Class Discussion

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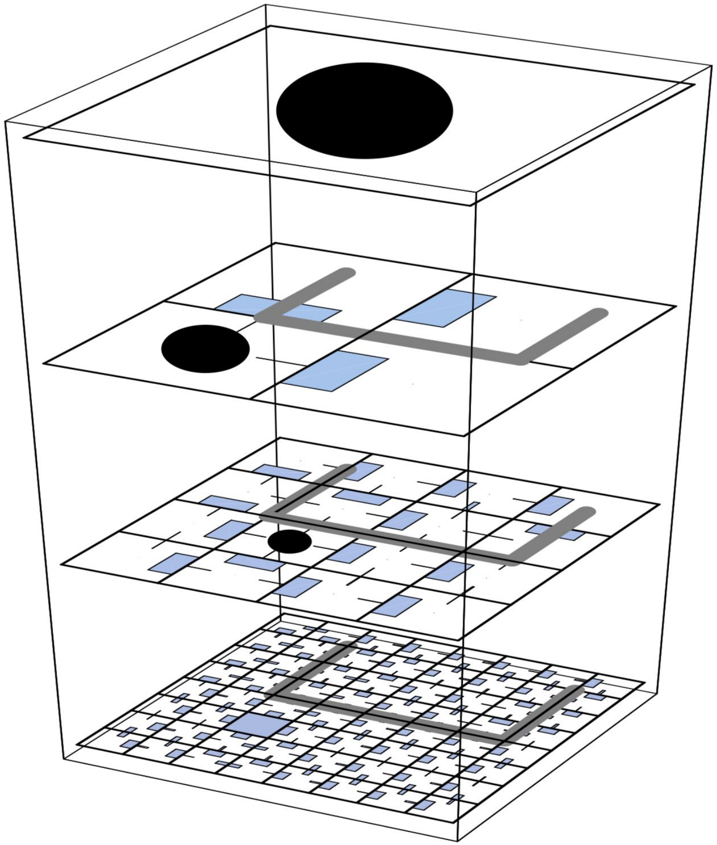
Problems with contemporary machine learning

- Sample Efficiency
- Scaling Up
- Generalization

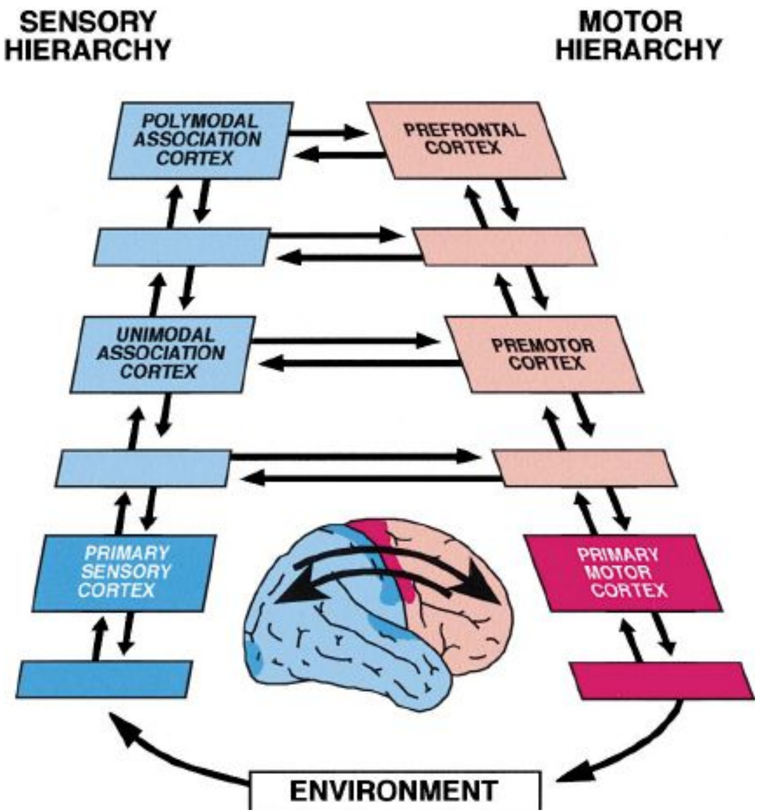
Content

1. Hierarchical Planning
2. Analogical Reasoning vs. Brute Force Search
3. Meta-learning / One-shot learning with complex workflows

