Machine Learning

Learning to learn within the bigger picture

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Lecture Overview

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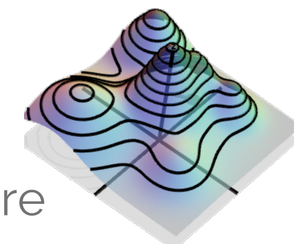
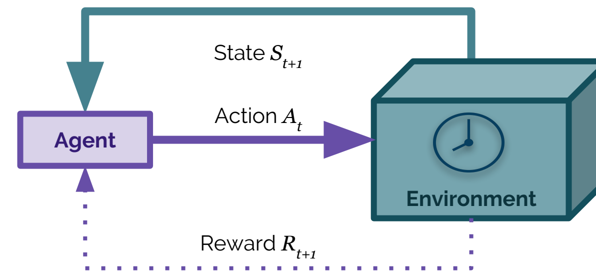
Recap

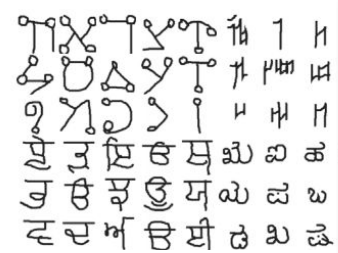
- Manifold Learning
- Reinforcement learning
- ….all the way back to learning in nature





Today's lecture

- Taking a step back
- Meta-learning (or learning to learn)
  - A field of machine learning still in its infancy
- Concepts
- Approaches and recent algorithms



