Deep Learning

Learning to learn within the bigger picture

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Lecture Overview

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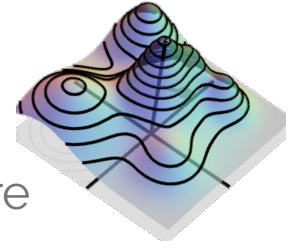
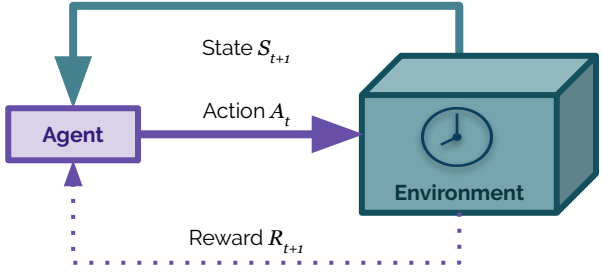
Recap

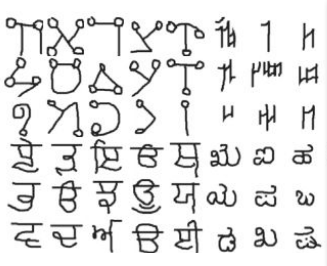
- Manifold Learning
- Reinforcement learning
- ….all the way back to learning in nature





Aims of today's lecture

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



A Big Distribution of Data

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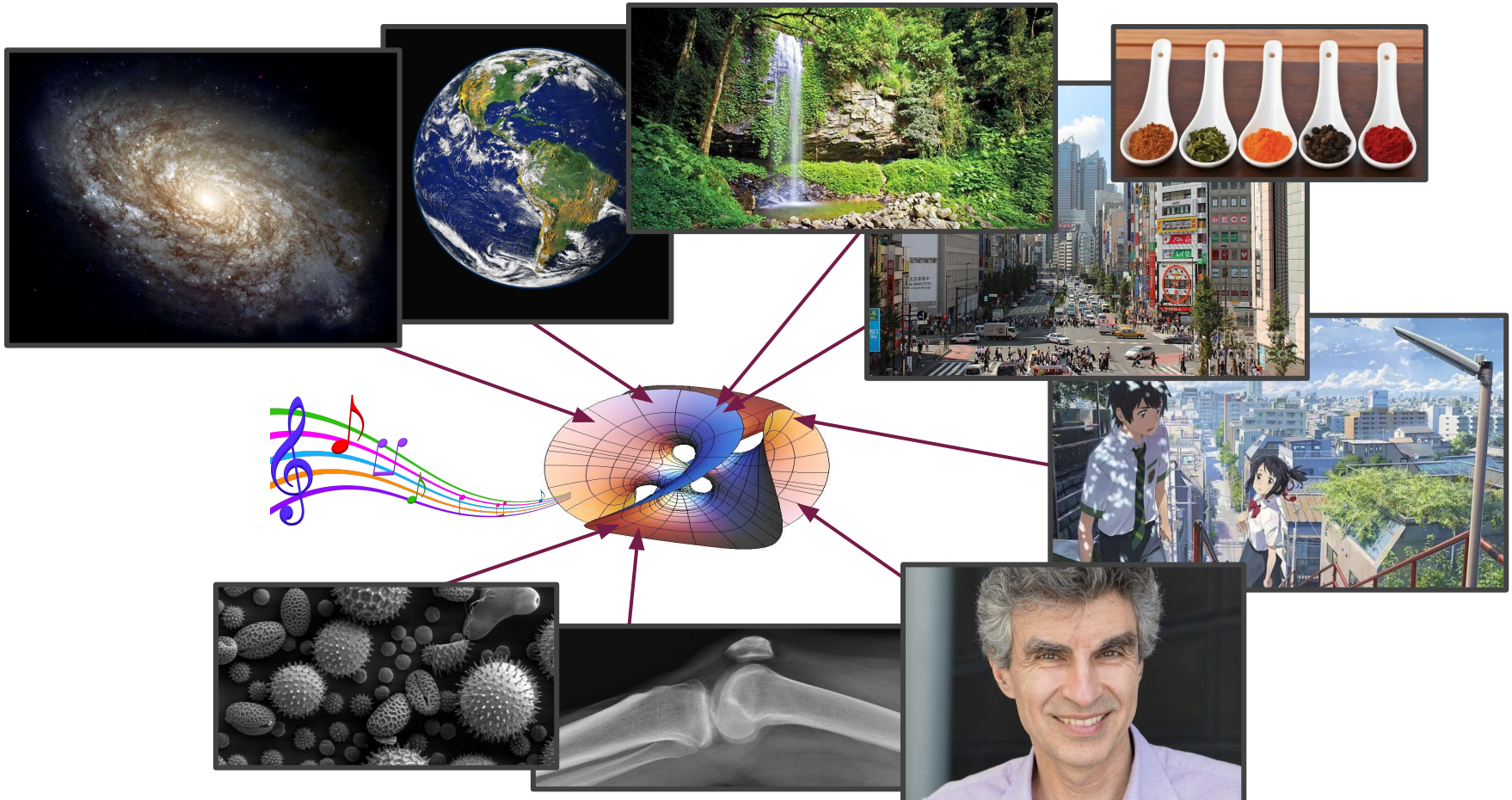