Hierarchical Planning

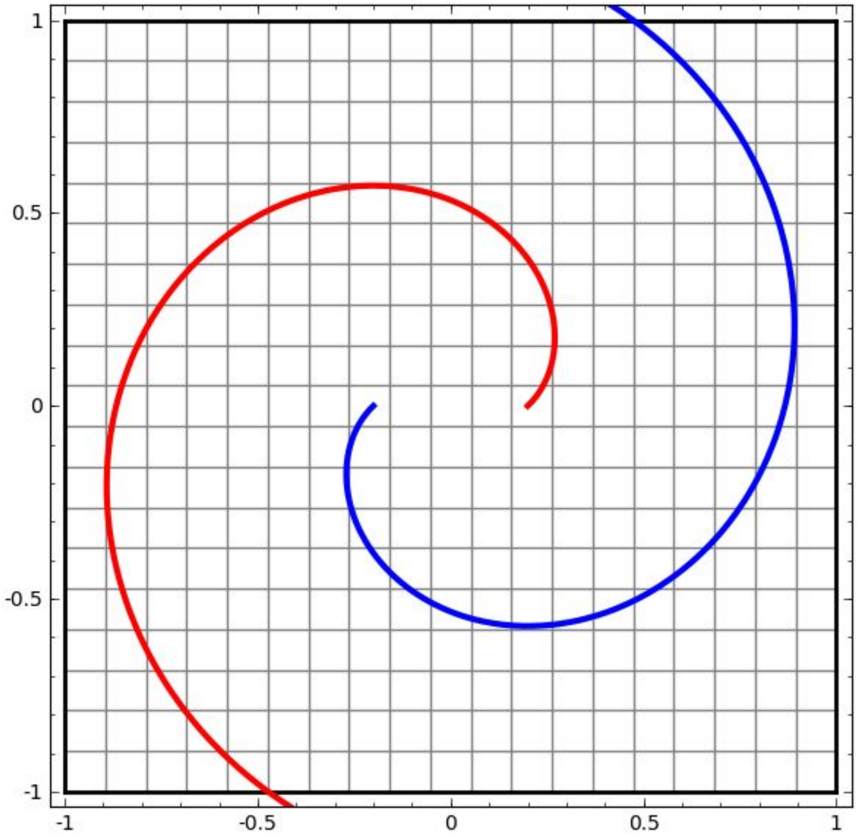


Feudal Reinforcement Learning (Dayan & Hinton 1992)

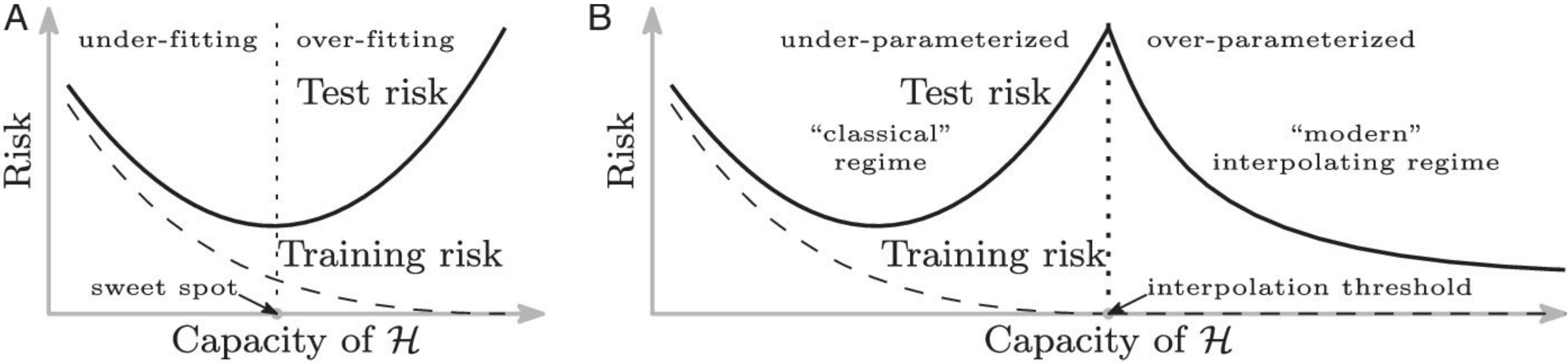


Fuster’s Hierarchy (Fuster, Joaquin 2001)

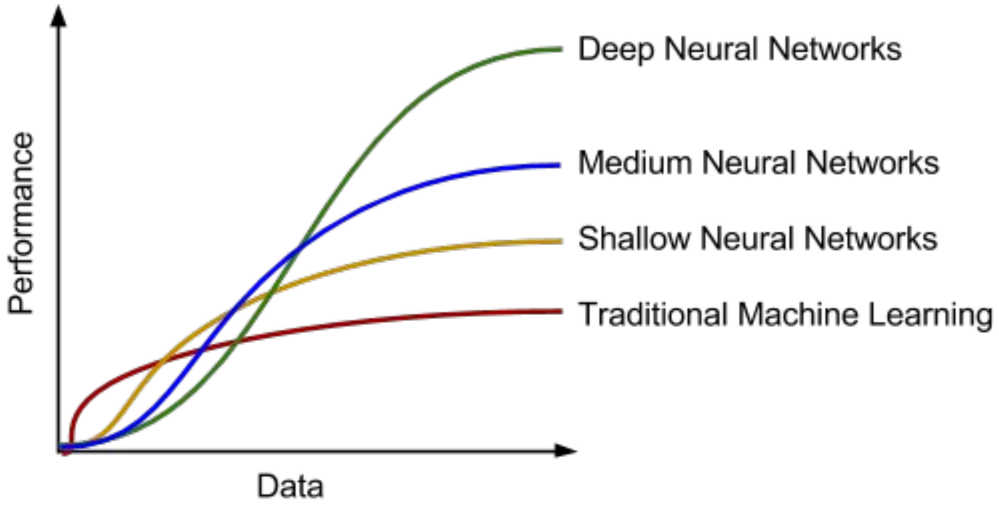
https://xkcd.com/1838/



[Neural Networks, Manifolds, and Topology (Olah 2014)]



(Belkin et. al. 2019)



[Sample complexity of machine learning algorithms]