A Big Distribution of Data

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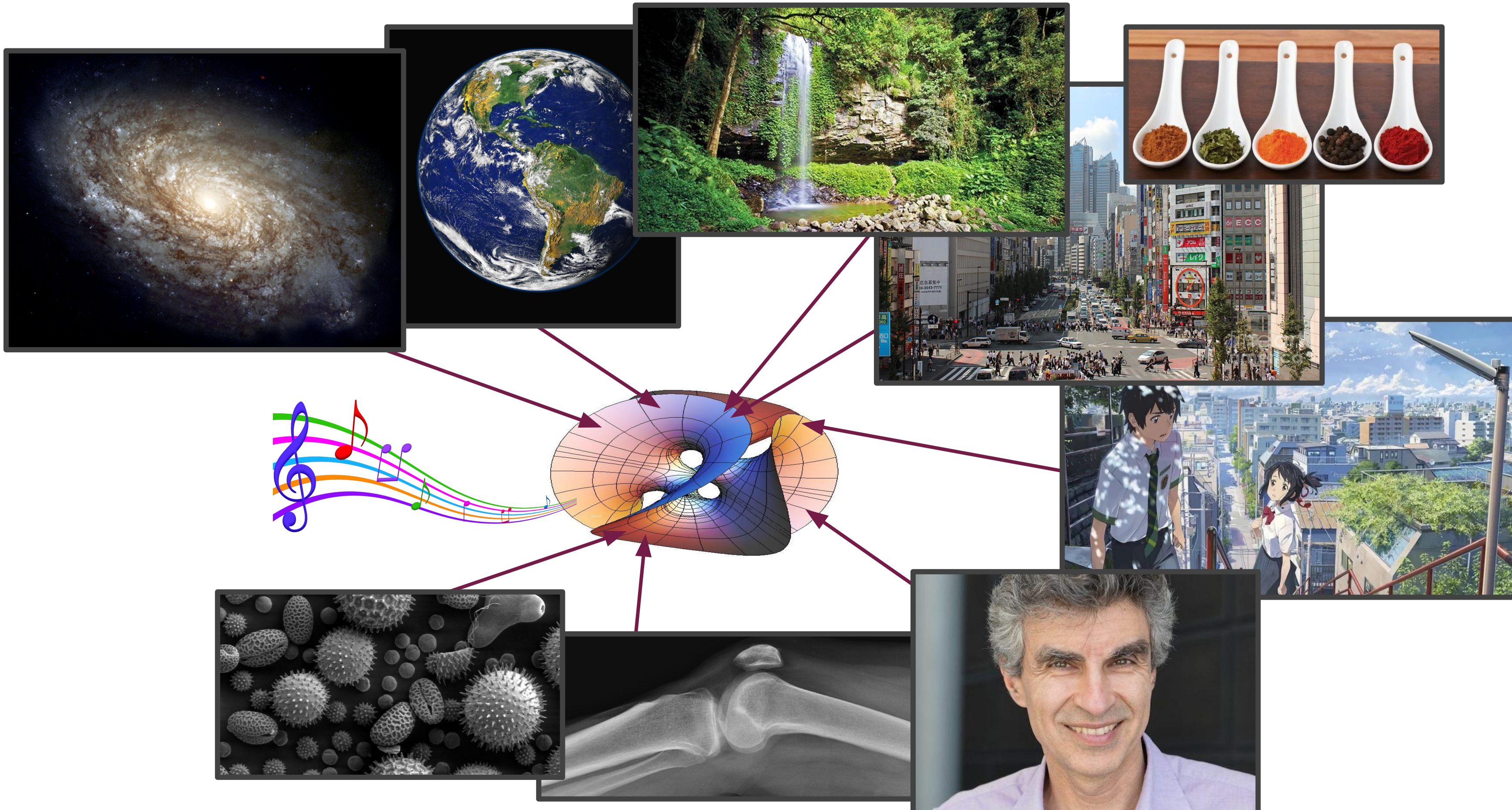
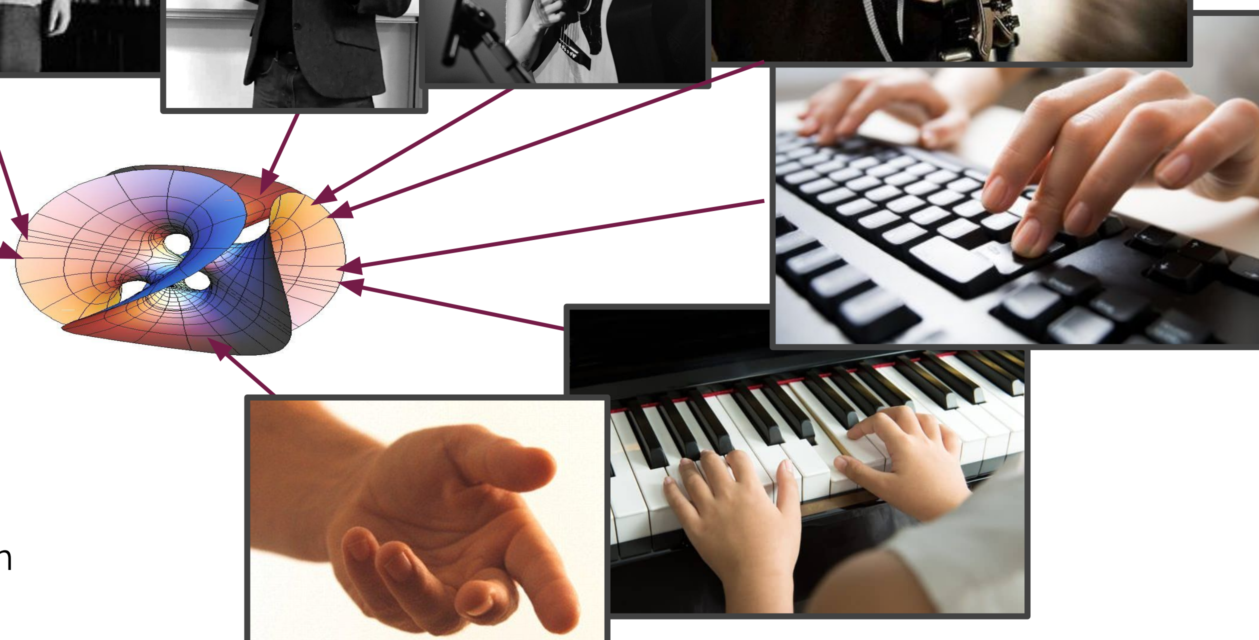


A Big Distribution of Tasks



Learning to learn to...

