict
 63.9% **Indian elephant**
 26.4% indri
 9.6% black swan

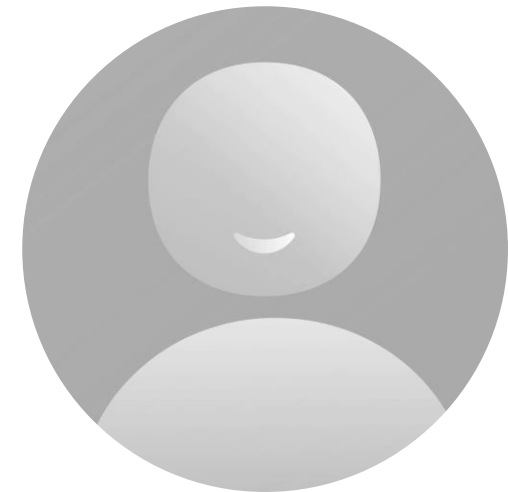


Granny Smith	85.6%
iPod	0.4%
library	0.0%
pizza	0.0%
toaster	0.0%
dough	0.1%

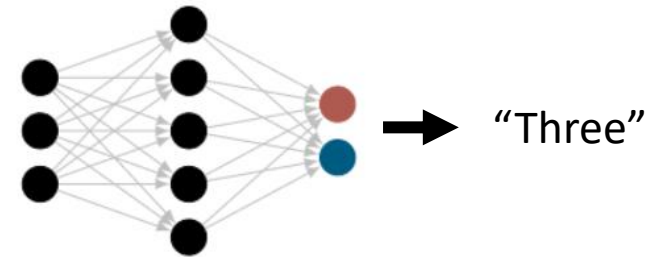
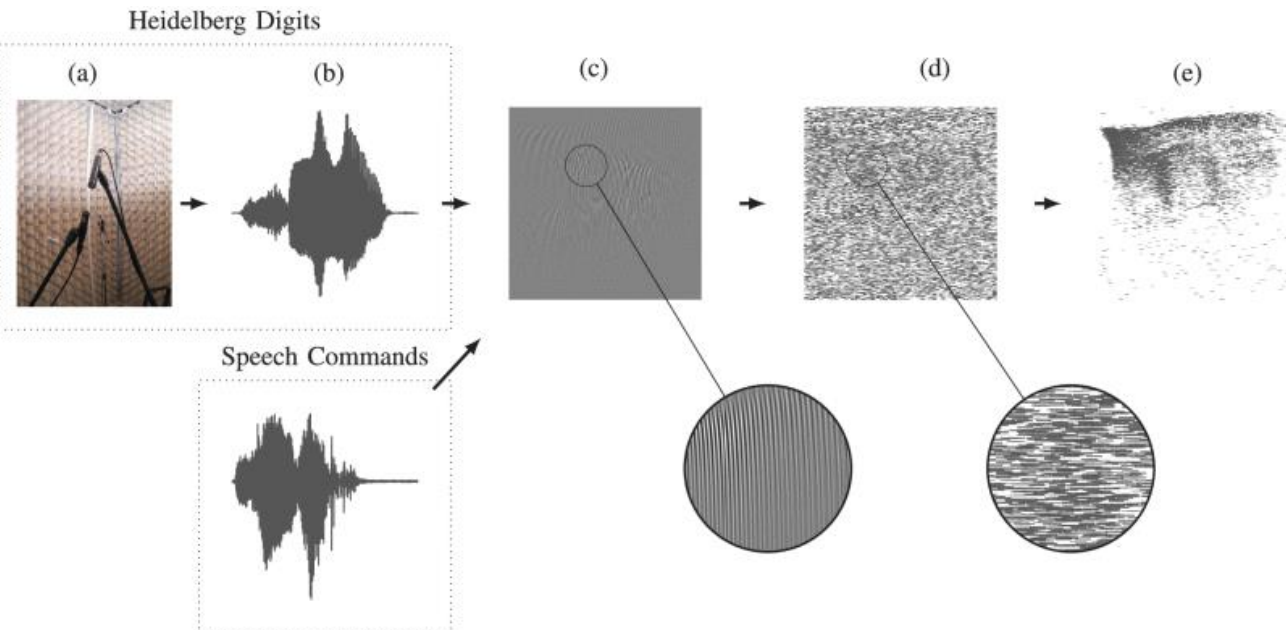
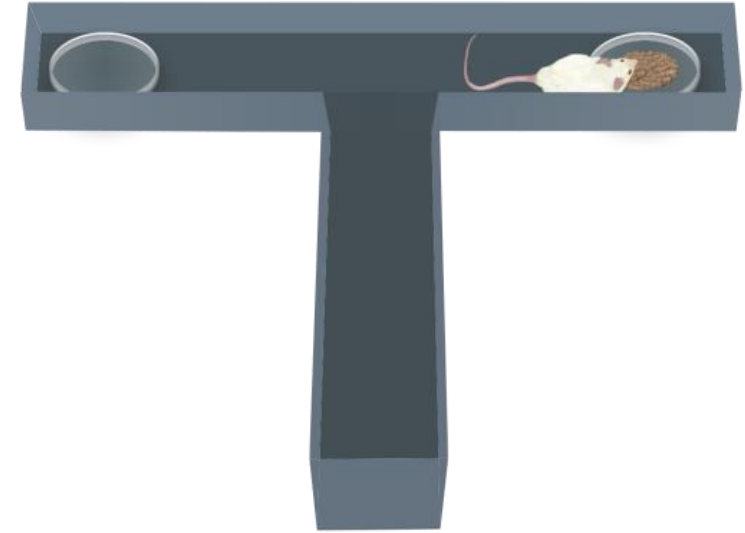