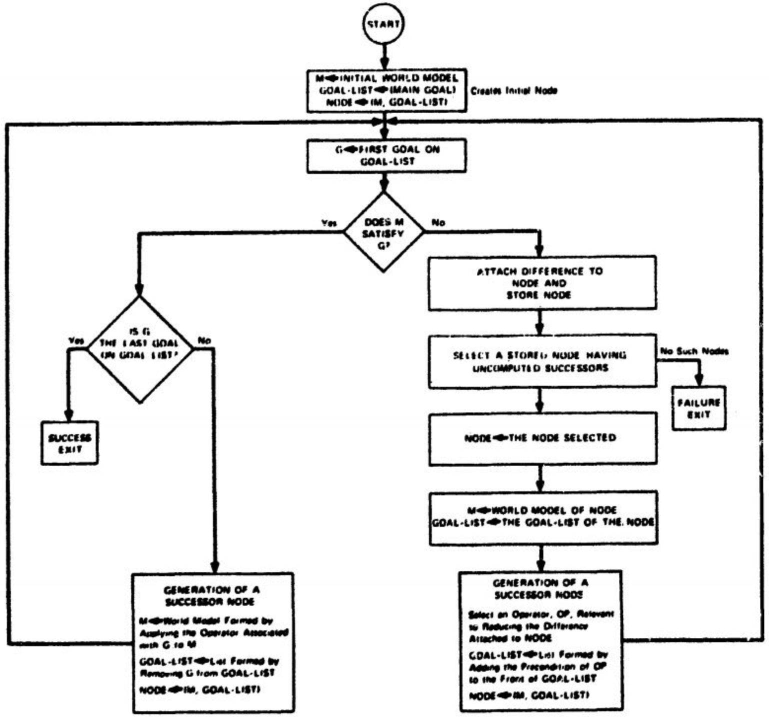
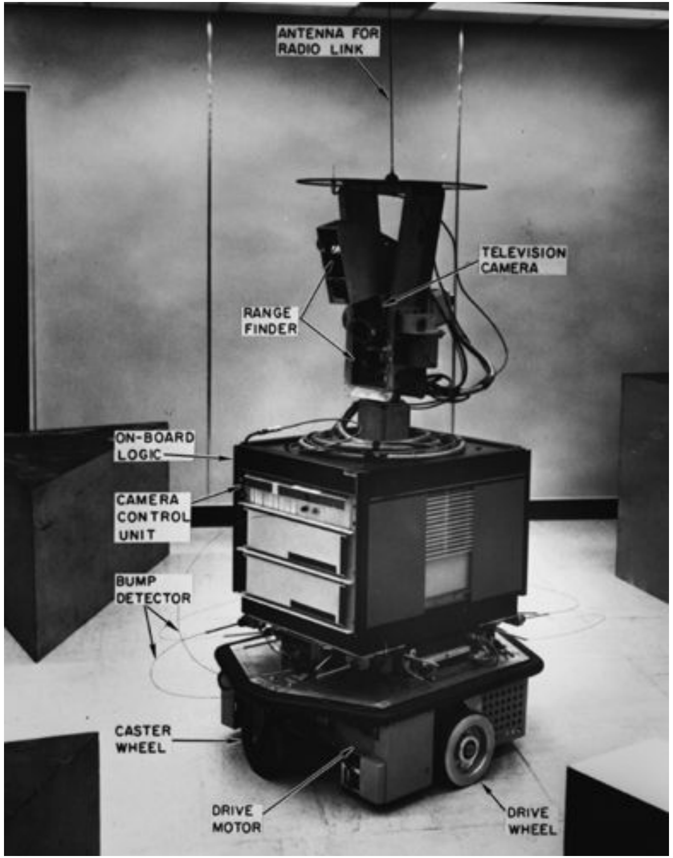
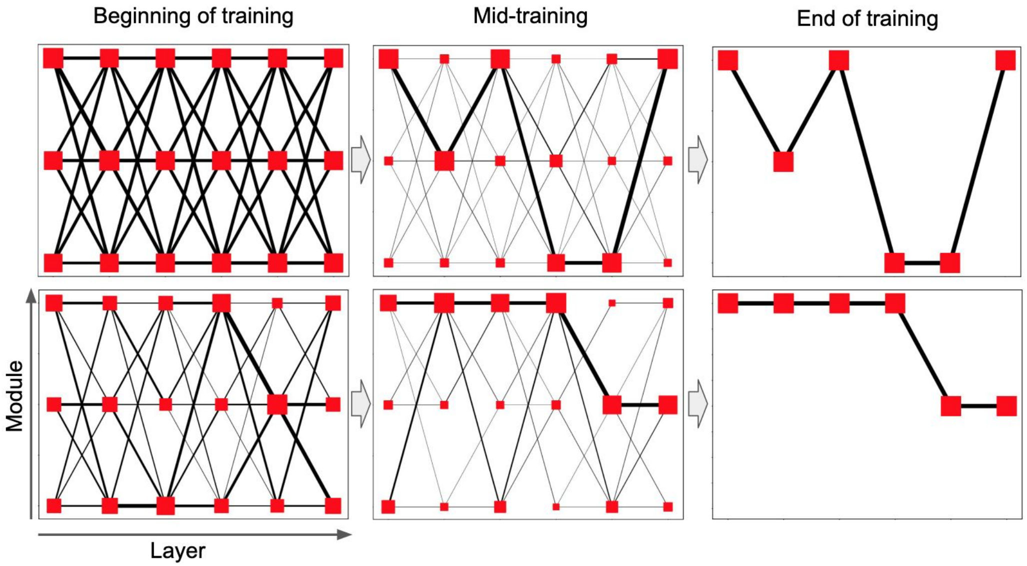


FIG. 2. Flow chart for STRIPS.