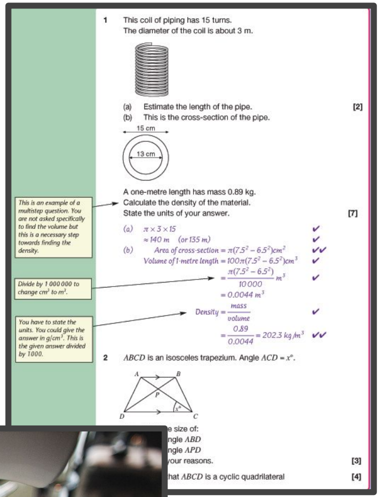
- move our fingers
- play music, type
- sing, talk
- ...
- think like Einstein & Hinton

A Big Distribution of Tasks

- What is this?
- What do you do with it?

Can we generalise to unseen tasks and unseen data?

Solve, comprehend, ...



1 This coil of piping has 15 turns.
The diameter of the coil is about 3 m.

(a) Estimate the length of the pipe. [2]
(b) This is the cross-section of the pipe.

15 cm
13 cm

A one-metre length has mass 0.89 kg.
Calculate the density of the material.
State the units of your answer. [7]

This is an example of a multistep question. You are not asked specifically to find the volume but this is a necessary step towards finding the density.

(a) $\pi \times 3 \times 15$ ✔
≈ 140 m (or 135 m) ✔
(b) Area of cross-section $= \pi(7.5^2 - 6.5^2)\text{cm}^2$ ✔✔
Volume of 1-metre length $= 100\pi(7.5^2 - 6.5^2)\text{cm}^3$ ✔
$= \frac{\pi(7.5^2 - 6.5^2)}{10000}\text{m}^3$ ✔
$= 0.0044\ \text{m}^3$

Divide by 1 000 000 to change cm^3 to m^3.

Density $= \frac{\text{mass}}{\text{volume}}$ ✔
$= \frac{0.89}{0.0044} = 202.3\ \text{kg/m}^3$ ✔✔

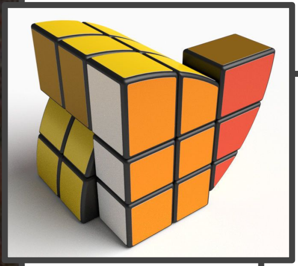
You have to state the units. You could give the answer in g/cm^3. This is the given answer divided by 1000.

2 $ABCD$ is an isosceles trapezium. Angle $ACD = x°$.

e size of:
ngle ABD
ngle APD
your reasons. [3]
hat $ABCD$ is a cyclic quadrilateral [4]

Solve, admire

Play, complete, improvise...



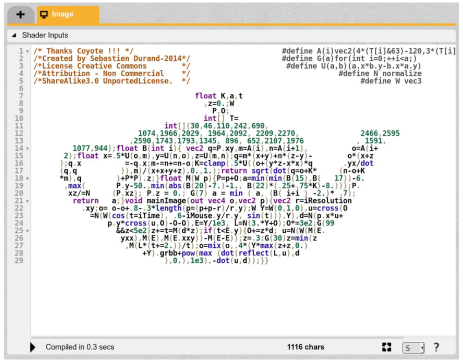
Play, measure, ...

Eat, taste, smell...

A Big Space of Programs

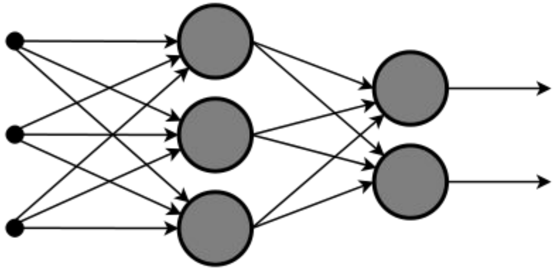
- Fact (from a provable theory):

"The smallest possible program that fits to your training data will achieve the best generalisation possible."