A Big Distribution of Tasks

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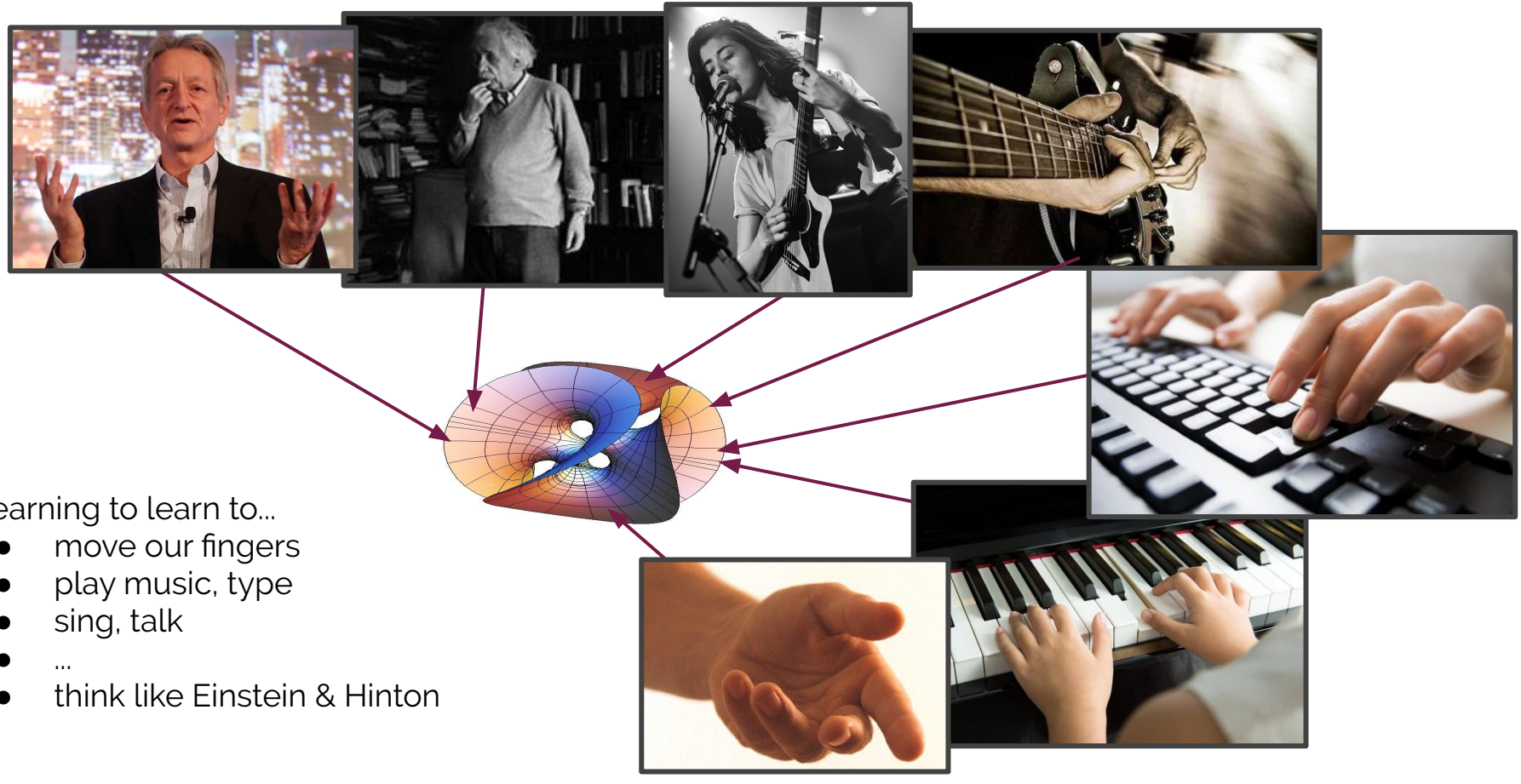


Learning to learn to...

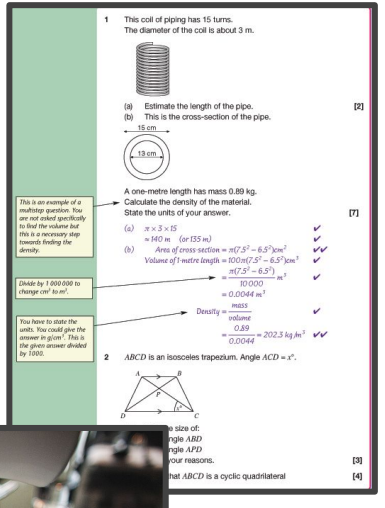
- move our fingers
- play music, type
- sing, talk
- ...
- think like Einstein & Hinton

A Big Distribution of Tasks

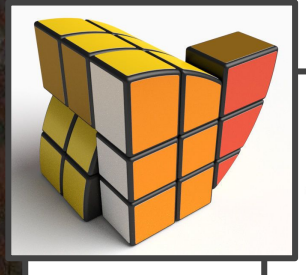
- What is this?
- What do you do with it?

Can we generalise to unseen tasks and unseen data?

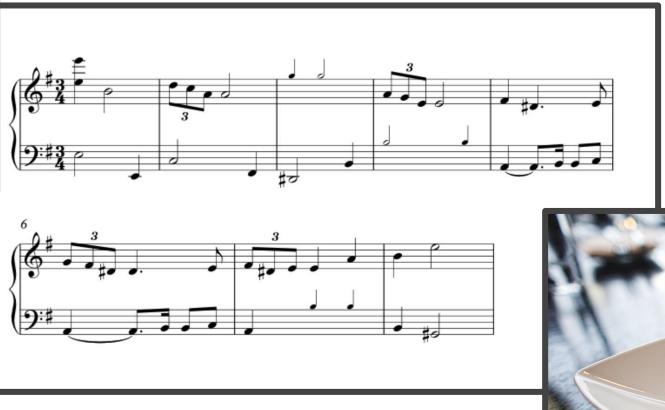
Solve, comprehend, ...



Solve, admire



Play, complete, improvise...



Play, measure, ...

Eat, taste, smell...