STRIPS (Fikes & Nilsson 1971) SHAKEY



Smooth, Robust Decomposition (Kirsch et. al. 2018)

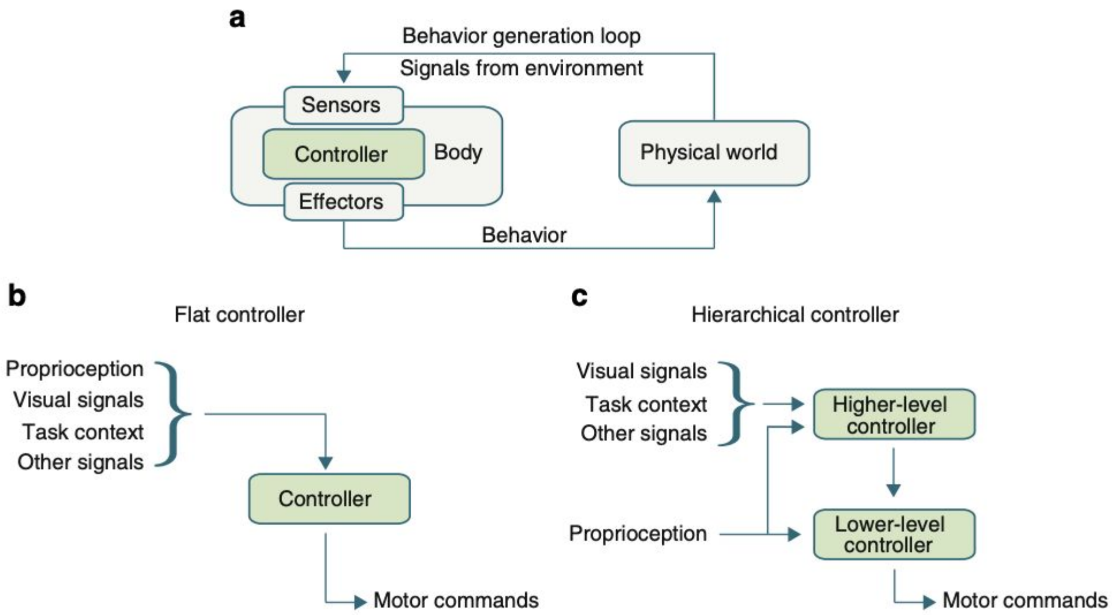
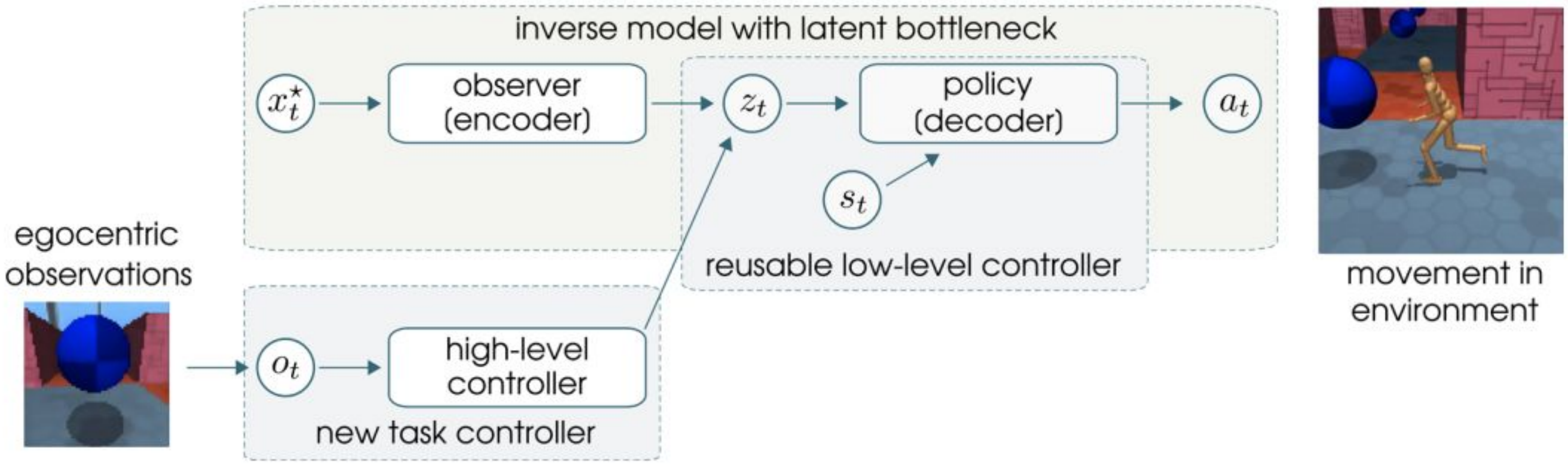


Fig. 1 a Interaction cycle between an embodied control system and a physical environment to generate behavior. **b** A flat controller with no architectural segregation of different inputs. **c** A basic, brain-inspired two-stage hierarchy: a lower-level motor controller directly generates motor commands to the effectors based on input from proprioceptive sensors and modulatory input from a higher-level controller, which is responsive to additional signals, including vision and task context signals.

(Merel et. al. 2017)



(Merel et. al. 2017)

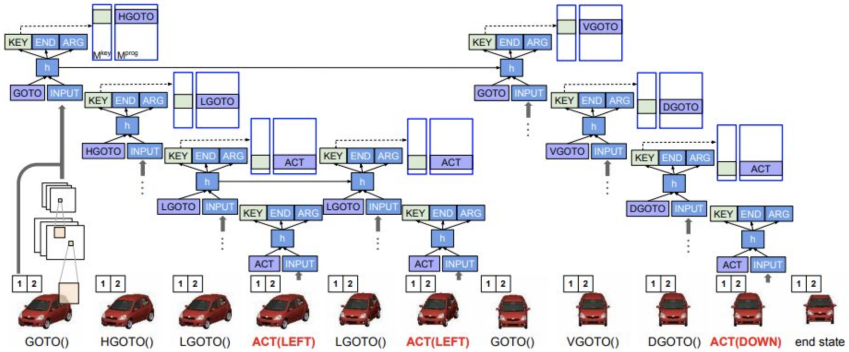


Figure 1: Example execution of canonicalizing 3D car models. The task is to move the camera such that a target angle and elevation are reached. There is a read-only scratch pad containing the target (angle 1, elevation 2 here). The image encoder is a convnet trained from scratch on pixels.