- We know how, but the search space is too large.

What about smallest possible constrained circuits?



...and we arrive at backpropagation (searching for smallest circuit).

Ian Goodfellow
@goodfellow_ian
Following

Replying to @ChombaBupe

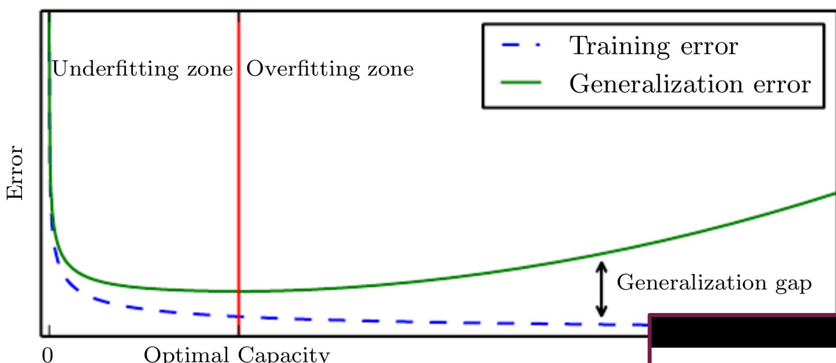
In situations where you can't use backprop, there are other methods you can fall back to. In situations where you can use backprop, I can't think of a situation where it would make sense to choose not to

11:27 PM - 15 Jan 2018

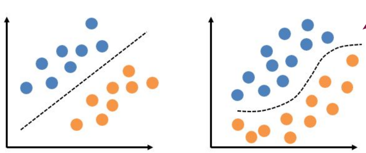
Statistical Learning Theory

if… not I.I.D:

"The discrepancy between training error and generalization error is bounded from above by a quantity that grows as the model capacity grows, but shrinks as the number of training examples increase."



Capacity



but I.I.D.!

- So how do we collect the dataset?
    - Close to <u>real I.I.D.</u> train/test/val
    - Get varied data
        - Varied photos
        - Varied camera types
        - Varied locations, views, scales, orientations, weather conditions, seasons, ...
    - Balanced classes
    - <u>Carefully</u> augmented data
    - ....
- And how to we build the model?
    - Dropout, L1/L2 regularisation
    - Tune layers/parameters
    - Weight sharing (convolutions)
    - Residual blocks
    - Transfer learning
    - Weight loss terms by imbalance
    - Early stopping...

Meta Learning

The goal:

- Learn to learn:

$$\theta^* = \arg\min_{\theta} \mathbb{E}_{\mathcal{D} \sim p(\mathcal{D})} [\mathcal{L}_{\theta}(\mathcal{D})]$$

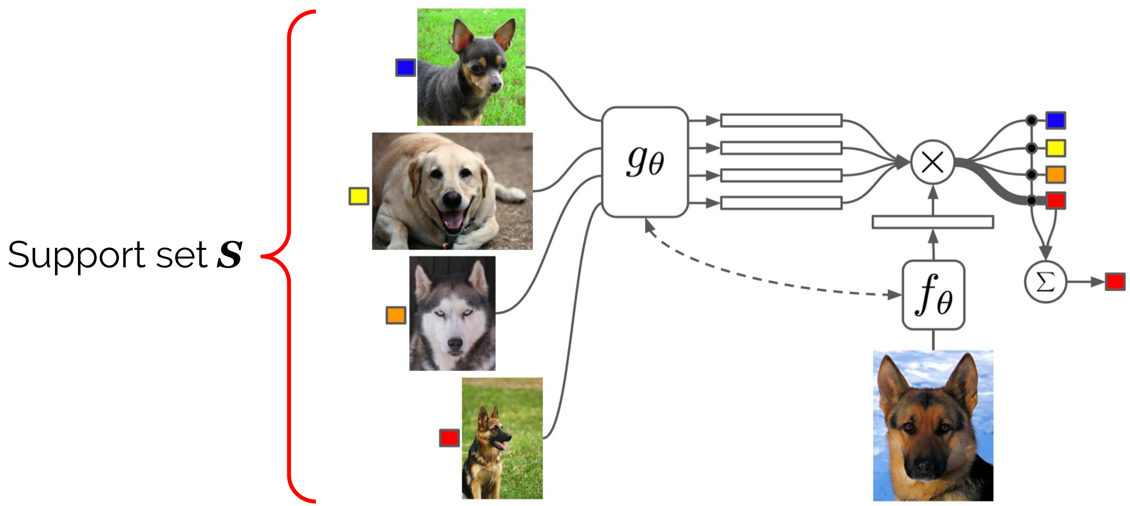
How?