A Big Space of Programs

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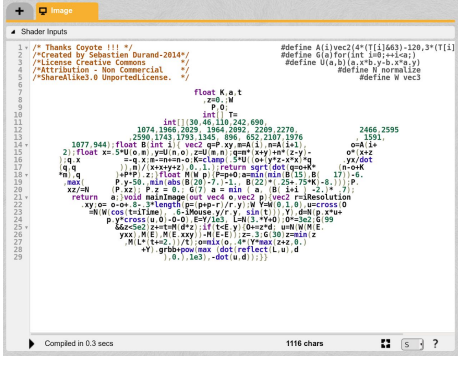
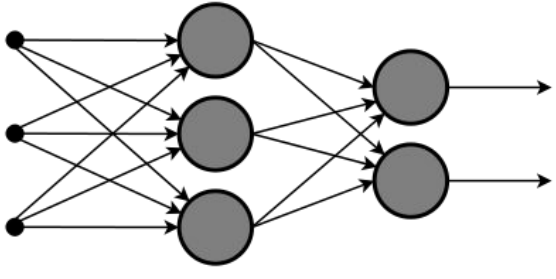
- Fact (from a provable theory):

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

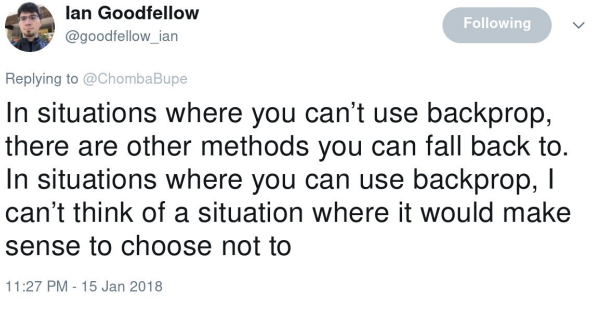


- We know how, but the search space is too large.

What about smallest possible constrained circuits?



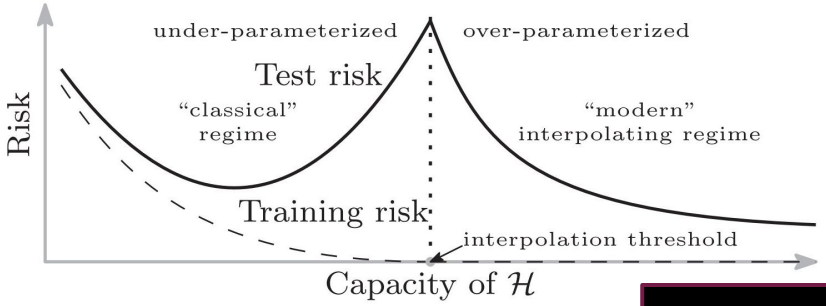
...and we arrive at backpropagation (searching for smallest circuit).



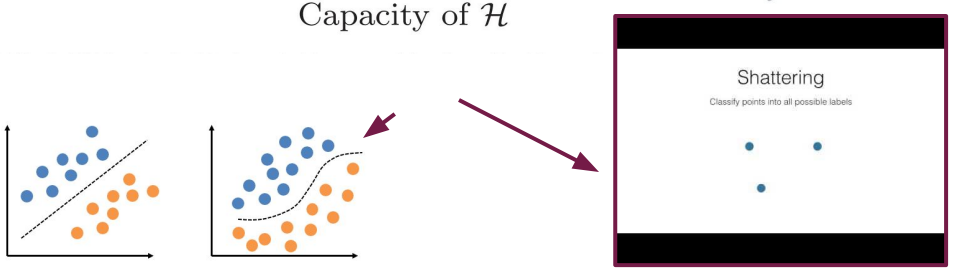
Statistical Learning Theory

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."



but I.I.D.!



- So how do we collect the dataset?
  - Close to real I.I.D. train/test/val
  - Get varied data
    - Varied photos
    - Varied camera types
    - Varied locations, views, scales, orientations, weather conditions, seasons, ...
  - Balanced classes
  - Carefully 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...

Thinking with Distributions

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Task dataset conditions are rarely IID to training conditions

!=

100,000 images
Samsung camera / mostly Android
Held in one orientation

Different/future product line
Different brands
Different expected cameras (mostly iPhone)
Different orientations
Different expected lighting, weather, …
Different user interests, ….

Thinking with Distributions

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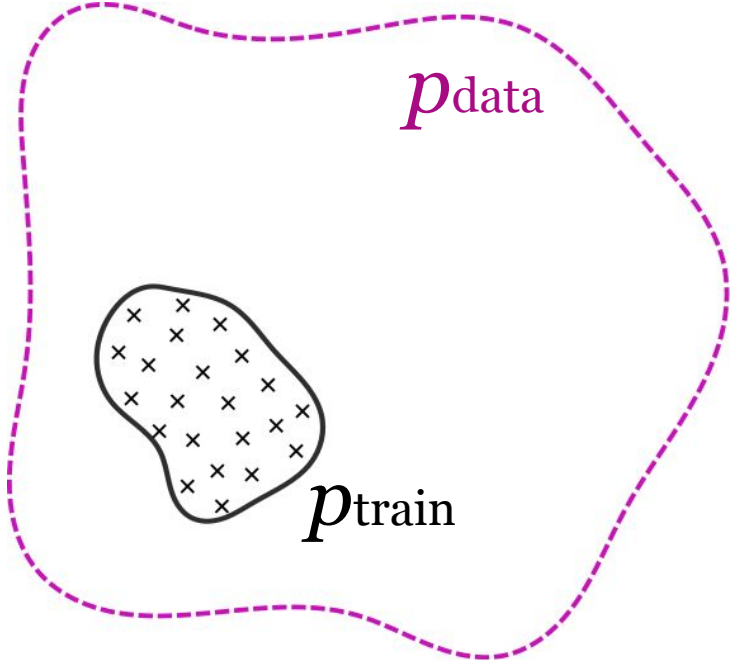
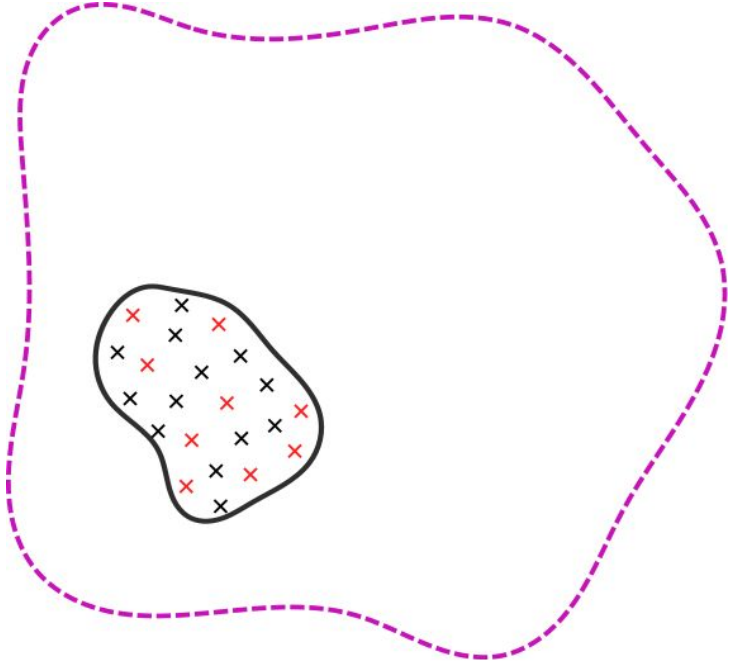
A common lie...