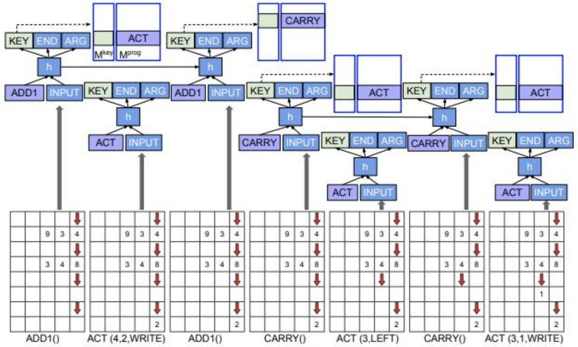


Figure 2: Example execution trace of single-digit addition. The task is to perform a single-digit add on the numbers at pointer locations in the first two rows. The carry (row 3) and output (row 4) should be updated to reflect the addition. At each time step, an observation of the environment (viewed from each pointer on a scratch pad) is encoded into a fixed-length vector.

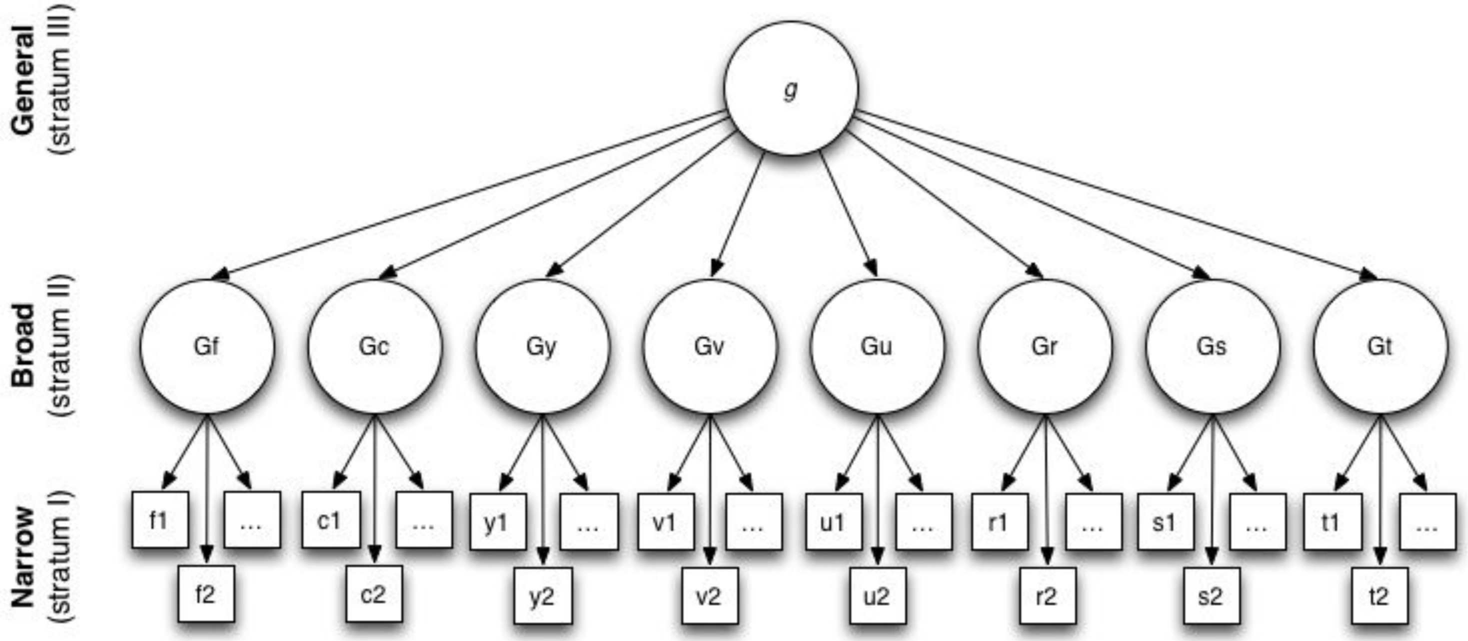
(Reed & Freitas 2016)