- Don’t just train on one task, but train on many tasks
- So we “*simply*” replace training examples with training tasks, and pretend that's normal learning

Meta Learning & Supervised Learning

Traditional Supervised Learning, **Meta Learning**

$$\theta = \arg\max_{\theta} \mathbb{E}_{L\sim\mathcal{T}}[\mathbb{E}_{S^L\sim\mathcal{D},B^L\sim\mathcal{D}}[\sum_{(x,y)\in B^L} P_\theta(y|x, S^L)]]$$



http://metalearning-symposium.ml/files/vinyals.pdf

Meta Learning Approaches

Categories

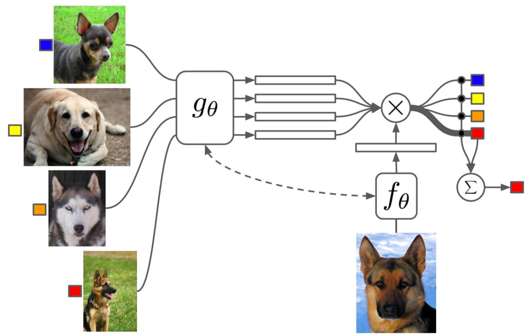
- Metric-based
- Model-based
- Optim-based

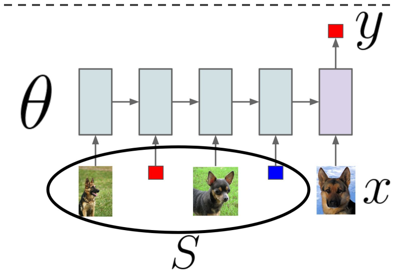
$$P_\theta(y|\mathbf{x}, S) = \sum_{(\mathbf{x}_i, y_i)\in S} k_\theta(\mathbf{x}, \mathbf{x}_i) y_i$$

$$P_\theta(y|\mathbf{x}, S) = f_\theta(\mathbf{x}, S)$$

$$\underbrace{P_\theta(y|\mathbf{x}, S)} = P_{g_\phi(\theta, S^L)}(y|\mathbf{x})$$

They all have this in common (S = a support set)



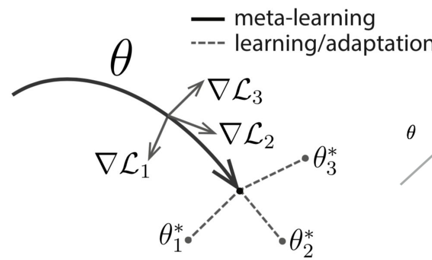


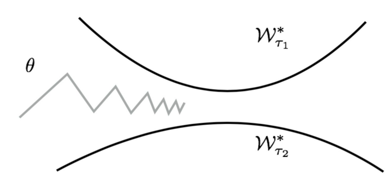
Research advances

- Few-shot datasets
- Simulation with error
- Self-play
- Interactive learning
- Curiosity-driven learning

Algorithm 2 Reptile, batched version

Initialize θ
for iteration $= 1, 2, \ldots$ **do**
  Sample tasks $\tau_1, \tau_2, \ldots, \tau_n$
  for $i = 1, 2, \ldots, n$ **do**
    Compute $W_i = \mathrm{SGD}(L_{\tau_i}, \theta, k)$
  end for
  Update $\theta \leftarrow \theta + \beta \frac{1}{n} \sum_{i=1}^{n} (W_i - \theta)$
end for