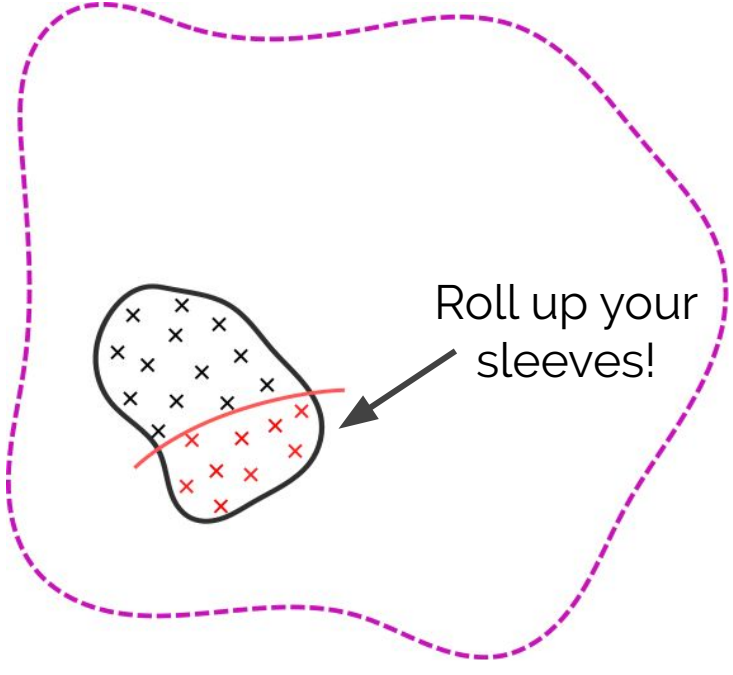


99.7% “test” accuracy!

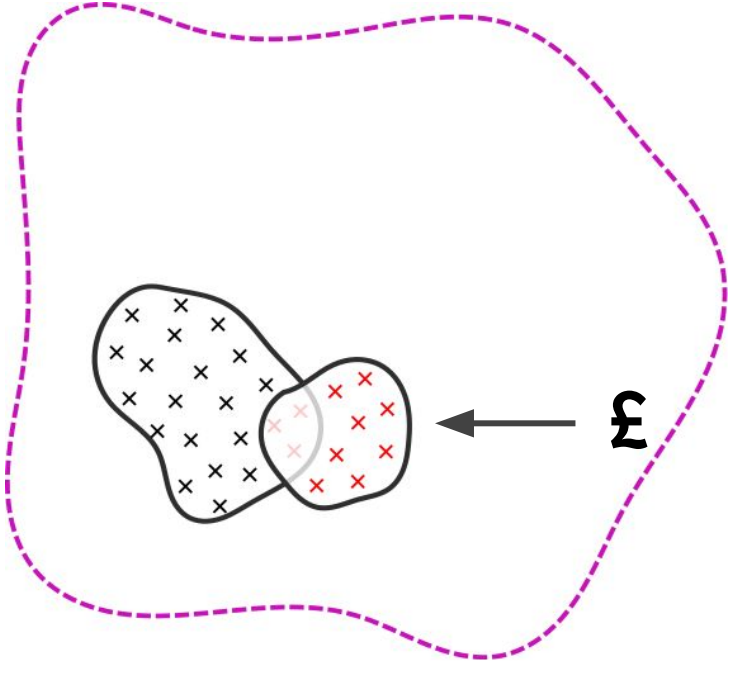


Thinking with Distributions

62% “test” accuracy
(but closer to the truth)



51% “test” accuracy
(even closer to the truth)



Thinking with Distributions

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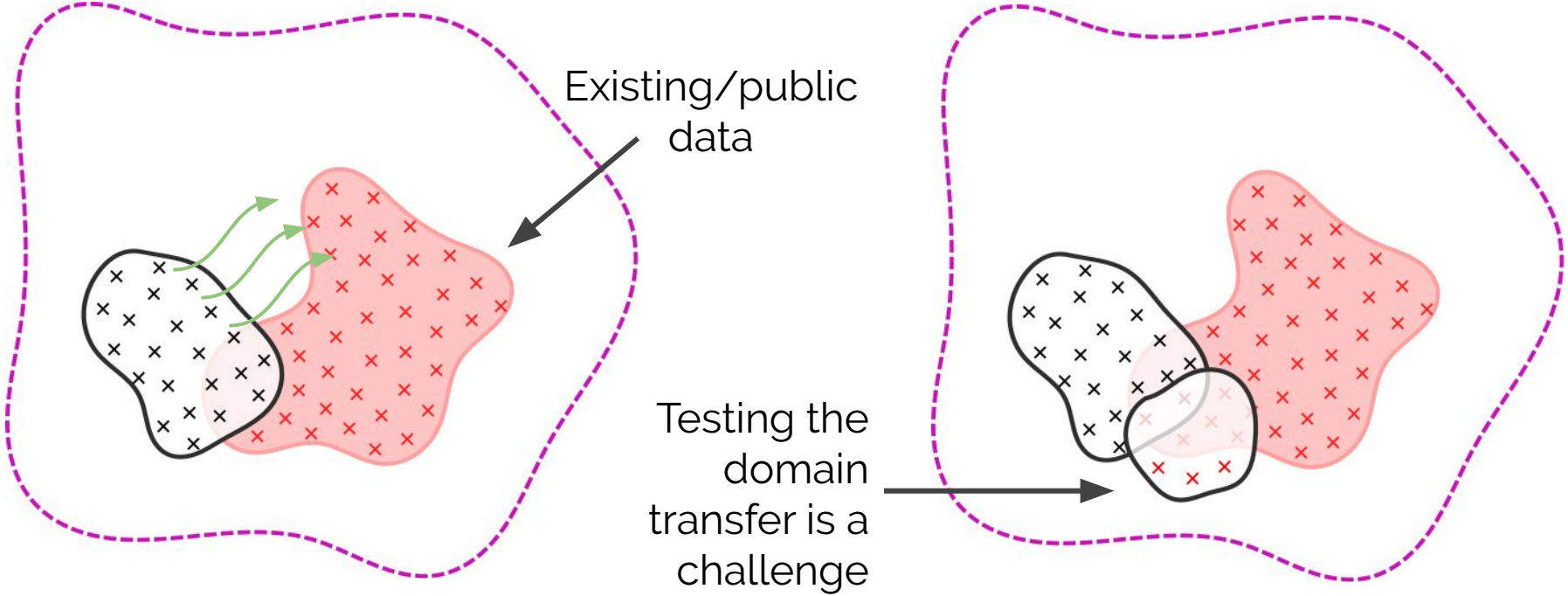
Generative models (e.g. Domain Adaptation)