Analogical Reasoning
v.s.
Brute Force Search

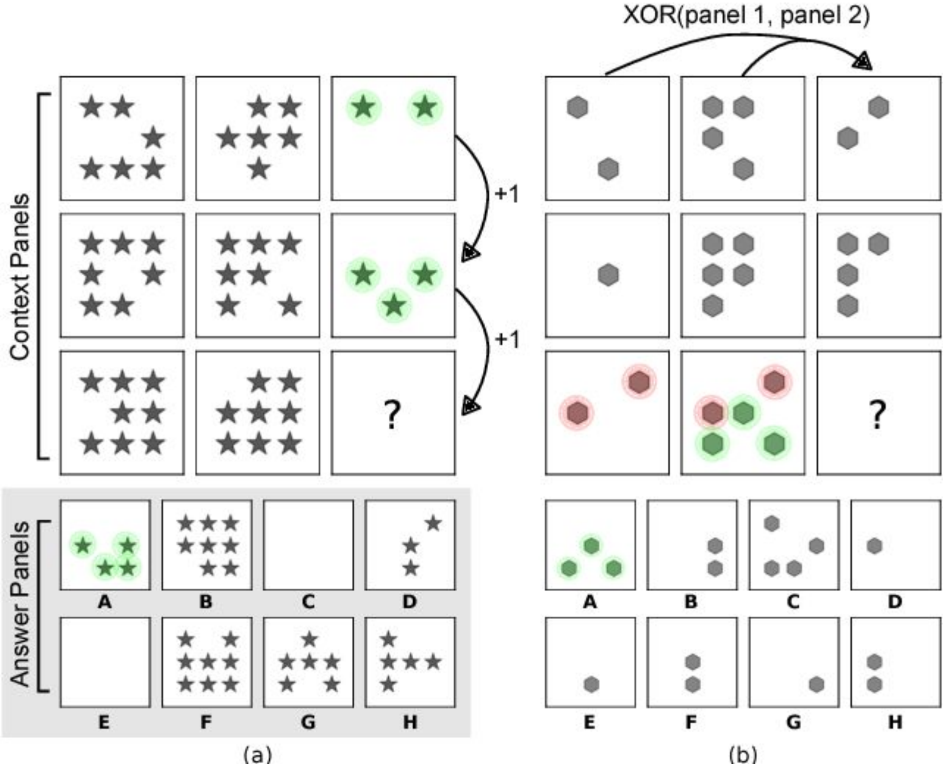
Carl Friedrich Gauss

In the 1780s a provincial German schoolmaster gave his class the tedious assignment of summing the first 100 integers. The teacher's aim was to keep the kids quiet for half an hour, but one young pupil almost immediately produced an answer: $1 + 2 + 3 + ... + 98 + 99 + 100 = 5{,}050$. The smart aleck was Carl Friedrich Gauss, who would go on to join the short list of candidates for greatest mathematician ever. Gauss was not a calculating prodigy who added up all those numbers in his head. He had a deeper insight: If you "fold" the series of numbers in the middle and add them in pairs—$1 + 100$, $2 + 99$, $3 + 98$, and so on—all the pairs sum to 101. There are 50 such pairs, and so the grand total is simply 50×101. The more general formula, for a list of consecutive numbers from 1 through n, is $n(n + 1)/2$.

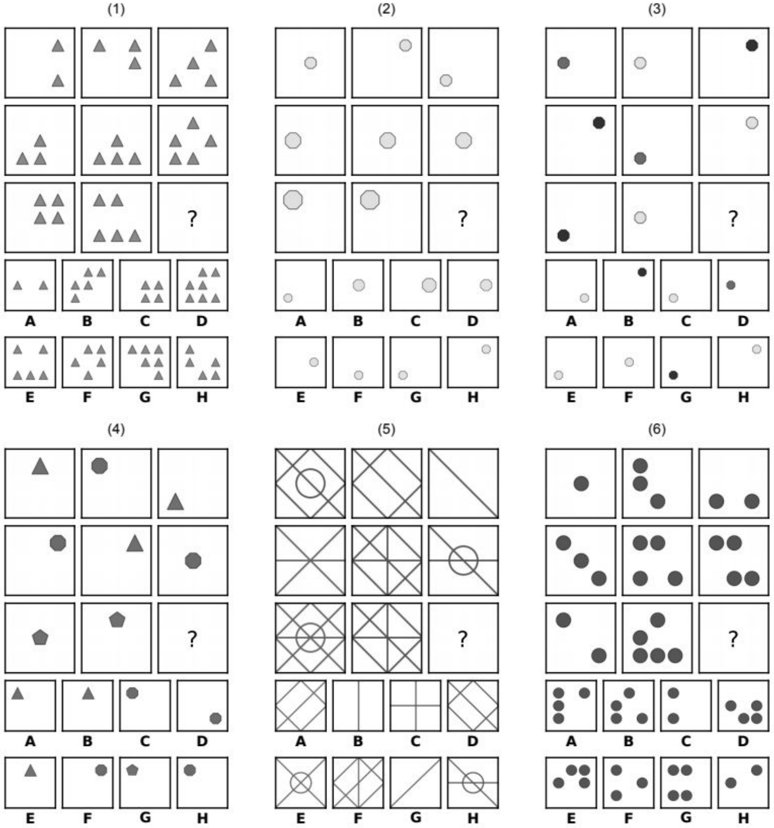
– [Gauss's Day of Reckoning]



[G Factor (Psychometrics)]



Raven’s Progressive Matrices (Santoro et. al. 2018)



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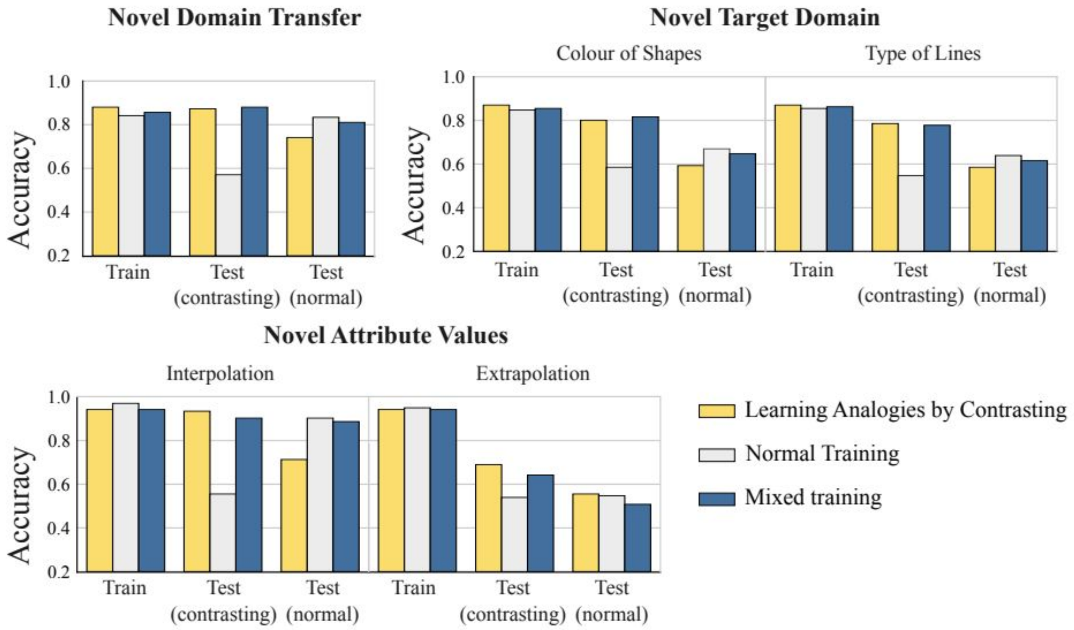
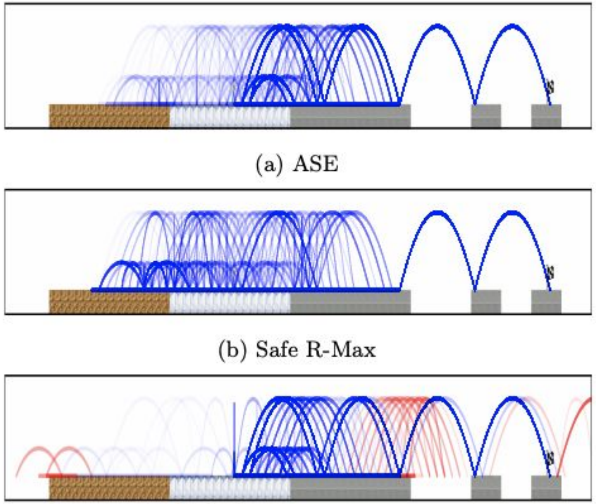