Few-shot Learning Datasets

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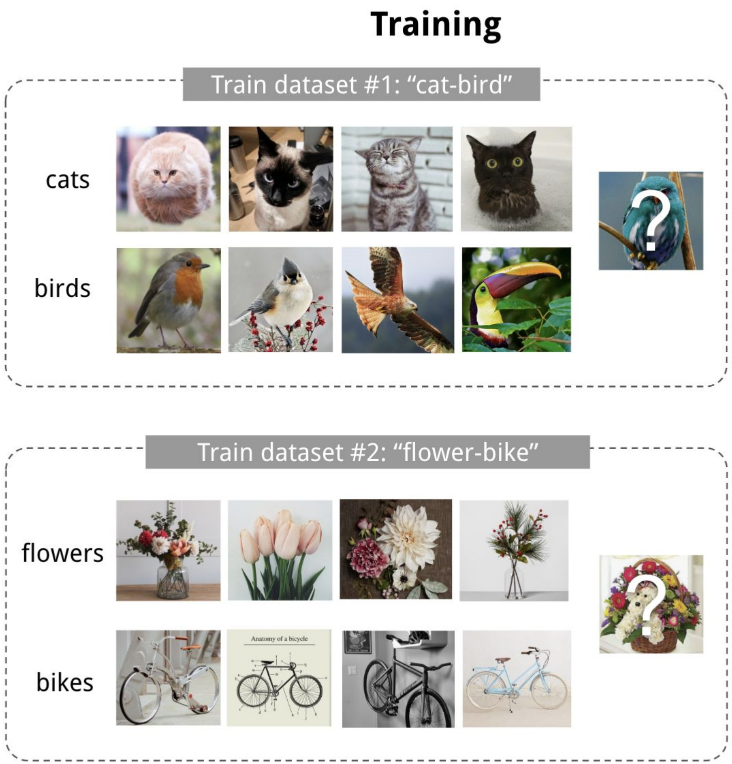
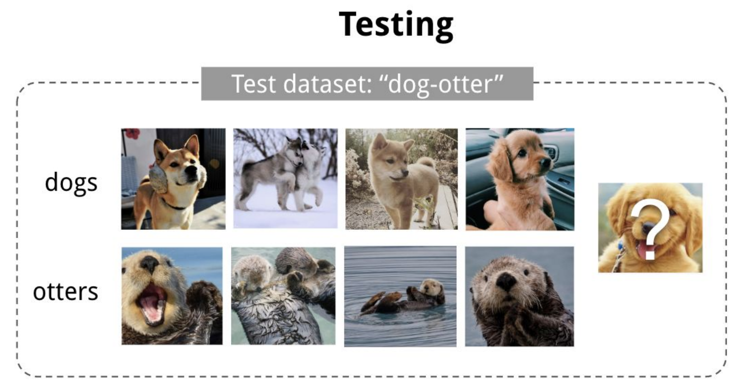
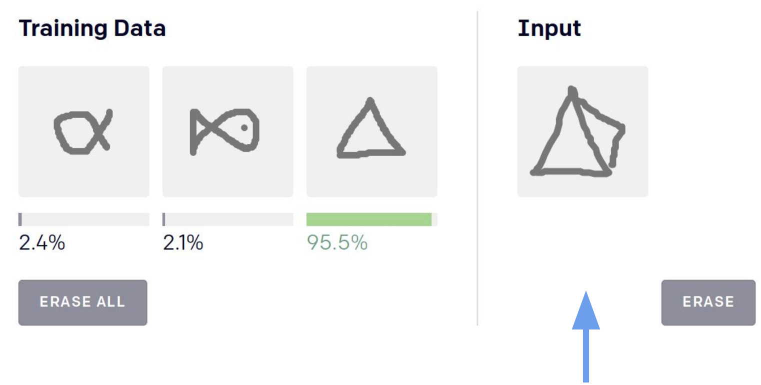
Omniglot