Meta Learning

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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

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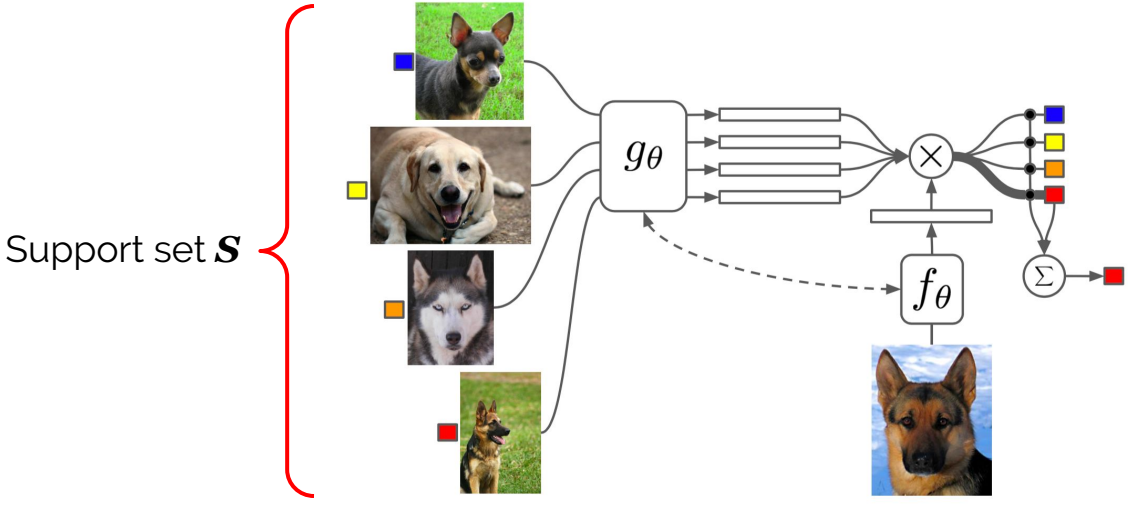
Traditional Supervised Learning, **Meta Learning**

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



Meta Learning Approaches

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Categories

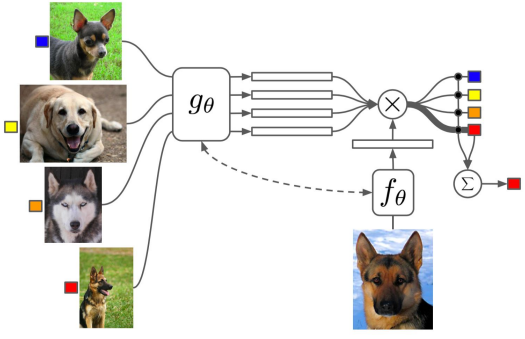
- Metric-based
- Model-based
- Optim-based

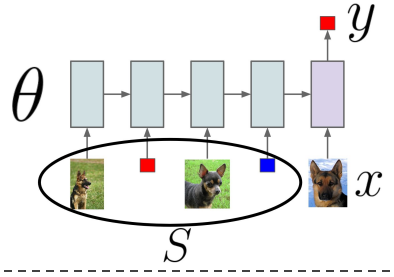
$$P_\theta(y|\mathbf{x}, S) = \sum_{(\mathbf{x}_i, y_i) \in S} k_\theta(\mathbf{x}, \mathbf{x}_i) y_i$$

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

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

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



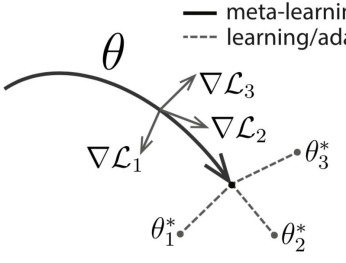


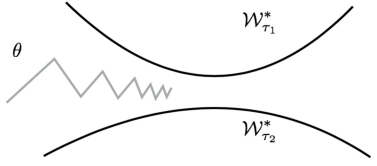
Research advances

- 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 $W_i = \text{SGD}(L_{\tau_i}, \theta, k)$
  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