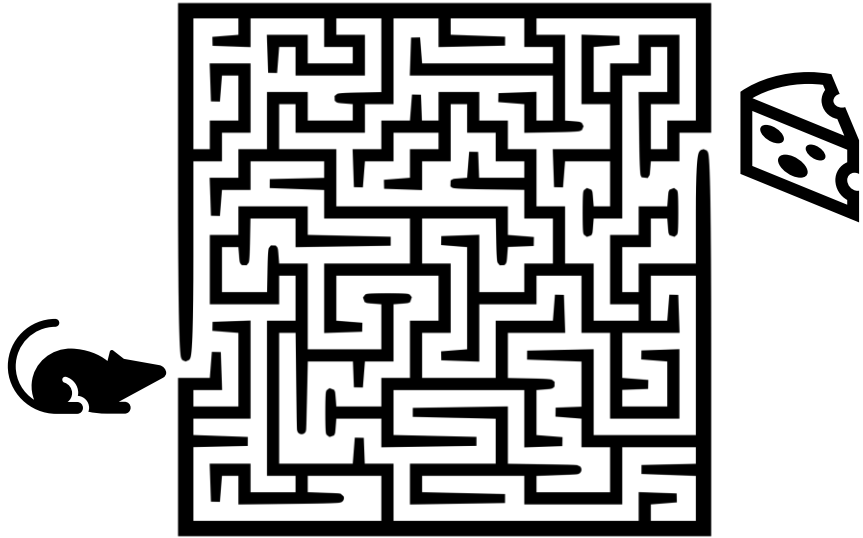


Granny Smith	0.1%
iPod	99.7%
library	0.0%
pizza	0.0%
toaster	0.0%
dough	0.0%

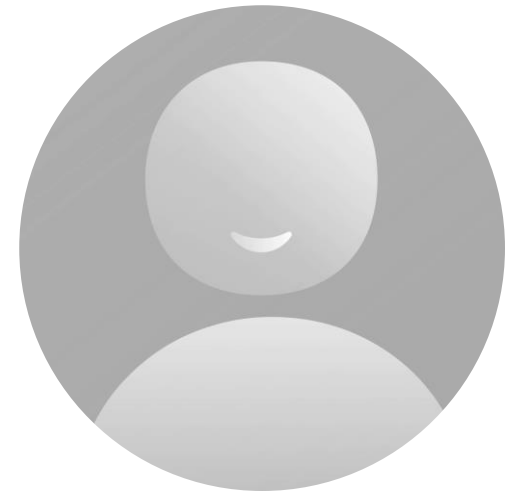
<https://openai.com/research/multimodal-neurons>



Challenges for neuroscience



[Cramer et al. \(2022\)](#)





Neuroscience ❤️ ML
A beautiful future?