Figure 4: **Results of the three experiments in the visual analogy domain for a network that learns from random candidate answers, by contrasting abstract structures or both types of question interleaved.** Bar heights depict the means across eight seeds in each condition; standard errors were < 0.01 for each condition (not shown – see the appendix Table 4 for the values)

(Hill et. al. 2019)



(a) ASE

(b) Safe R-Max

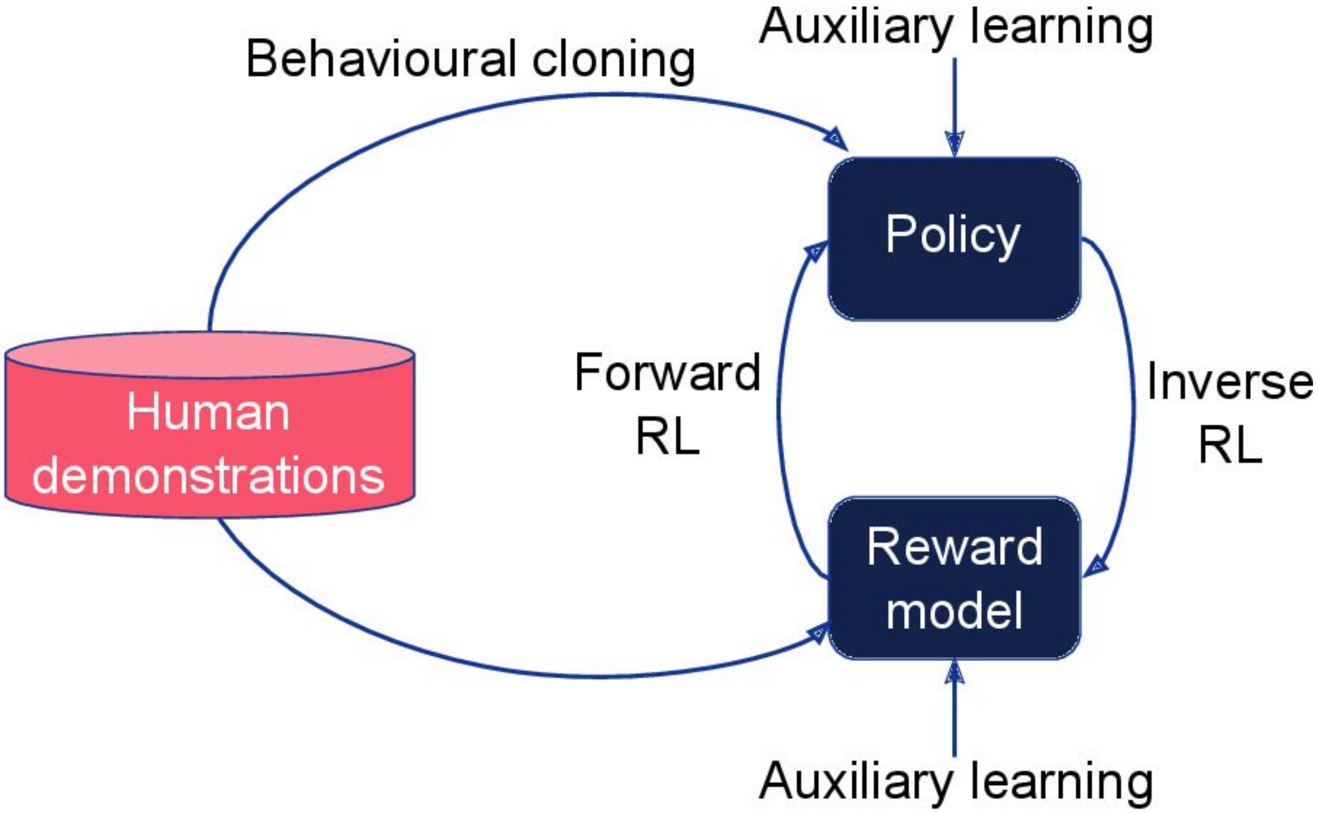
(c) MBIE (unsafe)

Figure 2: All trajectories of different agents on the Discrete Platformer domain. Unsafe trajectories are drawn in red. The brown, white, and grey squares correspond to the different surface types: sand, ice, and concrete, respectively. The agent starts in the center of the leftmost island. The flag represents the goal state.