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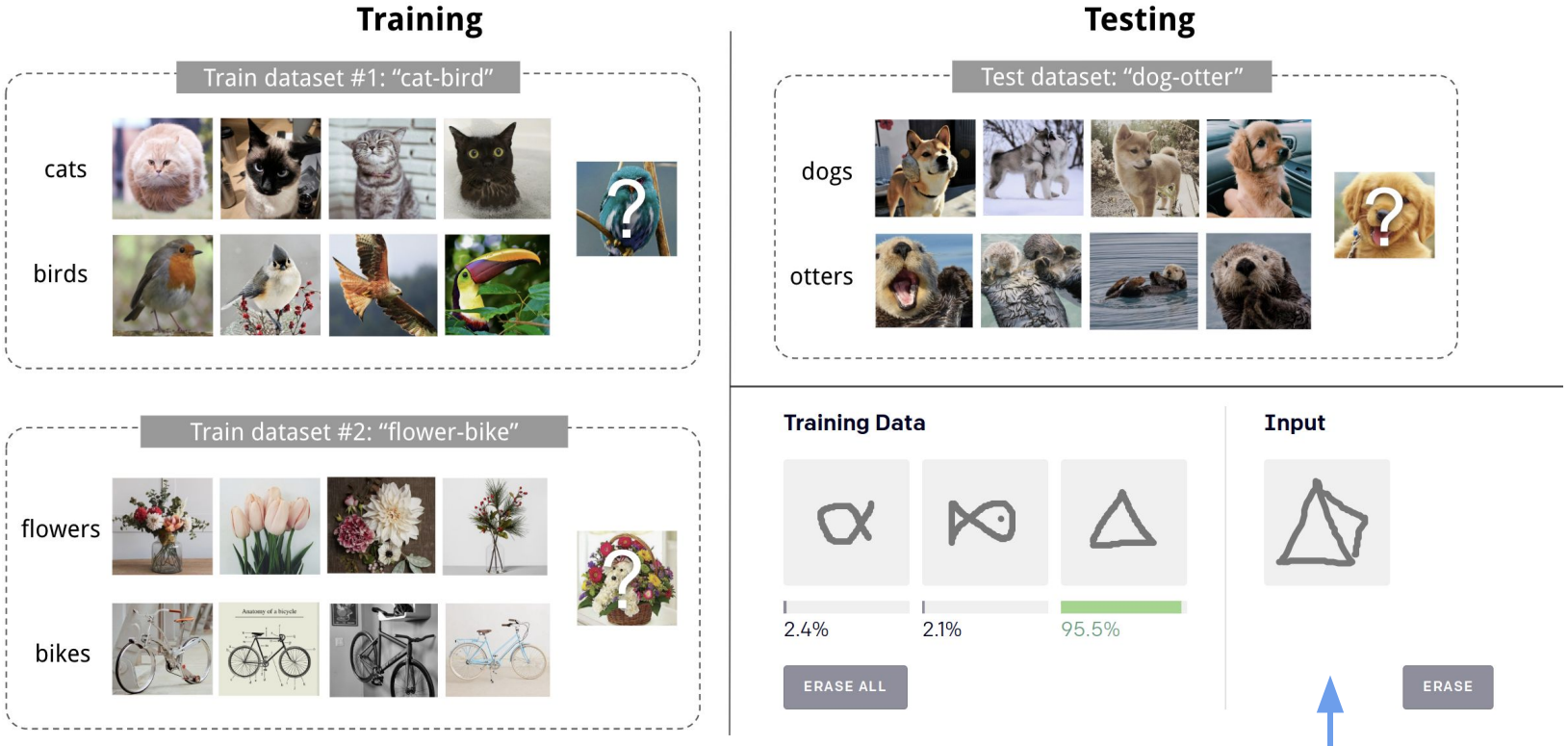

https://lilianweng.github.io/lil-log/2018/11/30/meta-learning.htm https://openai.com/blog/reptile/

Model-based

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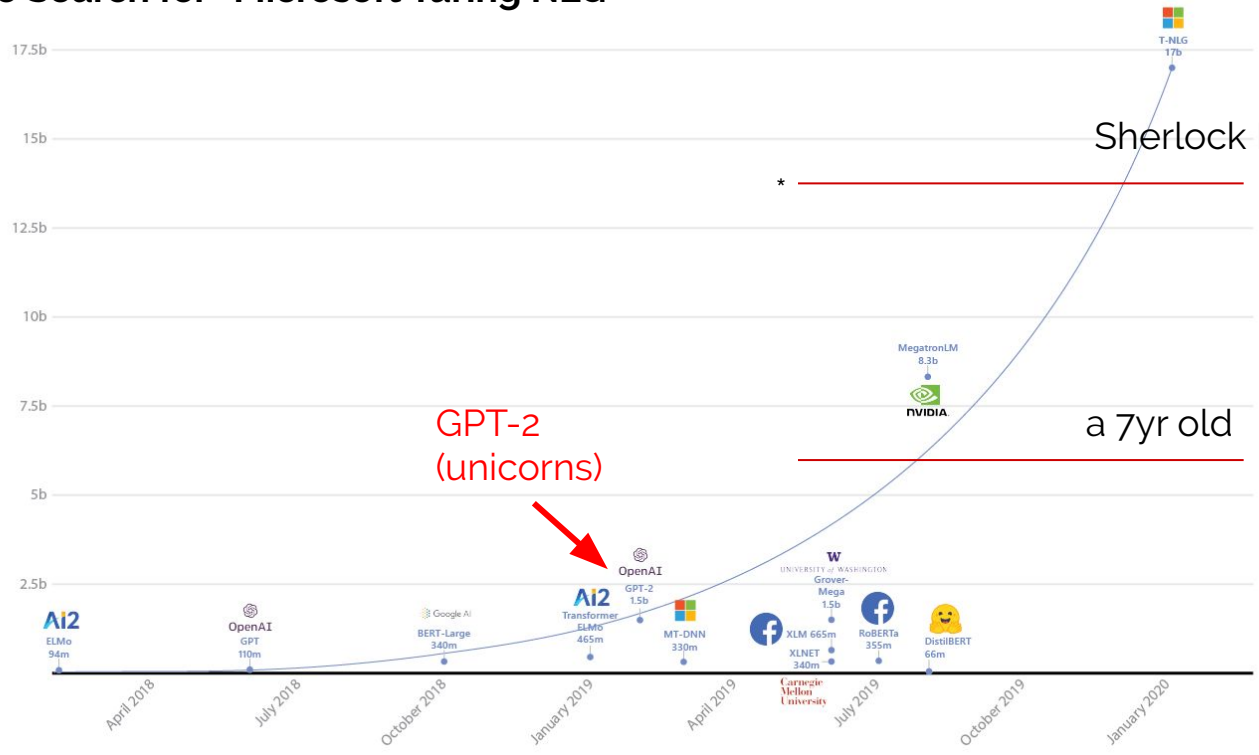
x,S = “The cat sat on the”

$$p(x) = \prod_{i=1}^{n} p(s_n | \overbrace{s_1, \ldots, s_{n-1}})$$

Trained on the internet… **“mat.”**

Recap: The *Meta* Learning Race

Do a Google Search for "Microsoft Turing NLG"