Mini-Imagenet

Few-shot Learning Examples





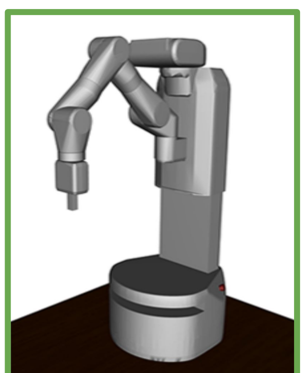


https://lilianweng.github.io/lil-log/2018/11/30/meta-learning.htm https://openai.com/blog/reptile/

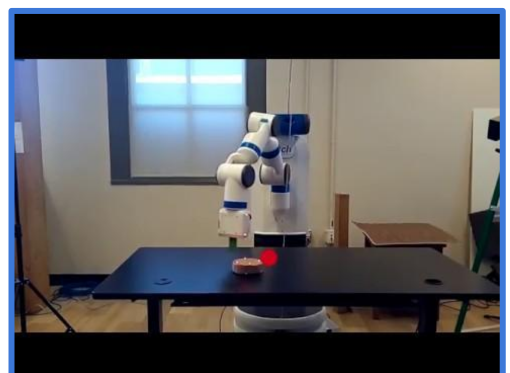
Simulation to Reality with Errors

Sim2Real

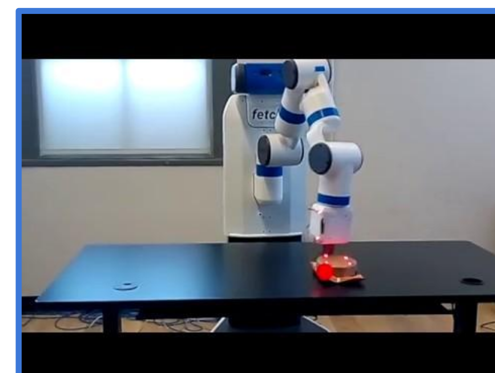
- Getting lots of simulation data is expensive/impossible
- If we randomise our simulation parameters, we can a policy that is able to quickly react to the unknown



Without Random Tasks

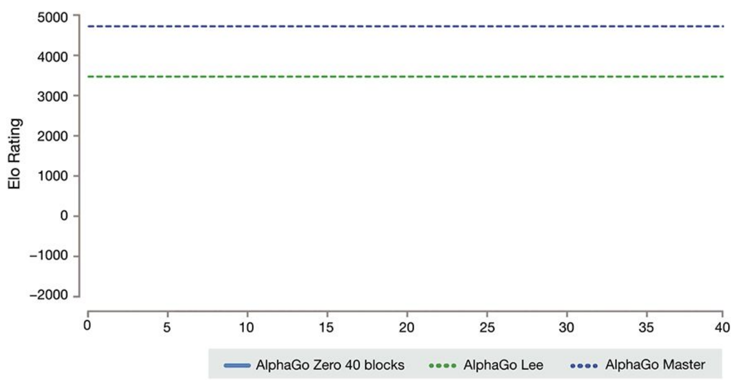


Random Task Dynamics



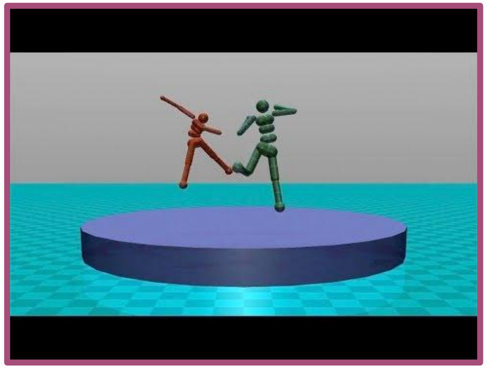
Self-Play

- Very old but very modern!
- Generates new data from the compute
  - That's big
- Self-play is a task that encompasses many other tasks
  - Moving, gravity, social interaction, responding to being shoved, ...



TD-Gammon, 1992!