(Roderick et. al. 2021)

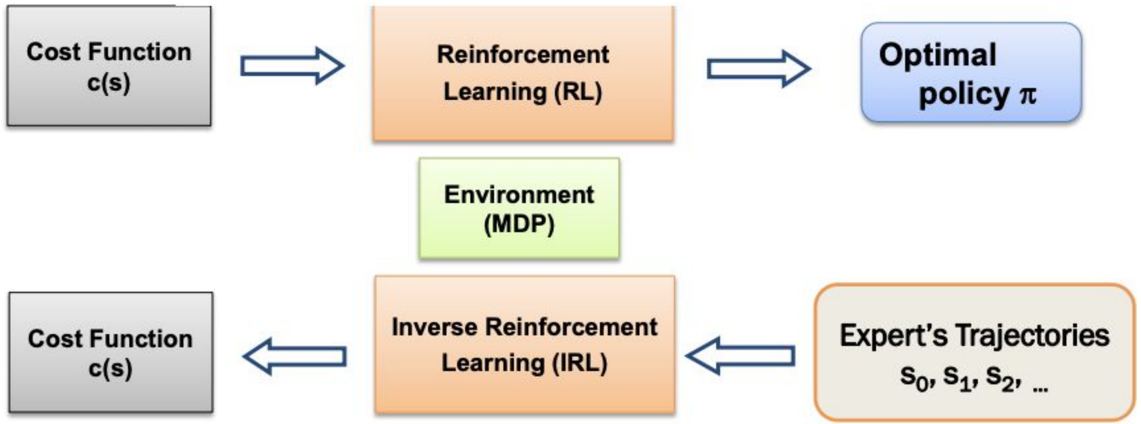
Meta-learning / One-shot-learning with Complex Workflows.

Children have inductive biases for curiosity, homeostasis, and imitation among others. The environment provides affordances for these rewards that the teacher can manipulate to teach the child.



(Abramson et. al. 2020)

$$\mathrm{RL}(c) = \underset{\pi\in\Pi}{\arg\min} -H(\pi) + \mathbb{E}_\pi[c(s,a)]$$



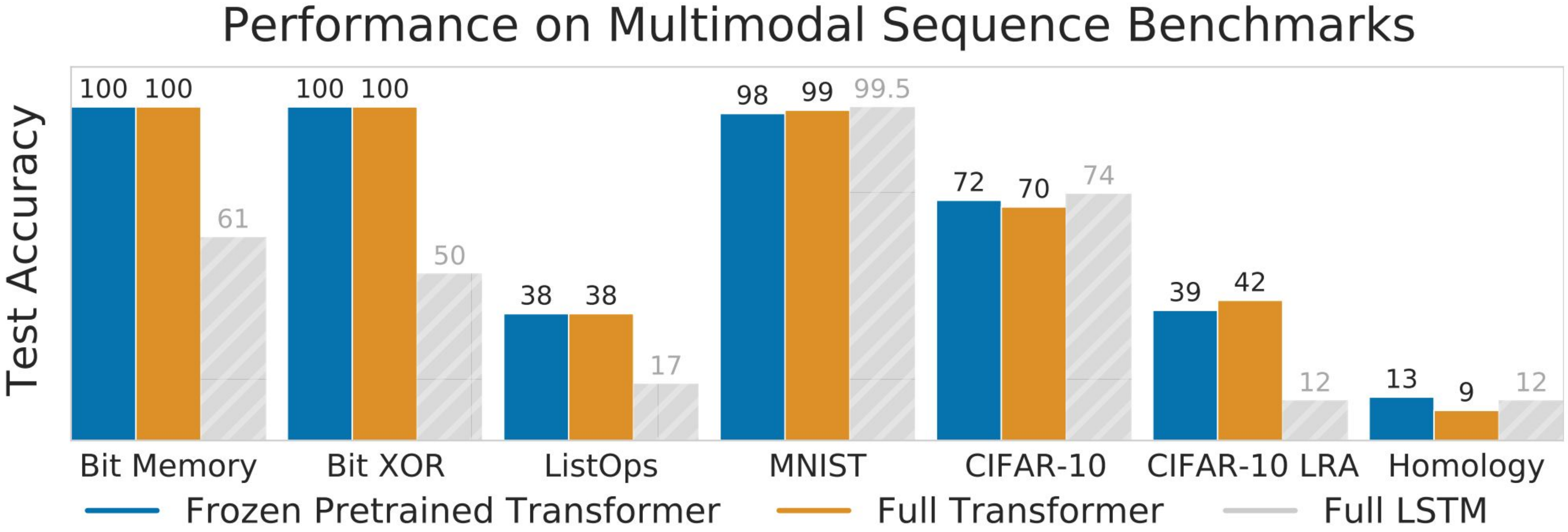
$$\underset{c\in\mathcal{C}}{\text{maximize}} \left(\min_{\pi\in\Pi} -H(\pi) + \mathbb{E}_\pi[c(s,a)] \right) - \mathbb{E}_{\pi_E}[c(s,a)]$$

Everything else has high cost

Expert has small cost

(Ziebart et al., 2010; Rust 1987)

(Ho, J., & Ermon, S. 2016)



Performance on Multimodal Sequence Benchmarks
Test Accuracy
100 100 61
100 100 50
38 38 17
98 99 99.5
72 70 74
39 42 12
13 9 12
Bit Memory
Bit XOR
ListOps
MNIST
CIFAR-10
CIFAR-10 LRA
Homology
Frozen Pretrained Transformer
Full Transformer
Full LSTM

(Lu et. al. 2021)

Thank you

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