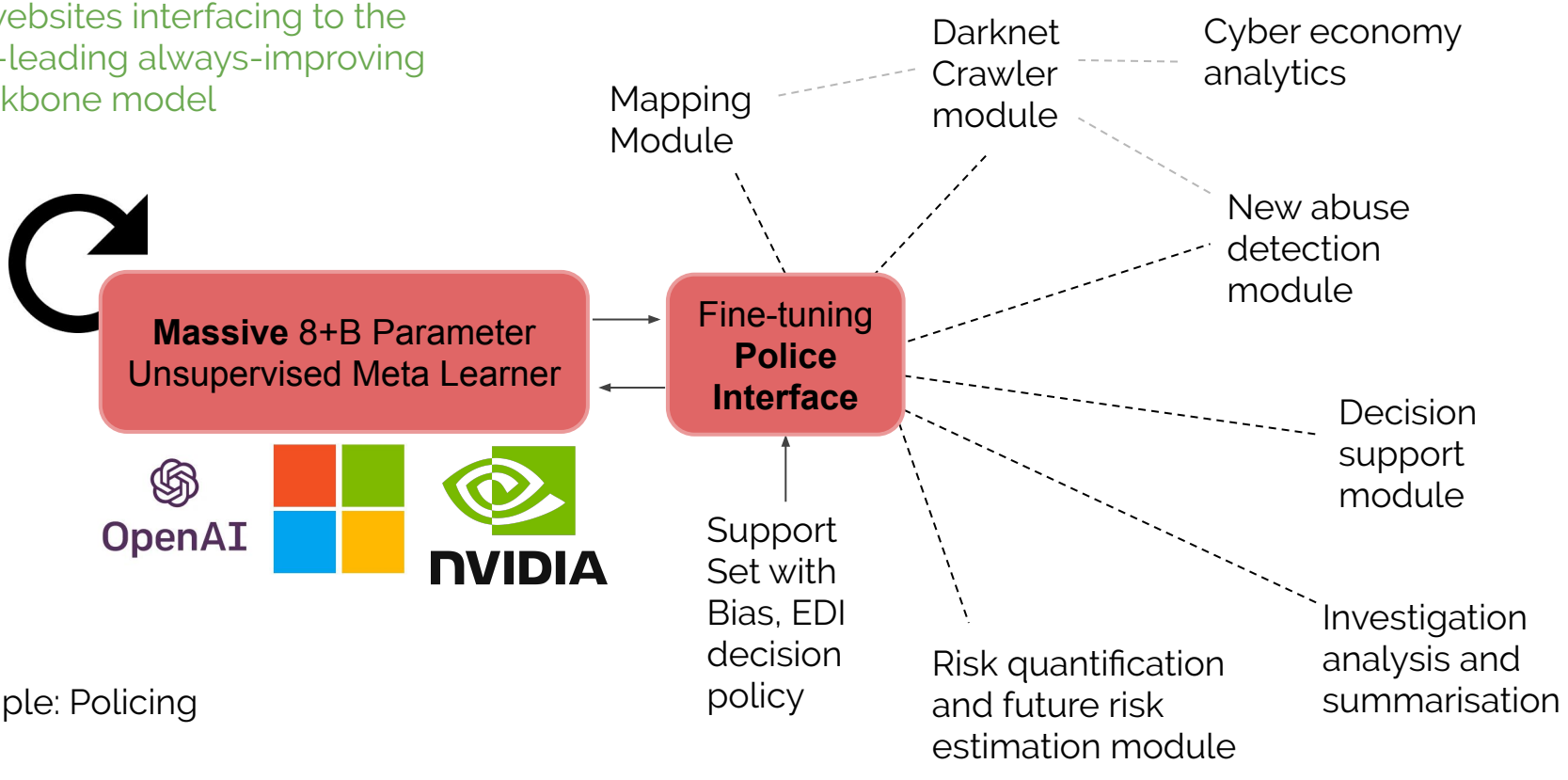


- Research
- Summarise
- Estimate risk
- Communicate
- Explain decisions

Released **February 10th**, 2020 - Microsoft Research

Interfacing

Small websites interfacing to the market-leading always-improving big backbone model