Competitive Self-Play https://openai.com/blog/competitive-self-play/



Curiosity Driven Learning

Given a state transition tuple:

$$\{x_t, x_{t+1}, a_t\}$$

the exploration reward is defined as

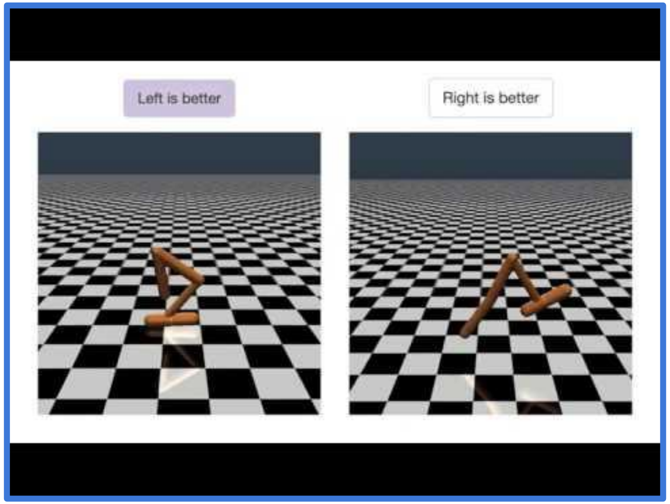
$$r_t = -\log p(\phi(x_{t+1})|x_t, a_t)$$

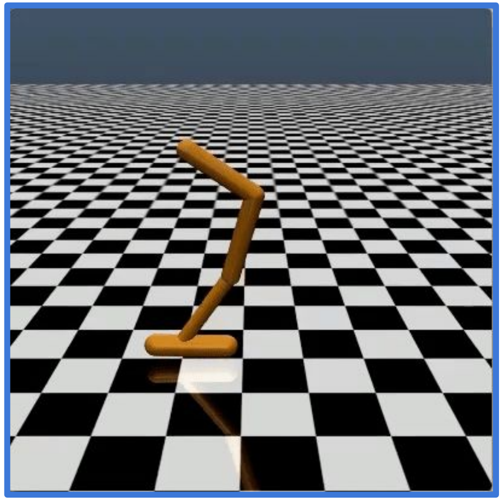
called is the **surprisal**. Maximising this reward favours transitions with high prediction error (regions where the agent has spent less time or with complex dynamics).

Interacting with Humans

Data efficient rewards: about 500 clicks to make a leg that backflips

A few clicks to get an atari game that does something totally unique (follow another car).

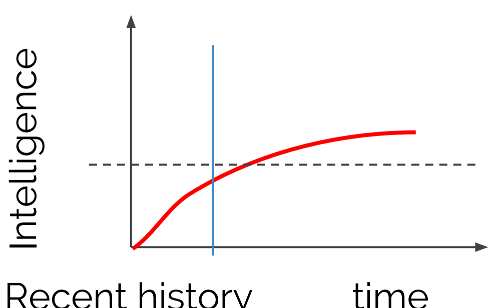


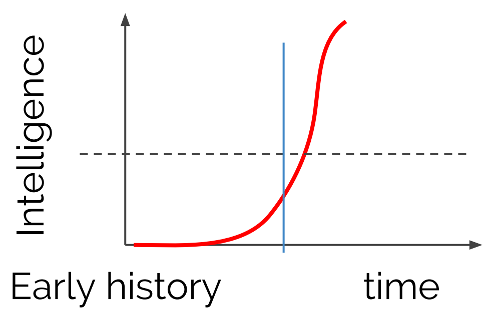


https://openai.com/blog/deep-reinforcement-learning-from-human-preferences/

Reflections

- Training task distribution ≠ testing task distribution (for meta and non-meta)
- If we go back to our big distribution of tasks, it doesn't seem *so far away*....
- Looking to the future
  - The need for task and dataset diversity
  - Meta learning towards meta level comprehension
  - What are the implications of meta learning?





We still don't know the future, but (from security)...

- low immediate threat, but high risk
- risk=impact * probability/cost