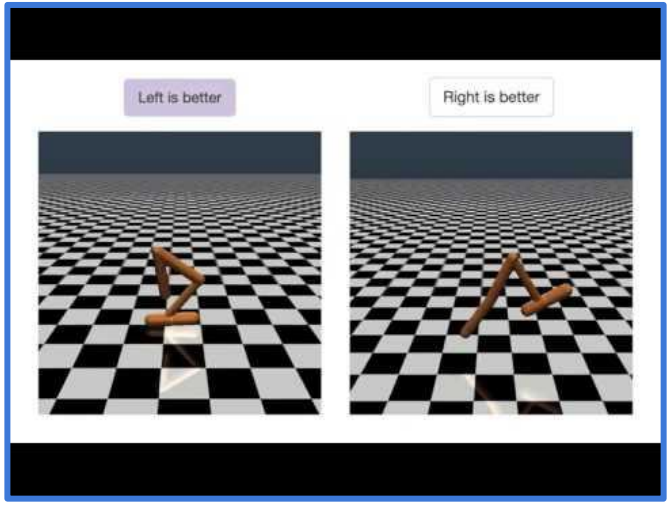


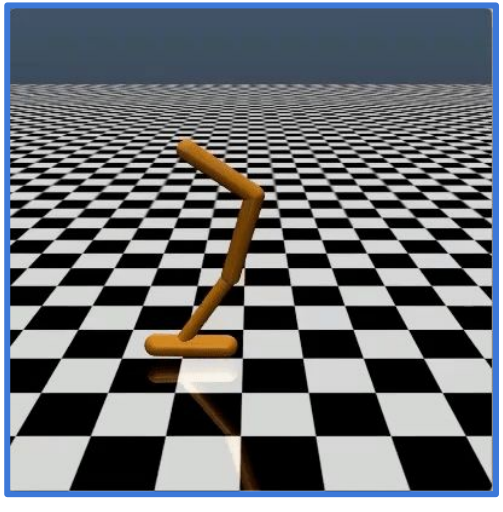
Example: Policing

Interfacing

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

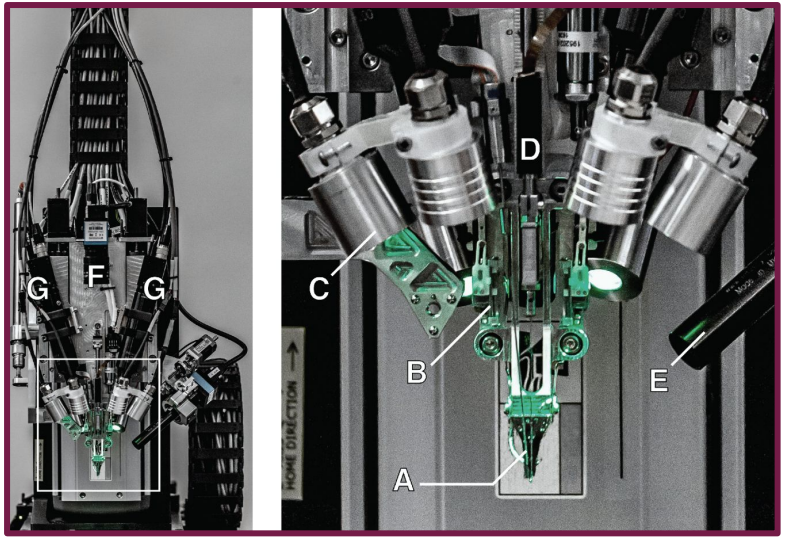
A few clicks to get an atari game that does something totally unique (follow another car).

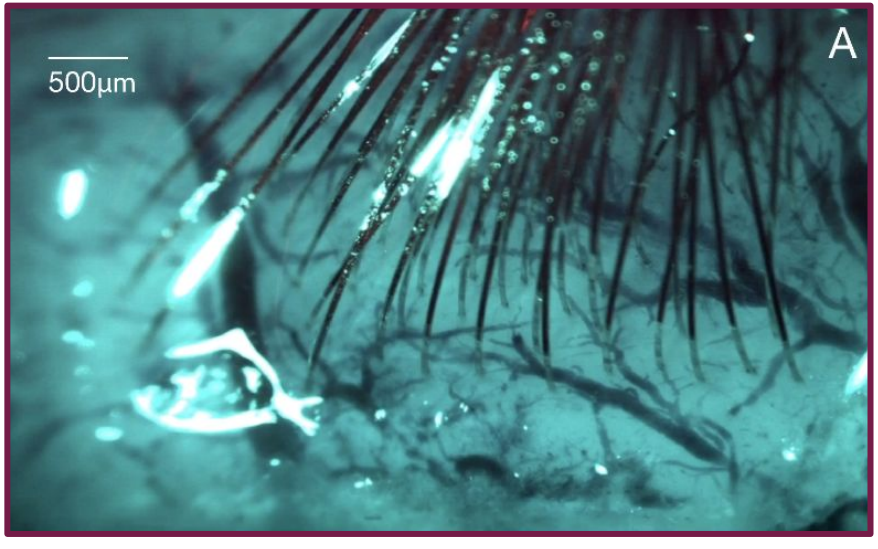




https://openai.com/blog/deep-reinforcement-learning-from-human-preferences/

Brain Machine Interfaces (BMI)

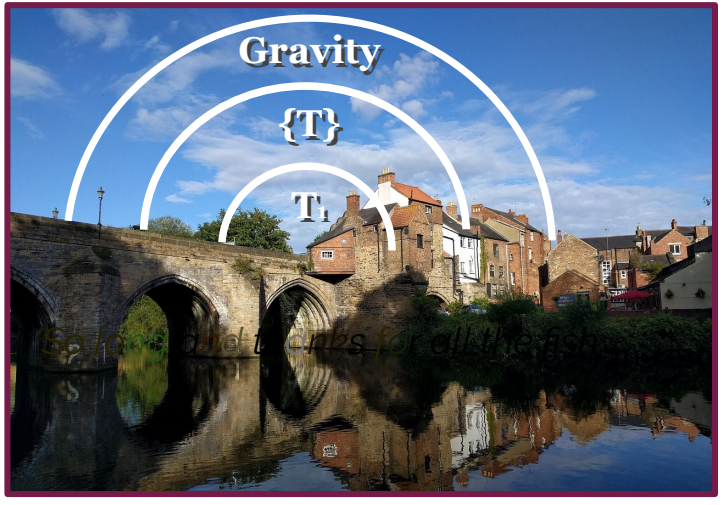


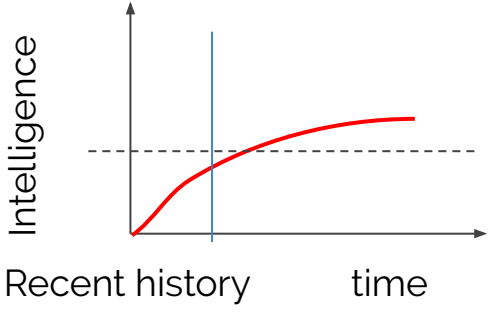


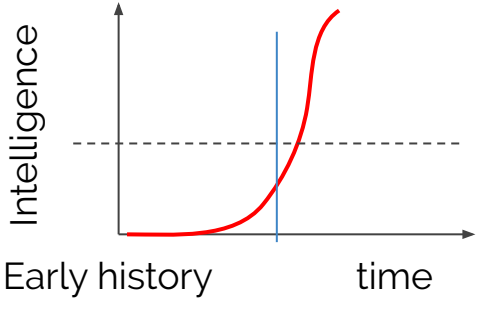
https://www.neuralink.com/

Reflections

- Big diverse datasets learning p_{data}
- Vision and text starting to align
- Staying in-the-loop
  - Natural dialogue/smart interfacing
  - Reinforcement learning to communicate goals
  - BMI
- Reasoning - is there more than imitation?







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

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